Generation of Music Patterns Using Realistic Artificial Neural Networks

German A. Chernykh, Yuri M. Pismak, Yuri A. Kuperin and Ludmila A. Dmitrieva*

Abstract--- *The goal of this study is to test the hypothesis about the models of the so-called realistic artificial neural networks that are in dynamic states, demonstrating behavior close to the self-organized criticality mode and are capable of generating musical patterns. The patterns are sequences of sounds subjectively perceived by a person as musical, which on a more formal level should mean such an internal organization of sound sequences that would allow us to speak about the presence in them, in particular, of such musical characteristics as melody, harmony or meter. An important condition for the generation of musical patterns is the absence of intervention in the dynamics of the neural network from the outside, like the training with the teacher. We talk about the numerical sequences, which subsequently are the base for creating the sound series. Numerical sequences are determined solely by the internal dynamics of the model. The realism of the network means the comparability of the dynamic behavior of the model with the processes occurring in the ensembles of human cortex nerve cells. The model of a modified neural network by Kropotov-Pakhomov is used in our work. The algorithm for constructing musical patterns is described. Examples of both monophonic and polyphonic musical patterns, which are the result of interneuronic interaction in a neural network, are given, and free parameters of realistic artificial neural network models are studied and described. As a result, it was found that the complex dynamics of a realistic artificial neural network can be transformed and interpreted in terms of musical patterns. We defined the areas of the neural network parameters that do not allow us to transform the dynamics of the network into musical patterns, that are far from the phases corresponding to the modes of self-organized criticality. Thus, the studies conducted in the work indirectly confirmed the fact known in neurophysiology and cognitive science that the normal (non-pathological) human brain functions successfully on the “order-chaos” border, namely in a state of self-organized criticality. The materials of the article are of practical value primarily for cognitive scientists and neuroscientists, who use quantitative methods in their research. They are also relevant for musicians, as they reveal some quantitative connections between music and consciousness.*

Keywords--- *Realistic Neural Network, Ensemble of Nerve Cells, Self-Organized Criticality, Musical Texts, Piecewise Scaling, Physiological Music, Dynamic Clustering.*

I. INTRODUCTION

It is proposed to use a model of an artificial neural network as a source of musical texts. The following requirements are imposed on the network structure and dynamics.

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The network must have properties that would make possible its stable functioning in a state of self-organized criticality, and also have a certain level of comparability with some physical processes that actually take place in the cortex of the human brain. All this form the term “realism of the model”.

On the one hand, the state of self-organized criticality implies the stability of the model’s dynamics, which makes it possible, while observing the evolution of the network, to obtain temporal numerical series with reproducible properties that can then be converted into sequences of sounds. Sustainability, in turn, implies a certain sort of independence of the dynamic system from external influences.

This idea is very important, because properties of the numerical series generated by the neural network will be determined by the internal dynamics of the network and do not depend on the information brought from outside, including musical one.

On the other hand, it is already well known that, both in music, which is the fruit of human brain activity, and in the brain itself, there are clear traces of activity, which can be safely attributed to the manifestation of critical dynamics (more information on this topic in sections 3 and 4). Thus, it becomes clear that the motivation for building and researching a neural network is not only able to be in a state of self-organized criticality, but also to possess properties related to the functioning of the human brain.

The requirement to correlate the properties of the neural network with the properties of the brain is also the starting point for its use as an additional tool in the study of those physical processes whose mechanisms are incorporated into it. Since the network is built to generate music sequences, the most interesting is the modeling of physical processes directly related to the functioning of the human cerebral cortex in the process of creating musical works.

At the same time, it is necessary to emphasize that many people, including the authors of this work, have the opinion that music, like other fruits of highly intellectual human activity, cannot be reduced only to the local interaction of neurons in its brain. Full coverage of such areas as music or mathematics must necessarily include an understanding of the nature of human consciousness. Therefore, the result of the work of the realistic neural network model proposed below should be treated accordingly (some thoughts concerning this point are outlined in section 7).

This paper presents a model of a neural network that satisfies all the stated requirements. The history of the occurrence and detailed description of the model is given in Section 2. Section 2.1 provides a formal definition of the model. Section 2.2 contains the criteria and justification for the choice of network parameters, with which the results were obtained.

The features of network dynamics in various modes are described in section 3, and section 4 discusses the specifics of network behavior in a state of self-organized criticality, used to build musical texts. Section 5 proposes general principles for constructing musical patterns by numerical series (Section 5.1) and the algorithm itself (Section 5.2), specific to the studied model. The description of the results is located in section 6. Finally, section 7 expresses an informal interpretation of the obtained results, as well as possible directions and prospects for further research relating to the studied issues.

