Dynamic Gait Recognition of Chinese Dance Based on Contour Features

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Abstract
Single feature recognition has certain limitations, which can't fully reflect the differences between dance gait information, resulting in low recognition rate of frame difference features. In this paper, a dynamic gait recognition method for Chinese classical dance is proposed based on contour features. The gait image of Chinese dance is preprocessed, the target region is segmented, and the gait cycle is extracted. The gait energy map is composed of the sequences in a cycle, which contains the information of the upper and lower limb motion frequencies of the dancer. The key distance, width, wavelet features and gait energy map are fused to form a group of feature vectors. The problem of low efficiency of single feature recognition is solved by feature fusion. Based on CNN model, a dynamic gait recognition model of Chinese dance is established based on contour features. Under the function of convolution kernel, the values of each channel are concatenated into a one-dimensional vector to express the contour features and complete the video sequence classification. The test results show that the design method retains the correlation between the gait data of Chinese classical dance, accurately locates the key points, and reflects the movement and time information of gait, so the recognition rate is improved.

Keywords: *Contour feature; China classic dance; Gait recognition; Dynamic identification*

1 INTRODUCTION

Gait is the posture that the human body shows when moving. Due to the differences of each person's bone density, muscle strength, center of gravity stability and limb coordination ability, gait can be recognized in different environments and body states. Compared with other motion recognition, gait can be collected without close contact, which is easy to be accepted by the public. Gait recognition technology belongs to the research field of high-level computer vision [1] [2]. Chinese dance is a way to convey emotions and emotions to the public through body movements. Different from other forms of movement, the movements of Chinese dance change with the music according to the law, and have the characteristics of rhythm and continuity. Chinese dance gait recognition processes the collected original video or image sequence to form dance action sequence, establishes the relationship mapping between gait and action, and completes gait pattern analysis through motion detection and feature extraction. The gait recognition of Chinese dance can be applied in competition and daily practice to analyze dance movements and play an auxiliary role in judgment or practice. Compare the dancer's movements with the standard dance steps, evaluate or correct them, so as to improve the dance quality.

Applying the gait dynamic recognition method to the research of Chinese dance can make the dance arrangement more efficient and expand the research field of computer intelligence technology. The frequency domain attention mechanism is introduced into the spatio-temporal feature analysis of gait recognition. Gait recognition and classification are realized based on the extracted gait features through C3D network [3]. This recognition model reduces redundant computation, distributes the importance of gait features evenly, and optimizes the effect of classification learning. According to the dynamic and static information during walking, a dynamic model is established, and the motion trajectory is characterized and extracted by fitting the current motion with the model. In order to enhance the robustness of clothing changes in the recognition process, the global and local discrimination information is extracted through the dual flow gait network. After the two features are fused, the random occlusion strategy is used to reduce the adverse effects of covariates [4]. The

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above gait recognition effectively solves the influence of carrying objects on the recognition effect. The fusion space pyramid pooling network is used to calculate the gait energy, transfer the feature ability to gait recognition, and improve the gait recognition performance through the transfer and learning of multi-scale information [5]. At present, some achievements have been made in the research of gait dynamic recognition, keeping the recognition angle and scale fixed, and establishing the gait feature space through the description of key frames [6] [7]. In the research of gait dynamic recognition, single feature recognition has certain limitations, which can not fully reflect the differences between dance gait information, resulting in low recognition rate of frame difference features and affecting the effect of gait recognition. To solve this problem, this paper proposes a Chinese dance gait dynamic recognition method based on contour features, which reflects the changing characteristics in the dance process, improves the dynamic recognition performance, and lays a foundation for the development of gait recognition.

