INNOVATION OF COLLEGE POP MUSIC TEACHING IN TRADITIONAL MUSIC CULTURE BASED ON ROBOT COGNITIVE-EMOTIONAL INTERACTION MODEL

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ABSTRACT

Emotional computing and artificial psychology is a new research direction that has received increasing attention in the field of harmonious human-computer interaction and artificial intelligence and is also a new intersection of mathematics, information science, intelligence science, neuroscience, physiology, psychological science and other multidisciplinary intersection. The current problems and drawbacks in the teaching of popular music in colleges and universities, and the search for methods and measures to reform and innovate popular music education in colleges and universities are the difficulties of current music teaching work. In this paper, we try to apply a robot cognitive-emotional interaction model to college pop music teaching, and establish an emotional interaction model based on reinforcement learning with the help of cognitive-emotional computing of human-computer interaction, to be able to integrate emotional interaction in pop music teaching and to make an accurate emotional analysis of students' singing effect. Different from traditional music teaching methods, the robot-based cognitive-emotional interaction model established in this paper can establish an innovative teaching model for college pop music teaching and optimize the teaching effect.

KEYWORDS

Robot cognition; Emotional interaction; Popular music; University teaching; Optimization and innovation

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1. INTRODUCTION

As human communication is natural and contains multiple emotions, it is also natural to expect computers to have the ability of emotional cognition in human-computer interaction. How to enable computers to recognize, understand, and generate human-like emotions has received widespread attention from disciplines such as computer science, brain science, and psychology, and has given birth to the intersection of cognitive-emotional computing [1-3]. As an important way to reflect the application value of artificial intelligence technology, the research of human-computer interaction systems has received common attention from academia and industry, and human-computer interaction products have gradually entered people's daily life. Influenced by the great satisfaction of material needs, people have begun to desire and pursue the sense of fit brought by human-robot interaction at the emotional level, and hope that robots can have the cognitive-emotional computing ability to generate advanced anthropomorphic emotions while satisfying daily interaction needs [4-5]. The study of cognitive-emotional computation for robots is the key to realizing advanced human-robot interaction technology with organic integration of emotions, which has important practical significance and high research value. The applications of robotic cognitive-emotional interaction models are also becoming more and more multifaceted. In the field of popular music teaching in colleges and universities, this paper is devoted to making innovations with the help of cognitive-emotional interaction robots for its disadvantages such as backward teaching model, preaching by the book and lack of vitality [6].

Intelligent human-robot dialogue systems, as an intuitive manifestation of intelligence in artificial intelligence technology, have become an important research component for achieving natural and harmonious human-robot interaction. In recent years, to improve robot anthropomorphism in human-robot interaction systems and create a harmonious and friendly human-robot interaction environment, researchers have conducted a lot of research around cognitive-emotional computing of robots in open domains, and numerous cognitive-emotional interaction models with important reference values have emerged. The literature [7-8] proposed an affective interaction model based on a guided cognitive reappraisal strategy to emotionally regulate external affective stimuli and promote the positive affective expression of the robot to some extent. In the literature [9-10], the cognitive emotion model of the robot is integrated into the smart home environment, and the cognitive reassessment strategy guided by positive emotion is obtained by optimizing and analyzing the cognitive emotion model of the service robot in the smart home environment using simulated annealing algorithm, and the probability of transferring emotional states is updated based on the cognitive reassessment strategy. Literature [11-12] proposed the multi-emotion dialogue system MECS, which tends to generate coherent emotional responses in dialogue and selects the most similar emotion as the robot response emotion. The literature [13-14] proposes emotional chat machines that can produce appropriate responses not only in terms of content relevance and syntax but also in terms of emotional coherence. In response to the teaching of popular music in colleges and universities, the American Education Act explicitly proposes that music

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education in schools should break with tradition and no longer be limited to the teaching and development of traditional resources, but expand to all aspects of popular music and contemporary music [15]. German universities believe that both elegant music and modern music should be actively drawn from the advantageous factors of these musicians in the teaching and development of universities so that students can have a richer musical vision from them and can be exposed to richer musical content [16]. With the continuous development of music education, the application of popular music in college education has become more and more extensive, making the music classroom in colleges and universities more colorful and further highlighting the function and value of popular music teaching.

Establishing and maintaining social connections with others is a basic human need in interpersonal relationships, and when users use more anthropomorphic robots as partners and establish relationships with them, they have a better willingness to continue interacting with these robots for a longer period than with those robots that are more rigid in their expression. As robots become more anthropomorphic, the user experience increases and the trust and dependence on the robot increase. In this paper, we investigate the application of emotional robots to the teaching of popular music in universities. First, we quantify the emotion analysis of human-robot interaction by multi-dimensional emotion description, which makes it possible for the robot to compute emotion. Then, the emotional input and output of human-robot interaction are simulated based on reinforcement learning algorithms, to establish its complete cognitive-emotional interaction model. Finally, the model is practiced in college pop music teaching, and a pop music teaching model that makes innovations in traditional music culture is proposed.

