Hindawi
Security and Communication Networks
Volume 2023, Article ID 9756450, 1 page
https://doi.org/10.1155/2023/9756450

Retraction

Retracted: Analysis of Artistic Modeling of Opera Stage Clothing Based on Big Data Clustering Algorithm

Security and Communication Networks

Received 26 December 2023; Accepted 26 December 2023; Published 29 December 2023

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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.

References

[1] W. Luo, "Analysis of Artistic Modeling of Opera Stage Clothing Based on Big Data Clustering Algorithm," *Security and Communication Networks*, vol. 2021, Article ID 5349916, 9 pages, 2021.

Hindawi
Security and Communication Networks
Volume 2021, Article ID 5349916, 9 pages
https://doi.org/10.1155/2021/5349916

Research Article

Analysis of Artistic Modeling of Opera Stage Clothing Based on Big Data Clustering Algorithm

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Received 15 October 2021; Revised 9 November 2021; Accepted 11 December 2021; Published 29 December 2021

Academic Editor: Jian Su

In order to deal with the problem that the traditional stage costume artistry analysis method cannot correct the results of big data clustering, which leads to deviations in the extraction of costume artistry features, this paper proposes a clothing artistic modeling method based on big data clustering algorithm. The proposed method provides a database for big data clustering by constructing the attribute set of the big data feature sequence training set and, at the same time, constructing a second-order cone programming model to correct the big data. Aiming at the problem that traditional stage costume art analysis methods cannot correct the clustering results of big data. On this basis, the costume elements of the opera stage are segmented, initialized, and transformed into a binary function. Finally, using the convolutional neural network, combining the element segmentation results and the large data clustering space state vector, a feature extraction model of stage costume art is constructed. Experimental results show that the model has good convergence, short time-consuming, high accuracy, and ideal feature recognition capabilities.

1. Introduction

In the process of performing operas, it is emphasized that the actors and actresses have the form and spirit at the same time, but they often pay more attention to the spirit. Spirit resemblance is mainly to capture the essence of performers as well as charm, but the form resembles the characteristics of opera performance costumes pay more attention to and do not care about the appearance realistic degree. In the process of development, the costume of traditional opera developed slowly from the life to the art [1]. However, it does not simply reproduce the authenticity of the historical life of traditional costumes but will be lifestyle costumes for the upcoming performance of the characters vivid lyric. This actually reflects the most aesthetic features of freehand brushwork. Stage costumes can also express a series of psychological changes such as anger, anxiety, and joy of the opera characters and have good dramatic effects in expressing the feelings of the characters and portraying the personalities of the characters in the drama [2]. Therefore, it is of vital importance to analyze the artistic characteristics of stage costumes.

For the research of feature analysis and extraction, experts in related fields have obtained some good research results. In reference [3], an artist feature representation model based on deep semantic mining of artist profile is proposed. In this model, word2vec and glove are used to map the word vectors of artist profiles, and convolution neural network is used to extract the semantic relevance of word vectors. Finally, the full connection network is used to verify the accuracy of artist features. Taking 5101 artists' profiles provided by Pandora website as experimental objects, the performance of the algorithm is tested. In reference [4], a multiscale feature detection model based on high-quality feature map is proposed. In this model, by reducing pooling and adding space and channel compression excitation module at the bottom of the network to highlight the available details, high-quality feature map is generated. In addition, a variable multiscale feature fusion module is added to the deep network, which has multiscale perception and can predict the sampling position according to the object boundary. Finally, by fusing multiscale features, the network has stronger feature expression ability and is more robust to different scale instances and their

boundary information. However, the above feature extraction and analysis model cannot correct the results of clothing big data clustering, which leads to a large deviation of clothing artistic feature extraction, and the performance of feature recognition is not ideal.

The traditional stage costume artistry analysis method cannot correct the results of big data clustering, which leads to deviations in the extraction of costume artistry features. In recent years, many new algorithms have been applied in this field, but the effect of existing algorithms still cannot meet the actual needs. Due to the development of big data and artificial intelligence technology, many new technologies have been paid more and more attention.

In order to further analyze the artistry of stage costume, a new modeling method of stage costume artistry is proposed by introducing big data clustering modification. Big data clustering algorithm is to divide the training data set into a group according to the characteristics of the data combined with a classification algorithm. Through the statistics of the laws of historical data, a large number of data are classified, and then, the relationship between data is found. In this way, when new data come in, the computer can use this relationship to classify automatically.

