# Υπολογιστική Μουσική Ανάλυση Παιδικών Αυτοσχεδιασμών με εξόρυξη δεδομένων

## Computational Music Analysis of Children's Improvisations

A Data Mining Approach

Doctoral Thesis

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# Abstract

Music improvisation is lately gaining considerable attention, as a skill that should be cultivated and promoted through the educational music process. Once a dexterity rather neglected, it is now recognised as a skill of significant importance in the development of musical abilities. Hence, children have been encouraged to improvise during their musical classes and new teaching techniques and tools have emerged, advocating the whole improvisation process and aiding both parties, students and tutors, throughout the training course.

These techniques have been developed towards the teaching process as well as the assessment of the progress of the children, and provide qualitative and quantitative measures in order to evaluate and assist children's improvisation efforts. With the introduction of informational technology, such tools have become sophisticated and automate the whole process; they provide at the same time the means for further analysis of the improvisations, by collecting the recordings, analysing the data and pinpointing at various interesting factors for further analysis.

The research reported in this thesis, has been conducted within the EU MIROR FP7 project. In the course of the project, a number of psychological experiments were performed, including a number of improvisations of children, between 4 and 8 years old. The improvisations were performed on a MIDI keyboard and the resulting data collected and analysed in a number of ways. The aim was on the one hand to identify significant patterns in the music produced and on the other to come up with a model of assessing the creativity embedded in those improvisations.

The results are explored towards a three-fold goal: (i) the identification and discovery of common repeated musical patterns (ii) the evaluation of the musical creativity exhibited through the assessment of the musical improvisations in terms of a newly constructed creativity model and (iii) the application of contrast data mining, i.e. the identification of differences of repeated musical patterns found in a corpus, with respect to another one.

In order to realise the above goal, a computational model has been introduced, designed and implemented. This work and its results are presented in this thesis.

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# Chapter 1

# Introduction

While improvisation has been an essential component of music throughout history, its manifestation in children's music-making is a debated issue (Azzara, 2002). Furthermore, while it is seminal to all human cultures, it is not as yet much studied or understood. Research has revealed that improvisation is a significant aspect of children's musical development and an important venue of creativity (Webster, 2002; Ashley, 2009), yet many aspects of children's improvisation constitute a rather newly emerged terrain, such as improvisation using music technology. When children are improvising, particularly at an early stage of development, they usually try to express themselves without following any particular rules. Creativity then can emerge naturally (Koutsoupidou & Hargreaves, 2009).

In the present work we explore the thesis that children's musical improvisations using interactive information technology, as well as the computational analysis of the musical output produced in order to find regularities and patterns of significance, can provide a useful addition and a valuable tool that can render even more constructively the blending of technology into children's musical routine. On one hand, they can offer a tool to assist the teacher in providing the musical dictions and on the other, provide the learner with a means that can advance his/her musical capabilities through playful interaction.

In order to achieve this, we employed specialised data mining techniques and developed a set of lexicographically empowered investigation software tools to analyse the musical output produced by the children's improvisations. These improvisations took place within the framework of carefully designed and executed psychological and educational experiments. All these experiments were performed within the framework of MIROR[1] FP7 European project (Grant agreement ID: 258338).

The results of the above investigation are herein analysed and presented and several conclusions are drawn. Future steps that this research may follow are also outlined and discussed.

## 1.1 Computational Musicology

Computational Musicology can be roughly defined as the study of music with computational models and processes. It is an interdisciplinary domain that draws both from musicology and computer science. Computational Musicology may be considered as sitting under the wide umbrella of Systematic Musicology. Systematic Musicology as a discipline is constituted of subdisciplines that are set out primarily to explain music in general, often through the manipulation of data-oriented and empirical manifestations of the musical process (Huron, 1999; Parncutt, 2007; Leman, 2008).

From the advent of modern day computer era, the usage of computational methods and techniques in music analysis emerged naturally and has gradually gained momentum in recent years. Huron (1999) predicted that computing will transform musicology into a data-rich field and hence will introduce smoothness and easiness on hypothesis testing. In a similar manner, as an advocate of the Computing Musicology field, Cook (2005) in his seminal paper incited musicologists not to lose the opportunity for a close relation to information technology.

Over the last 50 years Computer Science has developed numerous data structures and algorithms that can be utilised to represent and process music. The extent to which these constructs can be employed to represent music and how precise the

[1] **M**usical **I**nteraction **R**elying **O**n **R**eflexion; official website: http://www.mirorproject.eu

music representation can be are issues that became gradually more significant. It was found that readily available musical models for computational processing were neither yet widely available nor mature. As Hewlett & Selfridge-Field (1991) very accurately stated: *In order to understand the complexities of representing music in the computer, it is essential to appreciate that a musical work may be apprehended in several domains. These include what is heard (sound), what is read (notation), what is performed (gestures), what is consciously apprehended by the listener (a cognitive model)* (p. 382)

Therefore, Music Theory core elements, such as pitch, chords, intervals, rhythm, meter, have to be revisited in order to be able to be suitably processed automatically. Work has already taken place towards this direction, producing results such as pitch spelling algorithms – pioneered by Longuet-Higgins (1962) – or digitized models of scales – introduced by Honingh & Bod (2011) – as well as several approaches to representation (e.g. Butterfield, 2002; Cambouropoulos, 1998, 2006; Conklin, 2002), discussed in more detail in Chapter 2.

It is worth mentioning here that Computational Musicology shares a lot in processing methods with Natural Language Processing domain and gained a lot in the last years from the vast advancement in Computational Biology (aka bio-informatics). DNA sequences, text and music share the model of enormous sequences of attributes and hence similar algorithms can be employed to process data from all the above fields.

A note should be made about the two “different” worlds in music, as it is perceived by the Computational Musicology discipline: that is the world of acoustic representation (viz. audio) and the world of symbolic representation that is discrete music structures which are related to the musical score. The work discussed within this thesis falls into the latter domain. In symbolic representation we are not dealing directly with the musical sound or its direct digital representation as it is stored in computer files of various audio formats (e.g. aiff, mp3, aac, wav etc). Rather, we are dealing with the representation of music in a system that encodes discrete pitch and timing information, such as MIDI, which is much closer to the representation of the musical score.

There are advantages and disadvantages with both the audio and the symbolic approaches. Certainly, there are far more readily available data in audio formats.

However, audio has several associated components that "obscure" the music, which means that often we cannot even have the actual notes of the score: performance and recording issues should be taken into account, voice separation and melody identification issues are far from being solved, etc. In symbolic data, we are closer to the score, and therefore closer to the discipline of music analysis. That allows us to make headway to higher levels of musical knowledge, structures, abstract representations, relations etc. Using symbolic representation in order to look for patterns in a data set, is obviously much more promising since the elements to look for are already quantised and in a form convenient for computational processing.

Nevertheless, there is always a certain degree of uncertainty in how close the selection of the input to a computational work defines the music itself. As Marsden (2016) discussed the input to analytical process is always an approximation of the music itself and there is not clear distinction what is included in the input and is excluded. As he accurately stated: *the objective of computational music analysis should probably not be to generate 'an analysis' but rather, like forensic science, to answer specific music-analytical questions with a degree of complexity, speed and accuracy* (p. 26-27).

What is, however, the importance of identifying repeated patterns in a data set? The question brings us in the province of repetition in music that is in identifying repeated patterns in music. And repetition is one of the most significant features that give music its distinct fundamental nature – for some perhaps it is what distinguishes it from mere noise (see also 2.1.4).

## 1.2 The Background: The Reflexive Interactive Paradigm and the MIROR project

The substrate on which the research discussed in this thesis took place, was the data collected from children's improvisations administrated within the framework of MIROR project. The MIROR Project aimed at developing a platform for music learning and teaching in early childhood, based on the Reflexive Interactive paradigm. The platform was designed to promote specific cognitive abilities in the field of music improvisation, both in formal learning contexts (kindergartens, primary schools, music schools) and informal ones (at home, children's community centres, etc.).

The project was based on a novel spiral design approach involving coupled interactions between technical and psycho-pedagogical issues. It integrated both psychological case-study experiments, aiming to experiment cognitive hypotheses concerning the mirroring behaviour and the learning efficacy of the platform, and validation studies aiming at developing the software in concrete educational settings. The project aimed to promote the reflexive interactive paradigm not only in the field of music learning but more generally as a new paradigm for establishing a synergy between learning and cognition in the context of child/machine interaction.

The Reflexive Interaction Paradigm of learning is based on the idea of letting users develop new skills through their interaction with intelligent, interactive machines (Addessi & Pachet, 2004; Addessi, 2014). The new skills develop within novel cognitive frames evolving via the interaction of learners with machines (viz. new musical instruments, artificial intelligence constructs and new technology in general). The learners develop new musical concepts (e.g., tonal harmony, improvisation etc) not by direct teaching, but indirectly through the actual interaction between the learner and the machine.

Based on the above concept, an IT system was developed at the Sony CSL Laboratories in Paris, the Continuator (Pachet, 2002). The system consists of a MIDI input – that is usually a MIDI keyboard – and a MIDI output. The typical interaction with the system involves the learners playing a musical sequence of any kind and the reply of the Continuator. This procedure can be repeated many times with the machine adapting continuously to the user input.

The musical style is approached from a technical point of view as a collection of statistical distributions of notes, chords, their ordering as well as some other musical elements. The more consistent with the style the user input is, the more stylistically consistent the Continuator's output will be.


**Fig. 1. User input (top staff) and the Continuator response (Pachet & Addessi, 2004)**

The engine of the Continuator that produces musical responses is based on a Markov model (Rabiner, 1985) and retains certain musical characteristics (from the user input used for learning), such as melodic patterns, harmonic progressions, dynamics and rhythmic patterns. Hence the output produced is similar (but different) to the user input (see Fig. 1).

The Continuator has been used in experiments with young children (3-6 years old), producing remarkable results (Addessi & Pachet, 2005a, b; Rowe et al., 2015). The experiments followed specific protocols and the gathered data analysed and suggested that the Continuator triggers the development of music behaviours.

The Continuator is exploited in the MIROR (Musical Interaction Relying on Reflexion) project, within the 7th FP. It evolved into the MIROR-IMPRO system, which offers a much richer set of functions and also employed an advanced graphical user interface (Pachet, 2017).

The work presented herein, analysed the data gathered from the experiments that were performed within the MIROR project. Several experiments with children based on various protocols were performed. These experiments produced a large data set that was computationally analysed in order to assess the development of the musical process of the children, and the significance of the experimental parameters.

It should be made clear here what is meant by the term *improvisation*, throughout this work. Improvisation as The New Grove Dictionary of Music & Musicians defines it is *The creation of a musical work, or the final form of a musical work, as it is being performed. It may involve the work's immediate composition by its performers, or the elaboration or adjustment of an existing framework, or anything in between.* This binding with an existing framework, in other words with a particular style or tradition or musical idea renders a particular set of rules which is imposed on the typical actor of the musical improvisation.

Hence, someone for being able to improvise needs to be taught, either through a formal or informal way, a certain body of music culture. However, within the framework of this work we accept a more relaxed definition of improvisation. Since there was no prerequisite that the children had to know how to improvise when playing with the MIROR-IMPRO system, we considered musical improvisation to be any musical creation produced through the interaction with the system.

We are not going to discuss here further the issue, since it is a large topic by its own and its deeper coverage is beyond the scope of this work. Particular discussion on improvisation and new technologies is given in section 2.2.2.

## 1.3 The Context of the Work

It is worth clarifying here how the research, reported within the current thesis, fits into the greater picture and what it seeks to accomplish.

As mentioned above, the children interact through a MIDI keyboard with the MIROR-IMPRO system, thus producing music, which is realised as a set of MIDI files. The interaction with the MIROR-IMPRO is actualised in a musical dialogue form, with the child's initiative. The child enters a phrase, then the system responds, then the child enters a new phrase, the system again responds and so on.

The musical data gathered in such a way can be subsequently analysed to provide useful input and "diagnose" the child's performance. Our contribution lies in providing the technical methods and processes, based upon which this analysis can be performed.

Specifically, we propose a computational model through which the improvisation music will be automatically analysed, as illustrated in Figure 2 below.

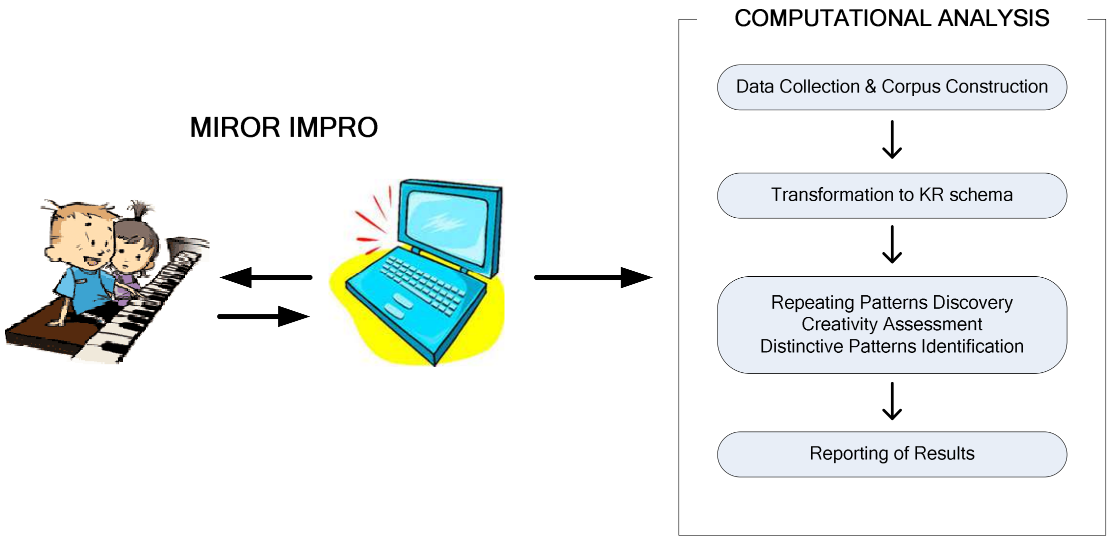



**Fig. 2. The context of the research.**

The conception and design of the MIROR-IMPRO system can be claimed to fall somehow in between formal and informal music training context, as defined in related literature, e.g. in Mak (n.d.), Vitale (2011), Jenkins (2011), Mok (2018) etc. What we mean by this is that although MIROR-IMPRO was initially perceived as a device that could be used as a mechanical musical partner to jam together – that is more or less in an informal context, the research conducted within the MIROR project indicated that it would be better exploited if a properly trained teacher was involved in the process. Thus, MIROR-IMPRO, or another such or similar device, could be introduced into a formal learning environment after carefully designed pedagogical administration. In such an environment, the device could show its full potential.

The experiments described here however were based on informal learning setups, that is, not in the formal classroom. Due to the nature of the technology involved, the utilisation of the MIROR-IMPRO device within an informal context can also be encouraged.

Our research described here within focused entirely and solely on the musical data produced by those experiments. We processed the musical data out of context and we are not dealing with the children's musical perception nor their intentions when producing their musical output. We concentrate only on the neutral level, as brought forward by Nattiez (1990).

## 1.4 Research Scaffold & Deliverables

The basic research hypothesis that the MIROR project, and consequently this thesis is examining is whether the interaction with the MIROR-IMPRO system promotes children's improvisation capabilities. For doing this, we are seeking to develop computational methods which will analyse children musical output produced during MIROR psychological experiments and will provide corroborating of refuting answers to the research hypothesis.

To achieve this, we orchestrated our efforts towards tackling four distinctive Research Questions (RQ):

**RQ1. How the children's improvisation capabilities are affected by the usage of MIROR-IMPRO? Put differently, if we compare pre- and post-improvisation sessions, are we detecting enhanced improvisation skills?**

**RQ2. Does the MIROR-IMPRO interaction influence musicians and non-musicians alike? Are we detecting differences on the way MIROR-IMPRO impacts improvisation skills according to whether children have or have not received formal keyboard music training?**

**RQ3. Do the visualisation constructs of MIROR-IMPRO impact the way that children improvise? In other words, does Visualisation affects children's musical manifestations?**

**RQ4. If we segment the music data according to some categories (e.g. country, gender or age) are we detecting patterns that are overrepresented on a musical corpus generated by a specific group (e.g. based on country, gender, etc) with respect to the rest of the data (anticorpus)?**

In order to respond to the above questions, the work conducted aimed to output two distinct deliverables:

**D1. A software tool, able to perform all necessary analysis. That is a computer program, that will (a) read all MIDI files produced by the interaction with the MIROR-IMPRO system, (b) parse input MIDI (c) transform it in a set of data structures suitable for algorithmic analysis (d) perform that musicological data mining and (e) output the results.**

**D2. A music database, in the form of MIDI files, with children's improvisations produced during the MIROR psychological experiments, used in conjunction with the above software tool.**

## 1.5 Motivation and Contribution

Improvisation is now recognised as a central component of musical creativity (Webster, 2002; Kanellopoulos, 2007; Ashley, 2009). Although it is a common form of musical practice it remains yet the least studied or understood from a music analysis point of view. When populations with no musical background engage in musical improvisation (such as young children), the analysis of the musical aspects becomes more challenging. The possible lack of common learned musical schemata and related technical skills requires the introduction of methods of analysis which can deal with these particularities. The research presented in this thesis aims to cover this research gap by providing means to computationally analyse improvisation data that symbolically represent young children's' creative musical thinking.

The work conducted aims mainly to contribute novelty by:

i. Providing specific analytical approaches to the study and analysis of improvisation, tailored to children. We introduce a data mining approach, by exploring a vast search space of musical patterns, with algorithms adapted from the stringology domain and by considering each pattern according to a specific set of attributes, i.e. its frequency or its length.
ii. Devising a methodology for assessing children's creativity and developing of new musical skills. Based on the literature in the field and providing our own metrics, we propose a creativity model against which the improvisation skills can be measured.
iii. Creating software tools, for realising the aforementioned contributions. The implementation aims to evaluate on real life data the above approach and

creative methodology and to provide an exemplar case which can be used in broader implementations or be evolved by employing additional functions and/or analytical approaches.

Furthermore, it seeks to provide essential input in:

- Evaluating the Reflexive Interactive Model in triggering the development of new musical concepts. The data analysis towards the creativity enhancement of the children can be a quantitative measure to be used as an indication for the value of the Reflexive Interactive Model.
- Evaluating the validity of the Model for introducing young children in to music. The development of musical characteristics in children improvisations through the interaction with the Model, can be made immediately evident via the data analysis of the music performed.
- Defining a new methodology in developing children improvisation skills. The interaction with the MIROR-IMPRO system and the music produced through it may lead to a new way of teaching improvisation to children, since it provides an asynchronous, automatic, responsive tool that can be used in order to assess improvisation achievements.
- Establishing a synergy between learning and cognition in the context of man-machine interaction. An issue to be addressed is the degree to which the interaction with the system renders a positive feedback loop in the improvisation creativity of the children.
- Developing a new adaptive, interactive and innovative learning system. Overall, the Reflexive Interaction Model, the MIROR-IMPRO system and the corresponding computational model for the data analysis we propose, may introduce a new paradigm in teaching improvisation to children.

The research conducted and discussed in this thesis, due to its interdisciplinary nature cannot penetrate to a large degree in all research fields involved. As a result, several concepts relating to computer science or the pedagogy of improvisation have not been addressed here. Future research is also important as it may extend the current model and study and expand its relevance to other fields, such as those mentioned above.

## 1.6 Outline of the Thesis

The structure of the thesis is as follows:

**Chapter 1: Introduction.** It outlines the work performed. It introduces the basic concepts and describes the rationale and the goals of the research done.

**Chapter 2: Literature Review.** It provides a survey of research related to the basic concepts of this thesis. It addresses research topics on Music Informatics and Music Training related to this work. It further explores work related to music education and children improvisation, pattern matching and pattern discovery algorithms, knowledge representation, digital representation of music, musical creativity etc.

**Chapter 3: Methodology.** The new work described in this thesis is presented according to its methods. The musical corpora used are described, along with the knowledge representation schema chosen. The algorithms encoded and the software developed are presented as well. The statistical constructs use to evaluate part of the results are also mentioned here.

**Chapter 4: Results.** The results produced from the method described in Chapter 3 are presented. Results are related to three distinct goals (as described in the introductory part of Chapter 3), therefore they are divided to results related to G1 (section 4.1), G2 (section 0) and G3 (section 4.3).

**Chapter 5: Conclusions & Future Steps.** Conclusions drawn are discussed. Also future work is prescribed along with applicability potentialities for additional uses. Implication and contribution in the domain are assessed.

**Appendix I:** Expert judge's assessments about the children's improvisations performed during the MIROR psychological experiments.

**Appendix II:** The publications that have been produced in the course of the work performed towards this thesis are listed here.

The actual code of the system is not included in the thesis as the purpose of the system is the music analysis, rather than the particularities on the implementation (code) level. However, it is described to a certain degree in order to give a clear inside to the interested reader.

# Chapter 2

# Background and Related Work

In this chapter we are reviewing the most recent developments in the fields mostly capitalised on, that is digital representation of music, knowledge representation constructs, music pattern recognition and discovery, children's improvisation and its connection with musical creative thinking and the educational paradigm that the MIROR interactive technology suggests.

The chapter is divided in two major parts, the first related to computational music analysis constructs and the second mostly dealing with issues pertained to creativity thinking and children's improvisation with technology.

The description of the technical details may go to a detailed level, but the our intention were that this text could be of valuable readily usage, to anyone that could draw further on this research.

## 2.1 Computational Music Analysis

In this section we present most prominent computational technologies that have been used in the area of computational music analysis. Most specifically we discuss the most important representation formats and constructs, computational tools developed specifically for musicology, and various pattern identification algorithms.

### 2.1.1 Digital Representation of Music

The algorithms utilised in computational musicology and in Music Informatics domain in general, are usually acting upon a set of *musical features.* Musical features are defined on the *musical objects*, such as pitch, interval, chords, scales, tempo, loudness and so forth, the interweaving of which comprises what we mean as *music*. Those musical features provide a first-level encoding of the underlying set of musical objects and might include things like the melodic motion (contour), the relative interval sequence, the duration ratio sequence, harmonic progression and so on. Additionally, common statistical measures can be used such as average of note values, standard deviation, median, minimum, maximum etc.

Musical representation in music information processing literature lies usually on two different levels:

- Musical Features. Used to hold the musical features, i.e. the music, in such a way as to be more convenient for the algorithmic processing to perform. This will be the subject of the next section which deals with Knowledge Representation.
- Data File Format. Lies on the specific format of the data files used to store the music itself and this is what will be discussed in this section.

The latter, the data file format, is standardized in a number of ways, since there is a need for applications to exchange musical data. Nonetheless, the topic is far from being exhausted since several issues have to be taken into consideration when choosing the data file format with which to work (Dannenberg, 1993; Wiggins et al., 1993). Such issues include hierarchy and structure, representation particularities of core musical characteristics (i.e. pitch, tempo duration etc), semantics of the representation schema (procedural of declarative) etc.

Several data formats for symbolic music representation have evolved. Most common are MIDI, Humdrum KERN, Lily Pond, MusicXML and GUIDO.

For a more thorough discussion of the above most important data format schemata along with some less prominent ones, the interested reader is referred to Hewlett & Selfridge-Field (1991, 2001) and Selfridge-Field (1997). In this chapter we will briefly discuss the most important ones, which are related to the present thesis.

#### 2.1.1.1 Musical Instrument Digital Interface (MIDI)

MIDI (International MIDI Association, 1988) was developed as a communication protocol in order to facilitate the communication among synthesisers, computers and other electronic musical instruments. It was defined in 1983 and makes possible the control and synchronisation of the various interconnected electronic equipments. MIDI protocol describes the exchange of data regarding pitch, duration (note on and note off) and volume of musical notes. Data is exchanged as "event messages" and apart from codifying musical information it also conveys control & clock signals to set the tempo. MIDI has become one of the most widely used industry standard.

MIDI taps in three levels (Guérin, 2006):

i. the protocol standards, that is "the language" it constitutes
ii. the hardware level, the various interfaces exchanging the MIDI events and
iii. the distribution format, that is the Standards MIDI Files (SMF).

MIDI was built on the notion that keyboard generated music is in essence a sequence of events. Hence, each one of these events can be encoded as a MIDI message. This is why a MIDI message is basically comprised of two parts: the first part codifies data that correspond to the pitch of the note whereas the second one deals with the amplitude of the note. Messages circulate among the interconnected devices conveying musical information. MIDI supports up to 16 channels of information.

That way MIDI is constructed is in essence capturing performance data. A MIDI message is transmitted when an instrument is starting to produce a sound. The message rather than containing the sound per se, it corresponds to the action of emitting the sound, which is the emission of a MIDI *Note On* event. It contains information about the pitch and how fast or slow was played – i.e. how hard the key was pressed to produce it. Both pitch and the velocity of the key pressed are encoded as integer numbers and are used from the interconnected machinery to produce the same sound. When the instrument stops producing that particular note, a *Note Off* message is produced in a similar manner. That way, the musical stream is communicated between connected equipment.

All MIDI generated data can be conveniently saved for later and repeated usage. As already mentioned MIDI has a particular format for saving the performance data to a file, the Standard MIDI File (SMF) format. SMF files have a very small footprint since they do not contain sound but rather a sequence of events, the detailed directions for a reproducing equipment to generate the encoded sounds. As an example, consider a four-note chord played for 1 min. In CD audio format, this would require about 10 MB; in MIDI recording it would require only 10 KB. This is 1000 times less.

The Standard MIDI File can be one of three different formats.

- Type 0 has just only one track. All MIDI message events, if they belong to different channels are merged on that track.
- Type 1 file has multiple tracks, where different music parts can be on different tracks. Type 0 and Type 1 contain just one recording.
- Type 2, which is not very much in use, can potentially contain multiple musical performances. It can be seen as a collection of several Type 0 performances, all in one MIDI file.

MIDI messages can belong to one of two different categories: Data or Status. MIDI encodes its messages using single byte (8-bit) words. The first byte, that is the Status byte of a MIDI message signifies the receiver what is the event and on which channel it belongs. For example, the *Note On* and *Note Off* messages are Status messages. The Data part tells the receiver what values are associated with the event found on the Status part. For example, if one presses the middle C on a MIDI keyboard, a MIDI message will be generated. The Status part of that message will be a *Note On* event. The Data part will contain the pitch number for C5 (that is 60) and the velocity value of, say 73; which corresponds to the power with which the C5 key was pressed by the musician.

The maximum length of a MIDI message is 3 bytes, 1 byte for the Status part and 2 for the Data one. A Status byte can take values from 128 to 255 (1000 0000 to 1111 1111 in binary format) and a Data one can take values from 0 to 127 (0000 0000 to 0111 1111 in binary). Looking at the binary representation of these values, one can notice that the Most Significant Bit (MSB) is always 1 for a Status byte and respectively 0 for a Data byte. Consequently, a receiver can immediately tell if a byte is a Status or a Data part and accordingly interpret it. The usage of the MSB, naturally leaves only 7 bits for useful information.

MIDI, over the years, has evolved into the most popular digital representation format for music. The reason certainly lays on its simplicity and its light footprint. But it has hard limits and disadvantages:

- The main limitation is its own nature, since MIDI actually captures performance data. As such, it lacks many parameters essential for notation, as metres, rhythm, clefs, keys, accidentals etc. It also lacks execution directives such as ties and dynamics.
- MIDI note information is unquantised. Note duration is measured in MIDI ticks. This needs to be interpreted and quantised in order to come up with ordinary note values (viz. quarters, halves etc).
- Modifiers handling. In Common Western notation (CMN) every note can be signified by one of the sharp, flat, natural, double sharp and double flat signs. MIDI however assigns to each pitch an integer number. Enharmonic notes, such as a C# or a Db, cannot be distinguished.

Users have to put substantial effort on interpreting and enhancing data. Subsequently, one can argue that MIDI on its own is not well-fitted for symbolic representation purposes. Systems discussed on the following sections are dealing well with the above symptoms and are much better suited for symbolic representation. Still though, MIDI – due to its simplicity and its age – has a predominant position among scholars. Over the years large corpora have been created in MIDI and it does not seem very likely to migrate to other system anytime soon. Thus, most researchers continue to use MIDI despite its disadvantages.

#### 2.1.1.2 MusicXML

MusicXML aims to overcome MIDI restrictions, since it is oriented to music score representation rather than to performance representation.

MusicXML was first introduced by Good (2001). It is currently maintained by Recordable© and it is royalty free. Since its introduction it has gained significant popularity, mainly due to the adoptions of the dominating XML web standard. Accordingly most of the IT music industry already supports or plans to support in the near future the MusicXML standard, now in version 3.1. It is mentioned[2] that more than 200 companies support MusicXML, including the flagships commercial software editing tools Finale© and Sibelius© and the lately gaining popularity open source cross-platform notation editor MuseScore[3].

MusicXML was designed to cope with the representation needs of CMN from 17th century onwards, including both classical and popular music. Due to its foundation, viz. the web standard XML, it can support the interchange between musical notation, performance, analysis, and retrieval applications effortlessly. It is an emerging standard that has a steady progress towards becoming the dominant one.

MusicXML is based primarily a build on two music formats:

- The MuseData format (Hewlett, 1997)
- The Humdrum format (see 2.1.1.5), developed by David Huron (1995)

MusicXML uses Extensible Style Sheet Transformations (XSLT) programs to convert between two hierarchical representations: a part-wise score where measures are nested within parts, and a time-wise score where parts are nested within measures.

MusicXML is particularly chatty, as most XML based constructs. For example, the MusicXML for  is:

```
<?xml version="1.0" encoding="UTF-8" standalone="no"?>
<!DOCTYPE score-partwise PUBLIC
	"-//Recordare//DTD MusicXML 2.0 Partwise//EN"
	"http://www.musicxml.org/dtds/partwise.dtd">
<score-partwise version="2.0">
	<part-list>
		<score-part id="P1">
			<part-name>Music</part-name>
		</score-part>
	</part-list>
	<part id="P1">
		<measure number="1">
			<attributes>
				<divisions>1</divisions>
```

2 http://www.musicxml.org/xml/software.html

3 https://musescore.com/press#about

```
                    <key>
                          <fifths>0</fifths>
                    </key>
                    <time>
                          <beats>4</beats>
                          <beat-type>4</beat-type>
                    </time>
                    <clef>
                          <sign>G</sign>
                          <line>2</line>
                    </clef>
              </attributes>
              <note>
                    <pitch>
                          <step>C</step>
                          <octave>4</octave>
                    </pitch>
                    <duration>4</duration>
                    <type>whole</type>
              </note>
        </measure>
  </part>
</score-partwise>
```

Naturally, contemporary editing notation programs use it in compression format (files with extension `.mxl`).

MusicXML score files do not deal with presentation issues. Since they are in essence XML files, formatting issues are kept separately from structure and semantics. Similarly, interpretive performance information is also not included.

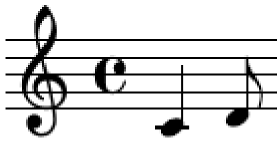
#### 2.1.1.3 LyliPond

LilyPond[4] is a GNU royalty free software for music engraving, introduced by Nienhuys & Nieuwenhuizen (2003). LilyPond does not come with a graphical user interface, so its user has to type in the music via a text editor. Large community projects, such as the Mutopia project[5] (distributes free content sheet music) and Musipedia[6] (a collaborative music encyclopaedia), are using LilyPond since it combines extensive engraving capabilities with a compact and easily to be keyed by hand format.

4 http://www.lilypond.org

5 http://www.mutopiaproject.org

6 http://www.musipedia.org

To give a simple example of its dense form, the musical expression  in LilyPond format is:

```
\notes { c’4 d’8 }
```

LilyPond bundles are coming with a Scheme[7] interpreter embedded. Scheme is accessed by a hash mark (#) followed by a Scheme expression. For example, the following statement includes a Scheme expression (A list containing two symbols, staff-bar and time-signature).

```
\property Score.breakAlignOrder =
  #(list ’staff-bar ’time-signature)
```

Having embedded the power of a Scheme interpreter, users can write their own function changing all data related to a music expression. Hence, users can analyse and modify music programmatically, rendering thus a “muscle” tool for computational musical data analysis

A simple example follows that shows how a piece of music is reversed by means of a user-defined Scheme function.

```
myMusic = \notes { c’4 d’4( e’4 f’4 }
\score { \notes {
\myMusic
\apply #reverse-music \myMusic
}
}
```

---

[7] ftp://ftp.cs.indiana.edu/pub/scheme-repository/doc/pubs/intro.txt

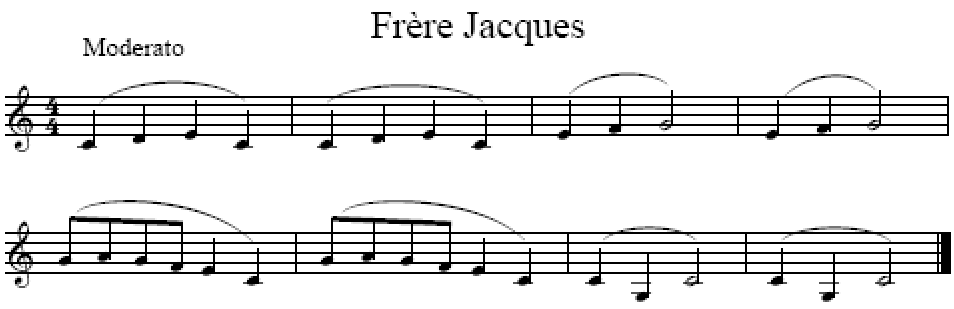
#### 2.1.1.4 GUIDO

GUIDO Music Notation (Hoos & Hamel, 1997; Hoos et al. 1998) was named after Guido of Arezzo (ca. 992-1050), who is considered to be the inventor of the modern music notation system. It is designed to be a digital music representation schema easily understood by humans.

It is organised in three layers: Basic, Advanced, and Extended. Basic GUIDO deals with the basic syntax and covers basic music concepts and terms; Advanced GUIDO offers support for advanced features, in both score formatting and music concepts and Extended GUIDO provides capabilities which are beyond CMN. Most CMN syntax is supported directly through Basic GUIDO.

The core syntactic elements are **events** and **tags**. Events are musical entities which have duration (e.g. notes and rests). **Tags** are used for musical attributes (e.g. a meter, a clef, a key etc). It is also possible for GUIDO to print partly specified musical terms; e.g. a scale with no durations.

An example of Basic GUIDO is given below:




```
[ \title<"Frére Jacques">
\tempo<"Moderato"> nclef<"treble"> nmeter<"4/4">
\slur(c1/4 d e c) nslur(c d e c)
\slur(e f g/2) nslur(e/4 f g/2)
\slur(g/8 a g f e/4 c) nslur( g/8 a g f e/4 c)
\slur(c g0 c1/2) nslur(c/4 g0 c1/2) ]
```

A note in GUIDO notation is like ‘`c#1*1/4`’ i.e. a dotted quarter note middle c-sharp. Notes are signified by their names followed by additional parameters:

duration, modifiers, register etc. Rests are represented like notes but instead of a note name, an underscore is used: `'*1/4'`.

GUIDO has two important constructs to be used for complete musical segments: **sequences** and **segments**. A **sequence** is a series of successive musical objects; segments used for simultaneities.

Advanced GUIDO copes with issues of advanced formatting, i.e. exact spacing, positioning and sizing of graphical elements. It also offers support for features such as glissandos, arpeggios, note clusters, different types of note-heads and staves etc. Furthermore, Advanced GUIDO features user-defined graphical elements. Hence, it is possible to support contemporary music notation, which often includes in scores graphical elements not used in CMN.

#### 2.1.1.5 Humdrum Kern

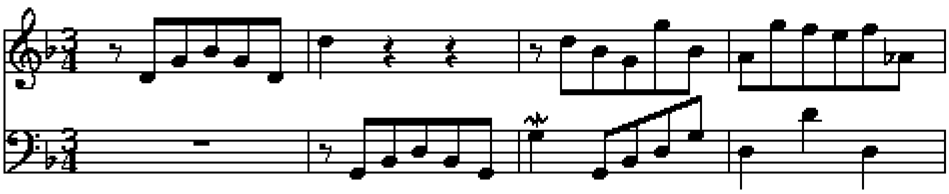
Humdrum was developed by Huron (1995) as a general-purpose music software system, to be used in computational music research. Humdrum was designed to allow the representation and manipulation of both sequential and concurrent music symbolic data. This distinction is retained within its syntax, so that sequential events are arranged vertically whereas simultaneities are worked on a horizontal manner. The Humdrum representation formal is named *kern.*

Kern was conceived mostly as a representation of the functional information contained in a musical score rather than as a means for score formatting and sound reproduction. Nevertheless, printed renditions can be fashioned from kern representations.

In the example that follows (J.S. Bach, Praeambulum BWV 390), two musical parts are encoded.

```
**kern     **kern
*staff2    *staff1
*clefF4    *clefG2
*k[b-]     *k[b-]
*M3/4      *M3/4
=1-        =1-
2.rr       8r
.          8d/L
.          8g/
.          8b-/
```

```
.          8g/
.          8d/J
=2         =2
8r         4dd\
8GG/L      .
8BB-/      4r
8D/        .
8BB-/      4r
8GG/J      .
=3         =3
4GWw\      8r
.          8dd\L
8GG/L      8b-\
8BB-/      8g\
8D/        8gg\
8G/J       8b-\J
=4         =4
4D\        8a/L
.          8gg/
4d\        8ff/
.          8ee/
4D\        8ff/
.          8a-/J
=5         =5
*-         *-
```



As we can see, there is a direct correspondence of each musical part to a different musical staff. Where the musical score is laid out horizontally, kern works vertically down the page.

Humdrum also supports a variety of other constructs like comment records, reference records etc.

### 2.1.2 Knowledge Representation

As far as Knowledge Representation formalisms are concerned, there is no such standardisation. Furthermore, it seems unlikely to evolve, since there is not much need for such standardisation. Each algorithm has its own necessities and particularities and naturally the knowledge representation scheme chosen will be the most convenient per case.

Knowledge Representation is a core concept in Artificial Intelligence. It encodes the necessary information from a domain in order to facilitate problem solving on this domain. Davis et al. (1993) argues that an adequate knowledge representation schema should, to a greater or lesser degree, assure five different provisions:

1. It should offer a substitute, *a surrogate,* for the thing itself. In other words, it should provide the mean that captures and surfaces adequately the attributes needed to the problem solving procedure. In our case the knowledge representation should sufficiently encode the musical object.
2. Inevitably, the representation cannot be a perfect representation of the real thing, which is the musical object. Taking into account the problem to be solved, some attributes are better encoded whereas others might be omitted. Hence, a knowledge representation schema provides a *set of ontological commitments.*
3. Imperfection lies also on the level of the credence that inspires the particular encoding. Moreover, the encoding cannot be separated from the inference process and therefore form human reason. Therefore, a knowledge representation schema offers a *fragmentary theory of intelligent reasoning.*
4. Knowledge representation and data structures are two separate things and should not be confused. Knowledge representation lies on the semantics level while the structure chosen to encode the representation lies on the data level. Nevertheless, since the processing will be via computers the data encoding of the information based on the knowledge representation is unavoidable. Consequently, it is always prudent to have a knowledge representation that eases the data transcription rendering it a *medium for efficient computation,* as well as keeping a sense of clarity to be understood by humans.
5. Inevitably, a knowledge representation scheme is a *medium of human expression.* It provides the mean to communicate with the machine. As a mean of expression it should be general, precise and it should be simultaneously adequate and economical.

A knowledge representation scheme that satisfies the above and performs very well on the analysis of symbolically represented music is the *Viewpoint representation*, introduced by Conklin & Witten (1995), further developed by Conklin & Anagnostopoulou (2006) and Bergeron & Conklin (2007). Viewpoints fall into the

*Structures Representation of Knowledge* division, in the categorisation that Clark (1989) did in his survey of knowledge representation schemata for machine learning.

It is interesting to note that the vast majority of music informatics works on the symbolic level to the present date use either this specific formalism, or any variation of it, still keeping the same ideas and representation concepts, despite some times changing the names. Therefore at this stage do not present any other representation formalism, based on the fact that they would mostly fall on this representation spectrum. Below this formalism is explained in detail.

#### 2.1.2.1 Viewpoints

The viewpoint formalism offers great flexibility in surfacing the attributes of the Musical Object (Butterfield, 2002) along with straight-forward representation on corresponding data structures. As explained above, the viewpoints formalism has been used in several research cases, due to its extensibility and its capability to capture in a well-defined representation set of symbols, a big variety of the musical features of musical data (Padilla & Conklin, 2018; Conklin, 2002, 2006, 2016, Goienetxea et al., 2016; Conklin & Anagnostopoulou, 2006; Bergeron & Conklin, 2007; Lartillot, 2003).

The musical object (`MO`) on which a viewpoint is defined is primarily a single note. It has duration, and when it occurs it becomes associated with an onset time relative to the beginning of the sequence; musical objects have time spans and are called **events**. Sequences of such events are ordered by increasing onset time. Music objects have several other basic attributes besides duration; e.g. notes have a pitch usually represented by a MIDI number, or have a step difference from the previous note etc.

More formally, the MO can be a sequence of notes (*`Seq(Note)`*), viz. a segment, or a simultaneity (a chord) (*`Sim(Note)`*), and at a later stage any combination of the two, as many times as desired in order to describe a score.

$$MO = \begin{cases} Note \\ Seq(Note) \\ Sim(Note) \end{cases}$$

Viewpoints can be **basic** (selecting basic event attributes) or **derived** (computed from basic viewpoints). They can be **melodic** (applying to notes) or **vertical** (applying to chords). Some melodic viewpoints represent familiar musical features—melodic interval, melodic contour, and pitch classes—whereas others are novel constructions made possible by utilising a viewpoint constructor method.

An event is the product of a musical object and time.

$$E = M \times T$$

Basic viewpoints are functions that map events to the values of their constituent musical features. Derived viewpoints are created from other viewpoints using functions called *Constructors*. These are functions that take viewpoints as arguments and return new viewpoints.

An example follows:


**Fig. 3. An excerpt from the Voice part of the Jetzt Meine Seele (Kalomoiris, 1953)**

For the example above, we define the basic and some derived viewpoints; one can define as many viewpoints as necessary for the computational task that has to be performed.

### *Basic Viewpoints*

**duration**. The shortest note in the music piece usually defines the fundamental time unit. For the example above, the sixteenth note of the triplet in the 3rd bar defines the unit, which is always an integer number. Naturally, in order to be able to use this viewpoint, the data should be pre-processed in order to be quantised.

**onset**. Indicates the time the event occurs. It has the same value range as the duration.

**pitch**. Indicates the MIDI number of the note and as such. It is an integer that can range from 0 to 127.

**fermata**. Indicates whether the note of the event includes a fermata. It has a Boolean type (yes/no).

**timesig**. The time signature, usually expressed in fundamental time units. Hence, in the segment in Fig. 3 since the fundamental unit is the sixteenth note of the triplet in the 3rd metre, the timesig is 16 – 16 fundamental units fill up a meter. Time signature information cannot be directly deduced from MIDI data. In such cases, time signature information should be provided in advance.

**keyesig**. The key signature, in the range *[-7, 7]*. It indicates how many accidentals contained in the key signature; the symbol '+' used to indicate sharps, whereas '- ' used for flats.

### *Derived Viewpoints*

**ioi**. Inter onset internal. The time between an event and its previous one. It cannot be defined on the first event.

**deltast**. Is it a rest? It indicates if a rest precedes an event. If this is so, then it indicates its duration. Since rests are not events, they are identified indirectly, if the difference between the onset of an event and its previous one is more than the duration of the previous event than the rest preceding it. E.g. the duration of the $e_{18}$ event below (see Table 2) is 3 and its onset is 63. The onset of the $e_{19}$ is 69. Therefore a rest of duration 3 (that is a eighth note) lies between $e_{18}$ and $e_{19}$. It cannot be defined on the first event

**posinbar**. Position in bar. It indicates the order of an event in its bar. It is expressed in time units.

**fib**. First/not first in bar. It indicates if an event is the first one occurring in the bar. Boolean.

**seqint**. Sequential melodic interval. It indicates in steps (viz. in semitones) the distance from the previous event. It cannot be defined on the first event.

**contour**. It indicates the melodic movement. Raising, falling or static. Denoting by {+, -, 0} values, respectively. It cannot be defined on the first event.

**intfib**. Interval from the first event in bar. It indicates in steps the melodic distance from the first event in the bar.

**intfip**. Interval from the first event in piece. It indicates in steps the melodic distance from the first event in the piece.

Given the viewpoint sequence $v_1, v_2, ..., v_n$, the constructors of the above derived viewpoints, are shown in the table below.

| **Viewpoint** | **Range** |
|---|---|
| ioi(onset) = $onset_{m-1}$ - $onset_m$ | $Z_+$[8] |
| deltast(onset, duration) = $onset_{m-1}$ - $onset_m$ + $duration_m$ | $Z_+$ |
| fib(onset) = (mod($onset_m$, timesig) == 0) | Boolean |
| seqint(pitch) = $pitch_{m-1}$ - $pitch_m$ | $Z_+$ |
| contour(pitch) = $pitch_{m-1}$ $[<\vert>\vert=]$ $pitch_m$ | {+, -, 0} |
| intfib(fib, pitch) = $pitch_m$ – $fib_{m-i}$, where i is the minimum with $fib_{m-i}$ = T | $Z_+$ |
| intfib(fib, pitch) = $pitch_m$ – $pitch_1$ | $Z_+$ |

**Table 1. Constructors for derived viewpoints**

Viewpoint sequences can be constructed accordingly. Viewpoint sequences represent patterns of musical attributes and can be the product of an extensive exploration and analysis in a musical corpus.

Thus, in the above example, for the sequence of events $<e_1, e_2, e_3, e_4, e_5>$, the corresponding sequence of the `pitch` viewpoint is *<70, 69, 67, 65, 67>* and the corresponding sequence of the ***intfib*** viewpoint is *<0, -1, -3, -5, -3>*.

| **Viewpoint** | **Events** | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **e1** | **e2** | **e3** | **e4** | **e5** | **e6** | **e7** | **e8** | **e9** | **e10** | **e11** | **e12** | **e13** | **e14** | **e15** | **e16** | **e17** | **e18** | **e19** |
| ***Basic*** | | | | | | | | | | | | | | | | | | | |
| **duration** | 3 | 3 | 3 | 3 | 3 | 3 | 9 | 9 | 3 | 3 | 3 | 1 | 1 | 1 | 3 | 3 | 9 | 3 | 3 |
| **onset** | 0 | 3 | 6 | 9 | 12 | 15 | 18 | 27 | 36 | 39 | 42 | 45 | 46 | 47 | 48 | 51 | 54 | 63 | 69 |
| **pitch** | 70 | 69 | 67 | 65 | 67 | 69 | 67 | 62 | 60 | 62 | 64 | 65 | 67 | 65 | 64 | 60 | 62 | 62 | 74 |

[8] $Z_+$ denotes the set of positive integers

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **fermata** | F | F | F | F | F | F | F | F | F | F | F | F | F | F | F | F | F | F | F |
| **timesig** | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 | 18 |
| **keysig** | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| ***Derived*** | | | | | | | | | | | | | | | | | | | |
| **ioi** | NA | 3 | 3 | 3 | 3 | 3 | 3 | 9 | 9 | 3 | 3 | 3 | 1 | 1 | 1 | 3 | 3 | 9 | 6 |
| **deltast** | NA | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 |
| **posinbar** | 0 | 3 | 6 | 9 | 12 | 15 | 0 | 9 | 0 | 3 | 6 | 9 | 10 | 11 | 12 | 15 | 0 | 9 | 15 |
| **fib** | T | F | F | F | F | F | T | F | T | F | F | F | F | F | F | F | T | F | F |
| **seqint** | NA | -1 | -2 | -2 | 2 | 2 | -2 | -5 | -2 | 2 | 2 | 1 | 2 | -2 | -1 | -4 | 2 | 0 | 12 |
| **contour** | NA | - | - | - | + | + | - | - | - | + | + | + | + | - | - | - | + | 0 | + |
| **intfib** | 0 | -1 | -3 | -5 | -3 | -1 | 0 | -5 | 0 | 2 | 4 | 5 | 7 | 5 | 4 | 0 | 0 | 0 | 12 |
| **intfip** | 0 | -1 | -3 | -5 | -3 | -1 | -3 | -8 | -10 | 8 | -6 | -5 | -3 | -5 | -6 | -10 | -8 | -8 | 4 |

**Table 2. Basic and some derived viewpoints for the above excerpt**

**Segmental** viewpoints (Conklin & Anagnostopoulou, 2006) can also be constructed. Rather than based on a basic attribute of a single note (e.g. pitch or melodic interval), as is the case of basic and derived viewpoints, segmental viewpoints are based on a segment of music. Hence the music is seen as a sequence of distinct segments. For each sequence, a set of segmental viewpoints can be constructed, such as the number of notes in the segment, the duration of the segment, the number of beats in the segment and others.