2. EMOTIONAL DESCRIPTION AND EMOTIONAL INTERACTION

2.1. AFFECTIVE DESCRIPTION MODEL

The ultimate goal of robotic cognitive emotion computing can be interpreted as giving human-like artificial emotions to robots in interactive systems by simulating human emotion processing to build trust between humans and machines. The main research content includes three parts: emotion recognition, emotion modeling and emotion understanding. Due to the complexity and abstraction of actual emotion, before establishing the robot cognitive emotion interaction model, it is necessary to recognize and quantify the emotion of the user interaction input content, and convert it into an emotion state vector that can be recognized and processed by the computer, and at present, according to its different ways of emotion description, the methods for emotion recognition and quantification The current methods for emotion recognition and quantification can be divided into dimensional emotion description models and discrete emotion description models.

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2.1.1. DIMENSIONAL SENTIMENT DESCRIPTION MODEL

The dimension-based emotion description model describes emotions as coordinate points in a state space composed of Cartesian product operations, each dimension in the state space corresponds to a psychological attribute of emotion, and the magnitude of the value on the dimension reflects the strength of the emotional characteristics corresponding to the psychological attribute, and the emotion description capability of this space covers all emotions [17-18]. In other words, that is, there is a one-to-one mapping relationship between the emotions that exist in reality and the coordinate points in the state space. At the same time, the similarities and differences between different emotions can be quantified and analyzed by calculating the distance between coordinate points. The basis of emotion calculation is to find this mapping dimensional theory, which regards the transition between different emotions as a continuous and smooth state transfer process. The dimensionality-based model of emotion description has received a lot of attention from scholars because it combines the characteristics of continuity and complexity of human emotion distribution. According to the different ways of dividing emotional attributes in psychology, dimension-based emotion description models have one-dimensional, two-dimensional, three-dimensional and more multi-dimensional spatial theories. Currently, the widely used dimensional description models are the two-dimensional activation-valence spatial theory (AV), where the Arousal axis is the activation dimension, representing the degree of pleasantness-unpleasantness, and the Valence axis is the valence dimension, representing the degree of agitation-calmness. The three-dimensional Pleasure-Activation-Dominance (PAD) spatial theory, in which the Pleasure axis is the Pleasure dimension, representing the degree of positive and negative affective states, and the Arousal axis is consistent with the Arousal axis in the AV spatial theory, representing the individual's level of neurophysiological activation. The AV spatial theory is shown in Figure 1, from which we can see that the emotional labels that exist in daily life can be mapped to coordinate points in space, and the magnitude of the corresponding coordinate values in each dimension varies according to the strength of each emotional attribute.

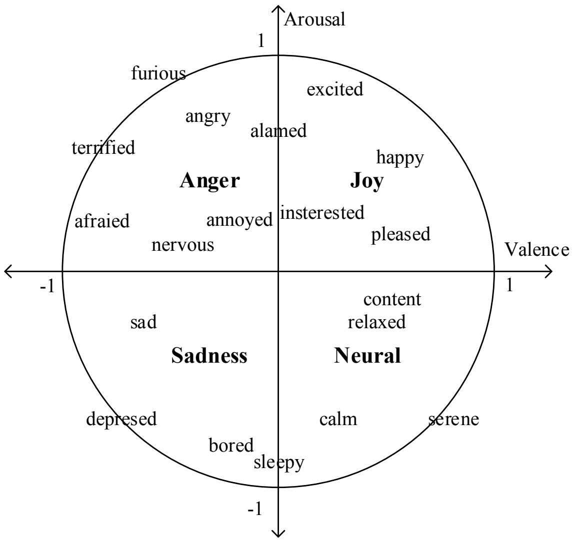

Figure 1. Activation Degree-Validity emotional space

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2.1.2. A DISCRETE SENTIMENT DESCRIPTION MODEL

Discrete models of emotion description describe emotions in the form of a finite number of adjective labels and are widely used in people's daily lives, as well as in early computational research on emotions. Rich linguistic labels can describe a large number of affective states, but which classifications are of higher research value? This question can be attributed to the classification of basic affective states based on adjectival labels [19-21]. In general, the categories of emotions that can cross different races and cultures and are shared by humans and socially oriented mammals are the basic emotions. Table 1 lists the definitions and classifications of basic emotions by different scholars.

