Mathematical Modeling of Musical Creative Process

Irina B. Gorbunova[a], Sergey V. Chibirev[b]

Music Computer Technologies Laboratory, Herzen State Pedagogical University of Russia, 48 Embankment the Moika River, Saint Petersburg, Russia

[a] gorbunovaib@herzen.spb.ru, [b] ondyon@yandex.ru

Keywords: computer modeling, creative process, difficult-to-formalize subject areas, identification, mathematical modeling, music computer technologies, musical text, text analysis, statistical analysis

Abstract: The aim of this study is to work out the formalized approach to mathematical and algorithmic modeling of subject areas that are difficult to formalize, such as creative processes, music or any sort of arts, data sequences of unknown logic, biological and social processes etc. For investigation following methodologies has been chosen: statistical analysis, data structure analysis, analysis of formal expert result evaluation and data screening. Music creative process has been chosen as the subject, since it typical difficult-to-formalize subject area. The authors have developed a method to construct models in subject areas difficult to formalize, applying it to create a model of musical creativity based on the structural analysis of musical texts, the cyclical structuring of statistical data, and the structural analysis of statistical information. This approach allows creating texts that satisfy the previously obtained or manually-provided parameters. This article considers applying mathematical modeling to write music scores. The musical scores in the MIDI (Musical Instrument Digital Interface) format are viewed as abstract text created by analyzing statistical parameters with the subsequent modeling of musical creativity as per the obtained data. *The fundamental scientific problem* that the research deals with is developing a method to construct models of difficult-to-formalize subject areas that can be represented as abstract texts. This is based on the statistical analysis of texts, the cyclical structuring of statistical data, and structural analysis of statistical information. *The specific fundamental task developed within this problem* is applying the method to create a model of musical creativity, which allows the research to analyze and synthesize musical texts that satisfy the previously obtained or manually-provided generalized statistical parameters.

1. Introduction

Several music and scientific centers across the globe are studying the ways of modeling the logical laws of creativity, by exploring generalized parameters of works of art including music. In recent years, Russian scientists have become more interested in modeling the process of musical creativity and music programming. Most frequently, these works are applied in the computer analysis of works of art, to determine the author or the period of creation, to attribute the work of art to a particular school or group.

Fewer papers provide a deeper analysis, including psychological aspects of the perception of art (in particular, music).

The study of creativity develops like any other science—from collecting facts and classification, to studying patterns and, finally, to experimenting. Most modern papers represent the stage of classification or search for patterns. To go further, one needs to take the next step. It is modeling that makes it possible to move to the stage of experimenting with creativity models.

European and American scientists attempt to digitally synthesize, analyze, and transform sounds using music computer technologies (MCTs). Such work is conducted at the University of Hertfordshire, the University of Salford, Access to Music Ltd., and Bedford College in the UK; Institut für Musik und Akustik (Zentrum für Kunst und Medientechnologie) in Germany;

  DOI: 10.25236/adlh.2019.029

CEMAMu (Centre d'Ètudes Mathématiques et Automatiques Musicales) and the Institute for Research and Coordination of Acoustics and Music (IRCAM) at the Pompidou Center in France; the Center for Music Experiment at the University of California, the Stanford Center for Computer Studies of Music and Acoustics (CCRMA), New York University, and the Full Sail University (Florida) in the USA, and others. In recent years, Russian scientists have also become more interested in music programming [1] and modeling the process of musical creativity [3, 2]. Another research direction includes practical developments. Here one should mention the work of WIDISOFT, in particular the WIDI Recognition System software, which is designed to identify music and can provide a readable MIDI music score of a music audio file.

In general, today one can talk about two groups of solutions in this area: systems comparing audio prints of a tune and systems that work with the object format of a tune, mostly intended for the general user. These systems are presented either as specialized software or software that can be integrated into the services of mobile operators on various devices. The latter implies the automatic creation of the object format from the analog-time one. There are some other systems [5–14]. The authors propose to use a continuous wavelet transform apparatus as a mathematical tool for generating an amplitude-frequency-time representation of a signal. The continuous wavelet transform apparatus uses standard wavelet functions. The bases of continuous wavelet transform representing the sound of musical instruments allowed the researcher [2] to configure the continuous wavelet transform itself. This made it possible to single out the sound of musical instruments with the same frequency as the base properties and to identify musical objects.

