Music Style Recognition and Simulation: Combining CAD and Reinforcement Learning Methods

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Abstract. Music, as an art form to express emotions, occupies an important position in people's spiritual world and social development. At present, the number of professional music creatives and music styles is limited, and the production cost is time-consuming and laborious. Although it accompanies us all the time in our lives, the art system of this special organizational structure still has great obstacles in the in-depth study. In this paper, based on CAD technology and reinforcement learning algorithm, music style recognition and music creation simulation are studied. Firstly, it analyzes the development of music style and the application status of CAD technology and reinforcement learning algorithm and analyzes the music style characteristics and influences elements from the music style system. Then, CAD technology will be used to identify the music style and establish the 3D model of the animation form. The CAD 3D simulation system is used to reflect the curve changes of different music styles and display them on the computer screen in real-time. Finally, with the help of a reinforcement learning algorithm, a method of training neural network generation is proposed to simulate music creation. The introduction of trained reinforcement learning decisions can evaluate the value of the output notes, thus updating the musical notation and allowing the generation of specific musical styles. This method breaks through the limitations of traditional music styles and can complete the music simulation task under the condition of multiple music styles and similar data types. The results show that the music style recognition based on CAD and reinforcement learning algorithm is accurate and that the quality of the generated simulated music material is high.

Keywords: Musical Style; Style Recognition; Music Simulation; CAD Technology; Reinforcement Learning Algorithm
DOI: https://doi.org/10.14733/cadaps.2025.S7.201-213

1 INTRODUCTION

As an element that appears in life all the time, music uses a variety of organizational factors to complete the content of viewing, listening, impression, and other influences [1]. Music is also an indispensable art in people's spiritual world, which can express the self-cognition of music creators to the external world. At the same time, the creators use this kind of explicit artistic communication to explain their pursuit and mood to the world. There are different languages and cultures in different parts of the country, but everyone can communicate across borders through music communication. Not only that, but music can also transcend time and space. Since ancient times, music has been everywhere, whether it is in daily life or participating in music appreciation and other activities, this artistic feature full of spiritual creation has been deeply rooted in people's hearts [2]. Music style itself contains immeasurable spiritual value; it can help people to complete spiritual communication, but it can also bring depressed people hope in life. It can not only enrich our bodies and minds but also improve work efficiency. When we hear a song in our lives, we can't help but adjust our body posture following the music style. Even people without musical cells can complete this involuntary action, which is the human instinct [3]. Musical style reflects the overall characteristics of musical works and is the basis for people's music appreciation and research in the field of music. The music style accessible to the public is the music with a relatively single melody, narrow vocal range, and high recognition. It can also be seen from the music list survey in recent years that various musical works of different instruments have gradually entered our field of vision. The characteristic structure of musical style can change with the choice of music, and this complicated music recognition process has always been a difficult problem for researchers [4].

Traditional music style recognition can only be based on artificial hearing, while the development of modernization has brought new opportunities for the style recognition of music genres. It has been found that CAD technology and reinforcement learning algorithms have good application effects in music style recognition and simulation. The three-dimensional modelling method of CAD technology is used to input the music style graph into the dynamic model and judge the correspondence of music styles according to the fluctuations of different tracks. Using reinforcement learning algorithms, Markov model, and other machine learning to simulate human learning style can also effectively realize the simulation and reconstruction of music style recognition. Various factors in works of different music styles may lead to deviations in the extraction of music signals. Using the network-level training of reinforcement learning algorithms, music-style features can be collected to improve accuracy further and automate creation [5]. Music, as a complex art form that integrates sound, rhythm, melody, and lyrics (if any), naturally requires collaborative processing of multimodal data for style recognition and simulation. By utilizing the powerful capabilities of CNN, local features such as spectrograms and Mel frequency cepstral coefficients (MFCC) can be effectively extracted from audio signals, which are crucial for capturing basic attributes such as rhythm and timbre of music [6]. By combining CNN with LSTM/Bi LSTM, a multi-level and multi-scale fusion of audio features can be achieved, improving the accuracy of music style recognition. Meanwhile, LSTM or Bi LSTM networks are adept at processing sequential data and can capture the structural and dynamic features of music that change over time, such as the ups and downs of melodies and the transitions of harmonies. Using NLP (Natural Language Processing) techniques, such as Bi LSTM-based text sentiment analysis models, can provide a deep understanding of emotional tendencies, themes, and cultural backgrounds in lyrics. These pieces of information are of great significance for accurately locating music styles [7]. For music works that contain lyrics, the lyrics often contain rich emotional information and stylistic clues. Similar to the combination of speech and text in emotion recognition, music style recognition can integrate audio features, lyrics content, and possible visual elements (such as scenes and costumes in music videos) to form a multimodal analysis system. In addition, word embedding techniques can be used to convert lyrics into representations in a high-dimensional vector space, further mining semantic information in the lyrics.