Table 1. Definition of basic emotions by different scholars

Scholars	Basic emotions
Weiner, Graham	Happiness, Sadness
Watson	Fear, Love, Rage
James	Fear, Grief, Love, Rage
Panksepp	Anger, Disgust, Anxiety, Happiness, Sadness
Ekman, Friesen, Ellsworth	Anger, Disgust, Fear, Joy, Sadness, Surprise
Fridja	Desire, Happiness, Interest, Surprise, Wonder, Sorrow
McDougall	Fear, Disgust, Elation, Fear, Subjection, Tender-emotion, Wonder
Plutchik	Anger, Interest, Contempt, Disgust, Distress, Fear, Joy, Shame, Surprise
Tomkins	Anger, Interest, Contempt, Disgust, Distress, Fear, Joy, Shame, Surprise
Arnold	Anger, Aversion, Courage, Dejection, Desire, Despair, Dear, Hate, Hope, Love, Sadness

In summary, considering the rich and strong emotions of participants in open-domain HCI systems, the continuous model based on the PAD emotion space is chosen for the quantitative analysis of emotions in the open-domain cognitive emotion study of robots [22-24]. In closed-domain HCI systems, the emotions of the participants are simpler, and the discrete emotion model is chosen to classify the emotions into positive, negative and neutral when studying the cognitive emotions of robots for the closed domain.

2.2. COGNITIVE-EMOTIONAL COMPUTING FOR HUMAN-COMPUTER INTERACTION

In the long history of robotics research, researchers have focused more on the design and manufacturing of robots, control systems, drive systems, and content representation, until the introduction of "affective computing" and the gradual shift of

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robotics research to intelligent robotics, robot cognitive emotion research has received increasing attention [25-27]. The study of robot cognitive emotion has received increasing attention from researchers [25-27]. Emotion is a subjective response to a valued relationship, which is simply the process of perceiving the impact of external values on oneself, and to facilitate an intuitive understanding of this process, a triad can be used to represent cognitive affective computing formally:

$$SC = (S, C, W) \tag{1}$$

where S denotes the set composed of different types of information carriers such as text, speech and pictures. Different carriers contain different emotional features, and there are large differences between the representations of different features.

C denotes the set composed of different sentiment categories. C can denote a discrete set of sentiment states composed of several basic sentiment states, or a spatial set of sentiment states composed of different sentiment dimensions.

W denotes the set composed of different emotional trait intensities, and the intensities can be initially quantified into basic high, medium and low levels, or further subdivided.

Emotional features combined with intensity features form the core of cognitive sentiment computing. Cognitive sentiment computing first identifies and quantitatively analyzes the data features related to objective things extracted from different information carriers. Secondly, the affective features in the data features are calculated under different polarity dimensions to achieve the subjective affective perception of objective things. Finally, it is fed back to the participant with an appropriate sentiment expression. The cognitive sentiment computation can be further described as a combination of state space composed of S, C and W by Cartesian product operation, i.e:

$$SC = S \times C \times W \tag{2}$$

In recent years, the emergence of smart speakers and other devices has largely promoted the productization of human-robot interaction systems. In the process of cognitive-emotional modeling of robots, existing research has achieved better results in the extraction and recognition of emotional features. With the development of intelligence in various industries, research in AI-related fields has been greatly promoted, and its ultimate development goal is to establish intelligent bodies with the ability to observe the environment and to think and decide independently.

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3. THE COGNITIVE-EMOTIONAL INTERACTION MODEL FOR ROBOTS BASED ON REINFORCEMENT LEARNING

3.1. COGNITIVE-EMOTIONAL COMPUTING BASED ON REINFORCEMENT LEARNING

In the process of human emotion generation, individual emotional state responses are not only related to external emotional stimuli but also related to their emotional states and emotional interaction motives. When performing affective state response, we should not only consider the influence of contextual multi-round interaction context on the probability of transferring the current affective state but also consider the influence of the current affective state response on the subsequent interaction relationship. Therefore, to effectively carry out robot emotional strategy learning, this paper proposes to use reinforcement learning features to establish the correlation between contextual multi-round emotional state and current response emotional state, and perform cognitive emotion computation for the robot, and the computational framework is shown in Figure 2.

