

Retraction

Retracted: Visual Classification of Music Style Transfer Based on PSO-BP Rating Prediction Model

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] T. Li, "Visual Classification of Music Style Transfer Based on PSO-BP Rating Prediction Model," *Complexity*, vol. 2021, Article ID 9959082, 9 pages, 2021.

Research Article

Visual Classification of Music Style Transfer Based on PSO-BP Rating Prediction Model

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In this paper, based on computer reading and processing of music frequency, amplitude, timbre, image pixel, color filling, and so forth, a method of image style transfer guided by music feature data is implemented in real-time playback, using existing music files and image files, processing and trying to reconstruct the fluent relationship between the two in terms of auditory and visual, generating dynamic, musical sound visualization with real-time changes in the visualization. Although recommendation systems have been well developed in real applications, the limitations of CF algorithms are slowly coming to light as the number of people increases day by day, such as the data sparsity problem caused by the scarcity of rated items, the cold start problem caused by new items and new users. The work is dynamic, with real-time changes in music and sound. Taking portraits as an experimental case, but allowing users to customize the input of both music and image files, this new visualization can provide users with a personalized service of mass customization and generate personalized portraits according to personal preferences. At the same time, we take advantage of the BP neural network's ability to handle complex nonlinear problems and construct a rating prediction model between the user and item attribute features, referred to as the PSO-BP rating prediction model, by combining the features of global optimization of particle swarm optimization algorithm, and make further improvements based on the traditional collaborative filtering algorithm.

1. Introduction

Music visualization is one of the expressions of music iconography that focuses on music feature extraction, emotion detection, and image processing [1, 2]. Visualization is a form of data expression and delivery, similar to the way computers simulate the way people express emotions that can be seen through expressions, body movements, and so forth. Music visualization focuses on the interaction, transformation, and expression of the auditory and visual senses. In the design process of visualization, there are multiple mapping modes and media used to convey ideas that may be inspired by thoughts and movements or express feelings, so that the expression of visual works today is often strongly influenced by the subjectivity of the creator [3], playing a role similar to that of other aesthetic creations in terms of “emotional communication” [4]. It has been found that visual aids can help listeners better identify the emotions

expressed in music if they are provided alongside the music performance [5], which helps listeners to deepen their understanding of the music through the visual presentation. Nowadays, more and more computer scholars and designers are focusing on the relationship between music and color, image, semantics, and emotion, through the correspondence of color brightness, purity, and hue with the color elements of visualization, and the correspondence of the point-line composition of images with the line style of the basic unit body of data visualization, and the design expression through information visualization.

Nowadays, the recommendation system is not only applied to e-commerce platforms, but also blogs, movie websites, personalized music software, social networking websites, and other platform websites all use the recommendation system to different degrees, and each website and platform has its own recommendation characteristics. With the rapid development of network economy, the

recommendation system plays an increasingly important role. The memory-based collaborative filtering recommendation algorithm is also known as neighborhood-based recommendation, and the memory-based collaborative filtering recommendation algorithm is divided into user-based collaborative filtering and project-based collaborative filtering [6, 7]. Model-based collaborative filtering recommendation algorithms can be further divided into matrix decomposition-based collaborative filtering and clustering-based collaborative filtering [8], whose basic principle can be understood as recommending items to users by transforming the user-project scoring matrix into different models and then using these models in different application scenarios. The hierarchical structure is given in Figure 1, and a more detailed classification diagram of the structure of the collaborative filtering recommendation algorithm will be presented later.

Although recommendation systems have been well developed in real applications, the limitations of CF algorithms are slowly coming to light as the number of people increases day by day, such as the data sparsity problem caused by the scarcity of rated items, the cold start problem caused by new items and new users (which in a sense can also be understood as the sparsity problem in extreme cases), the multi-interest problem of users, and so forth. Therefore, how to solve the problems of traditional recommendation systems has become an important research area in today's e-commerce. In this paper, we use the advantages of BP neural network to deal with complex nonlinear problems and combine the features of global optimization of particle swarm optimization algorithm to build a scoring prediction model between the user and item attribute features, referred to as PSO-BP scoring prediction model, and further improve it based on the traditional collaborative filtering algorithm. In this paper, we propose an improved collaborative filtering algorithm based on the scoring errors of neighboring users to address the problem of low accuracy of scoring prediction caused by the sparse matrix data of the traditional collaborative filtering algorithm. In this paper, we first construct a PSO-BP rating prediction model for each user. When the number of iterations or the threshold is reached, the particles stop updating and the corresponding network parameters reach the optimal values, and the training of PSO-BP rating prediction model is finished.