The writing contributions of the thesis are included as follows:

(1) This paper proposes a clothing artistic modeling method based on big data clustering algorithm, which provides a database for big data clustering by constructing the attribute set of the big data feature sequence training set.

(2) A second-order cone programming model is constructed at the same time to correct the clustering results of big data.

(3) The costume elements of the opera stage are segmented and initialized and transformed them into a binary function. Finally, using the convolutional neural network, combining the element segmentation results and the large data clustering space state vector, a feature extraction model of stage costume art is constructed.

2. Artistic Modeling of Opera Stage Clothing Based on Big Data Clustering Algorithm

2.1. Basic Idea of Big Data Clustering. In order to realize large data clustering, first of all, we need to mine the data features and build the information flow model. Data clustering is the process of mining regular features from a large number of noisy and fuzzy data. The first step of data clustering is data preprocessing and feature extraction. The process description of data clustering [5, 6] is shown in Figure 1. The main steps of this method are as follows:

(1) Data input: there must be many data inputs to this system

(2) Data preprocessing: according to this step, we can get the feature of the input data

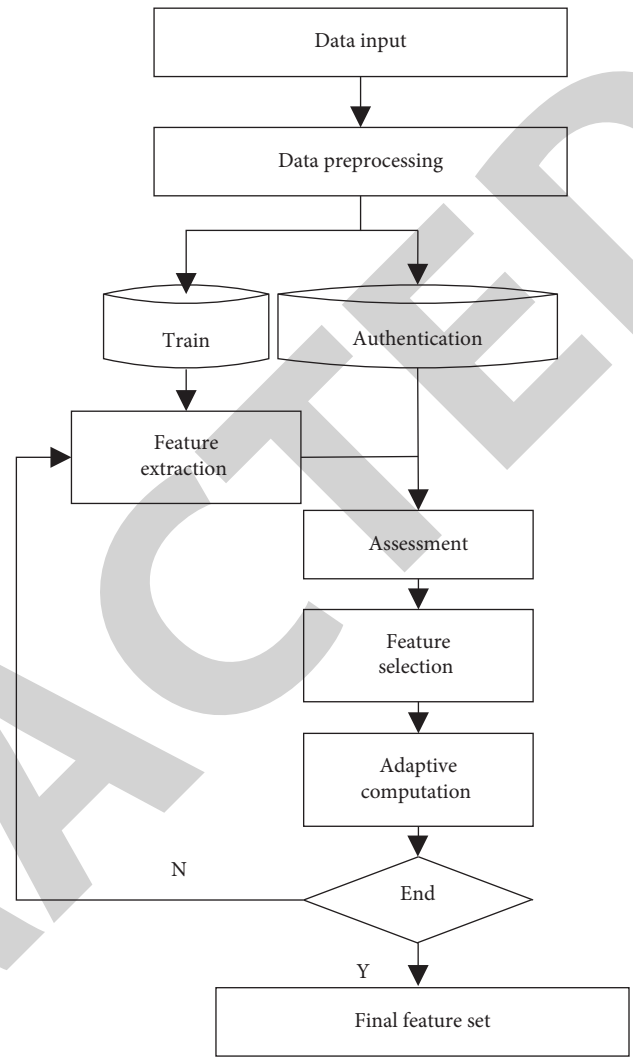

Figure 1: Big data clustering process description.

(3) Feature extraction and selection: the needed feature is selected

Combined with the flow of Figure 1, the big data clustering algorithm is designed. Setting $X = (x_1, x_2 \ldots\ldots\ldots x_D)$ is a feature vector in the big data clustering space, and the method of rough concept lattice is used to construct the second-order cone programming model for the big data information flow in the big database system, and the method of linear frequency modulation signal model is used to partition the big data information flow for maximum fitting, and the following decision function is selected:

$$G = X \cdot \max_{b} |W(b)|, \tag{1}$$

where $W(b)$ is the cluster center selection function and b is the initialization data cluster center.

Combined with the decision function, the second-order cone programming model is used to deal with the information of the data cluster sample set.

$$T = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} a_{mn} G_{mn}(b). \tag{2}$$

In the above formula, a_{mn} is called convex optimal expansion coefficient of second-order cone programming.