2 EXTRACTING GAIT CYCLE OF CHINESE DANCE

In the video sequence, the information of various gait data of Chinese dance is large, and there are also background areas that interfere with the recognition. In order to improve the efficiency of data analysis, gait cycle is extracted based on preprocessing the gait image of Chinese dance and segmenting the target region. In this paper, the mean filter is used to construct the background region model, which is expressed as:

$$w(\alpha,\beta,\gamma)=\frac{1}{m}\sum_{n=1}^{m}p(\alpha_n,\beta_n,\gamma_n) \tag{1}$$

In formula (1), α,β,γ are the image coordinate; $w(\alpha,\beta,\gamma)$ is the filtered background image; n and m are sequence numbers and total frames of the sequence; $p(\alpha_n,\beta_n,\gamma_n)$ indicates the nth frame image. The background region model of the Chinese Dance target image is grayed out, and the contour image is obtained after it is differentiated from the image of each frame, which is expressed as:

$$R_n(\alpha,\beta)=|p'(\alpha,\beta)-w'(\alpha,\beta)| \tag{2}$$

In formula (2), $R_n(\alpha,\beta)$ is the contour image of the nth frame; $w'(\alpha,\beta)$ and $p'(\alpha,\beta)$ are grayed background and gait images. Set a threshold value for the Chinese dance target image after binary segmentation. If $R_n(\alpha,\beta)$ is greater than the threshold value, assign a value of 1 to the position, otherwise it will be 0. The initial threshold is determined by the mean value of the foreground and background pixels. After iteration, the optimal value is obtained to achieve the purpose of noise reduction. After gait image segmentation, the morphological processing method of corrosion and expansion is used to filter out the incomplete parts of the image and reduce the holes of structural elements [8] [9]. With the change of Chinese dance video time, the dancer's contour width shows a periodic change trend with the movement spacing of both feet. When the distance between feet is small, the contour width is relatively small. At the same time, the width height also has a periodic change law. Gait cycle is extracted according to the width and height changes of human contour such as arm and lower limb [10]. In this paper, the time interval between the left foot and the right foot and the ground is set as one cycle. The sequences in a cycle are used to construct a gait energy map containing the information of the upper and lower limb motion frequencies of the dancer. Gait energy diagram $Q(\alpha,\beta)$ can be expressed by the following formula:

$$Q(\alpha,\beta)=\frac{1}{m}\sum_{n=1}^{m}R'_n(\alpha,\beta) \tag{3}$$

In formula (3), $R'_n(\alpha,\beta)$ is the gait sequence of standardization treatment. The energy information of Chinese dance video sequence in a period is obtained by marking and sorting $Q(\alpha,\beta)$ according to the gray value.

3 SELECT THE CONTOUR FEATURES OF CHINESE DANCE STEPS

In the Chinese dance gait energy map, the pixel brightness value of the high-frequency part is large, indicating that the Chinese dance gait features appear a high number of times, which can be regarded as static contour information. On the contrary, the brightness value of the low-frequency part is small, which can be considered as the area of body movement change in Chinese dance, reflecting the dynamic characteristics of the contour [11]. In the research of gait dynamic recognition, the ability of a single feature in depicting information details is limited and has certain limitations. This can’t fully reflect the difference between dance gait information, resulting in a low recognition rate of frame difference features, which affects the gait recognition effect. In this paper, the contour features of Chinese dance steps are extracted from multiple angles. Human contour features vary with height and center of gravity. The change of distance between contour points and center of mass during dance is a gait feature [12]. In this paper, the distance from the center of mass to the top of the head, hands and feet is selected as the contour distance feature. First, calculate the position coordinates of the centroid as follows:

$$\left\{\begin{aligned}\alpha_0&=\frac{1}{s}\sum_{i=1}^{s}\alpha_i\\ \beta_o&=\frac{1}{s}\sum_{i=1}^{s}\beta_i\end{aligned}\right. \tag{4}$$

In formula (4), α_0, β_o are the centroid coordinate; i and s are the sequence number and total number of contour points respectively. Then, the key points of the dancer's contour are extracted from the single frame image, and the distance is calculated. The distance characteristic D_i is calculated as follows:

$$D_i = \sqrt{(\alpha_i - \alpha_0)^2 + (\beta_i - \beta_0)^2} \tag{5}$$

The maximum, mean and standard deviation of the contour feature distance are set as the spatial features of the Chinese dance movement target, including five key distances, which represent the continuous distance changes in a cycle. Therefore, the distance characteristic is a vector with 20 dimensions. The number of rows represents the distance type, and the number of columns represents the value size at the statistical level. They respectively reflect the spatial and temporal differences and distribution rules of contour features. On this basis, the feature of contour width is determined. This feature includes the distance between hands and feet, arm swing amplitude and height span of lower limb movement [13] [14]. Similarly, the statistical data of four width distances of all frames of Chinese dance video sequence are calculated to form the contour width feature, which is also expressed as a 20 dimensional vector. Contour distance and width features can be used as static information in Chinese dance gait recognition. In order to reflect the internal information of the contour, the wavelet transform is used to extract the internal features. The function can be expressed as:

$$\kappa(\varsigma) = \{ \begin{matrix} -1, 0 \le \varsigma < 0.5 \\ 1, 0.5 \le \varsigma \le 1 \\ 0, \text{otherwise} \end{matrix} \tag{6}$$