2. Related Work

The earliest collaborative filtering recommendation system was born in the 1990s, which is also known as the mail system Tapestry. The mail system was originally designed to solve the problem of e-mail flooding and redundancy of a huge amount of information. And until the 21st century, recommender systems were known as collaborative filtering systems [9]. In 1997, the journal ACM Communications, a division of the Association for Computing Machinery, organized the first special issue on collaborative filtering technology and used the term recommendation system as the title of the special issue, after which the term recommendation system became familiar. Before 1997, recommendation systems were mainly used for information filtering, such as the email filtering mentioned in the above

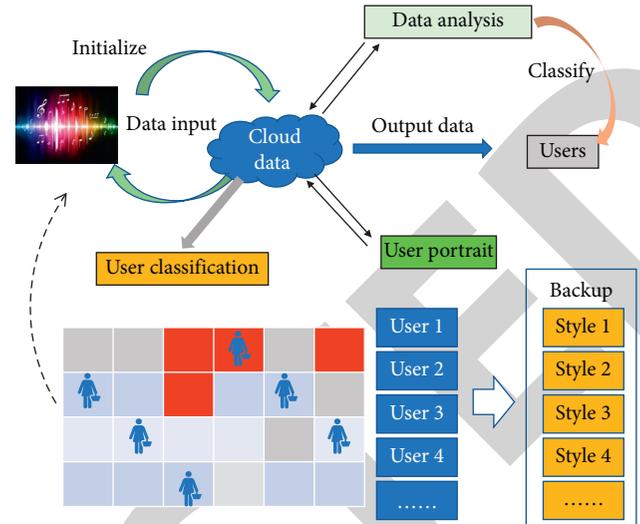


FIGURE 1: Particle swarm optimization strategy based on filtering mechanism.

article. After 1997, a new field of application was born: e-commerce and recommendation system (e-commerce system), which can find interesting products for customers, solve the problems brought by the huge amount of irrelevant information, clear the obstacles for users' shopping, and improve the platform transaction volume. The personalized recommendation system in e-commerce mode is also born in the background of this interest.

Nowadays, the more representative international recommendation websites include Amazon, Movie Lens, and Netflix. Among them, Amazon.com is one of the earliest companies in the world to apply a recommendation system, is also known as the leader of online bookstores in China, and is also crowned as the "king of recommendation system" in the industry. According to the information provided by Baidu search, at least 20% of Amazon.com's annual sales come from the recommendation system. Amazon's impressive performance is inextricably linked to the core algorithm used by the company. Amazon.com gives each customer a personalized VIP experience, each customer can categorize their favorite books into a beautiful personal bookstore according to their own needs, and the recommendation algorithm used by Amazon is the mainstream collaborative filtering algorithm. Unlike Amazon.com, Movie Lens is a noncommercial experimental site for movie recommendation research, which uses a combination of collaborative filtering and association rules to recommend movies of interest to users through information on their movie viewing preferences [10–12]. In recent years, international companies such as Yahoo and Google have also joined in the research of recommendation algorithms. Companies represented by Twitter (Twitter) have deeply studied the data sparsity problem and system scalability problem in recommendation algorithms and have achieved some relatively successful research results by introducing clustering technology into recommendation systems. In addition, the mainstream research direction of deep learning can also be combined with the recommendation algorithm,

and the typical representative website is YouTube, which has greatly improved the service capability of the website by combining the deep learning algorithm with the recommendation algorithm and well solved the data sparsity problem [13]. In addition, to address the data sparsity problem, foreign scholars [14, 15] used the average value of items to fill the missing values in the rating matrix and then preprocessed the data to achieve the decomposition of the singular values of the rating matrix, which solved the data sparsity problem. Scholars [16–18] improved the data sparsity problem by preprocessing the data and using a nonnegative matrix decomposition method. With the development of the economy of the times, how to use the current mainstream BP neural network to effectively improve the recommendation quality is also a popular direction for many scholars to study. A careful analysis of foreign mainstream recommendation sites can easily be seen that, compared to the previous recommendation systems, today's recommendation systems have a strong commercial flavor in addition to bringing convenience to customers [19–21].