For example, suppose that we automatically segment a piece of music in four consequent phrases, based on a simple rule – e.g. a rest larger than a half-note or a melodic interval larger that 5 steps. Further, suppose that we have the following:

| | **Segment #1** | **Segment #2** | **Segment #3** | **Segment #4** |
|---|---|---|---|---|
| **Number of beats** | 16 | 8 | 35 | 27 |
| **Number of notes** | 27 | 8 | 352 | 133 |
| **Number of simultaneities** | 5 | 0 | 32 | 8 |
| **Duration (in ms)** | 12873 ms | 7132 ms | 45463 ms | 39166 ms |

**Table 3. Segmental viewpoints**

Consequently, we can define the following segmental viewpoints and their corresponding sequences: *num_beats(seg), num_notes(seg), num_sim(seg), duration(seg).* Accordingly,

$$sequence < num\_beats(seg_1), num\_beats(seg_2), num\_beats(seg_3), num\_beats(seg_4) > = < 16,8,35,27 >$$
$$sequence < num\_notes(seg_1), num\_notes(seg_2), num\_notes(seg_3), num\_notes(seg_4) > = < 27,8,352,133 >$$
$$sequence < num\_sim(seg_1), num\_sim(seg_2), num\_sim(seg_3), num\_sim(seg_4) > = < 5,0,32,8 >$$
$$sequence < duration(seg_1), duration(seg_2), duration(seg_3), duration(seg_4) > = < 12873,7132,45463,39166 >$$

The above conception of segmental viewpoints encompasses what is also known as *feature.* Hence, a common underlining theoretical background can be provided, concerning two major constructs in music knowledge representation, namely viewpoints and features.

Features are another popular knowledge representation term for music encoding (Rossignol et al., 1999; Karpov, 2002; Barker & Kranenburg, 2005; Müllensiefen et al., 2008; Hillewaere et al., 2009; Kranenburg et al., 2013; Kranenburg & Conklin, 2016; Shanahan et al., 2016; Neubarth & Conklin, 2016, 2017; Neubarth et al. 2018). Bergeron & Conklin (2007) and Chordia et al. (2011) directly utilised the term viewpoint in building feature sets for pattern representation.

### 2.1.3 IT Tools for Musicology

The evolvement of home computers into home media centres and their oncoming unification with smartphone technology renders an abundant number of music digital resources available to anybody. Naturally, software suites and toolkits have been produced to enable automatic extraction of music information from all these vast digital music resources.

We are briefly presenting in this paragraph the most prominent ones for discrete music representations (i.e. some form of scores), viz. *Music21* and *MIRToolbox.*

#### 2.1.3.1 Music21

*Music21* (Cuthbert & Ariza, 2010) is an object-oriented cross-platform tool for computational musicology in symbolic form, implemented as a Python package. Python[9] is a popular high-level interpreted language that is offered as open source software for all major platforms (e.g. Windows, MacOS, Linux etc). Interpreted high-

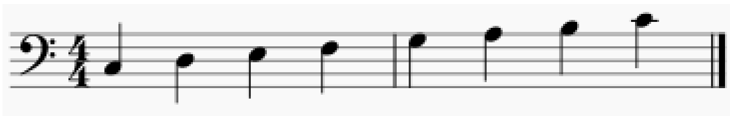
[9] https://www.python.org/

level language means that it can be readily used from non-programmers (e.g. Musicologists), but it is slow. Since Music21 is implemented as a Python packages all Python arsenal for manipulating complex data structures such as lists and dictionaries, can be used for manipulating symbolic music.

Music21 is building upon existing technologies for computational musicology such as Humdrum, MusicXML, MuseData, and Lilypond. And since it is incorporated into Python's ecosystem, it is making existing code re-usage fairly simple.

Starting using Music21 is very easy. After installing it, one can jump directly into issuing simple commands in Python front-end:

```
converter.parse("tinynotation: 4/4 C4 D4 E4 F4 G4 A4 B4 c4").show()
```

produces immediately: 

It supports a multitude of formats (e.g. ABC[10], Capella[11], Humdrum (see 2.1.1.5), MEI[12], MIDI (see 2.1.1.1), MusicXML (see 2.1.1.2), MuseData[13]) and can convert easily between them.

Hence, one in order to convert a score form `**kern` format to `MusicXML`, for editing with e.g. MuseScore, has to issue

```
>>> converter.parse('/music/humdrum/score1.krn').write('musicxml')
```

The basic object of music21 is the `Stream`, an abstract data structure that is used to keep any musical information. Every object stored in a `Stream` with an offset how many quarter-note units is beyond the beginning of the stream. For example:

```
>>> from music21 import *           # import all music21
```

[10] http://abcnotation.com/
[11] https://capellasoftware.com/capella-overview/
[12] https://music-encoding.org/
[13] http://www.musedata.org/

```
>>> a = stream.Stream()              # create a new stream
>>> a.insert(0, note.Note('c4'))     # insert Note c4 at offset 0
>>> a.insert(1, note.Note('d4'))     # insert Note d4 at offset 1
>>> a.show()                         # show the result
```

results: 

Streams can store other Streams, and further can have subclasses Score, Part, and Measure. Those in turn can have notes, rhythms, clefs, time signatures, and all other musical data. To find a particular musical object, you need to access the right level of hierarchy, and this can take some effort. Hence a hierarchy of streams is created and in order to access a single musical object one needs to access the right level in the hierarchy.

While simple tasks can be easier to be performed in Music21 than other similar tools the power of the toolkit comes from combing together high-level objects, such as Pitches, Chords, Durations, Time Signatures, Intervals, Instruments and standard Ornaments, with the power of the Python object-oriented language. Methods on the aforementioned particular classes allow objects to perform their own analyses and transformations. Chords can easily find their own roots, create automatically their own closed- and/or open-position, calculate Forte's prime forms from Pitch Class Set Theory, and so on. One can extend the above objects for their own needs, such as altering the pitch of open Violin strings to study scordatura, specializing (subclassing) the Note class into MensuralNote for studying Renaissance Music and many others.

### 2.1.3.2 MIRToolbox

While Music21 is oriented towards analysing symbolic music, the MIRToolbox (Lartillot et al., 2008) is dealing with the sonic aspect of music. It is oriented specifically to the extraction of musical features in music captured in audio recordings. It is designed particularly for the processing of audio databases and the simultaneous extraction of musical features, such as timbre, tonality, rhythm or form, for consequent processing by statistical methods. It is worth mentioning here that there exists an equivalent tool for symbolic music analysis, namely *The MIDI Toolbox*

(Eerola & Toiviainen, 2004), but this has been abandoned nowadays for the described above Music21.

The MIRToolbox has been conceived as an integrated set of functions written in MATLAB©. MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use interactive environment where problems and solutions are expressed in familiar mathematical notation. Typical uses may include math and computation, algorithm development, modelling, simulation, and prototyping, data analysis, exploration, and visualization and scientific and engineering graphics, application development including Graphical User Interface building.

Most of the musical features that are extracted from music recordings are computed using those same basic calculations. Hence, most musical features are co-dependent one upon the other. In order to avoid redundant computations, MIRToolbox calculates all these common components once and consequently it uses them as building blocks to form the various musical features. For example, the calculation of the MFCCs[14] can be done based on the wave of the audio signal or can be done using intermediate representations (e.g. spectrum, mel-scale spectrum etc).

Most of the musical characteristics found in theory can be thus correlated with a musical feature that can be extracted from the audio file. For example, the musical features *chromagram*, *key strength* and *key self-organising* are related to tonality; *Root Mean Square* and *energy* are related to dynamics. *MFCC*s are related to timbre and spectrum; autocorrelation and cepstrum are pitch indicators. MIRtoolbox includes more that 50 music feature extractors and statistical descriptors (Lartillot, 2014a).

In addition, the MIRToolbox provides a set of readymade functions for data analysis, such as functions to display histograms and various statistical measures. Its integration with MATLAB provides to enormous set of ready-to-be-used functions for statistical analysis and data visualisations. A set of advanced musicological tools has been included, such as tools for automatic segmentation based on various

[14] The mel-frequency cepstral coefficients (MFCCs) of a signal are a small set of features (usually about 10-20) which describe the overall shape of a spectral envelope. It is often used to describe timbre.

musical features and supervised classification using K-Nearest Neighbours or the Gaussian Mixture Model.

### 2.1.4 Pattern Identification

*Music is organised sound*[15]*.* These sounds are organized in such a way that a structure is defined – and this is the fundamental difference between music and noise. In a piece of music, each sound has an identity of its own and has relations with its predecessor, successor and simultaneous sounds. In most types of music multi-sound and hierarchical structures can be defined, where sounds are grouped into higher-level formations (e.g. motives, segments etc) which are associated with various musical relations. Pervasive to all these concepts is the concept of repetition. Repetition means that whole musical passages intact or in some way transformed are repeated within the body of the musical piece and this constitutes a central function in the perception of the music by human beings (Margulis, 2013, 2014). The identification of the repeated passages plays a significant role in analysing a music piece.

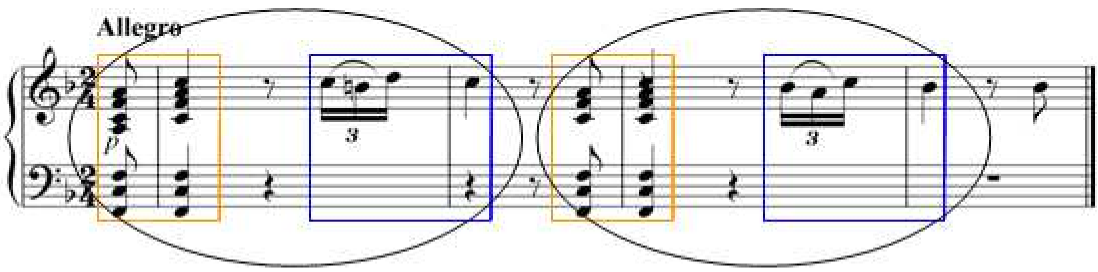



**Fig. 4. Repetition in Beethoven's Sonata opus 10, no 2, in F Major.**

Several methods have been proposed for revealing recurrent and important patterns in music, as discussed in the following sections.

#### 2.1.4.1 Repetition in Music

Imagine that we are watching a movie when suddenly, after 5-10 minutes from the beginning of the film, the first scene is repeated exactly the same. Wouldn't that be outrageous? Wouldn't it be unaccepted as a director's twist? However, this is more

[15] Attributed to Edgard Varèse in (Goldman, 1961)

or less what is going in the sonata form in music, and we all find this poignant and exhilarating.

Music is the only art form that exhibits to such great degree repetitiveness. All other human art forms, painting, sculpture, cinema, theatre literature, do not contain the huge amount of repetitiveness that characterises music. Architecture often suggests designs and implementations containing a lot of repeated elements, but to a clearly lesser degree than music. Only dance seems to compete with music on repetition, but then again almost no one is dancing without music (Huron, 2006). It seems that there is no other art resembling music in the receptiveness amount and in the emotional contentment as concurrent forms of pop music (i.e. trance, or hip-hop) that can keep captivated listeners engaged for endless hours. As Levitin (2006) wrote: *As scores of theorists and philosophers have noted [...] music is based on repetition. Music works because we remember the tones we have just heard and are relating them to the ones that are just now being played. Those groups of tones—phrases—might come up later in the piece in a variation or transposition that tickles our memory system at the same time as it activates our emotional centers [...] Repetition, when done skillfully by a master composer, is emotionally satisfying to our brains, and makes the listening experience as pleasurable as it is.* (p. 163)

Repetition in music is according to many (e.g. Bent, 1987; Agawu, 2009; Narmour, 1990; Krumhansl, 2001; Meyer, 1956; Schenker, 1954, Huron, 2013) one of the most prominent processes by which humans incept and comprehend music. The discovery and identification of repetitive musical elements is one of the core characteristics that expert listeners seek in music and through which they interpret music.

Even more, some postulate that repetition is what gives music its particular essence. As Margulis (2013) says: *Repetition is not an arbitrary characteristic that has arisen in a particular style of music; rather, it is a fundamental characteristic of what we perceive as music*" and "*Both the prevalence and the extent of repetition in music around the world argue for a special biological role*. (p. 5). And elsewhere: *The simple act of repetition can serve as a quasi-magical agent of musicalisation. Instead of asking: 'What is music?' we might have an easier time asking: 'What do we hear as music?' And a remarkably large part of the answer appears to be: 'I know it when I hear it again.'* (Margulis, 2014). As such, pattern recognition and discovery is one of the cornerstone topics in music data mining, both in audio and symbolic music processing.

The task of identifying repeated elements in a musical corpus is therefore a central analytical act. However, the set of repeated musical patterns in a musical piece (or even more in a large corpus) is vast. A repeated element's length can vary from a short motif's (see Fig. 4) to the full section of work (e.g. the exposition in a sonata form). Furthermore, this search space is populated with other less important patterns from the musical point of view. Hence, the task of constructing a computational model for discovering and identifying the repeated patterns of musical interest becomes of high importance from an analytical point of view.

Several methods have been proposed for revealing recurrent and important patterns in music.

### 2.1.4.2 String Pattern-Induction Algorithm

Cambouropoulos (1998) introduces SPIA – a String Pattern-Induction Algorithm. SPIA works in a bottom-up fashion. It begins with the smallest patterns and it builds them up to maximum length. The algorithm proceeds its way though a sequence, by firstly considering as a candidate pattern the first two members of the sequence. Then the whole sequence is searched against for this pattern. All matches found are reported. The algorithm terminates when the largest pattern is found.

The above algorithm is based on a pattern induction algorithm, presented by Crow & Smith (1981). This algorithm reports all maximal repeated factors in a sequence. A factor is a subsequence of the original sequence. I.e. if $s = <e_1 \ ... \ e_n>$ is a sequence, $f$ is a factor of $s$ if there exists $i, j$ such as $f = <e_i \ ... \ e_j>$.

### 2.1.4.3 Suffix trees and Suffix arrays based approaches

Conklin & Anagnostopoulou (2006) use a suffix tree-based algorithm in order to discover significant patterns as well as the longest significant pattern in a corpus. For a given viewpoint τ, the τ-viewpoint sequence is calculated for every music piece in the corpus. Afterwards, a suffix tree is built by these viewpoint sequences. The tree is traversed to find all repeated patterns.

Suffix trees (Weiner, 1973; Manber & Myers, 1993; Ukkonen, 1995) offer a very popular construct for string processing since they offer linear time traversal (in contrast the aforementioned SPIA which has linearithmic time (Cambouropoulos, 2006) – viz. $n*logn$). A suffix tree (sometimes called digital trees or PATRICIA trees) for a sequence S is a compressed *trie* (see 3.5.1) which has all nonempty suffixes of S as keys and their positions within S as values (see 3.5.2, 3.5.3). All suffixes are usually terminated by some special sentinel character (e.g. $ or #).

Even if suffix trees are very efficient constructs for pattern matching computations, they suffer from some ailments. Their biggest problem is that they are memory demanding. RAM, in contrast to disk space which is essentially unlimited, is finite. Hence, disk space version suffix trees started to emerge, but they are complex to implement and they are essentially database management systems. Naturally, a system like this trades the efficiency in searching with the lag of disk IO. As an alternative suffix arrays (see 3.5.4) were used. Suffix arrays are much simpler to implement and to use. Basically, a suffix array is an enumeration of all root-leaf paths of the corresponding suffix tree.

Knopke & Jürgensen (2009) use suffix arrays to identify common melodic phrases among 101 masses composed by Palestrina. The masses were available in Humdrum kern format. The processing considers each mass in turn. Each voice is cut into phrases, usually using as boundaries between phrases the rest in the score. Each music phrase is then segmented into individual notes and inserted into a suffix array, along with the remaining of the phrase. Once everything is placed within the array, then the array is sorted. Then every pair of consequent elements in the array is compared for common patterns and all matches are put into a queue.

#### 2.1.4.4 SIA and SIATEC

Meredith et al. (2002) depart from the common mentality that regards music as a string or a set of strings. They adopt a geometric perspective in which the music to be analysed is represented as a multidimensional dataset. Based on this approach, they introduce two algorithms for pattern matching and pattern discovery: SIA and SIATEC.

SIA finds all maximal repeated patterns within a dataset, following a series of steps.

Step 1: Sorting of the dataset.

Step 2: Computing of the vector table. The algorithm constructs a vector table, by computing the vectors from the datum at the head of the column of that cell to the head of the row of the same cell.

Step 3: Value calculation, vector sorting. Afterwards, all values in the table below the leading diagonal are computed. This means that all values from each element of the dataset to all elements greater that this, are calculated. Then the vector table is sorted via a modified merge sort algorithm.

Step 4: Identification of the maximal. The resulting list gives us the maximal translatable patterns (MTP). A maximal translatable pattern for a vector is defined as the largest pattern translated by the vector into another pattern (within the dataset).

SIATEC finds all occurrences of all maximal repeated patterns. SIATEC first generates all the maximal translatable patterns by running SIA, but instead of calculating all values in the vector table below the leading diagonal, it computes all values in the vector table. Computing the whole table rather than just the region below the leading diagonal, allows us to be much more efficient in calculating the set of translators for each MTP. Next the values below the diagonal are used to calculate the MTPs, the same as in the SIA algorithm presented above. To find all occurrences of a pattern, it suffices to find all vectors that can be translated to that pattern (which is the common set of the columns headed by the data in that pattern).

### 2.1.4.5 FIExPAT

Rolland (1999) introduces a pattern extraction algorithm named FIExPat (from **fle**xible e**x**traction of **pat**terns). FIExPat proceeds in two stages; *passage pair comparison* is the first stage and *categorisation* the second one. Passage pair identifies all more or less similar (pairs that have *significant resemblance*) pairs (called *equipollent* pairs) and constructs a similarity graph. The vertices of the graph correspond to distinct passages, while the edges correspond to weighed resemblance relations between passages. During the categorisation stage the actual patterns are extracted from the graph constructed during the first stage.

The algorithm commences its first stage by concatenating all sequences $s_i$ into a global sequence $S$ having length $L$. Two integer numbers $m_{min}$ and $m_{max}$ declare the minimum and maximum respectively length of patterns, in which we are interesting in. Two more constructs should be introduced here. Since the algorithm is not only after exact matching, a similarity model is used, which allows the comparison of musical sequences. Such a similarity model is the Multi-Description Valued Edit Model (MVEM), an instantiation of which can be the edit distance (Navarro, 2001). The second construct is the set of the allowed pairing types (APTS) such as `{insert, replace, delete}`.

The algorithm proceeds by comparing pairs of passages and computing their similarity value. If their similarity value is above a similarity threshold, the two passages of the pair are inserted in the graph and are connected with an edge. For a pair to be qualified as a candidate passage pair, it should satisfy some preconditions. First, the two patterns must not be overlapping. Also their length should be between $m_{min}$ and $m_{max}$ and their difference should also be limited. Hence, a passage $\pi$ is uniquely identified by the tuple $(i, m)$. Given two passages $\pi = (i, m)$ and $\pi' = (i', m')$, their similarity is calculated by the following equation.

$$Sim_{(i',m')}^{(i,m)} = \max\begin{cases} c\begin{pmatrix} S[i+m-1 \\ S[i'+m'-1] \end{pmatrix} + Sim_{(i',m'-1)}^{(i,m-1)} \\ c\begin{pmatrix} S[i+m-1 \\ - \end{pmatrix} + Sim_{(i',m')}^{(i,m-1)} \\ c\begin{pmatrix} - \\ S[i'+m'-1] \end{pmatrix} + Sim_{(i',m'-1)}^{(i,m)} \end{cases}$$

During the second stage, the categorisation phase, the similar patterns are extracted by the graph. For doing so, Rolland proposes the *Star Center* algorithm. The algorithm has two steps. During the first one, for each vertex $v$ of the graph it calculates $totalValuation(v) = \sum_{v' \in adj(v)} value(v, v')$. The operation forms a set of "stars", with each vertex $v$ in the centre and a number of rays leading to the adjacent vertices-stars. Along with each ray a `totalValuation` weight is associated. During the second step of the star algorithm, the set of stars is sorted, by decreasing `totalValuation`. This gives a list of decreased similarity degree between the passage in the centre and the passages next to it.

### 2.1.4.6 Other approaches

Karydis et al. (2007) discuss an algorithm, named M$^2$P – Mining Maximum-length Patterns, for finding all maximum length repeating patterns (MLRP) in music databases. Assuming that $S = <s_1 \ ... \ s_n>$ is a musical string of length $n$ and $rp_2$ is the set of all repeating patterns of length $2$, $S$ and $rp_2$ can form a directed graph $G$. The vertices of this graph correspond to the elements of $S$ and its edges correspond to the elements of $rp_2$.

The algorithm initially represents $S$ into a 2-dimentional array $M(128, \ 128)$, according to the MIDI pitch numbers of the members of $S$. Afterwards, it identifies all repeated pattern of length 2. These are from the $rp_2$ set. Then the graph $G$ is constructed, by using the adjacency matrix representation of $M$. The traversal of $G$ follows. The traversal procedure begins by setting the maximum length to 2 (current maximum length – CML). Then it visits one by one $G's$ vertices in a depth-first fashion. During the traversal the length of the current path $P$ is compared to $CML$ and if it is greater, then the frequency of $P$ is counted and $P$ is kept in a queue. Simultaneously, $CML$ is set to the length of $P$. If the length of $P$ is equal to $CML$, then its frequency is not counted and $P$ is merely stored in the queue. At the end the queue contains the MLRP's.

Hsu et al. (2001) present two algorithms to extract nontrivial repeating patterns in music data. A nontrivial pattern is defined *iff* there does not exist another repeating pattern $Y$ with $freq(X) = freq(Y)$ and $X$ is substring of Y.

The first algorithm adopts the *correlative-matrix* approach. Assume that $S = <s_1 \ ... \ s_n>$ is a musical string of length $n$. A correlative matrix $M(n \ x \ n)$ is constructed, the value of its cell of which indicates the length of a repeating pattern within $S$. If $s_i$ and $s_j$ are the same note then the value $M(i, \ j)$ is set to $1$. In addition, if $s_{i+1}$ equals $s_{j+1}$ the $M(i+1, \ j+1)$ element is set to $2$. The task to identify all repeated patterns and calculate their frequency follows. For every $M_{ij}$ element of the $M$ matrix, if $M_{ij} > 0$ then the corresponding substring $S' =< s_{j-M_{ij}+1} \ldots s_j >$ and all its substrings are repeated patterns. Now every suffix substring $S''$ of $S$ (all other substrings will be processed when some other cell of matrix $M$ will be considered) is labelled and its frequency is calculated. Finally the trivial patterns are removed and the remaining ones define the result set.

The second algorithm introduces a join operation and proceeds in finding the repeated patterns in a musical string by applying consecutive joins. If $S = <s_1 \ldots s_n>$ is a musical string of length $n$ and $\{S, freq(S), (p_1, \ldots, p_m)\}$ is a repeated pattern $S$ of frequency $freq(S)$ found in positions $p_1, p_2, \ldots, p_m$ within $S$, then the *order-k string-join* (the symbol $\infty_k$ is used) operation is defined as follows.

$$\{\alpha_1\alpha_2 \ldots \alpha_m, freq(\alpha_1\alpha_2 \ldots \alpha_m), (p_1, p_2, \ldots, p_i)\}$$
$$\infty_k \{\beta_1\beta_2 \ldots \beta_n, freq(\beta_1\beta_2 \ldots \beta_n), (q_1, q_2, \ldots q_j)\}$$
$$= \{\gamma_1\gamma_2 \ldots \gamma_l, freq(\gamma_1\gamma_2 \ldots \gamma_l), (o_1, o_2, \ldots, o_h)\}$$

where

$i = freq(\alpha_1\alpha_2 \ldots \alpha_m)$, $j = freq(\beta_1\beta_2 \ldots \beta_n)$, $h = freq(\gamma_1\gamma_2 \ldots \gamma_l)$,

$$\gamma_\tau = \begin{cases} a_t, \text{ for } i \le t \le m \\ \beta_{t-m+k}, \text{for } m+1 \le t \le l = m+n-k \end{cases}$$

$o_t = x = y - m + k$, where $x \in \{p_1, p_2 \ldots, p_i\}$ and $y \in \{q_1, q_2 \ldots, q_j\}$, $o_t < o_{t+1}$, for $1 \le t \le h - 1$, if $k > 0$, $\alpha_{m-k+s} = \beta_s$, for $1 \le s \le k$.

The algorithm has two stages. It commences by identifying repeating patterns of length 1. Then the repeated patterns of length $k$ are found by successive join-string operations. The algorithm proceeds until no further repeated patterns exist.

To find the length of the maximum repeated pattern, a binary search follows within the space of the patterns with length L, which lays within the range $2^{k_{l-1}} \le L < 2^{k_l}$. In the second stage the trivial repeated patterns are removed. In order to do that, a tree is built, where each node represents a pattern found. The tree is traversed and all trivial patterns are removed. Consecutively the algorithm identifies all repeating patterns whose length is not a power of two, and adds them to the tree. The removal of trivial patterns follows. Thus, the tree at the end contains only the non-trivial repeating patterns.

Stephenson (2007) produces an interesting algorithm which identifies the pattern that contributes most, i.e. the substring with the maximal number of occurrences in a set of strings. This is different from the longest common substring mainly in that the most contributory substring can occur only to some of the string set.

Assuming that $L = \{s_1, ..., s_n\}$ is the set of strings under question, the algorithm begins by concatenating all strings $s_i$ into one string: $S = s_1 + ... + s_n$.. Then the algorithm proceeds by constructing a suffix tree $T$ for $S$. In the next step, $T$ is transformed in order to have all $s_i$ strings correspond to an interior node and all strings containing a sentinel character to a leaf. Of course any string that contains the sentinel character does so due to the creation of $S$. When traversing the tree, any string represented by a leaf whose path begins with the sentinel character is disregarded.

When a leaf node labelled with a letter belonging to the constituent alphabet of $S$, is reached, then it is branched with a new interior node. The label attached to the branch of this new node comprises all characters found before the first sentinel. The remaining characters label the branch from the new node to the leaf node. When the splitting has been completed, depth-first traversal of the tree follows. Each node is assigned a score, which is calculated as follows: suppose the node is parent of $g$ leafs and the string depth of the node is $d$; then the score $\Omega := g * d$ is defined, The node with the largest score $\Omega$ is the most contributing substring for $S$.

#### 2.1.4.7 Approximate matching

All approaches aforementioned deal with exact matching. But there are of course patterns which could be matched if a degree of freedom was allowed. For example, we can identify patterns that can be grouped together based on a similarity measure. Similarity in music can be found not only in melody, but also in rhythm. In addition several measures can be defined in order to capture and group classes of patterns that share a similarity attribute.

Similarity approaches are beyond the scope of this thesis and the interested readers are referred elsewhere for a review of the concepts involved (e.g. Toussaint, 2003; Barthelemy & Bonardi, 2001; Cambouropoulos et al., 2002, 2005; Müllensiefen & Frieler, 2004). Cambouropoulos et al. (2001) suggests that exact matching can capture approximate matches depending on the abstraction level of the chosen representation, i. e. pitch interval can be represented as contour strings, intervals can be categorised according to their sizes etc.

However, since exact matching can be regarded as a subcategory of approximate matching, some interesting cases are reviewed briefly below.

Lartillot (2003) applies a set of interesting heuristics for discovering music patterns. He takes a different perspective and tries to introduce a computational approach that mimics human inference, as a music piece develops through time. Its method identifies approximate pattern matching by using a *distance* between musical attributes. It correlates together patterns, which are grouped together when measured against that distance, into the same *pattern class* (PC). This distance is based on the perception that a human listener, when hears for the second time a motif, is able to recall its first occurrence.

This is not an exact matching – the two motifs may be close enough to be grouped together, but not necessarily exact. Also the second occurrence may retrieve the first one, usually based on the cognitive characteristics of associative memory.

The distance is defined as:

If $n_1, n_2, n'_1, n'_2$ are four notes with $p_1, p_2, p'_1, p'_2$ pitches and $o_1, o_2, o'_1, o'_2$ onset time respectively, then

$$D((n_1,n_2),(n'_1,n'_2)) = (abs[(p_2-p_1)-(p'_2-p'_1)]+1)*(\max[\frac{o_2-o_1}{o'_2-o'_1},\frac{o'_2-o'_1}{o_2-o_1}])^{0.7}$$

As music unfolds, a human listener typically keeps in his/her associative memory the succession of every interval as it comes, is such a way as to be able to retrieve it if any similar succession of intervals pops up. In order to group together all associate intervals, a hush table is utilised. A new interval is similar or equal to an old one, if $abs[(p_2-p_1)-(p'_2-p'_1)]<\delta$. Hash tables like that can be defined for all other musical attributes, such as inter-onset time values etc.

Hence, similarity is judged by means of the above hash table. For every two intervals $(n_1,n_2)$ and $(n'_1,n'_2)$ that are similar, if their previous ones $(n_0,n_1)$ and $(n'_0,n'_1)$ respectively, are similar too, then a pattern is found.

The above ideas were further developed by Lartillot & Saint-James (2004) and Lartillot (2005).

Liu et al. (2005) suggest another approximate repeating pattern extracting method. They propose the term *prototypical melody* to denote groups of similar music patterns, which are compared utilising the edit distance. They also employ a variation of an R*-tree (Beckmann, 1990) to prune the search space, before the comparisons take place.

Before unfolding the algorithm, some definitions need to be posited. Assuming a `pitch sequence` $P = (p_1, ..., p_n)$ with length $|P| = m$, the corresponding `interval string` is $D = (d_1, ..., d_{n-1})$, where $d_i = p_{i+1} - p_i$. Let `min_len` and `max_len` be the minimum and maximum length respectively, of the patterns we are interested in.

Let's also denote the set of all unique intervals as $\Sigma_D$ and its size $|\Sigma_D|$.

A `distance threshold` $\delta$ is needed to determine when two segments are similar. Given two sequences, $P$ and $Q$ , if $edit(P, Q) < \delta$, then the two sequences are similar. The distance threshold for a sequence $P$ is defined as $\delta_P = |P|*\gamma$, where $\gamma$ is the distance threshold ratio and $0 \le \gamma \le 1$.

The overlapping degree between two sequences should also be defined. Given two sequences $S=(s_a, ..., s_b)$ and $S'=(s_c, ..., s_d)$, $a \le c \le b$, their overlapping degree is $\frac{b-c+1}{\min(b-a+1, d-c+1)}$ if $b<d$, and $1$ otherwise. The overlapping threshold for two sequences $I$ and $J$ is defined as $O_{IJ}=min((|I|, |J|)*\rho$, where $\rho$ is the overlapping threshold ratio and $0 \le \rho \le 1$.

If $S$ is the set of all similar patterns to $P$, then an extension of $P$, $ext(P)$, is the subset of $S$, where every two members of it are similar below the distance threshold. The $|ext(P)|$ is named *Support*. A constraint in the minimum threshold of the support is introduced as the `min_sup`. A pivot P is an approximate repeating pattern if there exists $|ext(P)| \ge min\_sup$.

Further, if $D$ is a sequence with $\Sigma_D=\{a_1, a_2, ..., a_n\}$, $S$ is a subsequence of $D$ and $h_k^s$ is the count ok $a_k$ in $S$, then the `histogram vector (Hvector)` is defined as $HV(S) = < h_1^S, h_1^S, ..., h_1^S >$. The length of the corresponding subsequences that are represented from a Hvector $V_p$, is $|V_p|$. All Hvectors, corresponding to all subsequences, form a multidimensional space, where each dimension corresponds to a distinct value in the sequence.

The algorithm proceeds in three steps. In the beginning the initial string is cut into pieces. Then each segment is associated to a Hvector and then put into the parametric R*-tree which is being built to serve as index. After the index is being built, the candidate list is generated. To do that, each segment is considered in turn as pivot and the segments that are found to be similar are regarded as candidate segments. The result of this procedure gathers the set of all approximate repeating patterns (ARP). Each member of the set can be regarded as prototypical melody and its validity can be tested by a human tester. Within each group of an ARP and its candidate segments, the edit distances are calculated pairwise. The segments that are found to be beyond the `distance threshold` are eliminated. The result is the set of similar segments.

Subsequently, all extensions of each candidate ARP are generated. The *Support* for every extension is measured against `min_sup`, and if found less, the extension is disregarded. That means that an ARP is output only if there exists at least one extension of it which satisfies the `min_sup` threshold.

### 2.1.4.8 Corpus & Anticorpus

The idea of comparing music patterns found in a corpus with respect to another corpus is explored by Conklin & Anagnostopoulou (2011), in order to compare music patterns found in various sets of Cretan folk music. It is further explored by Conklin (2013), Conklin & Weisser (2014), Conklin et al. (2015), Neubarth & Conklin (2015) and Shanahan et al. (2016).

This idea is also used in the present study in order to compare data sets produced by children's improvisations in various setups. We will be looking for patterns which are overrepresented in a corpus, with respect to another corpus (called from hereon *anticorpus*).

The concept of corpus and anticorpus was inspired by the application of contrast data mining techniques in computationally analysing music. Dong & Bailey (2012) identify contrast data mining as *the mining of patterns and models contrasting two or more classes/conditions*. Contrast data mining is a relative new trend in data mining

(Bay & Pazzani, 2001) and aims to discover patterns that contrast among different groups in a dataset. It has a vast application field since it can contrast objects at different time periods, objects for different spatial locations, objects across different classes, object positions within a ranking and various combinations of the above.

As in most related studies, in this work, a pattern is considered to differentiate between two subcorpora, if it is over-represented in the one subcorpus with respect to the other. The pattern can be any sequence of the viewpoints employed, as described in Chapter 3, Methodology.

## 2.2 Creativity, Children Improvisation & Technology

In this section we presented the fundamentals of creativity thinking and how these instantiate specifically in music creativity. Related to that, we then go on to discuss children's improvisation when coupled with IT technology.

### 2.2.1 Creative Thinking

Investigation of musical creativity development has been given considerable attention in the last years. However, the use of new technologies in teaching and therefore in the development of creativity has received relatively less attention. Creativity is a fundamental human ability, and at the same time a particularly challenging concept to define. Various attempts exist to date, and its meaning tends to shift across the various disciplines. Yet, however vague and slippery its definition may be, its core features are shared across domains, which makes it possible to model creativity, and in general to make it the subject of scientific investigation.

When discussing creativity, and according to the particular research viewpoint, one can distinguish between two basic entities, depending on what is the focal point of the creative explorations (Batey & Furnham, 2006; Riga & Chronopoulou, 2012; Jordanous, 2015):

- **The creative process.** The creative process focuses mainly in the procedural steps and in the cognitive processes which have to be accomplished in order to achieve a creative result.
- **The creativity product.** Another aspect of creativity, closely related with attempts to measure or assess creativity, is focused mainly, but not solely, on the creativity product. Creativity as 'product' is defined by Amabile (1982) as one which *[...] appropriate observers independently agree it is creative. Appropriate observers are those familiar with the domain in which the product was created or the response articulated* (p. 1001), hence introducing the idea of how a creative product is received and assessed by (as well as situated in) its environment.

### 2.2.1.1 Creativity Theories

In the following subsections most eminent scholars' perspectives about the above two issues, namely the creative process and the creative product, are briefly presented.

#### *2.2.1.1.1 Reflective Thinking*

Creativity is closely related with problem solving. Any novel solution to a problem may be qualified as creative. The way to reach novel, creative solutions to problems is linked to the way of thinking. The philosopher and educator John Dewey (1910) was one of the first to approach the whole mechanism and process of creative thinking in a systematic way. Dewey devised the Reflective Thinking model as a structured process, the function of which was *to transform from a situation in which there is experienced obscurity, doubt, conflict, disturbance of some sort into a situation that is clear, coherent, settled, harmonious.* (p. 101).

Dewey conceived the reflective thinking method as a mental process that may lead to creative solutions. He analysed it and elaborated it into four successive steps:

i. **Problem Definition**. The problem must be defined in a clear way. The scope of the problem should be identified and the boundaries should be more or less drawn. The definition of the problem into a clear statement should be pursued as much as possible.
ii. **Problem Analysis**. The problem should be analysed in terms of causes and consequences. Symptoms, effects and evidences should be described in detail. This step may lead to a description of the problem together with a detailed

diagnosis of causes and effects. Various interpretations of the problem should be included, as they might significantly affect the way the problem is conceived. Justification of a potential solution and background information should also be considered.

**iii.** **Solution Identification**. Based on the problem analysis, the criteria, conditions and restrictions that a solution should meet are identified. The pool of various candidate solutions is prescribed, but no evaluation or selection is made. The output of this step should be a list of tentative, hypothetical solutions, in light of the criteria produced during the previous step.

iv. **Solution Selection**. From the candidate solutions identified during the previous step, the best solution is chosen. The merits and disadvantages of the chosen solution are balanced and evaluated and the choice is justified. Its long- and short-term effects are weighted and an application and implementation strategy is prescribed.

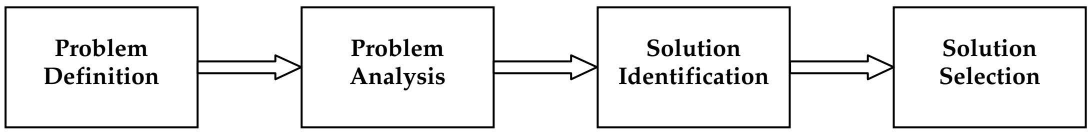



**Fig. 5. Reflective Thinking**

Dewey probably had not in mind to propose a breakthrough model for creative thinking, but his theory became one of the most prominent in the domain (Hermanovicz, 1961; Rosen, 1987). Even today, more than a century from the original publication, it is one of the foundational structures on which many educators built their propositions on teaching and creative thinking.

#### *2.2.1.1.2 Wallas' model of creativity*

After Dewey's initial approach, one of the first attempts to formally describe creativity was made by Wallas (2014)[16]. He modelled creative thinking as a four-step process:

[16] Original work published in 1926

i. **Preparation** – In the beginning, the problem is analysed from all its aspects. Information about the problem, along with specific knowledge, is put together. This is a fully conscious stage and it constitutes the foundation of the next stage. It is part researching, part planning and part marshalling the intellectual resources for entering the right state of mind.

ii. **Incubation** – At this stage the problem is kept in mind, but no conscious work is done. Wallas subscribes in the idea that many problem solving ideas come when kept away. He suggests a method for making the most out of this stage, by deliberately building interruptions of concentrated effort into workflow: As he noted: *We can often get more result in the same way by beginning several problems in succession, and voluntarily leaving them unfinished while we turn to others, than by finishing our work on each problem at one sitting.* (p. 42).

iii. **Illumination** – It is the moment when suddenly a great idea solution emerges. Illumination is often conceived as a new interpretation, superimposed on the information gathered during the previous stage. In other words it can be seen as a restructuring of the specific domain knowledge. Wallas bases this phase on Henri Poincaré's concept of *sudden illumination*. It is the most crucial step in the whole process since it is the outcome of this step that leads directly to novel and creative solutions. New features are attributed to the problem, during this step, as the emergent value presents itself during the course of the creative process. (McLaughlin, 1993).

iv. **Verification** – The idea emerged during illumination is verified and elaborated. Since most ideas do not usually behave well in practice, this stage is necessary to solve the problem. In this final step, as well as in the first one, unlike the second and the third, a lot of planned and deliberate work has to be done in testing the correctness of the idea and assessing the feasibility of its application as an acceptable and efficient solution.

Wallas' model has been widespread since its appearance because it is very much based on straightforwardness and simplicity. But exactly this simplicity is actually its major drawback. Wallas portrays the creative process as a rather uncomplicated, even naïve process. It is generally accepted that this is usually not the case: creativity requires exploration.

Another shortcoming lays in the conception of the Illumination stage. It is often the case that an emerging idea that at first seems to solve the problem might not be eventually the solution. However, it contributes to further elaborate the problem and frequently offers constraints to accommodate a future idea that might ultimately solve the problem. Consequently, illumination can only be considered as such retrospectively. What is more, there does not seem to be any fundamental difference between a good idea that plays some role towards the solution, and an illuminating one, except for the latter being able to solve the problem.

##### *2.2.1.1.3 Divergent Thinking*

The idea of problem solving is also closely related with the eminent contribution of J.P. Guilford in the field. He inaugurated modern day research on the field, when he drew attention to the very important nature of creativity as a research topic in 1949's presidential address to the American Psychological Association (Guilford, 1950) and again in 1967, when he distinguished between divergent and convergent types of creative problem solving (Guilford, 1967). Convergent thinking was associated with conventional intelligence while divergent thinking with creativity.

Convergent thinking is associated with situations where solutions to the problem exist and it is enough is to be retrieved by applying conventional logical search and decision-making techniques.  It affiliates with common sense and established domain knowledge. It is focused towards identifying a single best-fitted answer which ideally leaves no space for uncertainty. IQ test are regarded as a typical result of convergent thinking

On the other hand, divergent thinking is the cognitive opposite of convergent thinking. It involves the production of multiple or alternative ideas for a given topic from available information in an emergent cognitive fashion. Many possible solutions are coming from unusual arrangements that may differ considerably from one person to another. Ideas and solutions resulting from divergent thinking may come from rearranging existing information into unexpected structures and forms that may make surprising connections to appear. After the process of divergent thinking is over, ideas and solutions gathered are processed using convergent thinking.

Guilford describes several factors of divergent thinking, which can be captured to a great degree in the following attributes:

- **Complexity** – The capacity to conceptualise difficult, multidimensional and multi-layered ideas.
- **Curiosity** – The ability to demonstrate inquisitive thinking and learning, attain additional information and knowledge about a problem and being able to probe deep into concepts.
- **Elaboration** – The ability to add to an idea and spring branches to various directions. Also the ability to go into finer detail about an idea.
- **Flexibility** – The ability to propose a variety of views and categories where there are several approaches available in the same topic.
- **Fluency** – The capacity to generate several difficult and multi-layered ideas which can lead to a variety of possible approaches towards the solution.
- **Imagination** – The ability to be ingenious; to dream up, contemplate, invent and conceptualize novel approaches.
- **Originality** – The skill to generate remarkable, unusual, unique, different or completely bright new products or ideas.
- **Risk–taking** – The ability and the willingness to take risks and be experimental; to be courageous, daring, adventuresome.

Divergent thinking was considered mutually exclusive to convergent thinking and often was considered as 'good' whereas convergence thinking was 'bad'. However, contrary to what sometimes is believed, they both can produce new ideas and solutions.

Their main difference however is that convergent thinking leads to orthodoxy, in contrast to divergent thinking, which always produces variety. This is the reason why divergence thinking is linked to creativity. Nevertheless, variety alone does not guarantee creativity. It is however the leading force that may result in novelty and creativity.

##### *2.2.1.1.4 Boden's Creative Types*

Boden (2004) explores the idea of computer simulation of creativity from a philosophical point of view. She conceives the creativity notion beyond mere novelty-producing thought and regards it as rather novel exploration of and creation of mental representations.

She proposes two taxonomies of creativity. In the first she makes a distinction between "psychological" and "historical" creativity, viz. **P-creativity** and **H-creativity**. **P-creativity** and **H-creativity**. P-creativity involves coming up with a surprising, valuable idea which has never been created before by a person. It doesn't matter how many people have had that idea before. For a new idea to be H-creative, it has to arise for the first time in human history, with nobody having even thought about it before.

The second taxonomy is based on the different ways of generating novel ideas. She defines three different types of creativity: exploration, transformation and combination. These three types can be regarded as different forms of creativity altogether.

i. **The combinational creativity** involves new combinations of already known ideas in novel ways. The combinational creativity relies strongly on combining existing ideas in novel ways. In contrast to exploration type of creativity, combination creativity already entails the availability of established knowledge and ideas to be used as the basis for the derivation of new ones. This particular type has been further developed in the blending concept used in the EU FP7 COINVENT project (Schorlemmer et al., 2014).
ii. **The exploratory creativity** involves the formation of new ideas by the exploration of relevant information. The focus of the processes entailed to this type of creativity is being open at unexpected and new ideas and investigate the space of potential solutions.
iii. **The transformational creativity** involves the modification of some dimension of one existing idea, so that new perspectives are surfaced. That way a new idea comes to light, based on an old one.

These three creativity types can be visualised as creating a 3D space, each dimension becoming a specific creativity type. Along one dimension we have idea exploration, along the other dimension we have combination and along the third we have transformation. Hence a real life creative activity can be regarded as an amalgamation of the three types, the extremes being the ideal types of the definition.

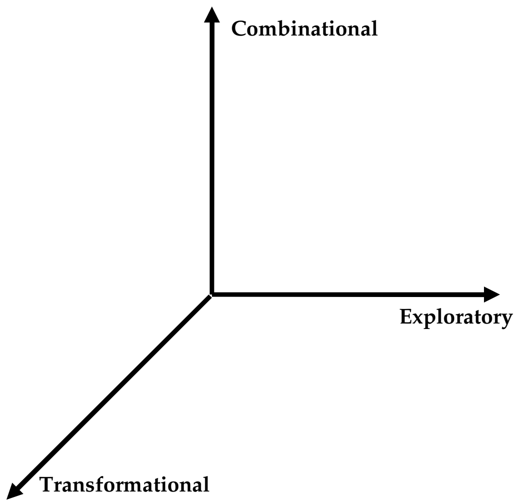



**Fig. 6. Boden's Creativity Types**

### 2.2.1.2 Creativity Assessments

But how is creativity assessed? The discussion presented in the previous section focuses mainly on the theoretical approaches to creativity. In this section the focus moves to the various models of evaluating and assessing creativity. Creativity tests have sprung during the last 60 year – Torrance has compiled a list of more that 220 (Haensly & Torrance, 1990) – although many believe that creativity cannot be evaluated quantitatively and therefore cannot be measured.

The most influential ones will be discussed bellow.

#### *2.2.1.2.1 Guilford's Tests*

J. P. Guilford (1956) created a test to measure creativity, by assessing divergent thinking. The subjects were given 180 ordinary life objects (e.g. a pencil, a spoon, a cap) and they were asked to score across four dimensions: originality, fluency, flexibility, and elaboration.

- **Fluency** has to do with the number of relevant responses; the number of alternative uses one can think of
- **Flexibility** is based on the answers' difference categories, areas and domains
- **Originality** deals with the unusualness of the responses; evidence of 'thinking different', and is measured by comparing the response to the total set of responses given by all people taking the test.

- **Elaboration** has to do with the level of detail captured in the responses and the extent of the development of the idea included

The Guilford approach is not comprehensive enough in measuring the creative output and tells nothing about its value or its relevance. However, it achieves a *quantified evaluation* of creativity.

Guilford et al. (1960) have expanded on these foundational measures to create a full battery of creativity tests that further refine these categories.

##### *2.2.1.2.2 Torrance Tests of Creative Thinking (TTCT)*

Extending Guilford's ideas, psychologist Ellis Torrance created a series of creativity tests (1966). Torrance Tests for Creative Thinking (TTCT) measure the four factors developed by Guilford – **originality**, **fluency**, **flexibility** and **elaboration** – plus two more added by Torrance:

- **Abstractness of Titles.** It is based on the idea that creativity requires capability of abstract thought. It is meant to measure the degree of which a title (attached to a picture) conveys meanings beyond the specific concrete label of the picture drawn.
- **Resistance to Premature Closure.** It measures the degree of psychological openness. It is based on the belief that creative behaviour requires a person to possess an *open mind.*

The measure of flexibility was removed in subsequent versions of the tests due to its high correlation with fluency (Hébert et al., 2002).