II. MATERIALS AND METHODS

2.1 Description of the realistic neural network model

The artificial neural network, being the basis for experiments on the generation of musical patterns, is the development of the realistic neural network (RNN) model proposed in a series of papers (1, 2, 3) to study the behavior of ensembles of nerve cells excited by external signals. Having sufficient simplicity, the original model reflects important characteristics of the dynamics of real neurons (4), such as the return of the membrane potential to the initial state after a neuron discharge, the presence of a threshold for generating action potential, a short-term decline in synaptic efficiency in response to a short-term stimulation of the presynaptic terminal, and others. RNN model can perform spatial filtering of the input signal (1, 2), which, in particular, is manifested in the ability of neurons to unite into clusters, synergistically excited or inhibited by a constant external stimulus. Some transient processes of the RNN model were considered by(3), and (5) constructed an analytical solution for the symmetric network (SRNN), stimulated by a constant-time signal.

Possessing a number of dissipative properties, the RNN model with parameters corresponding to the dynamics of real neurons, nontrivially evolves only when there is an external influence. To obtain stable dynamic modes in the absence of stimulation by external pulses, the RNN model was modified (6, 7), and in the modified version it has extensive phases of stable periodic and non-periodic modes.

A complete and detailed description of the dynamic modes of the modified RNN model (MRNN) can be found in (9), and the publication (8)describes the features of the state of self-criticality (see 4), in which the musical patterns are obtained.

2.1.1 Formal definition

The MRNN model is a group of n interacting neurons. The network evolves in discrete time k , and the change of its dynamic variables during the transition from one moment of time to the nextis given by a set of the following recurrence relations:

$$P_i(k+1) = (1-\alpha)P_i(k) + \frac{\sum_{j=1}^{n} W_{ij}(k) N_j(k)}{\sum_{j=1}^{n} N_j(k) + 1} - \beta N_i(k) + S_i(k), \quad (1)$$

$$W_{ij}(k) = \left(x_i^1(k) + x_i^2(k)\right) W_{ij}^0(k), \quad (1)$$

$$W_{ij}^0(k+1) = (1-\mu) W_{ij}^0(k) + \nu \sum_{\{m\}} N_i(k) N_j\left(k-m\right), \quad (2)$$

$$x_i^1(k+1) = (1-A_1)x_i^1(k) + B_1 N_i(k) + C_1, \quad (3)$$

$$x_i^2(k+1) = (1-A_2)x_i^2(k) - B_2 N_i(k) + C_2, \quad (4)$$

$$N_i(k) = \theta(P_i(k) - h_i), \quad (5)$$

$$\theta(x) = 0 \text{ при } x \le 0, \quad \theta(x) = 1 \text{ при } x > 0, \quad (6)$$

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where the index $i = 1,....,n$ numbers the neurons of the network; $P_i(k)$, $N_i(k)$ and h_i — these are potentials, activities and thresholds of the neurons activation; $S_i(k)$— external stimuli; $W_{ij}(k)$ and $W_{ij}(k)$ — matrices of relations; $x_i^1(k)$ and $x_i^1(k)$ — the so-called activators and depressants, which sum determines the effectiveness of synaptic connections of neurons.

α, β, μ, ν, $A_{1(2)}$, $B_{1(2)}$, $C_{1(2)}$ — parameters of the model. A neuron with a number i is considered active if $N_i(k) = 1$, and inactive if $N_i(k) = 0$.

The Bogdanov-Hebb[1] rule defines the second term in formula (3) with delays m (7). Delays allow us to obtain an asymmetric matrix of connections and naturally reflect the propagation of signals over connections, which in general leads to the possibility of introducing the concept of distance on a discrete set of neurons. The value $\frac{1}{\sum_{j=1}^{n} N_j(k) + 1}$ in formula (1) is called the "cooling" of the neural network, since it compensates the unlimited growth of potential due to the activation of the Bogdanov-Hebb rule in formula (3). The dependence of the matrix $W_{ij}^0(k)$ on the activation of neurons and cooling are those modifications that were introduced in the original model in order to obtain stable dynamic modes (for more details, see 2.4).

2.1.2 Parameter selection

The nature of the MRNN model dynamics is substantially determined by its numerous parameters. We limit the parameter domain to those indices with which the MRNN model retains some important properties of the original RNN model.