The Euclidean distance of weighted vector ω_j of the data cluster center is computed as follows:

$$D = \sum_{i=0}^{N-1} \left(x_i(t) - \omega_{ij}(t)\right)^2, \quad i = 0, 1, \cdots, N-1, \tag{3}$$

where $\omega_j = (\omega_{0j}, \omega_{1j}, \cdots, \omega_{k-1,j})^T$. In the process of data clustering, information scheduling is carried out in the special relational information of useful information and knowledge [7], and the attribute set of feature sequence training set of big data is constructed to provide data basis for data clustering.

2.2. Data Clustering Modification Based on Second-Order Cone Programming Model. Second-order cone programming model is used for data clustering. Second-order cone programming is a minimization and maximization linear function on the intersection of Cartesian space affine transformations of finite quadratic cones [8]. Using the modified second-order cone programming model and the convex optimization condition of the second-order cone, the big data clustering algorithm is improved. The modified homogeneous second-order cone programming model is described as follows:

$$X' = \left\{ \begin{matrix} a_1, a_2, \ldots, a_m \\ p(a_1), p(a_2), \ldots, p(a_m) \end{matrix} \right\}, \tag{4}$$

where $0 \le p(a_i) \le 1 \quad (i = 0, 1, 2, \ldots, m)$ and $\sum_{i=1}^{m} p(a_i) = 1$. a_m is the decay constant factor and $p(a_m)$ is the revised decay constant factor.

$$H(X) = -X' \cdot \sum_{i=1}^{m} p(a_i) \log_2 \; p(a_i). \tag{5}$$

If there are n samples in the data clustering sample set S' in the modified homogeneous second-order cone programming model, then

$$S' = \begin{bmatrix} 0 & y_1 & \cdots & y_n \\ y_1 & S_{11} & \cdots & S_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ y_n & S_{n1} & \cdots & S_{nn} \end{bmatrix}. \tag{6}$$

Through the above processing, the feature space of big data clustering is constructed, which lays the foundation for data optimization clustering.

2.3. Segmentation Method of Costume Elements in Opera Stage. The drama stage costume elements waiting for feature extraction are segmented, and the drama stage costume elements are initialized and transformed into binary functions [9].

Level set function L is initialized by the following formula:

$$L(x, t = 0) = \begin{cases} -\rho, x \in \Omega_0 \\ 0, x \in \partial\Omega_0 \\ \rho, x \in \Omega \end{cases}, \tag{7}$$

where ρ is a constant, usually greater than zero; Ω represents the corresponding area of the element in the opera stage costume; Ω_0 represents a subset of the region Ω; and $\partial\Omega_0$ is the boundary of Ω_0.

The local entropy image of drama stage costume elements is obtained by using the following formula:

$$R = -p_i \cdot \sum_{i=0}^{n} \lg p_i, \tag{8}$$

where L represents the total number of gray levels in clothing elements and p_i stands for frequency, and its calculation formula is as follows:

$$p_i = \frac{n_i}{M \times N}, \tag{9}$$

where n_i represents the total number of pixels of gray value in clothing elements; $M \times N$ is the size of the element [10, 11].

The following formula is used to obtain the local standard deviation image of drama stage clothing element image [12]:

$$\text{standard}(R) = \text{sqrt}\left[\frac{s(m,n) - \bar{s}}{M \times N}\right], \tag{10}$$

where $s(x, y)$ represents the gray value of the pixel whose coordinate is (x, y) in the traditional opera costume element [13]; $\bar{s}$ is the average gray value of all pixels in window W, and its calculation formula is as follows:

$$\bar{s} = \frac{s(m,n)}{M \times N}. \tag{11}$$

Each pixel can obtain the mean values $\text{mean}_{in}(x, y)$ and $\text{mean}_{in}(x, y)$ of the feature vectors corresponding to the pixels in the inner and outer neighborhood of the contour through the window function $W_k(x)$, and the calculation formulas are as follows [14, 15]:

$$\text{mean}_{\text{in}}(x, y) = \begin{cases} \text{entro}_{in}(x, y) = \dfrac{K_\sigma \cdot \left[H_g(\phi)\text{ENTRO}(x, y)\right]}{H_\varepsilon(\phi)} \\ \text{std}_{in}(x, y) = \dfrac{K_\sigma \cdot \left[H_\varepsilon(\phi)\text{STD}(x, y)\right]}{H_\varepsilon(\phi)} \end{cases},$$

$$\text{mean}_{\text{out}}(x, y) = \begin{cases} \text{entro}_{\text{out}}(x, y) = \dfrac{K_\sigma \cdot \left[(1 - H_\varepsilon(\phi))\text{ENTRO}(x, y)\right]}{(1 - H_\varepsilon(\phi))} \\ \text{standard}(R) = \dfrac{K_\sigma \cdot \left[(1 - H_\varepsilon(\phi))\text{STD}(x, y)\right]}{(1 - H_\varepsilon(\phi))} \end{cases} \tag{12}$$

