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Analyzing Traditional Cultural Elements and Style Integration Patterns in Dance Movements Based on Matrix Decomposition Technique

Tiantian Li[1,✉], Hewen Zhong[2]

[1] *Music and Dance Academy, Changsha Normal University, Changsha, Hunan, 410000, China*
[2] *General Education Center, Changsha Civil Affairs Vocational and Technical College, Changsha, Hunan, 410000, China*

ABSTRACT
This paper points out that dance movements can be regarded as the carrier of the fusion of traditional cultural elements and styles, and ethnic folk dance movements are used as the dynamic expression of inheriting traditional cultural elements and styles. Analyze the characteristics of non-negative matrix decomposition algorithm, and use the non-negative matrix decomposition algorithm to reduce the dimensionality of dance action images. In order to optimize the classification effect of the classifier on the data after dimensionality reduction, SVM algorithm is selected to form a dance movement recognition method based on matrix decomposition technology and SVM classifier. By adjusting the values of penalty factor C and kernel parameter γ, the effectiveness of matrix decomposition algorithm for image dimensionality reduction is verified. Analyze the feasibility of the dance movement recognition method based on matrix decomposition technique and SVM classifier by selecting different data sets. Establish the dance movement evaluation model based on matrix decomposition technology, compare the evaluation model scores with the dance expert scores, and test the effect of matrix decomposition technology on the classification of dance movement styles. The Spearman's correlation coefficient ρ between the expert's score and the model's score remains above 90% in the evaluation of different dance movements. Combined with the evaluation guidance of dance experts, the dance style movement evaluation model proposed in this paper can effectively evaluate and analyze dance movement styles.

Keywords: matrix decomposition technique, SVM, dance movement recognition, traditional cultural elements

✉ Corresponding author.
E-mail address: litiantian0323@163.com (T. Li).
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1. Introduction

There has been a trend to incorporate traditional cultural elements in dance. This trend reflects people's renewed understanding of traditional culture and their pursuit of contemporary cultural innovation. On the one hand, more university teaching or dance groups can draw inspiration from traditional cultural elements and try the creative combination of different elements, which enriches the creative thinking of dance and spreads the traditional culture at the same time [1-2]. On the other hand, with the continuous development of science and technology, more digital technology can be applied to dance, which provides more development space and innovation potential for the integration of traditional cultural elements and dance styles. At the same time, the fusion of traditional cultural elements and dance styles can not only play a positive role in the field of local culture, but also is expected to play an important role in international exchanges [3]. Nowadays, people's demand for cultural industry is increasing, which provides a better market and development opportunities for the fusion of traditional cultural elements and dance styles. With the help of new media platforms such as Tik Tok, the dissemination channels of cultural products have become more convenient, and traditional cultural elements can be better inherited and promoted [4]. However, the style and traditional cultural elements in the dance movements, after adaptation or deformation, can not be so obvious to express, and for scholars who need to learn this kind of dance movements in depth, want to quickly learn the characteristics of the movements in the dance, matrix decomposition technology provides a good solution.

Matrix decomposition technique refers to the process of splitting a matrix into multiple sub-matrices, through which the information of the matrix can be represented and processed more efficiently [5-6]. These sub-matrices are generally with specific structure or meaning, such as symmetric matrices, positive definite matrices, identity matrices, etc., and they can be computed and stored more easily. Matrix decomposition is a commonly used technical tool in the field of machine learning and data analysis, by decomposing the data matrix, we can get the potential features and laws of the data to better understand and utilize the data [7-9]. For example, detecting digital video for forgery, checking the wireless network situation, etc [10-11]. But actually, matrix decomposition technique has more applications than that. It can also be applied in many fields such as recommender systems, social networks, biomedicine, collaborative filtering, and so on [12-15]. In addition, matrix decomposition technique can be used to optimize the analysis of data with poor accuracy, incompleteness, and inconsistency [16], and dance styles and movements that incorporate traditional cultural elements belong to this type of data.

This paper analyzes the inheritance embodiment of traditional cultural elements in folk dance, pointing out the importance of dance movements for the inheritance of cultural elements. The matrix decomposition algorithm is proposed, and the algorithm characteristics of the traditional non-negative matrix decomposition algorithm are analyzed. Add the dance movement picture data and describe the role of non-negative matrix decomposition algorithm in dance movement recognition in steps. Select SVM classifier as the classification algorithm, and form the whole algorithmic flow of SVM classification to recognize dance movements after dimensionality reduction processing of dance movement images based on matrix decomposition algorithm. Analyze the recognition performance of this paper's algorithm on different data sets. Establish the dance movement evaluation model based on matrix decomposition algorithm to classify the movement style of folk dance movements.

2. Traditional cultural elements and stylistic heritage in dance movement

2.1. Expression of traditional cultural elements inheritance in dance movement

Traditional cultural elements, as unique cultural symbols and characteristics formed in the process of long-term historical development, are important carriers of national identity and cultural inheritance.