1. Thresholds of the neurons activation must satisfy the condition $h_i \geq 0$. This eliminates the possibility of activating each individual neuron network in the absence of an external stimulus and signals from other neurons. Let us imagine that

$$h_i = 0, \quad i = 1, \ldots, n. \qquad (7)$$

2. Parameters $A_{1(2)}$, $B_{1(2)}$ and $C_{1(2)}$ in formulas (4) and (5) are selected in such a way that the effectiveness of synaptic connections of active neurons decreases, and after the neurons transited to inactive states, the synaptic connections restored (Figure 1). In all experiments on the model

$$A_1 = 0.4, \quad A_2 = B_1 = C_1 = 0.2, \quad B_2 = 0.5, \quad C_2 = 0.1. \qquad (8)$$

[1] The ideas that form the basis of the Hebb principle were first presented in 1901 in the book by A.A. Bogdanov (18) long before the appearance of the work of Hebb (19). This gives grounds to call the well-known Hebb principle the Bogdanov-Hebb principle.

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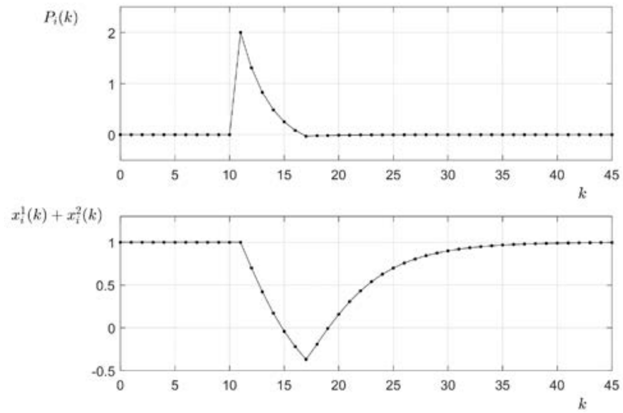

Figure 1: The potential and effectiveness of synaptic connections of a neuron before and after exposure to an external signal $S_i(10)=2$ ($S_i(10)=0$ when $k<10$) with the parameters $A_{1(2)}$, $B_{1(2)}$ and $C_{1(2)}$ given in formula (9)

It is easy to show that with such parameters and the condition $N_i(k)=0$, $\forall k>C$, $C\in\mathbb{N}$

$$\lim_{k\to\infty}\left(x_i^1(k)+x_i^2(k)\right)=1. \quad (9)$$

The constancy of the original model matrix $W_{ij}^0(k)$, where changes in relations depend only on their efficiencies $x_i^1(k)+x_i^2(k)$, in the modified version, is reflected by the condition

$$\frac{\left\langle \triangle W_{ij}^0(k)\right\rangle}{\max\left(W_{ij}^0(k)\right)-\min\left(W_{ij}^0(k)\right)} \ll \frac{\left\langle \triangle\left(x_i^1(k)+x_i^2(k)\right)\right\rangle}{\max\left(x_i^1(k)+x_i^2(k)\right)-\min\left(x_i^1(k)+x_i^2(k)\right)}, \quad (10)$$

where $\triangle f(k)=f(k+1)-f(k)$, and averages $\langle\ \rangle$ and extremes are calculated with the same rather wide interval $[k_1,k_2]$. The fulfillment of the relation in formula (11) is ensured by the proper choice of the parameters values $A_{1(2)}$, $B_{1(2)}$ and $C_{1(2)}$ (they are already defined above) and the parameters μ и ν. For receiving music texts, we selected

$$\mu=0.001, \quad \nu=0.1. \quad (11)$$

The condition (11) actually means that the changes in the dependences from time of the elements in the matrix W^0 occur more slowly compared to the matrix W. The example of the condition (11) influence on the network dynamics is shown in Figure 2, where we compare the graphs of the matrix elements of both matrices and the corresponding efficiencies of synaptic connections. Attention should be paid to the fact that in all the graphs presented in Figure 2, one value along the horizontal axis, in which the discrete time is set, corresponds to only one value along the vertical axis, despite the seeming illusion of several curves. In particular, it can be said that the values of the efficiency of the synaptic connection and the matrix element of the matrix W switch between a kind of *states* that evolve rather slowly, except for short periods of time where mixing occurs (see time intervals [6000, 7000] or [8000, 9000]).

Initial conditions were simplistic:

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$$P_i(0)=0, \quad W_{ij}(0)=W_{ij}^0(0)=0, \quad x_i^1(0)=x_i^2(0)=0, \quad i,j=1....,n. (12)$$

To enter the dynamic modes, the neural network was exposed to external influence. During the first 2000 steps, at each moment of time, a signal of 0.5 was applied to one randomly selected neuron.