The SPF function is improved by the following formula:

$$\begin{cases} \cos\theta_{\text{in}} = \dfrac{1}{\sqrt{\text{entro}_{in}^2(x,y) + \text{std}_{in}^2(x,y)}\sqrt{\text{entro}^2(x,y) + \text{std}^2(x,y)}} \\ \cos\theta_{\text{out}} = \dfrac{1}{\sqrt{\text{entro}_{out}^2(x,y) + \text{std}_{\text{out}}^2(x,y)}\sqrt{\text{entro}^2(x,y) + \text{std}^2(x,y)}} \end{cases},$$
$$\begin{cases} \text{MEAN}_{\text{in}}(x,y) = \exp\left(\dfrac{\left|f(x,y) - f_{\text{in}}(x,y)\right|}{\beta^2}\right) \in (0,1] \\ \text{MEAN}_{\text{out}}(x,y) = \exp\left(\dfrac{\left|f(x,y) - f_{\text{out}}(x,y)\right|}{\beta^2}\right) \in (0,1] \end{cases} \tag{13}$$

According to the cosine similarity between $\text{mean}(x,y)$, $\text{mean}_{\text{out}}(x,y)$, and $\text{mean}_{\text{in}}(x,y)$, the evolution direction of local standard deviation image pixels on the contour curve is determined. The SPF is improved by driving force and evolution direction [16, 17].

$$F = \begin{cases} F_{\text{in}}(x,y), & \text{if } \cos\theta_{\text{in}} \geq \cos\theta_{\text{out}} \\ -F_{\text{out}}(x,y), & else \end{cases} \tag{14}$$

The improved SPF is substituted into the level set evolution formula to realize the segmentation of stage costume elements.

2.4. Art Feature Extraction Modeling. Based on the big data clustering algorithm [18], this paper proposes a method to extract the artistic features of opera stage costumes.

$$M = [m(t_0), m(t_0 + \Delta t), \ldots, m(t_0 + (k-1)\Delta t)], \tag{15}$$

where $M(t)$ represents the information flow time series of big data clustering system; Δt is the sampling time interval of artistic features. The spectrum feature $M_p(u)$ of discrete samples of big data is calculated, and the main feature quantity is as follows:

$$M_p(u) = \frac{1}{\sqrt{T}}\text{rect}\left(\frac{t}{T}\right)e^{j2\pi}, \tag{16}$$

where $s_c(t)$ is the characteristic scalar time series of big data; $e^{j2\pi}$ is the discrete sample center of big data clustering data. When the data set is $\{M_1, M_2, \ldots, M_n\}$, the confidence level of node data package is determined [19], and the confidence interval is established.

$$z_{(i,d)}^{(k+1)} = M_p(u) + s_c(t)\cdot m(t),$$
$$Z_{(i,d)}^{k+1} = \begin{cases} Z_{i\,d}^{(t+1)} f_{\text{fitness}}^{t} < f_{\text{fitness}}^{*} \\ Z_{(i,d)}^{k+1} f_{\text{fitness}}^{t} \geq f_{\text{fitness}}^{*} \end{cases} \tag{17}$$

The vector matrix of particle optimal solution of data clustering center is as follows [20]:

$$\sum\nolimits_r = \text{diag}(\sigma_1, \sigma_2, \ldots, \sigma_r) \in R^{r\times r}, \tag{18}$$

where σ_r A is the position of the clothing element at time $k+1$, and $R^{r\times r}$ is the real matrix. The characteristics of costume art in opera stage are extracted by combining convolutional neural network [21] and autoencoder [22], as shown in Figure 2.

After the network is initialized, the reverse fine-tuning is realized on the basis of label data. Softmax can be used as classifier [23]. The feature extraction network of the art feature extraction method of opera stage costume based on big data clustering is shown in Figure 3.

