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Fuzzy clustering based self-organizing neural network for real time evaluation of wind music

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Abstract

In order to improve the effectiveness of the evaluation of the form of Western wind music, this paper proposes a method for evaluating the form of Western wind music based on self-organizing neural network. First of all, aiming at the problem of Western form of wind music art presentation, this paper formulates a set of objective criteria that can be quantitatively expressed, and introduces the extraction methods of western wind tone features. Secondly, this paper considers the use of a fuzzy clustering method of constructing a self-organizing neural model for the proposed evaluation matrix to achieve the classification and evaluation of the artistic presentation of western wind music. Finally, an example is used to verify the validity of the proposed self-organizing neural model in the evaluation of the presentation form of western wind music.

Keywords: Self-organization; Neural; Western wind music; Art presentation; Form evaluation

1. Introduction

With the development of our country's economy, the people's living standards have been continuously improved. After basic life needs such as clothing, food, housing, and transportation have been satisfied, people are more eager to meet higher-level spiritual needs (Ge, Kulatilake, Tang, & Xiong, 2014; Grenard, Divoux, Taberlet, & Manneville, 2014; Lange, Hekkink, Keizer, & Burggraaf, 2017; Neogi, Mohanta, & Dutta, 2014; Stateczny & Wlodarczyk-Sielicka, 2014). Learning western art of wind music is favored by more and more people. In recent years, there has been a significant increase in the number of people learning to play wind musical instruments in the society, and all age groups have enthusiasts who learn western wind instruments, among which young children learn western musical instruments with the largest number of musical performances. In middle- and high-level urban families, there is one family in every five families in which the parents hope that their children will learn the art of western wind instruments (Ai, Zhang, Zhou, & Pei, 2014; Grenard et al., 2014; Hanaor, Gan, & Einav, 2015; Li, Yu, & Zhou, 2014; Peng, Xiang, Lv, & Zhang, 2014; Tarquis et al., 2014). The number of applicants for the Western Wind Art Level Examination is even increasing at a rate of 20% per year. On the other hand, the reform of the national education system and the expansion of the education scale have greatly increased the demand for western wind music teachers (Al-Kadi, 2015; Ding, Zhang, & Yu, 2016; Hussein et al.; Lai & Wang, 2015; Mance, 2014; Yigitcanlar & Kamruzzaman, 2014). In the western art of wind music education, professional teachers who are engaged in the art of western wind music education have become a very scarce resource, and this state will not be greatly improved in a short period of time

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(Elhoseny et al., 2018; Sarvaghad-Moghaddam et al., 2018; Tharwat, Elhoseny, Hassanien, Gabel, & Arunkumar, 2018; Vardhana, Arunkumar, Abdulhay, & Ramirez-Gonzalez, 2018; Abdulhay, Elamaran, Arunkumar, & Venkatraman, 2018; Abdulhay, Arunkumar, Narasimhan, Vellaiappan, & Venkatraman, 2018).

The cost of Western art of wind music education is very expensive. It takes at least 10,000 yuan to buy an ordinary western wind instrument. The teaching of Western wind music art uses a one-on-one teaching method for teachers and students (Abdulhay, Mohammed, Ibrahim, Arunkumar, & Venkatraman, 2018; Arunkumar, Ramkumar, & Venkatraman, 2018; Liu & Arunkumar, 2018; Vardhana, Arunkumar, & Abdulhay, 2018). At the same time, due to the scarcity of Western wind-art teachers, the tuition fee for each section of Western wind art classes is between 100 and 400 yuan (Chen et al., 2017; Fernandes, Gurupur, Sunder, Arunkumar, & Kadry, 2017; Hamza, Muhammad, Arunkumar, & González, 2017; Meng & Arunkumar, 2018). In this case, most of the students' time for learning western art of wind music is only one week per week. In other times, students can only practice blindly so that the process of learning the art of western wind music takes a roundabout route, and the progress of learning is very slow. The learning of western wind music performance is also limited by geographical, time, and other aspects, so that many fans with learning intentions can only give up the learning of western wind art performance. The combination of music and modern electronic technology has become inseparable, and it is a combination of music and electronic technology from the early phonograph to the current electric western band. Multimedia computers are the combination of personal computers and digital video and audio, which have been applied to all aspects of music. A multimedia computer can store music in a large capacity and with high accuracy, can play music with clear effects, can efficiently produce music, and can vividly help people learn, understand, and enjoy music. In terms of music creation, multimedia computers store musical materials such as music scores, sound samples, and electric western wind instruments from multiple channels (Arunkumar, Ramkumar, & Venkataraman, 2017, 2016; Arunkumar, Ramkumar, Venkatraman, Abdulhay, et al., 2017). According to the requirements of music creation, the creators use different music materials to edit, synthesize and add various special effects to eventually create a complete electronic music work. In terms of music transmission, the physical characteristics of music are stored in digital computers after being digitized. This digitalized music is compressed and transmitted through various channels. Finally, after the music is decompressed, it is played. In the respect of music learning, multimedia computers provide students with a more vivid learning experience through the combination of video and audio. And through computer-student interaction, they can gain a deeper understanding of learning knowledge (Ding et al., 2016).