During the experiments on the model, it was revealed that the characteristics of stable dynamic modes do not depend on the initial conditions, as well as on the strength of the pulses and the number of the exposed neurons in one single time step. The nature of the initial network stimulation can only affect the very fact of the emergence of a stable mode. For example, the magnitude and frequency of the repetition of external pulses $S_i(k)$ should be sufficient both to activate the neurons and to form interneuron connections. There were 64 neurons in all the experiments on the model, which results are given in this research. The set of delays m in formula (3) consists of only one element $m=1$.

Thus, all parameters are fixed except for the value α ,which determines the degree of potential dissipation, and the parameter β ,which influences on the discharge rate of the potential of active neurons. The type of the network dynamic mode depends on the key control parameter α .

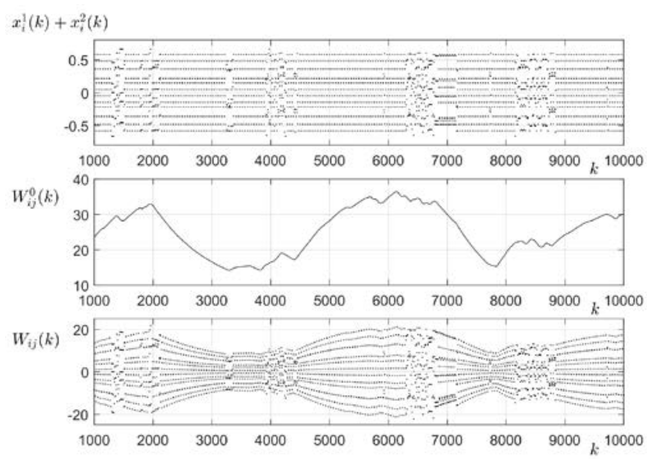

Figure 2: The time dependencies of the connections efficiency $x_i^1(k)+x_i^2(k)$ of the i - neuron network, connection $W_{ij}^0(k)$, coming from i - neuron to j - neuron, and the corresponding effective connection $W_{ij}(k)$, in non-periodic dynamic mode with the parameters values specified in formulas (9) and (12)

The MRRN model has extremely diverse dynamics depending on the parameters α and β. Details can be found in the work (7). In general, dynamic modes can be divided into two classes: periodic and non-periodic, which, in turn, can be stable and unstable. The instability of the network dynamic mode can manifest itself both in a limited lifetime, when all neurons of the network, starting from a certain moment, receive zero activity, and in the sensitivity of the network to small variations of parameters. Speaking further about stable dynamic mode, we will use the notion of stability in the both aforementioned senses.

In periodic mode, the network is divided into clusters of neurons. In each cluster, all neurons have the same frequency and phase of activity change. Clusters can differ both in the phase of changes in the activity of neurons and in frequency, which divides the periodic modes into simple and complex ones, respectively. It is curious, we detected the so-called *long-period oscillations*(9), which can be of the forced natureor self-provoked(7). The long-period oscillations emerge due to the fact that, in addition to the usual clusters, a small number of neurons appear in the network, wandering from cluster to cluster. One cycle of wanderings one period of the long-period oscillation. An interesting experimental fact is that the cycles of neuron, wandering through clusters, can be quite complex and exceed in several times the period of high-frequency oscillations of the neurons in ordinary clusters.

The network's property of splitting into clusters is preserved in some non-periodic modes, in particular, in the self-organized criticality mode (see section 4), where, in addition to the phase and frequency of activity oscillations, each cluster can have an attribute of lifetime.

One of the most noticeable features of the MRRN model compared to its original prototype is the presence of a high-frequency component in the dependences of dynamic variables on time. The reason is the use of fast-changing connections, which in practice are implemented by applying the Bogdanov-Hebb law (3). The question of the real existence of the fast-modifying synapses can be avoided, since everything related to short-period oscillations should be considered as a background against which the interesting dynamics develop in the studied model. With such an approach, the dynamic mode, in which a neuron has an activity, varying periodically according to a certain time interval, is defined as a steady state. Thus, it can be said that in a simple periodic mode, the entire network is in one steady state. In the complex periodic mode, the network is divided into clusters and each of them is in steady state. With long-period oscillations in the network, in addition to clusters of neurons that are in steady states, there are neurons that transit from one stationary state to another according to a periodic law. Finally, in the non-periodic mode, all neurons in the network change their steady states in an a periodicmanner. The number of steady states and the nature of the transition of neurons from state to state are determined by the type of non-periodic mode.