Talking about modeling the process of musical creativity, one should mention the development of systems for automatic creation of accompaniment embedded in most modern digital musical tools, as well as the so-called "composition software", "auto-arrangers" (such as Band-in-a-Box, etc. with a set of standard music styles). However, we could not find any models with statistical processing for subsequent use in the modeling process.

A new direction in music and the modeling of musical creativity patterns emerged in the second half of the 20th and the beginning of the 21st century due to the rapid development of electronic musical instruments (from the simplest synthesizers to powerful music computers). This new interdisciplinary professional field necessitated the creation and use of specialized music software and hardware and required knowledge and skills both in music and IT, and a complex model of the semantic music space was developed [4]. This was a firm basis for constructing a model of musical creativity, enabling the analysis and synthesis of musical texts based on the statistical parameters of musical fragments.

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2. Materials and Methods

Musical fragments in MIDI format (scores) were taken as the input data for the analysis. They are limited and therefore can be considered abstract text. We used such methods as statistical analysis, graph theory, Markov chains, and integer methods for solving statistical problems. The research focused on processing and structuring the statistical information obtained from the text analysis with standard methods. By doing this, we were able to identify a greater number of patterns (compared to the standard approach). It was possible to conduct modeling and interactive experiments, and later to perform semantic analysis.

The developed approach to the formalization of a difficult-to-formalize subject area includes the following methods:

Input data is analyzed as abstract text. The finite set of values allows a simple statistical analysis.

Simple statistical analysis of the source text is performed.

The focus is shifted from patterns already discovered: the "methodological sieve" is used, which,

by discarding known patterns, reveals new ones. This is similar to the principle applied in the nth order neural networks—detecting patterns in the outcomes of the neurons at the previous level.

A search for cycles (periods) in the studied sequence (text) is done and a statistical analysis regarding the beginning or the end of the period is carried out. This approach allows one to identify patterns that are invisible in other ways, since the values of the general type conceal these patterns.

The step-by-step analysis of the flow of sound events, the "methodological sieve," is applied at various levels/stages of abstraction.

This is a special feature of the proposed model and distinguishes it from similar ones, making it a more efficient tool for studying patterns in sound recordings in comparison with existing models. We proposed a method for the step-by-step analysis of the flow of sound events that identifies patterns in the analyzed flow:

1) Determining the analyzed parameters and their values type.
2) Determining the range of valid values for all parameters.
3) Preliminary frequency analysis of the parameter values.
4) Searching for cycles/periods.
5) Secondary frequency analysis taking into account the periods.
6) Analyzing the correlation of frequency and periods.
7) Analyzing matrices of transition coefficients.
8) Semantic analysis within the periods.

An object-oriented approach was used to build algorithms on the computer.

Also, when developing an algorithmic model of musical creativity, we applied the following approaches:

1) Building a model consisting of separate independent blocks reflecting the laws of a sound sequence; this allowed studying patterns both independently and in their interconnection and considering both the internal connections of a particular block of the model and the independent role of each block.

2) The model does not use any rigid templates containing parts of the finished sound fragments.

3) The model is constructed in such a way that changing the parameters does not lead to calculation errors and allows one to make changes in the operation of the model, which ensures that experiments are conducted interactively.

2.1. The Structure of the Obtained Model

A musical text is considered as a finite set of sounds, characterized by the position on the timeline (time of occurrence, playing time), pitch (fundamental frequency), volume (power of sound pressure) and timbre (time-frequency characteristics) determined conventionally. Thus, a piece of music is a set of vectors taking the following form:

$$A_i = (t_i, T_i, F_i, V_i, D_i(k,t)), \qquad (1)$$

where t_i is the sound start time; T_i is the duration of the sound; F_i is the fundamental frequency of the sound; V_i is the volume; $D_i(k,t)$ is the spectrum, a set of k harmonics that are functions of time t.

Specific characteristics for each sound are chosen according to the creative intention of a composer/musician and the tradition of writing and performing pieces of a given type in a given country and era. Thus, the choice of these characteristics is determined by two factors: stochastic and deterministic. Creative intention is a stochastic value that cannot be formalized now and is described by a sequence of random numbers (this can also be done by a human composer). Traditions entirely determine the form of the work, the scope of permissible and preferred values (i.e., their probability).