Take the Tibetan dance "The Clothier" as an example, it is a dance work that digs deeply into the Tibetan cultural elements and shows the spiritual outlook and cultural heritage of the Tibetan people.

Traditional cultural elements have distinct ethnicity, history and artistry. Still taking the Tibetan dance "The Clothier" as an example, ethnicity is one of the most prominent features in the dance of "The Clothier". This dance work shows the uniqueness and individuality of Tibetan culture through unique dance language.

In the dance work "Lhasa Welcome Dance", the classic movements of Tibetan dance, such as "fluttering sleeves" and "stepping", are skillfully integrated into the dance. These movements not only show the distinctive features and bold enthusiasm of the Tibetan dance, but also transmit the profound national cultural heritage in an invisible way.

In the process of imitating and learning these movements, people not only exercise their physical coordination, but also feel the unique charm and spiritual connotation of the national culture in their hearts. This form of inheritance not only lets the dancers and the spectators appreciate the artistic beauty of the dance, but also deepens their knowledge and understanding of the national culture in a subtle way, thus cultivating their love and respect for the national culture.

2.2. Traditional Cultural Elements and Folk Dance Creation Integration Performance

Ethnic and folk dances embody the unique customs and habits of each ethnic group through the art form of dance, and show the spirit and flavor of the nation. Dance art consists of three elements, namely, dance expression, dance movement and dance composition, and the integration of traditional cultural elements and folk dance can be carried out from these three aspects.

2.2.1. Dance Expressions. Dance expression is one of the important factors constituting the image of dance, and is also a bridge to arouse the aesthetic resonance of the audience. Dance expression is different from the general natural state of emotions, and is not limited to facial expressions. Rather, it embodies the inner emotion through the speed, strength and amplitude of body language. Emotion is the driving force of dance, and rich emotion gives dance a unique charm and meaning. In the choreography of folk dance, the distinctive personality of each ethnic group is integrated into the emotion, which makes the work more vivid and makes the viewers move and empathize.

2.2.2. Dance movements. Dance movement is the main expression of dance art, the most important element in the dance language system, and the basic material that constitutes the dance language [17-18]. Dance movement is the basic unit of dance language through various action gestures and modeling to refine, process and beautify the objective things and subjective emotions, such as riding a horse, rowing a boat, sitting in a sedan chair, embroidery, raising a whip and so on. Therefore, when choreographing folk dances, ethnic folk dances can incorporate the expression of national style, characteristics, aesthetics and culture into the dance movements. For example, intangible cultural heritage can be skillfully integrated with ethnic folk dance, and typical movements that can reflect traditional culture, such as Taiji and martial arts, can also be incorporated.

2.2.3. Dance Composition. Dance composition contains spatial factors, which can make the dance movement give people beautiful enjoyment in the process of continuous flow. Dance composition mainly includes rhythm, music, costumes, props and so on.

1) Rhythm is the soul of dance, the key to characterization, mood and style, and all human form movements should form a coherent dynamic according to certain rules.

2) Dance and music are inseparable. Dance is an art form that manifests itself in body movements, while music is an art form that manifests itself in rhythm and melody.

3) Clothing and dance have a close relationship, which is the key to characterization in dance performance and can enhance the aesthetic value of dance works.

4) Props can greatly enrich the artistic vocabulary of dance and enhance the artistic expression and

infectious force.

2.3. Integration of Traditional Cultural Elements and Styles in Dance Movements

1) Dance movement affects the communication of dance style. Body movement is the most basic body language of dance art, and “pace” is the dance of lower limbs, which is the most basic element of body movement. It determines the spatial amplitude, spatial direction and spatial level of the dance movement through different force points, force directions, strengths and amplitudes. In turn, it affects the whole dance space structure, and achieves the emotional tendency unified with the emotional intensity of the theme.

Dance movement (pace) directly affects the visual form of the dance, dance style and the formation of a sense of beauty, which in turn has a great impact on the character image, temperament, spiritual emotions and other aspects of the dance played to highlight the performance.

Take Shanxi folk dance steps as an example. Shanxi folk dance step is very rich, the pace carries the performer's thoughts and feelings, laid the foundation of Shanxi folk dance dance, showing the Shanxi people's internal experience, the pursuit of the mood and the need for technical skills, the mastery of folk dance style plays a very important role.

2) Inheritance of folk dance movements to traditional culture. The pace of folk dance is an art form naturally formed by the inheritance among the people, which is the treasure of traditional culture. Its art form should be protected accordingly, so that the folk dance can be inherited as a classic, and the “people's dance” can move from the square dance to the stage.