The above measures were meant to be scored in two dimensions: verbally (TTCT-Verbal) and visually (TTCT-Figural).

Both, TTCT-Verbal and -Figural, have two parallel forms, A and B, and entail open-ended activities. As their name might imply, TTCT-Verbal requires verbal responses while TTCT-Figural involves responses of pictorial nature. TTCT-Verbal consists of five activities: (i) **ask-and-guess** (ii) **product improvement** (iii) **unusual uses** (iv) **unusual questions** (v) **just suppose**. The stimulus for each task includes a picture to which people respond in writing. TTCT-Figural consists of three activities: (i) **picture construction** (ii) **picture completion** (iii) **repeated figures of lines or circles**.

The two sets of tasks corresponding to the two tests are presented below in Table 4.

| *Activities of the TTCT – Verbal* | |
|---|---|
| ***Asking*** | A list of all relevant questions about a given picture |
| ***Guessing Causes*** | The number of possible causes of the occurrence in the picture given |
| ***Guessing Consequences*** | Possible consequences of the situation pictured |
| ***Product Improvement*** | A list of possible improvements for the object pictured |
| ***Unusual Uses*** | A list of unusual uses for the object pictured |
| ***Unusual Questions*** | A number of unusual questions about the objects pictured |
| ***Just Suppose*** | Description of things that could happen if an improbable situation occurred |
| *Activities of the TTCT – Figural* | |
| ***Picture Construction*** | draw something clever and unusual using an egg shaped figure on a piece of paper as the basis for the picture |
| ***Incomplete Figures*** | stretch presented variety of abstract lines or designs into unusual pictures or objects |
| ***Parallel Lines*** | essentially the same as Incomplete Figures, except all the line forms are pairs of straight, parallel lines |

**Table 4. Open-ended Activities of the TTCT**

In new versions thirteen criterion-referenced measures were added, which Torrance called them creative strengths (Torrance, 1990):

1. **Emotional Expressiveness**. e.g. in drawings, title.
2. **Internal Visualization**. e.g. inside, cross section.
3. **Storytelling Articulateness**. e.g. contest, environment.
4. **Movement or Action**. e.g. running, dancing, flying, falling.
5. **Extending or Breaking Boundaries.**
6. **Expressiveness of Titles.**
7. **Humour**. in titles, captions, drawings.

8. **Synthesis of Incomplete Figures**. combination of two or more.
9. **Richness of Imagery**. variety, vividness, strength.
10. **Synthesis of Lines or Circles**.
11. **Colourfulness of Imagery**. e.g. exactingness, earthiness
12. **Unusual Visualization**. e.g. above, below, at angle, etc.
13. **Fantasy**. e.g. figures in myths, fables, fairy tales, science fiction

The TTCT also yields a creativity index. This index is a composite measure that serves as an overall indicator of creative potential.

TTCT made quite an impact and is still in use today. After so many years in practice, it proved to be a good measure, not only for identifying and educating the gifted but also for discovering and encouraging everyday life creativity in the general population (Kim, 2006).

#### *2.2.1.2.3 Consensual Assessment Technique (CAT)*

Amabile's contribution in the field is the Consensual Assessment Technique (CAT) for ranking the creativity of art objects (Amabile, 1982, 1983). Amabile's approach departs from divergent thinking measures, that both Guilford's and Torrance's techniques subsume, and advances into the thought that the most valid way to measure creativity is by using experts' global and subjective assessment.

CAT is based on the idea that expert judges within a field will have a valid opinion regarding the creativity values of an object of art. They should rate the creativity of the artistic object using their own subjective views and opinions rather than any given objective criteria or checklist. Gathering and examining such expert opinions may provide a good estimation of the creative worth of an object. This comes inline with the everyday stance upon the position: when we would like to assess the value of an artefact we ask the experts on the domain. The collective judgement of recognised experts on a field is the best measure for evaluating the creativity of a product or an idea.

One of the most fundamental questions in creativity theory and research is the issue of domain specificity. Are the skills, talents, personality characteristics, ways of thinking and other determinants of creative performance general-purpose traits that a person possessing them can bring to bear on any kind of task? For example, can one's creativity as a music composer help one produce more creative paintings? Can one's creativity as a chef help him write more creative short stories? Is it likely that a creative biologist is also creative as a teacher, a poet, and a dancer? Or, on the other hand, is creativity quite domain specific?

The Consensual Assessment Technique is very simple to exercise and is essentially a two-step procedure (Baer & McKool, 2009):

- Step 1: The subjects, the creativity of which will be evaluated, are given some basic instructions to create something.
- Step 2: A group of expert judges is assembled and assesses the creativity of the outcome.

All subjects are given the same instructions and may work in the same space. However, the expert judges should work independently. Judges are usually asked to use a scale, e.g. from 0 to 5, to grade the artefacts. They are instructed to use the full scale since the outcome should be a relative ranking of the objects being evaluated. They are not asked to justify in any way their opinion.

CAT can be used to assess creativity at all levels – Big-C and little-c[17] similarly. CAT evaluates directly the object under question and does not seek any elusive essence on which creativity is based. It does so by going directly on the ultimate measure that can be found: the expert in the domain. Hence, the technique is not bound to some creativity theory, nor is seeking to capture some attribute that could be linked to creativity. CAT is exclusively oriented to the creativity product.

CAT can be used to any domain as it relies on the expert opinion in the field and is the perfect measure since it is not dependent on the validity of any creativity theory. However, it has some limitations (Kaufman et al., 2009). Firstly, since its goal is to produce a relative ranking of the objects under question, it cannot be used to fabricate a standard score to compare rankings across settings. Moreover, since all opinions are bound by the zeitgeist – judgment of creativity changes and evolves as

[17] Big-C is referred to breakthrough creativity and little-c to every-day smart ideas. Consequently, Big-C is relatively rare whereas little-c rather common.

time goes by (Csikszentmihalyi, 1999) – there cannot exist any gold assessment on creativity. This holds equally on both Big-C and little-c levels.

Another restriction was found to be the availability of experts. For CAT outcome to be accepted, experts should be used – not semi-experts and definitely not novices. This raises the issue of domain specificity. CAT encompasses the common-sense idea that creativity lies within domain and it is not cross-domain evident. It makes no sense to use engineers to judge a painting or a chef to assess the creativity of engineering designs. Domain specificity is an issue that creativity theories and divergent thinking-based scores are tacit about. They are silently accepting that the creativity qualities they measure are valid for all domains of human knowledge. But this is of course highly controversial.

##### *2.2.1.2.4 Simonton's Historiometric Approach*

Simonton (1999b) considers creativity to be regulated by means of a basically darwinian process. He subsumes to Campbell's (1960) theory of creativity which advocates that Darwinism provides a theory of evolution which not only governs the evolution of biological phenomena, but also provides a more general framework that explains many phenomena in the behavioural sciences milieu.

He draws his opinion from the similarities that can be identified in biological evolution by natural selection and creativity, in the sense that both are involving the creation of something original and adaptive. Biological creatures have evolved through chromosome reshuffling and reorganisation which result in a series of mutations. These mutations are subjected to the pressure of the natural selection that eventually leads to the prevailing of the better suited. In a more or less similar manner, creative ideas are subjected to a mechanism of selection pressure, firstly cognitive and subsequently social and cultural. Thus, the ideas that are selected are those that conform to a set of criteria regarding the standards imposed by the zeitgeist about truth, beauty, utility etc.

His very prolific contribution regarding creativity comes mostly from a historiometric perspective (Simonton, 1975, 1980, 1989, 1990, 1999a, 1998, 2004). Simonton data collected from archival sources such as histories, anthologies, and biographical dictionaries are subjected to historical time-series analyses to test hypotheses about the effect of social variables such as role model availability and political instability on creative production.

He has also reached several interesting conclusions and promulgated corroborating results about the way in which talent development, professional career evolution, stylistic changes and social, cultural, political and economic factors impact on creativity. He performed computerized content analysis (Simonton, 1980) to assess the melodic originality of 15,618 themes of 479 classical composers, from Josquin des Pres to Shostakovich. Simonton defined a number of variables, each of which pertains to different qualities of the case under investigation, such as melodic originality, year's productivity, lifetime productivity, work size etc. In a similar manner, he investigated 1919 compositions of 172 classical composers (Simonton, 1989), spanning almost 500 years. A panel of experts manually scored several of the above variables, prior to the computer analysis.

He also found evidence (Simonton, 1999c) that eminent creators are also the "progeny" of other eminent creators serving as mentors and role models, since the opportunity to monitor, study and observe creativity in action seems to spring creativity.

In general, in his studies he stipulates four main facets of creativity that should be explored (Simonton, 2000).

- **Cognitive Processes.** Four main areas of research – insightful problem solving, creative cognition, expertise acquisition and computer simulation – are mostly mentioned.
- **Personal Characteristics.** Individual traits which enable some people to exhibit more creativity than others are studied. Two major such traits pinpointed are intelligence and personality.
- **Life Span Development.** A creative person develops his/her abilities over a life span. As these abilities are transformed and evolved, they have drawn scholar attention in two main areas: the acquisition of creative potential and how this potential is actualised.
- **Social Context.** The focus here is given mostly on the interpersonal, disciplinary and sociocultural environments.

#### 2.2.1.3 Music Creativity

The psychometric attempts to capture creativity lead to similar specialised approaches to music. Music creativity theories are closely connected to general creativity and can be seen as a special case of artistic creativity. As such music creativity aptitudes are tethered to general creativity ones and in a way, though a remote one, can be regarded as applications of general creativity theories to music.

In the followings, we review the most prominent music creativity theories and we identify when possible the general creativity ones on which are based. At the same time we are trying to surface the quantitative elements of the theories, since these provided the substrate on which we drew for constructing a quantitative creativity model, proposed in 3.4.

##### *2.2.1.3.1 Creativity Craftsmanship Assessment (CCA) and Consensual Musical Creativity Assessment (CMCA)*

Priest (2001) developed two tests in order to measure music students' perception of creativity. Priest based the tests on Amabile's CAT (see 2.2.1.2.3). The first one, Creativity Craftsmanship Assessment (CCA) was designed to identify the contributing factors for musical creativity and craftsmanship, while the second one, Consensual Musical Creativity Assessment (CMCA) was designed to examine the listening functions when assessing creativity and craftsmanship.

For CCA, the students are given a set of five pieces and listen to them three times. Then, the craftsmanship and the creativity of each piece are scored in the range from 1 to 5, relative to one another. Written instructions are given to the students along with descriptions of what is meant by the terms creativity and craftsmanship, in order to establish in a degree a common ground on what is being assessed.

To examine the listening capability of the students, their compositions are used in CMCA and judged by eight independent judges who taught music courses to elementary education students. Similarly to CCA, the score used ranged from 1 to 5. The judges were asked to rate the compositions relative to one another on four dimensions: creativity, melodic interest, rhythmic interest and personal preference. In order to keep under control the judge's fatigue, and in order to keep the judging task consistent, a rather large set of judges is used and written description of each dimension is given to the judges prior to the task.

### *2.2.1.3.2 Measures of Musical Divergent Production (MMDP)*

Gorder (1980) created another test, the Measures of Musical Divergent Production (MMDP), capitalizing on Guilford's and Torrance's research. The inspiration for the production of MMDP was the idea that musical divergent thinking abilities are emanating from relative abilities in figural and semantic spheres, as Guilford has conceived. Hence, MMDP was formulated in order to identify music abilities in accordance with Guilford classification. The four dimensions identified were **musical fluency** (production of musical content from given music information), **musical flexibility** (the production of music ideas that can be seen as modifications in content character; e.g. shift form staccato to legato), **musical elaboration** (production of musical ideas or phrases emphasizing in detail content development and augmented complexity), and **musical originality** (production and employment of musical content which cannot be categorized as belonging to the immediate musical environment). Gorder added a fifth dimension, **musical quality** (production of musical content that is pleased to the producer).

MMDP, in its final form included four subtests. Subjects were recorded improvising as a response to a given musical stimulus. They were given three minutes for each session and they could use whatever means were convenient for producing the musical content: singing, whistling or a music instrument. The music produced was scored in 78 divisions of nine content areas: melodic, rhythmic, pulse/meter, tempo, style, dynamic, timbral, expressive device and form. The musical phrased produced was assessed for the number of phrases produced (fluency), the number of shifts of content character (flexibility), the complexity of the music content (elaboration), the use of rarely used content (originality) and music appeal (quality). The level of execution and technical dexterity were not taken into account.

### *2.2.1.3.3 Measuring Vocal Jazz Improvisation Achievements*

Madura (1996) developed an instrument in order to investigate the extent to which creativity aspects affect students' level of dexterity in vocal jazz improvisation. Madura measured 18 items in three different dimensions:

1. **Tonal**.
   - Correct notes
   - Appropriate tonal language
   - Variety
   - Originality

- Motivic development
- Unity
- Intonation

2. **Rhythm**.
   - Rhythmic feel
   - Appropriate rhythmic figures
   - Variety
   - Originality
   - Motivic development
   - Unity

3. **Expression**,
   - Appropriate scat syllables
   - Appropriate vocal sound
   - Variety of sound
   - Variety of range
   - Variety of dynamics

Students were instructed to improvise in two successive sessions, each of which had an one-minute duration. Firstly the students were asked to improvise to a blues and then to a ii-V7-I progression. The improvisations were recorded and given to three judges to perform the evaluation. Judges followed a prescribed procedure and listened to each improvisation three times. Then they used a 5-point rating scale to score each item.

#### *2.2.1.3.4 Music Creativity Test (MCT)*

Vaughan (1971) created the Music Creativity Test (MCT) which is based on the Torrence's TTCT. MCT was designed as a measure to assess improvisation abilities and is considered appropriate for students of both primary and intermediate grades.

The test contains a number of open-ended improvisation activities (Kiehn, 2003; Giglio, 2015). The activities are:

- Rhythmic improvisation with accompaniment
- Rhythmic response to an antecedent
- Pentatonic melodic response to an antecedent
- Natural sounds over an accompaniment or an ostinato
- Composition based on an uncommon musical practice

MCT evaluates four scoring criteria: music fluency, rhythmic security, ideation and composition.

### *2.2.1.3.5 Webster's Measurement of Creative Thinking in Music (MCTM)*

In the field of music creativity, Webster's (1983, 1987, 1990, 1994) work continues to be prominent among scholars. Webster built on Guilford's, Torrance's and Vaughan's ideas and created a tool to evaluate the creative aptitude of children (ages 6-8), the Measurement of Creative Thinking in Music (MCTM) (Webster, 1983).

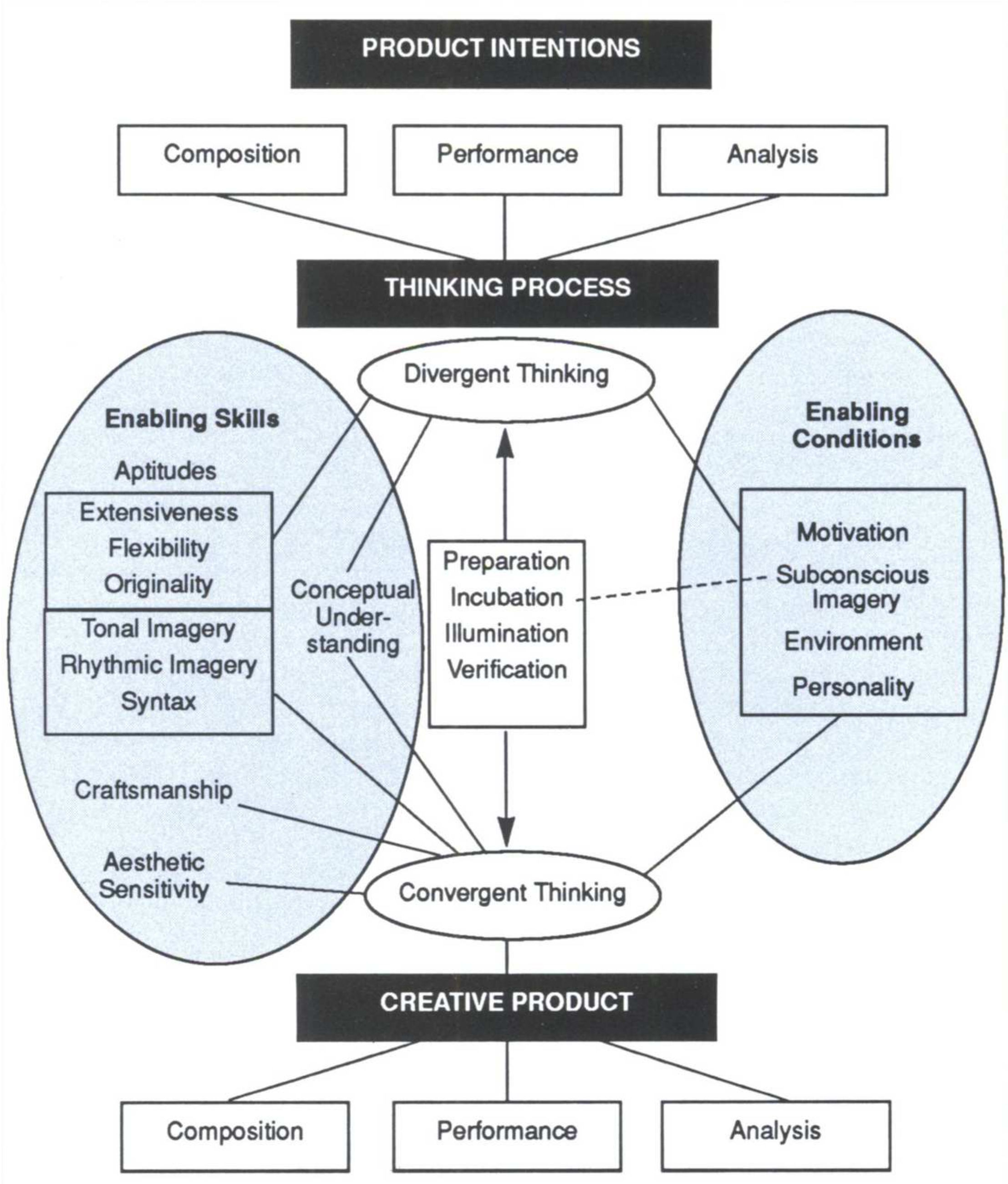



**Fig. 7. Model of Creative Thinking in Music (Webster, 1990)**

The MCTM evolved into MCTM-II (Webster, 1994). Children's creative thinking is evaluated through a ten-task session of about 20-25 minutes each. The creative thinking qualities that are scored are musical expressiveness (ME), musical flexibility

(MF), musical originality (MO) and musical syntax (MS). Like TTCT (see 2.2.1.2.2), MCTM-II measures divergent thinking factors plus the convergent factor of musical syntax. Children's achievements in the tests are scored by one or more judges. The above qualities, as defined by Webster (1994), are:

- **Musical Extensiveness (ME).** The time the child spends in creative tasks
- **Musical Flexibility (MF).** How much the musical parameter dynamics (soft to loud), tempo (fast to slow) and pitch (low to high) are manipulated.
- **Musical Originality (MO).** The extent to which the child's response is unique or unusual
- **Musical Syntax (MS).** The extent to which the child produces musical logical responses in a way that makes sense.

Musical Extensiveness (ME) and Musical Flexibility (MF) can be measured objectively whereas Musical Originality (MO) and Musical Syntax (MS) have to be scored by one or more human judges.

The ten tasks are scored to all the above factors, i.e. ME, MF, MO and MS. During the tasks, the children can use one of three materials: tempo blocks, a round sponge ball on a piano or a keyboard. Each child taking the test is recorded and the performance is scored at a later time.

Each task belongs to one of three sections: explorations, application and synthesis. During the Exploration section, the child familiarises him/herself with the instruments they can use. The Application section requires from the children more advanced musical activities, asking them to create music and/or songs using their voices and the instruments provided. For the Synthesis section, the child is asked to create music in a less structured manner. The child is given a story describing a space trip in sounds and images and he or she is required to create a composition with a beginning, a middle and an end.

##### *2.2.1.3.6 Cantometrics*

In the specific field of ethnomusicology, Lomax (1976) developed the "cantometrics". The initial inspiration for Cantometrics was Lomax's perception of emotion conveyed by world folk musicians, as he experienced it on the field. As first glance Lomax's work seems to not match here, but essentially what Lomax did was devise a measuring system based on a set of variables for ranking music's attributes, something that more or less is what most scholars in the field do.

Alan Lomax was a field researcher and collector of folk music, who, over a period of almost 40 years, collected a vast volume of work folk music – mostly oral. Initially he travelled in the United States together with his father, folklorist John Lomax, and later by his own and together with others in Britain, Ireland, the Caribbean, Italy and Spain.

Lomax contemplated on the songs accompanying the usual activities of every day life escorting physical labour, mothering and teaching children, in the lives of the folk. From these thoughts, along with the impassions that personal histories and backgrounds of the singers and musicians he recorded made on him, he developed the idea of folk songs as symbols of basic cultural human emotions. Lomax regarded the great folk artists as expressing brightly recurrent motifs of human very own culture and identity. He stipulated that there were families or clusters of style (traditions) that had emerged over the course of human history. He developed this notion when he travelled in Europe after WWII. There, his studies on natural history and ethology guided him to envisage a classification of world folk songs by aesthetic means conceived in behavioural and psychological terms.

When he realised Cantometrics, one of his first steps was to create a number of descriptive variables on qualities of folk music that he noticed to be present almost everywhere. Because of his special interest in songs, he concentrated mostly on vocal music, with the occasional exception of instrumental accompaniment.

The coding system he realised eventually consisted of 37 items, each measuring some characteristic as group organization, level of cohesiveness, rhythmic features, melodic features, dynamic features, ornamentation, choral blend (e.g. tonal blend of the vocal parts), voice quality (e.g. nasalization) and use of body in performance setting.

His system was received by musicologists with mixed feelings and was criticised on a number of grounds (Leroi & Swire, 2006). The main objection was about the statistical method he followed, as he sampled too few songs from each culture, he sampled the wrong songs from each culture,  his sampling was biased and that he sampled too few cultures.

#### *2.2.1.3.7 McPherson's Tests*

McPherson (1993, 1995) also developed measures to assess young students' musicianship. These new measures evaluated three distinct facets of music learners' performance skills: playing from memory, by ear and through improvising. McPherson considers improvisation as a measure that indicates a musician's ability in divergent thinking, and as such it needs to be evaluated along with other musical skills.

He tested the measures he devised on a group of 101 high school students, trumpet and clarinet players. The McPherson measures require a number of judges to score each musician for each measure. A short description of those measures follows.

**Test of Ability to Play from Memory (TAPFM).** This is defined as the ability to play without the aid of a score. The purpose of the test is to assess the skill of reproducing a piece of music learnt in advanced – is the same pitch, rhythm, metre, dynamics etc, as indented by the composer? Students are evaluated by three judges, through a score ranging from 0 to 5.

**Test of Ability to Play by Ear (TAPE).** It is defined as the ability to reproduce a piece that was learnt previously aurally. In contrast with playing from memory, it involves the reproduction at the same pitch as the original or transposed to another key. The ability to play by ear involves three main procedures. The first one has to do with the first attempts of memorisation when a musician immediately tries to reproduce the music just heard. The second one involves the retrieval from the long-term memory a piece that was already learnt by singing or repeated hearings. The last one has to do with the ability to transpose automatically into other keys. The scoring is here as well, in a similar to TAPFM manner, from 0 to 5.

**Test of Ability to Improvise (TAI).** It is defined as the ability to create music spontaneously, without the aid of a score. It tests the ability of the student to think in sound. During the test, the student is asked to improvise in an array of modes, stylistically or freely conceived. The scoring is also performed by three judges, on a 0 to 5 range, but here 4 different dimensions are scored: instrumental fluency, musical syntax, creativity and musical quality.

As it is made apparent from the above literature, scholars most often are assessing creativity through the instantiation of particular creativity attributes on specific scoring quantitative measures. Regardless of how well they approach the notion of creativity, the above measures require more or less the engagement of (often numerous) human experts in scoring. They also often employ statistical processing in order to eliminate human errors and individual particularities.

At the same time, the broad introduction of computer technology in music educational processes created the possibility to computationally automate the whole process. Hence it becomes more and more pertinent to come up with proposals that require no human intervention, even if the range of the investigated qualities is decreased.

Our approach builds on Webster's (see 2.2.1.3.5) and Simonton's (see 2.2.1.2.4) ideas and proposes a creativity model that, in our opinion, captures most of the musical qualities that should be present in creative musical efforts. Webster's work seems to be the most eminent among musical educators and pedagogists, whereas Simonton offers a very attractive point of view, as far the methodological impact of statistics employment is concerned. The creativity model we suggest is presented in 3.4, and was constructed in a way to be convenient for automatic computational possessing. The results are presented in 0 and are discussed in 5.5.

### 2.2.2 Children's Improvisation and new Technologies

Even though children's improvisation has been recognized as a central component of musical creativity, it is still a relatively young area of study. Nevertheless, its educational value has been discussed both musically and socially, as has its collective and collaborative dimension (Tafuri, 2006). More specifically, young children's musical improvisations have been explored through a variety of methods and from diverse paradigmatic viewpoints: cognitive, developmental, educational, sociological and others (Azzara, 2002).

The focus of each research is also varied and scholars have contributed in the investigation of the field from various facets. Brophy (2005) and Paananen (2007) have looked at the development of children as improvisers. Kratus (1989) found improvisation to be beneficial to the musical learning of very young children. Burnard (1999, 2002) studied group improvisational behaviours while Young (2003a) examined child-adult interaction as a source of children's creative behaviours. As Kanellopoulos (2007) points out *Improvisation […] creates the possibility for children to create imaginative leaps and to be really present to music-making and discursive thinking, both their own and others* (p. 135). Ashley (2009) indicates that improvisation is not an isolated element of human music-making; *it connects musical structure our bodies and our sense of selves as individuals and members of social units in powerful ways* (p. 419).

Although development in other areas regarding children's improvisation resulted in the evolvement of new aspects in the domain, the technology advancements and their intervenience and implications to children's improvisations have received less attention. Hence, the introduction of new technologies to support children's improvisations, only recently has been brought to the foreground in relative studies. The role of technology in music education is prominent in discussions about teacher effectiveness (Mills, 1997). Folkestad (2006) discusses young people's out-of-school musical lives, whereas Dillon (2003) explores its impact on learner's creativity. Burnard (2007), on the other hand, delves into its complex relationship with creativity as agents for pedagogic change. The processes of creative music-making with computers, particularly those of composing are centred in the works of Hickey (1997a, b) and Collins (2005). Addessi and Pachet (2005b) note *how new technologies in music education should be considered not only as 'instruments' for didactic support, but also as languages and experiences that affect, form and shape profoundly the processes of music learning and the musicality of children.* (p. 14)

From a pedagogical point of view, technology is thought to transform several aspects of the educational process by encouraging teachers to question what should be taught, how it should be taught, as well as where, when and why it should be taught (Burnard, 2007). Early in the 20th century for example, in the musical methods of influential music educators, such as Jaques-Dalcroze (1865 – 1950), Kodaly (1882 – 1968) and Orff (1895 – 1982), improvisation took the form of experiencing and creating sounds, often using gestures, movement and games. Since then, there has been a surge of research in early childhood music education that stresses the importance of developing aural perception skills to support children's musical understanding and of connecting music with play, as a form of enjoyable, embodied musical action (Young, 2008a, b). This 'embodied' way of improvising has been the focus of some research to date.

Trying to understand the ways in which young children interact with instruments, Young (2003b) asserts that children's improvisations are multi-faceted, arising from a number of generative sources, or modes: bodily movement; instrument morphology; social interactions; musical memories of songs or performed music; interest in numbers and patterns; dramatic play and story. A focus on children's embodied ways of playing around with music reminds us of the need to understand children's musical play, including improvisations, on their own ground, rather than from pre-conceived adult expectations of these.

Classroom applications using technology to compose are amply represented in the literature (Nilsson & Folkestad, 2005; Mellor, 2007). However, technology facilitation of other facets of creative music-making, such as musical improvisation, is less explored, particularly with younger children. Thanks to the wide availability of new music media and ICT, musical engagement no longer demands traditional music skills. Possessing little or no prior conceptual understanding of music no longer forms a barrier in young children's musical engagement. This is not to say that children use such media haphazardly. More often than not, they intentionally engage with technology to make music they find personally and culturally valuable and relevant. In doing so, children discover new pathways for musical expression and develop their musical agency (Ruthmann, 2008).

Finney and Burnard (2008) argue that this ease of access to music and their capacity to exercise finely grained judgments about the ways they choose to use it, create an ever greater challenge for the music educator. With this new focus on children's musical agency, traditional educational modes which are teacher-centred, text-based and knowledge-driven are put aside in favour of educational perspectives where children are placed centre-stage in the learning process.

This blurring of the boundaries between formal and informal contexts of music making and training is caused partly by the advancement and omnipresence of technology-powered devices on children hands. Even a low-end contemporary smartphone has many times the processing power of previous decade's advanced desktops. These smartphones, carried everywhere by almost every child in western societies nowadays, offer access to thousands of music apps, making the informal context's music related activities practically ceaseless. This often leads to, as Triantafyllaki (2017) eloquently posed it, the *[…] paradox that often exists in musical transmission in formal educational settings – young children already posses a kind of musical sensibility, yet with no technical skills.* (p. 39). Consequently, traditional educational modes cannot ignore this reality, but rather encompass it, trying to make the most out of it. This process falls inline with the current trend of liberalisation of virtually all educational activities that move the child in the centre of the formal learning processes.

Lubart (2005) categorises the various ways with which computers are taking part in the creative process, gradually ascending from the most fundamental level to the most advanced – from the *computer as nanny*, proceeding to the *computer as pen-pal*, then to the *computer as coach* and finally to the *computer as colleague*. As the names of the categories signify, the role of the computer ranges from managing, monitoring and supporting the creative process (the *computer as nanny*) to providing an equal partner in an joined synergetic creative process (the *computer as colleague*). Nonetheless, Lubart cautions that a human intervention is crucial to switch the computer to the most suitable operative mode. MIROR-IMPRO interactive session can be said to falls well into the *computer as colleague* category, as it is apparent throughout this work.

#### 2.2.2.1 Improvisation and Flow

The theory of flow (Csikszentmihalyi, 2008) is defined as the psychological state of maximum optimism and satisfaction that a person perceives during the course of an activity and it is closely related to the concept of creativity. The state of flow is defined as the optimal experience that results from the balance between the challenges that s/he wants to achieve and the personal skills to achieve her/his goals.

The state of flow pairs with increased levels of conditions like focused attention, clear-cut feedback, clear goals, pleasure, control of situation, merged awareness, no worry of failure, low levels of self-consciousness and distortion of the perception of time. Other emotional states can also be present, such as arousal, control, boredom, anxiety, worry, relaxation and apathy.

Csikszentmihalyi (2004) states that during the state of flow, the self cuts off most of the input coming from the environment and hence acquires the maximum arousal and concentration on his/her goal. That levies all resources one possesses towards the achievement of the goal, i.e. the problem to be solved, thus achieving the maximum creativity engagement. This cut-off also creates the feeling of flow, which gave its name to the theory

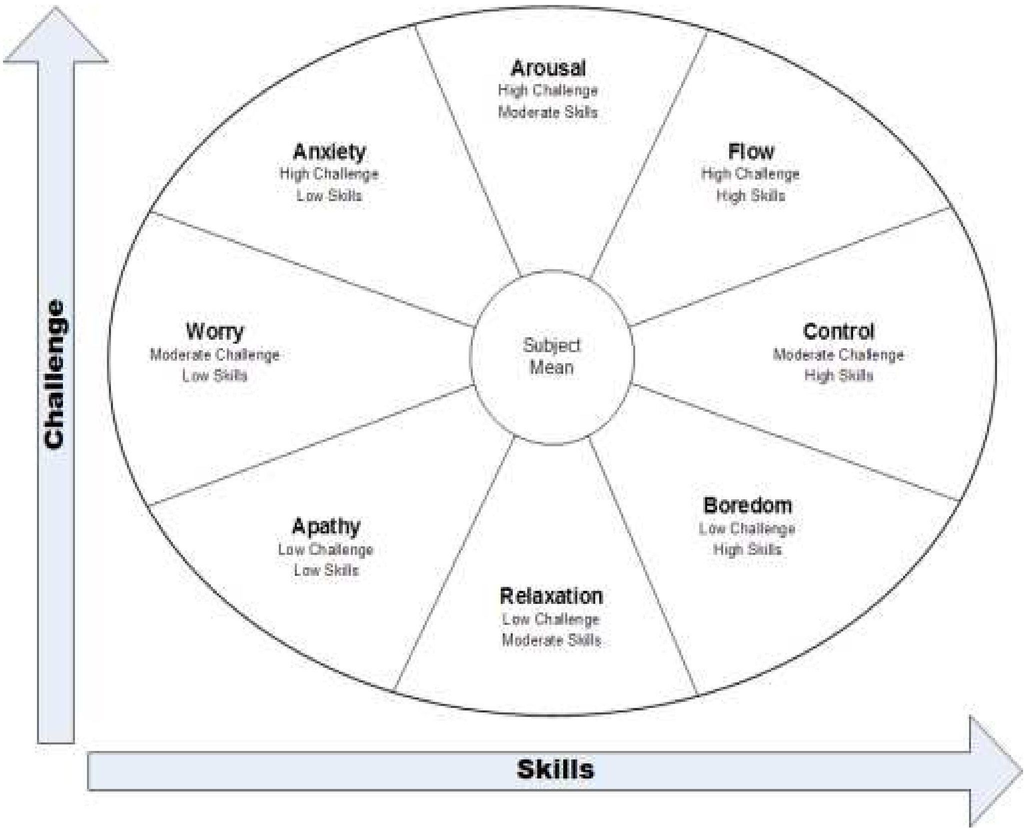



**Fig. 8. Csikszentmihalyi's Flow Diagram**

Recent neurological studies, although preliminary, suggest that certain areas of the brain are much more active during improvisation than they are when playing music from memory (Limb, 2010; Donnay et al., 2014). In addition, some areas essentially turn off activity from memorized performance when improvising. These areas are the areas involved in self-monitoring – an evidence that seems to support Csikszentmihalyi's Flow Theory

### 2.2.2.2 The Concept of Interactive Reflexive Music Systems

The introduction of new music technologies in the educational process involves also the introduction of new interaction paradigms between the user and the machine. An instance of such a paradigm is Interactive Reflexive Music Systems (IRMS) (Pachet, 2006b; Addessi, 2014, Ferrari & Addessi, 2014).

The notion of IRMS was introduced by Pachet (2002, 2003), which described an IT system capable of producing musical output based on a given input. The user interacts with the system, which replies back with a response mimicking the style of the user. Within the context of IRMS, two phrases are said to have the same style when they have more or less the same statistical distribution of notes, chords and other musical attributes in general (Pachet, 2004).

The user interacts with an entity that shares with him a large part of his/her musical personality, a virtual copy of oneself (Pachet, 2017). The focal point of the whole process is not the quality of the music produced by the system, but the music produced by the user, due to the provocation caused by interacting with the system.

An indicative list of attributes that a system should have in order to be characterised by reflexivity follows:

**Similarity or mirroring effect.** The musical output of the system should be in the same style as the user's style. The user acquires the sensation that the system produces music that it could have been produced by him/herself (Khatchatourov et al. 2016). I.e. the user should feel that s/he interacts with a virtual copy of her/himself.

**Agnosticism**. The system should be able to learn to produce output in the same style as the user by its own means, i.e. previous knowledge of the user is not a required option.

**Scaffolding of complexity.** The system should be able to constantly learn from the user input. That means that the system should be able to increase the complexity of its response as a reaction to the user altering his/her input. Incremental learning should be a central mechanism of such a system.

**Seamlessness**. The system should be able to produce music that can be interchangeable with the user's own production; i.e. a third party should not be able to tell apart which part belongs to the human and which to the machine.

Such a system should include core modules at least for the following functions:

- **Phrase-end detector.** This is a mechanism able to detect when a musical phrase has ended. The mechanism should be able to dynamically adapt its threshold to user input; if the input is slow, for example, then the speed at the end could be decreased accordingly.
- **Gradual learning.** A central machine learning mechanism should be able to analyse the user input and gradually learn as the user continues to input music of diverse complexity. To speed up learning, the system should also learn all transpositions of the input phrase.
- **A global parameter analyser.** A core arbitrating mechanism should be capable of detecting during runtime all changes on the various global properties of the user musical phrases, such as the density (number of notes per second), the tempo, and the meter (location of strong/weak beats), the overall dynamics (loud or soft), and so on. These parameters directly affect the generated system response.
- **A response generator.** The module responsible to produce the system's response output. It uses the information produced by the parameter analyser and the learning module in order to produce a note-by-note phrase that imitates the user input.

Studies by Pachet (2004, 2006a) and Addessi et al. (2006, 2015) contribute corroborating evidence that the experience of interacting with an IRMS leads to states of Flow (Csikszentmihalyi, 2008) and that it triggers creative behaviours or creative output.

#### 2.2.2.3 The MIROR-IMPRO System

The MIROR-IMPRO system is an IRMS implementation, which came as the evolution of The Continuator (Pachet, 2002, 2003, 2006b). The system was initially built with adult users in mind, but several experiments showed that it is particularly attractive to children (Addessi & Pachet, 2003, 2005a, b; Addessi et al., 2004, 2015; Pachet & Addessi, 2004).

The core concept of the system is that basic musical elements can be taught and musical cognitive processes can be developed not only by the traditional teacher/learner dipole but also by the direct interaction of the learner with the system, without the involvement of a human instructor.

**Fig. 9. Interacting with MIROR-IMPRO**

The flow of information in the system is shown in Fig. 10. The user generates MIDI events by pressing the keyboard of a synthesizer, connected to a PC, on which the MIROR-IMPRO system runs. The music phrase is sent to the system, which generates a new phrase, created as a response to the input phrase. The phrase is generated according to whatever the system has learnt by the learning module so far. The output phrase is then sent back to the synthesizer and subsequently to the sound reproduction module.

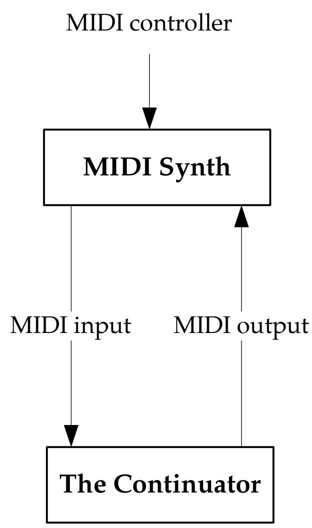



**Fig. 10. Basic flow in the MIROR-IMPRO system**

The system generates different kinds of output melodies based on the user's musical input, stimulating the reflexive interaction between the user and the application. This generation is based on a specific Markovian mechanism designed by Sony CSL Paris, allowing a meaningful musical output (Pachet, 2003, Pachet et al., 2011).

As the user plays in new musical phrases, the learning module segments the music and builds up a database of patterns. The learning module is learning incrementally as the user continues to interact with the machine. The machine's replies mimic the user's style.

During these years, additional AI musical improvisation systems based on markovian inference have been devised, such as the OMax system (Cont et al. 2006; Déguernel et al., 2016).

Given that the machine's responses are built based on the user-generated musical input, the system does not only mimic the user's style in terms of melodic patterns, but also in terms of technical and expressional aptitudes. This means that in terms of the Flow theory briefly described above, the system keeps its users within their flow zone. Hence the system can be regarded as a *Flow machine*. Recall that *Flow* describes the balance that occurs when challenges counterpart skills. When the challenges are too demanding to be met, anxiety occurs. When they are too simple boredom emerges. The interaction with a copy of oneself offers the perfect match to challenge (Pachet, 2017).

Below is an example of a user's input and the answer from the system. Each response of the system comprises of musical material close to the user's style, but at the same time prompts the user to explore, as the next step, new ways to express musical ideas.


**Fig. 11. A chromatic scale played by the user and the MIROR-IMPRO response**

Although there is a graphical user interface in order to regulate the system's various parameters, the standard mode requires no other interface than the MIDI keyboard itself.

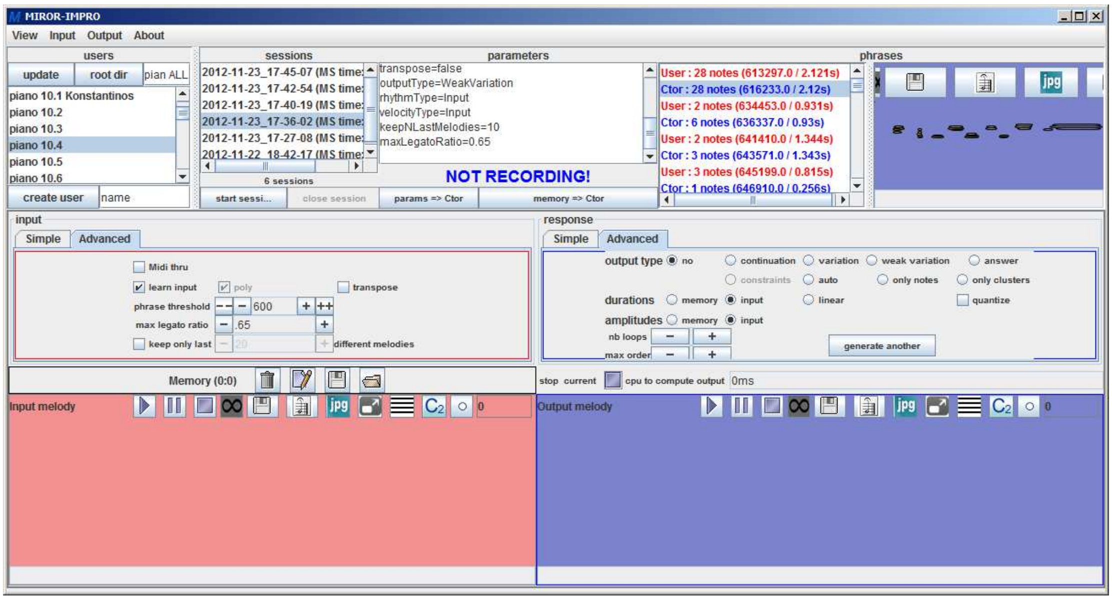



**Fig. 12. System's main screen**

One of the system parameters adjusts the machine Type of Response. There are 4 types of MIROR-IMPRO's replies:

- **Nothing**. The System responses are turned off.
- **Same**. The machine plays back exactly what the user input.
- **Different**. The machine reply is similar (but different) to the user input
- **Very Different**. The machine reply is further away from user input

Even though setting the machine's Type of Response to *Different*, was described by the project experiments' prescription, each country diverted, and as a result there is no guarantee that all elicited data was drawn using the same kind of Response.

Most of the parametres that affect MIROR-IMPRO system behaviour are exposed on this GUI and the user can calibrate through this their values to better suite it to his/her needs.

# Chapter 3

# Methodology

In this chapter, the methodology and technical details of this research will be presented. Specifically, the data collection mechanism, the musical corpora, the pattern discovery methods, the creativity model, the computational processing and the implementation details will be discussed.

The methods that are presented below were formed in order to tackle 3 goals:

**G1. Musical pattern recognition and discovery**
**G2. Exploration of musical creativity development**
**G3. Identification of overrepresented patterns in a corpus with respect to another corpus (called "anticorpus")**

In order to achieve the goals above, data was collected during a number of psychological experiments, which took place within the framework of MIROR FP7 project. The data is in the form of MIDI files and was produced by children interacting with the MIROR-IMPRO system.

The formulation of the above three goals was made with the one eye towards confronting the research questions, posed in section 1.4. We remind that our research questions are:

**RQ1. How the children's improvisation capabilities are affected by the usage of MIROR-IMPRO?**

**RQ2. Does the MIROR-IMPRO interaction influence musicians and non-musicians alike?**

**RQ3. Do the visualisation constructs of MIROR-IMPRO impact the way that children improvise?**

**RQ4. If we segment the music data according to some categories are we detecting patterns that are overrepresented on a musical corpus generated by a specific group with respect to the rest of the data (anticorpus)?**

Hence we devised a set of three goals and a research path to pursue them that when accomplished will provide answers to our research questions. More specifically, as shown diagrammatically to the figure below, we were expecting that G1 will tackle RQ3, G2 RQ1 and RQ2 and G3 RQ1 and RQ4.

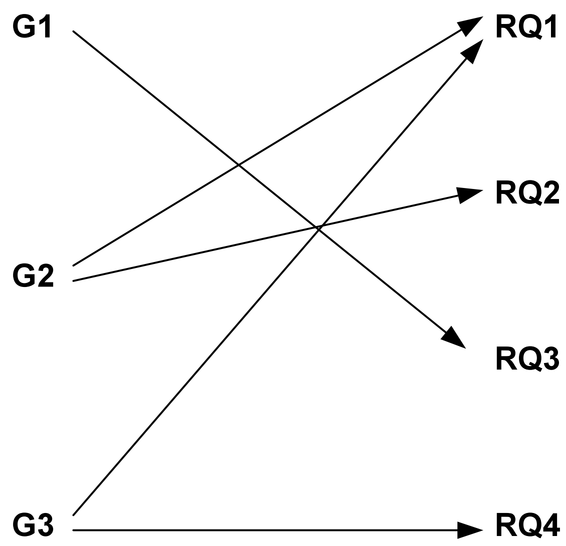



**Fig. 13. How our Research Questions are answered by out methodological Goals.**

A number of key decisions and assumptions are stated below and they hold true for all data processing used within the context of this work:

- All music resides in first track (viz. MIDI Track 0). Channel 0 holds user music whereas Channel 1 holds MIROR-IMPRO generated music.
- Channel 1 is eliminated prior to processing.

- The smallest note is the sixtyfourth note
- Music is quantised. All notes are modified to match to precise multiples of $64^{th}$ note size slots. Note that MIDI data is performance data and as such the value of each note is rarely exactly as notated on a score.
- When a musical phrase is cut into segments, the boundaries of the segments are defined by a simple rule of thumb; that is, a new segment starts when two conditions are met simultaneously: the melodic distance from the last note of the previous segment to the first note of the new one should be at least 7 semitones and a pause of at least 300 milliseconds (actually MIDI ticks) should intervene. Our decision for music phrase segmentation is based loosely on the Gestalt principles of proximity and similarity (Wertheimer, 1923) – rather on the segregative than the unifying aspects of the principles.

A common computation substrate lies below the 3-goal computation and this will be discussed in the next sections. Divergences occurred of course, since each goal has its own particularities. This will be pointed out and discussed separately.

In the following, we sometimes get into too many technical and implementation details. But as we said already in the previous chapters, our aim is also this text to be of usage to anyone who might explore the same or nearby research pathways.

# 3.1 Data Collection

Data used for this work was collected in psychological experiments that took place in three countries, namely, Greece, Sweden and the U.K. between 2011-12 in primary schools and nurseries. Rigorous quantitative experiments were also carried out in Italy, but the data has not been taken into account as it was based on different conditions, and these results have been analysed separately by the Italian team (Addessi, 2014; Addessi et al., 2014, 2015; Ferrari & Addessi, 2014). The sessions took place during or immediately after school hours[18]. Consent forms were signed by the

[18] The detailed procedure is presented in the MIROR project Deliverable *D5.1 Report on psychological experiments with MIROR-IMPROvisation, Composition and Body Gesture*

parents of all children taking part in the study and country-specific ethical regulations were adhered to.

The aim of these experiments was to provide children an opportunity to improvise in interaction with a responsive partner. It was hoped that the children would learn to relate what they heard in the replies, with what they played on keyboard. This skill enables them to re-interpret what they have just played, on the basis of the replies and imagine what they might play next. This is reflexive musical perception and imagination as conceived within the MIROR project. Reflexive musical abilities were essential in creating time-based narrative structures which were, in turn, fundamental to creative improvisation and composition.