Each steady state i , in which we can find the neurons of the network with fixed parameters, can be described by level T_i and weight G_i . The steady state level is defined as the length of the half-period of the neuron activity oscillations. The weight of state is the probability of finding a neuron in a given steady state. Since in non-periodic modes the neurons go from state to state, then, by observing the evolution of a neuron for quite a long time, it is possible to calculate the above-mentioned probabilities. In Figure 3 we can seean example showing how one of the neurons of the network changes its steady states in the mode of self-organizing criticality. For example, the neuron stays much shorter time in a state with a half-period of oscillations equal to 10, compared to the other two states. Weights and number of states vary depending on the control parameter α .As shown in the work(8), when the value of the parameter α tends to increase chaos, the number of states becomes larger, and their weights are aligned with each other. Figure 4 illustrates the variation of weights depending on the parameter α ,where the dependences of the states weights are shown in the area of the point α_{cr} , where we can observed a self-organized critical behavior.

In the self-organized criticality mode, the number of steady states with statistically significant weights is strongly limited, and the times when neurons stay in steady states obey *piecewise scaling*(8).Figure 5 shows the discrete function of the probability density constructed for the times when neurons are in the state with the maximum weight in the self-organized criticality mode. These are the times of the neurons presence in the states that were used to form numerical series, from which musical patterns were built then.

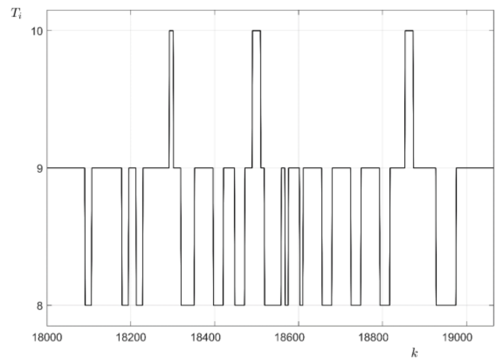

Figure 3: Transitions of a neuron from state into state in a mode of self-organized criticality. k — discrete time, T_i — steady state level

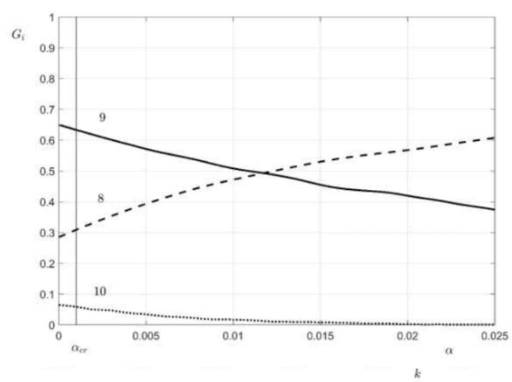

Figure 4: The steady state weights of the neurons in the network depending on the parameter α in the area of the point α_{cr}, corresponding to the self-organized criticality mode. Numbers indicate state levels

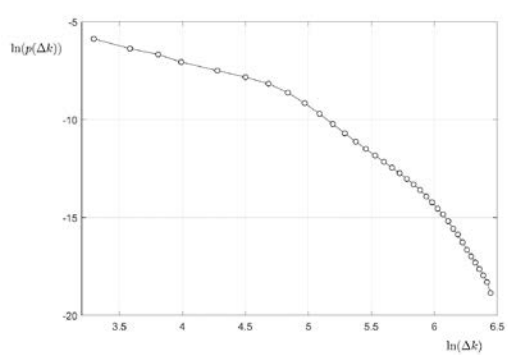

Figure 5: An example of the distribution, to which the times of a neuron in one state in the mode of self-organized criticality obey. The horizontal axis represents the logarithm of time intervals and vertical axis represents the logarithm of the probability density

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2.2 About the state of self-criticality

Critical dynamics arise in complex systems, usually defined as multitudes, consisting of a large number of non-linearly interacting objects. The nature of the interaction should ensure the flow of the avalanche processes, which would lead to the rapid transfer of information from the local level of individual objects to the global level of the system in general. The criterion for the presence of a critical mode is a power type of statistical distributions, which can be constructed from the observation resultsof various dynamic characteristics of the system. In a state of self-organized criticality, the dynamics of a complex system must be stable, which is ensured by constant energy feed from the outside and dissipation of this energy within the system, in other words, such a system is far from the thermodynamic equilibrium.

In the MRNN model, energy is fed at the level of interneuron connections by introducing the Bogdanov-Hebb rule (3), and dissipation is provided by cooling according to formula (1).