The pace of folk dance is the basis of the dance rhythm, rhythm is the fulcrum of the dance performance, determines the time occupied by the dance action performance, the size of the action, fast and slow, strong and weak, and the relationship between each other. The formation of dance pace is closely related to the local natural environment, humanistic features, character traits of Shanxi people and other factors. Dance movement is an art form in traditional culture and an important cultural heritage in human culture with far-reaching research value, so it is very important to study the artistic expression and inheritance of folk dance movement.

3. Non-negative matrix decomposition and the basic process applied to action recognition

3.1. Non-negative matrix factorization algorithm

3.1.1. Non-negative matrix factorization algorithm. For a dance action representation V, where each column of V is a vectorized representation of a dance action image. Suppose a dance action image is a matrix of 32 rows and 32 columns. Therefore, its vectorized representation of a dance move is a vector of length $32 \times 32 = 1024$. Each dance move constitutes each column of V, resulting in a total of $40 \times 10 = 400$ columns for a database with 40 dance moves and 10 dance moves for each person. Thus, in this example, V is a matrix of 1024 rows and $\times 400$ columns, denoted by $V \in \mathbb{R}^{1024 \times 400}$, and for generality, the length of the vectorized representation of each dance move is denoted by n, and m is the number of dance move images, thus $V \in \mathbb{R}^{n \times m}$.

For a given dance action representation V, two non-negative matrices W and H need to be found such that:

$$V \approx WH \tag{1}$$

In Eq. (1), this paper defines a parameter r such that the matrices $W \in \mathbb{R}^{n \times r}$, and $H \in \mathbb{R}^{r \times m}$. Typically, r is chosen to be a much smaller number than n and m. As a result, matrix W and matrix H add up to a much smaller number of elements than the original matrix V.

Next, rewrite Eq. (1) by setting v_i to be the i th column of matrix V and h_i to be the i th column of matrix H. Thus:

$$v_i \approx Wh_i \tag{2}$$

Therefore, it can be understood that vector v_i is an approximation of a linear combination for each column of W, with a combination factor of h_i. To put it in another way, the n-dimensional representation of the dance movement $v_i\left(v_i \in \mathbb{R}^{n\times 1}\right)$ is disassembled according to matrix W, resulting in a r-dimensional linear representation $h_i\left(h_i \in \mathbb{R}^{r\times 1}\right)$. Since $r \ll n$ is usually the case, the purpose of dimensionality reduction of the original picture of the dance movement is thus achieved, and the parameter r is the dimensionality of the reduced representation.

In order to find the W and H matrix decompositions, two error functions are given here.

1) Error function based on Euclidean distance. Its basic formula is as follows:

$$\|A-B\|^2 = \sum_{ij}\left(A_{ij}-B_{ij}\right)^2 \tag{3}$$

By bringing in $A=V$, $B=WH$, the error function can be derived as:

$$F_{EU}(W,H) = \|V-WH\|^2 = \sum_{ij}\left[V_{ij}-(WH)_{ij}\right]^2 \tag{4}$$

The result of the matrix factorization is obtained by finding the W and H that minimize Equation (4):

$$\min_{W,H} F_{EU}(W,H)\ s.t.\ W \ge 0, H \ge 0 \tag{5}$$

2) Error function based on Kullback-Leibler quotient. Its basic formula is as follows:

$$D\left(A\|B\right) = \sum_{ij}\left(A_{ij}\log\frac{A_{ij}}{B_{ij}} - A_{ij} + B_{ij}\right)^2 \tag{6}$$

By $A=V$, $B=WH$, the error function can be derived as:

$$F_{KL}(W,H) = D\left(V\|WH\right) = \sum_{ij}\left[V_{ij}\log\frac{V_{ij}}{(WH)_{ij}} - V_{ij} + (WH)_{ij}\right] \tag{7}$$

It is sufficient to minimize Equation (4) by finding the W's and H's that minimize Equation (4):

$$\min_{W,H} F_{KL}(W,H)\ s.t.\ W \ge 0, H \ge 0 \tag{8}$$

3.1.2. Algorithmic characteristics. Compare the original dance movement pictures, feature pictures of non-negative matrix decomposition algorithm, and feature pictures of PCA algorithm. When combining into a dance movement, the PCA algorithm is to add or subtract the corresponding feature movements according to the combination coefficients one by one, and finally get the reconstructed dance movement. However, the non-negative matrix decomposition algorithm is to increase one feature movement according to the combination coefficients, and finally get the reconstructed dance movement [19-20]. The whole process of non-negative matrix decomposition is due to the coefficient matrix requirement must be non-negative. Therefore, there is no subtraction of the characteristic movements (the coefficients are negative when the characteristic movements are subtracted), thus better modeling the visual perception habits of the human eye. The reconstruction process of the non-negative matrix decomposition algorithm is very similar since the image seen, is the result of the superposition of many elements.