2.4.1. Convolution Layer. In the traditional convolutional neural network, the weight parameter map is obtained through continuous iteration and gradient descent. The convolution layer is the second layer in the network. The total number of map in the convolution layer is nummap, and the size of any map node is mapwidth × mapheight, and each node shares a convolution core $W_i\,(i = 1, 2, \ldots, \text{nummap})$. The convolution core can be obtained by training the autoencoder network. The convolution W_i corresponding to map in the second-level convolution neural network can be obtained by initialization of the weights of nodes in the AutoEncoder network [24].

In the segmented drama stage costume art, the small block patch_j with size sizepw1×sizeph1 is selected, moved it from top to bottom and from left to right, and calculated with the convolution kernel W_i corresponding to each map to obtain the value value_{ij} corresponding to the node in map. The calculation formula is as follows:

$$\text{value}_{ij} = \frac{\omega_i}{|\omega_i|}\cdot\frac{\text{patch}_j}{|\text{patch}_j|}. \tag{19}$$

2.4.2. Filter Layer. In order to optimize the ability of feature extraction, the opera stage clothing art feature extraction method based on big data clustering adds the filter layer to the model, and each map has noise in the node [25, 26].

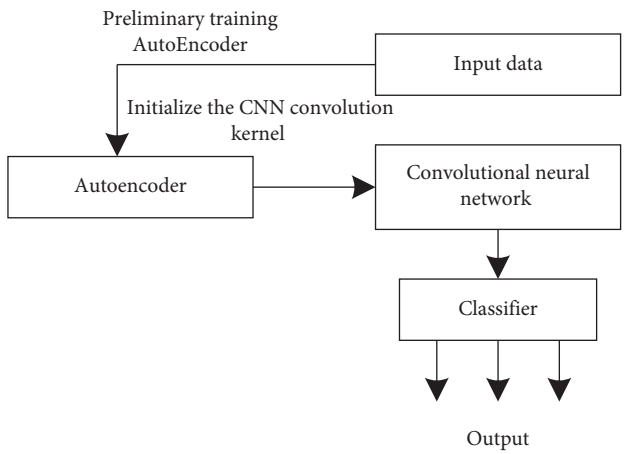

Figure 2: CNN and autoencoder fusion model.

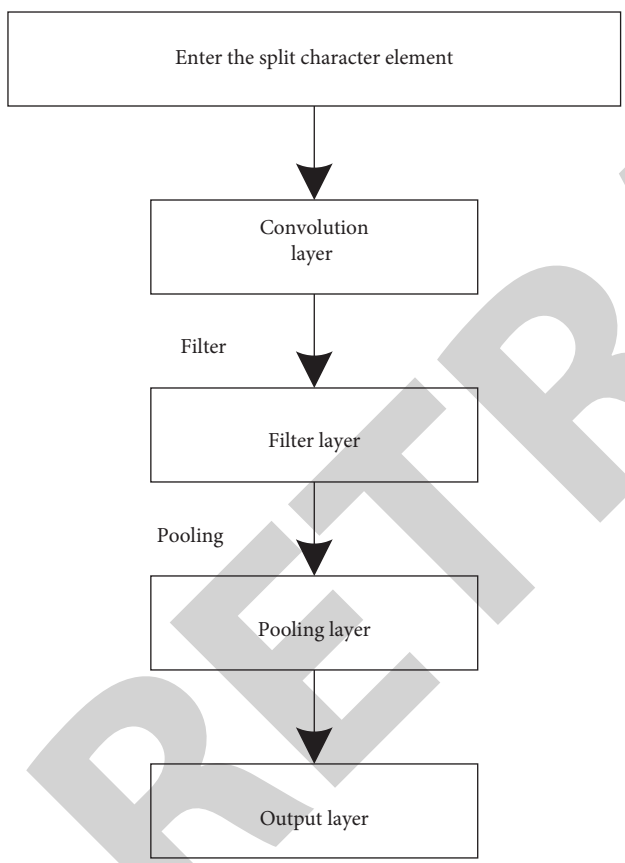

Figure 3: Feature extraction model.

$$t = \frac{s}{1-u} + [s(1-u)]^{1/3},$$

$$k = [\exp(-\varepsilon \times t) \times \text{mapwidth} \times \text{mapheight}]$$

$$= \left[\exp\left(-\varepsilon \times \frac{s}{1-u} + \left((1-u)s^{1/3}\right)\right) \times (\text{mapwidth} + \text{mapheight})\right], \tag{20}$$

where s represents variance; u represents the mean value of all nodes in map_i; mapwidth is the width corresponding to map_i; mapheight is the height of map_i; and ε is the free parameter.