Regarding the interpretability issue of the BMNet-5 model, some scholars have introduced the SHAP (Shapley Additive exPlans) model school to develop optimized results for subsequent interpretable models. In summary, BMNet-5 technology and its potential applications in music style recognition and simulation provide new ideas and tools for the inheritance and development of language music and even global music culture. This not only enhances the transparency of model decision-making but also helps us to gain a deeper understanding of how the model judges music simulations based on audio features and provides more accurate guidance. Single-mode emotion recognition technology has made it difficult to meet the increasingly complex needs of emotion analysis, especially in the field of music style recognition and simulation. Moreover, CAD (computer-aided design) and reinforcement learning (RL) methods can be combined to achieve more accurate and personalized music creation and recognition [8]. The use of the Bi LSTM network can effectively parse the context dependency and semantic information of lyrics, further enhancing the accuracy of style recognition. Similar to speech processing in emotion recognition, the combination of CNN and LSTM (or its variants such as GRU) can be used to capture local features (such as notes and pitch) and long-term dependencies (such as melodic lines and rhythm patterns) in audio. CAD technology provides a highly visual and interactive platform for music creation, enabling composers to design music structures and elements [9] accurately. However, CAD tools often focus on technical implementation rather than creative generation. These algorithms can learn and simulate specific music creation rules and generate music works that conform to the target style through continuous trial and error and optimization. In this way, CAD not only serves as a creative tool but also becomes an experimental field and feedback source for reinforcement learning models. In music style simulation, a reward function can be set to encourage the generation of music sequences that conform to specific style characteristics [10]. In order to enhance the performance and creativity in this field, some scholars have proposed the concept of multimodal emotion recognition models based on speech and text, which can inspire us to explore new ways of multimodal fusion in music style recognition and simulation. Meanwhile, as a textual modality, lyrics contain rich emotional and thematic information, which is particularly important for distinguishing certain styles such as pop, rock, and folk. In music style recognition, audio signals (such as melody, rhythm, harmony, etc.) are the primary and crucial source of information. Reinforcement learning guides AI systems in learning how to make decisions to achieve predetermined goals by defining reward functions.

In the future, with the continuous advancement of technology and the accumulation of data, we can expect more breakthroughs in the field of music style recognition and simulation. By combining CAD, reinforcement learning, and 3D-DCDAE, we can construct a comprehensive music style recognition and simulation system. The system first learns latent representations from a large amount of unlabeled music data using 3D-DCDAE and then uses these representations as inputs for CAD and reinforcement learning models. In addition, the system can also make adaptive adjustments based on user feedback, further improving the satisfaction and personalization of music creation. CAD systems create music based on style features, while reinforcement learning models continuously optimize the generated music works to make them more in line with the target style. Meanwhile, interdisciplinary cooperation and communication will inject new vitality into the development of this field. By integrating various technologies such as CAD, reinforcement learning, and deep learning, we are expected to create more diverse and innovative music works, promoting the deep integration of music art and modern technology.