This paper proposes an evaluation method of western wind music art presentation form based on self-organizing neural network. It develops a set of objective criteria that can be used to represent the representational form of western wind music. In consideration of the proposed evaluation matrix, it considers using a fuzzy clustering method to construct the self-organizing neural model, so as to achieve the classification and evaluation of the western wind music art (Yigitcanlar & Kamruzzaman, 2014).

2. Evaluation model construction

2.1. Western wind music evaluation system

In different Western wind instruments competitions and assessments, a set of objective criteria that can be quantitatively expressed should be formulated. Evaluation scheme design is shown in Table 1.

The score range of each indicator in this evaluation system is [0, 10]. There are n experts to participate in the scoring. Each expert will score the players according to their professional specialty, and each player can obtain an evaluation matrix $A_{i,j}$. Row vector e is the score of each indicators from each expert. Since different experts have different specialties, experts can only score for a few indicators. The column vector x is the score given to each player by the experts on an indicator.

2.2. Extraction of tone features

When Western wind art music are performed, the music is composed of players who play one tone on the keyboard according to music scores. When playing each note, the performer first looks at the score to determine the pitch, strength, and duration of the current note that needs to be played. Then the pitch corresponds to a specific key, and the intensity corresponds to the intensity of the keystroke. The duration corresponds to the time of pressing the key and releasing the key, and the sound is accurately played on the keyboard of western wind art instrument.

The quality of the sound effect played by the performer is directly related to whether the key is correct or not, as well as to the strength and duration of the play. The essence of the extraction of sound features is to determine the three indicators including the grasp of the strength, the grasp of the duration, and the correctness of the press. The grasp of the strength: the severity of the keystrokes displayed is the value of volume, the score obtained in the score is relative, and more is the need for the performer's own understanding of the score. The volume value in the MIDI signal is absolute and cannot be converted from the formula. To get the standard value of MIDI volume, it can only be obtained from MIDI files. As mentioned earlier, MIDI files are created by professional western wind instruments artists. This is actually the process of manually

Table 1
Western standards for wind music evaluation.

Category	Items
Skills	Singing posture, use of breath, support and stability of breath, range of sound ranges, clarity of speech, accuracy of pitch, accuracy of rhythm, difficulty of the song
Art	Stage image, performance of timbre, natural degree of sound, fluency, roundness, grasp of melody
Style	The emotional expression of songs, the degree of emotion in the right place, originality

converting the relative volume of music scores to MIDI volume. In view of the application of this system is mainly the western wind music art teaching, the standard volume value also integrates the MIDI volume value played by western wind music artist's teacher. The pitch value obtained by the MIDI file occupies half of the weight, and the western wind music artist's pitch value obtained by playing the MIDI keyboard against the score is half of the weight. Finally the standard MIDI pitch value is synthesized. After the standard MIDI volume value is obtained, it can be used as a criterion to judge a student's ability to grasp the strength of a single keystroke when performing a practice, that is, the difference between the sound volume value and the standard value of the MIDI signal acquired during performance. The grasp of the duration: As the same as the volume, the one obtained from the score is only a relative value. The processing method for extracting the value of the duration when playing the "sound" is the same as the grasp of the strength value: the difference between the time of pressing the key and the standard time plus the difference between the release key and the standard value. Here, since the speed of music is not absolutely invariable during the performance of the music, the change of speed does not have a great influence on the effect of the performance, or the change of speed does not bring about poor playing performance. Therefore, the standard value of the duration cannot use absolute time value. The method used here corresponds to the total duration of the music and the total duration of the performance. That is, the long-term standard value corresponds to the total duration of the performance.