The non-negative matrix decomposition algorithm has more feature action parts than those obtained by the PCA algorithm, implying that the non-negative matrix decomposition algorithm is more sparse than the PCA algorithm. Therefore, the non-negative matrix decomposition algorithm is a natural sparse algorithm.

In summary, there are two advantages of the non-negative matrix decomposition algorithm:

1) The non-negative restriction makes the operation results simulate the visual perception habits of the human eye.

2) With natural sparsity, it can effectively deal with the lighting and occlusion of dance action images.

3.2. Basic flow of non-negative matrix factorization based algorithm

3.2.1. Processing of dance movement picture data. Since the database has a total of 40 dance moves, each move has 10 images, thus the entire database has a total of $40 \times 10 = 400$ dance move image. Thus, these 400 column vectors are combined to form a dance representation matrix $V \in \mathbb{R}^{10304 \times 400}$. Without loss of generality, n is used to denote the length of the vectorized representation of each dance movement, m is the number of dance movement images, and thus $V \in \mathbb{R}^{n \times m}$. In practice, since each pixel of a grayscale image takes on a value range of $[0,255]$, larger values tend to make the product of matrix multiplications very large. In order to facilitate the operation, the value range of the original image is usually mapped from $[0,255]$ to $[0,1]$. Let the current image matrix be P, $\max$ and $\min$ are the largest elements in image P, so the mapping function can be defined as:

$$P \leftarrow (P - \min) / (\max - \min) \tag{9}$$

3.2.2. Flow of non-negative matrix factorization algorithm. After obtaining the action representation matrix V of the dance action image, the next step is to learn the parameters using non-negative matrix factorization algorithm for matrix V.

STEP1: Set parameters r, r denote the dimensions of the dance image after dimensionality reduction, assuming $V \in \mathbb{R}^{n \times m}$, and so matrices $W \in \mathbb{R}^{n \times r}$, $H \in \mathbb{R}^{r \times m}$.

STEP2: Randomly initialize each element of matrices W and H.

STEP3: Compute matrices W and H according to the iteration formula to get the result of the matrix after the current round of iteration.

STEP4: Normalize matrix W or H so that the sum of each column element of W (or H) is 1.

STEP5: Calculate the current error $\|V - WH\|_F^2$ and determine whether the absolute value of the difference between the error functions of the two iterations is less than the threshold value. If it is less than the threshold value, the algorithm is finished, and the matrices W and H are the claimed solutions. If it is greater than or equal to the threshold, the algorithm has not converged, continue to run step3 until the algorithm converges.

3.2.3. Selection of Classification Algorithm - SVM Classifier. In statistical theory, SVM is one of the youngest and fastest growing machine learning techniques and it is also in a state of continuous development. It adopts the idea of SRM, and compared to traditional methods based on the idea of ERM, SVM has an outstanding performance ability in problems such as nonlinear and high-dimensional pattern recognition, as well as regression estimation and small-sample learning, and the solutions obtained are globally optimal. So it is greatly favored in the whole field of machine learning.

Suppose the set of training samples is $\{x_i, y_i\}$, $i = 1,2,\ldots,n$, $x \in R^d$, $y \in \{1,-1\}$ for classification labels. Then the general form of the linear discriminant function in the d-dimensional space can be expressed as: $g(x) = \omega * x + b$. The classification surface equation is:

$$\omega * x + b = 0 \tag{10}$$

The decision function is:

$$f(x)=\operatorname{sgn}(\omega * x+b) \tag{11}$$

where $\operatorname{sgn}(\cdot)$ is the sign function.

Then the function $g(x)$ is normalized so that $|g(x)|=1$ of the samples closest to the classification surface, at which point the classification interval is $2/\omega$. The problem of maximizing the classification interval can be replaced by the problem of minimizing ω (or ω^2). Then the problem of optimizing the solution of linearly divisible SVM can be summarized as follows:

$$\begin{gathered}\min \frac{\|\omega\|^2}{2} \\ s.t. y_i(\omega * x_i+b) \geq 1, i=1,2,\ldots,n\end{gathered} \tag{12}$$

Next, the following function is defined using Lagrange's method for finding extreme values:

$$L(\omega,b,\alpha)=\|\omega\|^2/2-\sum_{i=1}^{n}\alpha_i\left[y_i(\omega * x_i+b)-1\right] \tag{13}$$

where $\alpha_i>0$ is called the Lagrange multiplier, and the primary problem is to find the optimal ω^* and b^* to make the function reach a minimal value. The original convex quadratic optimization problem can be converted into its dual by taking the partial derivatives of ω and b in Eq. (13), respectively, and then making them equal to 0, i.e., in the constraints:

$$\begin{gathered}\sum_{i=1}^{n} y_i\alpha_i=0 \\ \alpha_i \geq 0 i=1,2,\ldots,n\end{gathered} \tag{14}$$

Solve for the maximum value of the following function under α_i:

$$\max Q(\alpha)=\sum_{i=1}^{n}\alpha_i-1/2\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j(x_i * x_j) \tag{15}$$

if α_i^* is the optimal solution:

$$\begin{cases}\omega^*=\sum_{i=1}^{n}\alpha_i^* x_i y_i \\ b^*=-\frac{1}{2}\omega^*(x_r+x_s)\end{cases} \tag{16}$$

This means that the weight coefficients of the optimal classification plane can be represented by a training sample vector, where x_r and x_r are an arbitrary pair of support vectors in both categories.