In formula (6), ς is the range of support region; $\kappa(\varsigma)$ is Haar wavelet function. After wavelet transformation, the Chinese dance video sequence is decomposed into two-dimensional images, and the mean and standard deviation of different parts are calculated to form a parallel same period vector, which is the contour wavelet feature [15]. Combining the above three static features with gait energy map, the above features can well describe the dynamic process of Chinese dance gait. Gait energy contains the information of the whole sequence. Threshold segmentation is performed on it, and distance transformation is used to divide and extract the dynamic features of a single frame [16] [17]. Through the recognition model to distinguish the pixel changes in different regions of Chinese dance video sequence, the classification and recognition are completed.

4 DYNAMIC GAIT RECOGNITION MODEL BASED ON CONTOUR FEATURES

The key distance, width, wavelet features and gait energy map are fused to form a set of feature vectors, which are input into the recognition model. The Chinese dance gait dynamic recognition model based on contour features can effectively solve the problem of low recognition rate of frame difference features. In multi-resolution image classification, CNN can better extract features and realize training and learning from low-level to high-level. Its essence is a fitting function. In high-level semantic recognition, the data fitting effect is adjusted through reverse iteration and weight parameters to avoid the low individual classification probability caused by the accumulation of all pixel values.[18]. The recognition model minimizes the loss function as the target, and makes the classification result close to the optimal value. In order to avoid falling into local optimization due to the rapid decline of random gradient, Adam optimizer is used to adjust the learning step and speed of parameters. The learning step update amplitude is calculated as follows:

$$\lambda_z = \vartheta\lambda_{z-1} + (1 - \vartheta)\varpi_z \tag{7}$$

In formula (7), z is time; λ_z means learning step length; ϑ is exponential decay rate; ϖ_z represents the gradient of the z time step. ϑ is mainly responsible for controlling the weight distribution, and using a small step size to adjust the parameters with high change frequency. After Adam optimization, the update formula of learning rate is expressed as:

$$\psi_z = \theta\psi_{z-1} + (1 - \theta)\varpi_z^2 \tag{8}$$

In formula (8), ψ_z is the learning rate of time z; θ is the gradient decay rate. Using a large learning rate for the parameters with sparse characteristics, the recognition model can gradually become stable. For the four eigenvectors constructed in this paper, GAP is used instead of FC to improve the output performance of convolution layer. The number of channels is set according to the number of categories of the contour feature vector. Under the action of convolution kernel, the values of each channel are connected in series into a one-dimensional vector, which expresses the contour feature [19] [20]. The data in the five channels are added and summed, and input into softmax to calculate the probability results of the corresponding classification units. The above average pooling process can reduce the parameter values and calculation amount of different feature dimensions, directly give practical significance to each category, and realize the unification of the feature dimensions of the outline of Chinese dance steps. According to the model, the Chinese dance video sequence samples are classified to complete the dynamic gait recognition.