The correctness of the press: The standard value of the press can be obtained from the score, and the pitch of each note in the staff has a definite expression. After conversion, the number expressed by the pitch relative to the MIDI signal can be obtained. The characteristics of the pitch of the "sound" are only two values, namely equation and inequation. For the sake of convenience and consistency, the key value of the MIDI file is also used as the correct judgment criterion value of the press.

3. A fuzzy clustering method based on self-organizing neural model

3.1. Calculating fuzzy similarity matrix

Fuzzy clustering based on fuzzy similarity relationship firstly establishes a fuzzy similarity matrix, and the key to establish a fuzzy similarity matrix is to calibrate similarity coefficients. The similarity coefficient reflects the degree of similarity of the sample with respect to certain attributes. There are many methods for determining the similarity coefficient, such as the scalar product method, angle cosine method, correlation coefficient method, maximum-minimum method, arithmetic mean minimum method, children's average-minimum method, absolute value index method, exponential similarity coefficient method, absolute value reciprocal method, absolute value reduction method, non-parametric method, closeness method, expert scoring method, etc.

Let $s = \{x_1, \cdots, x_N\}$ be the entire sample object and $(x_{i1}, \cdots, x_{iN})$ represent the feature data of each sample x. The fuzzy similarity matrix is that the similarity coefficient represents the degree of similarity between sample i and sample j. This paper uses the maximum and minimum method to calibrate the similarity coefficient, namely:

$$r_{ij} = \left[\sum_{k=1}^{m} \left(x_{ik} \wedge x_{jk}\right)\right] / \left[\sum_{k=1}^{m} \left(x_{ik} \vee x_{jk}\right)\right] \tag{1}$$

where $\wedge$ represents the minimum value; $\vee$ represents the maximum value.

After the calibration process, the elements in the similarity matrix R have been compressed into the closed area (Lange et al., 2017) and can be directly used as input values for self-organizing nerves.

3.2. Self-organizing neural model structure

The self-organizing neural model is a multi-layer tree structure model composed of an input layer and a competition layer (ie, an output layer). Each input wind note of the model is associated with all neural tree and wind notes by the weight W;}, in order to achieve a non-linear dimensionality reduction of the input signal and keep the topology invariant when the input is mapped onto the same musical notes of the tree. The number of neurons in the input layer is the number of rows or columns of the fuzzy similarity matrix (ie, the number of samples in the sample set), as shown in Fig. 1. Through repeatedly learning the input, this structure can capture the characteristics of the patterns contained in each input pattern, and self-organize it to present the classification results at the competition layer. When accepting a similar pattern of memorized input, the pattern will be recalled and correctly classified. For patterns that do not exist in memory, self-organizing nerves can memorize this new pattern without affecting existing memories.

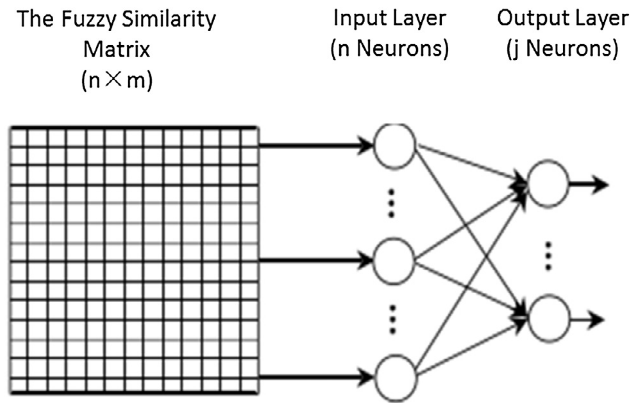

Fig. 1. Self-organizing neural model structure.