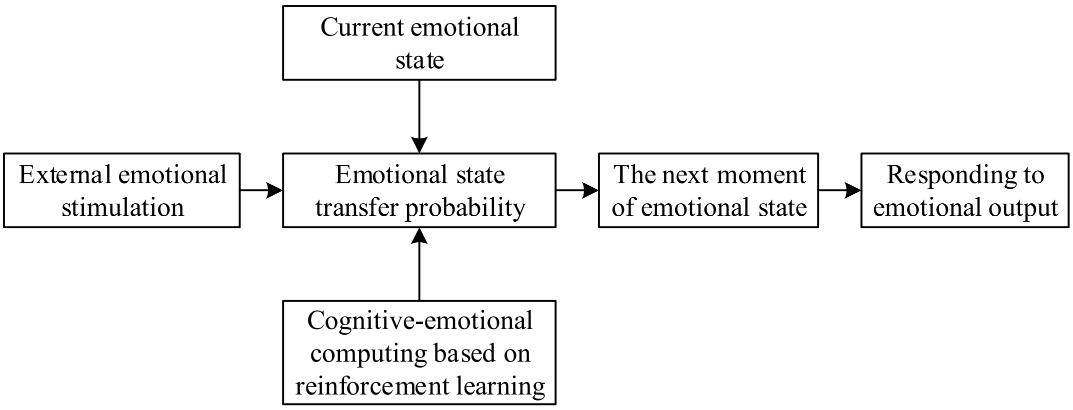

Figure 2. The framework of robotic affective computing

To facilitate the implementation of participant sentiment state tracking, sentiment quantification and state evaluation are performed on the interactive input content. In this paper, we quantify the sentiment of the interactive input content and obtain its corresponding sentiment value $E_i = (p, a, d)$ in the PAD continuous sentiment space. Secondly, the interaction sentiment value vector E_i is evaluated in terms of state, and its sentiment state vector $I(E_i)$ under the action of six basic sentiment states in the PAD continuous sentiment space is obtained. The emotion state evaluation function is defined as:

$$I(E_i) = [i_1, i_2, i_3, i_4, i_5, i_6] \tag{3}$$

$$\left.\begin{array}{ll} i_j = \dfrac{1/h}{\sum_6^{j=1} 1/h_j}, & h_j \neq 0 \\ i_1 = 0, i_2 = 0,1,\cdots, i_j = 1,2,\cdots, i_6 = 0 & \end{array}\right\} \tag{4}$$

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$$h_j = (E_i - E_j)C_j(E_i - E_j)^T, j = 1,2,\cdots,6 \quad (5)$$

where E_i denotes the interactive input sentiment value. j = 1, 2, …,6 denotes the six basic sentiment states of happy, surprised, disgusted, angry, fearful, and sad, respectively; E_j denotes the sentiment value corresponding to basic sentiment j.G_j denotes the covariance matrix of the clustering region of basic sentiment j. h_j denotes the distance between E_i and E_j. then denotes the assessed value of the affective state of E_i under the action of E_j.

3.2. EMOTIONAL INTERACTION MODEL BASED ON REINFORCEMENT LEARNING

The reinforcement learning model is based on the principle that intelligence, in its current state, performs a behavior to interact with the environment and enters a new state, while obtaining the corresponding immediate reward from the environment, and then evaluates this behavior according to the reward, and the reward value increases for behaviors favorable to goal achievement and decays for behaviors unfavorable to goal achievement, and this process continues to cycle until the termination state [28-31].

3.2.1. STATUS

The state s indicates the emotional state in which the intelligent body is, which is usually given by the external environment. To reduce the granularity of emotion division and increase the continuity and delicacy of robot emotion expression, the PAD continuous emotion space containing 151 emotion states is taken as the emotion state space of the intelligent body in this paper, and the emotion state vector of each emotion state in the space under the action of six basic emotion states is taken as the possible interaction input response emotion states.

3.2.2. BEHAVIOR

Behavior a denotes an action executed by the intelligent body in the interactive response process when selecting the next round of response emotional state with the search space of the emotional space size. The activity process of the intelligent body in the emotion space is the Markov transfer process between the emotional states in the emotion space.

3.2.3. DISCOUNT FACTOR

The discount factor γ can be used to calculate the future reward decay of the cumulative rewards of a state sequence when the environment is stochastic. In this paper, we consider that the more distant the future moment is from the current session, the smaller the effect of future rewards on the satisfaction used to measure the affective state of the next round of sessions. Its value is between 0 and 1. The

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greater the importance of future rewards is considered, the greater the value of γ, and vice versa the smaller the value of γ.

3.2.4. REWARDS

The reward r can be used to measure the future satisfaction of the obtained affective state after the intelligent body performs the corresponding action a. Both sides of the human-robot interaction have certain emotional motivations during the interaction. Based on the principle of interpersonal attraction in social psychology, the emotional motivation of robot interaction is set to achieve a certain degree of emotional affirmation, emotional guidance and emotional empathy for the participant, and the emotional reward function is constructed accordingly.

1. Similarity emotional reward function: Considering the process of interpersonal interaction, people often hope that the other party can produce similar emotional responses to themselves, to achieve the emotional affirmation of the participant, the cosine similarity is calculated to measure the similarity function between the emotional state vectors as

$$r_1 = S\left(E_{k+1}, E_k\right) = \frac{I\left(E_{k+1}\right) \cdot I\left(E_k\right)}{\left\| I\left(E_{k+1}\right) \right\| \left\| I\left(E_k\right) \right\|} \tag{6}$$

2. Positive affective reward function: Considering the process of interpersonal interaction, people will achieve some kind of emotional guidance to others by adjusting their emotional expression state. Therefore, to achieve emotional guidance for participants, this paper increases the participants' willingness to interact by setting the robot's emotional positivity guidance. In fact, the higher the positivity, the better, especially when the participant's emotion is negative, it may be counterproductive. The synergistic effect of positivity and similarity can effectively solve the problem of over-guidance. Therefore, in this paper, the positivity of the response emotional state vector is calculated as

$$r_2 = P\left(E_{k+1}\right) = P\left(I\left(E_{k+1}\right)\right) = \sum_{j=1}^{6} l_j i_j \tag{7}$$