In the training samples, there will be many samples α_i^* will be zero and only a small fraction of samples α_i^* will be non-zero. The optimal classification surface is determined by the support vectors i.e. the samples where α_i^* is not zero.

Then the optimal classification function is:

$$f(x)=\operatorname{sgn}(\omega * x+b^*)=\operatorname{sgn}\sum_{i=1}^{n}\left[\alpha_i^* y_i(x_i \cdot x)+b^*\right] \tag{17}$$

b^* is the threshold for classification, which can be obtained from any support vector.

Except for the linearly differentiable case mentioned above, most problems in real situations are linearly indistinguishable. When linearly indivisible cases are encountered, the optimal classification surface needs to be improved accordingly. What is used is to add a slack term $\xi_i \geq 0$ to the constraints, then the optimization problem of solving the optimal plane becomes solving for the minimum value of Eq. (18):

$$\begin{cases} \phi(\omega,\xi)=\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}\xi_i \\ s.t. y_i\left(\omega x_i+b\right)\geq 1-\xi_i,\xi_i>0 \end{cases} \tag{18}$$

where C is a constant used to penalize the misclassified samples to a greater degree. As the penalty for misclassification increases, the value of C increases. This is done to enhance the learning model to make it more generalizable.

For the very small value problem of Eq. (18), the approach taken is also to utilize the Lagrangian dyadic form, with the difference being that the constraints are a little bit different from linear differentiability. Namely:

$$\max Q(\alpha)=\sum_{i=1}^{n}\alpha_i-1/2\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j\left(x_i * x_j\right) \tag{19}$$

The constraints are:

$$\begin{gathered} 0\leq\alpha_i\leq C, i=1,2,\ldots,n \\ \sum_{i=1}^{n}\alpha_i y_i=0 \end{gathered} \tag{20}$$

There are three possible values of ① $\alpha_i=0$, ② $0<\alpha_i<C$, and ③ $\alpha_i=C$ for α_i in Eq.

The x_i satisfying ② is the standard support vector, and the x_i satisfying ③ is called the boundary support vector. From the above analysis, it can be seen that only the support vectors play a role in determining the optimal hyperplane and the decision function.

Meanwhile, from the optimal classification function in equation (17), it can be seen that there is a dot product between the classification samples and the support vectors. In the case of binary classification, it can be well understood. However, if it is on the high-dimensional space, an inner product way should be sought to replace the dot product, so that the original feature space can be transformed to the new feature space, and here $K\left(x,x'\right)$ is used to replace the dot product in the optimal classification surface. The optimization function at this point then becomes:

$$Q(\alpha)=\sum_{i=1}^{n}\alpha_i-1/2\sum_{i,j-1}^{n}\alpha_i\alpha_j y_i y_j K\left(x_i * x_j\right) \tag{21}$$

And the corresponding discriminant function Eq. (17) should also become:

$$f(x)=\operatorname{sgn}\left(\omega * x+b^*\right)=\operatorname{sgn}\left\{\sum_{i=1}^{n}\alpha_i^* y_i K\left(x_i * x\right)+b^*\right\} \tag{22}$$

Therefore, the idea of SVM can be summarized as the use of a suitable inner product function to deal with a nonlinear problem, which aims to map the input space to high dimensions to find the optimal classification surface.

4. Dance movement decomposition based on matrix decomposition technique

4.1. *Matrix Decomposition Techniques and SVM Classifier Effects*

In order to verify the effectiveness of the method proposed in the text, experiments were conducted on the publicly available datasets UTKinect dataset, MSRAction3D dataset, and the folk dance movement dataset constructed in this paper.

Both UTKinect movement dataset and MSRAction3D movement dataset are acquired by Kinect depth sensor, which contains 20 joint point movement data of human body, which is consistent with the dance movement data structure of this paper.

The UTKinect dataset contains 10 classes of actions, totaling 200 action samples, and the MSRAction3D dataset contains 20 classes of actions, totaling 612 action samples.

The dataset constructed in this paper contains a total of 800 ethnic dance movement skeleton data samples. Among them, 8 ethnic dances are included, and each ethnic dance includes 5 action categories, totaling 40 action categories, and 20 action samples are collected for each action.