The model learning sample consists of samples with N classification indicators. Suppose these N-dimensional space points are obviously similar in type or similar in N-dimensional space, and these relatively close samples will form a class as well as a cluster in N-dimensional space. When the input samples belong to multiple types, the N-dimensional space will show multiple cluster-like distribution characteristics. Each cluster represents a type, and the center of the cluster is the type of cluster center. Samples of the same type have a small distance from the cluster center of the type. This distance can be measured through the Euclidean distance:

$$D_j = \sqrt{\sum_{i=1}^{N} \left(x_i - W_{ij}\right)^2} \tag{2}$$

where x_i is the classification index; W_{ij} is the cluster center of the j-th dynamic type; D_j is the Euclidean distance.

3.3. Algorithm steps

The self-organizing neural learning algorithm does not require a teacher signal. It uses the Euclidean distance between the sample and the cluster center to determine the sample type. The algorithm steps are as follows:

- Step 1: Give the threshold β, β is used to control the classification of the thickness. The larger the β, the thicker the classification, the less the number of types; the smaller the β, the finer the classification, the more the number of types. Therefore, the determination of the β value should be based on specific circumstances.
- Step 2: Make the output layer initial neuron number 1 (ie, $j = 1$), and optionally assign a learning sample the connection weight W_{ij} as the initial value.
- Step 3: Input a new learning sample and calculate the Euclidean distance D_j between it and each dynamic type of cluster center W_{ij}.
- Step 4: Neurons output with minimum Euclidean distance D compete to win:

$$D_j^* = \min\{D_j\} \tag{3}$$

- Step 5: If $D_j^* < \beta$, the current input sample is considered to belong to the dynamic type represented by the output neuron. The connection weight W_{ij} is adjusted as follows:

$$W'_{ij} = \left(x_i - W_{ij}\right)/h_j \tag{4}$$

where W'_{ij} is the adjusted value of W_{ij}; h_j is the current number of samples belonging to the j-th dynamic. Then go to step (3).

- Step 6: If $D_j^* \geqslant \beta$, it means that the output neuron competes to win, but the current input sample can still not be considered as belonging to the dynamic type represented by the output neuron, but should belong to a new type. Therefore, the output neuron should be increased by one $j = j + 1$, which indicates the new dynamic type. This input sample is used as the initial value of $W_{i(j+1)}$. Then go to step 3.
- Step 7: Repeat the cycle until all samples are completed. The number of output neurons of the final model is the number of types of all samples, and the connection weight is the cluster center value of each dynamic type.

The above learning algorithm shows that the self-organizing nerve has the features of plasticity and self-organization. At the same time, the learning and training process is the process of dynamically classifying measured data. After the training is completed, the established model is the classification model. When new measured data is obtained, the model can be input, and the dynamic type represented by the output layer neurons that ultimately win the competition is the type to which the sample belongs. This is the dynamic identification process of the new data by the model.

4. Experimental analysis

Based on the established evaluation model, the MATLAB BNT toolbox's joint tree inference engine is used for reasoning. Input the initial data and observation data (Li et al., 2014).

The initial state of the Western form of wind music presentation is set to a high, medium, and low probability distribution (0.4, 0.3, 0.4), which is in line with the assumption of actual conditions. This reflects the uncertainty of the performer's assessment of the situation due to the lack of necessary performance knowledge, making the probability distribution of the various states at the initial setting similar. After the model is initialized, it enters the waiting state. Once the updated situation information is input into the Western wind instrument, the western wind musical instrument is triggered to update the state distribution probability of the individual musical notes, and the probability distribution of the root note musical state is finally obtained.

After discovering that the other party initiated performance on our system, assuming that the playing time is continuous, the sensor monitors the system performance situation in real time and continuously observes at nine time points, and sets the observation value according to the data obtained at different times.

① Based on the dynamic Bayesian situation assessment, input the conditional probability distribution, state transition probability distribution and 9 time points observation data of initial wind music notes in the dynamic Bayesian assessment model, and perform simulation analysis to obtain a comprehensive performance situation. The results of the evaluation analysis are shown in Fig. 2.