The key parameter that determines the nature of the interaction of neurons and, as a result, the dynamics of the network in general, is the parameter α .The dissipation degree of the neurons potentials in formula (1) or, that is to say, the previous states memory of the neurons depends on parameter α . In (8), it was shown that the state of self-organized criticality arises in the network only at a very narrow interval, at small positive values, approximately, in the area of the value $\alpha_{cr} = 0.001$.The values $\alpha < \alpha_{cr}$ correspond to stable non-periodic modes with an exponential distribution of dynamic characteristics, which indicates that the network is a conglomerate of objects, which interaction can be neglected. This behavior can be attributed to the dynamics of deterministic chaos. If we move to the right from the state of self-organized criticality, in other words, we increase the parameter α from values α_{cr} to 1, then we will see a gradual decrease in the network lifetime to zero, after which a vast area of periodic states occurs, and the higher is α , the simpler is the periodic state (7).

The state of self-organized criticality in the MRRN model is the boundary between chaos in the set of independent objects and stationary states. Chaos with an exponential distribution correspond to small or negative values of dissipation, which means the suppression of interneuron interactions by the intrinsic dynamics of the neurons. On the contrary, for large values of dissipation, interaction plays a crucial role. In this case, the intrinsic behavior of the neurons does not matter, which leads to stagnation of the system. Thus, the state of self-organized criticality is the only possible compromise that takes into account both the individual behavior of neurons and their systemic interaction, and, therefore, is a mode in which something interesting can happen.

There are good reasons to assume that the processes occurring in the human cortex at the level of neurons demonstrate the manifestation of self-organized critical dynamics(10, 11, 12). Consequently, music, as a product of human activity, obviously, should, in some way, reflect the specifics of the brain activity (13). Now the motive to use the MRRN model in a state of self-organized criticality for generating musical patterns is becoming clearer.

There are two significant clarifications that need to be made when speaking about the state of self-organized criticality in the modified model of the realistic neural network by Kropotov-Pakhomov.

The first clarification is that, in contrast to simple models, where there are no control parameters governing the nature of the dynamics[2], in the studied model there are such parameters. Moreover, the adjustment of parameters to the values corresponding to one or another dynamic mode, including critical dynamics, is not automatic in the process of model evolution, but it must be made a priori. Therefore, broadly speaking, the critical dynamics is not completely self-organized, in the sense that the model itself does not adjust the parameters. However, if the required values of the control parameters are chosen, then regardless of the initial conditions (potentials of neurons, values of connections, etc.), the model necessarily falls into the corresponding dynamic mode. If it is the critical mode, then we are talking about the state of self-organizing criticality in our model. The second clarification concerns the piecewise scaling observed in the MRNN model. “Pure” critical dynamics are manifested in the presence of power distributions calculated according to the dynamic characteristics of the model. In our case, instead of power distributions, there are the piecewise-power distributions(8), which formally do not allow anyone to call the dynamics of the model critical in the generally accepted sense. Some thoughts on this aspect are expressed in (7).

III. RESULTS

3.1 Creating music patterns

3.1.1 General principles

In addition to the algorithm for transforming dependencies of dynamic variables of the MRNN model into numerical series, and then in the sequence of sounds, it is necessary to proceed from a combination of some provisions defining the general strategy for obtaining musical patterns. The features of the MRNN model and the self-organizing criticality mode were discussed above. Additionally, we emphasize that the self-organizing criticality mode is determined solely by the intrinsic properties of the neural network and does not depend on any initial conditions, initialization methods, and so on. Therefore, the influence of a person on the structure of the dependencies produced by the network is excluded. However, with the further processing of the numerical series, we cannot avoid the introduction of the “human” subjective information into the result. It is necessary either to minimize this effect, or to use methods where we clearly differ the actual neural network dynamics from external subjective human factors. It is clear that only global transformations should be carried out with numerical series, namely those that, while maintaining the internal local structure of numerical series, act on their elements in a uniform way. For example, the choice of a time quantum, octaves, musical instruments can be attributed to such transformations.

Before proceeding to the next aspect, which describes the algorithm for obtaining numerical series, it is important to note the following two important facts. Firstly, in addition to the actual numerical series, which are then interpreted as a sequence of note heights, also, a neural network allows us to obtain a series that will contain time points for playing notes. Secondly, different neurons of the network produce different numerical series, which makes it possible to build polyphonic musical patterns and thus, to hear not only the “music of individual” neurons, but also the music of their interaction.

[2] As an example, we can cite the well-known model of the biological evolution by Bak-Sneppen (20).

3.1.2 Formal algorithm

Let us describe the procedure for obtaining a pair of numerical series (heights of notes, moments of playing notes) for a monophonic melody. Polyphonic melody can be obtained by combining several monophonic melodies simultaneously.