2 THE DEVELOPMENT OF MUSIC STYLE, CAD, AND REINFORCEMENT LEARNING ALGORITHM

CAD system utilizes computer technology and combines multiple disciplines to complete data collection, storage, and analysis. In the field of music, using CAD models to construct music structures is also an important component of music analysis. From the classification of music styles, rock, jazz, classical, and modern music all have their unique characteristics in form and content. The development of works is not only influenced by the times, themes, society, and culture but also showcases the development process of each society. Many people prefer music styles with high pitch, light tone, moderate speed, and intensity. How to accurately find one's favorite music style is the basic task of music recognition and classification. To accomplish this task, Qiu et al. [11] used a CAD system to filter out all content outside of sound objects, simplify the noise in the environment, and treat the audio in the music style as subjective objects to analyze the music structure in a scientifically intelligent way. CAD technology is far from limited to the field of music, and in large enterprises, using CAD to complete drawing design and 3D modelling has become the main means of increasing business revenue. When developing new design products, the technical department will add detailed parameters to the CAD model according to product requirements. This computer-aided modelling tool is widely used in the manufacturing of 3D animation products in the United States. Based on the client's requirements for animation elements, Rajesh and Nalini [12] will create these design concepts in a CAD modelling system. In addition, Japan has also applied CAD systems to virtual factory production lines. Through this virtual modelling, observers can see how the production workshop constructs related products. Designers can also make detailed adjustments to various parameters in the 3D model provided by CAD. Given the development of reinforcement learning algorithms, we can also study the field of music. In the 1990s, people began to add machine learning to manual judgment to distinguish music genres and styles. The main task of this project is to have experts divide different music details into modules based on their understanding of music, and then add the data from the modules to the training process of reinforcement learning algorithms. Faced with massive amounts of data, reinforcement learning algorithms have demonstrated their outstanding computing power. On this basis, people began to attempt to simulate music styles and conduct research on automatic generation for the first time. Later, Solanki and Pandey [13] proposed that reinforcement learning algorithms should be added to the computation of massive music data to determine autocorrelation coefficients and further analyze music features in advance. This advanced analysis enables people to easily perceive changes in loudness, pitch, timbre, and other content, and then complete recognition and classification through classifiers. It can be seen that CAD technology and reinforcement learning algorithms play a prominent role in the field of music.

Music genre classification (MGC), as a key technology for organizing and managing music data, is not only crucial for optimizing music recommendation systems, precise advertising placement, and streaming services, but also provides a foundation for in-depth exploration of music style recognition and simulation. Therefore, combining deep learning (DL) methods, especially exploring the classification of different language music genres, is not only a technical challenge but also a contribution to protecting cultural diversity. The BMNet-5 technology proposed by Yang and Li [14] is an innovative attempt to solve the multi-category classification problem of different language music genres. BMNet-5 is based on advanced neural network architecture and achieves high-precision classification of music genres by extracting audio features from large-scale music datasets in different languages. In addition, the research results of BMNet-5 can be combined with the concept of "music style recognition and simulation. Combining CAD and reinforcement learning methods" to explore its potential applications in music creation and style simulation. However, relying solely on CAD technology may make it difficult to capture subtle changes and improvisational elements in specific music styles. CAD (Computer Aided Design) technology provides powerful tools for music composition, enabling composers to accurately design music elements and structures. At this point, the BMNet-5 model can serve as a style recognition engine, providing real-time style guidance for CAD systems. Especially in the unique and rich cultural field of music in different languages, although traditional statistical and machine learning methods have achieved significant results in music classification in mainstream languages such as English, research on music classification in different languages is still in its infancy. Ensure that the created music works meet the predetermined style requirements while maintaining personalization and innovation. Its success is not only reflected in an accuracy of 90.32% but also opens up new research directions for the classification of different language music genres.