Special care was taken for the participating children to be as relaxed as possible. Hence, effort was made to produce an environment as friendly as possible through an informal atmosphere. A designated space was created for the system set-up and each child was introduced to the system by a teacher or researcher. The teacher/researcher remained in the room with the child throughout the experiment, and interacted with the children only when providing some encouragement at the beginning of the sessions or when explaining the use of the equipment.

As being informed[19], specific guidelines as to how or what to play/improvise were not given to the children. This was done on purpose, to avoid any interference in the interaction with the MIROR system and also avoid to bias the children towards any direction. It merely prompted the children to play to see what happens. In other words, they were invited into free music improvisation – this is apparently very different from adult music improvisation.

The equipment used consisted of a laptop with the MIROR-IMPRO Improvisation software version 2.5, connected to a Korg X50 keyboard with two speakers. Neither the laptop nor its link to the keyboard was visible to the children. Children were encouraged to play on the keyboard for as long as they liked.

[19] Personal communication with Dr. A. Triantafyllaki, member of the Greek MIROR team, who oversaw the implementation of the psychological experiment on the Greek site

Two settings of the MIROR-IMPROvisation system were used: *Same* and *Very Different*. All melodies were kept in memory and used in this work for the computational analysis. The *Same* output type is defined by the program as variation output type keeping the same duration and amplitude as given in the input, without transposition allowed. The *Very Different* output type is defined by the program as continuation output type with duration and amplitude drawn from the ones that are kept currently in memory, without transposition allowed.

In total three experiment groups have taken place.

**Experiments Group I – EG'I**

In total, twelve children participated in the study from each country, six 8-year-olds and six 4-year-olds. The ages were selected to represent two stages of schooling, preschool and primary education. Equal numbers of boys and girls participated in the study in each of the two groups, 4- and 8-year-olds. Children participated in the study for three consecutive days, each time with both settings (Same and Very different). The aim was to record six sessions in total for each child –two each time s/he played for each setting. Each recorded session consisted of a number of dialogues of music phrases, alternating between human and machine.

The human-generated music phrases were recorded into one MIDI channel, while the machine-generated music phrases were recorded in another MIDI channel. This facilitated extraction of all human phrases for analysis.

**Experiments Group II – EG'II**

Two additional studies, using the same equipment and setup, though in a smaller scale, took place in Greece only.

The first study, where thirty children took place, involved two groups. One experimental group was children with no previous knowledge of keyboard playing, and the other group  was with children who had already been studying the piano for 1-4 years.

We chose these two different groups of children because our initial work with non-musicians indicated that the keyboard as an object seemed to draw the attention of children, rather than the interaction and the actual responses of the system. In this work we analyse the data from both groups of children.

- The experiment with the young pianists group took place in a small music school (junior's Conservatory) and involved 10 children (six girls and four boys) playing alone with the MIROR-IMPRO system for six weeks (that is six sessions of 15 to 20 minutes).
- The experiment with the non-musician's group took place in a primary school and involved 20 children (sixteen boys and four girls) playing with MIROR-IMPRO in a span of six weeks, in similar conditions.

In both studies we conducted a pre-test (before the six weeks) and post-test (after the six weeks) with the children. This consisted of asking each child individually to improvise a short tune (1-2 minutes long) on the keyboard.

**<u>Experiments Group III – EG'III</u>**

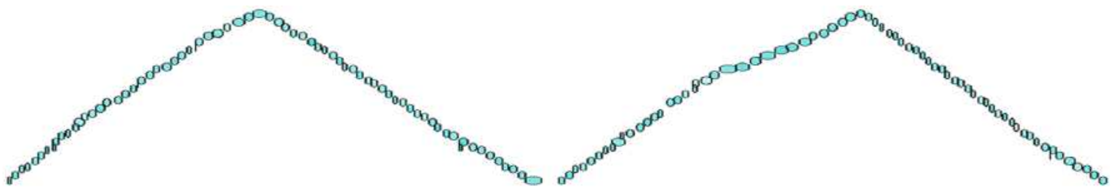


**Fig. 14. How MIROR-IMPRO visualises a glissando.**

The second study had to do with one specific feature of the MIROR_IMPRO system, the visualisation of the music while the children were playing. Every time a key is pressed, the note produced triggers a corresponding visual signal on the screen of the laptop connected. The features of this visual construct are directly dependant on the features of the note. Hence, the volume, the pitch, the duration (and other attributes) of the note are affecting the size, the colour, the gleam of the visual construct.

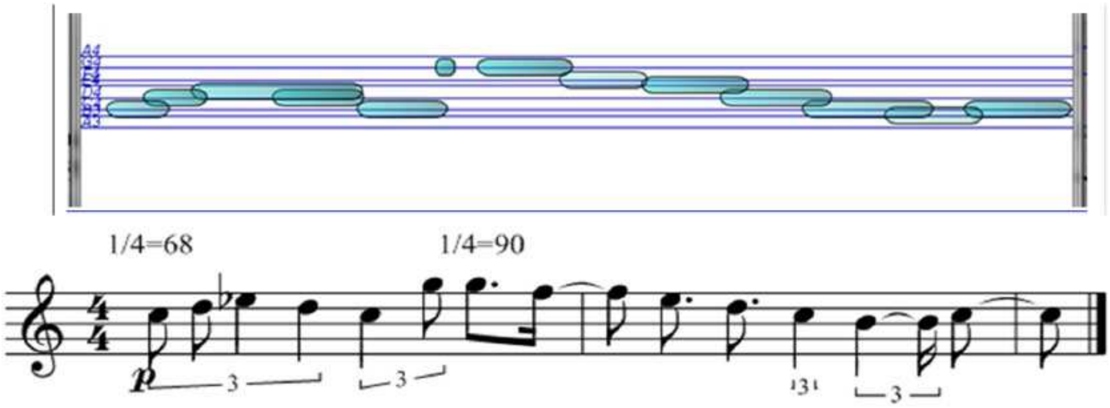



**Fig. 15. A type of visualisation as appears onscreen.**

The data was collected through experiments with 6- to 8-year-old children, three boys and three girls. Each child performed 3 sessions and each session involved one improvisation with no visualisation and one with visualisation setup. In each session the child played with and without having a visualization screen in front of them (simple representations of pitch, amplitude and tempo displayed on a laptop screen which was placed in front of/removed from children's visual span in each session) (Gromko & Russell, 2002; Gromko, 1994).

The adult (researcher) did not interact with the child (as much as this was possible). The children were asked to play as much as they liked during each set-up with and without the visualization, stopping when they were tired.

After the session, the researcher discussed informally with each child about the experience of playing with the prototype, followed by a more structured discussion after their third session. It should be mentioned that the prototype can be set to respond with more or less variation to the child's input melody. In this study, the MIROR-IMPRO setting was set to *Different*, providing an output that was slightly varied to the child's input melody.

Besides the musical data collected in MIDI format, 6 semi-structured interviews were performed (after one week of playing with MIROR-IMPRO). Also fieldnotes with informal discussions with children after each session were taken.

The experiment groups are named EG'I, EG'II and EG'III for convenience. However the names do not indicate the specific time or order the experiments took place.

It should be stated here that the character of the experiments that took place during the MIROR project was mostly qualitative. However, in our work we do not assess the experiments nor their results. What we do is rather evaluate in a quantitative manner the melodies produced by the children, independently from the particular characteristics and conditions of each experiment. The only determining factors that we took under consideration are whether the visualisation capabilities of the MIROR-IMPRO were turned on and if the child has taken piano lessons. In other words, our focus within the framework of this research is on studying the melodies out of context, focusing solely on the neutral level (Nattiez, 1990).

# 3.2 Corpus Description and Organisation

The experiments described above produced a number of MIDI files. Each file captured a session between a child and the MIROR-IMPRO system. Not all files were used for all goals (G1 – G3). For each of the G1 – G3 goal a corpus was organised. The description of these corpora follows.

## 3.2.1 Data Set for task G1

The data used for this goal was the data collected during EG'III. The corpus collected is divided in two sub-corpora: one with the visualisation capabilities turned on (the *V melodies*) and one with no visualisation (the *N melodies*). Both contain 18 MIDI files, with the no visualisation sub-corpus being slightly larger (28988 note events — as opposed to the visualisation corpus with 24361 note events). The no visualisation data sum up to 1282 musical phrases whereas the visualisation one to 1075.

## 3.2.2 Data Set for task G2

The data used for this goal was the data collected during EG'II. The corpus was divided in two parts, one before and one after children's interaction with the system, as discussed in the previous section. We compare the pre-test sessions to the post-test sessions of both the young pianists' and the non-musicians' group (before and after their experience with the system) in order to find out if their creativity was enhanced in the post-test session. This way, we could potentially attribute such development to the impact of the in-between sessions during which they interacted with the MIROR-IMPRO system.

The 10 young pianists' pre-corpus consists of 5,218 note events having duration of 2,359,916 msecs. The post-corpus consists of 2,427 note events having duration of 662,627 msecs. The 20 non-musicians' pre-corpus consists of 8,990 note events having duration of 2,022,753 msecs. The post-corpus consists of 6,477 note having duration of 1,030,853 msecs.

### 3.2.3 Data Set for task G3

In G3, we used all data collected in EG'I along with the non-visualisation data from EG'III. In total, the corpus consists of 299 MIDI files. From them 138 were collected in Greece, 77 in Sweden and 84 in the UK. 140 were from boys and 159 from girls. 137 were 4 years old whereas 162 were 8 years old.

The task was to assess pattern over-representation in a corpus with respect to an anti-corpus. In order to do that, we separated the above corpus in two distinct subsets by using various criteria in order to use one as a corpus and the other as anticorpus. For the grouping of the data we used 4 different criteria and thus we performed 4 different experiments.

**Experiment 1: Geographic division.** In this experiment we looked for characteristics which could be attributed to differences on the cultural and educational environment.

- Case I: Corpus Greece; Anticorpus: Sweden & UK
- Case II: Corpus Sweden; Anticorpus: Greece & UK
- Case III: Corpus UK; Anticorpus: Sweden & Greece

**Experiment 2: Gender division.** In this experiment we looked for characteristics which could be attributed to gender-related differences.

- Case I: Corpus Boys; Anticorpus: Girls
- Case II: Corpus Girls; Anticorpus: Boys

**Experiment 3: Age-related division.** In this experiment we looked for characteristics which could be attributed to age-related differences. We focused on ages 4 and 8, since fast progress occurs to all cognitive abilities between the ages of 4 and 8.

- Case I: Corpus 4-year-olds; Anticorpus: 8-year-olds
- Case II: Corpus 8-year-olds; Anticorpus: 4-year-olds

**Experiment 4: Session-related division**. In this experiment we looked for characteristics which could be attributed to the different session setup. The interaction with the MIROR-IMPRO system triggered differences in the children's improvisation capabilities. Keep in mind that the setup of the experiments consisted of a session during which the child improvised by its own means, then a number of sessions when interaction with the system took place, and finally a session by the child alone again concluded the experiment. Hence we checked the first session against the final session for differences.

The data used was only from the Greek and the British experiments, since the other countries didn't follow exactly the same collection procedure.

- Case I: Corpus pre session; Anticorpus: Pos session
- Case II: Post session; Anticorpus: Pre session

The idea behind all the above groupings was to investigate each case of the aforementioned experiments by using contrast data mining approaches, for patterns that might differentiate one corpus from another – viz. the anticorpus.

## 3.3 Knowledge Representation

Having in mind the data manipulation task, the Viewpoint representation formalism (see 2.1.2.1) was used as the knowledge representation schema throughout all work reported within this thesis. Viewpoints, besides being a mentally easy-to-perceive construct, also offer a direct and straightforward implementation on corresponding data structures.

As an example in the table below a set of viewpoints are given for the melody in Fig. 3.

| Viewpoint | Sequence |
|---|---|
| `Pitch` | `70, 69, 67, 65, 67, 69, 67, 62, 60, 62, 64, 65, 67, 65, 64, 60, 62, 62, 74` |
| `Interval` | `NA, -1, -2, -2, 2, 2, -2, -5, -2, 2, 2, 1, 2, -2, -1, -4, 2, 0, 12` |
| `Contour` | `NA, -1. -1, -1, 1, 1, -1, -1, -1, 1, 1, 1, 1, -2, -2, -2, 1, 0, 1` |
| `Interval range`[20] | `NA, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 2` |
| `Duration`[21,22] | `8, 8, 8, 8, 8, 8, 24, 24, 8, 8, 8, 3, 3, 2, 8, 8, 24, 8, 8` |
| `Duration range`[23] | `1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1` |
| `Duration ratio`[24] | `NA, 1, 1, 1, 1, 1, 3, 1, 1/3, 1, 1, 3/8, 1, 2/3, 4, 1, 3, 1/3, 1` |

**Table 5. The viewpoints used for G3, applied in the example of Fig. 3.**

The specific viewpoints used for each of the goals G1, G2 and G3 follows:

**For task G1**

The goal here is to recognise and identify repeated patterns – sequences of musical attributes – within a corpus. The patterns we looked for are sequences of one of the viewpoints used for representing the music stored in the MIDI files of the corpus. The musical object on which viewpoints are based here is the single note.

---

[20] 0 for unison, 1 when interval is between 2 & 5 steps, 2 for larger intervals

[21] The actual duration found within the MIDI file will be most likely different from the number herein, calculated from the score. This is because, as already mentioned MIDI is actually performance data and as such will be slight different from the "ideal" notated in the score. Hence some eighth notes will not be 8 sixtyfourths but 9 or 7 or whatever the performer decides. The same applies for the triplet <F, G, F> - events $e_{12}$, $e_{13}$, $e_{14}$ (see Fig. 3). Duration is used here as a means to comprehend rhythmical aspects.

[22] Also mentioned as `Rhythm`

[23] Also mentioned as `Rhythm range`

[24] Also mentioned as `Rhythm ratio`

The viewpoints used are shown in Table 6.

| Viewpoint | Description |
|---|---|
| `Pitch` | The MIDI number of the note |
| `Interval` | The difference from the previous note's MIDI number in steps (semitones) |
| `Contour` | The melodic movement of the higher voice; 0 for unison, + for rising and – for falling |
| `Interval range` | 0 for unison, 1 when interval is between 2 & 5 steps, 2 for larger intervals |
| `Duration` | Multiple of time units, i.e. $64^{th}$ notes |
| `Rhythm range` | 0 for less than a eighth note, 1 for between eighth note and half-note and 2 for greater note values |
| `Rhythm ratio` | The ratio of the duration of the current note over the previous one |

**Table 6. Viewpoints used for goal G1**

The selection of the above viewpoints (except pitch and duration which are the very basic ones) was made in order to capture the particularities of children playing. Children are playing using a lot of gestures, thus we tried to employ viewpoints abstract enough to capture those gestures. Hence, *`Interval`* can be seen as an abstraction of *`Pitch`* and similarly *`Contour`* and *`Interval range`* can be seen as abstractions of *`Interval`*. This line of inference accords to the modular functional architectural model purposed by Peretz & Coltheart (2003). In this architecture, Contour Analysis, Interval Analysis and Tonal Encoding comprise a distinct Pitch Organisation processing component where music input is fed and where the processing flows from Contour Analysis to Interval Processing to Tonal Encoding.

In the same way *`Rhythm range`* and *`Rhythm ratio`* are considered abstractions of *`Duration`*. Finding exact repetitions on those abstract levels, which are some steps above the musical surface, can be viewed as an approximate matching on the surface level (Cambouropoulos et al., 2001). The usefulness of these choices will be evaluated and the results will be examined in accordance to the expected accuracy in capturing the children improvisational particularities.

**For task G2**

The goal here was to explore the creativity that can potentially arise when children are interacting with the MIROR-IMPRO device. The creativity model against which the children are measured is presented in 3.4. Each creativity variable is calculated directly from a distinct segmental viewpoint or from a combination of multiple viewpoints.

The viewpoints used for G2 goal are shown in Table 7 (described in 3.4).

| **Segmental Viewpoint** | **Description** |
|---|---|
| `sd[seq]` | Standard deviation of sequence seq |
| `uniq_patt[seq]` | Number of unique patterns in sequence seq |
| `diff_patt[seq]` | Number of different patterns in seq |
| `tot_patt[seq]` | Number of total patterns in seq |
| `Avg_sise[seq]` | Average size in number of note events of seq |
| `Avg_dur[seq]` | Average duration |
| `Tot_size[seq]` | Total size in number of note events of seq |
| `Tot_dur[seq]` | Total duration |
| `Interval[seq]` | Percentages of interval in 3 different divisions; small, medium or large |
| `Note[seq]` | Percentages of pitch in 3 different divisions; small, medium or large |
| `Rhythm[seq]` | Percentages of rhythm in 3 different divisions; small, medium or large |
| `velocity[seq]` | Percentages of dynamic in 3 different divisions; small, medium or large |
| `Texture[seq]` | Measures how “thick” is the music texture |
| `Cluster[seq]` | Number of chords in seq |

**Table 7. Segmental viewpoints used for task G2.**

**For task G3**

The goal here was to identify patterns that are overrepresented in a corpus with respect to an anticorpus. The Viewpoints used were:

| Viewpoint | Description |
|---|---|
| `Pitch` | The MIDI number of the note |
| `Interval` | The difference from the previous note's MIDI number in steps (semitones) |
| `Contour` | The melodic movement of the higher voice; 0 for unison, + for rising and – for falling |
| `Interval range` | 0 for unison, 1 when interval is between 2 & 5 steps, 2 for larger intervals |
| `Duration` | The rhythmic values of the notes quantised to 1/64th grid; hence a 1/64th is 1, a 1/32nd is 2, a 1/16th is 4 and so on |
| `Duration range` | 0 for notes less than a eighth note, 1 for notes with values between eighth note and half-note and 2 for greater notes |
| `Duration ratio` | The ratio of the Duration of a note to its previous one |

**Table 8. Basic and derived viewpoints, used in the current work.**

For each segment a set of *segmental* viewpoints (see p.30) was also calculated, such as the number of notes in the segment, the duration etc. In these patterns the basic unit is not the note, but the whole segment.

| Segmental Viewpoint | Description |
|---|---|
| `huron[seg]` | Number of melodic arch types, as defined by Huron (1996) |
| `sim[seg]` | Number of simultaneities, i.e. notes that occur at the same time |
| `ls_ratio_n[session]` | Ratio of long over short segments (as defined per number of notes per segment). Is defined in session level, i.e. in multiple segments |
| `ls_ratio_d[session]` | Ratio of long over short segments (as defined per duration of segment). Is defined in session level. |
| `Compr_ratio[session]` | Ratio of the size of a compressed sequence of viewpoint over the size of same sequence uncompressed. Is defined also in session |

| | |
|---|---|
| | level. |

**Table 9. Segmental viewpoints**

The **huron viewpoint** is drawn on Huron's (1996) seminal paper. He defines 9 types of melodic arches: ascending (ASC), descending (DSC), concave (COV), convex (COX), horizontal-ascending (HA), horizontal-descending (HD), ascending-horizontal (AH), descending-horizontal (DH), horizontal (HHH).

The **compression viewpoint** is a rough approximation for measuring repetitiveness in music. This is because compression algorithms mainly rely on repetition in order to compress a buffer with data. `GNU zlib` is a good choice (it is used in the well-known `gzip` utility), as it uses Huffman coding and LZ77 compression algorithms.

The viewpoint sequence is gathered in a buffer and the buffer is compressed. The ratio $R = \frac{Size(compressed\_buffer)}{Size(uncompress\_buffer}$ can be conceived as a measure of repetitiveness in music. Therefore, smaller $R$'s mean higher repetition.

# 3.4 Creativity Model

In order to assess creativity we propose a creativity model realised as a set of variables that we calculated for each subject for the improvisation sessions with the MIROR-IMPRO device. The idea of assessing creativity through a set of metrics (realised as variables) is drawn directly from the creativity literature, as most scholars are proposing to measure creativity based on a set of measures, scored by one or more experts.

Our aim is to come up with a set of metrics that can be scored automatically, eliminating thus the need of experts and lead to the readiness of use of a quantitative creativity assess tool. It should be mentioned, however, that to measure creativity computationally is not an idea accepted by everyone, as already mentioned, as people believe that only experts can come up with such evaluations, and that it is not possible to formalise the process computationally.

As evident in the creativity literature, we assume that advancement in musical variation and diversity is an indicator of musical creativity. As Creativity is a hard concept to quantise and formalise, several of the variables described below might not describe all aspects of creativity.

The creativity variables discussed below are based on the work by Simonton (see 2.2.1.2.4), Webster (see 2.2.1.3.5) or are part of our own contribution, inspired by and formalised based on the creativity literature reviewed in Chapter 2. As already mentioned in 2.2.1.2, in some cases, these are controversial. For example, measuring the standard deviation as high is thought to show more adventurous thinking, and thus more creativity. In other cases, measuring the SD as low might show more thoughtful reactions, with more repetition (and thus more musical).

The following variables were devised:

**V1 – Standard Deviation.** Standard deviation is a metric on how far away from the average most of the values fall. A low standard deviation means that data tends to be close to the average. It indicates the diversity of the musical vocabulary. Calculated for the viewpoints `Pitch`, `Interval` and `Rhythm`.

**V2 – Number of patterns with frequency 1.** We identify all sequences of the 3 viewpoints (pitches, intervals, rhythmic values) that appear only once in the corpus. We borrowed this idea from the lexical analysis made by Simonton (1990), as it seems to indicate novelty and musical variety. Suffix arrays (see 3.5) make straight forward the identification of such patterns, since we count the number of rows in the array that have no common with their following one. Calculated for the viewpoints `Pitch`, `Interval` and `Rhythm`.

**V3 – Average Size, Average Duration.** The idea of this indicator is taken from Webster's MCTM (Webster, 1983, 1985). We calculate two variants of this variable. Firstly, we calculate the segmental viewpoints size (in number of notes) and duration (in msecs) for each subject. Then we calculate the average of all segments per subject. Next, we calculate the total size and total duration for each subject.

**V4 – Ratio of different per total patterns.** This variable is drawn by analogy from lexical content analysis in psychotherapy (Holsti, 1968) and is also used by Simonton (1990). There is evidence that the greater the ratio of different words per total number of words, the greater lexical diversity (Holsti, 1968). Thus we assume that the higher the above ratio the greater musical variability and hence more advanced musical creativity. We identify all sequences of the 3 viewpoints (notes, intervals, rhythmic values). Calculated for the viewpoints `Pitch`, `Interval` and `Rhythm.`

**V5 – Interval Range Variation.** This is an indicator on musical intervals diversity. We calculated the segmental viewpoint `interval (small, medium, large).` Then we calculated for each subject's music (viz. each MIDI file) the percentages of small, medium and large intervals. We assume that small intervals are less than 4 steps and large ones more than 8 steps – recall that a 'step' is a semitone.

We assume that the more evenly distributed the percentages are the more variation we have. This applies also to V6, V7 and V8.

**V6 – Pitch Range Variation.** We calculated the segmental viewpoint `note(low, medium, high).` Then we calculated for each subject's music the percentages of low, medium and high pitches. We assume that low pitches are below F3 (MIDI number 53) and high ones over C#5 (MIDI number 73).

**V7 – Rhythmic Range Variation.** We calculated the segmental viewpoint `rhythm(slow, medium, fast).` Then we calculated for each subject's piece of music the corresponding percentages. We assume that medium rhythmic values lie around the quarter note duration; that is MIDI 500 ticks for our MIDI files. Hence we take +/- 10% of that for identifying the slow and fast rhythms.

**V8 – Dynamics Range Variation.** We calculated the segmental viewpoint `velocity(soft, normal, hard).` In order to identify the dynamics of each note we took into consideration the velocity recorded along with the notes within the MIDI file. The velocity ranges in the [0, 127] interval. We calculated the percentage for each subject's music similarly to the above variables. We assume the *piano* range lies below velocity value of 40 and the *forte* one above 60.

**V9 – Texture Richness.** For all notes in each subject's corpus we sum up their duration. Then we divide the duration of each piece of music with the total duration of all notes. The more notes we have (and the more lengthy they are), the lower the value of V9 will be. It indicates how much populated with notes the music is.

**V10 – Clusterness.** For each segment, we calculated the number of simultaneities. It is an indicator of the number of chords/clusters and consequently the richness of harmony produced. Simultaneity occurs when a `'note on'` MIDI event is transmitted while other `'note on'` events are still alive.

All variables have been realised as segmental viewpoints.

### 3.4.1 Qualitative Analysis

No matter how accurately and precisely creativity traits can be captured by a computerised tool, if we would like to truthfully appraise children's musical creativity, it is our opinion that no automatic, computational analysis and assessment should be considered alone but with conjunction with a qualitative listening analysis, which complements the quantitative analysis and validates it by means of a human expert listener.

Hence, we chose some cases that we considered as exhibiting typical characteristics of their classes, and performed a listening and score music analysis. We report the findings of the music analysis on these case studies. At the same time, an empirical session with 3 expert judges took place, where they were asked to describe the exact same musical excerpts. Their views, together with our analysis, are presented and discussed in the relevant section.

## 3.5 Computational Processing Structures

In order to be able to process the music within the computer memory, appropriate data structures should be employed. The data structure chosen as most convenient for our research was the *suffix array*. In order to gain a better understanding on suffix arrays, we offer a short discussion of a number of close interconnected tree-based data structures, that comprise more or less a family, used often in lexicographical representation and search. The members of this family are tries, suffix tries, suffix trees and suffix arrays.

The structures discussed in this section were used as the foundation, in order to support the computational model we constructed which was used for the analysis of the music corpus, for all tasks G1, G2 & G3.

### 3.5.1 Tries

A *trie* is a tree-based tree structure used for storing and searching string tokens over an alphabet. Tries are also known as digital trees, radix trees or prefix trees. The name is coined from re**trie**val and was introduced by Fredkin (1960). They are commonly used to store large dictionaries of words in spell-checking programs, since they support fast tests for string existence. They are also frequently used for storing a predictive text or autocomplete dictionary, for example while texting when using a mobile telephone.

The elements in a string can be recovered in a scan from the root to the leaf that ends a string. The idea is that all strings sharing a common stem or prefix hang off a common node.

Suppose the string alphabet $\Sigma$ and further suppose that

$$X = x_1, \ . \ . \ ., \ x_m, \ x_{m+1}, \ . \ . \ , \ x_n$$

$$Y = x_1, \ . \ . \ ., \ x_m, \ y_1, \ . \ . \ , \ y_n$$

$$Z = x_1, \ . \ . \ ., \ x_m, \ z_1, \ . \ . \ , \ z_n$$

are 3 sequence-strings from $\Sigma$.

When these 3 strings are stored in a trie, the part from $x_1$ to $x_m$, which is the common prefix to all strings, will be only once represented, and the path will split in three branches, one for each suffix (X, Y, Z).

Each node of the trie represents a symbol of the string's alphabet $\Sigma$, and a path from the root to a leaf corresponds to a single substring. A sequence of nodes from the root to a branching node corresponds to a common prefix to more than one sequence. Branches in a trie spring where strings with different suffixes diverge.

An example of a trie is depicted below in Fig. 16. As shown, the words `rob`, `roger` and `ryan` share the same common prefix `r.` Further, `rob` and `roger` share the prefix `ro`. Every node that has more that one child corresponds to a common prefix among those children. All those prefixes can be reconstructed by joining together all of the nodes between the root and the branching node.

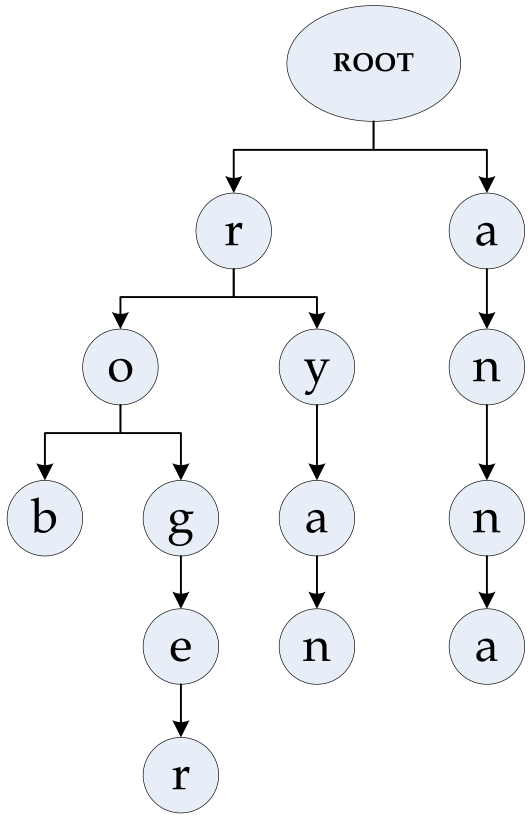



**Fig. 16. A trie for the lexical tokens *rob, roger, ryan* and *anna***

### 3.5.2 Suffix Tries

Tries first mentioned by Briandais (1959). Suppose the string $X = x_0, . . ., x_n$, formed from symbols of alphabet $\Sigma$. The set of all $X$'s suffices, that is formed from each symbol of $X$ towards the end of $X$, is the collection of $X$'s substrings $\{x_0, ..., x_n\}$, $\{x_1, ..., x_n\}$, . . ., $\{x_n\}$. The special terminator $\$$ symbol is added to the end of each substring and is also used to represent the empty string.

The trie constructed for the above set of tokens is called a suffix trie.

Along with each leaf of the tree structure, the position of that suffix within the original string is stored. Each path leading from the root to a leaf represents a suffix of the original string. Furthermore, the index from where this substring starts is stored in the leaf.

Let's take for example the string `bananas`. The set of suffixes is shown in the Table 10, below.

| **Starting Position** | **Substrings** |
|---|---|
| *0* | b a n a n a s $ |
| *1* | a n a n a s $ |
| *2* | n a n a s $ |
| *3* | a n a s $ |
| *4* | n a s $ |
| *5* | a s $ |
| *6* | s $ |
| *7* | $ |

**Table 10. The set of suffices for the string *bananas***

The respective suffix trie for *bananas* is created by inserting each of the substrings shown in the Table above, into a trie structure. This way, substrings that have common prefixes are grouped together in the same branches. Each leaf corresponds to a single suffix of the string and the number stored along shows the starting position of this substring in the original string.

The suffix trie for *bananas* is shown in Fig. 17.

Suffix tries play a crucial role in many applications and they can be used to address many different problems, such as:

- testing whether a substring *s* is a suffix of string *S*
- checking whether a string *s* is a substring of string *S*
- counting the number of occurrences of a substring *s* in of string *S*
- finding the longest repeated substring in string *S*
- finding the lexicographically (alphabetically) first suffix

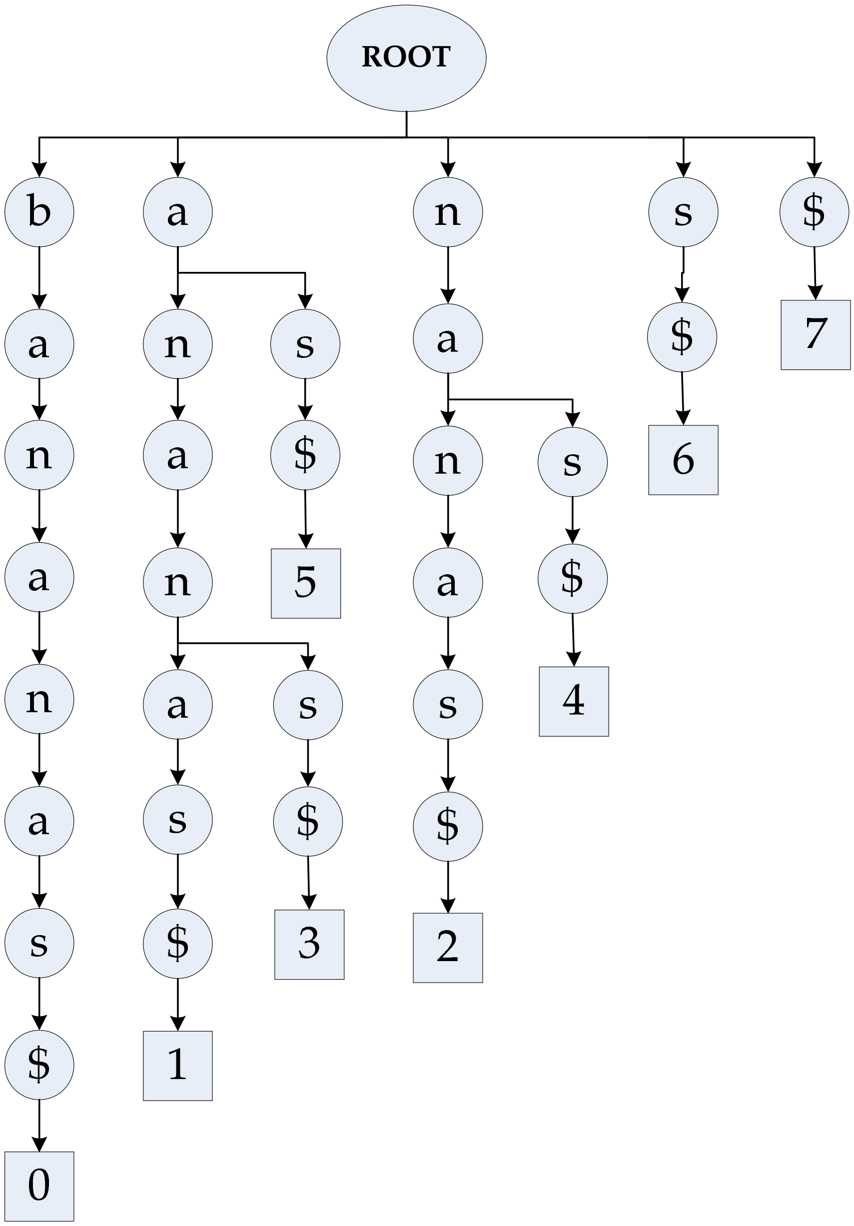



**Fig. 17. A suffix trie for the string *bananas (Nelson, 1996)***

### 3.5.3 Suffix Trees

When collapsing together sequences of nodes, i.e. individual paths, that do not contain branches, we end up with another flavour of tree structure, called *suffix tree* (Weiner, 1973; Aluru, 2004). In other words, a suffix tree is a compressed suffix trie, where chains of nodes that end up into a single leaf are grouped together into a single node. A suffix tree has only nodes with multiple children.

The suffix tree that represents the string *banana* is shown in Fig. 18

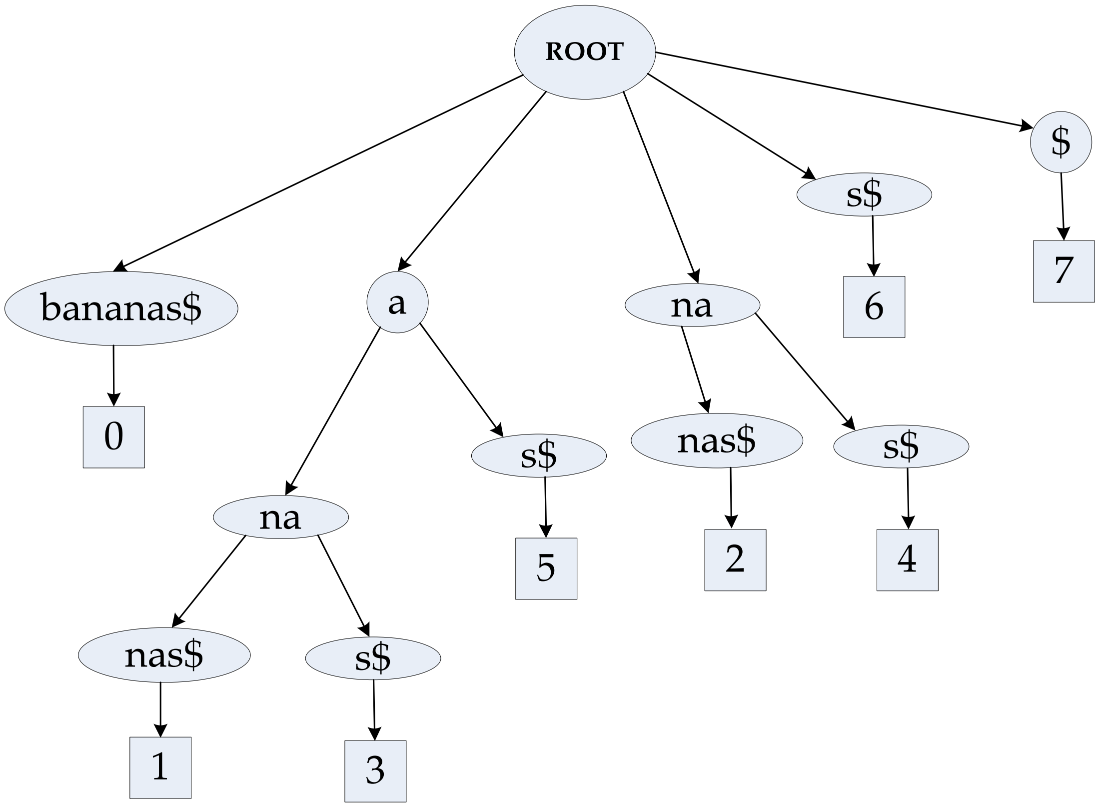



**Fig. 18. The suffix tree for the string *`bananas (Mansour et al., 2012)`***

Suffix trees are among the most important data structures used in string processing. Gusfield (1997) devotes about 70 pages of his book to applications of suffix trees.

The suffix tree may be an excellent data structure for searching huge quantities of data strings but it consumes a lot of space. The *suffix array* data structure (Manber & Myers, 1993), an improvement of the suffix tree, handles memory better. Using suffix arrays we may lose some convenience in usage (e.g. on-line construction, the capability to save an already made suffix tree on a HD and load it late on – in case of an SSD this renders a very fast tool) but we save a lot of space. Moreover, as Abouelhoda et al. (2004) showed, every algorithm that uses a suffix tree as data structure can be replaced with an algorithm that uses an enhanced suffix array and solves the same problem in the same time complexity. In addition suffix arrays are much easier to implement and maintain. Thus, they offer a very attractive alternative to suffix trees.

### 3.5.4 Suffix Arrays

Suffix array is an alternative construct to suffix tree (Wener, 1973; Manber & Myers, 1993). The suffix array of $X = X\$$, denoted $SA(X)$, is an array that contains all suffices of $X$ lexicographically sorted. Each suffix is represented by its starting position in $X$. $SA[i] = j \ iff \ Suff_j$ is the $i^{th}$ lexicographically smallest suffix of s. This array can be constructed using references to the positions of the suffices on the original string or, if space allowed, as an actually lining up of the suffices. Thus, music representation can be much more easily and conveniently explored than the tree-structure representation.

Table 11 shows the suffix array for the string *bananas*.

| Starting Position | Substrings |
|---|---|
| 1 | a n a n a s $ |
| 3 | a n a s $ |
| 5 | a s $ |
| 0 | b a n a n a s $ |
| 2 | n a n a s $ |
| 4 | n a s $ |
| 6 | s $ |
| 7 | $ |

**Table 11. The set of suffices sorted in a suffix array for the string *bananas***

Since the strings are ordered, all suffices beginning with the same prefix will be found in continuous rows in the array. Hence, the identification of a particular string can be done very easily. Additional string processing problems can also be suitably pursued. For example, comparing each pair of successive suffices and reporting the maximum length pair can solve easily the longest common substring problem.

A recurrent way to purge the search space on a suffix array if through the usage of an auxiliary array termed $LCP$ array (Manber & Myers, 1993). This array contains the lengths of the longest common prefixes between every successive pair of suffixes in $SA$. We usually denote the longest common prefix between strings $X$ and $Y$ with $LCP(X, Y)$. $LCP[i]$ is the length of the $LCP$ between $suff_{SA[i]}$ and $suff_{SA[i+1]}$, viz. $LCP[i] = LCP(suff_{SA[i]}, suff_{SA[i+1]})$. The suffix and $LCP$ arrays of the *bananas* string are shown in Table 12.

| Starting Position | Substrings | LCP |
|---|---|---|
| *1* | a n a n a s $ | 3 |
| *3* | a n a s $ | 1 |
| *5* | a s $ | 0 |
| *0* | b a n a n a s $ | 0 |
| *2* | n a n a s $ | 2 |
| *4* | n a s $ | 0 |
| *6* | s $ | 0 |
| *7* | $ | |

**Table 12. Suffix and LCP arrays for the string *bananas***

As one easily envisages the above debited mechanisms can be directly applied onto musical cases. For instance, instead the *bananas* string one could be fairly easily use the musical sequence BACACAD (which is taken from *bananas* substituting C for n and D for s)

In the computational model we built, we employed a data structure based on a suffix array construct, since it combines the easiness of perception with direct mapping onto automated processes.

In the following will be presented how the aforementioned structures are applied in our musical case.

## 3.6 Processing Model

In order to achieve the goals stated in the beginning of the chapter, we built a processing model, realised as a computational system. The system was built using the C programming language (Kernighan & Ritchie, 1978). C was used because it offers great flexibility to manipulate files and data, even on the bit level – very convenient when dealing with MIDI events where information is stored in bit level. It also offers direct access to memory manipulation, which is an extremely valuable capability when handling large sets of data and is necessary to do things as efficiently as possible.

In the next sections we present the model built, as well as the computational details of the most important processes. The main data structures used are presented and the calculations performed together with the choices made are discussed.

All development took place in a two-core PC (Intel® Core™ DUO CPU E8400 @ 3.00 GHz) running a 32bit Ubuntu 11.04 (natty). The machine had 2 GB RAM. The software code was written for GCC (version 4.5.2) using GLIB2 (version 2.28.6).

### 3.6.1 Reading the Corpus

The computation starts by loading the corpus into memory. The corpus is in the form of a collection of MIDI files (see. 2.1.1.1), produced by the interaction of a child with the MIROR-IMPRO system. Along with every MIDI file there exists a corresponding CSV (i.e. comma separated values) file, where a set of metadata are stored. From there the parameter that defines the MIROR-IMPRO output type of reply (e.g. *Same*, *Different*, *Very Different* e.t.c. – see 2.2.2.3) is read. The CSV file has the same name (but different extension) with the corresponding MIDI file that holds the music interaction data but with different extension.

Every MIDI file is in turn loaded into a memory buffer. This buffer is then processed and the music data is extracted. Initially the MIDI header chunk is read. The header chunk offers information on how many tracks follow and time information on how many ticks are per beat. The matching of ticks per quarter note (considering that beat and quarter note are synonymous), a.k.a. "parts per quarter" (or "PPQ") to terms of absolute time depends on the designated tempo. By default, the time signature is 4/4 and the tempo is 120 beats per minute. This can be changed later with a specific META event. In the MIDI files we used PPQ = 500 ticks[25].

The track chunk is afterwards read. For every track, the track head is read followed by the sequence of track events. A track event consists of a delta time since the last event, and one of three types of events: MIDI, META or SYSEX events. META and SYSEX events are read and ignored (META are checked to see if PPQ has change). MIDI events, along with delta time, are read one by one and the musical information is extracted:

- Channel number

[25] Usually MIDI sequencers by default implement ticks as msec, so that an "unwritten" coidentity of ticks and msecs is usually imposed. But it should bear in mind that this is not always the case and depends on the particularities of the various MIDI sequencer implementations.

- Time information
- NOTE ON and NOTE OFF events
- Velocity information
- Pitch information

Every event occurs on a specific time, which is measured in delta ticks. The difference in ticks between a NOTE ON and the corresponding NOTE OFF events gives us the duration of the note. Velocity is a measure of the pressure that the child bears down to the key. It is in essence the volume of the note. Pitches are pulled out in the form of MIDI numbers[26].

As the duration of the notes is calculated a quantisation is performed so that the notes are arranged to 64$^{th}$ note time frames. Recall that MIDI data is performance data and as such it does not correspond exactly to score data. For example, although MIDI file header may declare a PPQ of 500 ticks, it is rarely the case that a quarter note as it is played will correspond to exactly 500 ticks. For our experiments, we chose that the smallest note is the sixtyfourth note. In other words, the smallest note is 500/16 = 31.25 (rounded to 31 ticks). Hence, as notes are retrieved from the MIDI events, they quantised to multiples of this elementary **unit** note.

Discrepancies also arose and in the timing of notes. As performance data, the NOTE ON events rarely occur at times divided exactly by multiplicities of the unit note. Hence in addition to quantisation of the duration of the notes, an additional quantisation should be applied to the onset of the notes. In other words, notes are snapped onto a grid which is divided in 64$^{th}$ note duration, in ticks.

Every note read from a NOTE ON events, is placed into a special buffer and is removed from there when the corresponding NOTE OFF event pops up. This way all notes that echo concurrently are signified and simultaneities can be calculated. The number of concurrent notes can be very large (more that 10), since many children have the habit to press the keyboard with their forearms.

---

[26] http://www.midimountain.com/midi/midi_note_numbers.html

As information is extracted from the MIDI events, several viewpoints are calculated and fed into an array of `viewpoint struct` (see 3.6.2). By the time all MIDI files have been read, all music is represented into an array that holds almost all basic viewpoints needed.

The flowchart representing the process of reading the corpus and building the viewpoints array is depicted in Fig. 19.

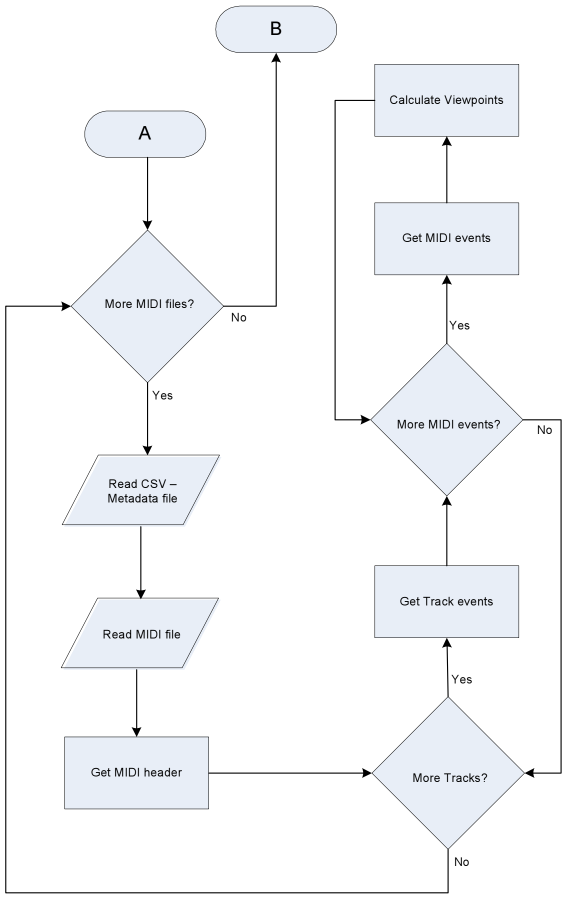



**Fig. 19. Reading the corpus and calculating basic viewpoints**

## 3.6.2 The Viewpoint Data Structure

The following structure is used in order to store music information. It is also used to implement the related suffix array.

```
struct viewpoint
{
     int aaintrk;     // a/a in track
     int midi;        // midi number
     int onset;       // start time in ticks
     int dur;         // duration in units - that is ticks per
```

```
                    // 64th  - unit is PPG/16, ie 1/64th is
                    // the smallest note
      int ddur;      // duration in ticks
      int trail;     // ticks after note off
      int ioi;       // interonset interval - start time from
                    // previous event in units
      int ioid;      // interonset interval - start time from
                    // previous event in delta ticks
      int fnitioid;  // distance drom first note in track
                    // in delta ticks
      int absdelta;  // absolute delta - distance from
                    // first event in track in ticks
      int deltast;   // rest - time between start and
                    // end of previous in units
      int deltastd;  // rest - time between start and
                    // end of previous in ticks
      int seqint;    // sequential melodic interval – pitch
                    // distance from previous event
      float rhyrat;  // Rhythmic Ratio
      int contour;   // rising:1 - static:0 - falling: -1
      int intfip;    // interval from first event in piece
      char used;     // for this entry in vp array
      char simul;    // number of simultaneous notes
      int vel;       // velocity of the midi note
      char trkid;    // track number
      char *f;       // filename;
      char ot;       // outputType;
      char channel;  // channel number
      int leap;      // leap steps - above 7 large,
                    // above 15 huge
      int invrange;  // Interval range - 0 for unison,
                    // 1 for small 2 & 5 steps,
                    // 2 for larger
      int rhyrange;  // Rhythm range - 0 less than a quaver,
                    // 1 for between quaver and minim
                    // 2 for greater note values
      /*
       * pointer to vp according to which the sorting is
       */
      void *sort_agent;
};
```

**Snipcode 1. The main viewpoint structure**

All music information of a corpus is stored into an array of `struct viewpoint`'s (Snipcode 1). The pointer `sort_agent` points to the member of the structure, according to which the sorting will take place. The repeated patterns that will eventually be discovered will belong to sequences of those members. Having such a pointer is a convenient way to implement a generic mechanism and procedure that holds for almost all viewpoints. Hence, all sorting and searching will be carried out through this pointer, which every time may point to a different viewpoint, as we choose.