When studying the stochastic component, one can trace probabilistic regularities that immediately place the resulting law into the category of probabilistically determined. This greatly reduces the role of non-deterministic factors and allows one to fully concentrate on the study of traditional laws.

Thus, the task of modeling is to describe the greatest number of patterns determined by various traditions used in a random sequence to “filter out” the musical text from it.

2.1.1. Performance

To narrow the boundaries of the model, let us select the sound characteristics that depend on the performance and exclude them from consideration. The characteristics determining performance include:

* Timbre which is the individual tone of the instrument determined by its design, the individual features of the sound production of a musician, the articulation indicated in the score:

* Volume which is determined by the design of the instrument and listening conditions, the desired volume of the instrument during listening, as well as manner and articulation specified in the score.

The selected performance patterns are quite complex and require further study. This paper does not analyze these phenomena. However, it covers the minimal possibilities of synthesis. When modeling the synthesis, it is enough to use the potential of available synthesizers that can reproduce the sound of various musical instruments with some fixed timbre and volume.

2.1.2. Rhythm and Pitch (basic parameters).

In the initial experiments, let us introduce a restriction in the model under consideration which will exclude another characteristic — the duration of the sound. The sound of most instruments has a short rise time and a long decay time, so the start time of the sound is more important than the end time. We assumed that the end time of the sound coincides with the moment of the beginning of the next one. The duration of the sound will be defined as the time interval between the beginning of the sound and the start of the subsequent sound. This assumption is essential for instruments with continuous sound, however, the vast majority of such instruments are single-voice (that is, they cannot produce several sounds at the same time). Therefore, in their case the previous and subsequent sounds are not mixed either.

Thus, after a series of simplifications, the piece of music will appear as a set of vectors of the form:

$$A_i = (t_i, F\imath), \qquad (2)$$

where t_i is the sound start time; Fi is the fundamental frequency of the sound (pitch).

In this form, a score will represent the object of analysis/synthesis of the model. In addition, one can analyze both parameters separately, i.e. consider separately the set of time values (t_i) and the set of tone values (F_i). Let us name the set (t_i) rhythm, and the set (F_i)—pitch.

2.1.3. Discretization of Note Values

To describe the values of the times of sound occurrence, one can simply use a system of time coordinates, i.e. the reference point and the minimum time step (usually 0.2 sec). Since in all known musical traditions note values are multiple to each other, it is convenient to take the minimum time step that equals the minimum duration of an elementary sound in a musical piece or a class of musical works (indicated with a note), for example, a note value “1/64”.

Then the vast majority of values can be described by the formula:

$$D = C / 2^n \qquad (3)$$

where C is the duration of the whole note; n is a natural number of the range [1..6]. The problem of the duration that continues to the next part of the bar (the simplest example is a “dotted note”; also in the section “Phrasing and Mode”) is solved by adding the necessary additional duration (durations) from the same series, merging with the main one while sounding. When analyzing the existing music, one does the reverse by giving additional duration. The beginning of a musical fragment is logically taken as the reference point.

2.1.4. Discretization of tone. Chromatic scale

Let us see the sound as a function of instantaneous amplitude of time. According to mathematical laws, any function can be represented with its spectrum, that is, by an infinite sum of harmonic oscillations with frequencies *F*, *2F*, *3F*, *4F*... called *harmonics*.

$$f(t) = A_0 \sin(F) + A_1 \sin(2F) + A_2 \sin(3F) + A_3 \sin(4F) + ... \qquad (4)$$

Frequency F is the *fundamental frequency*. The 4th–7th harmonics are the most important, and their ratios are similar to the ratios of the tones of traditional chords. Giving a physical description of the motion of an oscillating body (for example, a string), one can also consider the oscillations of its half, third, quarter, etc. The frequencies of such oscillations will also be multiples of the whole parts of the fundamental frequency of the oscillating body, thus, it is also true from the perspective of physical laws.