With the explosive growth of music data, especially the widespread application of unlabeled data, how to effectively utilize these resources to improve the performance of music style recognition and simulation has become a key challenge. However, traditional CAD tools often focus on the automation of structural design and orchestration processes, while ignoring subtle differences and dynamic changes in music styles. CAD technology has been widely applied in the field of music creation due to its precision and flexibility. It not only opens up new paths for music genre classification but also provides strong support for in-depth exploration of music style recognition and simulation. On this basis, Yang [15] believes that further exploration can be conducted on how this method can be combined with CAD (computer-aided design) and reinforcement learning (RL) methods to promote cutting-edge developments in music creation and recognition. By incorporating the potential musical expressions learned from 3D-DCDAE into CAD systems, style-based creative guidance can be provided for composers. In terms of music style simulation, reinforcement learning has demonstrated its powerful learning ability. Specifically, 3D-DCDAE can capture deep features in music data, such as melody direction, harmony patterns, etc., which are key factors defining music style. By defining a reward function to encourage the generation of specific styles of music clips, reinforcement learning algorithms can continuously optimize the generation model to make its output closer to the target style. CAD systems can automatically adjust music parameters based on these features, helping composers quickly generate music works that meet specific style requirements. However, traditional reinforcement learning methods may face challenges such as complex state spaces and difficulties in designing reward functions. The potential music representations extracted by 3D-DCDAE can serve as input features for reinforcement learning models, greatly simplifying the complexity of the state space while providing rich music-style information. In this way, reinforcement learning algorithms can more effectively learn and simulate music works of different styles, achieving more natural and personalized music creation.

3 RESEARCH ON MUSIC STYLE RECOGNITION AND SIMULATION

3.1 Research on Music Style Recognition System Based on CAD Technology

With the rapid development of the Internet and modern cities, people have begun to come into contact with different musical elements across the country, and the happy mood brought by music styles is shown in various forms in our lives in different countries and regions. It is always able to express people's thoughts and convey people's thinking in the spiritual world. It can be seen that music, with its own special value, occupies a position in the field of research. Until now, the variety and number of Musical Instruments related to music is also countless, and the storage of music is more diversified. The creation of Musical Instruments and the way music was stored promoted the formation of musical genres. This paper focuses on the research of music style recognition. Firstly, through the literature review related to music style recognition, it is found that people gradually try to apply computer-aided design systems in the field of music recognition. CAD software is used to analyze the basic elements of music, and various elements such as treble, bass, timbre, and tone quality of music are added to the model calculation. The functional process of music style recognition by CAD system is briefly expounded, as shown in Figure 1.

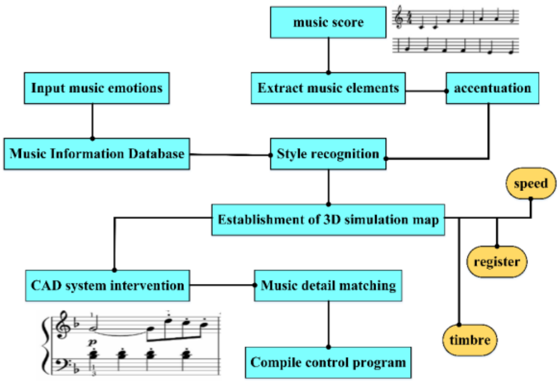

Figure 1: Functional flowchart for music style recognition.

As can be seen from Figure 1, we imported music style music into the CAD system, extracted music elements according to the audio changes in the score, and completed the comparison of the song information database in pattern recognition. Then the control program is formed through 3D simulation and music detail matching. In the process of recognition, the emotional template is also added, which can be classified and identified by analyzing the emotional tendency of the music style. In order to better distinguish the changes in different musical styles, we have calculated the speed, range, and intensity of various musical styles, as shown in Table 1.

Style types	*Style tendency*	*tempo*	*register*	*strength*
Jazz style	sacred	70-85	Baritone	50-60
	serious	60-70	Baritone	45-55
	noble	70-90	Baritone	40-50
Modern style	express one's emotion	90-95	middle note	90-130
	Cheerfulness	95-115	middle note	95-125
	excite	110-120	high profile	110-120
classical music	calm	65-70	middle note	70-80
	elegant	70-75	middle note	75-85

Table 1: The speed, range, and intensity of various music styles.

As can be seen from Table 1, in jazz-style music, the three tendencies of sacred, serious, and noble are also different in speed, and they are basically in the middle of the vocal range classification. In modern style music, the three tendencies of lyric, cheerful, and exciting music are faster. In the classical music style, the strength of the two tendencies of calm and elegance fluctuates in the medium range. Next, we analyze the musical rhythm characteristics in different musical styles. The music signal is decomposed into coefficients of different sizes, and the fluctuation of coefficients is processed. In general, when the signal frequency is low, it shows stronger regularity in the time domain. However, when the signal frequency is higher, it shows a more volatile curve in the time domain. Using the above characteristics, we collect the frequencies of music signals of jazz, classical, and modern music styles, and their fluctuations in the time domain are shown in Figure 2.