The training recognition accuracies of different datasets using this paper's method are shown in Fig. 1, and the recognition accuracies of this paper's method for all three datasets reach about 80%.

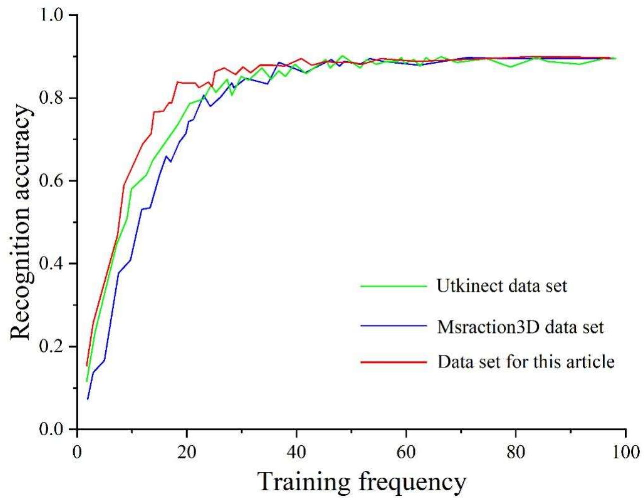


Fig. 1. Different data sets use the training recognition accuracy of this method

The validation recognition accuracies of different datasets using this paper's method are shown in Figure 2. In the range of 0~20 iterations, the recognition accuracy of this paper's method on the dataset shows large fluctuations. In the late stage of iterative validation (40~100), the recognition accuracy tends to stabilize, and the recognition accuracy is about 82%.

The results show that this paper's method also obtains good results in other movement datasets, which can verify the effectiveness of this paper's method and also shows that the construction of this paper's dataset is more reasonable.

The reasons why the typical movements of folk dance dataset can obtain better recognition effect are analyzed as follows:

1) During the screening process of typical movements of folk dance, the dance movements with relatively large differences in movements were selected.

2) More sample numbers of movements were collected and more deep learning data were obtained.

3) The collected dance movements have more durations than the typical movements, and more movement representations were also acquired.

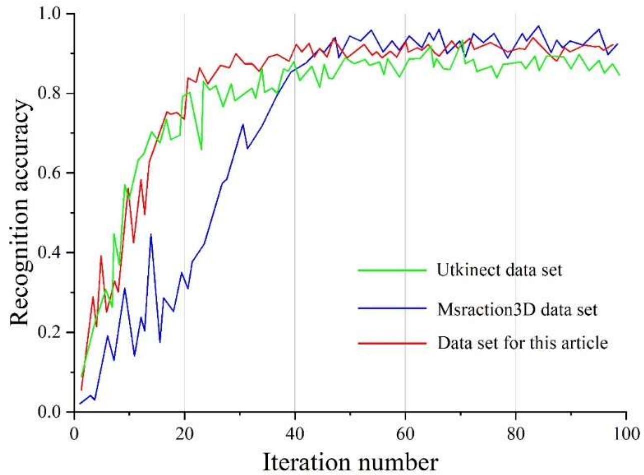


Fig. 2. Different data sets use the validation recognition accuracy of this method

In order to further validate the effectiveness of the proposed method in this paper, this paper carries out action recognition performance testing before and after the dimensionality reduction processing of the matrix decomposition technique.

In the experiment, the training and testing images are all to be normalized to the same size. The experiment was divided into three groups, normalized images of 64*64, 52*52 and 48*48, respectively, for the experiment.

Then the image features are extracted, according to the calculation steps of HOG features, the cell size is taken as 8*8 pixels, block size as 3*3cell, sliding window size as 32*32 pixels, and step size as 10 pixels. Then the obtained feature dimensions are 1850, 1500 and 1000 dimensions respectively. For SVM, RBF-SVM is used in this paper.The SVM training results are saved in the form of XML for SVM detection to read and classify the test images. The relevant parameters of the three sets of experiments are shown in Table 1.

Table 1. The relevant parameters of the three groups of experiments

Experimental frequency	Image normalized size (pixel)	HOG characteristics (dimension)
I	64*64	1850
II	52*52	1500
III	48*48	1000

In order to verify the effectiveness of the algorithm proposed in this paper, 600 positive and negative samples each are firstly selected for the training of SVM classifier. A total of 600 positive and negative test samples each are selected to be recognized by the trained classifier, and there is no intersection between the test samples and the training samples. By adjusting the penalty factor C and kernel parameter γ, the best recognition effect achieved by the three sets of experiments is shown in Table 2.

Experiments show that when the penalty factor C is fixed, changing the value of γ affects the recognition results. Usually, when γ is large, the recognition results of negative samples are good, even up to no misdetection, but the recognition results of positive samples are not so good. And when γ is larger than a certain degree, the recognition accuracy of negative samples will also decrease. As γ decreases, the number of negative samples recognized becomes smaller. But the number of recognized positive samples can be increased a lot. As γ decreases further, the recognition results of negative samples will decrease significantly, while the recognition results of positive samples do not increase significantly, but also appear to decrease.