Before proceeding with our computation, we need to remove from our processing all computer-generated music. This is easy to implement, since computer-generated music is stored on Channel 1. Therefore, we eliminate Channel 1 from the viewpoints array.

### 3.6.3 Identifying Segments

In order to calculate segmental viewpoints the segments have to be identified first. For doing so, we use a special segment structure, where references to the main viewpoint array are held.

```
struct segment
{
    int start;        // Beginning of a segment; this is an
                      // index to vp[]
    int end;          // End of a segment
    int len_all;      // Length of all notes; differs from
                      // segment length due to simutaneeities
    int len;          // length of segment
    int nn;           // number of notes in segment
    int hi;           // the most high pitch in the segment
    int lo;           // the most low onr
    int sum;          // sum/nn gives the avg pitch – used to
                      // calculate huron
    unsigned char num_sim;  // number of simultaneities
    unsigned char num_sin;  // number of single notes
    unsigned char num_b;    // number of black-keys notes
    unsigned char num_w;    // number of white key notes
    /*
     * The following used for creativity variables
     */
    int inv_small; int inv_med; int inv_large;
    int pitch_low; int pitch_mid; int pitch_hi;
    int speed_slow; int speed_q; int speed_fast;
    int vel_soft; int vel_med; int vel_hard;
};
```

**Snipcode 2. The main segment structure**

Segment boundaries are defined in a number of cases: at the end of the user's parts in the child-machine dialogue, when a MIDI file reaches its end and when a time or music interval "gap" occurs – we define a new segment when 300 ticks and 7 steps interval simultaneously incur.

Along with each segment, a number of segmental viewpoints pertained to this segment are held. Whenever possible, the segmental viewpoints are calculated along with the segment identification course. If this is not possible the segmental viewpoints calculation follows immediately. The creativity variables, presented in 3.4, are realised as segmental viewpoints.

Four segmental viewpoints are calculated for the whole corpus. These are:

- **Huron arches.** The number of segments belonging to each of the nine arches (Huron, 1996) is calculated.
- **Number of Simultaneities.** The number of distinct chords in corpus.
- **Ratio of long to short segment (number of notes).** The breaking point is the average number of notes in the segments.
- **Ratio of long to short segment (ticks).** The breaking point is the average number of ticks of the segments.

### 3.6.4 Building the Patterns Array

After all MIDI files belonging to a corpus have been read, all music is loaded onto the `viewpoint struct` array. Next the suffix and LCP arrays are built.

Due to the successive ordering of all music within the viewpoint array, the suffix array can be very easily built as an array of references to the viewpoints array. Together with the reference to the original succession, an index to the original position is held along with the LCP array, which will be filled up after the sorting. The suffix array is implemented as an array of the structure `suff_arr.`

```
struct suff_arr
{
      struct viewpoint *_2_vp;
      int idx;
      int lcp;
```

```
} *sa;
```

**Snipcode 3. The suffix array structure**

The suffix array can be very easily built, by assigning the `_2_vp` pointer to successive members of the viewpoints array and then sorted.

First, the suffices' array is built.

```
for(i=0; i<=note_cnt;i++)
{
      sa[i].idx = i;
      sa[i]._2_vp = &vp[i];
      sa[i].lcp = 0;  //init lcp

}
```

**Snipcode 4. Building the suffix array**

The array is then sorted by using the well know Quicksort algorithm (Hoare, 1961), as it is implemented by the standard C library.

At this stage, the suffix array is sorted and the LCP calculation can be performed.

```
str_sa ( s1, s2 )
 const struct suff_arr *s1, *s2;
{
      int i;

      for(i=0;
            *(float *)s1->_2_vp[i].sort_agent ==
            *(float *)s2->_2_vp[i].sort_agent;
            ++i);

    return i;
}

compute_lcp(s)
 struct suff_arr *s;
{
      int i,j;

      for(i=0; i<note_cnt-1; i++)
            s[i].lcp = str_sa( s+i, s+i+1);
}
```

**Snipcode 5. LCP calculation**

Now we are ready to execute the searching operation. In the Table below the sorted suffix array that corresponds to the music passage of Fig. 3 is shown.

| Viewpoint Sequence | LCP | Length |
|---|---|---|
| CDDD$~15 | 2 | 4 |
| CDEFGFECDDD$~8 | 0 | 11 |
| DCDEFGFECDDD$~7 | 1 | 12 |
| DDD$~16 | 1 | 3 |
| DEFGFECDDD$~9 | 1 | 10 |
| DD$~17 | 0 | 2 |
| ECDDD$~14 | 1 | 5 |
| EFGFECDDD$~10 | 0 | 9 |
| FECDDD$~13 | 1 | 6 |
| FGFECDDD$~11 | 2 | 8 |
| FGAGDCDEFGFECDDD$~3 | 0 | 16 |
| GDCDEFGFECDDD$~6 | 1 | 13 |
| GFECDDD$~12 | 2 | 7 |
| GFGAGDCDEFGFECDDD$~2 | 1 | 17 |
| GAGDCDEFGFECDDD$~4 | 0 | 15 |
| AGDCDEFGFECDDD$~5 | 2 | 14 |
| AGFGAGDCDEFGFECDDD$~1 | 0 | 18 |
| A#AGFGAGDCDEFGFECDDD$~0 | 0 | 19 |
| D$~18 | 0 | 1 |
| $~19 | 0 | 0 |

**Table 13. Sorted suffix array and corresponding LCP of the excerpt in Fig. 3. An excerpt from the Voice part of the Jetzt Meine Seele (Kalomoiris, 1953)**

The process flow is shown in the figure below.


**Fig. 20. Building and sorting the suffix array.**

### 3.6.5 The Searching Process

Having the suffix array sorted, we can now proceed to the next step, which is the searching process, i.e. the identification and discovery of the repeated patterns.

The searching process has the goal to identify all repeated patterns in the suffix array. What we would like to have at the end is a list with all repeated patterns, their frequency, their length and their location in the string of the original music, viz. the viewpoints array. The data structures used in order to store this information are shown below.

```
struct position
{
     int x;     // index to the position in the original
                // viewpoint srray
     char *f;   // the filename containing the pattern
     struct position *next; // pointer to the next position
                            // where the patterns exists
};

struct rep_pattern
{
     unsigned short freq;  // how many times the patterns
                           // occurs
     unsigned short len;   // the lngth of the pattern
     void *attr;           // the pattern itsself
     struct position *p;   // where the patterns dwell?
     char used;            // binary flag
};
```

**Snipcode 6. The data structures holding the repeated patterns**

The list with the repeated patterns is realised as an array of `rep_pattern`. Each element of the array holds a repeated pattern and its associated information. This includes the number of the pattern occurrences, its length and a linked list holding the positions where the pattern resides. The patterns we are interested in are those that have length at least 2, as repeated patterns with length = 1 are considered to be trivialities. We are also interested only in patterns that occur 2 or more times (have frequency > 1).

Before going into the details of the discovery and identification procedure let's take a closer look into the sorted suffix array and go through the procedure step by step. In the Table 14 the sorted suffix array for the exemplary string `mississippississ` is shown.

| Starting Positions | Substrings | LCP |
|---|---|---|
| 8 | i p p i s i s $ | 1 |
| 14 | i s s $ | 3 |
| 5 | i s s i p p i s s i s s $ | 4 |
| 11 | i s s i s s $ | 6 |
| 2 | i s s i s s i p p i s s i s s $ | 0 |
| 1 | m i s s i s s i p p i s s i s s $ | 0 |
| 10 | p i s s i s s $ | 1 |
| 9 | p p i s s i s s $ | 0 |
| 16 | s $ | 1 |
| 7 | s i p p i s s i s s $ | 2 |
| 13 | s i s s $ | 4 |
| 4 | s i s s i p p i s s i s s $ | 1 |
| 15 | s s $ | 2 |
| 6 | s s i p p i s s i s s $ | 3 |
| 12 | s s i s s $ | 5 |
| 3 | s s i s s i p p i s s i s s $ | 0 |
| 17 | $ | |

**Table 14. Suffix and LCP arrays for the string `mississippississ`**

With a first scan of the array, using the LCP column, we can immediately identify the patterns that have at least 2 occurrences, and their lengths. So, we come up with the Table 15.

| Starting Positions | Pattern | Length | Frequency |
|---|---|---|---|
| 14, 5 | i s s | 3 | 2 |
| 5, 11 | i s s i | 4 | 2 |
| 11, 2 | i s s i s s | 6 | 2 |
| 7, 13 | s i | 2 | 2 |
| 13, 4 | s i s s | 4 | 2 |
| 15, 6 | s s | 2 | 2 |
| 6, 12 | s s i | 3 | 2 |
| 12, 3 | s s i s s | 5 | 2 |

**Table 15. First identification of unique patterns in the string `mississippississ`**

Of course, one can notice immediately that if "`i s s i`" is a unique pattern, so are "`i s s`" and "`i s`", which are patterns that are missed from the result set. Therefore, we modify the original search by adding an additional searching process in order to capture the occurrences of these patterns, as well. We do this, by adjoining an additional loop, taking one by one the patterns of the Table above, so that new patterns added or the frequency of existing ones increased by checking existing entries prefixes. By the end of this process all repeated patterns of the original string will be identified. The Table 15 will acquire some new rows and will become Table 16, below.

| Starting Positions | Pattern | Length | Frequency |
|---|---|---|---|
| 14, 5, 11, 2 | i s s | 3 | 4 |
| 5, 11, 2 | i s s i | 4 | 3 |
| 11, 2 | i s s i s s | 6 | 2 |
| 7, 13, 4 | s i | 2 | 3 |
| 13, 4 | s i s s | 4 | 2 |
| 15, 6, 12, 3 | s s | 2 | 4 |
| 6, 12, 3 | s s i | 3 | 3 |
| 12, 3 | s s i s s | 5 | 2 |
| 14, 5, 11, 2 | i s | 2 | 4 |
| 11, 2 | i s s i s | 5 | 2 |
| 13, 4 | s i s | 3 | 2 |
| 12, 3 | s s i s | 4 | 2 |

**Table 16. Complete identification of unique patterns in the string *`mississippississ`***

The algorithm consists of two basic parts. The first one scans the sorted suffix array and ensures that each row that has LCP > 2 is added in the repeated patterns array. Together with that row, all immediate successive rows that have LCP greeter than the one just added, are added as well.

```
for(i=0, j=0; i<note_cnt; i++)
{
      int pos;
      if (s[i].lcp<2)  // ignore common notes less than 2
            continue;  // as trivialities

      /*
       * add all elements of suffix array
       * into repeated patterns array with frequency 2
```

```
     */
    if (!(pos=is_in_pat(s+i)))
    {
          rep1[j].freq=1;
          rep1[j].len=s[i].lcp;
          cpy_attr(s+i, j ); // copy attribute string
                             // from position i in SA
                             // to rep1 in position j
          add_pos(&rep1[j].p, s[i].idx, s[i]._2_vp[0].f);
          put_succ(j, s, i+1); // add all successive s[i]
                               // entries with
                               // lcp >= rep1[j].len

          rep1[j].used=1;

          rep1_used = ++j; // count the number
                           //of repeated patterns
    }
    else
    { // shouldn't ever come here
          if ( !is_in2(s[i].idx, rep1[pos].p ) )
          {
                rep1[pos].freq++;
                add_pos( &rep1[pos].p, s[i+1].idx,
                          s[i+1]._2_vp[0].f);
          }
    }
}
```

**Snipcode 7. The first part of the discovery & identification process**

The function `add_pos()` appends a suffix array's entry in the list with the positions of a repeated pattern.

The function `put_succ()` adds to the repeated patterns set all successive patterns of a suffix array with a LCP greater than a repeated pattern's length.

The function `cpy_attr()` copies the patterns of a suffix array to the repeated patterns array.

The function `is_in_pat()`checks if a suffix array entry's pattern is in the repeated patterns array.

The flow of the process is shown below.

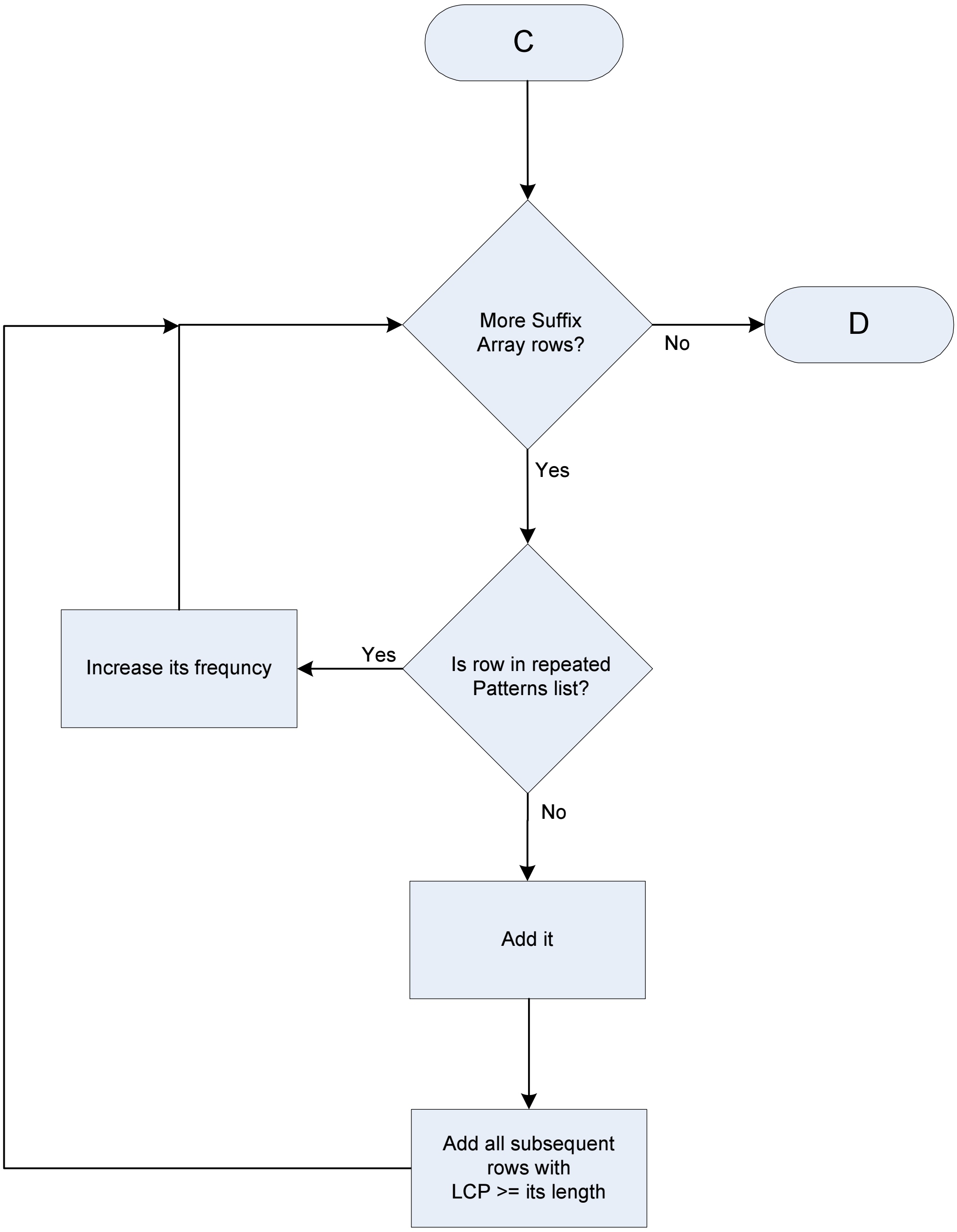



**Fig. 21. Discovery & Identifications of unique patterns (step 1)**

So far we have identified a first set of repeated patterns which have been stored into the array `rep_pattern` (see Snipcode 6). Now the array will be populated with more entries, produced from the suffices of the already existing repeated patterns.

```
for (i=0; i<j; ++i )
{
     // take one by one rep1[i]'s prefices and check if are in
```

```
	for(k=2; k<rep1[i].len; k++)
	{
		int pos;
		// check if prefix rep1[i] from start to len-k+1
		// is already in
		if (!(pos=ck_prx(i, rep1[i].len-k+1) ) )
		{
			// if not added it
			rep1[rep1_used].len=rep1[i].len-k+1;
			rep1[rep1_used].attr =
				(void *)malloc(sizeof(void *)*
				rep1[rep1_used].len);
			memcpy(rep1[rep1_used].attr,
				rep1[i].attr,
				rep1[rep1_used].len*sizeof(void *) );
			rep1[rep1_used].freq +=
				merge_pos(&rep1[rep1_used].p,
				rep1[i].p);
			rep1[rep1_used].used=1;

			++rep1_used;
			// count the number of repeated patterns
		}
		else
		{	// if yes increase its freq
			// and add its positions
			rep1[pos].freq +=
				 merge_pos(&rep1[pos].p, rep1[i].p);
		}
	}
}
```

**Snipcode 8. The first part of the discovery & identification process**

The function `ck_prx()` checks if a suffix is already into the repeated patterns array, and if it is returns its position.

The function `merge_pos()` takes two repeated patterns and merges the positions of the one with the positions of the other.

The flow of the second (and last) step is shown below.

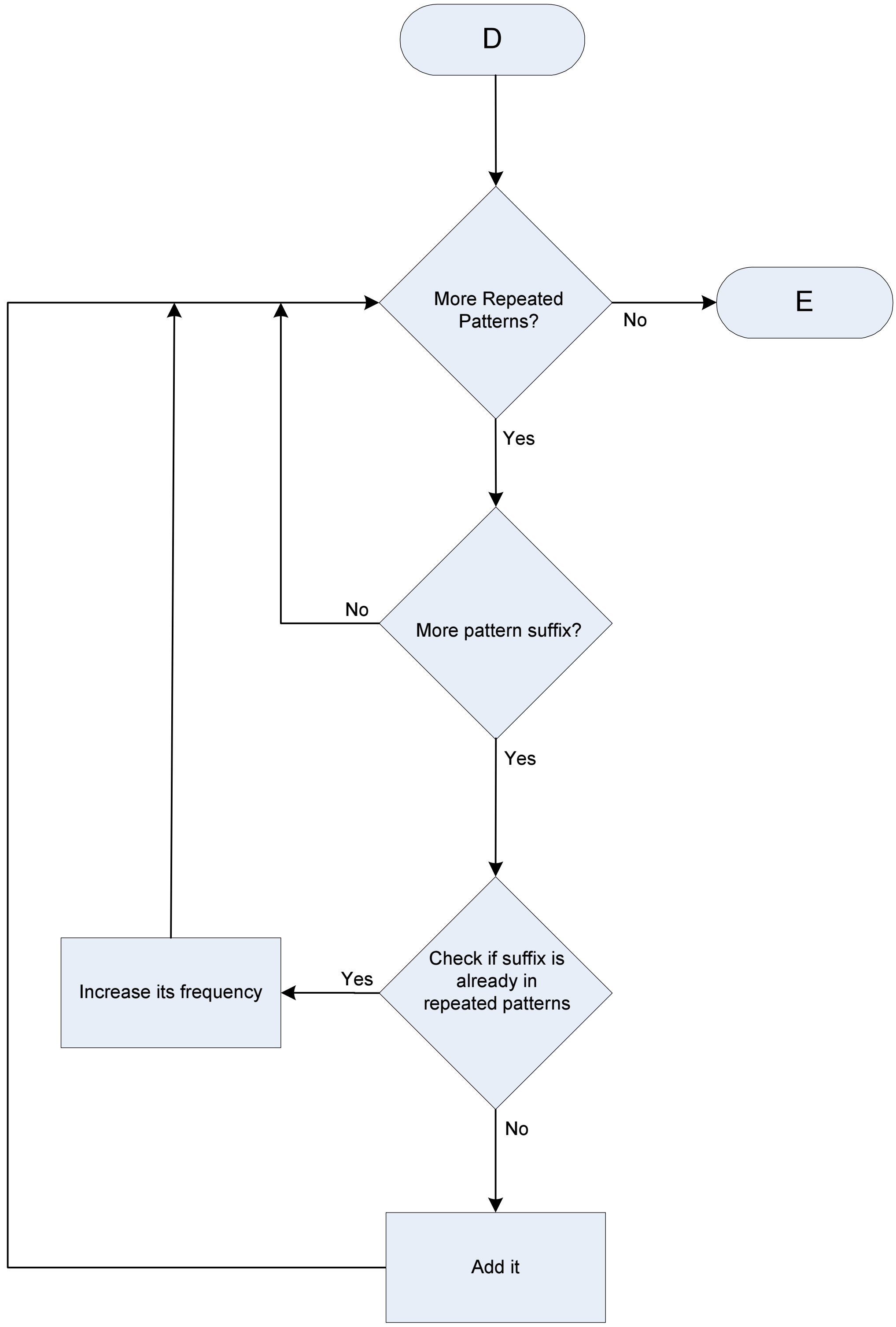



**Fig. 22. Discovery & Identifications of unique patterns (step 2)**

Now the `rep_pattern` array stores all unique patterns (from length 2 and beyond) along with their positions in the original stream and their frequencies.

### 3.6.6 Mining for Distinctive Patterns

We refer to a pattern as *distinctive pattern* if it is overrepresented in a corpus with respect to another one, called *anticorpus* (Conklin & Anagnostopoulou, 2011). The corpora are in the form of two MIDI file collections.

The computation proceeds by reading one by one all MIDI files in the corpus and building from the corresponding MIDI events a sequence of viewpoints. Consecutively, repeated patterns within each viewpoint sequence are extracted using suffix arrays, as described above.

In order to compare the occurrences of the patterns found, we need to store the repeated patterns found in a data structure which offers almost instant access when queried. As such the Hash Table data structure offers the best choice.

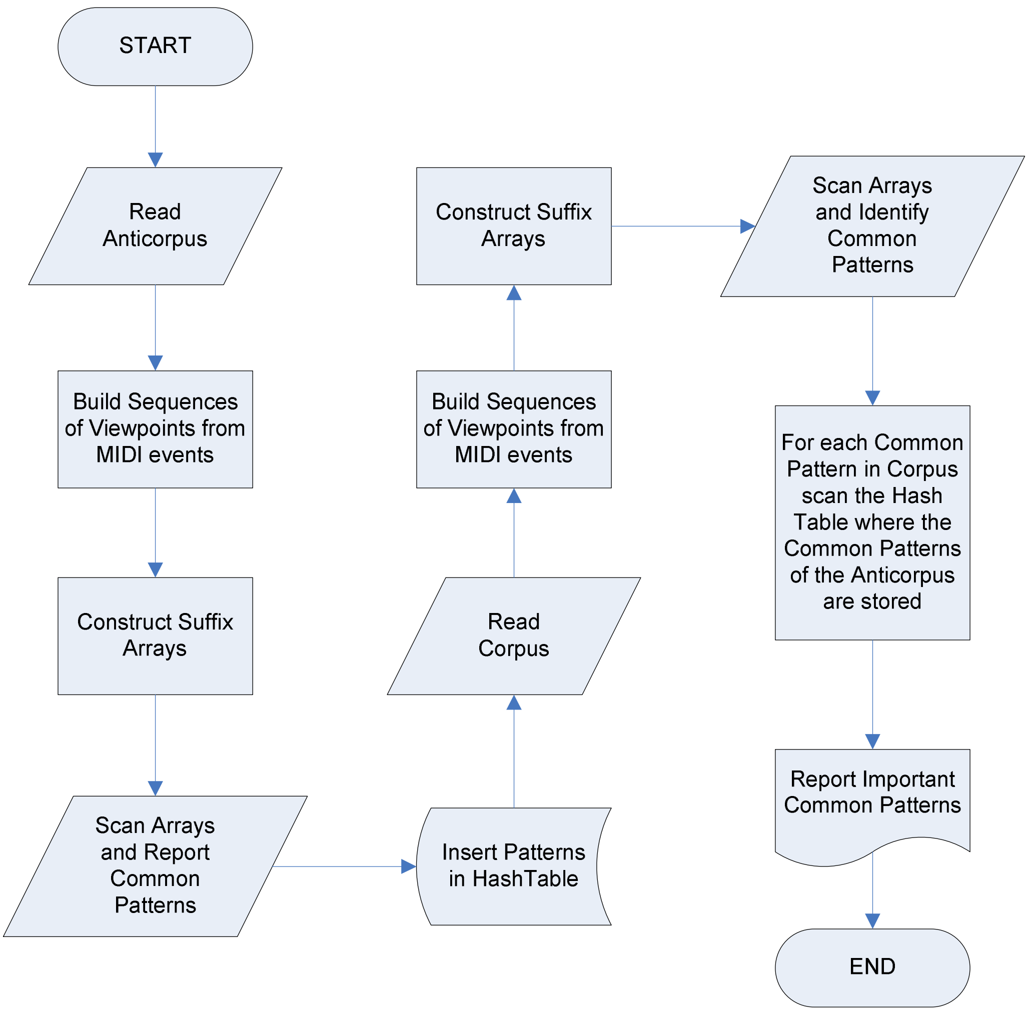



**Fig. 23. The high level flow of the computational process**

Firstly the anticorpus is read. After the identification of the repeated patterns set in the anticorpus, each pattern and its frequency is inserted as a *(key, value)* pair in a hash table. To implement the hash table, the CLIB2 GNU library is used.

After the processing of the anticorpus, the reading of the corpus follows. In a similar manner, the repeated patterns are identified. When all repeated patterns are indentified, the hash table (already built from the patterns of the anticorpus) is queried with each one of the corpus repeated patterns and consequently its importance is calculated.

### 3.6.6.1 Identifying the Distinctive Patterns

A pattern $p$ is considered as distinctive if: $\frac{P(p|S)}{P(p|S')} > Delta$, where $S$ is the set of all patterns in corpus, $S'$ is the set of all patterns in anticorpus, $P(p|S)$ is the conditional probability of $p$ given $S$, $P(p|S')$ is the conditional probability of p given $S'$ and $Delta=3$.

The problem of dealing with patterns of zero presence, that is $P(p|S')=0$, is a well known problem and is addressed in the relative literature as *smoothing*. Several techniques have been proposed to deal with the problem (Chen & Goodman, 1999). The one used here is the Witten-Bell smoothing (aka *Method* C), as it offers a rather simple approach with good results and minimum computations.

The choice of $Delta=3$ is empirical, since a pattern that has three times greater probability in finding it in a corpus than the anticorpus, can be considered as important one in common sense. Hence, it can be used as a metric to identify overrepresented patterns as far as their importance within a corpus respective to another one, is concerned. It should be added here that a different number could have been chosen instead, depending on how bigger probability a different approach would desire.

We presented in this chapter most significant details of the computational processing mechanism that we built in order to investigate the musical data we gathered within the MIROR psychological experiments. We proceed now to present the results.

# Chapter 4

# Results

In this chapter we present the results obtained from the computational work described above. The results were produced in pursuing the goals G1, G2 & G3, in the course of the work described in Chapter 3. We remind that G1 stands for musical pattern recognition and discovery, G2 stands for exploration of musical creativity development and G3 for identification of overrepresented patterns in a corpus with respect to another corpus. The chapter contains three subsections, one for each of the G1, G2, G3 goals. In each one of these subsections, we present the results obtained by analysing the musical data collected, which were produced through the interaction of the children with the MIROR-IMPRO. The data collection procedure has been introduced in section 3.1 and the organisation of the corpora is presented in 3.2.

For analysing the data towards the G1 goal, the computational process applied is presented in section 3.6. The creativity model used in pursuing the G2 goal is described in section 3.4. The specific contrast data mining techniques used for processing the data towards the G3 goal are portrayed in section 3.6.6.

We also remind from 3.2.1 that the corpus for G1 used is divided in two sub-corpora: one with the visualisation capabilities turned on (the *V melodies*) and one with no visualisation (the *N melodies*). Also, according to the conditions of the data collection methodology we named the distinct experiments **EG'I, EG'II and EG'III**. They described in section 3.1.

# 4.1 Recurrent Pattern Identification

The first goal pursued in this research, G1, is the identification and discovery of common repeated musical patterns.

In order to discover and identify repeated patterns occurring in the children's melodies we used the sequences of the viewpoints defined in Table 8, i.e. `Pitch, Interval, Contour, Interval range, Duration, Rhythm range & Rhythm ratio.` We are looking for patterns of a minimal frequency of 2 in the corpus collected during EG'III (see 3.1).

| Data Set | Boys | Girls | Age | Sessions | Number of Notes (with machine answers) | Number of Notes (without machine answers) | Number of Phrases (without machine answers) | Notes per Phrase (avg) | Duration per Phrase (ticks) |
|---|---|---|---|---|---|---|---|---|---|
| Without Visualisation – N melodies (n=18) | 3 | 3 | 6-8 | 6 | 28988 | 23573 | 1913 | 12.32 | 3818 |
| With Visualisation – V melodies (n=18) | 3 | 3 | 6-8 | 6 | 24361 | 18023 | 1412 | 12.76 | 4559 |

**Table 17. Corpus description for G1 (identification & discovery of repeated patterns)**

## 4.1.1 Experiments using the viewpoint `Pitch`

Pitch is the lowest level representation used in this study. A large number of short patterns was found, which did not have a high frequency count. We noticed several patterns of stepwise motion, going either up or down, and some patterns of repeated notes in the children's corpus.

The most frequent sequence in the N melodies is the `[G4, A4]`, with 249 occurrences. It is also the second most frequent in the V melodies, with 169 occurrences. The third most frequent in V melodies, `[A4, G4]` with 162 occurrences, is also the third most frequent in N melodies, with 229 occurrences.

| | Pattern | Frequency | Order of frequency |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **N melodies** | [G4, A4] | 249 | 1 |
| | [A4, B4] | 235 | 2 |
| | [A4, G4] | 229 | 3 |
| | [G4, F4] | 211 | 4 |
| | [F4, G4] | 198 | 5 |
| | [B4, C5] | 193 | 6 |
| | [B4, A4] | 190 | 7 |
| | [G5, A5] | 180 | 8 |
| | [C5, D5] | 171 | 9 |
| | [F4, E4] | 171 | 10 |
| **V melodies** | [G4, A4] | 169 | 2 |
| | [A4, G4] | 162 | 3 |
| | [E4, F4] | 155 | 4 |
| | [F4, E4] | 153 | 5 |
| | [D4, C4] | 153 | 6 |
| | [G4, F4] | 150 | 7 |
| | [C4, D4] | 146 | 9 |
| | [B4, C5] | 143 | 10 |
| | [C5, B4] | 141 | 11 |
| | [F4, G4] | 139 | 12 |

**Table 18. The 10 most frequent patterns of the `Pitch` viewpoint, of length 2, not unison.**

As it seems, children like to play on the middle of the keyboard and they more or less choose the same keys (the white keys – that is C major), regardless of the setup (with or without visualisation). However there are some striking differences: the most frequent sequence in V melodies is the sequence `[C7, C7]`, with 174 occurrences. The pattern `[C7, C7, C7]` occurs 146 times, the pattern `[C7, C7, C7, C7]` occurs 127 times and the pattern `[C7, C7, C7, C7, C7]` occurs 112. To take this further, 2 times a pattern with 27 C7 occurs two times (in contrast the longest C7 string in N melodies has a mere 8 length). Apparently, if we were looking for patterns with only 1 occurrence, we would have ended up with lengthier C7 strings. The same mould produces a C2 string of length 24 (in N melodies the longest C2 string is of length 5), an F5 string of length 26 (respectively in N melodies 6) and an C#5 string of length 37 (in N melodies 9). We should note here that in the implementation we realised, we allowed for melody overlapping, such that the count of `[C7, C7]` occurrences includes the count of `[C7, C7, C7]` - and naturally in turn all respective longer sequences of `C7's.`

A reason for these significant differences in unison frequencies between the two subcorpora could be attributed to the attractiveness of the visual display. The child's attention is captured by the response the note produces on the laptop screen and is repeating it again and again. From this, one can deduce that the utilisation of visual effects might draw children focus away from the music. The frequencies of lengthier patterns support this point of view as shown in the Table below.

| | **Pattern** | **Frequency** | **Order of frequency** |
|---|---|---|---|
| **N melodies** | [A4, G4, F4] | 60 | 84 |
| | [G5, A5, B5] | 57 | 89 |
| | [B4, A4, G4] | 57 | 90 |
| | [G4, A4, B4] | 56 | 91 |
| | [F4, G4, A4] | 54 | 93 |
| | [F4, E4, D4] | 54 | 94 |
| | [D4, E4, F4] | 49 | 110 |
| | [E5, D5, C5] | 46 | 119 |
| | [E4, F4, G4] | 45 | 127 |
| | [C5, D5, E5] | 44 | 130 |
| **V melodies** | [B4, A4, G4] | 41 | 130 |
| | [G4, A4, B4] | 39 | 138 |
| | [A3, B3, C4] | 37 | 155 |
| | [C5, B4, A4] | 35 | 169 |
| | [E4, F4, G4] | 33 | 186 |
| | [B3, A3, G3] | 33 | 188 |
| | [G4, E4, D4] | 31 | 205 |
| | [A4, G4, F4] | 30 | 212 |
| | [B3, C4, D4] | 30 | 215 |
| | [F4, G4, A4] | 29 | 221 |

**Table 19. The 10 most frequent patterns of the `Pitch` viewpoint, of length 3, all notes different.**

The same pattern occurs more eminently on lengthier sequences.

### 4.1.2 Experiments using the viewpoint `Interval`

In both subcorpora, a large number of interval patterns was found, from very short to very long ones. These included straight movements across the keyboard, either ascending or descending, several oscillating movements (the alternation of two notes on the keyboard), a significant amount of stepwise downward movement (white keys), and some stepwise upward movement, some unison patterns, and others.

| Interval Pattern | Frequency |
|---|---|
| [-41, -2] | 16 |
| [-2, -7] | 46 |
| [-2, -5] | 86 |
| [-2, -1, -2, -2, -2, -1] | 26 |
| [-2, -1, -2, -2, -2, -1, -2, -2, -1, -2, -2, -2, -1, -2, -2, -1, -2, -2, -2, -1, -2, -2, -1, -2, -2, -2, -1, -2, -2] | 2 |

**Table 20. Patterns of straight downwards movement in the no visualisation subcorpus.**

The patterns `[2, -2]` and `[-55, 55]` (see Table below), the first one much more frequent than the second, denote oscillating movement between two notes. The first one includes a tone, whereas the second one a very large interval of more than two octaves. Below, apart from the oscillating ones, one can find several others which go up and down interchangeably, though not on the same two notes.

| Interval Pattern | Frequency |
|---|---|
| [-48, 48] | 9 |
| [-55, 55] | 8 |
| [2, -2] | 515 |
| [-60, 60] | 13 |
| [-57, 55, -53, 51, -50, 48, -46, 45, -43] | 2 |
| [-3, 3, -3, 3] | 9 |

**Table 21. Example patterns of oscillation for pitch in the no visualization subcorpus.**

Below, the pattern in the last row of Table 20 presents a diatonic stepwise downward movement (for an example see Figure below), obviously using all the white keys of the keyboard.

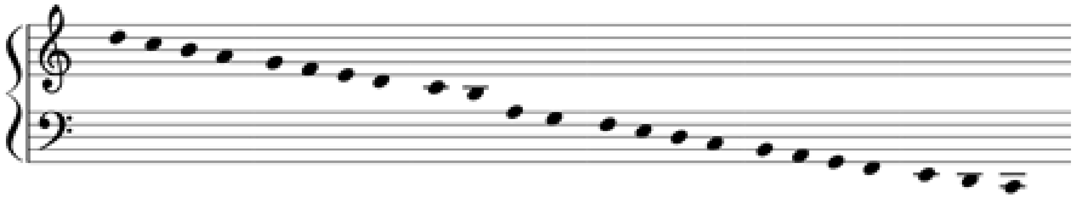


**Fig. 24. Example of melody containing stepwise downward movement.**

In the table below we can see examples of upwards, mostly stepwise diatonic movement (most likely on the white keys).

| **Interval Pattern** | **Frequency** |
|---|---|
| `[2, 1, 2, 2, 2, 1, 2, 2, 1, 2, 2, 2, 1]` | 18 |
| `[2, 2, 2, 1, 2, 2, 1, 2]` | 30 |
| `[2, 2, 1, 2, 2, 2, 1, 2, 2, 1, 2]` | 26 |
| `[1, 2, 2, 1, 2, 2, 2, 1, 2]` | 9 |
| `[2, 2, 3, 2]` | 21 |

**Table 22. Example patterns of upward movement in the no visualisation subcorpus.**

We also observed many patterns of unison: e.g. `[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]` (length 10, frequency 7) – denoting a repetition of the same note.

**Fig. 25. Example of interval pattern `[0,0,0,0,...]`**

In the visualisation subcoprus, we observed again three types of patterns: long downward movement, oscillation, unison – and some stepwise upward movement.

| | Pattern | Frequency |
|---|---|---|
| **Oscillation** | `[-60, 60, -60, 60, -60]` | 4 |
| | `[-9, 9, -9, 9]` | 6 |
| **Downward movement** | `[-3, 2]` | 136 |
| | `[-3, -2, -10]` | 2 |
| | `[-3, -2, -5]` | 2 |
| | `[-3, -2, -2, -1, -2, -2]` | 2 |
| | `[-2,-1,-2,-2]` | 54 |
| | `[-2, -1, -2, -2, -2, -1, -2, -2, -1, -2, -2, -2]` | 7 |
| **Unison** | `[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]` | 99 |
| **Upward movement** | `[1, 2, 2, 2, 1, 2, 2, 1, 2, 2, 2, 1, 2, 2, 1, 2, 2, 2]` | 6 |

**Table 23. Example patterns in the visualisation subcorpus.**

In general, the patterns with high frequency were found in both N and V melodies, so they could not be used to distinguish between the two. Patterns with low frequency could be found in either or both corpora.

One noticeable difference however is the longest unison patterns found in the visualization sub-corpus: the longest `0`'s sequence has a length of 34 (13 in the case of no visualization sub-corpus) and the `[0, 0]` pattern (two 0 in turn) has a frequency of 725 (225 respectively) — even if the visualisation corpus has 7.6% less notes. This can be explained, as said before, due to the visualisation setup turned on and capturing the children's attention, while their hand remains still.

Another difference is that in the visualisation corpus the most frequent patterns (apart from the unisons mentioned above) are oscillations.

Both these differences suggest that children were experimenting, playing the same note and looking at the screen or playing with only two different notes and looking at the animation on the screen.

No other differences in the sequence of intervals, between visualisation and no visualisation subcorpora were found.

### 4.1.3 Experiments using the viewpoint `Contour`

Patterns of melodic contour found have higher frequencies than Intervals, as they are more abstract representations (and therefore describe a bigger number of pitch patterns of the musical surface) ones. As with intervals, we observe the same movements (oscillating motions, straight ascending or descending movements, unisons, and others).

| **Pattern** | **Length** | **Frequency (N melodies)** | **Frequency (V melodies)** |
|---|---|---|---|
| [+, -, +, -, +, +, -, -, +, +] | 10 | 8 | 7 |
| [+, +, -, +] | 4 | 982 | 724 |
| [+, -, +, -, +, -, +, -, -] | 9 | 59 | 53 |
| [+, +, +, +, +, +, +, +, +] | 9 | 230 | 127 |

| | | | |
|---|---|---|---|
| [-, +, -, +, -, -, -, -, +, -, +] | 11 | 7 | 2 |
| [0, 0] | 2 | 225 | 725 |

**Table 24. Example patterns of the `Contour` viewpoint**

The pattern `[+, -, +, -, +, +, -, -, +, +]` is an example of a pattern moving in changing directions. The pattern `[+, +, -, +]` is a very common one and was found in all sessions – and thus perhaps trivial as it did not characterise any of the corpora. The pattern `[+, -, +, -, +, -, +, -, -]` is a typical example of an oscillating motion (though the exact intervals in each direction may vary), whereas another one, `[+, +, +, +, +, +, +, +, +]` includes a long upward motion. The pattern, `[-, +, -, +, -, -, -, -, +, -, +, +, -]`, is a good example of an almost oscillating motion, while the pattern `[0, 0]`, is a short example of the unison pattern found very often in both subcorpora.

The dominant oscillation pattern reflects on the following findings: the `[+, -]` and `[-, +]` sequences have been found 5369 and 5456 times respectively, in the N melodies. The frequencies are 3986 and 4038 respectively, in the V melodies. This might suggest that the visualisation setup does not provoke different children behaviour, as far as the oscillation pattern presence is concerned. The differences in the frequency seem to be directly analogous to the subcorpora size. In fact, these types of intervals can be found in many types of music, therefore they cannot be characterised as significant ones.

We also observed long stepwise movements; for instance an upward stepwise sequence of length 12 was found 164 times in the N melodies and 89 times in V melodies, which is about 45% fewer. Downward stepwise movements are also very common, but their occurrences are fewer in both subcorpora. A downward stepwise movement of length 12 was found 125 times in N melodies and 74 times in V melodies – almost 40% less. Clearly, the difference in the numbers suggests that the visualisation setup imposes different behaviour in children, since the visualisation display splits children attention.

It is very interesting, in our opinion, to take a closer look in what this particular viewpoint reveals regarding the extent to which children employ gestures in their playing. It is also worthy to see if the choice of this viewpoint was well-aimed and abstract enough to capture the children's gesture playing on the keyboard.

Hence, in Table 25 the 10 most frequent patterns are shown in both subcorpora, while in Table 26 the lengthier patterns are shown accordingly.

| | **Pattern** | **Frequency** |
|---|---|---|
| **N melodies** | `[-, +]` | 5456 |
| | `[+, -]` | 5369 |
| | `[+, +]` | 3457 |
| | `[-, -]` | 3428 |
| | `[-, +, -]` | 3037 |
| | `[+, -, +]` | 2992 |
| | `[-, -, +]` | 1878 |
| | `[+, -, -]` | 1852 |
| | `[-, +, +]` | 1815 |
| | `[+, +, -]` | 1811 |
| **V melodies** | `[-, +]` | 4038 |
| | `[+, -]` | 3986 |
| | `[+, +]` | 2376 |
| | `[-, -]` | 2368 |
| | `[+, -, +]` | 2292 |
| | `[-, +, -]` | 2292 |
| | `[-, +, -, +]` | 1330 |
| | `[+, -, +, -]` | 1305 |
| | `[+, -, -]` | 1295 |
| | `[-, +, +]` | 1286 |

**Table 25. The 10 most frequent patterns of the `Contour` viewpoint**

As one can immediately notice, the most frequent pattern children playing, belongs exclusively to oscillating movements. The Contour viewpoint seems to encapsulate those movements well enough.

| | Pattern | Frequency |
|---|---|---|
| **N melodies** | 34 0’s | 2 |
| | 34 +’s | 2 |
| | 33 0’s | 3 |
| | 33 +’s | 3 |
| | [+, -] + 30 +’s | 2 |
| | 32 0’s | 4 |
| | 32 +’s | 4 |
| | 31 0’s | 5 |
| | - + 30 +’s | 2 |
| | 31 -’s | 2 |
| **V melodies** | 35 -’s | 2 |
| | 34 -’s | 4 |
| | 34 +’s | 2 |
| | 33 -’s | 6 |
| | 33 +’s | 3 |
| | 32 -’s | 8 |
| | 32 +’s | 4 |
| | 31 -’s | 10 |
| | 31 +’s | 5 |
| | 30 -’s | 12 |

**Table 26. The 10 lengthier patterns of the `Contour` viewpoint**

As our pattern finding mechanism allows for overlapping, the above table contains what Lartillot (2014b) calls *cyclic patterns.* That is, for example, if someone plays one sequence of 116 repeating notes, then she has also played 99 sequences of 16 notes length.

One might reason that using such an abstract viewpoint does not reveal anything interesting and that most of the Western Art Music corpus exhibits such characteristics, as the ones reported above. While this might be true, we have to keep in mind that children mostly express themselves musically with gestures and in our opinion this particular viewpoint captures exactly those gestures. It does not capture though the extent or in other words the “tension” of those gestures. That is why if we would like to delve into gestural details we need to use it in conjunction with the viewpoint Interval, which captures that level of detail. For example the two Interval sequences `[3, -3]` and `[50, -30]` are mapped onto the same Contour sequence `[+, -]`. Nevertheless, while qualitatively they might represent the same gesture quantitatively they differ substantially, as far as the strain of the movement is concerned.

### 4.1.4 Experiments using the viewpoint `Interval range`

The representation of `Interval range` – we remind that the viewpoint `Interval range` takes the values 0 for unison, 1 when interval is between 2 & 5 steps, 2 for larger intervals – was chosen in order to achieve a representation more abstract than `Interval` and less abstract than `Contour`. It also seemed useful to be able to distinguish between smaller and larger intervals. Many patterns, short and long, were found. Some indicative results are presented below.

| | **Pattern** | **Frequency** |
|---|---|---|
| **N melodies** | [1, 1] | 7500 |
| | [1, 1, 1] | 5074 |
| | [1, 1, 1, 1] | 3707 |
| | [2, 1] | 3521 |
| | [1, 2] | 3493 |
| | [2, 2] | 3196 |
| | [1, 1, 1, 1, 1] | 2893 |
| | [1, 1, 1, 1, 1, 1] | 2320 |
| | [1, 2, 1] | 1957 |
| | [1, 1, 1, 1, 1, 1, 1] | 1896 |
| | [2, 1, 1] | 1667 |
| | [1, 1, 2] | 1641 |
| **V melodies** | [1, 1] | 5393 |
| | [1, 1, 1] | 3677 |
| | [2, 2] | 2693 |
| | [1, 1, 1, 1] | 2652 |
| | [2, 1] | 2354 |
| | [1, 2] | 2328 |

| | | |
|---|---|---|
| | [1, 1, 1, 1, 1] | 2071 |
| | [1, 1, 1, 1, 1, 1] | 1676 |
| | [2, 2, 2] | 1409 |
| | [1, 1, 1, 1, 1, 1, 1] | 1392 |
| | [1, 2, 1] | 1179 |
| | [1, 1, 1, 1, 1, 1, 1, 1] | 1179 |

**Table 27. The 12 most frequent patterns of the `Interval range` viewpoint.**

The most frequent pattern is the `[1, 1]` in both subcorpora. It appears 7,500 and 5,393 times, respectively. However, this could be true of many other types of music, so musically it might not be a most interesting one. Concerning the children's playing though it becomes more interesting as it shows no or small hand movement. The pattern `[2, 2]`, 6th most frequent in N melodies and 3rd in V melodies, was found 3196 and 2693 times, respectively. The largest number occurs in the larger corpus – the N melodies. The frequencies of the two sequences are the first one 28% smaller in the V melodies and the second 16% smaller. Having in mind that the size of the visualisation subcorpus is 26% smaller, the above differences suggest that the visualisation setup props up the creation of small intervals while suppressing the creation of large ones, which makes sense as children could control better their hand in small intervals while not looking at the keyboard, as opposed to larger intervals.

The visualisation setup seems to also promote the creation of long melodies with large consecutive intervals; for instance we found 12 consecutive large intervals 23 times in V melodies and 14 times in N melodies – a difference of 35%.

Similarly, the visualisation setup seems to promote the creation of small interval melodies: we found melodies of consecutive 25 & 28 small intervals to be much more common in the visualisation subcorpora – 174 and 128 times in the V melodies; 117 and 74 times in the N melodies. Also the longest melodies were affected: we found 2 times 101 small interval melodies in the V melodies whereas the longest in the N melodies was only 53, which has a frequency of 50 in V melodies.