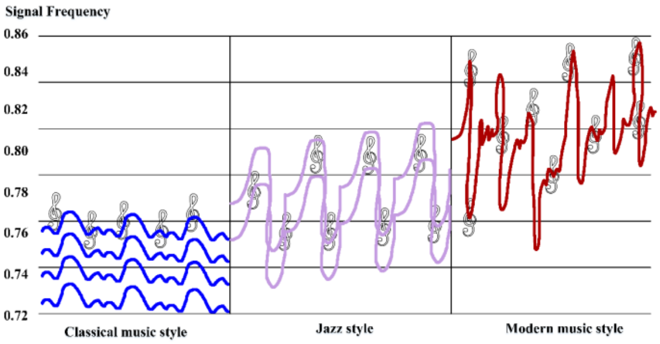

Figure 2: The frequency of music signals for three different music styles.

As can be seen from Figure 2, the classical music style signal frequency is lower, and the music signal fluctuation is more regular. Jazz is in the middle range, and modern music is mostly upbeat, so the signal frequency feedback is strong volatility. In the same style of music works, its sound frequency, vibration, time, sound wave and other parameters have partial and overall similar characteristics. Any musical work is an independent living body. In the whole process, timbre and sound are most easily perceived by people. Therefore, in order to objectively identify the differences in musical styles, we also need to complete the simulation of musical styles under different conditions in the future to judge the effect of musical style recognition.

3.2 Research on Music Style Simulation Generation Based on Reinforcement Learning Algorithm

For a long period of time, music style and music style classification have been influenced by the market and the creation of artists. Each music style has its own different characteristics, some styles are duller, some are more cheerful, and these music styles show the personality differences of different musicians and composers. At the same time, there are some music classification labels that are not defined according to people's sensory levels but contain the appropriate style types formed by regional culture. In order to make the classification of music style more accurate, there are many types of research such as music style recognition. The characteristics of each piece of music not only show the essential properties of music but also show their own unique scale in order to distinguish different structures from other music. In order to simulate the same type of music after music style recognition, we need to extract music features. There are many methods of extraction, but in the face of such dynamic irregular changes, the reinforcement learning algorithm in machine learning can effectively solve the problem. In order to verify that the reinforcement learning algorithm is the most suitable for handling the music-style simulation task in machine learning. We input the audio wave image of each piece into the learning model and use all the data to complete the evaluation of different algorithms. The frequency capture efficiency of four types of algorithms, namely support vector machine, random forest, logistic regression and reinforcement learning, was tested respectively, as shown in Figure 3.

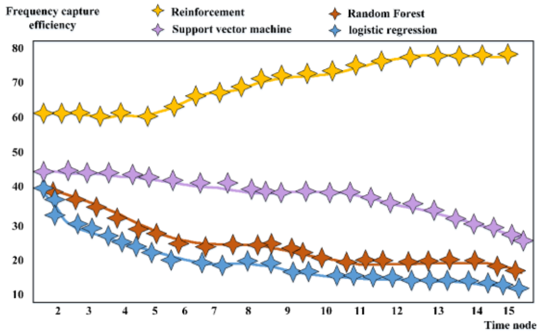

Figure 3: Frequency capture efficiency of four types of algorithms.

It can be seen from Figure 3 that in cross-validation, when faced with time-frequency fluctuation characteristics, the best performance of the machine learning model is the reinforcement learning algorithm, while the other three algorithms have a poor ability to capture frequency. Reinforcement learning algorithms, as an important part of machine learning, do not rely on dynamic data but use learning strategies in environmental interaction to achieve target calculation, etc. Data will be saved in each training, which is the most important data source for reinforcement learning. This method can not only avoid the system complexity caused by the pre-marked data in the training data but also guide the agent to complete the learning task in the automatic case by setting a reasonable reward function. We will demonstrate the reinforcement learning model and its structural components in music style simulation, as shown in Figure 4. As can be seen from Figure 4, the music graph data is input into the reinforcement learning environment, and the final result output is completed through the training of states, agents, and optimal actions.