Most musical traditions are based on tones whose frequencies are multiples of each other or are considered as whole numbers. Some low-order harmonics have the same frequency in the spectra of such oscillations, while others will differ. Coincident harmonics are perceived as harmonious (consonance), whereas these that do not coincide arouse a feeling of dissonance. A large part of traditional tonal systems is built on the combination of these phenomena. However, different traditions have different approaches to building modes and do not use all possible intervals or even have a different number of these. We studied European diatonic scale in detail. The interval between a fourth (4/3) and a fifth (3/2) has historically become a unit of measurement and is called a “tone“. Its half was called a “half-tone“. If the octave is divided into half-tones (logarithmically), then it will encompass about 12 of them, and the integer intervals of the natural scale within the fourth and the fifth octaves will very closely coincide with the resulting frequencies.

The scale of 12 sounds separated by half-tones is now called “*chromatic*”. To set the sound parameter “pitch”, it is necessary to specify one of the discrete values of the chromatic scale.

$$F = C2^{(n/12)}, \qquad (5)$$

where C is a constant defining the beginning of the scale, given according to a particular tradition. The parameter *n* will be called *the step of the chromatic scale*. In this model, the pitch range is limited to three octaves, so the parameter *n* takes on natural values in the interval [1.. 36].

2.1.5. Mode

Studying the diagrams that present how often different pitches are used in some musical works, one can see that some intervals are used frequently, while others do not occur at all. The main reason for this phenomenon is the use of a particular traditional scale, which is based, in varying degrees, on integer ratios between frequencies. Different cultures use different sets and numbers of musical intervals. Thus, there are cases when all sounds of the selected musical fragment will correspond (with high accuracy) to some steps of the chromatic scale, but not all steps of the chromatic scale will be used. This conclusion can be made as there are numerous examples in the European tradition when the scale with only seven tones was used. Besides, various traditions indicate the special role of scale tones in a musical fragment: for example, some tones tend to be used in the endings of musical phrases (the final tone, semi-cadence sounds, etc.), others are declared “unstable” according to the tradition and are always followed with “stable”ones, etc. The role of tones will be considered below, when discussing the structure of musical phrases. Now, to study the mode, let us just specify the used and unused tones of the chromatic scale.

To describe the pitch in a piece of music, it is enough to set the number n_t in the range [1..k] that denotes the *tone number of the traditional scale* (within the European musical tradition). *K* is the *dimension of the traditional scale* and takes on values less than or equal to 12 (often 7 or even 5). To obtain the value of the sound frequency, first one should perform the conversion $n_t \to n$, and then $n \to F$ using the formula from the previous section.

Let us write transformation $n_t \to n$ as a one-dimensional matrix (vector) containing *k* values in

the range [1..12] and a constant defining the key note, that is, the pitch of the first tone.

$$n = M_m (n_t) + C_m, \qquad (6)$$

where M_m is the transformation matrix that uniquely defines the traditional mode; C_m is the key note—the first note of the traditional scale.

According to musical terminology, M_m defines the mode, while M_m and C_m define the key of the piece.

2.1.6. Intervals

By applying transformation M_m to a musical extract and conducting another statistical analysis of pitch use, one can see that again different pitches are used unevenly. There is a *secondary* cause of unevenness. It is explained, most likely, by the specifics of the traditions, the characteristic features of the creative personality of the author and the specific artistic intent. To describe the uneven use of the tones of traditional scales, we used Markov chains. The vertex space is the set of values [1..k], i.e. its dimension will coincide with the dimension of the traditional scale. To describe the frequency of choosing a tone depending on the previous one, we used the matrix of transition probabilities between the tones of the traditional mode:

$$n_t = M_p (n_{t\ prev}), \qquad (7)$$

where n_t *is* the tone number of the next sound; $n_{t\ prev}$ is the tone number of the previous sound; M_p is the transition probability matrix. The row number of the matrix is selected according to the tone number of the previous sound. The row of the matrix represents the values of the discrete probability distribution function. The sum of the values per row is 1. The value in the column indicates the probability of choosing the next value with a number equal to the number of this column. A subsequent value is selected according to the given probability law.

2.1.7. Rhythm

Since note values are discrete and are described by the law $D = C / 2^n$, to specify the note value, it is enough to determine the number *n*, which lies in the range [1..6] (as stated earlier). When analyzing a written piece of music, it is necessary to determine the probability of the occurrence of all possible note values from a given set. Thus, the probability vector will describe the rhythm.