3. Empathic affective reward function: Consider the process of interpersonal interaction in which interpersonal attraction is not only related to the similarity between individuals but is also influenced by complementary relationships with each other. Complementary relationships are influenced by the fact that people sometimes tend to prefer people who can complement them in some way. In emotional interactions, this can be interpreted as the expectation that the other person has empathy and resonates with them in terms of emotional expression. Therefore, this paper measures emotional empathy by calculating the interrelationships between emotional state vectors

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$$r_3 = M(E_k, E_{k+1}) = \frac{1}{1 + rank(E_{k+1})} \log_2 P(I(E_k) | a) + \frac{1}{1 + rank(E_k)} \log_2 P(a | I(E_k)) \tag{8}$$

For behavior a, the final reward it receives is the weighted sum of the above 3 reward measures

$$R(a | I(E_k)) = \alpha_1 r_1 + \alpha_2 r_2 + \alpha_3 r_3 \tag{9}$$

where α_1, α_2, and α_3 are the corresponding weight parameters, respectively.

3.2.5. STRATEGIES

The policy P is used to represent the probability distribution corresponding to when the intelligence chooses the next emotional state in the current state and can be expressed by the formula

$$\pi(a | s) = P_{RL}(I(E_{k+1}) | I(E_k)) \tag{10}$$

The initial value is the initial transfer probability between affective states. The model is generally optimized using a strategic gradient algorithm, so its value is related to the future reward value available for selecting the next affective state, with a greater probability of occurrence for actions that receive a large future reward value and correspondingly a smaller probability of occurrence for actions that receive a small future reward value.

3.2.6. MODEL OPTIMIZATION

The model update training is achieved by parameterizing the policy through the policy gradient algorithm, to maximize the future cumulative reward expectation by optimizing the model parameters. Therefore, the objective function is to maximize the expected value of future rewards, defined as

$$L_{RL}(\theta) = E_{RH(a_{1:T})}\left[\sum_{k=1}^{T} R(a_k, I(E_k))\right] \tag{11}$$

where $R_k(a_k, I(E_k))$ denotes the reward value obtained by acting a_k in the state $I(E_k)$; then the gradient is updated using the likelihood ratio technique

$$\nabla_\theta L_{\mathrm{RL}}(\theta) = \sum_{k=1}^{T} \nabla_\theta \log_2 P(a_k, \mathbf{I}(\mathbf{E}_k)) R(a_k, \mathbf{I}(\mathbf{E}_k)) \tag{12}$$

Finally, the parameter θ is updated using the obtained gradient values

$$\theta_{new} = \theta_{old} + \beta \nabla_\theta L_{\mathrm{RL}}(\theta) \tag{13}$$

When the cumulative reward expectation is maximized, the sentiment state corresponding to the resulting optimal policy is the optimal response sentiment state for the interaction input.

3.2.7. EMOTIONAL INTERACTION PROCESS SIMULATION

This chapter uses two Agents to simulate the emotional interaction process between the Agent and the external environment by continuously interacting with each other. The interaction process between two Agents can be described as follows: first, Agent 1 is given a random emotional state E_1, and then Agent 1 converts it into an emotional state vector $(E_1)1$ through emotional evaluation and then transmits this vector to Agent 2 as input, after which Agent 2 converts the corresponding response emotional value E_2 evaluation into an emotional state vector $I(E_2)$ back to Agent 1, and this process is repeated until the maximum number of interaction rounds is simulated. The interaction goal is to be able to select the optimal emotional state with the maximum future reward under the current interaction input emotional state. The emotional interaction process between Agents is shown in Figure 3.

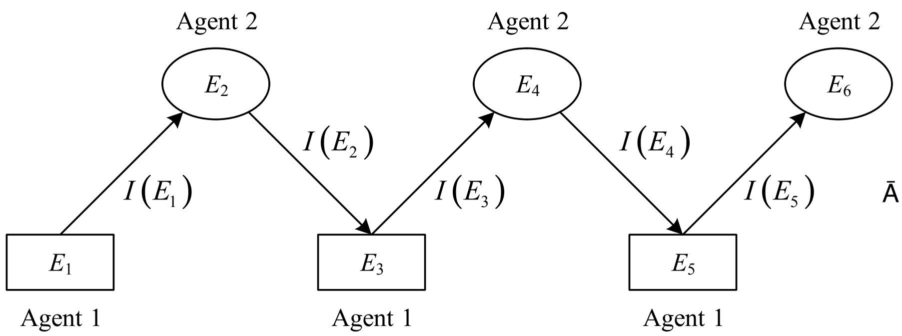

Figure 3. Emotional interaction process

The distance of spatial distance is used to map the similarity between different affective categories in the affective space. The transfer probability between emotional states differs with different distances and similarities between categories. The closer the distance, the greater the state transfer probability; conversely, the farther the distance, the smaller the state transfer probability. Therefore, to facilitate the calculation and analysis of the emotional states in response to external emotional stimuli, this chapter uses the top n emotional states in space that are closest to the Euclidean distance from the external emotional stimulus point as the candidate emotional states for each round of Agent interaction.