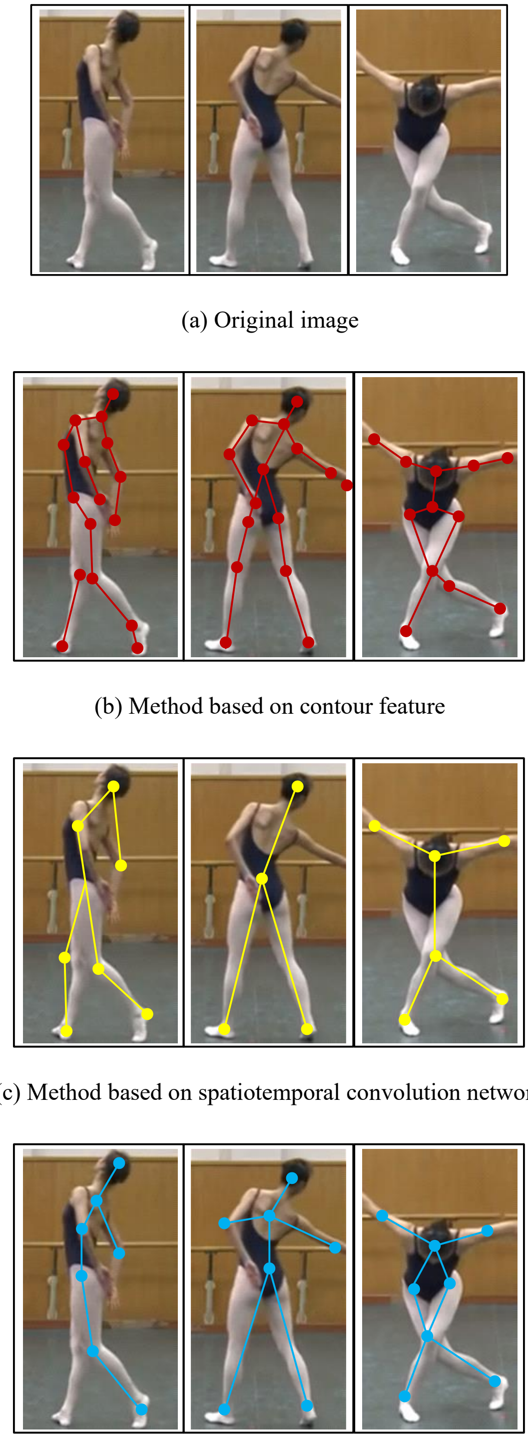
5 EXPERIMENT

5.1 *Experimental data set and environment setting*

In order to test the effectiveness of the Chinese dance gait dynamic recognition method based on contour feature design in this paper, it is verified on different data sets. Due to the lack of research on the combination of gait recognition and dance, the relevant data sets are relatively limited. In terms of gait recognition, CASIA B is a large-scale, multi view database, containing gait sequence diagrams of 11 views from 0 ° to 180 °. Each view contains three states, namely, normal, wearing a coat and carrying a backpack. In this test, the normal gait sequence with 90 ° angle of view is selected from CASIA B for recognition. Each sequence extracts four cycles, three of which are training samples and the other cycle is test data. In the aspect of dance recognition, firstly, the public DanceDB is selected as the data set. DanceDB has 48 videos in total, and its viewing angle is fixed. DanceDB is divided into 12 dance videos according to different emotions, including angry, bored, pleased and tired. The training and test samples were selected according to the ratio of 3:1, and the dance movements were classified and identified according to the emotional labels. Because this paper mainly studies the method of Chinese dance gait dynamic recognition, we use motion capture equipment to collect Chinese dance videos and establish Classic data sets. Classic is mainly the performance of single person Chinese dance, and there are more body movements. The angle of the device and the video background remain unchanged during the acquisition process. Each video clip is a combination of dance movements in about 15 seconds, a total of 52 videos, 49 of which are selected as training samples, and the rest are test data. The above data sets meet the needs of this paper for the research of Chinese dance gait dynamic recognition, and can be verified by experiments. The CPU of the experimental environment is Intel(R) Core (TM) i5-12400/16G/1T HDD+256G SSD, and the operating system is Ubuntu. The dynamic recognition of Chinese dance gait is carried out in MATLAB.

5.2 *Experimental results and analysis*

In order to ensure the fairness of the test results, this experiment is compared with other identification methods under the same conditions to evaluate the feasibility of the design method. The comparison methods selected in this paper are Chinese dance gait dynamic recognition methods based on frequency domain attention space-time convolution network, dual flow gait network and multi-scale feature transfer learning. In the Classic dataset, the recognition effect of each method is shown in Figure 1.