### 4.1.5 Experiments using the viewpoint `Duration`

This viewpoint can be used as an estimation of the rhythm variety induced in an improvisation session. Recall that the tiniest note that we employ is the 64th note. So there are no notes that are less that 64th and all notes are rounded to 64th slots. For example, the sequence `[3, 2, 8]` indicates a dotted 32-note, followed by a 32-note, followed by a eighth note.

| | **Pattern** | **Frequency** |
|---|---|---|
| **N melodies** | `[3, 3]` | 850 |
| | `[4, 4]` | 730 |
| | `[5, 5]` | 583 |
| | `[4, 3]` | 470 |
| | `[6, 6]` | 445 |
| | `[5, 4]` | 421 |
| | `[2, 2]` | 411 |
| | `[6, 5]` | 387 |
| | `[7, 7]` | 364 |
| | `[3, 3, 3]` | 363 |
| **V melodies** | `[3, 3]` | 932 |
| | `[4, 4]` | 732 |
| | `[3, 3, 3]` | 500 |
| | `[5, 5]` | 444 |
| | `[4, 3]` | 433 |
| | `[6, 6]` | 418 |
| | `[2, 2]` | 347 |
| | `[3, 4]` | 347 |
| | `[7, 7]` | 340 |
| | `[5, 4]` | 339 |

**Table 28. The 10 most frequent patterns of the `Duration` viewpoint.**

As one can see the most frequent values in both subcorpora are largely the same, with the exception of the `[3, 3, 3]` pattern, which is much more frequent in the V melodies, despite the smaller size of the corpus. This can again be attributed to the visualisation enablement.

One can argue that the above findings are due to the quantisation step we used (the 64th note) and if we had used coarser quantisation step different patterns would have emerged. As expected, coarser steps smooth out the differences of consequent notes and aggregate the patterns in larger sets.

| Quantisation | Pattern | Frequency |
|---|---|---|
| **32$^{nd}$ note** | `[2, 2]` | 2138 |
| | `[3, 3]` | 1332 |
| | `[2, 2, 2]` | 1309 |
| | `[1, 1]` | 1124 |
| | `[2, 2, 2, 2]` | 867 |
| | `[4, 4]` | 846 |
| | `[1, 1, 1]` | 716 |
| | `[3, 2]` | 704 |
| | `[2, 1]` | 663 |
| | `[4, 3]` | 651 |
| **16$^{th}$ note** | `[1, 1]` | 5226 |
| | `[1, 1, 1]` | 4095 |
| | `[1, 1, 1, 1]` | 3367 |
| | `[1, 1, 1, 1, 1]` | 2828 |
| | `[2, 2]` | 2592 |
| | `[1, 1, 1, 1, 1, 1]` | 2416 |
| | `[1, 1, 1, 1, 1, 1, 1]` | 2092 |
| | `[1, 1, 1, 1, 1, 1, 1, 1]` | 1845 |
| | `[1, 1, 1, 1, 1, 1, 1, 1, 1]` | 1635 |
| | `[2, 2, 2]` | 1610 |
| **8$^{th}$ note** | `[1, 1]` | 6720 |
| | `[1, 1, 1]` | 5262 |
| | `[1, 1, 1, 1]` | 4290 |
| | `[1, 1, 1, 1, 1]` | 3596 |
| | `[1, 1, 1, 1, 1, 1]` | 3076 |
| | `[1, 1, 1, 1, 1, 1, 1]` | 2667 |
| | `[1, 1, 1, 1, 1, 1, 1, 1]` | 2341 |

| | | |
|---|---|---|
| | [1, 1, 1, 1, 1, 1, 1, 1, 1] | 2076 |
| | [1, 1, 1, 1, 1, 1, 1, 1, 1, 1] | 1856 |
| | [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1] | 1653 |
| | [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1] | 1473 |

**Table 29. The 10 most frequent patterns of the `Duration` viewpoint of V melodies, with different quantisation steps**

The table above shows exactly this. As the quantisation step gets thicker, less frequent patterns disappear, gathering together to more common, or more trivial one might say, ones.

There is a trade off in choosing a different quantisation step between loosing details in the children playing – if we use a coarse quantisation step – and revealing details that might not exist – if we choose to use a very fine one. One can argue that the children, especially the ones with no prior familiarisation with the keyboard, are not yet musically developed enough and therefore not able to express fine rhythmic schemata, so the patterns that might emerge if we use a fine quantisation step are mostly coincidental. There is however some evidence in the literature that children do perceive irregular relations between notes and complicated meters (Soley & Hannon, 2010; Glover, 2000: 23) and one could also argue that a coarse quantisation step would cover out all particularities, hiding potential interesting patterns.

Another interesting difference appears if we look at the longest notes patterns, as is shown in the Table below.

| | **Pattern** | **Frequency** |
|---|---|---|
| **N melodies** | [612, 612] | 2 |
| | [289, 289] | 2 |
| | [124, 5] | 3 |
| | [105, 11] | 2 |
| | [84, 11] | 2 |

| | | |
|---|---|---|
| | [81, 8] | 2 |
| | [78, 8] | 3 |
| | [76, 8] | 2 |
| | [68, 5] | 2 |
| | [67, 19] | 2 |
| | [65, 64] | 2 |
| | [64, 64, 64] | 2 |
| **V melodies** | [540, 540] | 2 |
| | [397, 397] | 2 |
| | [332, 332] | 2 |
| | [237, 236] | 2 |
| | [179, 179] | 2 |
| | [139, 139] | 2 |
| | [125, 124] | 3 |
| | [124, 125, 124] | 2 |
| | [124, 125] | 3 |
| | [124, 124] | 2 |
| | [117, 117] | 2 |
| | [115, 115] | 2 |

**Table 30. The top 12 patterns with the largest note values.**

As it seems, with the exception of the `[612, 612]` pattern in the N melodies which seems coincidental, V melodies contains much more slow pieces that N melodies. This can also be said to be due to the split attention of the children, between the keyboard and the display. The display is pretty fast, almost instantaneously, so one can rule out the spit of attention due to display delay.

Below we present some viewpoints related to the rhythmical aspects. As it is evident from the results achieved, the whole issue of capturing rhythmic elements might be a controversial one, which depends on the quantisation, and also it is hard to find the right level of abstraction. The viewpoint rhythmic ratio seems to be the most interesting one in revealing interesting patters.

### 4.1.6 Experiments using the viewpoint Rhythm range

Recall that the viewpoint Rhythm range takes values 0 for less than a eighth note, 1 for between eighth note and half-note and 2 for greater note values.

The results found exhibit a rather similar appearance. In both corpora the most frequent patterns are mostly sequences of 0's. As it seems, children prefer to play rather fast. In the list of the most frequent patterns only [1, 1], [1, 1, 1] and [1, 1, 1] appear.

| Length | Pattern | Frequency |
|---|---|---|
| 2 | [0, 0] | 9771 |
| 3 | [0, 0, 0] | 8179 |
| 4 | [0, 0, 0, 0] | 7113 |
| 2 | [1, 1] | 6478 |
| 5 | [0, 0, 0, 0, 0] | 6342 |
| 6 | [0, 0, 0, 0, 0, 0] | 5749 |
| 7 | [0, 0, 0, 0, 0, 0, 0] | 5254 |
| 8 | [0, 0, 0, 0, 0, 0, 0, 0] | 4828 |
| 3 | [1, 1, 1] | 4631 |
| 9 | [0, 0, 0, 0, 0, 0, 0, 0, 0] | 4479 |
| 10 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 4185 |
| 11 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3928 |
| 12 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3697 |
| 13 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3483 |
| 4 | [1, 1, 1, 1] | 3446 |

**Table 31. The 15 most frequent patterns of the Rhythm range viewpoint in N melodies in order of frequency.**

| Length | Pattern | Frequency |
|---|---|---|
| 2 | [0, 0] | 8328 |
| 3 | [0, 0, 0] | 7170 |
| 4 | [0, 0, 0, 0] | 6383 |
| 5 | [0, 0, 0, 0, 0] | 5766 |
| 6 | [0, 0, 0, 0, 0, 0] | 5284 |
| 7 | [0, 0, 0, 0, 0, 0, 0] | 4874 |

| | | |
|---|---|---|
| 8 | [0, 0, 0, 0, 0, 0, 0, 0] | 4530 |
| 9 | [0, 0, 0, 0, 0, 0, 0, 0, 0] | 4235 |
| 2 | [1, 1] | 4195 |
| 10 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3971 |
| 11 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3742 |
| 12 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3541 |
| 13 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3353 |
| 14 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3184 |
| 15 | [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0] | 3029 |
| 3 | [1, 1, 1] | 2974 |

**Table 32. The 16 most frequent patterns of the `Rhythm range` viewpoint in V melodies in order of frequency.**

We have to move beyond the 20 most frequent patterns in order to find some interesting, asynchronous rhythmic patterns. Hence, in N melodies (that is melodies produced without the visualisation capabilities of MIROR-IMPRO enabled) the patterns `[1, 0]` and `[0, 0, 1, 1]` occur with frequencies 2693 and 763 respectively. In V melodies the patterns `[1, 0]` and `[1, 1, 0]` occur with frequencies 1848 and 968 respectively. In order to find rhythmic patterns with longer notes we should move further down the pattern frequencies list. The pattern `[2, 1]` occurs 509 times in N melodies and the pattern `[2, 2]` occurs 619 times in V melodies.

N melodies have greater frequency numbers, but this can be attributed to the greater size of the corpus. Conversely, N melodies have shorter longest common pattern, the lengthiest one being of length 153 in N melodies and of 264 in V melodies. This can be attributed to the visualisation effects.

As shown below, both subcorpora are hugely populated with 0's and 1's.

| | Percentage | Rhythm range value |
|---|---|---|
| **N melodies** | 5.12 | 2 |
| | 39.80 | 1 |
| | 55.08 | 0 |
| **V melodies** | 6.40 | 2 |

| | |
|---|---|
| 34.49 | 1 |
| 59.11 | 0 |

**Table 33. Distribution of values of `Rhythm range` viewpoint.**

The differences in the values of 0's and 1's between N and V melodies are small, seem rather circumstantial, and cannot be easily attributed to visualisation enablement.

From the results found, one might fairly say that his does not seem to be a very interesting representation choice.

### 4.1.7 Experiments using the viewpoint `Rhythm ratio`

This viewpoint can be seen as an assessment of the degree of the sophistication of the rhythmic schemata employed.

| | **Pattern** | **Frequency** |
|---|---|---|
| **N melodies** | [1/1, 1/1] | 1542 |
| | [1/1, 1/1, 1/1] | 654 |
| | [1/1, 1/1, 1/1, 1/1] | 323 |
| | [1/1, 3/2] | 229 |
| | [4/3, 1/1] | 215 |
| | [3/2, 1/1] | 192 |
| | [1/1, 4/3] | 189 |
| | [1/1, 3/4] | 183 |
| | [1/1, 1/1, 1/1, 1/1, 1/1] | 171 |
| | [3/4, 1/1] | 167 |
| | [2/3, 1/1] | 161 |
| | [5/4, 1/1] | 145 |
| **V melodies** | [1/1, 1/1] | 1558 |
| | [1/1, 1/1, 1/1] | 745 |
| | [1/1, 1/1, 1/1, 1/1] | 412 |
| | [1/1, 1/1, 1/1, 1/1, 1/1] | 247 |
| | [1/1, 3/2] | 212 |
| | [4/3, 1/1] | 205 |

| | | |
|---|---|---|
| | [1/1, 4/3] | 186 |
| | [3/2, 1/1] | 181 |
| | [1/1, 3/4] | 177 |
| | [2/3, 1/1] | 156 |
| | [1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 154 |
| | [5/4, 1/1] | 152 |

**Table 34. The 12 most frequent patterns of the `Rhythm ratio` viewpoint.**

As one can see from the Table above, there are no considerable differences on the patterns appeared in the two subcorpora. This can be interpreted as the changes in the rhythm being rather smooth, with no frequent abrupt shifts. This regularity in the two corpora is interesting because it shows stability and perhaps an induced sense of stable speed that the children play on. Even if someone might say that the elaborated ratios found (e.g. 5:4, 3:4 etc) are due to the quantisation step, this particular viewpoint brings smartly the rhythmical steadiness out of the children's musical product and therefore is a much interesting representation.

However, if we look at the lengthiest patterns (see Table below) a slight difference emerges. While in both subcorpora the 1/1 ration is prevalent, in V melodies it appears that its dominance is not so thorough. This can also be attributed on the appeal of the display to the children, as they were trying to make interesting displays with the sounds.

| | **Pattern** | **Length** | **Frequency** |
|---|---|---|---|
| **N melodies** | [1/1, 1/1, 1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 16 | 2 |
| | [1/1, 1/1, 1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 15 | 2 |
| | [1/1, 1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 15 | 2 |

| | | | |
|---|---|---|---|
| | [1/1, 1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 14 | 2 |
| | [1/1, 1/1, 1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 14 | 2 |
| | [1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 14 | 2 |
| | [1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 13 | 2 |
| | [1/1, 1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 13 | 2 |
| | [1/1, 1/1, 1/1, 2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 13 | 2 |
| | [2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 13 | 2 |
| | [1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 13 | 3 |
| | [2/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 12 | 2 |
| **V melodies** | [3/2, 1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1, 3/4, 4/3] | 20 | 2 |
| | [3/2, 1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1, 3/4] | 19 | 2 |

| | | | |
|---|---|---|---|
| | [1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1, 3/4, 4/3] | 19 | 2 |
| | [2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1, 3/4, 4/3] | 18 | 2 |
| | [3/2, 1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1] | 18 | 2 |
| | [1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1, 3/4] | 18 | 2 |
| | [3/2, 1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3] | 17 | 2 |
| | [1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1] | 17 | 2 |
| | [2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1, 3/4] | 17 | 2 |
| | [1/1, 1/1, 3/2, 2/3, 3/2, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 17 | 2 |
| | [1/1, 1/1, 1/1, 3/2, 1/1, 2/3, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1] | 17 | 2 |
| | [1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 1/1, 3/4, 1/1, 4/3, 1/1, 3/4, 4/3] | 17 | 2 |

**Table 35. The top 12 lengthiest patterns of the `Rhythm ratio` viewpoint.**

Nevertheless, the above assumption holds only for the lengthiest patterns, since the eminence of the 1/1 ratio is much more salient in V melodies (42.74%) that in N melodies (35.09%).

| | N Melodies (n=28717) | V Melodies (N=27188) |
|---|---|---|
| **Standard Deviation** | 0.77 | 0.65 |
| **Mean** | 1.14 | 1.10 |
| **% less than 1/1** | 29.62 | 26.24 |
| **% greater than 1/1** | 35.36 | 31.01 |

**Table 36: Description of the set of repeated patterns of the `Rhythm ratio` viewpoint.**

Very much alike to what has been said in 4.1.5, the differences can be attributed to the on screen display visuals drawing children's attention, in the case of V melodies (remember that the visual drawings are representations of the sounds produced by the children; since the children are mostly playing with gestures it is possible that the drawings attract the children attention causing them to differentiate their usual playing). Also, as discussed in 5.3.3, children interviewed after their performance mentioned that they did not remember what they were playing because they were looking at the screen rather than paying attention to the keyboard.

Further, one can say that the rhythmic patterns emerged are very much due to the quantisation step chosen (viz. the 64$^{th}$ note) and that the musical cognitive capabilities of the children are not yet developed enough as to give us more elaborate rhythmic schemata such as 3:2 or 4:3. If we had chosen a larger unit in our quantisation, these fine distinctions would be smoothed out, resulting in an overwhelming presence of 1:1.

# 4.2 Creativity Assessments

As already mentioned in 3.1, in order to pursue the G2 goal, we collected data from two groups, one with no music training (the "non-musicians") and one which has been in piano training courses between one and four years (the "musicians"). In order to assess whether the interaction with the MIROR-IMPRO had any impact on these groups, and to see if their musical creativity advanced, we use the model already described in 3.4.

Table 37 reports the mean values on pre- and post- conditions for the two groups, non-musicians and musicians. The general trend indicates increase in creativity when we compare mean values on pre and post sessions.

The numbers in the Table below are units in which the respective variable is expressed. The table shows the means of each variable, as it has been calculated for the whole sample, for both musicians and non-musicians. Hence, *V1 pitch SD* is the mean of the SD's calculated for each child's pre- and post- improvisations, *V3 duration* is the mean in MIDI ticks, *V8* is in MIDI velocity units and so on.

| | **Non-musicians** | | **Musicians** | |
|---|---|---|---|---|
| | **Pre** | **Post** | **Pre** | **Post** |
| V1 pitch SD | 10.75 | 13.16 | 8.84 | 9.65 |
| V1 interval SD | 10.08 | 10.75 | 9.36 | 9.24 |
| V1 rhythm SD | 0.93 | 0.97 | 15.11 | 19.84 |
| V2 unique pitch | 23.90 | 30.00 | 20.3 | 17.8 |
| V2 unique interval | 39.70 | 40.3 | 27.5 | 24.9 |
| V2 unique rhythm | 23.85 | 24.15 | 46.4 | 40.0 |
| V3 Nb notes / segmented | 48.70 | 48.42 | 42.62 | 29.42 |
| V3 duration /segmented | 12324 | 7598 | 25299 | 9822 |
| V3 Nb notes / total | 449.5 | 323.85 | 521.8 | 242.7 |
| V3 duration/ total | 101138 | 51543 | 235992 | 66263 |
| V4 different pitch | 0.35 | 0.37 | 0.29 | 0.31 |
| V4 different interval | 0.32 | 0.35 | 0.25 | 0.35 |
| V4 different rhythm | 0.29 | 0.30 | 0.31 | 0.38 |
| V5 variation interval small | 57.87 | 59.00 | 50.45 | 49.92 |
| V5 variation interval medium | 15.30 | 18.13 | 25.05 | 25.09 |
| V5 variation interval large | 26.82 | 22.79 | 24.50 | 24.98 |
| V6 variation pitch low | 13.85 | 20.09 | 12.25 | 15.62 |
| V6 variation pitch medium | 58.30 | 50.71 | 55.35 | 55.00 |
| V6 variation pitch high | 27.84 | 29.20 | 32.40 | 29.37 |
| V7 variation rhythm slow | 12.22 | 11.60 | 69.99 | 53.60 |
| V7 variation rhythm medium | 4.42 | 3.52 | 7.13 | 10.35 |
| V7 variation rhythm fast | 83.36 | 84.90 | 22.88 | 36.05 |

| | | | | |
|---|---|---|---|---|
| V8 variation dynamics soft | 37.26 | 15.59 | 14.76 | 8.11 |
| V8 variation dynamics normal | 27.30 | 14.93 | 31.13 | 26.89 |
| V8 variation dynamics hard | 35.44 | 69.49 | 54.10 | 64.99 |
| V9 texture richness | 0.89 | 0.70 | 1.35 | 0.66 |
| V10 clusterness | 17.43 | 21.60 | 19.56 | 26.39 |

**Table 37. Variables mean values for non-musicians and musicians, on pre and post session.**

However, due to the small sample size and the limited number of in-between musical sessions, not all of shifts are statistically significant.

The pre vs post treatment comparison was performed with asymptotic Wilcoxon signed rank test with Pratt zero handling (using the *coin* package in the *R*© statistical software suite[27]). The two groups were assessed separately, so no direct statistical comparison between groups was made.

The tables below report only statistically significant differences between pre- and post-conditions. For the variables not reported below no significant difference was found. For variables V1, V2, V4, V5medium, V6 we have predicted greater values in post session, i.e. greater values indicating the progress of creativity. For variables V5small and V5large we have predicted smaller values in post session (see the explanation in the section 5.4). Accordingly, a one-tailed test was used for these variables. For variables V3, V7, V8, V9, V10 no directional hypothesis was made. Accordingly, a two-tailed test was used.

We choose here to include a very short introduction to some basic statistics, in order to avoid the possible confusion of the terms used.

### 4.2.1 Statistical Measures Used

In plain language, *significant* means important. In Statistics *significant* means probably true, in other words a statistically significant result is a result that cannot be attributed to chance. Conventionally, we define the *Null Hypothesis* as the case that a result has occurred by chance (or equivalently that there is no relation between

[27] http://cran.r-project.org/web/packages/coin

results). Hence, statistical significance means that if the Null Hypothesis is true, then there's a low probability of getting a result that extreme – or, in other words, that there is a low probability to receive an extreme result by chance.

This probability is the **p-value (σ).** A conventional (and arbitrary) threshold for declaring statistical significance is a p-value of less than 0.05 (the interested reader is referred to Canning (2014)).

The **standard deviation** is another important statistical concept. It describes the amount of variation in a measured process characteristic. More specifically, it computes how much an individual measurement should be expected to deviate from the mean. Hence, in our case, it indicates how close (to the mean) the notes (or intervals or other viewpoints) are.

A Z**-score** (aka, a standard score) indicates how many standard deviations an element is distanced from the mean. A Z-score can be calculated from the following formula.

$Z = \frac{X - \mu}{\sigma}$, where Z is the z-score, X is the value of the element, μ is the population mean, and σ is the standard deviation.

**One-tailed** and **two-tailed** tests indicate alternative ways of utilising the statistical significance of a parameter inferred from a data set. A two-tailed test is used if deviations of the estimated parameter in either direction from some benchmark value are considered theoretically possible. In contrast, a one-tailed test is used if only deviations in one direction are considered possible.

Given the aforementioned statistical measures, we proceed now to the presentation of the results of the experiments.

## 4.2.2 Non-musicians

In the tables below, we present the basic statistical measures that were found to have statistical significant differences between pre- and post- sessions.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 10.75 | 3.34 | 10.87 |
| **Post** | 13.16 | 2.88 | 13.72 |
| | | | |
| Z = -2.65, p-value = 0.004 (one-tailed) | | | |

**Table 38. V1 – Standard Deviation on pre- and post-corpus.**

As seen in Table 38, the average pitch SD was higher in the post-session than in the pre-session, indicating that greater variety in the notes was used in the post-session.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 101137.65 | 36301.93 | 96031.50 |
| **Post** | 51542.65 | 19238.46 | 49255.00 |
| | | | |
| Z=3.40, p-value=0.001 (two-tailed) | | | |

**Table 39. V3 – Duration, total.**

As it can be seen from Table 39, the average total duration was almost two times shorter in the post-session than in the pre-session. This is discussed in Chapter 5 below, as it is considered to be a feature having to do with the whole setup of the experiment.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 15.30 | 6.51 | 16.20 |
| **Post** | 18.13 | 6.00 | 18.45 |
| | | | |
| Z = -1.75, p-value = 0.039 (one-tailed) | | | |

**Table 40. V5 – Percentages of medium intervals**

As it can be seen from Table 40, the average medium intervals were more often present in the post-session than in the pre-session. This can be interpreted as the children leaving the particularly small and large intervals, producing more consciously medium sized intervals.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 37.26 | 25.40 | 29.98 |
| **Post** | 15.59 | 12.32 | 11.93 |
| | | | |
| Z = 2.65, p-value = 0.008 (two-tailed) | | | |

**Table 41. V8 – Dynamics Variation, soft.**

As it can be seen from Table 41, on the average, "soft" dynamic was more than two times less present in the post-session than in the pre-session. This can be interpreted as the children getting more confident in keyboard producing more voluminous output in their post-sessions.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 27.31 | 9.11 | 28.06 |
| **Post** | 14.93 | 9.58 | 14.07 |
| | | | |
| Z = 3.06, p-value = 0.002 (two-tailed) | | | |

**Table 42. V8 – Dynamics Variation, normal.**

As it can be seen from Table 42, on the average, "normal" dynamic was more than two times less present in the post-session than in the pre-session. This endorses the previous one (see Table 41) and validates that on average the children played much more loudly in their post sessions.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 35.44 | 24.67 | 34.40 |
| **Post** | 69.49 | 19.54 | 70.40 |
| | | | |
| Z = -2.99, p-value = 0.003 (two-tailed) | | | |

**Table 43. V8 – Dynamics Variation, hard**

As it can be seen from Table 43, on the average, "hard" dynamic was more than two times more present in the post-session than in the pre-session. Again, seen in conjunction with Table 41 & Table 42, this demonstrates more confident playing in the post-sessions.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 0.89 | 0.26 | 0.86 |
| **Post** | 0.70 | 0.07 | 0.72 |
| | | | |
| Z = 3.92, p-value = 0.001 (two-tailed) | | | |

**Table 44. V9 – Texture Richness**

As it can be seen from Table 44, on the average, the musical excerpt played by the child is more "populated" in the post-session than in the pre-session (smaller values of this variable reflect more "populated" excerpt). This can potentially signify more complicated structures in the post-session and in general indicates evidence of a more experimental behaviour in the post-sessions.

Concluding, we found that the interaction with the MIROR-IMPRO system altered the musical behaviour of the non-musician children in a statistical significant manner on variables V1, V3, V5, V8 and V9. We did not find any statistical significant impact on V2, V4, V6, V7 and V10 (the creativity variables are presented in 3.4)

### 4.2.3 Musicians

In the section below the same values are investigated for the musicians' group. Again, we report only on the variables that have been found to have statistical significant differences between pre- and post- sessions.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 235991.60 | 111207.17 | 257527.50 |
| **Post** | 66262.70 | 31756.15 | 57980.50 |
| | | | |
| Z= 2.60, p-value = 0.009 (two-tailed) | | | |

**Table 45. V3 – Duration, total**

As it can be seen from Table 45, the average total duration was more than three times shorter in the post-session than in the pre-session. This follows the tendency observed also in the non-musicians and it is discussed in Chapter 5, considered relevant to the whole setup of the experiment – it might be however harder to interpret in this case.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 0.25 | 0.06 | 0.26 |
| **Post** | 0.35 | 0.07 | 0.38 |
| | | | |
| Z = -2.29, p-value = 0.021 (two-tailed) | | | |

**Table 46. V4 – Ratio of different per total, intervals.**

As it can be seen from Table 46, the average ratio of different intervals was higher in the post-session than in the pre-session, thus we assume increased musicality. In contrast with the case of non-musicians where no statistical significance was found, it seems that the interaction with the MIROR-IMPRO triggered the musicians to respond with extended musical variety to the machine's pokes.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 22.88 | 6.51 | 16.20 |
| **Post** | 36.05 | 22.17 | 31.60 |
| | | | |
| Z = -2.09, p-value = 0.037 (two-tailed) | | | |

**Table 47. V7 – Rhythm variation, fast.**

As it can be seen from Table 47, the average percentage of fast rhythm was almost twice higher in the post-session than in the pre-session. Since this concerns the musicians' group, where they play with some already acquired complex technique, their playing can be assumed to be more "conscious", pointing towards an increaded ease on the improvisations.

| | MEAN | STD DEV | MEDIAN |
|---|---|---|---|
| **Pre** | 1.35 | 0.66 | 1.21 |
| **Post** | 0.66 | 0.04 | 0.68 |
| | | | |
| Z = 2.80, p-value = 0.005 (two-tailed) | | | |

**Table 48. V9 – Texture Richness.**

As it can be seen from Table 48, on average, the musical excerpt played by the child is almost twice more "populated" in the post-session than in the pre-session (smaller values of this variable reflect more "populated" excerpt). This again may be due to more "complicated" musical output – denser harmony or faster playing – produced by the children.

Concluding, we found that the interaction with the MIROR-IMPRO system alter the musical behaviour of the musician children in a statistical significant manner on variables V3, V4, V7 and V9. We did not find any statistical significant impact on V1, V2, V5, V6, V8 and V10 (the creativity variable are presented in 3.4).

It is interesting to notice that the only variables affected in a statistical significant manner in both groups were V3 duration and V9; the first one indicating the length of the improvisations and the second one how much populated with notes was the music produced. The first one (V3) is obvious in all cases from the qualitative analysis too; the children in both groups were much more laconic in their post sessions. This might be attributed to a certain degree of weariness of the children during the experiments. However, taking into account the qualitative analysis discussed below where a certain essence of purpose is revealed during the post sessions, it could be the case that the children did not perform laconically in their post sessions due to weariness, but because they produced what they had in mind and concluded their performances gracefully. In a similar line of thinking, the richer texture (variable V9) in the post sessions might have occurred due to the children's intentional attempts to be more musically adventurous and accomplished.

### 4.2.4 Some Cases

The results above are musically and statistically significant, and can point us towards some trends and general tendencies on how the two groups evolved before and after the sessions with the system. In this section we are taking a more qualitative approach, presenting some exemplary cases, both of children with musical background and of children with no musical background. We discuss the pre-and post MIROR-IMPROvisation from the same child each time.

We selected 3 musician and 4 non-musician children, on the basis that they exhibited typical behaviours and musical attributes in their performances to more or less all children that took place in the experiments.

In the listening analysis we performed, we tried to not only assess the musicality of the children and theorise about their potential progress after the interaction with the MIROR-IMPRO system, but also to speculate about their latent intentions and how these are expressed and interwoven into the musical output.

At the same time as performing these analyses, we submitted the files (audio and scores) to a group of 3 experts and we recorded their opinions. Therefore for each child below, we also discuss the experts' judgement (three experts, two on musical improvisation, and one on children's musical education).

All scores presented in the following examples are transcriptions from the corresponding MIDI files.

The names of the children mentioned below are not their real names, in order to protect their anonymity.

#### 4.2.4.1 Musicians

All musicians in the experiment were pupils of junior conservatoires where they were taught and acquired in various degrees the standard curriculum, comprising from material such as playing both hands independently within a small range of the keyboard, some scales, simple pieces, finger exercises and so on. Once on their third year, the children get into more advanced pieces, like small studies, easy Bach repertoire, well-known songs etc. None of the children has been taught anything on improvisation. The ability of improvisation is not really cultivated, nor encouraged, in a typical conservatoire setting in Greece.

**John** is a nine-year-old boy, which has taken piano lesson for nearly two years (as to the date of the experiment). John approached the keyboard reluctantly but certainly bolder that the rest of his cohort. He demonstrated musicality and his learnt abilities but he totally lacked improvisation aptitudes. He experienced difficulties keeping a steady beat, an issue more or less typical for his age. When told to play whatever he wants, he seems to pondering and after a while he started playing some Christmas carols (see Fig. 26).

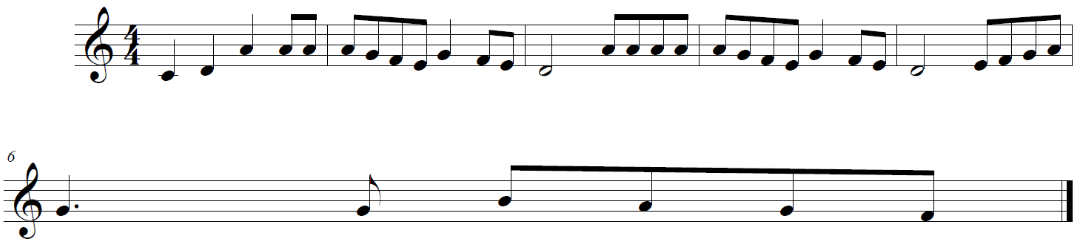


**Fig. 26: John's first improvisation attempt – first tune**

After a mere 10 bars he stopped, not knowing what to do. After apparently a short conversation and a little encouragement by the experimenter, he started again on the keyboard. Again, he reverted to a well-known Greek pop song[28] (see Fig. 27), while at the same time trying to escape from it and go towards a more improvised version of the tune. The whole process repeated another 2-3 times.

**Fig. 27: John's first improvisation attempt – second tune**

[28] "Deka palikaria", by Manos Loizos (music) & Lefteris Papadopoulos (lyrics)

At the end of his initial session, John started tentatively to introduce his left hand in the playing. John also performed his initial improvisation session exclusively on the white keys of the keyboard.

Then 6 interactive sessions with MIROR-IMPRO followed. And then John was trying again to improvise (this process was followed exactly by all musician children).

This time John exhibited clearly a much more gallant attitude. He started right from the beginning with two hands and tried to explore an arpeggio (C major to D minor back to C major etc) (see Fig. 28).

**Fig. 28: John's improvisation excerpt after the interaction with MIROR_IMPRO**

He continued on this mode for a while and then tried to bring in something different (see Fig. 29). However, this did not seem to lead anywhere so he reverted to his initial arpeggio, giving his improvisation a loose ABA form.

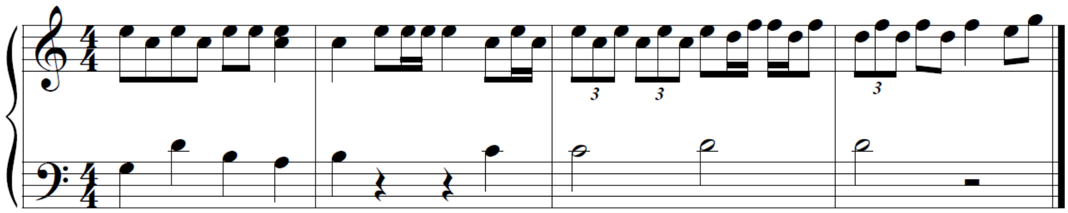


**Fig. 29: Another John's improvisation excerpt after the interaction with MIROR_IMPRO**

John had another attempt to play something different but it did not succeed either. It is noticeable however the absence of the long pauses, when compared with the initial improvisation attempts – John did not need any more encouragement by the experimenter in order to improvise. John was confident and knew exactly what he wanted to do. His rhythmic abilities also seem to progress by introducing more complex rhythmic patterns. Nonetheless, he only explored a small range of the keyboard, playing a repetitive motive with thirds with only 2-3 notes (D, E, C).

**Fulvia** is another interesting case. Fulvia was a 10-year-old girl with 3 years piano lessons behind her, as to the day of the experiment. Fulvia in her initial session approached the keyboard in a much more confident way than John and tried to improvise something novel and meaningful. She refrained from playing readymade pieces from her piano lessons. She started right on to play a rather sentimental melody with a fast beat, and she used her left hand right from the beginning, though not continuously. She initiated a rhythmically interesting arpeggio, then changed octave but she was focusing on almost solely two notes – G, D. She is also demonstrating lack of rhythmic skills.

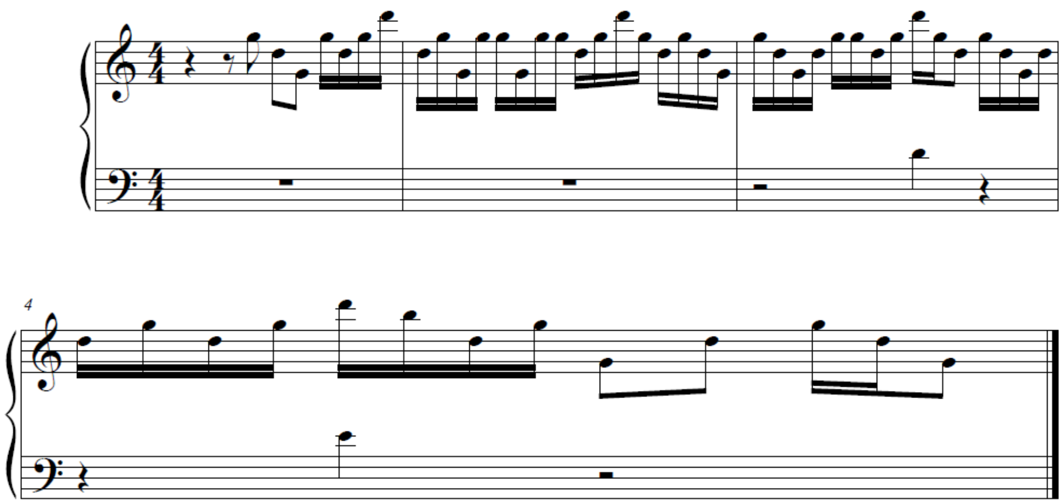


**Fig. 30: Fulvia's initial improvisation excerpt**

She was also exhibiting the long pauses and the need of encouragement in order to go on. She was more rhythmic than John – maybe due to being a little older and more advanced in piano lessons.

After the interaction with the MIROR-IMPRO, Fulvia showed much progress. She still liked to play fast but now she was using extensively her left hand and the confidence that she gained from the in-between sessions was notable. She was much more adventurous and she explored a much larger range of the keyboard.

**Fig. 31: Fulvia's post-MIROR-IMPRO improvisation excerpt**

She did not hesitate at all (gone are the long pauses and the need for encouragement) and performed her improvisation with almost perfect rhythmic tempo. She performed almost exclusively on white keys in contrast to her initial performance.

The third and last musician case that we will discuss is **Gregory**. Gregory was a 9-year-old boy with 3 years of piano lessons, as to the time of the experiment. Gregory exhibited almost all typical pre-MIROR-IMPRO behaviours. In his initial improvisations performance he started to play with confidence, using both hands, a refrain of a well-known Greek pop song[29] (see Fig. 32), which he constantly played for over 50 bars. He also demonstrated the expected for his age rhythmical inconsistencies.

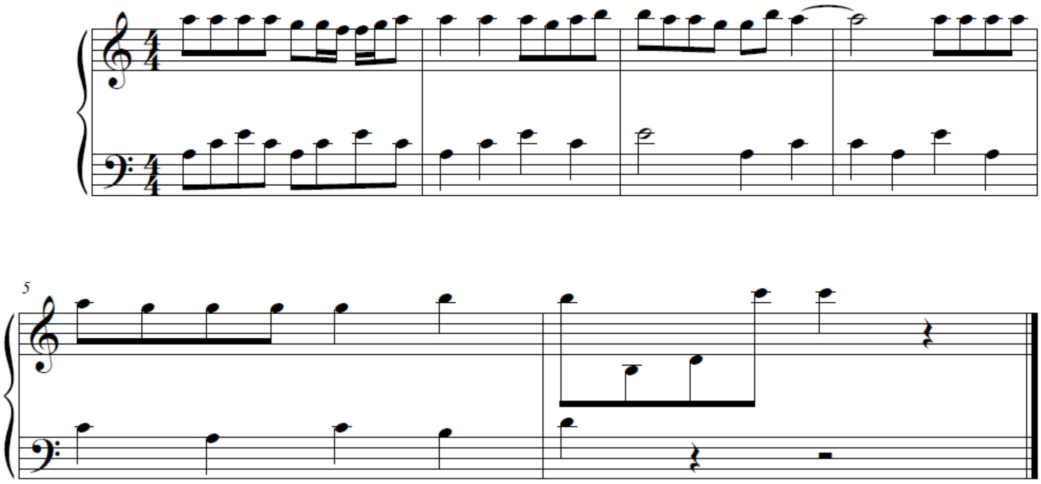


**Fig. 32: Gregory's initial improvisation excerpt – greek pop song**

After that initial bold introduction, he had a very long pause, during which apparently he had a conversation with the experimenter about what to do and what to play. In the following part his musical behaviour radically changed. Obviously he better understood what was expected from him and tried to satisfy the experimenter. He played timidly now, with one hand mainly, almost exclusively on the white keys exploring only a small range of the keyboard (see Fig. 33 & Fig. 34).

[29] "Milise mou", by Manos Hadjidakis (music) & Nikos Gatsos (lyrics)

Fig. 33: Gregory’s initial improvisation – an excerpt

He also demonstrated the pauses where he obviously got encouragement from the experimenter, in order to continue his improvisation. After 3-4 such attempts Gregory finished his initial improvisation session.

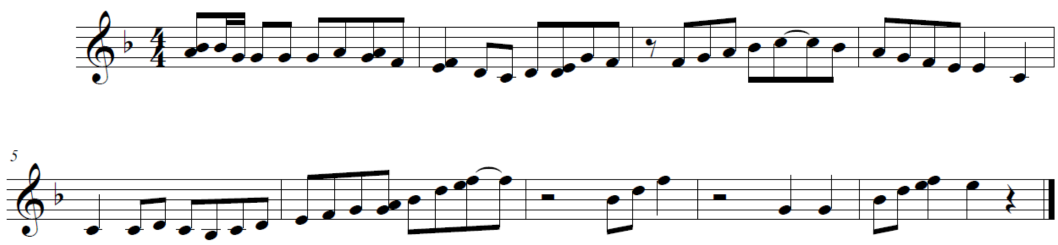


Fig. 34: Gregory’s initial improvisation – another excerpt

In the post MIROR-IMPRO improvisation session Gregory did not show much improvement. He played a very short passage – a mere 12 bars – where again he started with known pieces form his piano lessons (see Fig. 35). He played with both hands, exclusively on the white keys.

**Fig. 35: Gregory's post-MIROR-IMPRO improvisation excerpt**

He certainly kept a steady tempo of 4/4, but showed no evidence of improvement as far as improvisation aptitudes are concerned.

### 4.2.4.2 Non-musicians

Non-musicians were children from a primary school from a medium to lower socioeconomic status neighbourhood of Athens. The primary school was within a conglomerate of several other schools, both of primary and secondary education – children aged from 6 to 17 years old. The children had no musical background and most of them were sitting in front of a keyboard for the first time in their lives.

**Claudio** was a 7-year-old boy. His initial improvisation was quite confident. He explored quite some range of the keyboard, with both hands, although sticking only to the white keys. He demonstrated changes in dynamics and in tempo. He started rhythmically and then suddenly changed rhythm and dynamics (see Fig. 36). While he was constantly changing playing gestures, a structure emerged. Certainly Claudio tried to express himself musically, but he lacked the technical skills for that.

**Fig. 36: Claudio's initial improvisation excerpt**

Claudio's post MIROR-IMPRO performance was quite short, only 20 bars. He played much more consciously this time, listening carefully to what he played. He played in a narrower register this time, still only on the white keys (see Fig. 37). He still demonstrated changes in dynamics, but he is much more rhythmically consistent now, slower but without alteration in rhythm. He seemed to focus in a smaller subset of the musical universe, trying to be more explorative and profound in this, demonstrating a much more introvert behaviour in contrast to the extrovert attitude adopted in the initial session.

**Fig. 37: Claudio's final improvisation excerpt**

**Nigel** was a 6-year-old girl, from the same class as Claudio. She also played with both hands, only on the white keys (see Fig. 38). After some initial reluctant explorative attemptss, she established a beat and kept it throughout the rest of her performance. She clearly demonstrated musicality and seemed to enjoy the sonic exploration of the keyboard.

**Fig. 38: Nigel's initial improvisation excerpt**

Nigel's final improvisation was also shorter that the first one – almost half in time. She played much more confidently this time; louder and staccato (see Fig. 39). She also used many clusters, something that lacks from her initial improvisation. Her rhythmic establishment was much more assertive now, she proceeded eagerly, even if from time to time she sounded troubled – she sometimes seemed ambivalent as to which direction to choose – however, she managed to overcome her difficulties and concluded with a steady and confident pace.

**Fig. 39: Nigel's final improvisation excerpt**

**Lina** was a 9-year-old girl. In her initial performance, she played fluently and rather sentimentally. She started confidently and continued to the end without hesitation. She establishes a steady pace and used a large part of the keyboard, though only the white keys (see Fig. 40). Lina seemed to be quite mature musically and expressed herself eagerly, even if she lacked institutional music training.

**Fig. 40: Excerpt from Lina's initial improvisation excerpt**

In her post MIROR-IMPRO improvisations Lina's was more adventurous. She was still using both hands and occasionally travelled to the black side of the keyboard. She was using some clusters but she appeared less rhythmical. She seemed to be more careful to what she is doing now and she seemed to be more mindful experimenter. This is a case that demonstrates an initial will and ability, and points towards a child that could benefit from instrumental tutoring in order to become more advanced. She definitely seemed very promising and showed certain advancement.

**Fig. 41: Excerpt from Lina's final improvisation excerpt**

Our final case was **Dimitri**, a six-year-old boy. This was his first time in front of a keyboard. Dimitri played with only one hand and mainly on the white keys, even if he permitted some attempts on the black part. He experimented mostly with the sonic dimension – he hit twice each key on multiple occasions, as to be sure for the sound it produces – but he exhibited some gestural playing too (see the downwards motion in Fig. 42). In general, his playing was timid, with little variation, no rhythm and with relatively less musicality than the other children.

**Fig. 42: Dimitri's first improvisation excerpt**

In his post MIROR-IMPRO improvisation his behaviour changed considerably. He was using both hands now and a much larger range of the keyboard. He attempted many more explorations on the black keys and he even used clusters. He was still non rhythmical but he was more adventurous and much more confident than in his initial session. He played louder and exhibited larger variation and much more sophisticated texture.

**Fig. 43: Dimitri's final improvisation excerpt**

In general, adding a qualitative dimension to the work and looking at some case studies in depth reveals how the children modified their playing after the practice sessions with the system. Musicians tended to start with a known piece, understanding at the end the idea behind improvisation. Non musicians were more varied, though seemed to be afraid of the keyboard's black keys – probably because for most of them, this was their first time on a keyboard.

In the following section the expert judge's opinion is presented, for the above cases.

### 4.2.4.3 The experts' opinion

The expert's opinion is briefed and consolidated as to be more conveniently encompassed in this text. One point that all experts seem to stress out is that musicians mostly played known pieces and their attitude was not oriented towards improvisation; they didn't show that they have developed cognitive processes for thought organisation and methods for creating improvisations. The non-musicians seemed to be affected much more from the experience with the MIROR-IMPRO system.

Their original contribution is presented below, and the original words are attached in Appendix I.

**Fulvia** has some facility on the piano and sounds much more structured on the post performance. She seems a bit afraid and hesitating on the pre performance; she constantly stops and seems to contemplate how to continue.

It is clearly evident that on the post performance she wants to expand and explore. She seems confident and plays much more loudly, exhibiting decisiveness;

**John** tries to play a Christmas carol on the pre take and other pieces he knows. He tries various pitches and seems to hesitate. He tries something different but cannot find his way; he stops and reverts to known pieces;

On the after take, we get a much different picture with him improvising and expanding on themes and ideas exhibiting some significant progress. He tries various motives and moves chromatically up and down the keyboard. Eventually, he settles in a basic motif and adds volume to accompany it.

**Gregory** has agility on the piano similar to Fulvia and on the long pre take he is trying to play things he knows. He moves uncertainly towards other directions but he loses his way. He keeps a beat on his left hand and tries to find a tune.

On the after take, he becomes much clearer and more economical, obviously affected by the program trying to stress clarity, economy and accuracy. He performs more confidently implying that he has something in mind, although it does not expand since his performance is very short.

**Claudio'**s case is very interesting as on the pre take he plays random things just for fun. He seems rather to investigate the sonic facets of the sound he produces than the melodic ones. As he develops, he seems to follow an idea. He moves stepwise and he reverts on the sonic investigation. He explores the whole keyboard, trying each one note separately.

On the after take, he becomes very solemn, laconic and melodic. He continues to investigate the sounds but now he seems more confident. He holds down the keys and creates simultaneities.

**Nigel** is a similar case to Claudio – he plays randomly and investigates various sounds. He stepwise oscillates on the whole keyboard.

On the after take, he becomes more definite, rhythmically more articulated and dramatic, again showing a profound effect. He tries to create a voluminous effect by playing clusters of notes. He moves up and down stepwise using double and triple notes. He plays loudly with a lot of accentuation.

**Lina** is interesting, she sounds very talented! On the pre take she has a kind of natural flow. She moves stepwise up and down using both hands and seems to enjoy it, producing a long performance.

On the after take, a dramatic change occurs again with a much more rhythmic and aggressive approach. She continues her stepwise mode of playing, but she seems to play with more intent and insists on particular motives. She concludes with a single note and it seems she has pre decided to do so.

**Panayiotis** seems to play random stuff on the pre take. He uses the whole keyboard mostly in a stepwise fashion.

On the post take, he becomes more dense and complicated and seems more adventurous and more confident. He tries notes on the whole keyboard and he plays more loudly.

Given the comments of the experts, transcribed above, there seems to be a general agreement with our evaluation. The experts are able however to draw some conclusions on the intention and the motives behind each musical behaviour. One expert in particular, seems to consciously group the children into two groups, the musicians and the non-musicians, as the improvisation task had a different character for these two groups. The other two experts also agreed with this distinction but did not stress it that much.

The bottom line of this exercise is that the three experts, who have no knowledge of the psychological experiments included in the MIROR Project, and no knowledge of what the system could do, agreed with our initial evaluation and in thus validated the progress the children made.