The essence of the method can be quickly understood by studying the graph in Figure 3. Let us take, for example, a state with the level 9, where the probability of detecting a neuron at a fixed time is maximum. Then the lengths of the horizontal intervals when $T_i = 9$ will form a numerical series of the notes heights, and the moments of time k corresponding to the left boundaries of the above-mentioned intervals will form a series of moments for playing notes. Thus, the algorithm is reduced to the selection of intervals of the neuron location in a predetermined steady state, considering the positions of the left boundaries of the corresponding intervals, from the dependence of the neuron activity on the time $N_i(k)$.

Let us consider, as an example, the binary sequence $N_i(k)$ on the interval $18000 \le k \le 18250$ for the case in Figure 3:

000000000111111111000000000111111111000000000111111111000000000111111111
0000000001111111110000000011111111000000000111111111000000000111111111
0000000001111111110000000001111111110000000011111111000000000111111111
0000000011111111000000000111111111000000000111111111000000000111111111

It can be seen that the sequence consists of blocks of zeros and ones. Let us write it in a more compact form:

$$(0,9)(1,9)(0,9)(1,9)(0,9)(1,9)(0,9)(1,9)(0,9)(1,9)$$
$$(0,8)(1,8)$$
$$(0,9)(1,9)(0,9)(1,9)(0,9)(1,9)(0,9)(1,9)$$
$$(0,8)(1,8)$$
$$(0,9)(1,9)$$
$$(0,8)(1,8)$$
$$(0,9)(1,9)(0,9)(1,9)(0,9)(1,9)$$

where the first number in brackets is the activity of the neuron, and the second is the length of the block. Each individual line in the above expression corresponds to one of the steady states with levels 8 or 9 and can also be written more briefly:

$$(9,\ 10)\ (8,\ 2)\ (9,\ 8)\ (8,\ 2)\ (9,\ 2)\ (8,\ 2)\ (9,\ 6)$$

Here the first number determines the length of the block, and the second number determines the number of blocks. Please note that the information on the value of the neuron activity, which started the sequence, is lost, but it is not important for further construction.

Then we form two numerical series. The first numerical series is made from the numbers obtained after dividing the second numbers in the pair by two. The second numerical series is formed from values obtained after the division of the moments of time by two.

The moments of time correspond to the left boundaries of steady states, starting from zero time, which, obviously, can be obtained by calculating the partial sums of a series from second numbers in a pair, dividing the result by two.

5	1	4	1	1	1	3
0	5	6	10	11	12	13

Finally, we delete from the obtained sequence the elements corresponding to the steady state with level 8.

5	4	1	3
0	6	11	13

The obtained pairs of numbers form the two required series. The first series form the notes heights of musical pattern. The second series is the time points for playing the notes. Often there are cases when in the series of the note heights there are elements with the same value, in other words, notes of the same height are taken consecutively. In such situations, we can replace several notes with the same height by one note.

After using the above-described algorithm and obtaining pairs of numerical series corresponding to future musical patterns, it is necessary to superimpose the global parameters described in the previous paragraph. Technically, the procedure was performed by generating a file in the MIDI format (14) using special software written in C++. Then, MIDI files were converted to MP3 format.

IV. DISCUSSION

Examples of musical patterns, obtained with the technology described in the previous paragraph, can be found on the Internet in the reference (15). There are monophonic and polyphonic melodies. The presented patterns have clear signs that make it possible to classify them as musical, which, in fact, is the main result of this work. A detailed discussion of the features of the musical component in the patterns is obviously far beyond the scope of the article. In particular, it should be emphasized that, at the moment, the authors do not have any formal comparative analysis of various patterns generated by the MRNN model in the area of the parameter corresponding to the critical mode. For this reason, the values of the parameters with which certain patterns were obtained are not given (the choice of parameters was discussed in paragraph 2). Since the global characteristics of melodies, such as octaves, tempo, instruments, etc., on the one hand, can be well recognized by experts, and on the other hand, are a subjective component introduced by the authors, does not relate directly to the essence of the result, this information is omitted. At the beginning of the article it was said that far from the critical area, the generated patterns are no longer perceived as musical. It is obvious that both periodic modes and areas corresponding to deterministic chaos are of no interest in the sense of generating musical patterns. In periodic mode, in principle, we cannot talk about any patterns, since the network is in a steady state, and no series can be obtained, and in the case of chaos, the network can be regarded as a kind of random number generator with an exponential distribution.