3.3. ROBOT EMOTIONAL STATE UPDATE

In this paper, the optimal response emotional value P_{RH}^{k+1} of the robot in continuous emotional space is calculated by combining the six basic emotional values with the probability of emotional state transfer E_{RH}^{k+1} obtained by the robot after being subjected to external emotional stimuli to achieve the emotional state transfer of the robot in

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continuous emotional space [32-33]. First, assuming that the optimal response emotional state vector obtained from the reinforcement learning model corresponds to a strategy p, the probability of transferring the response emotional state to the six basic emotional states based on the user input can be obtained as:

$$P\left(E_{k+1} | E_{HR}^{k}\right) = [P(1), P(2), P(3), P(4), P(5), P(6)] = \left[i_{p1}, i_{p2}, i_{p3}, i_{p4}, i_{p5}, i_{p6}\right] \quad (14)$$

Second, the $k-1$ rounds of robot response emotional state transfer probability P_R^{k-1} are updated by combining the $k-1$ rounds of robot emotional state transfer probability P_{RH}^{k+1} and the k rounds of interactive user input optimal response emotional state transfer probability $P(E_{k+1} | E_{\mathrm{HR}}^{k})$ with the following equation:

$$P_R^{k+1}(j) = P_{RH}^{k-1}(j) + c_j P(j) \quad (15)$$

$$c_j = \frac{P(j) - \min\left\{P\left(E_{k+1} | E_{HR}^{k}\right)\right\}}{\max\left\{P\left(E_{k+1} | E_{HR}^{k}\right)\right\} - \min\left\{P\left(E_{k+1} | E_{HR}^{k}\right)\right\}} \quad (16)$$

where c_j represents the confidence level of transferring the interaction input response emotional state to the 6 basic emotional states [34-35]. The resulting transfer probability P_R^{k+1} is then normalized to obtain the transfer probability of the $k+1$-round interactive robot response emotional state as:

$$\left.\begin{aligned} P_{k+1}(j) &= \frac{P_R^{k+1}(j)}{\sum_{j=1}^{6} P_R^{k+1}(j)} \\ P_{RH}^{k+1} &= \left[P_{k+1}(1), P_{k+1}(2), P_{k+1}(3), P_{k+1}(4), P_{k+1}(5), P_{k+1}(6)\right] \end{aligned}\right\} \quad (17)$$

Finally, the coordinate position$(p_{k+1}, a_{k+1}, d_{k+1})$ of the $k+1$ -round robot optimal response emotional value E_{RH}^{k+1} in the emotional space is calibrated based on the obtained robot emotional state transfer probability P_{RH}^{k+1}, which is calculated as follows:

$$\left.\begin{aligned} p_{k+1} &= \sum_{j=1}^{6} p_j P_{k+1}(j) \\ a_{k+1} &= \sum_{j=1}^{6} a_j P_{k+1}(j) \\ d_{k+1} &= \sum_{j=1}^{6} d_j P_{k+1}(j) \end{aligned}\right\} \quad (18)$$

$$E_{RH}^{k+1} = \left(p_{k+1}, a_{k+1}, d_{k+1}\right) \quad (19)$$

Based on the above conditions, the interaction input content emotion is quantified and evaluated based on the PAD emotion space, the user and robot emotion generation process in the human-robot interaction system is modeled using reinforcement learning, the long-term correlation between the current interaction input emotion state and the contextual long-term emotion state is established, and the model parameters are optimized and updated by maximizing the reward value expectation, and finally, the optimal response emotion state corresponding to the obtained user input is realized by updating the transfer probability of k + 1 rounds of robot emotion state, and the optimal response emotion state of the robot in the continuous emotion space can be obtained.

4. INNOVATION OF POPULAR MUSIC TEACHING IN COLLEGES AND UNIVERSITIES

4.1. POPULAR MUSIC AND TRADITIONAL MUSIC CULTURE

In the new era, the traditional music teaching mode is increasingly unable to meet the continuously growing spiritual and cultural needs of students, and pop music teaching in colleges and universities needs to develop in a diversified direction so that students can express their real emotions more intuitively through learning and mastering pop music. Pop music teaching in colleges and universities mainly presents the following characteristics.