The research of recommendation technology has a high economic value not only for the enterprise but also for the country with a high strategic value of science and technology. Recommendation systems are nowadays mainly oriented to users of e-commerce activities, so it is crucial to study recommendation systems for the development of enterprises, who want to survive, then he has to occupy the market first, and the prerequisite to occupy the market is to have a large customer base. Because customers are the source of profit, who can provide better services and products to customers, retain and attract more customers, who can win the market. In the e-commerce model, the merchant and the customer never meet in person and transact in a virtual environment. Merchants also cannot directly know the shopping habits of customers and can only match their shopping needs by browsing their shopping history, so recommendation algorithms have bright application prospects in e-commerce [22]. In addition, with the rapid development of e-commerce and the growing demand of users, personalized recommendation technology is facing a serious situation. A good recommendation system can not only effectively solve the problem of overload caused by the massive amount of information but also enable users and enterprises to achieve a win-win situation by simulating a shopping guide salesperson to intimately and meticulously recommend various goods that may be of interest to customers and finally complete the purchase. However, with the development of the economy, traditional collaborative filtering-based recommender systems can no longer meet the needs of customers, and problems such as sparsity, cold start, single recommendation, and scalability have hindered the development of recommender systems [23, 24]. Therefore, to continue to capture customers and win the market, research on the improvement of traditional collaborative filtering algorithms is imperative. In this paper,

we combine the above problems and propose a research topic to improve the prediction accuracy of personalized recommendation systems in an e-commerce environment.

3. BP Neural Network and Particle Swarm Optimization Algorithm Analysis

3.1. Neural Network Structure. BP neural network (back-propagation neural network) is a multilayer feed-forward neural network model based on the Error Inverse Propagation algorithm and has typical representation. In addition, because of its simple operation and single structure, it is now being widely used in various fields of life. Artificial neural network models are often used to deal with nonlinear, classification problems. The basic idea is that after repeated training of sample data, excellent network parameters are summarized and used to model the input-output relationship, which can output prediction results with high accuracy. Secondly, although neural networks are composed of multiple interconnected neurons, the internal composition of neural network models may vary slightly from one neural network model to another. Each layer is composed of several neurons and the upper and lower layers are connected by means of power linkage, while there is no connection between the nodes of neurons in the same layer, as shown in Figure 2.

Second, the number of neurons in each layer of the BP neural network depends on the actual application requirements: in general, the number of neurons in the input layer is equal to the dimensionality of the input vector, and each neuron corresponds to each component of the input vector; the number of neurons in the output layer is determined by the specific application scenario. The number of neurons in the output layer is determined by the application scenario. The neurons in the implicit layer are generally called implicit units, which are not visible and have no specific criteria for constant number. As mentioned in the first paragraph of the chapter, the upper and lower layers of a BP neural network communicate with each other by means of a power linkage, that is, the neurons in the upper and lower layers are connected by connection weights and there is no network connection between the neurons in the same layer, so the training process of a BP network model is a process of constantly updating the connection parameters of the whole network. In the BP neural network, each neuron is divided into two steps: input and output, the input information of each neuron needs to be processed by the activation function before it can be output, and each neuron has its own activation function. In addition, the activation functions of neurons in different layers may be different, but the activation functions of neurons in the same layer must be the same. The input layer is generally responsible for accessing the information with a linear function, but the implicit layer is designed to deal with nonlinear problems, so the implicit layer neurons generally choose an activation function to process the information passed from