# 4.3 Distinctive Patterns Discovery

The results of pursuing the G3 goal, that the assessment of the pattern over-representation with the concept of corpus and anticorpus for comparison purposes, using EG'I (see 3.1), are presented in this section. Only the patterns reported as significant by the computational processing described in previous corresponding sections, are mentioned below.

We remind that DELTA is discussed in 3.6.6.1. A pattern $p$ is considered as distinctive if: $\frac{P(p|S)}{P(p|S')} > Delta$, where $S$ is the set of all patterns in corpus, $S'$ is the set of all patterns in anticorpus, $P(p|S)$ is the conditional probability of $p$ given $S$, $P(p|S')$ is the conditional probability of p given $S'$ and $DELTA=3$.

We used all data collected in EG'I along with the non-visualisation data from EG'III. In total the corpus consisted of 299 MIDI files. 138 were collected in Greece, 77 in Sweden and 84 in the UK. 140 were from boys and 159 from girls. 137 were 4-year-olds whereas 162 were 8-year-olds.

| **Length** | **Frequency** | **Pattern** | **Frequency in Anticorpus (unsmoothed)** | **Corpus Probability** | **Anticorpus Probability** | **DELTA** |
|---|---|---|---|---|---|---|
| 5 | 27 | 2 0 -2 2 -2 | (null) | 0,000165 | 0,000005 | 31,352595 |
| 3 | 24 | -29 29 -29 | (null) | 0,000147 | 0,000005 | 27,868974 |
| 4 | 23 | 33 -33 33 -33 | (null) | 0,000141 | 0,000005 | 26,707766 |
| 5 | 23 | -4 4 -4 2 0 | (null) | 0,000141 | 0,000005 | 26,707766 |
| 5 | 22 | 4 -4 2 0 0 | (null) | 0,000135 | 0,000005 | 25,546559 |
| 5 | 22 | 2 3 -3 3 -3 | (null) | 0,000135 | 0,000005 | 25,546559 |
| 8 | 22 | 1 1 1 1 1 1 1 1 | (null) | 0,000135 | 0,000005 | 25,546559 |
| 6 | 22 | -4 4 -4 2 0 0 | (null) | 0,000135 | 0,000005 | 25,546559 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 4 | 22 | -4 2 0 0 | (null) | 0,000135 | 0,000005 | 25,546559 |
| 2 | 21 | 41 -41 | (null) | 0,000128 | 0,000005 | 24,385352 |
| 9 | 20 | 1 1 1 1 1 1 1 1 1 | (null) | 0,000122 | 0,000005 | 23,224145 |
| 5 | 19 | -33 33 -33 33 -33 | (null) | 0,000116 | 0,000005 | 22,062937 |
| 4 | 19 | 2 0 -2 0 | (null) | 0,000116 | 0,000005 | 22,062937 |
| 3 | 18 | -22 22 -22 | (null) | 0,00011 | 0,000005 | 20,90173 |
| 5 | 18 | 33 -33 33 -33 33 | (null) | 0,00011 | 0,000005 | 20,90173 |
| 13 | 18 | 2 -2 2 -2 2 -2 2 -2 2 -2 2 -2 2 | (null) | 0,00011 | 0,000005 | 20,90173 |
| 10 | 18 | 1 1 1 1 1 1 1 1 1 1 | (null) | 0,00011 | 0,000005 | 20,90173 |
| 3 | 35 | 33 -33 33 | 2 | 0,000214 | 0,000011 | 20,321127 |
| 2 | 16 | 37 -37 | (null) | 0,000098 | 0,000005 | 18,579316 |

**Table 49. Raw results – Corpus Greece; Anticorpus Sweden & UK – Viewpoint `Interval`**

In the table above, some of these patterns can be seen as subpatterns of others, e.g. the pattern [-4, 2, 0, 0] (Frequency 22) can be seen as subpattern of [4, -4, 2, 0, 0] (Frequency 23). In cases like this, the more general pattern occurs less frequently than the less general one, since the appearances of the more general pattern encompasses the appearances of the less general pattern. In our approach we have not taken into account the overlapping issue and patterns are reported every time they occur, irrespective of whether they are reported elsewhere.

This raises also the related controversial issue of statistical versus musical significance (see also 5.5.3, p. 204). We usually consider more significant the most frequent and longest patterns. Nevertheless, since most of the frequent patterns used to be the short length ones, it would be useful perhaps in the future to introduce a metric that combines these two in a single rank. Cambouropoulos (1998) proposes a combination of frequency, length and pattern overlap as a metric to rank significance of patterns. These quantities are parameters that are specified by the experimenter based on his/her experience or his/her perception about musical significance and are calibrated accordingly.

In the following section, we discuss each experiment's most prominent results and we present some of the most typical ones.

### 4.3.1 Experiment I: By Country

In this experiment, we looked for characteristics that could be attributed to differences on the cultural and educational environment. We ran three different cases:

- Case I: Corpus Greece; Anticorpus: Sweden & UK
- Case II: Corpus Sweden; Anticorpus: Greece & UK
- Case III: Corpus UK; Anticorpus: Sweden & Greece

From the 299 MIDI files in total, 138 were collected in Greece, 77 in Sweden and 84 in the UK.

We found much larger presence of oscillating movement patterns with large leaps in the data from Greece. This perhaps can be attributed to different cultural and educational background – e.g. lack of familiarisation with the keyboard. Also, even if sound effort was made towards keeping the same conditions in executing the psychological experiments, some differences in the setup and in the environment could not be avoided and might have naturally affected the children's performance. These could include the room where the experiment took place, the personality of the experimenter etc.

We also found that Greek children played much slower than children from the other countries, obviously meaning that they used slower movement-gestures; or that they were focusing on executing the gestures consciously and with great attention rather than focusing on the sound patterns produced.

The Swedish data is characterized by upward motion with long patterns. Very few patterns with unison found, with respect to other countries' significant patterns.

| **Length** | **Frequency** | **Pattern** | **Frequency in Anticorpus (unsmoothed)** | **Corpus Probability** | **Anticorpus Probability** | **DELTA** |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| 2 | 44 | C8 C8 | (null) | 0,0004 | 0,000004 | 97,447162 |
| 11 | 38 | G4 A4 B4 C5 D5 E5 F5 G5 A5 B5 C6 | (null) | 0,000346 | 0,000004 | 84,158913 |
| 12 | 36 | F4 G4 A4 B4 C5 D5 E5 F5 G5 A5 B5 C6 | (null) | 0,000328 | 0,000004 | 79,729497 |
| 9 | 35 | F5 G5 A5 B5 C6 D6 E6 F6 G6 | (null) | 0,000319 | 0,000004 | 77,514788 |
| 5 | 33 | F2 G2 F2 G2 F2 | (null) | 0,0003 | 0,000004 | 73,085372 |
| 12 | 33 | E6 D6 C6 B5 A5 G5 F5 E5 D5 C5 B4 A4 | (null) | 0,0003 | 0,000004 | 73,085372 |
| 10 | 33 | E5 F5 G5 A5 B5 C6 D6 E6 F6 G6 | (null) | 0,0003 | 0,000004 | 73,085372 |
| 11 | 33 | C5 D5 E5 F5 G5 A5 B5 C6 D6 E6 F6 | (null) | 0,0003 | 0,000004 | 73,085372 |
| 12 | 33 | B4 C5 D5 E5 F5 G5 A5 B5 C6 D6 E6 F6 | (null) | 0,0003 | 0,000004 | 73,085372 |
| 3 | 32 | C8 C8 C8 | (null) | 0,000291 | 0,000004 | 70,870664 |
| 13 | 32 | A4 B4 C5 D5 E5 F5 G5 A5 B5 C6 D6 E6 F6 | (null) | 0,000291 | 0,000004 | 70,870664 |

**Table 50. Experiment I, case II (corpus SWE; anticorpus GRE & UK) – Viewpoint `Pitch`**

The Swedes along with the British exhibit the most rigid rhythmic values (see Table 51), in their improvisations.

| Length | Frequency | Pattern | Corpus Probability | Anticorpus Probability | DELTA |
|---|---|---|---|---|---|
| 19 | 103 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000937 | 0.000004 | 228.1149 |
| 20 | 91 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000828 | 0.000004 | 201.5385 |
| 21 | 80 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000728 | 0.000004 | 177.1767 |
| 22 | 70 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000637 | 0.000004 | 155.0296 |
| 23 | 62 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000564 | 0.000004 | 137.3119 |
| 24 | 54 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000491 | 0.000004 | 119.5942 |
| 25 | 48 | 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000437 | 0.000004 | 106.306 |

| | | | | | |
|---|---|---|---|---|---|
| | | 2 2 2 2 2 2 2 2 2 2 2 2 2 | | | |
| 26 | 43 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000391 | 0.000004 | 95.23245 |
| 23 | 40 | 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 | 0.000364 | 0.000004 | 88.58833 |
| 27 | 36 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000328 | 0.000004 | 79.7295 |
| 28 | 34 | 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 | 0.000309 | 0.000004 | 75.30008 |

**Table 51. Experiment I, case II (corpus SWE; anticorpus GRE & UK) – Viewpoint Rhythm**

The Convex shape is predominant in all countries – up to 8 times more than the 2nd choice ascending. Not many differences were found as this segmental viewpoint is concerned. The distribution of the Huron shapes follows a uniform distribution regardless from the country of origin of the children.

| Huron Shape | Corpus (% in total) | Anticorpus (% in total) |
|---|---|---|
| **Ascending** | 481 (15.51%) | 1722 (14.22%) |
| **Descending** | 355 (11.44%) | 1228 (10.14%) |
| **Concave** | 182 (5.87%) | 565 (4.67%) |
| **Convex** | 1968 (63.44%) | 8234 (67.99%) |
| **Horizontal-Ascending** | 11 (0.35%) | 46 (0.38%) |
| **Horizontal-Descending** | 37 (1.19%) | 140 (1.16%) |
| **Ascending-Horizontal** | 43 (1.39%) | 125 (1.03%) |
| **Descending-Horizontal** | 19 (0.61%) | 36 (0.30%) |
| **Horizontal** | 6 (0.19%) | 15 (0.12%) |
| TOTAL | **3102** | **12111** |

**Table 52. Experiment I, case II (corpus SWE; anticorpus GRE & UK) – segmental viewpoint `Huron shape`**

When corpus is the Swedish data (see Table 50), there exists an even stronger preference in the Convex schema in the anticorpus. Other than that the results are more or less uniform.

| Huron Shape | Corpus (% in total) | Anticorpus (% in total) |
|---|---|---|
| **Ascending** | 1158 (13.80%) | 1045 (15.32%) |
| **Descending** | 828 (9.87%) | 755 (11.075) |
| **Concave** | 382 (4.55%) | 365 (5.35%) |
| **Convex** | 5749 (68.50%) | 4453 (65.29%) |
| **Horizontal-Ascending** | 34 (0.41%) | 23 (0.41%) |
| **Horizontal-Descending** | 105 (1.25%) | 72 (1.25%) |
| **Ascending-Horizontal** | 99 (1.18%) | 69 (1.18%) |
| **Descending-Horizontal** | 27 (0.32%) | 28 (0.32%) |
| **Horizontal** | 11 (0.13%) | 10 (0.13%) |
| **TOTAL** | **8393** | **6820** |

**Table 53. Experiment I, case II (corpus GRE; anticorpus SWE & UK) – segmental viewpoint `Huron shape`**

The most varied results were produced when the corpus was the Greek data set. We observed a slight increased preference in Convex and diminished preference in Ascending and Descending schemata.

| Huron Shape | Corpus (% in total) | Anticorpus (% in total) |
|---|---|---|
| **Ascending** | 564 (15.17%) | 1639 (14.26%) |
| **Descending** | 400 (10.76%) | 1183 (10.29%) |
| **Concave** | 183 (4.92%) | 564 (4.91%) |
| **Convex** | 2485 (66.84%) | 7717 (67.13%) |
| **Horizontal-Ascending** | 12 (0.32%) | 45 (0.39%) |
| **Horizontal-Descending** | 35 (0.94%) | 142 (1.24%) |
| **Ascending-Horizontal** | 26 (0.70%) | 142 (1.24%) |
| **Descending-Horizontal** | 9 (0.24%) | 46 (0.40%) |
| **Horizontal** | 4 (0.11%) | 17 (0.15%) |

| | | |
|---|---|---|
| TOTAL | 3718 | 11495 |

**Table 54. Experiment I, case II (corpus UK; anticorpus GRE & SWE) – segmental viewpoint Huron shape**

Having UK data set as the corpus produced the most uniform results. The differences between corpus and anticorpus in almost all schemata were less than 1%.

In order to calculate the following measures, we define that a segment is bordered by a pause longer than 300 milliseconds (roughly one third of a second) and a leap of 7 steps or more. Obviously, we also consider as segment boundaries the beginning and the end of a MIDI file.

In order to calculate the ratios of short/long segments, we consider long segments to be the ones above the average, either in number of notes or duration in seconds, and short the ones below.

| | Corpus | Anticorpus |
|---|---|---|
| **Number of notes** | 56,926 | 202,888 |
| **Duration (approx in minutes)** | 254 | 910 |
| **Number of segments** | 3,718 | 11,495 |
| **Average segment (number of notes)** | 15.31 | 17.65 |
| **Average segment (duration in seconds)** | 4.1 | 4.8 |
| **Number of Simultaneities** | 43,052 (75.63%) | 140,633 (69.32%) |
| **Ratio of Long/Short segments (number of notes)** | 0.35 | 0.32 |
| **Ratio of Long/Short segments (duration in seconds)** | 0.41 | 0.38 |

**Table 55. Experiment I, case III (corpus UK; anticorpus GRE & SWE) segmental viewpoints**

UK has the smallest corpus. Its average segment has shorter sizes compared to the anticorpus average segment size, in both number of segments and duration. However British children seem to prefer playing with clusters much more than the average children in the anticorpus. The ratio of long to short segments is quite similar to all countries, revealing, as one might expect, that the longer segments appear 30-40% less than he shorter ones.

The percentage of notes belonging to clusters is also quite comparable to the one of the other countries, comprising about 70% of the total notes. This comes at no surprise as the keyboard is naturally a polyphonic instrument and invites children to produce simultaneously many notes/sounds.

| | **Corpus** | **Anticorpus** |
|---|---|---|
| **Number of notes** | 126,683 | 202,888 |
| **Duration (rounded in minutes)** | 625 | 910 |
| **Number of segments** | 8,393 | 6,820 |
| **Average segment (number of notes)** | 15.09 | 19.52 |
| **Average segment (duration in seconds)** | 4.5 | 4.7 |
| **Number of Simultaneities** | 90,778 (71.66%) | 92,907 (69.79%) |
| **Ratio of Long/Short segments (number of notes)** | 0.32 | 0.33 |
| **Ratio of Long/Short segments (duration in seconds)** | 0.37 | 0.40 |

**Table 56. Experiment I, case III (corpus GRE; anticorpus UK & SWE) segmental viewpoints**

Greeks were also found to use more clusters – about half the notes belong to simultaneities. They also played the shortest phrases – possibly because there were less familiar with the keyboard and eager to make loud sounds.

Greece has by far the largest corpus, contributing to the total almost half of the files. However, the mean segmental extents are quite similar. Thus, the average segment has quite similar size and duration, both in corpus and in anticorpus. At the same time, the number of simultaneities and the ratios long-to-short segments are quite close.

| | **Corpus** | **Anticorpus** |
|---|---|---|
| **Number of notes** | 76205 | 183609 |

| | | |
|---|---|---|
| **Duration (approx in minutes)** | 284 | 879 |
| **Number of segments** | 3102 | 12111 |
| **Average segment (number of notes)** | 24.57 | 15.16 |
| **Average segment (duration in seconds)** | 5.5 | 4.4 |
| **Number of Simultaneities** | 49855 (65.42%) | 133830 (72.88%) |
| **Ratio of Long/Short segments (number of notes)** | 0.30 | 0.33 |
| **Ratio of Long/Short segments (duration)** | 0.42 | 0.39 |

**Table 57. Experiment I, case III (corpus SWE; anticorpus GRE & UK) segmental viewpoints**

Swedish children produced the largest segments. Their average segment has the longest size compared to anybody else – 24.57 notes while the average anticorpus segment is 15.16 notes. Also it lasts more – in average more that 1 sec extra. On the other hand, Swedish children produced the fewest simultaneities, while they played relatively the shortest segments (calculated within a single corpus).

There are both differences and similarities in the manner the children played. In general, we can only speculate why these differences occurred, what influenced the children, and whether these differences are significant. These issues are discussed in more detail in chapter 5.

### 4.3.2 Experiment II: By Gender

In this experiment we looked for characteristics which could be attributed to gender-related differences.

- Case I: Corpus Boys; Anticorpus: Girls
- Case II: Corpus Girls; Anticorpus: Boys

From the total of 299 MIDI files, 140 were from boys and 159 from girls.

Looking at the `Interval` viewpoint sequence we found that girls used longer patterns of stepwise diatonic movement, upwards and downwards, e.g. `[2,1,2,2,2,1,2,2,1,2,2,2,1,2,2,1,2,2,2,1,2,2,1]`. This means that girls liked mostly to press in turn only the white keys; the boys on the other side liked to press all keys in turn, thus exhibiting a much more chromatic interval movement preference, e.g. [1,1,1,1,1,1,1,1].

| Length | Frequency | Pattern | Frequency in Anticorpus (unsmoothed) | Corpus Probability | Anticorpus Probability | DELTA |
|---|---|---|---|---|---|---|
| 5 | 35 | 0 - + 0 - | (null) | 0,000204 | 0,000006 | 37,060563 |
| 27 | 34 | - + - + - + - + - + - + - + - + - + - + - + - + - + - | (null) | 0,000198 | 0,000006 | 36,00169 |
| 8 | 32 | + + - + - + 0 0 | (null) | 0,000187 | 0,000006 | 33,883944 |
| 28 | 31 | + - + - + - + - + - + - + - + - + - + - + - + - + - + - | (null) | 0,000181 | 0,000006 | 32,825071 |
| 29 | 28 | - + - + - + - + - + - + - + - + - + - + - + - + - + - + - | (null) | 0,000163 | 0,000006 | 29,648451 |
| 6 | 27 | + 0 - + 0 - | (null) | 0,000157 | 0,000006 | 28,589578 |
| 30 | 25 | + - + - + - + - + - + - + - + - + - + - + - + - + - + - + - | (null) | 0,000146 | 0,000006 | 26,471831 |
| 9 | 24 | + + - + - + 0 0 0 | (null) | 0,00014 | 0,000006 | 25,412958 |
| 7 | 23 | - - - 0 + + + | (null) | 0,000134 | 0,000006 | 24,354085 |
| 31 | 22 | - + - + - + - + - + - + - + - + - + - + - + - + - + - + - + - | (null) | 0,000128 | 0,000006 | 23,295211 |
| 6 | 21 | + + - 0 0 + | (null) | 0,000122 | 0,000006 | 22,236338 |
| 32 | 21 | + - + - + - + - + - + - + - + - + - + - + - + - + - + - + - + - | (null) | 0,000122 | 0,000006 | 22,236338 |

**Table 58. Experiment II, case I (corpus Boys; anticorpus Girls) – Viewpoint Contour**

As far as the Contour viewpoint sequence is concerned, we found that boys use oscillating motion, e.g. [+, -, +, -, +, -, +, -, +, -, +, -, +, -, +, -, +, -, +, -, +, -, +, -, +, -, +] (see Table 58), whereas girls use ascending motion: [+, +, +, ...].

Both girls and boys use medium size intervals (2-5 semitones).

| Huron Shape | Corpus (% in total) | Anticorpus (% in total) |
|---|---|---|
| **Ascending** | 1215 (12.62%) | 988 (17.69%) |
| **Descending** | 944 (9.80%) | 639 (11.44%) |
| **Concave** | 432 (4.49%) | 315 (5.64%) |
| **Convex** | 6732 (69.91%) | 3470 (62.14%) |
| **Horizontal-Ascending** | 38 (0.39%) | 19 (0.34%) |
| **Horizontal-Descending** | 120 (1.25%) | 57 (1.02%) |
| **Ascending-Horizontal** | 101 (1.05%) | 67 (1.20%) |
| **Descending-Horizontal** | 34 (0.35%) | 21 (0.38%) |
| **Horizontal** | 13 (0.14%) | 8 (0.14%) |
| **TOTAL** | **9626** | **5584** |

**Table 59. Experiment II, case I (corpus Boys; anticorpus Girls) – segmental viewpoint Huron shape**

Huron shape follows the same pattern in the country-wide cases. They do not seem to suggest substantial differences between the two groups. Convex schema is predominant in both corpus and anticorpus, although the boys seem to prefer it slightly more – 7% more than the girls. On the other hand girls seem to prefer the Ascending shape – 5% more that the boys.

| | Corpus | Anticorpus |
|---|---|---|
| **Number of notes** | 154733 | 105081 |
| **Duration (approx in minutes)** | 736 | 428 |
| **Number of segments** | 9629 | 5584 |
| **Average segment (number of notes)** | 16.07 | 18.82 |
| **Average segment (duration in seconds)** | 4.6 | 4.6 |
| **Number of Simultaneities** | 112451 (72.73%) | 71234 (67.79%) |
| **Ratio of Long/Short segments (number of notes)** | 0.31 | 0.34 |
| **Ratio of Long/Short segments (duration in seconds)** | 0.38 | 0.40 |

**Table 60. Experiment II, case I (corpus boys; anticorpus girls) segmental viewpoints**

The boys' corpus is almost 50% larger the girls' one. At the same time, while the average girl segment is a little larger the boy's – 18.82 vs 16.07 notes – their duration is almost the same – 4.6 sec. The boys also produced some 5% more simultaneities.

### 4.3.3 Experiment III: By Age

We found that 4-year-olds use almost exclusively minor thirds and major seconds, whereas 8-year-olds use more major thirds. The 8-year-olds use more oscillating patterns than the 4-year-olds, which can be attributed to the more developed musical abilities of the older kids. The 8-year-olds also prefer medium size intervals, in contrast to 4-year-olds which indifferently use all kinds of intervals in a rather random manner.

We remind that 137 melodies were by 4-year-olds, whereas 162 were by 8-year-olds.

| Length | Frequency | Pattern | Frequency in Anticorpus (unsmoothed) | Corpus Probability | Anticorpus Probability | DELTA |
|---|---|---|---|---|---|---|
| 5 | 19 | 4 2 1 1 2 | (null) | 0,000169 | 0,000004 | 40,573899 |
| 4 | 18 | 0 1 1 0 | (null) | 0,00016 | 0,000004 | 38,43843 |
| 11 | 18 | 1 1 1 1 1 1 1 1 0 0 0 | (null) | 0,00016 | 0,000004 | 38,43843 |
| 11 | 17 | 1 1 1 1 2 1 1 1 1 1 1 | (null) | 0,000151 | 0,000004 | 36,302962 |
| 9 | 16 | 2 1 1 1 1 2 1 1 1 | (null) | 0,000142 | 0,000004 | 34,167494 |
| 5 | 16 | 1 2 1 0 2 | (null) | 0,000142 | 0,000004 | 34,167494 |
| 5 | 15 | 0 1 1 0 1 | (null) | 0,000133 | 0,000004 | 32,032025 |
| 7 | 15 | 1 1 1 0 0 1 1 | (null) | 0,000133 | 0,000004 | 32,032025 |
| 7 | 15 | 1 1 0 1 1 1 0 | (null) | 0,000133 | 0,000004 | 32,032025 |
| 6 | 14 | 1 1 0 0 1 1 | (null) | 0,000124 | 0,000004 | 29,896557 |
| 8 | 13 | 1 1 1 0 0 1 1 1 | (null) | 0,000115 | 0,000004 | 27,761089 |
| 6 | 12 | 1 0 1 1 0 1 | (null) | 0,000107 | 0,000004 | 25,62562 |
| 4 | 24 | 0 1 0 1 | 2 | 0,000213 | 0,000008 | 25,62562 |
| 9 | 12 | 1 1 1 1 1 0 0 0 0 | (null) | 0,000107 | 0,000004 | 25,62562 |
| 10 | 12 | 1 2 1 1 1 1 2 1 1 1 | (null) | 0,000107 | 0,000004 | 25,62562 |
| 9 | 12 | 1 1 1 1 2 1 2 2 2 | (null) | 0,000107 | 0,000004 | 25,62562 |
| 6 | 23 | 1 1 0 0 0 0 | 2 | 0,000204 | 0,000008 | 24,557886 |
| 8 | 11 | 2 1 1 2 1 2 1 1 | (null) | 0,000098 | 0,000004 | 23,490152 |

**Table 61. Experiment III, I case II (corpus 8y's; anticorpus 4y's) – Viewpoint Duration**

The sense of pulse (beat) seems to be more developed with the 8-year-olds since they use isochronous note durations more than the 4-year-olds. They also play more with medium size duration ranges, while the 4-year-olds commingle short and medium sized durations.

| Huron Shape | Corpus (% in total) | Anticorpus (% in total) |
|---|---|---|
| **Ascending** | 892 (12.51%) | 1311 (16.22%) |
| **Descending** | 663 (9.30%) | 920 (11.38%) |
| **Concave** | 309 (4.33%) | 438 (5.42%) |
| **Convex** | 5047 (70.80%) | 5155 (63.77%) |
| **Horizontal-Ascending** | 29 (0.41%) | 28 (0.35%) |
| **Horizontal-Descending** | 86 (1.21%) | 91 (1.13%) |
| **Ascending-Horizontal** | 72 (1.01%) | 96 (1.19%) |
| **Descending-Horizontal** | 20 (0.28%) | 35 (0.43%) |
| **Horizontal** | 11 (0.15%) | 10 (0.12%) |
| **TOTAL** | **7129** | **8084** |

**Table 62. Experiment III, case I (corpus 4y's; anticorpus 8y's) – segmental viewpoint `Huron shape`**

Looking at the Huron shapes, we found that the Convex shape is, also in this case, the prevalent one. The 4-year-olds scored higher than everybody else in this – 70.8%. The 8-year-olds seem also to prefer a little more the ascending schema – 16.22% vs 12.51%.

| | Corpus | Anticorpus |
|---|---|---|
| **Number of notes** | 107,074 | 152,740 |
| **Duration (approx in minutes)** | 570 | 593 |
| **Number of segments** | 7,129 | 8,084 |
| **Average segment (number of notes)** | 15.02 | 18.89 |
| **Average segment (duration in seconds)** | 4.8 | 4.4 |

| | | |
|---|---|---|
| **Number of Simultaneities** | 76,787 (71.71%) | 106,898 (69.99%) |
| **Ratio of Long/Short segments (number of notes)** | 0.34 | 0.32 |
| **Ratio of Long/Short segments (duration)** | 0.41 | 0.36 |

**Table 63. Experiment III, case I (corpus 4 years; anticorpus 8 years) segmental viewpoints**

The 8-year-olds were more prolific players. Their corpus is more than 40% larger than the 4-year-olds'. This however does not reflect on the total duration of the musical output – the 4-year-olds played approx. 570 min while the 8-year-olds played approx. 593 min. The older children produced larger segments in average, by an extent of more that 3.5 notes, while the average segment duration is comparable – 4.8 secs vs 4.4 secs, the older children's was somewhat longer. All other measures are quite comparable.

This is an interesting finding, suggesting that musical maturity might come with larger musical phrases but not necessarily longer ones. In other words the musical texture is denser in the older children's musical expressions.

### 4.3.4 Experiment IV: The impact of the MIROR-IMPRO system

The fourth experiment we ran was an attempt to evaluate the impact of the interaction with the MIROR-IMPRO system in the development of the children musical abilities.

Since this is a central question in this work, we decided to use only the Greek and the British 4-year-olds' data, since we would like to be absolutely certain about the gathering data conditions, and the other countries used slightly different experimental conditions. Nevertheless, although the sample is relatively small (we use 34 MIDI files for the corpus and 39 for the anticorpus), we can still draw some interesting conclusions.

It was found that after the interaction with the system, children used much more major and minor seconds, in either upwards or downwards fashion. They also displayed a lack of unison patterns, while their rhythmic skills seem to be sharpened. Hence, when using as corpus the post session and as anticorpus the first session, long strict rhythmic schemata emerge (see Table 64).

| Length | Frequency | Pattern | Corpus Probability | Anticorpus Probability | DELTA |
|---|---|---|---|---|---|
| 9 | 12 | 2/1 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000449 | 0.000031 | 14.441652 |
| 9 | 11 | 1/2 2/1 1/2 2/1 1/1 1/1 1/1 1/1 1/1 | 0.000411 | 0.000031 | 13.238181 |
| 12 | 11 | 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/3 | 0.000411 | 0.000031 | 13.238181 |
| 11 | 11 | 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/3 | 0.000411 | 0.000031 | 13.238181 |
| 9 | 11 | 1/1 1/1 1/1 1/1 1/1 1/2 2/1 1/2 2/1 | 0.000411 | 0.000031 | 13.238181 |
| 19 | 11 | 1/1 1/1 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000411 | 0.000031 | 13.238181 |
| 22 | 10 | 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000374 | 0.000031 | 12.03471 |
| 13 | 10 | 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/3 | 0.000374 | 0.000031 | 12.03471 |
| 10 | 10 | 1/1 1/1 1/1 1/1 1/1 1/2 2/1 1/1 1/1 1/2 | 0.000374 | 0.000031 | 12.03471 |
| 20 | 10 | 1/1 1/1 1/1 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000374 | 0.000031 | 12.03471 |
| 20 | 10 | 1/1 1/1 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000374 | 0.000031 | 12.03471 |
| 9 | 10 | 1/1 1/2 2/1 1/2 2/1 1/1 1/1 1/1 1/1 | 0.000374 | 0.000031 | 12.03471 |
| 6 | 10 | 1/1 0.333333 1/3 1/1 1/1 3/1 1/1 | 0.000374 | 0.000031 | 12.03471 |
| 23 | 10 | 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000374 | 0.000031 | 12.03471 |
| 9 | 10 | 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/2 | 0.000374 | 0.000031 | 12.03471 |
| 20 | 9 | 1/1 1/2 2/1 1/1 1/1 1/1 | 0.000337 | 0.000031 | 10.831239 |

| | | | | | |
|---|---|---|---|---|---|
| | | 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | | | |
| 21 | 9 | 1/1 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000337 | 0.000031 | 10.831239 |
| 24 | 9 | 1/2 2/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 | 0.000337 | 0.000031 | 10.831239 |
| 16 | 9 | 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/3 | 0.000337 | 0.000031 | 10.831239 |
| 15 | 9 | 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/1 1/3 | 0.000337 | 0.000031 | 10.831239 |

**Table 64. Experiment IV, case II – Viewpoint Duration Ratio (corpus post – anticorpus pre)**

In contrast, when using as corpus the initial sessions and anticorpus the final ones, rather random duration ratio patterns seems to surface (see Table 65).

| Length | Frequency | Pattern | Corpus Probability | Anticorpus Probability | DELTA |
|---|---|---|---|---|---|
| 2 | 23 | 8/7 7/9 | 0.000715 | 0.000037 | 19.111387 |
| 2 | 17 | 1/2 3/1 | 0.000528 | 0.000037 | 14.125808 |
| 4 | 15 | 3/1 1/3 3/2 1/1 | 0.000466 | 0.000037 | 12.463948 |
| 4 | 15 | 1/2 2/1 1/2 2/3 | 0.000466 | 0.000037 | 12.463948 |
| 3 | 12 | 5/3 1/1 3/5 | 0.000373 | 0.000037 | 9.971159 |
| 3 | 12 | 5/3 3/5 5/3 | 0.000373 | 0.000037 | 9.971159 |
| 2 | 12 | 9/7 7/10 | 0.000373 | 0.000037 | 9.971159 |
| 3 | 12 | 5/4 4/5 5/4 | 0.000373 | 0.000037 | 9.971159 |
| 5 | 12 | 1/1 2/1 1/2 1/1 2/3 | 0.000373 | 0.000037 | 9.971159 |
| 5 | 12 | 2/3 1/1 3/2 2/3 1/1 | 0.000373 | 0.000037 | 9.971159 |
| 3 | 12 | 2/3 3/4 1/1 | 0.000373 | 0.000037 | 9.971159 |
| 4 | 11 | 2/1 1/2 2/3 3/1 | 0.000342 | 0.000037 | 9.140229 |
| 3 | 11 | 1/1 7/9 1/1 | 0.000342 | 0.000037 | 9.140229 |
| 6 | 11 | 1/1 2/3 1/1 1/1 1/1 3/2 | 0.000342 | 0.000037 | 9.140229 |
| 5 | 11 | 2/3 3/2 1/1 1/1 2/3 | 0.000342 | 0.000037 | 9.140229 |
| 5 | 10 | 3/1 1/3 3/2 1/1 1/1 | 0.000311 | 0.000037 | 8.309299 |
| 3 | 10 | 5/2 2/1 1/1 | 0.000311 | 0.000037 | 8.309299 |
| 3 | 10 | 5/2 2/3 1/1 | 0.000311 | 0.000037 | 8.309299 |

| | | | | | |
|---|---|---|---|---|---|
| 2 | 10 | 5/2 1/3 | 0.000311 | 0.000037 | 8.309299 |
| 5 | 10 | 2/1 1/2 1/1 2/3 1/1 | 0.000311 | 0.000037 | 8.309299 |

**Table 65. Experiment IV, case I – Viewpoint Duration Ratio (corpus pre – anticorpus post)**

Once more various conspicuously rhythmical schemata (8:7, 7:9 etc) might be attributed to the quantisation factor we chose, and if we had chosen a coarser quantisation, these factors might have been smoothed out. However, we would like to draw the attention here in the large variety of rhythmic ratios found, suggesting a rather haphazard and unsystematic playing in the pre corpus.

| Huron Shape | Corpus (% in total) | Anticorpus (% in total) |
|---|---|---|
| **Ascending** | 262 (16.14%) | 231 (18.08%) |
| **Descending** | 163 (10.04%) | 153 (12.10%) |
| **Concave** | 91 (5.61%) | 58 (4.59%) |
| **Convex** | 1045 (64.39%) | 789 (62.42%) |
| **Horizontal-Ascending** | 6 (0.37%) | 3 (0.24%) |
| **Horizontal-Descending** | 23 (1.42%) | 11 (0.87%) |
| **Ascending-Horizontal** | 27 (1.66%) | 12 (0.95%) |
| **Descending-Horizontal** | 6 (0.37%) | 4 (0.32%) |
| **Horizontal** | 0 (0.00%) | 3 (0.24%) |
| **TOTAL** | **1623** | **1264** |

**Table 66. Experiment IV, case I (corpus pre – anticorpus post) – segmental viewpoint Huron shape**

The distribution of the Huron shapes follows more or less the patterns already encountered. The Convex schema is also more predominant here. Slight differences emerge – a small preference on ascending and descending in the post corpus – but overall no substantial differentiation was found.

| | Corpus | Anticorpus |
|---|---|---|
| **Number of notes** | 24669 | 19173 |
| **Duration (approx in minutes)** | 119 | 88 |
| **Number of segments** | 1623 | 1264 |

| | | |
|---|---|---|
| **Average segment (number of notes)** | 15.20 | 15.17 |
| **Average segment (duration in seconds)** | 4.4 | 4.2 |
| **Number of Simultaneities** | 17190 (69.68%) | 15010 (78.29%) |
| **Ratio of Long/Short segments (number of notes)** | 0.38 | 0.35 |
| **Ratio of Long/Short segments (duration)** | 0.43 | 0.39 |

**Table 67. Experiment IV (corpus pre – anticorpus post), segmental viewpoints**

We found however noticeable differences to the other segmental viewpoints which can be attributed to the interaction with the system. The size of corpus (viewpoints duration and number of notes) is the first noticeable difference. The post corpus is more that 20% smaller that the pre corpus. This at first glance might seem counter intuitive since we might have expected that the interaction with the system would attract the children to play more. On the other hand, one has to keep in mind that during the pre sessions the children exhibit much more playful behaviour and enthusiasm towards investigating and exploring a new toy. In the post sessions, after several interactions with the system, this enthusiasm has naturally degraded and a certain amount of fatigue, as well as musical satisfaction in using the system, might come forward. When hearing the corpus, the sense of completeness and achievement become apparent in the post sessions.

Nevertheless, the number of simultaneities is noticeably larger in the post corpus – some 10% - suggesting that the interaction with the system produced thicker musical textures. This comes in line with the findings mentioned in the previous paragraph suggesting that the development of musicality is associated with a richer musical texture.

We also found interesting results on the Compression segmental viewpoint. Recall that the compression viewpoint is the ratio of the compressed music over the uncompressed. Thus, since the compression factor is proportional to the amount of repetition (recall that we are using Huffman coding and LZ77 compression algorithms which compress the most when large repetition occurs), the smaller the ratio, the more repetition is found. And since repetition in music is considered a developed musical ability (see 2.1.4.1 for a short discussion on repetition in music), the smaller the ratio, the higher level of musicality achieved in the data under question.

| Viewpoints | Compression Ratio | |
|---|---|---|
| | Corpus | Anticorpus |
| **Pitch** | 0.28 | 0.36 |
| **Interval Steps** | 0.29 | 0.37 |
| **Contour** | 0.13 | 0.22 |
| **Leap** | 0.18 | 0.20 |
| **Rhythm** | 0.25 | 0.33 |
| **Rhythmic Range** | 0.08 | 0.18 |
| **Rhythmic Ratio** | 0.47 | 0.57 |

**Table 68. Compression results; Corpus Pre – Anticorpus Post**

Interestingly enough, this does not seem to be the case. What we expected was that in the anticorpus data we would obtain smaller values, since the anticorpus contains the data pertaining to the improvisations after the interaction with the MIROR-IMPRO system. However, in all cases these values are greater. From this, one can conclude that the repetition was reduced, and since repetition in music is an indicator of musical development, this might lead to the conclusion that the interaction with the MIROR-IMPRO decreased the musicality of the children. That would be a misleading conclusion because one has to keep in mind that the interaction with the MIROR-IMPRO alters the musical behaviour of the children. Hence the children in the beginning used to play long repeated sequence of notes, trying to decipher the machine's responses and behaviour, which resulted in the vast amount of repetition in the initial sessions. When the machine's behaviour was "decoded", the children started to experiment with a variety of musical phrases, causing the repetition to be dropped off.

In addition, young pianists were in the initial sessions mostly playing pieces of known music learnt in their conservatoires (see 0). Almost all of them in the post session played more freely exhibiting superior improvisational attitude. But this resulted in less repetition, since the known pieces in the initial session were made by renowned composers and naturally their products were much more musically fledged than the creations of the young disciples. Hence the paradox of having less musical repetition in an otherwise more musically challenged pieces can be resolved.

# Chapter 5

# Conclusions & Future Steps

In this chapter we present our conclusions from the work conducted, we relate them to the goals of the research asserted in the Introduction and we proceed in discussing them and connecting them with the greater context. We also discuss the major decisions taken in designing this research and we present briefly the children's attitudes throughout the experiments. This is important since it provides the context of our work and the background for seeing some of our results under a different light. Then we proceed in discussing our findings on each of the three distinct goals (G1, G2, G3) that we pursue through this work. Finally, we provide some thoughts on how the evolution of MIROR-IMPRO and similar devices might integrate into musical tuition. We conclude by suggesting potential paths that this research could follow.

As it can be deduced from the previous chapters, the work conducted and reported in this thesis succeeded in pursuing the aims set, as stated in section 1.4. Specifically:

i. We developed an analytical approach with a novel application for the study and analysis of children improvisations.
ii. We devised a creativity model addressing children's musical creativity advancements, occurring through improvisation.
iii. We produced a software prototype tool built upon the above theoretical framework and implemented it in order to validate in practice the model and the concrete methodological approach.

In the final chapter, we take a step further into how we answered the research questions and discuss the most important decisions taken in pursuing the research goals. Then we proceed in presenting how children perceived the MIROR experiments and which was their stance within its framework. It should be stressed that the children's point of view and the benefits the sessions had for them were the topic of the three-year MIROR project, discussed in detail in the various deliverables produced within the framework of that project. Even if this is not the topic of our focus, we need to array some information in order to put our results into perspective and relate our findings within the big picture. Then we go into discussing each of the three goals, e.g. Repeated Pattern Identification, Creativity Assessment and Distinctive Pattern Identification and we conclude by discussing the impact of MIROR-IMPRO to musical education. Finally, we suggest a roadmap for future research.

# 5.1 Research Questions

As already stated in chapter 3, the pursuing of the three distinct goals was set in order to draw a path in order to respond to our research questions posed in 1.4. We are now in a position to answer these research questions, as follows:

*Q1. How are the children's improvisation capabilities affected by the usage of MIROR-IMPRO? Put differently, if we compare pre- and post- improvisation sessions, are we detecting enhanced improvisation skills?*

We can say that the interaction with the MIROR-IMPRO enhances the improvisation skills of the children. In general, the children in the post session exhibited a more confident attitude, they explored a greater area of the keyboard, they became less timid, more adventurous and more rhythmical. They also seem to pay closer attention in listening what they played.

Although these are desirable outcomes, one cannot conclusively say that the children became more *musical,* i.e. that their musical thinking became more sophisticated, neither that they expressed stronger emotions in their playing. One can argue that as far as children with no familiarisation with the keyboard are concerned, those aptitudes would emerge anyway as the children became more accustomed to play the keyboard. For this to be concluded, a control group should be employed in a future experiment, in order to provide the baseline against which comparison can be made.

*Q2. Does the MIROR-IMPRO interaction influence musicians and non-musician alike? Are we detecting differences on the way that MIROR-IMPRO sessions impact on improvisation skills according to whether children have or have not received prior formal music training?*

As mentioned above, in the post session children exhibit in general a more confident attitude towards improvisation. Non-musicians seem to be less timid, more playful and more rhythmical. Musicians in the pre sessions were almost always playing known pieces from their piano lessons. After the MIROR-IMPRO sessions this attitude was found to be considerably less.

In terms of statistical analysis,, the non-musicians were found to have statistical significant differences in creativity variables V1, V3, V5, V8 & V9.

- The average pitch SD (V1) was higher in the post-session than in the pre-session, indicating the increased variety in the notes used
- The average total duration (V3) was almost two times shorter in the post-session than in the pre-session, suggesting that perhaps some weariness might have occurred (see also 4.3.4)
- The average medium intervals (V5) were more present in the post-session than in the pre-session
- On average, "soft" dynamic was more than two times less present in the post-session than in the pre-session; also on average, "normal" dynamic was more than two times less present in the post-session than in the pre-session; "hard" dynamic was more than two times more present in the post-session than in the pre-session (V8)
- The musical excerpt played by the child was more "populated" or dense in the post-session than in the pre-session (smaller values of this variable – V9 – reflect a more "populated" excerpt)

As far as the musicians were concerned, we found statistically significant differences on V3, V4, V7 & V9 variables.

- The average total duration (V3) was more than three times shorter in the post-session than in the pre-session – again, as in the non-musicians case, some weariness could have surfaced
- The average ratio (V4) of different intervals was higher in the post-session than in the pre-session
- The average percentage of fast rhythm was almost twice higher in the post-session than in the pre-session (V7)
- The musical excerpt played by the child was almost more than twice "populated" in the post-session than in the pre-session (V9)

*Q3. Do the visualisation constructs of MIROR-IMPRO have any impact on the way that children improvise? In other words, does Visualisation affect children's musical output?*

The answer to this question is not conclusive. We found results of every possible type. Some children did not like at all the visualisation constructs and asked the experimenter to switch it off, since they found it distracting from the musical tasks. On the other end, some other children were mesmerised by the visuals and they were trying to display interesting visuals on screen. And the remaining lie in-between those two extremes. We definitely found strong evidence that the visualisation effect of the MIROR-IMPRO affect the musical behaviour of the children, but we cannot say for sure if it has a positive effect on their musical output.

*Q4. If we classify the music data according to some categories (e.g. country, gender or age) are we detecting patterns that are overrepresented on a corpus with respect to an anticorpus?*

We clearly found evidence that discriminates corpora from anticorpora. For example, we found that oscillating movement patterns with large leaps were more common in the data from Greece. We also found that Greek children played much slower that the children from the other countries, meaning that they use slower movement-gestures. The Swedes also, along with the British, exhibit the most rigid rhythmic values, in their improvisations. Further research in this topic is needed to provide additional results as well as a thorough investigation to the reasons why these differences are observed.

We also found that girls use longer patterns of stepwise diatonic movement, upwards and downwards, meaning that girls preferred mostly to press in succession only the white keys; the boys on the other side hand liked to press all keys in turn, so they exhibit a much more chromatic interval movement preference. We also found also that boys used mostly oscillating motions whereas girls used ascending motions, indicating that boys are using different gestures than girls. Again further research might shed more light in investigating differences in gestural playing between boys and girls. In general, however, something that is obvious from the listening analysis performed is that, girls played much more sentimentally and timidly than boys, who presented more punctual and voluminous performances.

Rhythm has also been more developed in 8-year-olds than 4-year-olds. They use more often isochronous note durations than the 4-year-olds. They play also more with medium size duration ranges, while the 4-year-olds mix short and medium size durations. We also found that the 8-year olds play with more (more than double) concave shapes than 4-year-olds. The 8-year-olds also exhibit greater harmonious curiosity since they use double more simultaneities than 4-year-olds.

The above differences can be attributed to various reasons. Clearly the differences between 4- and 8-year-olds can be partially attributed to differences in the developmental stage. Other differences can be attributed to different cultural and educational background – eg. lack of familiarisation with the keyboard. Also, even though sound effort was made towards keeping the same conditions in executing the psychological experiments, some differences in the setup and in the environment cannot be avoided and they could naturally affect children performance, e.g. the room where the experiment took place, the personality of the experimenter etc.

Differences in gender can be attributed to certain degree to the different social, educational and cultural environments that boys and girls occupy in different countries. Even if the way that societies deal with children of different gender tends to be equalised nowadays, there are still differences and these differences are inevitably reflected in the various ways that children interact with their environment and form their particular umwelt, sex-wise.

## 5.2 Major Decisions on Representation and Techniques

Certainly many problems have arisen during the development of this work. Many decisions had to be made, which might make one think about the suitability of those decisions, especially since these are also points of debate and/or criticism. The results presented in the previous chapter, naturally presented themselves under the guise of those decisions and if other decisions were made, other perspectives would have potentially unearthed. By this we don't mean that our results are lacking validity nor that our way of presenting and analysing them lacks formality. Rather we mean that research from a different point of view could lead to complementary results which would enhance the study and the automatic analysis of children's improvisations.

If we would like to distil our experience from this research, we would come up with three significant topics that crucial decisions were taken when choices had to be made.

► **Viewpoint Selection.** The selection of the knowledge representation schema was made with a view to utilise a suitable medium not only appropriate for the data processing task but also for capturing and representing the musical qualities and characteristics of the data. Further, the choice of the particular viewpoints came about after noticing the aptitudes and trends exhibited by the children as far as the playing and improvisational style are concerned, and contemplating the particularities of the data produced. As already mentioned elsewhere (see 2.2.2), children, especially the youngest ones, demonstrate a lot of gestural playing.

However, the level of detail of the data produced is too finely grained (as of course denoted by the relevant MIDI files) and as such may hinder interesting patterns that could potentially be unveiled on a coarser level. At the same time, this might highlight patterns which might be trivialities of no interest. In order to cope with this problem, we needed to choose viewpoints that are abstract enough as to unveil important patterns, but not too abstract so as to miss out the focal point and oversee the level of concern.

The triptych *note value* → *interval* → *contour* that we employed in our representation is supported by Peretz's work (Peretz & Coltheart, 2003) for being important in musical comprehension.

Debatable remarks may be stated for the segmental viewpoint Compression. From a first instance, it seems that the selection of the compression ratio as a measure of repetition (see Table 68) might not to be a suitable construct for a 4-year old, since it might capture a cognitive ability still underdeveloped at this age. That is, it indicates that in post sessions less repetition in music occurs. This is counter intuitive since repetition is commonly considered a typical pervasive musical attribute. However, there is another way to interpret this, which is that young children at first were experimenting – not only musically but also with a keyboard as an object of curiosity – using long repeating notes. After acquiring a certain degree of familiarity with the device, purer musical behaviour arose, effecting in ebbed repetition.