In map_i, according to the calculated k, the first k nodes with large values are selected, and the states of other nodes are set to inactive.

2.4.3. Pooling and Feature Output. The pooling layer is the fourth layer of the network, and the number of map is nummap. In the third-layer map, the small block patch with size sizepw2 × sizeph2 is selected and moved from top to bottom and from left to right, the maximum value in the small block patch is taken as the output, and the output value is used to form the fourth layer. Through pooling, the data dimension can be reduced, and the corresponding maximum activation value can be obtained in a certain range.

The method based on big data clustering does not use the reverse fine-tuning mechanism to obtain the artistic features but initializes the model to improve the ability of extracting the artistic features of opera stage clothing. There are differences between the neuron function used in the output layer and the SIGMOD neuron function. The activation of each basic component in different positions can be described by map in the fourth layer.

The node j in the output layer is connected with the node map. Through competition, the node in the output layer obtains the change corresponding to the maximum activation value map in the fourth layer and takes it as the output value. The output value is the characteristic of drama stage costume art as follows:

$$\text{output}_j = \arg\max_i \text{map}_{ij}^4, \tag{21}$$

where output_j is the output of the j node in the output layer and map_{ij}^4 represents the value of node j in the fourth layer of the network.

3. Experimental Design and Result Analysis

In order to verify the advantages of the model, simulation experiments are designed. As shown above, we should get the input data, firstly. So, we design a system which can get the input data [27]. Then, we select the feature of these data. After that, we use the proposed method to get the classification results.

The hardware platform of simulation experiments is the personal PC of ADSP-BF561 (hereinafter referred to as BF561) processor, two 16-bit MAC, two 40-bit ALU, compatible with 3.3 V and 2.5 V I/O for outputting the data of the costume elements of the opera stage, two full-duplex serial interfaces for timing and counting of data clustering, and a low-power 12-bit digital/analog converter is used for data sampling. In parameter setting, the resolution of big data clustering is 24 bit, data sampling rate is 64 kps/s, and filter length $L = 25$. Firstly, we sample the big data of the elements of the opera stage clothing and get the characteristic waveform of the sampling data as shown in Figure 4.

Taking the data to be processed shown in Figure 4 as the test sample, the simulation experiment of big data clustering of drama stage clothing elements is carried out. The modified second-order cone programming model is used to obtain the information feature vector of big data clustering. On this

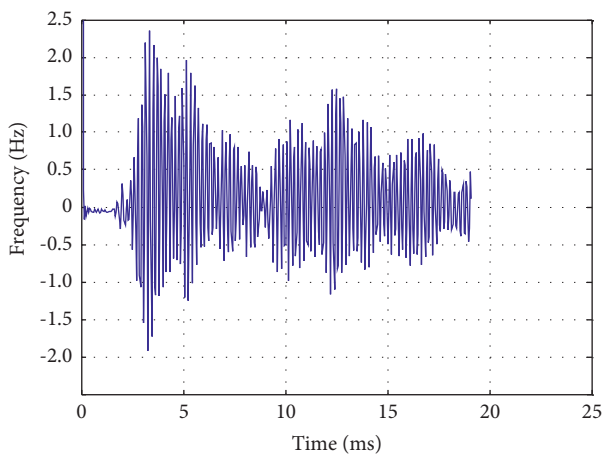

Figure 4: Data sampling waveform of costume elements in opera stage.

basis, the feature information classification method is used to improve the big data clustering algorithm, and the second-order cone programming model is constructed according to the determined parameters. The power spectral density feature is extracted, and the feature extraction result is shown in Figure 5.

According to the Figure 5, the blue line represents the sample value of the power spectral density at different times. As can be seen from Figure 5, the results of feature extraction have different sampling results according to different features, presenting a normal distribution on the whole. Based on the above feature extraction results, 16 groups of data in this group are clustered, and the output results are shown in Figure 6.

