opción

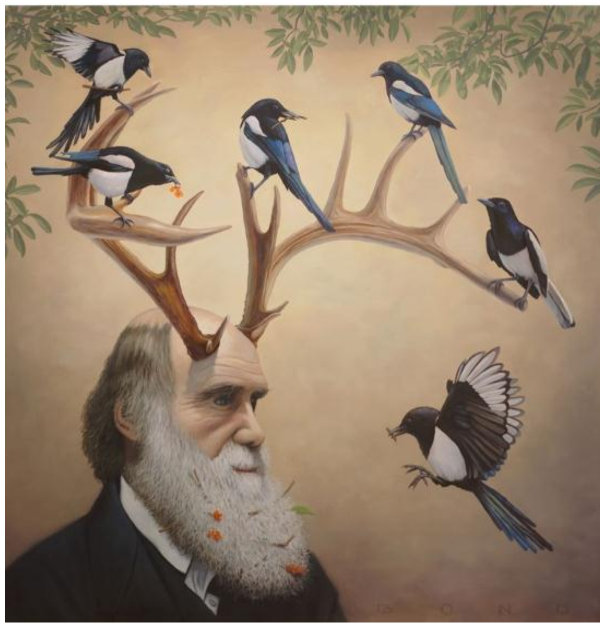
Revista de Antropología, Ciencias de la Comunicación y de la Información, Filosofía, Lingüística y Semiótica, Problemas del Desarrollo, la Ciencia y la Tecnología

Año 35, 2019, Especial N° 22

Revista de Ciencias Humanas y Sociales

ISSN 1012-1587/ ISSNe: 2477-9385

Depósito Legal pp 198402ZU45



Universidad del Zulia

Facultad Experimental de Ciencias

Departamento de Ciencias Humanas

Maracaibo - Venezuela

Opción, Año 35, Especial No.22 (2019): 392-409
ISSN 1012-1587/ISSNe: 2477-9385

Modeling the process of musical creativity in musical instrument digital interface format

Irina B. Gorbunova
Herzen State Pedagogical University of Russia, St. Petersburg, Russia
gorbunova7575@yandex.ru

Sergey V. Chibirev
Herzen State Pedagogical University of Russia, St. Petersburg, Russia

Abstract

This article considers applying mathematical modeling to write music scores in the MIDI (Musical Instrument Digital Interface) format. The scores are viewed as an abstract text created by analyzing statistical parameters with the subsequent modeling of musical creativity as per the obtained data. As a result, the developed method can be used to analyze other types of difficult-to-formalize abstract texts in various subject areas—for example, when studying biological and social processes. In 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.

Keywords: Mathematical, Modeling, Computer, Identification, Technologies.

Modelado del proceso de creatividad musical en formato de interfaz digital de instrumentos musicales

Resumen

Este artículo considera la aplicación de modelos matemáticos para escribir partituras musicales en el formato MIDI (Interfaz digital de instrumentos musicales). Los puntajes se ven como un texto abstracto creado mediante el análisis de parámetros estadísticos con el modelado posterior de la creatividad musical según los datos obtenidos. Como resultado, el método desarrollado puede usarse para

Recibido: 10-12-2018 •Aceptado: 15-03-2018

analizar otros tipos de textos abstractos difíciles de formalizar en diversas áreas temáticas, por ejemplo, al estudiar procesos biológicos y sociales. En conclusión, el enfoque desarrollado se puede utilizar para analizar otros tipos de textos abstractos difíciles de formalizar en diversas áreas temáticas: por ejemplo, al estudiar procesos biológicos y sociales.

Palabras clave: matemática, modelado, computación, identificación, tecnologías.

1. INTRODUCTION

Several kinds of music and science 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 (COBANOGLU, SERTEL & SARKAYA, 2018: LAUREANO, FERNANDES, HASSAMO & ALTURAS, 2018).

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 the abstract text. We used such methods as statistical analysis, graph theory, Markov chain, 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 an 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 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 (GUCK, VANBEMTEN, REISSLEIN & KELLERER, 2018).

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 the type of value;

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 between 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.

3. RESULTS AND DISCUSSION

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:

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

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. The 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. Performance. 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 (FADEEV, 2008).

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:

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

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. 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:

$$D = C / 2^n$$

Where C is the duration of the whole note; n is a natural number of the range. 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 (duration) 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. Let us see the sound as a function of the 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 (BLENK, BASTA, JOHANNES, REISSLEIN & KELLERER, 2016).

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

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 those 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 (FILATOV-BECKMAN, 2015).

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

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. 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 (GORBUNOVA & ZALIVADNY, 2018).

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, and then using the formula from the previous section.

Let us write transformation $n_t \rightarrow n$ 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.

$$n = M_m (n_t) + C_m,$$

Where Mm the transformation matrix is that uniquely defines the traditional mode; Cm is the keynote—the first note of the traditional scale. According to musical terminology, Mm defines the mode, while Mm and Cm define the key of the piece. By applying transformation Mm 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 a Markov chain. 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 model:

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

Where nt is the tone number of the next sound; $n_{t\ prev}$ is the tone number of the previous sound; Mp 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. Since note values are discrete and are described by the law, 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 (GORBUNOVA, ZALIVADNY, CHIBIREV, 2017).

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 a possible recurrence of the rhythm: phrases, musical sentences, bars. For instance, in the European musical tradition of the modern and partially in 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. A typical feature of any musical piece in any tradition is repeatability (or partial repeatability) of individual parts, that is longer than 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.

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

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 end of musical phrases, as well as the correlation among phrases. When creating a model, it is necessary to consider all the dependencies observed. 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 Mp 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) (X);
- 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.

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.

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

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.

4. CONCLUSION

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. 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 information flow;

- Recreating sound signals of a given character.

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opción
Revista de Ciencias Humanas y Sociales

Año 35, Especial No. 22 (2019)

Esta revista fue editada en formato digital por el personal de la Oficina de Publicaciones Científicas de la Facultad Experimental de Ciencias, Universidad del Zulia.
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