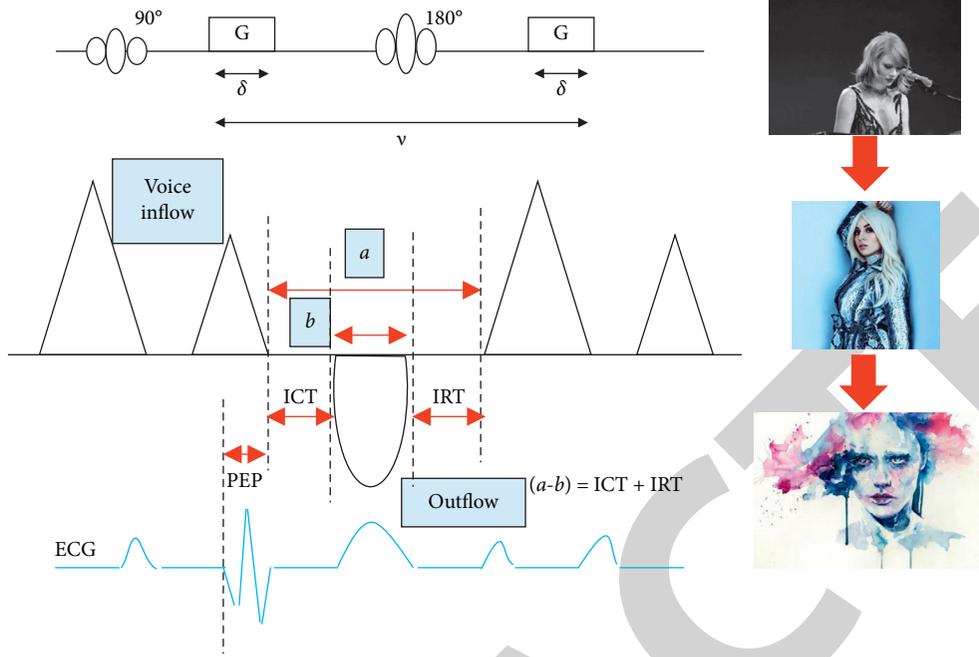


FIGURE 2: System functional structure diagram.

the input layer, and the activation function chosen for the implicit layer depends on the actual problem requirements. The expression of the Sigmoid function is shown as follows:

$$f(x) = (1 + e^{-x})^{-1}. \quad (1)$$

The activation function Sigmoid, also known as the S-curve, takes values in the range:

$$f(x) \in [0, 1], \quad x \in [0, 0.5]. \quad (2)$$

The image of the Tanh function is similar to the S-curve, but the output interval of the Tanh function is between $[-1, 1]$ and is monotonically increasing with 0 as the center of symmetry. The expression of the function is

$$f(x) = \tan\left(\frac{e^x - e^{-x}}{e^x + e^{-x}}\right). \quad (3)$$

The Re LU function, also known as the modified linear function, simplifies the computation process compared to the Tanh function and Sigmoid function, reducing the time computation cost of the BP neural network and improving the prediction efficiency. The expression of the Re LU function is

$$f(x) = \max(e^x - e^{-x}). \quad (4)$$

3.2. Network Training Process. The training process of the BP network is divided into two stages: signal forward propagation and error backpropagation, characterized by signal forward transmission and error backpropagation. In the forward propagation process, the signal is introduced from the input layer, then passed to the implicit layer, and then

processed by the activation function of the implicit layer and passed to the output layer for processing and outputting the prediction results. If the error between the predicted value and the expected value is greater than a preset threshold, the error information is propagated backward and the corresponding network parameters are optimized based on the error information. These two propagation mechanisms are repeated until the prediction error is below a set threshold and the training process is stopped. In the following, the structure of the BP neural network model is used as the basis for introducing the principles of the two propagation mechanisms of the BP neural network in solving the regression prediction problem.

(1) *Forward Propagation Process.* Let the input sample be $X = \{1, 2, 3, \dots, 4\}$, and the output layer output value is $T_m = [Y1, Y2, \dots, Y3]$; the number of neurons in the input, hidden, and output layers are n, q, m ; the weight connection parameter between the input layer and the hidden layer is v_{ij} ; and the weight connection parameter between the hidden layer and the output layer is w_{jk} . Then, the gradient of the weights between the input layer and the output layer can be expressed as the matrix V :

$$Q_{ixj} = \{q_{11}, q_{12}, \dots, q_{ij}\}_{ixj}. \quad (5)$$

The gradient of the weights between the output layer and the implied layer can be expressed as the matrix W :

$$P_{ixj} = \{p_{11}, p_{12}, \dots, p_{ij}\}_{ixj}. \quad (6)$$

In a neural network, each neuron is divided into input and output and during forward propagation, sample data are introduced from the input layer and then passed to the implicit layer neurons, which are processed by the activation function to predict the output. In addition, the input of each

neuron depends on the output of the neuron in the previous layer and its connection weights. In contrast to the forward propagation process, the first step to be done in the backward propagation process is to update w_{jk} and then update v_{ij} . Based on the stochastic gradient descent method the update of the weights can be computed as follows:

$$Q_{ij} = Q_{jk} - \frac{\partial E}{\partial Q}. \quad (7)$$

The parameter α , which has been introduced above, represents the descent step in the gradient descent method, its value is determined experimentally, and the range of values is generally between $[0, 1]$:

$$\frac{\partial E}{\partial Q_{ij}} = \frac{\partial E}{\partial x_{ij}} + \frac{\partial E}{\partial y_{ij}} + \frac{\partial E}{\partial z_{ij}} = (y_e - f)F(y). \quad (8)$$