According to the Figure 6, the blue line represents the data fluctuation frequency at different times. As can be seen from this figure, the model realizes the accurate search of big data cluster center, the accuracy of data cluster is high, the change range of recording weight coefficient is known, the convergence error of the model is 0, and the performance is superior.

The method of extracting artistic features of stage costumes of opera based on big data clustering, the model of artist characteristic representation based on deep semantic mining of artist profile proposed in reference [3], and the model of multiscale feature detection based on high-quality feature map proposed in reference [4] are, respectively, used to test and compare the time taken for extracting artistic features of stage costumes of opera by the above methods. Feature extraction time of three methods is shown in Figure 7.

Figure 7 shows that the time taken to extract the features of stage costume model based on big data clustering algorithm is less than 4 s, while the time taken to extract features by other two methods is as high as 6 s and 8 s, respectively. Compared with the feature extraction time of the feature extraction method based on big data clustering, the feature extraction method based on big data clustering, the artist characteristic representation model based on deep semantic mining of artist profile [3],

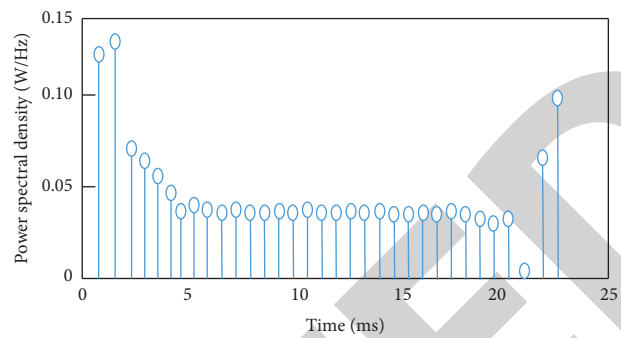

Figure 5: Data clustering feature extraction results in second-order cone programming model.

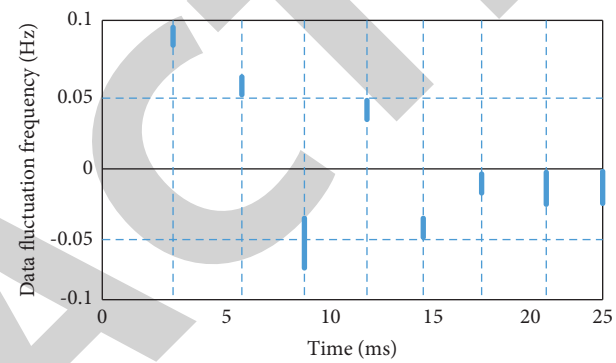

Figure 6: Output result of data clustering.

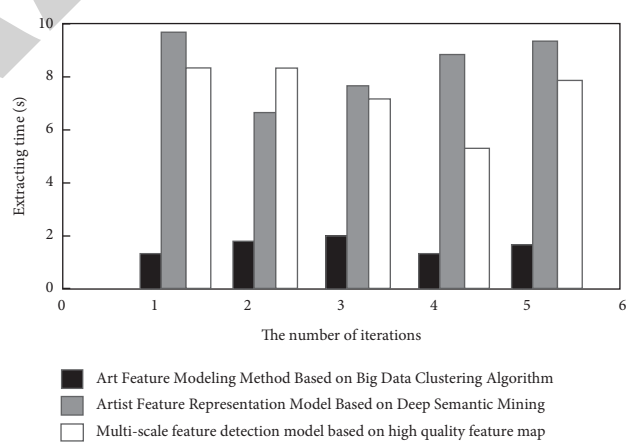

Figure 7: Feature extraction time of three methods.

and the feature extraction time of the multiscale feature detection model based on high-quality feature map [4], the feature extraction time of the feature extraction method based on big data clustering is less, because the feature extraction method of the feature extraction method based on big data clustering is used to segment the character elements before extracting the artistic feature of the stage costume of the opera, which reduces the amount of data to be calculated, improves the efficiency of the feature extraction method, shortens the time used, and verifies the high efficiency of the feature extraction method based on big data clustering.

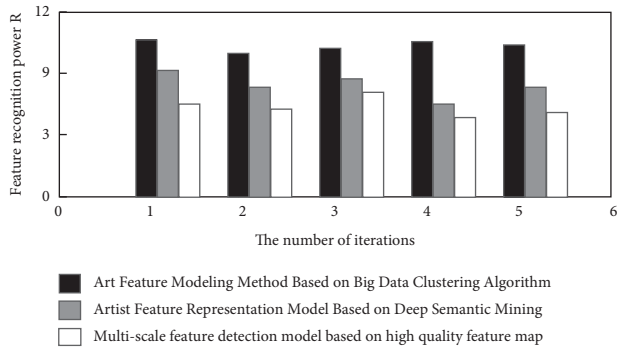

Figure 8: Feature identification power of three methods.