When the kernel parameter γ is fixed, changing the value of C also affects the recognition results.

When the value of C is taken smaller, the positive samples are recognized better and the negative samples are relatively worse. When the value of C gradually increases, the recognition results of negative samples will be better, but the number of positive samples recognized will decrease. When the value of C exceeds a certain value but is within a certain range, the recognition results do not change much. When the value of C is too large, the accuracy of the recognition decreases sharply.

Through cross-validation experiments, it can be found that when the image size is 48*48 and the HOG features are 1000 dimensions, the best recognition results are achieved when the penalty factor C=6 and the kernel parameter γ=0.3, and the accuracy of recognition reaches about 82%.

Table 2. Results of the three groups of experiments

Image size (pixel)	Sample type	Correct identification (amplitude)	Correct identification rate	SVM parameter
48*48	Specific copy	496	0.8267	C =6, γ =0.3
	Negative sample	531	0.8850	C =6, γ =0.3
52*52	Specific copy	458	0.7633	C =6, γ =0.3
	Negative sample	556	0.9267	C =6, γ =0.3
64*64	Specific copy	487	0.8117	C =6, γ =0.01
	Negative sample	529	0.8817	C =6, γ =0.01

Although the image is normalized to a smaller size in the experiment, the HOG features are computed by chunking the image and extracting the HOG features block by block, so the dimension of the extracted HOG features is high. Since too high feature dimensions may have redundant information and lead to a complex and inefficient feature matching process, this paper hopes to reduce the dimensionality of the features by means of dimensionality reduction, and here the dimensionality reduction method of matrix decomposition technique is proactively used.

In the experiment, the HOG feature is first extracted from the image and then the feature is downscaled by matrix decomposition. The dimensionality reduction is performed on 1000, 1500 and 1850 dimensional features respectively. The dimensions after dimensionality reduction are 230, 280 and 320 dimensions respectively. The optimal recognition results are achieved by adjusting the penalty factor C and kernel reference γ. The recognition results after dimensionality reduction by matrix decomposition technique are shown in Table 3. The recognition rate of images after dimensionality reduction by matrix decomposition technique is improved in all three sets of experiments. Among the three sets of recognition results, the SVM classifier achieves the lowest recognition rate of 83.17% for dance movements when C=6, γ=0.3 and the image is 52*52 pixels. When is significantly higher than the 76.33% recognition rate before dimension reduction.

Table 3. The degradation of the matrix decomposition technology is identified

Image size (pixel)	Sample type	Correct identification (amplitude)	Correct identification rate	SVM parameter
48*48	Specific copy	527	0.8783	C =6, γ =0.3
	Negative sample	564	0.9400	C =6, γ =0.3
52*52	Specific copy	499	0.8317	C =6, γ =0.3
	Negative sample	565	0.9417	C =6, γ =0.3
64*64	Specific copy	532	0.8867	C =6, γ =0.01
	Negative sample	567	0.9450	C =6, γ =0.01

4.2. Scoring the cultural elements and styles of dance movement

4.2.1. Dance movement evaluation model. This paper applies the dance movement recognition technology based on matrix decomposition technology and SVM classifier to dance movement quality evaluation.

The dance movement quality evaluation system proposed in this paper emphasizes the traditional cultural elements contained in dance movements, and pays attention to the integration of dance movements and dance styles. The system architecture includes four main modules: movement feature input, standard movement library setting, dance movement recognition and comparison, and evaluation result output. The input of movement characteristics is the data of dance movement characteristics mentioned above. The standard movement library adopts the movement data of top professional dancers as the standard movements through the analysis and guidance of domain experts. Dance movement identification and comparison is mainly done by using matrix decomposition technology and SVM classifier to identify the dance movements to be classified, and comparing the identified dance movements with the standardized movements. The output of the evaluation results is to provide vivid feedback to the dance practitioners by means of visual charts and interactive displays of the movement quality evaluation results.

4.2.2. Results of the dance movement evaluation. Experiments are conducted to verify the effectiveness of the dance movement evaluation model designed above. From the folk dance dataset constructed in this paper, 2 dancer's movement video samples are randomly selected. The samples include 15 ethnic dance movements, each containing 20 dance movement videos. These folk dance movement samples were scored by the evaluation method described above. Five experts in the field of folk dance were also invited to score the dance movement samples professionally. The effectiveness of the movement evaluation method proposed in this paper was verified by comparing the scoring gaps.