When creating a piece of music, one should generate a random number in the range [1..6] according to the given probabilities, and then calculate the note value using the formula described above.

However, this is not enough. Traditions in different cultures have different periods of possible recurrence of the rhythm: phrases, musical sentences, bars. For instance, in the European musical tradition of the modern and partially in the contemporary history, the *bar* is the minimum period. Let us assume that the bar does not always mean the mandatory repetition of the rhythm, but is a minimal rhythmic construction, which should have a beginning and an end. For the first experiments, let us conclude that all bars of the musical extract have the same duration. Therefore, the sum of the durations within all cycles must have the same value. To ensure this restriction is relevant, let us use the simplest algorithm:

1) Set the generator value to nil.

2) Generate a random number in the range [1..6] according to the discrete function of probability distribution.

3) Use the formula $D = C /(2^n)$ to determine the duration of the time interval.

4) If the sum of the generator value and duration value D is greater than the specified bar size, *n* should be increased by 1 (i.e., halve the duration) and go to step 3.

5) Add the duration value to the generator value.

6) If the value of the generator is equal to the specified bar size, the task is completed, otherwise go to step 2.

In music practice, there may be other recurring temporal structures, including those whose size is less than the size of the bar, but which also play a certain role in some traditions. We created a

special heuristic algorithm to take these into account, and it will be considered separately.

2.1.8. Phrasing

A typical feature of any musical piece in any tradition is repeatability (or partial repeatability) of individual parts, that is longer that a bar and make up the structure of the fragment. In this study such parts are called musical phrases. We assumed that a musical piece consists of a certain number of musical phrases with given lengths.

$$\{ A(l, l..il), A(2,1..i2), A(3,1..i3),...A(J, i - Ij) \}, \qquad (8)$$

where J is the number of musical phrases; Ij is the length of the j-th musical phrase.

It is obvious that there are many dependencies related to the moments of the beginning and ending of musical phrases, as well as correlation among phrases. When creating a model, it is necessary to consider all the dependencies observed.

2.1.9. Phrasing and Mode

As already mentioned, the steps of the traditional mode perform a different function, for example, certain steps can be mainly used in special places of the musical piece, fragment, or a bar. They can be chosen due to a high probability value in the matrix of transition probabilities. However, in this case, such a probability will be high in any part of the musical piece. Therefore, these probabilities must be different in different places of the musical fragment, phrase, or a bar. To take into account this pattern, it is logical to introduce several different matrices M_p for various cases, the occurrence of which is completely determined by the structure of musical phrases and bars.

So, when creating a musical extract, before choosing the value of the next step, one should first determine special features of this place in the musical fragment, and then select an appropriate transition probabilities matrix. The special features may include the following:

- The main matrix (used by default)
- The second downbeat of the bar
- The downbeat of the bar
- The end of the musical phrase
- The end of the musical piece.

Since these cases are listed by their degree of “stability”, it is possible to use matrices for neighboring cases, instead of specially calculated ones.

2.1.10. Phrasing and Correlation of Musical Phrases

In any tradition, repeatability is a feature of musical phrases. In this model, the correlation of musical phrases is described by probabilistic laws. Since, entering the repetition state, the system remains like that for some time, it is convenient to describe a group of correlation laws in the form of a state space with probabilistic transitions between them. For each state, let us introduce the probabilities of transition to all other states. Again, it is convenient to do this in the matrix of transition probabilities between states. Let us call these states *microstyles*.

$$s = M_s(s_{prev}) , \qquad (9)$$

where s is the subsequent microstyle; s_{prev} is the previous microstyle; M_s is the matrix of styles transitional probabilities.

This formula shows the change of a microstyle: which microstyle will be selected next. To determine at what point this occurs, i.e. how much time is spent in a given state or what the probability of leaving it is, let us introduce the vector of the probability of leaving the state M_{out}. The possibility of altering the state can be determined after each sound is generated, or at the boundaries of the bar. The microstyle is more likely to change at the boundaries of musical phrases, since a new musical phrase should differ, if it is possible, from the previous one. To do this, one can introduce a special probability vector or just change of the microstyle at the end of each phrase.