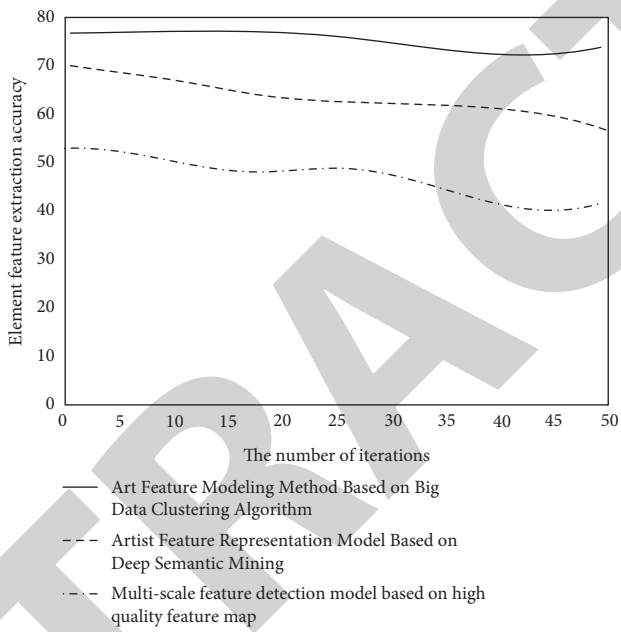

Figure 9: Accuracy results of element feature extraction.

Table 1: Average value of 40 experiments.

Name	Average value
Art feature modeling method based on big data clustering algorithm	76
Artist feature representation model based on deep semantic mining	67
Multiscale feature detection model based on high-quality feature map	44

Taking the feature recognition ability R as the index, the modeling model of opera stage costume art based on big data clustering is further tested. The calculation formula of feature recognition ability R is as follows:

$$R = \frac{\text{ave}\left[\text{sum}\left(d_i\right) - d_{\min}\right] - d_{\min}}{d_{\min}}. \tag{22}$$

In the above formula, D_M is the matching matrix; ave stands for average operation; and $d_{\min}$ is the minimum value of the matching matrix D_M.

The feature identification force R of different models is shown in Figure 8.

Figure 8 shows that in many iterations, the feature recognition ability of the proposed model is higher than that of the other two models. The higher the feature recognition ability is, the higher the accuracy is. The big data clustering based modeling method combined with convolution neural network and autoencoder improves the feature recognition ability of the big data clustering based feature extraction method and verifies the high accuracy rate of feature extraction.

On the basis of data clustering, the accuracy of feature extraction is improved. The accuracy of feature extraction is shown in Figure 9. In order to obtain more accurate results, we have done 40 experiments and counted the average value of the 40 experiments. The results are shown in Table 1.

As can be seen from Figure 9 and Table 1, the accuracy rate of artistic feature extraction of the model is high, which is close to the average accuracy rate and maintained at about

70%, while the accuracy rate of the other two methods shows a downward trend and is gradually lower than the average level with the change of iteration times. The main reason is that the large data clustering method is introduced in the modeling process of this paper, which effectively realizes the artistic feature extraction, and the focusing performance of the beam is good.

According to these experimental results, we can conclude that the algorithm proposed in this paper has good performance.

4. Conclusion

Aiming at the problems of traditional stage costume artistic feature analysis methods, a modeling method based on big data clustering algorithm is proposed. The attribute set of the big data feature sequence training set and the second-order cone programming model to correct the clustering results of big data are constructed. The elements of Peking Opera stage costumes are divided, constructed a Peking Opera stage costume artistic feature extraction model, and completed the artistic modeling of Peking Opera stage costumes. Experimental results show that the proposed modeling method has ideal convergence. The extraction of artistic features of stage costumes is time-consuming, high in accuracy, and high in feature recognition.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

This research was funded by Hubei University Humanities and Social Sciences Key Research Base Hubei IFA Fashion Art Research Center Traditional Structure and Technology research of Han Opera Costumes, subject number: IFA-2020-8.

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