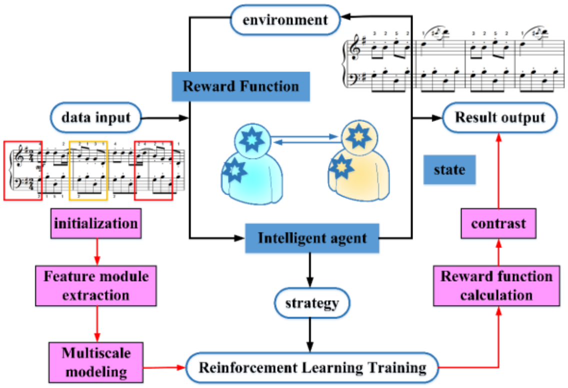

Figure 4: Structure of music style simulation system.

At the same time, in the process of reward function optimization, feature extraction is carried out for the training data of each section of the music atlas. After multi-scale modelling, new notes are generated in the optimization of the reward function. The generated notes also need to be compared with stylistic characteristics to ensure that the automatically generated music score is consistent with style. Excellent reward function setting can guide the target to complete more reasonable tasks. Achieve maximum accumulation according to corresponding rewards and punishments. Because of the high abstractness of music composition rules, there are great differences in the creation of each music style. Therefore, this approach, which is difficult to quantify, requires additional attention in the construction of reinforcement learning reward functions. First, we use the reinforcement learning model to model the structural features of music style. In the model, the topic task is solved using the sampling method for clustering music data of different sizes. The formula is as follows:

$$p(z_i = k \mid z, w) = \frac{n + B}{\left| \sum_{z=1}^{k} n_k \right| - 1} \tag{1}$$

$$p(w) = n + a_k \times [\sum_{i}^{m} n(v) + b_v] + 1] \tag{2}$$

The formula, z_i Indicates the deleted musical scale. Based on the number of times a fragment appears in the theme music, verify which level of the musical category the style is distributed in. According to the conditional probability distribution of music fragments, the probability formula is used to converge all the calculated results iteratively. Take two invariants as key feature points of music works and define the formula as follows:

$$H_r = H - H_{\min} \tag{3}$$

$$L = \frac{L}{L_{\min}} \tag{4}$$

Among them, H_r For the lowest pitch, considering the arbitrariness of the music graph itself, we also add the autocorrelation function as the input value of the model. For the two-dimensional features of such fragmented music, the binary graph formula is defined as:

$$f(x,z) = \begin{cases} 1,(x,y) \\ 0,(x,y) \end{cases} \tag{5}$$

$$g(u,v) = \int_{-\infty}^{+\infty} f(x,y) f(x+u, y+v) dx dy \tag{6}$$

Among them, $g(u,v)$ Represents the autocorrelation function, in the geometric sense, the overlapping regions of the frequency features of the music map are the same musical style works. Standardize the autocorrelation function to simplify the calculation process:

$$G_0(u,v)=\frac{g(u,v)}{A} \tag{7}$$

$$G_0(u,v)_0=g(x,y)+f(x,y)dxdy \tag{8}$$

The calculation results can meet the invariants and the same frequency characteristics at the same time, and the reward function is redesigned in the formula. Ordinary manual rewards can only complete the definition of specific data according to the upper and lower characteristics, which is rough and can only consider limited information content. We design a theme-extracted reward function formula for the musical style corpus and transform the musical sequence into a separate encoding content, which is linked to the current structural features. Define the reinforcement learning rate and the reward function formula under the current strategy:

$$r_t=\ln p(a\mid s)+\sum_{i}^{w} w\ln p(note) \tag{9}$$

Add loss function to complete further optimization of the formula:

$$L(o)=IEb[r+y\max Q(s,a,o)] \tag{10}$$

$$\pi_o=\arg\max Q(s,a,o) \tag{11}$$

Considering that the selection of the conditional probability principle will lead to a higher repetition rate of the generated musical style, in order to solve this problem, we also add polynomial calculations to the corresponding notes. The probability of generation for each music style varies with the audio characteristics:

$$e_t=(s_t,a,r_t,s+1) \tag{12}$$

Among them, e_t Indicates the current status. In the reinforcement learning model, if the action selection meets the reward function condition, the resulting sequence formula is as follows:

$$m_t=\ln p(o\mid s)+r_m \tag{13}$$

By maximizing the reward purpose of the decision execution action, the prediction of the future reward factor is completed:

$$Q(s,a,u)_t=r+y(m,o)_{\min} \tag{14}$$

$$L(p)=\sum_{a+1}^{t}[(a\mid s)+y(x)mn] \tag{15}$$

Through the above formula, we can realize the simulation and generation of music style frequency characteristics.

4 RESEARCH RESULT ANALYSIS OF MUSIC STYLE RECOGNITION AND SIMULATION

4.1 Analysis of Research Results of Music Style Recognition System Based on CAD Technology

Music style reflects the basic characteristics and attributes of music works and is also the basis of music appreciation, analysis and research. The classification and recognition of musical styles are of great practical significance to the creation and innovation of works. Since the music genre is a fuzzy problem in judgment and discrimination, we use a CAD computer-aided model to transform it into a visual music map to complete the style recognition and classification. As the need for retrieval, the key influencing variables must be found for the rhythm, melody, harmony and timbre of different musical styles. Usually, the characteristics of a piece of music will change with the structure of the music, and it is not unique. In our research, we found that the most closely related to music is rhythm and pitch. When the rhythm is determined, it is possible to identify which style the music belongs to regardless of the timbre or speed. In order to verify the effect of the CAD computer-aided model on music style recognition, we selected two pieces of music with different styles and used a CAD model to generate a music map, as shown in Figure 5.

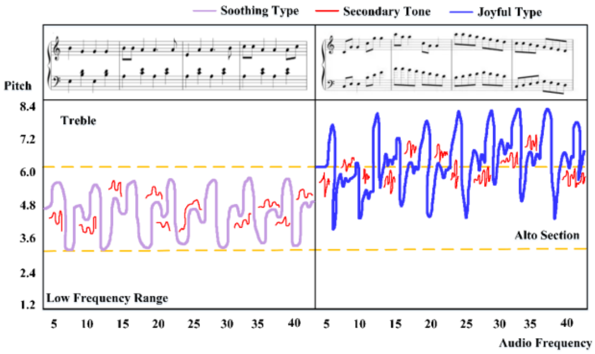

Figure 5: CAD model music graph generation results.

As can be seen from Figure 5, the two styles of music are soothing and cheerful, respectively. It is evident in the soothing type that the tempo is slower, and the pitch stays in the middle range. The cheerful music style has a large frequency fluctuation, and the pitch fluctuation is between the middle and the high. Next, we choose the score of Blue Danube as the detection source of recognition accuracy and compare the changes in recognition accuracy between CAD technology and ordinary audio analysis technology, as shown in Figure 6.

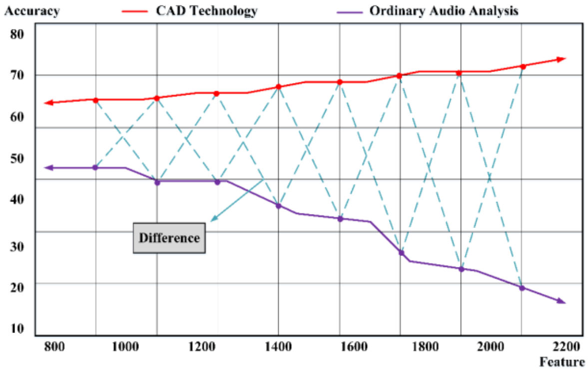

Figure 6: Changes in recognition accuracy between CAD technology and conventional audio analysis technology.