② Set up a static Bayesian model from input the data and obtain the evaluation values, as shown in Fig. 3.

Judging from the experimental results, with the increasing frequency of confrontation activities, the state probability of protecting the form of "high" western wind music art gradually decreases, while the probability of "medium" or "low" state gradually increases and tends to be stable. It shows that in the confrontation, the confrontation style and intensity were adapted, and the performance system of the western band music performance gradually increased.

From the comparison between Figs. 2 and 3, it can be seen that the evaluation result of the dynamic Bayesian model integrates the feedback relationships and observation information among more situational elements. It can more accurately and continuously reflect the objective law of the changes in the playing state of the western wind power playing with time, facilitating the player to better grasp the playing direction and key points. With the increase in the frequency of confrontation, the probability

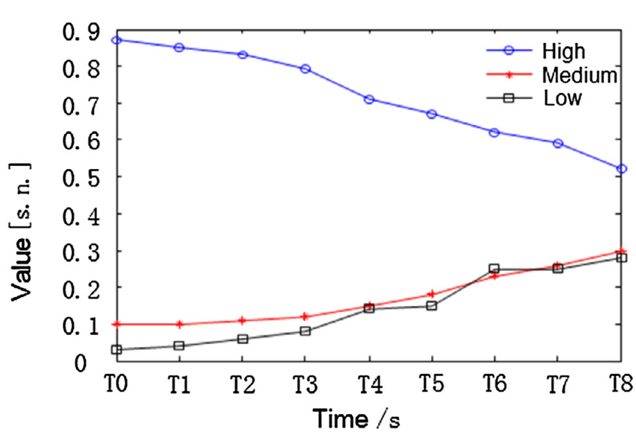

Fig. 2. Fuzzy dynamic bayesian simulation results for western wind music performance.

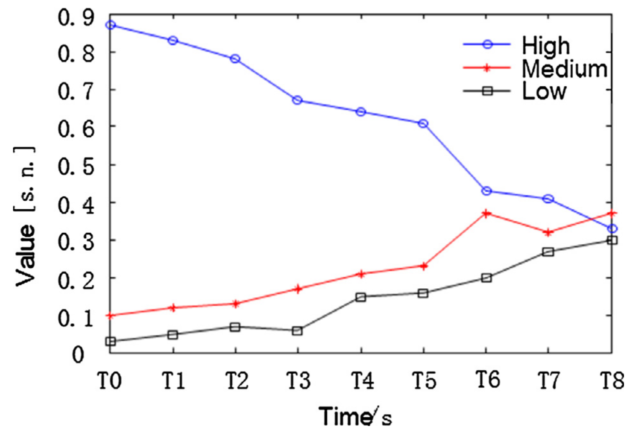

Fig. 3. Static bayesian simulation results for western wind music performance.

distribution gradually changes and tends to be stable, and the playing situation is developing in favor of one's own.

5. Conclusion

The use of computers to simulate human activities, behaviors and thoughts to complete more productive activities that can only be accomplished by humans, and to reduce the burden on people and increase production efficiency has always been the direction of artificial intelligence efforts. Through an in-depth study on neural models, Western teaching methods of wind music, music theory and MIDI technology, this paper proposes a music evaluation system using artificial neural models and a framework for the realization of western wind music teaching software from the perspective of modeling western wind music artists. This paper analyzes the current situation of the western wind-art teaching, which is characterized by high costs, scarcity of teachers of western wind-dancing arts, and increasing demand for people to learn the performance of western-style wind music. This paper also proposes a method of using computer music technology to carry out the teaching of western wind music, and its core part is the teaching software of western wind music. The teaching software of western wind music arts must simulate the teaching process of western wind music artists and need to complete the teaching of theoretical knowledge and the guidance of students' playing practice. In the theory teaching of western wind music, this paper introduces the foreign products and their deficiencies, and puts forward the steps and framework for the realization of a western wind music software. In the counseling of students playing practice, this paper proposes a music evaluation system based on neural model, which is also the core part of this paper.

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