In the case of the musicians group this can be easily explained, since musicians played in their pre session ready-made pieces from their conservatoire lesson. These pieces are composed from expert composers and naturally contain much more repetition from the novice experimentee impromptu attempts.

► **Creativity Model.** The musical creativity model developed could potentially give rise to a fair amount of criticism, if one considered one by one the variables that comprise it and poses questions whether their change in value could be really interpreted as advancement of musical creativity. For example, the V9 variable meant to encode the degree of harmony employed, but may mislead us into considering a child playing clusters with both forearms, as more creative than another that shows original creativity in harmony (if we look into combinations of variables, this kind of "cheating" becomes less probable). However, the goal of building this model was not to include some definitive musicological knowledge about what is musical creativity (it is unlikely that there exists such definite knowledge) but rather to reflect and contemplate on current trends in children's musical creativity developments, propose some enhancements and provide a potential formalised, implemented assessment. Certainly, one could come up with a much more sophisticated model, but our aim was rather to develop a prototype tool and a way of thinking about incorporating a quantitative creativity model based on previous research, than to provide a fully-fledged model of musical creativity.

► **Contrast Data Mining Techniques.** The methods developed for differentiating a corpus from another, is another matter of debate. As a rather new field, contrast data mining is still evolving and much can be added as far as the elaboration of the methods employed is concerned. Our target in employing contrast data mining techniques was to capitalise on previous research and to come up with a concrete and elaborate application on analysing children improvisations. We did not attempt to develop a much more sophisticated method for doing so, as this could be in itself a subject for another thesis. As we have already mentioned, it is the peril of multidisciplinary research that might receive the critique of scholars of each of the domains involved. However, it was not the scope of this work to cope in depth with contrast data mining.

A plethora of other less important choices and decisions were taken and are mentioned in the rest of this chapter, as appropriate. In the forthcoming sections, we go into detail in discussing each of the result sets produced and in expressing thoughts about the complete setup and the children playing stance.

## 5.3 Children's Stance

Albeit uncommon for a PhD thesis to bring in new knowledge in its final chapter, we decided to proceed in this unusual way and discuss the children's stance here, and not earlier, because all this knowledge was discussed in detail in the various Deliverables of the MIROR project and as this thesis forms part of the project's written output, we base our work on what has already been written. Furthermore, this was the work carried out by the various partners. Our purpose here is solely the computational modelling of the results, so this information might be useful in helping us go deeper into the discussion of our findings.

An issue that should be highlighted here is the children's perspectives for their involvement in the improvisation experiments. These perspectives do not pertain only to the EG'III milieu (recall that this refers to the experiments with the visualisation capabilities of the MIROR-IMPRO – see also 3.1), but to the whole interaction experience with the IMPRO-MIROR line, so it is worth mentioning in our discussion how the children experience the interactions with the MIROR-IMPRO (Triantafyllaki et el., 2012).

As already mentioned (see 3.1), by the end of the experiments the researchers that conducted them interviewed the children. After each of the three sessions, the researcher discussed with each child their engagement with MIROR (*what happens when you play*?) and also conducted more structured interviews after their final session (*what did you think of the music?*, *is it same or different to what you play?*, *can you remember what you played?*).

As it seems the **Type of Response** (a parameter of MIROR-IMPRO – see 2.2.2.3) is an important factor of the system. However we did not study this in this thesis, nor the psychological experiments were focused in collecting data according to the Type of the MIROR-IMPRO response. As it seems from the children's responses, it is an essential part of the system and future work should be focused more in the Type of Response.

In our opinion, the software module of the system should surface more parametres to be in tune with the user. Having just 3 types of response (Same, Different, Very Different) might not be enough for a more advanced user, knowledgeable of computational musicology, who would like to know more about the settings and how to change them himself/herself. Additional parametres should also be fine-tuned along with each of these types, viz. parametres that categorise a response as different, how is this differentiation defined and how it is calibrated.

### 5.3.1 Who Has the Lead

An important principle of MIROR-IMPRO is that children are in control of the situation and that they actually attempt to "teach" the system their "own" music. More than half the sample verified the principle and supports that it is MIROR-IMPRO who follows the children and not the other way round. This is important as it may be an indication that children understand that they "lead" MIROR-IMPRO or "teach" it what they play: i.e. *I did not play what it played – it played what I played*"

### 5.3.2 Type of Response

Around half the sample – all girls – suggest that they preferred when the system responded with more variation rather than when the response was similar to their own input melodies: *It responds differently to me, so that the music is nicer*. Another child said that the different response of MIROR-IMPRO was pleasant to listen to and that it helped her do more with her playing, i.e. *I played more notes as it played more notes*. So, whilst in initial discussions the child-machine interaction seems to be initiated by the MIROR-IMPRO prototype, the development of the interaction is assisted by the machine's response to the child's playing.

Around half the sample preferred to play without the visualization feature activated. That happens for a number of reasons, i.e. the children did not want to look at the screen but rather at their hands. Most of the children who preferred to play with the visualization activated explained that they liked being able to see what they were playing. One or two children switched their preference from playing without visuals to having the visualisation activated during the final interview. This happened because through the discussion with the adult, they reached a better understanding of how their own playing was represented on the screen.

### 5.3.3 Impact on the way of playing

During discussions the children were asked if they remembered how they played during interaction with the prototype. Their responses were not solely verbal. They also indicated/played out the various gestures they had used during the sessions rather than actually re-playing on the keyboard particular rhythmic patterns (only one child did do this) or humming any particular melodies/tunes (none of the children did this).

For example, one child said *I don't remember which notes I played because I was looking at the screen*. Nevertheless, later when asked again, she showed us the positioning of her hands on the keyboard throughout her playing saying *I remember this hand was here, the other was here and then I played also in the middle of these two hands*, signifying the pitch or range of notes she used in her playing. She also said when prompted where else she played that she made a gesture with both hands from the notes further away towards the centre of the keyboard (stepping movements with both hands).

Another child also remembered what he played through gestures and categorisation: he showed hand movements on the keyboard all of which he used in his playing during his sessions: glissando, using black-white notes, etc.

Some other children similarly showed they remembered the stepping movement, and they enacted it in an upward movement on the keyboard when asked what they had played. It is interesting to note that those children that displayed more dense interaction with the machine were also those that were able to re-enact a more embodied type of playing, using whole body movements and gestures. This is of course observed in a small corpus of data from six children only, yet it may indicate that MIROR-IMPRO may in some children encourage particular ways of engaging with music, both musically and kinaesthetically.

# 5.4 Repeated Pattern Identification – Goal I

As it appears, there are no significant differences between the improvisations that had the visualisation component of the MIROR-IMPRO system turned on or not (although there are some results indicating that some differences exist). As expected, the most common patterns (with the highest frequencies) were the shorter patterns. It is obvious that the longer the pattern, the less likely it is to be repeated in other sessions.

The visualisation feature of the device does seem to affect children's musical behaviour as far as this basic level is concerned, since it attracts children attention and diverts it to produce interesting visual rather than sonic schemata.

It became evident, that most of the discovered patterns tended to fall in one of the following categories: a straight upward or downward movement, oscillating motion between two pitches and repetition of the same pitch.

In pitch patterns, we had many of the instances of patterns found in more abstract representations. For example, the patterns `[C3, D3, E3]` and `[G3, A3, B3]` which were found, are both instances of the contour pattern `[+, +]`. Pitch patterns tended to have lower frequencies, since they were more specific patterns. In that respect, pitch patterns did not prove to be very interesting, and no significant conclusions could be drawn from them.

The similarities between interval patterns such as `[-55, 55]` and `[2, -2]` can be captured by the contour representation `[-, +]`, whereas they can be distinguished in the interval class representation. Of course, as already stated in 4.1.3 (p. 132) `Contour` captures the movement but not the extent of the movement. However, these interval patterns, of type `[X, -X]` are interesting because they show a departure from one note to another, and then back to the same note, which means that the child keeps track of the length of the movement, and of which note exactly has been played.

The long pattern of repeated unison intervals is found more frequently in the visualisation subcorpus. The pattern of oscillating movement (contour getting alternating values of `-, +`) was also found much more often in the visualisation subcorpus. The pattern of stepwise downward movement was very common in both subcorpora. Upward movements through the whole range of the keyboard were also found in both subcorpora.

Although the melodic contour representation seems to capture the most interesting patterns, there are also patterns that appear in all sessions and therefore might be considered trivial to mention (such as the pattern `[+, +, -, +]`). This is a general issue that raises again the question of statistical vs musical significance. Elaborate statistics could potentially be used to construct an automatic method to rank the triviality of the patterns based on some predefined criteria. However, since subjectivity is to a large extent interwoven into musical significance appreciation, maybe a different musicological approach would be better suited to "decouple" musical significance from subjectivity. This raises in turn the issue of subjectivity in art perception, a hard problem beyond the scope of this discussion.

The `Interval range` parameter–viewpoint gave us some interesting results. We found that the visualisation enablement promotes both long and small interval utilisation, while in non-visualisation melodies – the melodies produced without the visualisation capabilities of the MIROR-IMPRO switched on – medium intervals were most common. This could be due to the arbitrary choice of threshold defining which intervals are large (and thus have value 2) and which intervals are small (and thus have value 1). An alternative potential explanation is the desire of the children to create different shapes in the visualisation, which is why they used a big range of intervals.

Simultaneities of notes, clusters played by all fingers of the hand or even by the whole brachium, were also encountered in the data sets, but not analysed further. A vertical viewpoint representation (Conklin, 2002) would be needed to capture these types of textures and this consists part of future work (see section 5.8).

In general, the patterns extracted tend to point to specific gestures. For example, the patterns of oscillation found in all representations (up and down interchangeably), the patterns of repeated notes and the patterns of long downward and upward movements. These gestural patterns can be well captured by more abstract types of representations, such as the melodic contour. In other words, the level of abstraction in the initial representation needs not be very low (i.e less abstract), in order to capture the similarities in the corpus. Melodic contour seems to be an adequate representation to capture pitch-related patterns. This could be explained from the lack of musical background in any of the children that took part in the experiments for this goal. More work is needed on this in order to verify the connection.

The topic of music in relation to gesture has received a lot of attention in literature. Mead (1999) talks about *some of the ways physiology, the study of bodily function, inhabits how we talk and think about music, both directly and metaphorically* (p. 3), introducing the idea of kinaesthetic empathy as a significant contributor to our musical understanding. In relation to young children's improvisations, Young (2003b) discusses the gestural ways they improvise on various musical instruments.

We also need to contemplate on the intentions of the children when interacting with the MIROR-IMPRO (Rowe et al., 2005). It seems that often, their primary target is the exploration of the keyboard, its structure and what it can do, or trying to play with certain finger movements. This can deceive us into assuming musical thinking of the children, when what they actually exhibit is a much more complex stance, interwoven with many other intentions. By that, we do not mean that musical thinking is not complicated enough and just trying out various gestures/physical movements on keyboard is more complex. What we mean is that over and above than the musical behaviour children simultaneously interact with the device as mere object of curiosity, exhibiting thus a much more complicated behaviour.

## 5.5 Creativity Assessment – Goal 2

This section pertains to EG'II. Both musicians and non-musicians improvised on the keyboard. In general, it was observed that musicians improvised by creating musical sequences based on previously known pieces. Non-musicians, who were not familiar with the keyboard, played mostly in the form of gestures, such as upward and downward melodic movement, oscillation between two notes, continuous repetition of a pattern etc. as described in section 5.4.

The students' teachers were supportive of the study, although their role in the process was not studied nor was the impact of children's participation measured in some way, when they returned to their 'normal' musical activities. A follow-up study may be able to explore this aspect, particularly teachers' perceptions of students' musical skills after having participated in such activities.

Webster (1990) suggests that certain divergent, imaginative skills among others, are also critical to creative thinking, such as musical extensiveness (the amount of time invested in creative imaging), flexibility (the range of musical expression in terms of dynamics, tempo, and pitch) and originality (the unusualness of expression). Our variables explored mostly variances in flexibility, between the pre and the post test.

### 5.5.1 Non-musicians

The pre- tests and post- tests for the players without any musical background show some differences, which could potentially be attributed to the use of the MIROR-IMPRO system. More specifically, the standard deviation of the pitches used increases in the post test. This shows that the children start to be more adventurous and explorative in their choice of pitches, using a bigger range of the keyboard.

While the pitch standard deviation increases, the medium intervals also increase compared to small and large intervals. This fact could indicate that children stop playing at random, in all the registers (i.e. they don't make huge intervals any more between high and low register), and they avoid repetitions of the same note (i.e. they don't use very small intervals any more). Instead they use intervals that are more or less typically used in music, of medium size.

Another interesting difference between pre and post test is that children play louder, which could indicate a stronger confidence in their playing, and at the same time use more notes in the same amount of time, to create a thicker texture. However, it is interesting that in the post test they also play for significantly less time. This could be seen in two ways: the first suggests that they play in a more focused way for less time, while the second suggests that they might be getting tired by the time they reach the post test, and decide to play less. Of course, this is a constant peril in experiments involving children and is up to the careful design of the experiment, as well as on the personality of the experimenters, to minimise the risk of losing children’s attention. However, no matter how much one is cautious to avoid situations like this, it is an intrinsic challenge to all psychological experiments involving children.

### 5.5.2 Musicians

Before discussing the results of the pianists, there is one fact that needs to be addressed in order to better evaluate the results. Children with a background in piano playing, during the pre- test, mainly played known pieces from their piano lessons, and improvised less. This is not unusual, as evidenced in the music education literature (Scripp et al., 1988; Folkestad et al., 1998; Hewitt, 2009), but it does suggest that their pre- test had a lot of features that we would normally find in known music. By the time the children reach the post-test, all of the children leave the security of the known pieces and prefer to play more freely their own tunes. This was particularly interesting to us, and we believe that this can be attributed to the use of the MIROR-IMPRO system, as there was scant interaction with the researcher throughout the study. The post-test improvisation sessions are also significantly shorter. As they played more freely, it could be explained as more focused improvisational playing (see also Rowe et al, 2015, for a pedagogical take on this issue).

In the post-test, their ratio of `different per total` intervals used is higher, which means that there is less repetition and more originality in their playing. At the same time, pianists play almost twice as fast as in the pre test, which could indicate more confident playing, especially as this is coupled with decreased soft and timid playing. Like the non-musicians, they also use more notes per unit of time, to create a thicker texture.

### 5.5.3 General Discussion on the Creativity Model

The work described here – related to goal G2 – is introducing a model for measuring creativity and creativity development. This model in essence defines and describes musical creativity via a set of attributes realised as distinct variables. We remind the creativity model we utilised was described in section 3.4 and our results on children's creativity assessment against this model are presented 4.2.

While the utilization of a set of variables for describing creativity is something that most of the scholars in the field are employing, the appropriateness of a particular variable can always be under question. For example, is it valid to hypothesise that a different distribution in the (small, medium, large) range of intervals (measured by variable V5) indicates musical creativity advancement? Of course in general, in the borderline cases this hypothesis holds true; for instance if the interval sequence `[95, 3, 2]` becomes `[40, 40, 20]`, the player is musically exploring a larger interval range and this seems to be consistent with what is considered in literature as musical divergent thinking (e.g. Barbot & Lubart, 2012). But in most in-between cases, the extent to which changes in the variables indicate creativity development, is open to discussion. In general the concept of creativity evades a clear definition and the issue of defining criteria for assessing creativity development is a challenging topic which can be dealt with in many ways. Future work may include fine-tuning of variables, eventually defining significant thresholds for the experimental basis.

The non-musicians' post tests free improvisations included higher diversity of musical vocabulary, more medium intervals and richer texture, indicating a sensible progress in improvisational creativity. At the same time, they included more intensity in dynamics, indicating more confident playing behaviour. Interestingly, this seems also to be the case with the young pianists, as their post tests include similar features. However, there is increased use of different intervals with less repetition and faster playing, even though they move away from the familiarity of their known piano pieces by their final session. It can be argued, that pre- and post-test differences observed in the musician and non-musician groups can be attributed to the increased familiarity of the keyboard by the musicians, rather than the interaction with, and subsequent indulgence, in the MIROR-IMPRO system.

Concluding, the musical creativity assessment methodology discussed, proposes a set of variables to measure creativity in music, based on existing literature on creativity assessment, and investigated the development of creative music improvisations to young children, after playing an Interactive Reflexive Music System. It drew on two examples, a group of 20 non-musicians and a group of 10 young pianists, and measured the development of their creativity in free improvisation before and after six sessions of using the system. Our approach outlines an impression on musical creativity assessment and reaches some conclusions, however cannot definitely verdict about the impact of the machine.

## 5.6 Distinctive Pattern Identification – Goal 3

The distinctive pattern identification methodology presented an initial computational exploratory study using contrast data mining techniques on young children's improvisations, as obtained by the experiments when running a number of interactions with the MIROR-IMPRO device (EG'I). In order to explore the corpus, we used pattern discovery techniques to reveal interesting repeated patterns and to compare the patterns found in two corpora (one defined as corpus and the other as anticorpus) in order to see if there is overrepresentation of patterns in one with respect to the other.

The results point to repeated patterns, which are dictated by children's gestures:

- upward or downward movements
- oscillating motion between two notes or clusters
- repetition of a single note or cluster

These three series of experiments with the MIROR-IMPRO confirmed more or less the results of the previous two set of experiments, as far as the most common gestures were concerned.

We did find some differences between corpus and anticorpus in the various experiments (described analytically in 4.3) Why these differences appear is something that cannot be deduced by the music itself. It is not clear whether the differences in the results can be attributed to differences in the musical abilities of the children, to differences in the various conditions of the psychological experiments, or to differences in cultural background. Furthermore, the keyboard used to communicate with the system and to express children's musicality hinders the musical capabilities of the children due to technical reasons. Some children were familiar with the instrument while others were not. Another technical obstacle was the improvisation ability: Improvisation is a technique that is explicitly kept out from most of the conventional conservatoire curricula, and for most individuals, even those that are musically trained, does not come naturally in the educational context.

Another major question is the choice of appropriate representations. In order to reveal differences, would it be better to choose viewpoints that codified more abstract representations, such as `Contour` or `Interval`, or is it preferable to stay on lower abstraction grounds (and choose `Pitch`)? The evidence we found seems to advocate the former. On the other hand, the abstract representations are smoothing out all subtle differences and maybe conceal patterns that the children wilfully produced.

The choice of the distinctive pattern differentiator is another issue that needs to be examined more closely. Is the choice of `DELTA=3` an appropriate choice? Should we consider more factors? It is very often the case that statistically significant patterns are not the same with musically- salient patterns. For example, a beating of a large tympanum or a chime most of the times signifies something very important, from a musical point of view. On the other hand, since this may be only a short note in a very long musical piece, it may be statistically insignificant if one does not search for under-represented patterns in a corpus with respect to an anticorpus.

We are still in need of a narrative that meaningfully interconnects statistical and musical significance, if we would like the statistical processing of a musical piece to have a direct musicological correlation. Cambouropoulos (2000, 2006) is approaching the problem by means of a selection function. He constructs a function depending on the length of a melody, its frequency and some empirical defined constants. This function when applied to a melody, assigns a prominence number and thus the musical significance is calculated. While this is an appropriate approach when considering musical children it might produce non-pertinent results when applied to non-musical children. For example many non-musical kids were hitting continually the same key or alternatively hitting two keys at the two edges of the keyboard. On the other hand one might argue that producing statistical significant patterns could also lead to non-pertinent results. What can be said is that the problem of deciding (and defining) what is significant in music has hardly been generally solved for all cases.

## 5.7 Implications to musical tuition

Our research in computationally analyzing the musical output produced by the children – MIROR-IMPRO interaction raises the question of how the research findings may reflect in the instrumental tuition of young learners. This is due to the fact that we found clear evidence that this very interaction alters the child's musical behaviour. This section explores the pedagogical implications arising from this work. The methodology of the study could be utilized for pedagogical purposes, thereby advancing different aspects of musical development in young children e.g. generic musical education, instrument tuition, music schools, formal and informal musical training.

From our methodology applied in pursuing the G1 goal and from the musical output produced, a number of interesting points can be discussed. In the instrumental music classroom, we can envisage the construction of a set of practical keyboard exercises coupled with tailor-made viewpoints targeted at developing a specific musical ability.

For instance, as it seems from the analysis of the `Pitch` viewpoint (see 4.1.1 & 4.3.2), children seem to prefer to play in a specific key, for example C major. We also found that while interacting with the machine in a dialogue fashion, children clearly get the impression of a lead-follow (see 5.1.1.1) exchange of musical ideas. Hence, we could modify the Markovian production of the dialogue (see 2.5.3) to gradually bias the machine's response with melodic patterns in additional keys, guiding the child towards exploring a larger musical universe. This "hacking" may have the form of introducing short motifs in the machine's responses, in order to be captured by the child and used in his/her own music improvisations (Dean, 1989).

The same idea could be applied to a large set of musical artefacts and produce several practical exercises. For example, the viewpoint `Interval range` (see 4.1.4) is meant to measure the distribution of small, medium or large intervals. Noticing that one child's music output are mostly populated with small intervals, a trainer could parameterise the MIROR-IMPRO device to suggest large intervals in its answers, in order for the child to adopt the idea.

We also noticed that children that had received formal musical training and have not been taught how to improvise preferred to play their already known music rather than create new musical forms (see 5.2.2). This is an effect well-documented in the related music education literature (Scripp et al., 1988; Folkestad et al., 1998; Hewitt, 2009). In a similar way, we could design the machine answers to forward new rhythmic and melodic patterns to the children, directing them that way into exploring their own musical creativity and proposing their own musical ideas. The infusion of such music patterns, within the child-machine musical dialogue, could aid children to explore new improvisational skills and depart from the already learned music pieces. This will open up new musical horizons for the children, help them break the security of the "known" and engage in making new, original music. Improvisation is a tool, a medium and a goal in most – if not all – music education programmes.

Special mention here should be made to the role of the teacher as critical in the development and encouragement of such improvisational abilities in young instrumentalists. Moreover, teacher's role is not only vital but also delicate since improvisation is not just an ability to be taught. It is also a potent pedagogical tool, which can be utilised to introduce young learners to new concepts.

The conclusion drawn from the above is that the MIROR-IMPRO can be a powerful tool, especially focused on augmenting the improvisation capabilities of young keyboard learners, by giving them the opportunity to explore new musical trajectories. Of course, in order to accomplish this role, it must be scaffolded appropriately by a knowledgeable educator, able to put into practice the full spectrum of its potentialities. After all, it seems that 21$^{st}$ century teachers will eventually experience interaction with AI empowered machines, such as the MIROR-IMPRO.

We must, therefore, stress that a prerequisite for the success of these ideas is the central role of the educator. As every emerging training methodology, especially one involving young children, it should be closely monitored by educators involved directly in the process. As a new methodology, it may require frequent intervention and fine-tuning. Well-qualified educators could here play a dual role: not only as supporter of the child, but also able to come up with propositions for the evolvement of the technology.

The MIROR Project worked collaboratively with teachers, ICT experts and researchers in an attempt to realistically integrate practitioners' comments in the design of the software. It should be stressed that the wholehearted devotion of the educators, especially in the initial stages, is necessary in any similar implementation. Thus, educator training is key, since they should be equipped with all the necessary dexterities for utilisation of the full potential of technology into music tuition. Of course, right now a large percentage of the music educator population might be "digital immigrants" who probably could not easily adapt to the technology demands. We believe that it is the task of educational institutions to provide opportunities to those teachers to further be trained in the usage of technology in music, as well as create a younger generation of educators who will have a good grasp of technological advancements and artificial intelligence.

Further, we found that the visualisation function of the MIROR-IMPRO generated some form of children reaction. Apparently, this was produced through drawing children's attention to the visual effects displayed on the laptop screen. The knowledgeable educator might thereby develop exercises that are based on the images displayed, in order to enhance children's musical skills and develop new musical ideas. Of course, this would have to be based on a much more elaborated visual effect armoury, but the idea was clearly demonstrated to have some effect within this research.

Furthermore, the visualisation capabilities of the MIROR-IMPRO could be utilised by educators to enhance improvisational and dispense musical knowledge not only to children that are already learning music in some capacity, but also to non-music learners. We should keep in mind that the omnipresence of ICT technology nowadays renders the traditional musical skills necessary for engaging in music making activities non mandatory. Children in the beginning of the 21st century are no longer required to learn an instrument in order to be able to make music. Hence music is considered as language and experience (Addessi & Pachet, 2006), and children could use musical expression and exploration as a vehicle of communication and integration into every day cultural and social life. Consequently, MIROR-IMPRO can be evolved into a music tool that can attract young children to music in a playful, fun manner, in a form that connects music with play (Young, 2008a, b). Children can use the device to play with it, and in the process discover how the machine's features can be affected in order to produce the desirable musical result. This way, MIROR-IMPRO can be regarded as a specific electronic device, so much abundant in contemporary residences, yet with clear educational potential.

Another important idea worthy of exploration is the use of MIROR-IMPRO as a tool to introduce music to non-music initiated children, in order to develop children's aural skills. It has been argued that introducing young music learners to music notation systems and then developing other musical skills can lead to degraded aural sensitivity (McPherson, 2002). Eminent music educators (Dalcroze, Kodaly, Orff) have proposed educational methods that introduce music to young children initially by producing sounds through a playful manner with gestures and games and later introducing them to music notation. This way, the aural skills of the learners are more naturally developed, an aptitude that is of outmost importance in impromptu music making, since it unleashes the full potential of forward planning (McPherson, 2002; Azzara, 1993). Improvisation is both a tool and a goal in this approach.

In addition, the analysis of musical data produced by children can provide a digitally aware teacher with informative feedback as to their musical development. This data may be available to teachers in a form that renders it useful for music teaching and allows teachers to interpret the data in multiple ways in order to utilise it in their lessons. What is more, if MIROR-IMPRO evolved in such a way as to provide live feedback to children during their playing, it could also provide a slightly different educational template, much more technology-empowered and much more centred to the child. This diverts from the traditional diction by enabling a greater independence of the child and using the machine in the role of the child's partner.

The employment of contrast data mining techniques in pursuing the G3 goal, can also lead to interesting practical implication, especially if it could be combined with live feedback. With altering MIROR-IMPRO's answers new musical ideas could be presented to the child and by contrasting old musical production with a new one the implementation of those new ideas and their interweaving into children's musical repertoire could be monitored. After all, improvisation techniques is nowadays used as a pedagogical tool for creating new musical knowledge to children.

Besides a top-down dictation, even indirectly as it occurs through a child-machine musical dialogue, we could create within the MIROR-IMPRO device long-term monitoring constructs that could report on the evolvement of new musical abilities. For example, the harmonical development (one can see creativity variable V9 as a measure of that – see section 3.4) or the repetition ability (see section 4.3.4) may not become evident as a child starts to exchange ideas with the machine. However, as time passes, musical abilities that lead to more elaborated harmony or repetition usage could be developed and monitored by a suitably built construct. Hence, we could have a very accurate evaluation tool that if used thoughtfully may be of great aid in children's musical abilities development. It will pinpoint the exact moment when a new musical skill emerges and therefore the trainer could act in time, accordingly.

Similarly, based on the creativity analysis we performed in pursuing the G2 goal (section 4.2) and besides the accuracy issues of the model we proposed, concrete pedagogical implications can be proposed. All creativity variables used (section 3.4) are meant to codify a unique musical ability. Hence, the feedback on the development of these abilities mined out from the children's musical achievements may be of use to the teacher. This form of data may be used for delivering tuition targeted towards developing particular musical skills, such as listening, or even purely cognitive ones, such as attention span, both of significance to instrumental learning.

Above all, MIROR-IMPRO can be immediately used as a partner with whom a child can jam together and which can provide parameterised responses. The result of such sessions, as this thesis has shown, can be automatically analysed and provide valuable input to both disciple and trainer. This input can be used by the teacher to diagnose a learner's weaknesses and design special exercises in order to attack the spotted drawbacks. It could be also used by the teacher as a dispatching tool for conveying to the pupil a new musical concept. It could be also used by the learner as self-evaluating tool when trying to accomplish a certain achievement. Finally, it can become a musical instrument targeting non-music learners and aiding them to conceive and explore music as an expression faculty and engage them into music making activities.

Lastly, it can be said that the MIROR-IMPRO system and its associative research, triggered the introduction of new knowledge along with new musical vocabulary in the domain of children improvisation. However, although we proposed some input on how MIROR-IMPRO could be exploited in an institutionalised environment, our research did not delve much in the intricacies and the issues that the utilisation of MIROR-IMPRO might surface when introduced within a formal, educational musical context. W we did not go into studying educational topics that might arise when digitally trained teachers use it on a daily basis. Certainly, pedagogical research should be directed to this direction, since it seems inevitable that similar devices, taking also into consideration the surge of continuously growing AI-powered new technological forms, will eventually land onto formal music training contexts.

It is worth mentioning here as a final point, that as it is conceived and designed, the use of the MIROR-IMPRO system falls somehow in-between formal and informal learning music context (as it was mentioned in section 1.3). What this thesis postulates is that the introduction of the MIROR-IMPRO system within the formal pedagogical process would be of great advantage to music learners. Of course, much research should come previously, not only in the technological part – in order to improve the capabilities and the user interface friendliness of the device – but also in the educational and pedagogical domain, since the role of the teacher and educational targets prescription should be adequately investigated.

The above issue is addressed in detail within the framework of the MIROR project and is extensively discussed in the project's deliverables, to which the interested reader is referred for further information.

# 5.8 Future Steps

As far as creativity assessment is concerned, further analysis of the in-between six sessions with the MIROR-IMPRO system may provide more ideas regarding the variables that seem to shift across sessions in both groups of melodies (regarding pre & post data). Future work may also include the direct comparison of the two groups of children (musicians & non-musicians), to investigate the differences between the young pianists and the children with no musical background, as well as the introduction of a control group to assess an eventual development of keyboard creativity without the MIROR-IMPRO answers. Especially in the case of non-musicians, this is important in order to eliminate the familiarity with the keyboard factor.

This would also allow fine-tuning of the creativity assessment model and its testing in various new settings in order to improve the definition of the variables used, as well as the introduction of new related variables.

A far as distinctive pattern discovery is concerned, future work may include the further interpretation of the results, the use of more elaborated contrast data mining techniques, using a much larger number of children's improvisations and a more robust statistical method battery, using more abstract representations and comparing our findings with the results of the psychological and educational experiments carried out during the MIROR project.

A promising course of research would also be the calculation of additional viewpoints. Musical attributes measuring harmonic progression (viz. vertical viewpoints) could be of large musical significance when identified in a corpus and not in an anticorpus. These can lead to a measure towards an automatic classification and another interesting automatic way in identifying different musical styles.

It would also be very interesting to use the MIROR-IMPRO system with users that have developed musical abilities, whose traditional improvisation skills are already developed. This would be the philosopher’s stone for such an educational system, regarding the improvisation added value.

Another direction that could be worth exploiting is the expansion of the MIROR-IMPRO platform towards offering a more integrated education platform and providing live, on-line feedback. This would mean equipping the platform with a module which analyses in real time the users' musical output, compare it maybe with past improvisations and provide a response based on a much larger set of parameters (than merely *same*, *different*, *very different* as the system now provides). This could also involve the developing of a more elaborated functionality, which allows past interactions to be saved into the system, loaded into memory and exploit them on-line.

The statistical analysis could be also more developed and elaborated in all goals but mostly in G1 and G3. The data gathered offer a very suitable field for statistical processing but it was not the target of this thesis to get too much into statistical calculation.

Most of the steps and ideas suggested above need the technology behind the platform to be significantly evolved.

Valuable addition to the methodology would be the incorporation of an approximated matching mechanism (see section 2.1.4.7). Introducing a set of distances to compare music sequences is a method that is often employed by scholars and has a solid ground (Barthelemy & Bonardi, 2001; Lartillot, 2003, 2005; Rolland & Garancia, 2002; Cambouropoulos et al., 2002, 2005; Cilibrasi et al., 2004, Hofmann-Engl, 2004). Hence, the computation will not only deal with the identification of exact pattern matching, but it will also identify and match patterns that have a specific distance among them. This way a clustering of similar melodies would be identified, the degree of similarity among them dependent on the distance allowed.

This could be coupled with the introduction of a selection function, as a means to accommodate the statistical vs musical significance distinction.

Another valuable addition would be the detection and identification or elimination of the cyclic patterns very often encountered. Lartillot (2014b) suggests ways to cope with that issue but some more could be come forward.

A very interesting approach that would provide leads to improvisation assisting schemata is discussed, in another context, by Mauch et al. (2015). They investigated the evolution of pop music, by constructing a lexicon of harmonic and timbral features, such as chord changes and timbre clusters. Of course, one needs to work with audio in order to access timbre as musical attribute or better work with a digital format of music capable to incorporate part information, such as Music XML. However, the chord changes provide a very promising candidate to be represented as a viewpoint and consequently look for interesting patterns in the sequence of chord changes. Alternatively, one could utilise one of the lately introduced chord representation schemata, by Cambouropoulos (2015).

From the pedagogy point of view, if could be of interest to design courses based on the ideas expressed in section 5.4, and to assess in real life the extent to which IRMS could benefit young instrumentalists improvisation abilities or assist children with no music training through a playful manner to get to know the joy of musical life.

Another direction worth exploring is the introduction of a new computational construct for the pattern matching. Suffix arrays is a technique that can be searched in a very time-efficient manner, but requires a lot of memory. Lately a rather new technique is gaining popularity in stringology, namely factor oracle (Allauzen et al., 1999). Factor oracles can be built in linear time and space and lately have also found application in automate music improvisation (Assayag & Dubnov, 2004). It would be very interesting to use factor oracle in the software built within the framework of this research, in order to most efficiently search for musical patterns and to be able to accommodate much larger corpora.

A tight qualitative methodology could also be developed and coupled with the quantitative methods that were developed within the framework of this work. As it happened, this was the field of other partners in the project and was covered extensively (see the deliverables of the MIROR project reports on this). However, it is our opinion that the relevant discussion, albeit extensive and voluminous was not systematic, nor was it following some precise methodology. We believe that the impact of the MIROR-IMPRO in the musical tuition would benefit a lot by the accompaniment of a sound qualitative methodology for interpreting the results produced and also fine-tuning the usage of the system into practical needs.

## 5.9 Final Remarks

As posited in the Introductory Chapter, the aim of this thesis was to explore the idea that the computational analysis of the music produced by children using interactive information technology can surface useful musical traits that can be otherwise hardly detected. In order to achieve this, we designed and built a data mining computational model, adopting and adapting techniques from lexicography and contrast data mining. We believe that this goal has been successfully met.

As part of the MIROR project, we devised a model capable to automatically analyse children's improvisations, through a multi-stage process. This is described in detail in Chapter 3. We firmly believe that the computational approaches to any analytical application to music should be prescribed from the musicologist's point of view and not the other way around. As such the `Viewpoint` knowledge representation schema was chosen to encode the sequences of the patterns of the musical attributes, since it is oriented towards the musicologist's mentalité rather than the computer scientist's one.

The computational model implemented was exercised on a three-fold goal, as described in Chapter 4, where also the results are presented. The results we found set the ground for an evaluation of the appropriateness of using the Reflexive Interaction Model for teaching young music disciples how to improvise. We found evidence that the interaction with the MIROR-IMPRO system, that is a realisation of such a model, advances the musical creativity of the children using it. We also analysed the music produced towards identifying important repeated musical patterns, in sequences of various musical attributes, such as pitch, musical intervals, contour etc. In addition, we utilised and elaborated a contrast data mining approach, in order to investigate which might be the differentiating patterns in a corpus with respect to another one and we devised a methodology for doing so.

Concluding, we suggested a number of promising future courses that this research can follow. These future trajectories could include additional psychological experiments with more elaborate and strict protocols followed as well as addition of users with more diverse and advanced musical qualities. Also, the statistical processing of the data obtained could follow a more elaborated procedure and could benefit by the addition of control groups. Additional Viewpoints could also be employed, preferably collaborating with musicologists and pedagogues, in order to come up with a more advanced set than the one employed in this work. The lexicographical analysis process could also benefit, by enhance it with approximate matching techniques. Further, another promising course could be the technological evolvement of the MIROR-IMPRO, in order to provide live feedback to the user, to be able to compare the current improvisation with already stored ones, implement a lexicon for melodic and timbral analysis etc. Also, from the computational point of view it could be interesting to utilise additional pattern matching techniques. Additionally, we discussed pedagogy topics that can explore new directions through the interweaving of traditional ideas with new technological paradigms.

Finally, the MIROR-IMPRO system complements the domain of machine-generated music partner with a model that is readymade for music analysing computational methods that also provides for rich potential for musicological study. It also offers for a model to enrich the current musical tuition with contemporary computational tools. The idea pushed forward should not be seen as an alternative or substitution of the current teacher-pupil conventional model but as an enrichment of this, that can be used by the pupil 24x7, without the necessary presence of human guidance. That is a model, and an accompanying tool, that can be of use in both formal and informal educational context. It also provides for a great source for musicologically better analysing and understanding musical product.

The results presented in this thesis are positive, though some aspects of the research were not developed as deeply as could be. The supplementary research paths pinpointed here could further advance the field of automatically analysing the musical output.

We believe that the work presented in this text empowers the MIROR-IMPRO device with a sound methodological background along with a suite of software tools, together with a music database, that can be used to automatically analyse the musical output produced. We suggest a prototype quantitative musical creativity model that can be used to assess children progress through improvisation. Finally, we discuss and contribute on the role that the MIROR-IMPRO can take in an educational environment and propose ideas and directions that future work can follow not only in the technological milieu but also in the educational and pedagogical one.

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# Appendix I

# Expert Judges' Assessments

Three experts judged the children's improvisation cases presented in 4.2.4. The three experts were:

- Expert I, renown Jazz improvisator
- Expert II, Pedagogist and Musicologist
- Expert III, renown Jazz improvisator

# Expert I

Λόγω του ότι δεν γνωρίζω τη μέθοδο προσέγγισης στον αυτοσχεδιασμό η οποία ακολουθήθηκε, θα προσπαθήσω να περιγράψω με λίγα λόγια την αίσθηση που αποκόμισα σαν ακροατής ακούγοντας τα παιδάκια να παίζουν στο πιάνο.

Από τη μία, οι «μουσικοί» της παρέας πιστεύω ότι αποδεικνύουν την κατάρτιση που έχουν, αν και στην περίπτωση μας αυτό ίσως δρα λίγο περιοριστικά.

Από την άλλη, τα υπόλοιπα παιδιά αυτοσχεδιάζουν τόσο πριν όσο και μετά το μάθημα ωστόσο, κάποια από αυτά, φαίνονται να έχουν ωφεληθεί περισσότερο από τη διαδικασία.

Fulvia, John και Gregory

Τα παιδιά έχουν κάποια εκπαίδευση στη μουσική και προσπαθούν να θυμηθούν και να παίξουν τυχαία μουσικά αποσπάσματα που ήδη ξέρουν. Το παίξιμο τους δεν δείχνει οργάνωση σκέψης και μεθοδικότητα για δημιουργία αυτοσχεδιασμού πριν τη διαδικασία εξοικείωσης, απλά προσπαθούν να παίξουν γνωστά σε αυτά κομμάτια.

Στη συνέχεια και μετά τη διαδικασία εξοικείωσης, οι John και Fulvia φαίνεται ότι συνεχίζουν, με μεγαλύτερη επιτυχία τη φορά αυτή, απλά να αποτυπώνουν μουσικά αποσπάσματα τα οποία ήδη ξέρουν. Ο John ξεκινώντας με ένα μοτίβο φαίνεται να προσπαθεί να το εξελίξει μελωδικά αν και αυτό ακούγεται πάλι σαν μέρος μιας σπουδής την οποία έχει δουλέψει. Η άποψη μου είναι ότι αυτός ίσως να έχει ωφεληθεί λίγο περισσότερο από τη διαδικασία αν και μάλλον μικρότερος σε ηλικία. Γενικά πιστεύω ότι η διαδικασία εξοικείωσης με τον αυτοσχεδιασμό δεν φαίνεται να έχει επηρεάσει πολύ τα παιδιά αυτά μιας και η μουσική τους κατάρτιση, αλλά και το ότι έχουν αποστηθίσει κάποια μουσικά αποσπάσματα, τα οδηγεί σε γνωστά μονοπάτια. Το παίξιμο τους οπωσδήποτε ακούγεται πιο συγκροτημένο μετά την εν λόγω διαδικασία, δεν μπορώ όμως να πω ότι υπάρχουν πολλά περισσότερα αυτοσχεδιαστικά στοιχεία σε αυτό μετά, σε σύγκριση με πριν.

Claudio, Nigel, Lina, Dimitri

Οι Claudio και Nigel έχουν σημαντική διαφορά στην προσέγγιση τους πριν και μετά τη διαδικασία εξοικείωσης. Μετά τη διαδικασία, το παίξιμό τους ακούγεται πολύ πιο συγκροτημένο κυρίως από ρυθμικής σκοπιάς με τον Nigel να δείχνει περισσότερη κλίση στη «ρυθμική περιπέτεια». Γνώμη μου είναι ότι ο Dimitri δεν φαίνεται να έχει πάρει κάτι σημαντικό από την όλη διαδικασία αν και ίσως να ακούγεται κάπως πιο εξοικειωμένος με το όργανο μετά το μάθημα. Σε κάθε περίπτωση, το σίγουρο είναι ότι αυτοσχεδιάζει τόσο πριν όσο και μετά. Το παίξιμο της Lina πριν το μάθημα είναι κατά τη γνώμη μου πιο αβίαστο και συγκροτημένο από ότι μετά. Σίγουρα έχει επηρεαστεί από την διαδικασία εξοικείωσης με τον αυτοσχεδιασμό και μάλλον προσπαθεί υπερβολικά. Παρόλα αυτά το παίξιμο της είναι φανερά πιο έντονα αυτοσχεδιαστικό μετά το μάθημα, κυρίως από ρυθμική σκοπιά.

## Σχολια για τους αυτοσχεδιασμούς (EXPERT II)

**Fulvia**
Πριν. Διστακτική. Σταματά. Σκέφτεται;
Μετά. Πιο σίγουρη. Παίζει δυνατά, με στόχο και αποφασιστικότητα.

**John**
Πριν. Ψάχνει να βρει τα κάλαντα; Σταματά. Ξεκινά κάτι άλλο. Δοκιμάζει νότες και τις επανλαμβάνει. Σταματά. Δοκιμάζει κάτι άλλο που έχει στο μυαλό του. Σταματά. Το ίδιο.
Μετά. Δοκιμάζει μοτίβα και κινείται χρωματικά. Ενα βασικό μοτίβο το κρατά σε ολη τη διάρκεια. Κινείται πάνω – κάτω στο κλαβιέ.προσθέτοντας και ηχητικό όγκο ως συνοδεία.

**Gregory**
Πριν. Δοκιμάζει ένα γωνστό τραγούδι. Το ψάχνει. Σταματά. Ξεκινά. Κρατά σταθερά έναν τύπο συνοδείας στο αριστερό και δοκιμάζει να βρει τη μελωδία.
Μετά. Ξεκινά με σιγουριά. Φαίνεται να έχει κάτι στο μυαλό του. Πολύ σύντομο.

**Claudio**
Πριν. Τυχαίες νότες. All over. Ηχητική εξρεύνηση παρά μελωδική. Βρίσκει κάτι και το ακολουθεί – βηματική κίνηση. Επανέρχεται στην ηχητική εξερεύνηση. Κινείται σε όλη την έκταση. Κλίμακα –δοκιμάζει μία-μια τις νότες.
Μετά. Εξερεύνηση και πάλι. Ακούγεται πιο σίγουρος – σα να περιμένει να ακούσει κάτι. Κρατά νότες και δημιουργεί συνηχήσεις.

**Nigel**
Πριν. Τυχαίες νότες – εξερεύνηση ηχητικη. Επανλαμβάνει κάτι που της άρεσε. Εξερευνά όλο το κλαβιέ. Βηματική κίνηση κυρίως – μπρος-πίσω.
Μετά. Πιο σίγουρη. Δημιουργία ηχητικού όγκου με συνήχηση. Βηματική κίνηση πάνω κάτω με διπλές και τριπλές νότες. Κινείται σε όλο το κλαβιέ. Παίζει δυνατά με ένταση.

**Lina**
Πριν. Κίνηση συνεχόμενη μπρος – πίσω και τα δύο χέρια, κυρίως βηματική κίνηση, χωρις μαυρα πλήκτρα. Παίζει για πολύ ώρα συνεχόμενα. Σταματά λίγο πριν το τέλος. Προσθέτει δύο νότες και τελειώνει.
Μετά. Παρόμοια κίνηση με το «πριν». Ακούγεται πιο σίγουρη, επιμένει σε συγκεκριμένα μοτίβα. Τελειώνει με μία μόνο νότα. Ακούγεται σα να το ειχε προ-αποφασίσει ότι θα τελειώσει έτσι.

**Dimitri**
Πριν. Δοκιμάζει νότες σε όλο το κλαβιέ – κυρίως βηματική κίνηση σα να παίζει κλίμακα που ανεβοκατεβαίνει. Σταματά για αρκετή ώρα. Προσθέτει 2-3 νότες και μία ππολύ χαμηλή και τελειώνει.
Μετά. Δοκιμάζει νότες ξανά σε όλο το κλαβιέ. Ακούγεται πιο σίγουρος, πιο δυνατά.

EXPERT III's comments on Antonis Alexakis Thesis

Fulvia has some facility on the piano and sounds much more structured on the post performance.
She seems a bit afraid on the pre performance and its clearly evident that on the post performance she wanted to expand and explore.

John tries to play a Christmas carol on the pre take and other things he knows, while on the after take we get a much different picture with him improvising and expanding on themes and ideas, really impressive change!

Gregory has facility on the piano similar to Konna and on the long pre take he is trying to play things he knows, on the after take he becomes much clearer and more economical, obviously affected by the program trying to stress clarity, economy and accuracy.

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Claudio s case is very interesting as on the pre take he plays random things just for fun and he becomes very solemn, laconic and melodic on the after take!

Nigel is a similar case to Claudio but on the after take he becomes more definite, rhythmically more articulated and dramatic, again showing a profound effect.

Lina is interesting she sounds very talented!
On the pre take she has a kind of a natural flow, while on the after take again a dramatic change occurs with a much more rhythmic and aggressive approach plus she plays with more intent!

Dimitri plays random stuff on the pre take and the change again is very interesting on the post take as he becomes more dense and complicated trying to explore.

While Fulvia, John and Gregory have some facility on the piano, equally interesting and even more dramatic

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changes for the better occur for the other kids that probably haven't taken piano lessons.
Although the 1st 3 are more self aware they also do change for the better.

«Better» meaning, for all the kids, that they try to become more accurate, explorative and interesting.
They sound like trying to reply again to the system saying OK we can be equally clever and creative too!

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# Appendix II

# Publications

During the course of the work towards this thesis, the following publications have been produced:

Anagnostopoulou, C., Alexakis, A. & Triantafyllaki, A. (2012). A Computational Method for the Analysis of Musical Improvisations by Young Children and Psychiatric Patients with No Musical Background, *In Proceedings of 12th International Conference on Music Perception & Cognition,* Thessaloniki, 23-28 July.

Triantafyllaki, A., Anagnostopoulou, C. & Alexakis, A. (2012). An exploratory study of young children's technology-enabled improvisations, *In Proceedings of 12th International Conference on Music Perception & Cognition,* Thessaloniki, 23-28 July.

Anagnostopoulou, C., Triantafyllaki, A. & Alexakis, A. (2012). Analysing Children's Improvisations During Child-Machine Interactions, *Perspectives on Musical Improvisation Conference,* University of Oxford, 10-13 September.

Alexakis, A., Khatchatourov, A., Triantafyllaki, A. & Anagnostopoulou, C. (2013). A Computational Method for Exploring Musical Creativity Development, *In Proceedings of SMC 2013,* KTH Royal Institute of Technology, Stockholm, 30 July—3 August.