Then, the threshold iteration formula corresponding to the j th node of the hidden layer is as follows:

$$\alpha(i+1) = \alpha(i) + \beta\gamma. \quad (9)$$

After training with two propagation mechanisms, forward and backward propagation, the BP neural network model is roughly built, and then we can test it with test data other than the training samples to see if the model can predict our desired output values, as shown in Figure 3.

3.3. Particle Swarm Optimization Algorithm. From ancient times to the present, many inventions have been inspired by observing and analyzing the behavioral patterns of animals to conclude applications that can be of practical help to humans. The particle swarm optimization algorithm is no exception. The algorithm design idea comes from the behavior of birds hunting for prey, and the American experts Kennedy and Eberhar were inspired by the observation that, in the process of hunting for prey, each bird will find the nearest bird's neighborhood in the current position, and thus proposed the particle swarm optimization (PSO) algorithm in 1995. Particle swarm optimization (PSO) is another population intelligence algorithm in addition to the simulated annealing algorithm and ant colony algorithm. The basic idea of the PSO algorithm is to treat each bird as a vector particle with velocity and position, and each particle may be a candidate solution to the problem. In the algorithm, each particle will update its position in time by combining its current moving experience and speed with the moving experience of its neighbors to close the distance to the target position, as shown in Figure 4. Each particle in the PSO represents a candidate solution in the solvable space, and the fitness function is the determinant of the solution and is set according to the optimization objective. In the PSO algorithm, each particle has two learning methods, the first one comes from itself, referred to as the self-learning phase. The second learning method comes from other particles in the sample space, referred to as the learning phase. The self-learning phase represents the optimal value of the particle from the beginning to the current number of iterations (individual optimum), which is denoted by p-Best in this

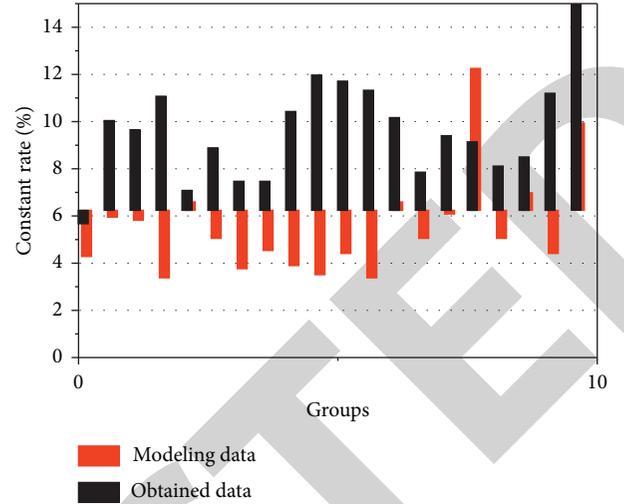


FIGURE 3: Comparison of model correspondence results.

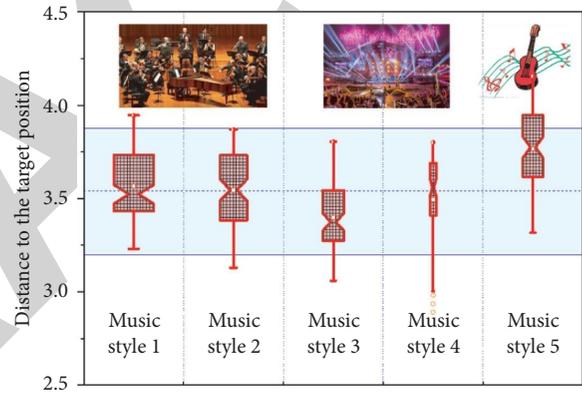


FIGURE 4: Distance to the target position.

paper, and the learning phase represents the optimal solution generated by the population of particles from the beginning to the current number of iterations (global optimum), which is denoted by g-Best in this paper.