Let us assume that each microstyle has its own dependence and degree of correlation of musical

phrases, i.e. its own correlation algorithm. Correlation algorithms can be different, and their number can be increased while working on the model. The creation of a new melody/rhythm according to the algorithms described above is a special (but most frequently used) case. Repetition can be either full or partial, for example, a repetition of a rhythmic pattern (an exact copy of the duration with different pitches), or melodic (exact observance of the same pitch, but based on a different rhythmic pattern). Thus, one can distinguish microstyles of the temporal characteristics of the sound (rhythm) and the microstyles reflecting the correlation of pitches, and these can be considered separately.

Let us name some possible pitch microstyles: creating a new melody according to pitch dependence algorithms; copying a melody from the phrase specified in the parameter; copying the melody from the beginning of this phrase; creating a new melody by transforming the steps for another instrument of the orchestra; using alternative pitch matrixes for different microstyles.

Rhythmic microstyles for building a phrase include: creating a new rhythm according to probabilistic parameters; copying the rhythm (all note values) from the phrase specified in the parameter; copying the rhythm (all note values) from the beginning of the given phrase; multiplying the rhythm (doubling the note values) of the specified orchestra instrument; dividing the rhythm (reducing the note values) of the specified orchestra instrument; and using alternative probabilistic parameters for different microstyles.

It should be noted that the analysis of the correlation of musical phrases is a rather complicated task, and at present researchers are only exploring ways of solving it.

2.2. Results

1) Developing an approach for modeling difficult-to-formalize areas represented by abstract text.

2) This approach can be used to build a model of musical creativity.

3) Creating a method for analyzing sound recordings in MIDI format using ICT and applying it in the model.

2) Developing a mathematical model for generating sound fragments according to a set of parameters and reflecting the nature of the fragment.

3) Creating a user interface for running the model.

4) Developing a software package for studying and generating sound fragments using ICT.

5) Estimating the dependences linking the parameters of the model and the quality characteristics of the sound fragment.

The developed research tool allows obtaining results in the following musical-theoretical and practical areas:

- Creating new musical works with specified sound characteristics according to the composer’s intention.
- Studying the perception of sound signals and musical works as information flows.
- Attributing a musical fragment to a particular type; establishing the authorship of musical works; restoration of the lost fragments of musical works.
- Creating sound fragments with a given character.

2.3. Further Development of The Created Model May Include:

1) Expanding the set of probabilistic macroparameters.

2) Increasing the functionality of the developed model so that it can act as a model of a virtual orchestra.

3) Developing a mobile application that uses the created orchestra model.

4) Improving the classification of ancient and modern systems of musical notation, reflecting the spatial-acoustic synesthesia, and the possibility of pictorial-iconic representation of the musical text and its formalization based on music computer technologies (MCTs).

5) Creating services for recognizing and identifying tunes online, which became possible due to the development of MCTs that include a wider range of indicators reflecting important generalizing characteristics of a musical piece? The mathematical apparatus of group theory is used to describe these. A musical piece as a complex of private and complex indicators can be viewed as a kind of

musical database. Its elements function in the network as a model that summarizes complex indicators of a musical piece and acts as a way of transferring musical data. Search, processing, transfer, recognition and identification of data with public access can be perceived as a kind of online music search engine.

At the moment, on the one hand, it is important to train musicians to use modern MCTs and information technologies in music. On the other hand, there is a need for technical specialists with basic general music education and knowledge in the field of sound programming, sound synthesis, audio engineering, sound timbre programming, modeling of musical creative processes and professional knowledge of technologies of studio sound recording and specialized software, as well as specialists proficient in modeling that is one of promising methods for objective study of musical creativity.

3. Conclusion

The developed approach can be used to analyze other types of abstract difficult-to-formalize texts in various subject areas: for example, when studying biological and social processes.

The created model of musical creativity can serve as a tool for further research. Such a research tool can be applied to obtain results in the following theoretical and practical areas:

- Building models of sound sequences that meet specified conditions.
- Attributing various sound fragments to particular types.
- Attributing sound recordings.
- Restoring the lost fragments of sound recordings; studying the perception of sound signals as an information flow.
- Recreating sound signals of a given character.

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