As can be seen from FIG. 6, more musical feature points are produced by musical scores. As the number of feature points increases, the accuracy of common audio analysis techniques decreases significantly, which indicates that the processing of audio information is susceptible to external interference. However, CAD technology modelling is significantly more accurate in detecting the two kinds of music. Using CAD modelling and simulation, the music map is displayed in the virtual software, and the designer can complete the classification of music style according to the change in music frequency. At the same time, the accuracy and efficiency of the CAD model can meet the experimental requirements. It can be seen that the CAD model is effective in music style recognition and can provide help for the subsequent music style simulation generation.

4.2 Analysis of Research Results of Music Style Simulation Generation Based on Reinforcement Learning Algorithm

In this study, we choose the CAD model as the basic structure of music style recognition and randomly extract audio information from network data as the input sound source. The advantage of the sound source in this big data environment is that the music characteristics are easy to obtain. On this basis, we can analyze the complex characteristics of melody, harmony, rhythm, and so on, identify the style types of musical scores, and divide the whole piece into several fragments. Since a music score is often composed of hundreds of bars, it will be very time-consuming and laborious to identify and simulate the melody style in the whole music range. Considering that the change of rhythm and tone often means the emergence of a new style, we make a preliminary division of these two characteristics in the music style simulation, in order to narrow the range of melody and improve the time of simulation generation. In order to complete the automatic generation of music style simulation, we add a reinforcement learning algorithm to the research and automatically generate the required music works based on the three-dimensional map provided by the CAD model. During the experiment, we input 2000 groups of music elements as the basic structure of work generation, and compare the changes in the efficiency of music style simulation generation between the reinforcement learning algorithm and general machine learning algorithm, as shown in Figure 7.

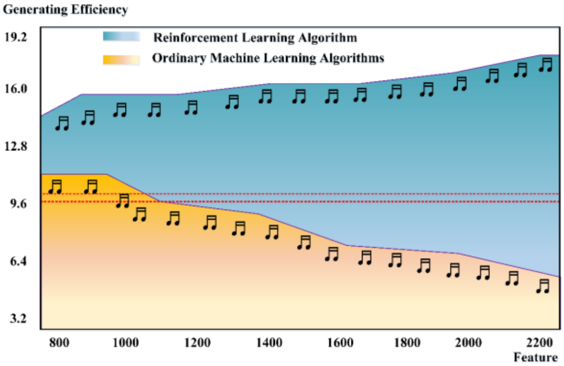

Figure 7: Changes in the efficiency of music style simulation generation between reinforcement learning algorithms and ordinary machine learning algorithms.

As can be seen from Figure 7, due to the large number of input music element feature points, the efficiency of the general machine learning algorithm in music style simulation generation is significantly reduced. The reinforcement learning algorithm can quickly generate the same music style works according to the three-dimensional map provided by CAD, and its music simulation efficiency is always above the standard range. This way of using music characteristics and information quantification processing can also save the simulated music works in the reinforcement learning database so as to facilitate creators to extract relevant content and realize the establishment of multi-style portfolios.

5 CONCLUSIONS

With the continuous development of information technology and artificial intelligence algorithms, the automatic generation of different styles of music is a relatively important link in music production. More and more researchers have begun to devote themselves to the field of music style recognition and simulation generation. On this basis, this paper also uses CAD and reinforcement learning algorithms to study the process of music style recognition and the effect of music simulation generation. Firstly, a CAD computer-aided design system based on music feature recognition is proposed. The music characteristic rhythm is collected and distinguished in detail, the wavelet transform is used to extract the data, and the fuzzy theory is used to calculate the music rhythm recognition task. On this basis, the music style curve fluctuation is added to the CAD system, and the three-dimensional sound wave display is realized in the system. This system can complete the real-time monitoring of music characteristics in the process of music style switching. Finally, with the help of a reinforcement learning algorithm, the simulation of music style is studied, the classification of music genres is completed by using a reinforcement learning network, and the effective feature points are added to the training decision to complete the pre-processing of music data. In the simulated music material generated by the reinforcement learning algorithm, the content of timbre, tone, and loudness is processed, the music data is quantitatively calculated, and a finished product closer to the style requirements is formed by using note value evaluation. The research results show that CAD technology and reinforcement learning algorithms perform well in the process of music style recognition so as to optimize the generated music products that can meet the needs of different people for music styles.

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