The particles are searched in the solvable space by the individual optimum p-Best and the global optimum g-Best until the specified error criterion and the number of iterations are reached. In addition, the velocity of the particle in the process of finding the optimum must be within the set velocity range; that is, rv must be between $[\max, \min]$, and the larger the maximum velocity of the particle $\max v$, the stronger the global search capability of the particle population, and vice versa. The particle fitness function is calculated by the objective function, followed by the sequential calculation of p-Best and g-Best, the parameters of the two extremes are updated after each iteration of the calculation, and finally, the algorithm ends when the number of iterations is reached or the error criterion is less than the set value. The specific steps of the PSO algorithm are shown below :

- (1) A group of particles is randomly selected from the sample and initialized with respect to each of their parameters.

- (2) Set the adaptation function of the particles according to the optimization objective.
- (3) Update the p-Best according to the particle fitness, compare the calculated particle fitness value with the p-Best, and select the better value as the p-Best.
- (4) Update the g-Best according to the particle fitness, compare the calculated particle fitness value with the g-Best, and select the better value as the g-Best.
- (5) Constantly update the particle velocity and position parameters according to equations (2)–(4).
- (6) The end of the specified condition is reached, otherwise it goes back to step (2). The algorithm flow is shown in Figure 5.

The PSO algorithm is slowly becoming a popular algorithm today because of its simplicity, ease of implementation, and lack of excessive parameter settings. In addition, the PSO algorithm uses the velocity-displacement model, which can avoid complicated parameter settings and adjustment operations, and thus lay the foundation for its widespread application, so the PSO algorithm is a simple and excellent algorithm:

- (1) Strong self-learning and adaptation capabilities, the training process can actively learn the input-output data laws and automatically update the network connection weights
- (2) Strong robustness, where the necrosis of some neurons during training does not have a large impact on the prediction results
- (3) Strong generalization ability, that is, the ability of BP neural networks to apply knowledge learned during the training process to new, unexposed things
- (4) Strong nonlinear mapping capability

4. Music Style Visualization Migration Test

The improved collaborative filtering algorithm based on the neighboring user's rating error is implemented based on the PSO-BP rating prediction model, and by improving the PSO-BP rating prediction model in the algorithm, the error between the predicted rating of the neighboring user and the actual rating of the same item in the target user's history is used as the judgment criterion to determine the rating and the similarity between the target user and the neighboring user. Therefore, the first step of the experimental test is to set the network parameters of the BP neural network :

- (1) The number of neurons in the input layer n : the number of neurons in the input layer of the model is equal to the number of item attribute features selected by the system recommendation algorithm, and in this paper, we use movie and book attribute features as the number of item attribute features, so n is equal to 19.
- (2) Number of neurons in the hidden layer q : in this paper, the number of neurons in the hidden layer is

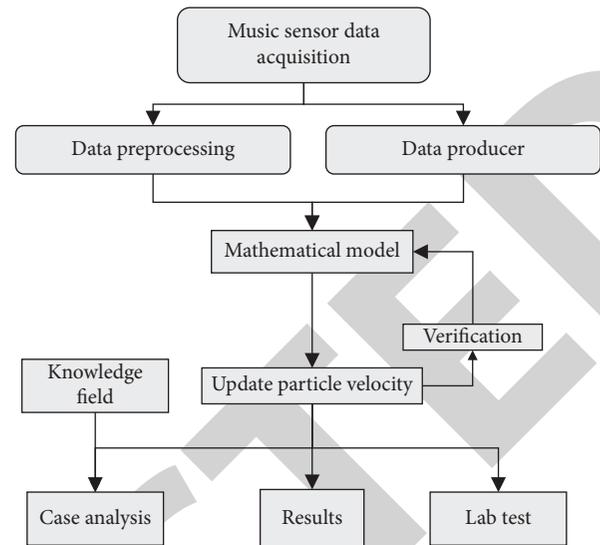


FIGURE 5: PSO flow chart.

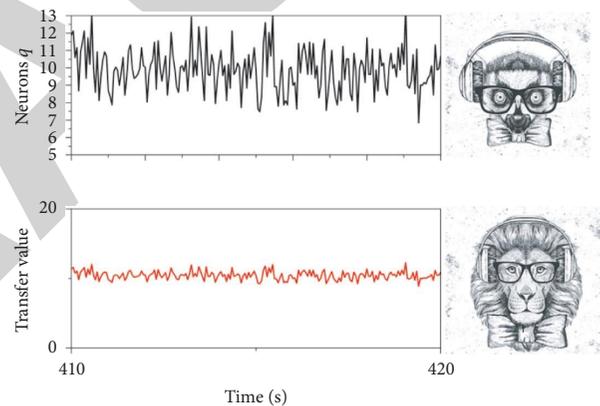


FIGURE 6: Experimental measurement of the number of neurons q in the hidden layer.

generally determined by experiment as shown in Figure 6.