1. Both artistic and popular
   The teaching of popular music in higher education should be fully based on art education, but on top of that, it should also ensure that it is more significantly popular to ensure that students can understand and accept it in the teaching process. In the teaching of pop music in colleges and universities, it is because of the artistic and popular characteristics that students are more likely to understand and sing it. In conclusion, the teaching of pop music needs to be both popular and artistic. In the process of development, universities should firmly grasp the pulse of the development of art education, distinguish it from other types of music, and make the teaching height continuously improve through more professional control.
2. Tradition and fashion intermingle
   The content of popular music teaching in colleges and universities have both characteristics of tradition and fashion. Tradition refers to the unique ideological nature of popular music over the years of development, which can, to a certain extent, pass on the culture and values of the era in which it lives, and has a stronger ideological appeal and influence, and that influence is fundamental to the continuous development of popular music, as well as being a characteristic that needs to be observed in the process of building popular music.
3. Integrating and diversifying at the same time
   The reason for this is that the curriculum should take into account the comprehensive quality and development requirements of students, and needs to have a certain degree of comprehensiveness, but also needs to add corresponding special practical courses to fully ensure that students can have a high level of comprehensive quality. In addition, pop music was established late, and it needs to integrate instrumental music, vocal music and music management in the actual teaching process to improve its perfection and become one of the more mature music majors, so it has a more significant comprehensive.

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4. Unity and independence are common

   Popular music in colleges and universities can also fully reflect the unity and independence of music in the teaching process. Unity mainly refers to the teaching process, teachers set the subject construction plan, curriculum system design and other content based on the curriculum design and other music majors' teaching methods. Based on this, the construction of each music major can maintain a high degree of unity, and the basic construction steps in the implementation process will not have a high degree of deviation, and can jointly promote the orderly development of the overall music major construction.

5. Inheritance and innovation co-exist

   Heritage and innovation is one of the characteristics of teaching popular music in colleges and universities, and also the purpose of teaching popular music in colleges and universities. Artistic, popular, traditional and fashionable belong to the characteristics of pop music itself, while inheritance and innovation are based on the artistic level for enhancement. The inheritance of teaching and professional construction of popular music in colleges and universities is mainly reflected in a variety of musical concepts, music construction and inheritance of traditional art music, in addition to the inheritance and expansion of the way of professional construction of conventional music and the development of the experience of art education in colleges and universities. Compared to other contents, the way of building conventional music is the inheritance of methods, while the way of developing popular music mainly targets the innovation level and is the most innovative compared to other characteristics. In actual teaching, the combination of inheritance and innovation can fully reflect the developmental qualities of the professional construction of popular music.

4.2. THE ROLE OF COGNITIVE-EMOTIONAL INTERACTIVE ROBOTS IN MUSIC TEACHING

The form of education is an inherent requirement of educational work, and it is also an inevitable requirement of society and the times for educational work. Educators in general should make more innovative and diligent research in teaching methods and approaches, work with diversified, multi-level and multi-angle music teaching methods, and incorporate the healthy parts and excellent parts of the many traditional music forms in China into the teaching contents, meanwhile, they should widely absorb the advanced teaching experiences at home and abroad, and show the many excellent music forms to students in the teaching process, so that they can It is also beneficial to the promotion and growth of these excellent forms of music to have more choices while relying on popular music.

Cognitive-emotional interactive robots can be used to create an intimate teaching atmosphere of mutual respect, mutual trust and mutual help, thus making the teaching relationship more pleasant and harmonious. In such a relaxed and pleasant atmosphere, students' self-confidence will be improved and they will develop lively, cheerful and positive psychological qualities, which can not only relieve some of the

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more common bad emotions such as nervousness and anxiety in the college pop music classroom, but also increase the fun of learning pop music and turn pop music learning into a happy and joyful thing, and face the future with a more positive They will be able to face the present and future with a more positive attitude.

The high school pop music classroom is required to teach specific one-on-one lessons. The teaching process begins with listening to the student's singing of the song, then finely identifying any vocal problems that arise and giving the student specific instructions on how to perform the song. The student then imitates and sings according to the Emotion Robot's analysis and suggestions, while at the same time, the Emotion Robot accurately listens to see if the sound the student is making is up to snuff, similar or consistent with what the Emotion Robot expects, and guides the student to find the correct vocal method for singing.

The classification results of the cognitive-emotional interaction robot are shown in Figure 4 by recording and analyzing 15 pop music singing performances of multiple students.