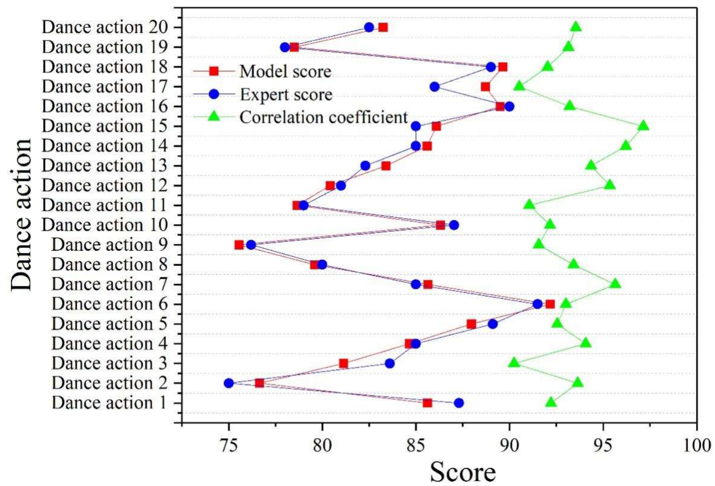
The Spearman rank correlation coefficient was used as an evaluation index in this experiment. The Spearman correlation coefficient can indicate the degree of correlation between the predicted scores and the reference scores without focusing on the real values, and is generally expressed as ρ.

The Spearman rank correlation coefficient can be used to evaluate the correlation of two statistical variables using monotonic equations, reflecting the closeness of the relationship between two sets of variables. It is usually used as a nonparametric measure of the correlation between two sets of variables, taking values between -1 and +1. When the predicted scores and the expert ratings are perfectly monotonically correlated, the correlation coefficient ρ is either +1 or -1. For a sample with a sample size of n, the n raw data are converted into rank data. In this paper, the Spearman correlation coefficient ρ is expressed as a percentage, then the correlation coefficient ρ is calculated as shown in equation (23):

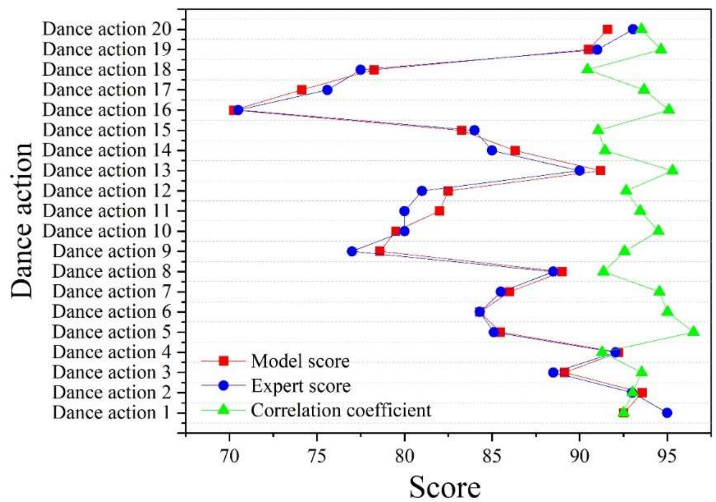
$$\rho = 1 - \frac{6\sum d_k^2}{n\left(n^2-1\right)} \times 100\% \tag{23}$$

where d_k is the difference between the positions of the original data x_k and y_k in the sorted list. x_k denotes the predicted score value of the kth sample given by the dance movement evaluation model proposed in this paper. y_k denotes the mean value of the score of the kth sample given by three experts in the field of dance. Descending order is given to x_k and y_k, and the positions of x_k and y_k are labeled as $x_k^{'}$ and $y_k^{'}$, respectively.

The scores of the folk dance movements of the two dancers are shown in Figure 3. The Spearman's correlation coefficient ρ was above 90% for the different dance movements evaluated experimentally. According to the guidance and analysis of experts in the field of dance, the dance style movement evaluation model proposed in this paper has high accuracy and can effectively evaluate and analyze the dance movement styles.



(a) Dancer 1 action score



(b) Dancer 2 action score

Fig. 3. The two dancers' national dance action scores

5. Conclusion

This paper proposes a non-negative matrix decomposition algorithm and SVM classification algorithm for dimensionality reduction and classification recognition of dance movement images. A dance movement evaluation system based on matrix decomposition algorithm and SVM classifier is established to score the traditional cultural elements and cultural styles of folk dance movements.

The dance movement image dimensionality reduction and classification method proposed in this paper achieves about 80% recognition accuracy on the public dataset UTKinect dataset, MSRAction3D dataset and the folk dance movement dataset constructed in this paper. Establishing the folk dance movement scoring model based on matrix decomposition technology, comparing the scoring model with the scoring data of the folk dance experts, the Spearman correlation coefficient ρ between the dance movement style evaluation model established in this paper and the expert scoring is calculated to be consistently above 90%. It shows that the dance movement evaluation model based on matrix decomposition algorithm and SVM classifier designed in this paper can analyze and judge the traditional style elements of folk dance movements.

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