In this paper, we introduce that the particle swarm optimization algorithm has three main components: particle position, particle velocity, and adaptation function, and the velocity-position model is used for optimization search. Assuming that the total number of particles in the swarm is 30, the learning factors $1c$ and $2c$ are set to 2, and the maximum velocity $\max v$ is set to 1, the swarm is updated iteratively according to three update formulas after the initialization operation, and the adaptation graph of the swarm is finally obtained. The randomness of the appearance of the new picture is established using particle guidance (Seeker), which represents the coordinate pixels in the image space, and defines the corresponding data structure, as shown in Figure 7. It has parameters such as position, velocity, and inertia. As each note arrives, the velocity and track size will be updated according to the intensity of the

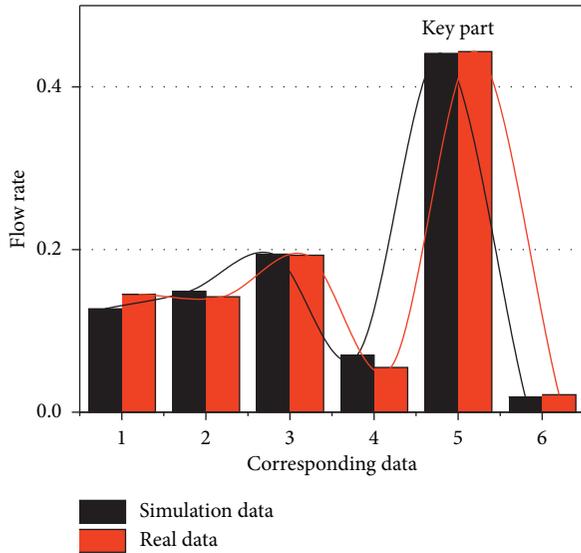


FIGURE 7: Corresponding data structure.

audio, and the immediate channel intensity is greater than the threshold of 0.8, allowing the generation of new worm particles and also new picture pixels. The position of the current particle can then be inferred from the inertia of the object. Finally, a smooth motion trajectory is obtained.

Overall, this artistic expression effect reflects a high degree of freedom. This new artistic expression effect is different from the traditional art genre, which not only has the delicate expression of dotted color in impressionist paintings but also has the visual impact of abstract paintings and also has the dreamy color of futurism, which is a new form of artistic expression created through artificial intelligence. It can be seen that the improvement in the method of information visualization design pays more attention to the association of information in the visual representation of unitary individuals and the visual representation of large data sets of groups. The choice of the unitary individual requires not only the aesthetic judgment of the designer but also the design judgment through the combination of several aspects, such as conceptualization, beauty, and pleasure of the user experience. The information visualization design follows the design ontology in the overall outline, while in the design details, different visual elements are used to express the design through a different arrangement and combination, interpolation and fusion, deconstruction, and reconstruction. At the same time, the interaction design required for information visualization contains the artificial intelligence-driven changes of data self-interaction and also the changes of human-computer interaction interface between designers and users after viewing the information visualization images. Through the choice of the shape of the basic unit body of visualization, the control of the number of dense

arrangement, and the choice of the way of arrangement and combination, the custom design of large-scale customers is carried out to reach the diversification of nondeterministic interaction changes Design results.

In order to simplify the names of the algorithms involved in the later experiments, this paper will better describe the experimental results by abbreviating the names of the algorithms and creating a cross-reference table of names. To address the problem of low prediction accuracy of traditional collaborative filtering algorithms due to sparse matrix data, this paper proposes an improved collaborative filtering algorithm based on neighboring user rating errors. In the following, the improved algorithm proposed in this paper will be tested experimentally based on the data set partitioning situation and compared with the other three algorithms to demonstrate the advantages of the improved algorithm in prediction accuracy in this paper. When the ratio of the four algorithms in the training set to the test set is 9:1, the experimental test results are shown in Figure 8.