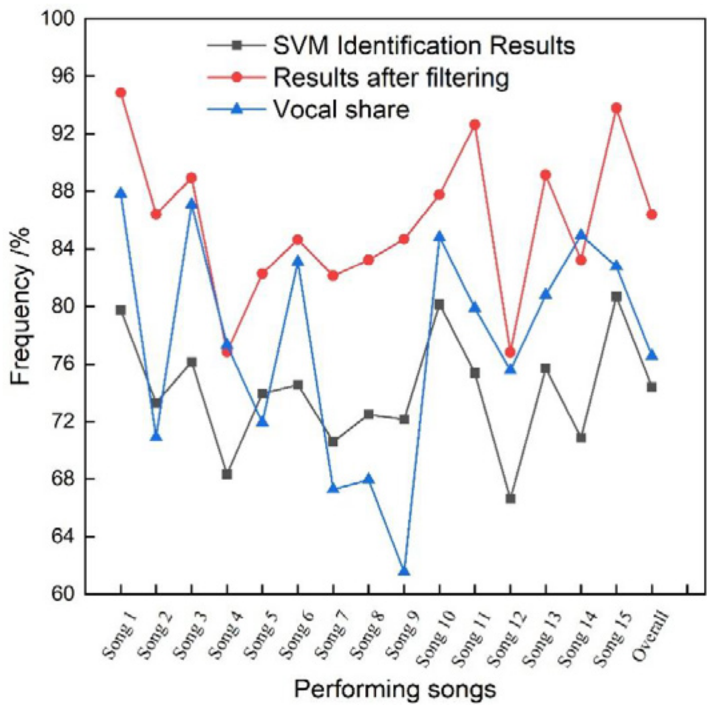

Figure 4. Vocal and musical classification

Figure 4 gives a detailed comparison of the intermediate results of classification based on the SVM classifier and the final classification results after low-pass filtering, as well as the percentage of human voices in each song. It can be seen that the SVM-based classification method and the post-processing filtering mechanism are effective. The first two songs are rap-style songs, which show strong linguistic properties, so MFCC combined with the classical model of traditional speech recognition like SVM has got good results on them. The classification effect of the 4th song and the 12th song is poor, the former as a Cantonese song has a great difference in vocal characteristics from the training data; the latter female voice is more difficult to distinguish from the music and cannot effectively capture the difference between the

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human voice and music. In contrast, the classification method of the cognitive-emotional interactive robot is effective in terms of the overall classification effect.

The cognitive-emotional interaction robot was also able to identify the emotion of the student's pop music singing to compare it with the emotional tone of the original song, and the results are shown in Figure 5.

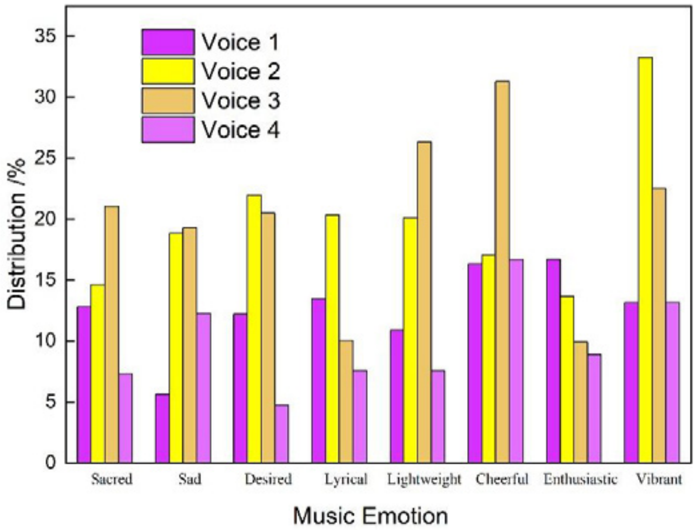

Figure 5. Emotion recognition in music singing

It is not difficult to find that data points of various types of emotions are intertwined on the vector space due to the existence of errors in the data, and since the projection process is a linear transformation, the fusion of data with each other has a small impact on the accuracy of the robot cognitive-emotional discrimination based on reinforcement learning. Based on the basic rhythmic information, the cognitive-emotional interactive robot can perform the initial recognition of basic emotions. Although the recognition results need to be further improved, this conclusion can be applied to musical emotion recognition systems where recognition accuracy requirements are not very stringent. Further, we can use a neural network approach to perform more accurate emotion information recognition using a more adequate set of feature parameters and apply it to improve the recognition rate and robustness of the music recognition system and achieve more human and intelligent human-robot emotion interaction.

5. CONCLUSION

The current intelligent development of human-robot interaction systems has reached a high level, and robotic cognitive-emotional computing has received more and more attention from researchers as an important research component of its intelligent development. In this paper, we carry out research work on the problems of robot cognitive-emotional research in open-domain and closed-domain systems, propose a robot cognitive-emotional interaction model based on reinforcement learning, and apply the model to the innovation of university popular music teaching in traditional music culture. The integration of Chinese traditional music culture in pop music professional education can well cultivate students' traditional music culture literacy and traditional music culture communication ability. The combination of modern information technology and artificial intelligence technology is in line with the development trend of pop music, and the efficient combination of the two can inject more contemporary vitality into pop music, stimulate the musical creativity of college students, and improve the students' artistic professionalism and social competitiveness.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

CONFLICTS OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this paper.

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