The main purpose of this work was to test the hypothesis that realistic neural networks that are in dynamic modes and in some sense are close to or similar to the self-organized critical dynamics mode are capable of generating series of sounds that are subjectively perceived by humans as musical. The hypothesis was confirmed, but it makes sense to express a number of considerations and ideas. The first thing we would like to mention is the theoretical value of the results obtained in the context of the problems of consciousness and artificial intelligence.

Of course, the presented method does not pretend to be used for the practical generation of music. For this purpose, there are much more effective methods based on learning with a teacher. Therefore, we are not talking about the development of artificial intelligence systems capable of generating musical patterns. The very possibility of synthesizing music (especially considering the success of modern deep learning technologies in related fields) seems to be less interesting from a fundamental theoretical point of view than the issues associated with the emergence of complex systems, such as the human brain, being the result of evolution. Of course, the modeling of objects and their abilities, already existing in nature, is an interesting and useful task. But it is equally important to find out how such systems actually appeared evolutionarily. If such knowledge is obtained, it will allow us to create fundamentally new complex systems, which have no analogues and, perhaps, we will approach the mystery of consciousness.

The obtained musical patterns clearly demonstrate the presence of a musical component. However, it would be naive to believe that the development of such a technique could lead to the creation of an artificial intelligence system capable of replacing a talented composer. The simple conclusion is that, if we assume that some of the mechanisms involved in writing a musical work by a person are somehow reflected in the MRNN model, they are clearly not enough to describe and understand the whole process. The question arises: “What does the model reflect?” The answer is that it reflects the dynamics of the interneuron interaction in the model. Since the answer is obvious, it is worth advancing further and express the following hypothesis. The presented musical patterns are subjectively perceived by a person as musical, precisely because the model reflects some specific features of a real interaction processes of neurons in the cerebral cortex. That is to say, that we are dealing with a kind of “physiological component” of the phenomenon, which is called music. The assumption of this hypothesis raises a number of interesting questions that deserve consideration in future research. In particular, it would be interesting to study the dynamics of models that receive external influence in the form of signals generated by the method described in this work, or consider the possibility of building models that have a hierarchical structure and generate musical patterns that are perceived by a person as “more musical”. The phenomenon of piecewise scaling, which arises in the presented model, also deserves close attention. According to the authors of the work, it is the presence of a fixed number of states, between which neurons switch in a critical mode, leads to the appearance of fractions in power distributions, and, as a result, to the possibility of obtaining musical patterns. Generally speaking, the presence of non equally probable states reveals the existence of some hierarchy in a complex system. It is likely that the rudiments of the observed harmony, detected in the presented patterns, are the result of the above-mentioned hierarchy. If we assume that the harmony, observed in musical patterns, is a consequence of the hierarchical component of the network dynamics, then this reveals quite curious directions for future research.

It must be emphasized that such ideas expressed in one form or another, begin to appear in modern publications. As an example, we can refer to the following two works (16, 17), where the importance of hierarchical structures is emphasized, when generating music. According to the authors of the present work, all such questions should be combined into a single complex research concerning the evolutionary development of consciousness and artificial intelligence.

V. Conclusion

In this study, the authors hypothesized that models of realistic artificial neural networks that are in a state of self-organized criticality, provided that the network does not receive information from outside, can generate rhythmically organized sound sequences that have characteristics, which can be perceived by humans as musical sequences.

The conducted study confirmed the hypothesis. More precisely, as a result of experiments with dynamic modes of the neural network modified model by Kropotov-Pakhomov, network parameters were found that lead to the desired effect. A special technique of transforming numerical signals into note sequences made it possible to obtain musical meaningful patterns. As a result, it was shown that the complex dynamics of realistic artificial neural network models can be transformed and interpreted in terms of musical patterns. However, as a result of experiments with dynamic modes of the model, it was also found that not all dynamic numerical sequences generated by the network can create musical patterns. The study established the following important facts.

Some specific domains ofthe chosen model parameters of a realistic neural network lead to irregular dynamic modes that can be interpreted in terms of meaningful musical images. Dynamic modes in which it is possible to produce musical patterns by their properties, on the one hand, are close to the dynamics of self-organized criticality, but on the other hand, have significant specificity, manifested in the presence of dynamic hierarchical structures in the neural network. The areas of the parameters values in the neural network model which did not allow us to transform the corresponding dynamics into musical patterns, were investigated. Such areas lie far from the aforementioned phases of dynamic modes.

The materials of the article are valuable for cognitive scientists, neurophysiologists, musicians and all specialists interested in the theoretical problems of consciousness and artificial intelligence.

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