New images or music are created by combining computer-recognizable parameters in music or images with the content of the expression of the parameters prebuilt by the designer. In this paper, the image position of a child within a defined range is scanned and identified, and the position is corresponded to two octaves of C major to generate new music. di Paola S and Arya A developed Music Face, which combines expressive cues with emotional color cues through structures such as rhythm, loudness, and time, translating them into emotional states based on defined associations. This in turn determines facial emotions and movements to create visual effects. This approach provides freedom of expression for music visualization, but it still requires the designer to set a fixed expression paradigm, allowing only a high degree of freedom for single-sided data for music files to generate images, or for image files to generate sounds, and thus still does not allow for free interaction between music and images to a certain extent.

Both of the above studies of music visualization are based on human labeling of music or images, or the unilateral transformation effect of algorithm application, which to some extent achieves the highly subjective creative expression of the artistic field of trial and error, but misses the music creator and the image shooter. The extraction of information through the essence of music or image delivery no longer increases the subjective labeling of the creator but allows the computer to complete the two links of identification and output of the initial music and image files, which not only maximizes the retention of information in the original files but also creates more possibilities and unknown expressions. In summary, this paper bilaterally processes the data between music files and image files, identifies music features and image features simultaneously to control the effect of real-time generation of image style migration, and allows the computer to pick up the brush and become a flux artist to

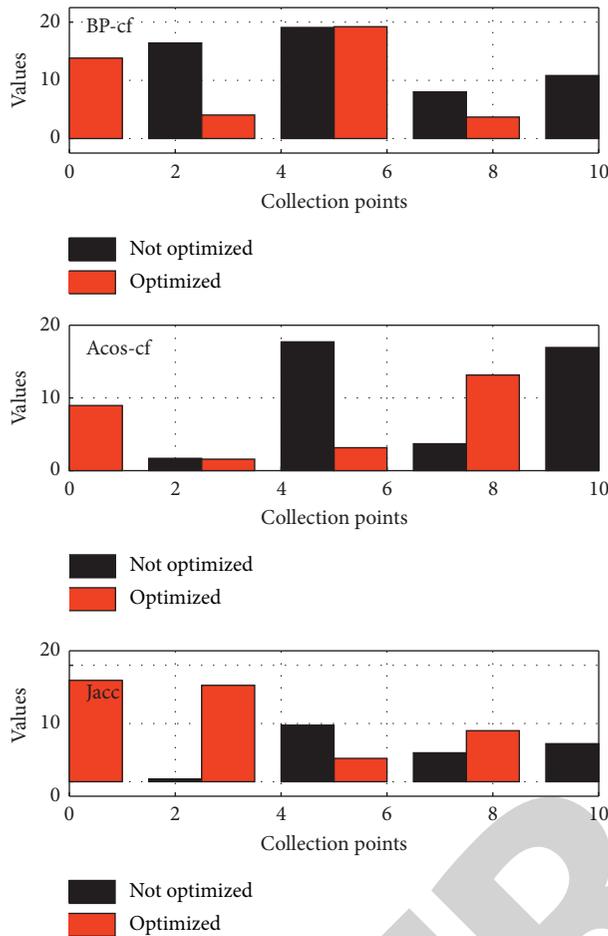


FIGURE 8: Comparison of MAE by the algorithm.

visualize and simulate the human association of music and images. Compared to previous work, the BP neural network is easy to handle complex nonlinear problems and construct a rating prediction model between the user and item attribute features.

5. Conclusion

Music visualization combines the auditory with the visual to enhance the comprehensibility and emotional resonance of music. For music visualization, a large number of results have been available for the research between music and images. To address the problem of poor prediction scoring accuracy of traditional algorithms due to sparse matrix data, this paper proposes an improved collaborative filtering algorithm based on neighboring users' scoring errors, and this paper conducts a detailed experimental test on the prediction performance of this algorithm. The results show that the improved algorithm proposed in this paper has a more stable prediction accuracy of ratings compared with other algorithms. The collaborative filtering-based recommendation algorithm has the advantages of high novelty, strong real-time, good automation, wide coverage, and so forth, and is gradually being widely used. For various cases, although neural networks are composed of multiple interconnected neurons, the internal composition of

neural network models may vary slightly from one neural network model to another. However, the most important reason is that the collaborative filtering-based recommendation algorithm is easier to implement and cheaper in terms of technical feasibility, so it is an excellent personalized recommendation algorithm based on collaborative filtering.

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 are no conflicts of interest.

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