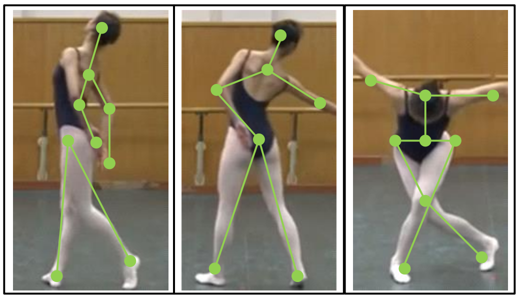


(a) Original image

(b) Method based on contour feature

(c) Method based on spatiotemporal convolution network

(d) Method based on dual stream gait network



(e) Method based on multi-scale feature transfer learning

Figure 1: Gait recognition effect of Chinese dance

According to the results in Figure 1, compared with other comparison methods, the Chinese dance gait dynamic recognition method based on contour feature design has a stronger ability to describe the details. On the basis of not destroying the characteristic data structure, it preserves the correlation between Chinese dance gait data, accurately locates key points, and reflects the movement and time information of gait. Further, the recognition rate of each method is calculated by using the experimental data set, and the dynamic gait recognition is evaluated from an objective point of view. The comparison of the recognition rates of the four methods in CASIA B, DanceDB and Classic data sets is shown in table 1-3.

Table 1: Recognition rate of CASIA B dataset (%)

Number of tests	Dynamic gait recognition of Chinese dance based on contour features	Dynamic gait recognition of Chinese dance based on frequency domain attention space-time convolution network	Dynamic gait recognition method of Chinese dance based on dual stream gait network	Dynamic gait recognition of Chinese dance based on multi-scale feature transfer learning
1	97.4	90.2	89.4	86.3
2	96.8	89.5	88.5	85.5
3	98.7	85.8	87.6	87.0
4	96.1	86.6	85.2	84.5
5	95.2	87.5	86.5	86.8
6	97.5	85.2	85.8	82.6
7	96.6	86.3	87.6	85.3
8	98.3	85.6	89.3	83.8
9	95.8	90.8	85.5	85.4
10	97.9	90.4	86.2	84.2

In the test results of CASIA B data set, the recognition rate of the Chinese dance gait dynamic recognition method based on contour feature design is 97.0%, which is 9.2%, 9.8% and 11.9% higher than the methods based on frequency domain attention space-time convolution network, dual flow gait network and multi-scale feature transfer learning.

Table 2: Recognition rate of DanceDB dataset (%)

Number of tests	Dynamic gait recognition of Chinese dance based on contour features	Dynamic gait recognition of Chinese dance based on frequency domain attention space-time convolution network	Dynamic gait recognition method of Chinese dance based on dual stream gait network	Dynamic gait recognition of Chinese dance based on multi-scale feature transfer learning

1	85.4	79.4	78.4	72.6
2	86.5	75.5	76.8	74.2
3	85.6	76.6	74.6	76.5
4	87.3	78.0	72.0	75.8
5	86.5	75.2	73.2	76.6
6	89.8	76.5	74.5	71.5
7	88.6	74.8	71.9	72.3
8	87.5	78.6	72.6	73.5
9	85.7	72.3	75.8	78.8
10	86.2	75.7	76.2	75.2

In the test results of DanceDB data set, the recognition rate of the Chinese dance gait dynamic recognition method based on contour feature design is 86.9%, which is 10.6%, 12.3% and 12.2% higher than the methods based on frequency domain attention space-time convolution network, dual flow gait network and multi-scale feature transfer learning.

Table 3: Recognition rate of Classic dataset (%)

Number of tests	Dynamic gait recognition of Chinese dance based on contour features	Dynamic gait recognition of Chinese dance based on frequency domain attention space-time convolution network	Dynamic gait recognition method of Chinese dance based on dual stream gait network	Dynamic gait recognition of Chinese dance based on multi-scale feature transfer learning
1	84.5	72.4	69.4	72.4
2	85.9	74.8	68.8	70.0
3	82.6	71.6	71.6	74.6
4	83.8	70.5	72.5	75.5
5	84.5	72.2	74.2	72.8
6	81.7	73.3	71.3	73.6
7	82.4	72.5	70.5	74.3
8	83.1	71.7	73.9	69.5
9	84.5	72.5	72.6	68.4
10	85.2	73.4	69.5	71.2

In the test results of Classic data sets, the recognition rate of the Chinese dance gait dynamic recognition method based on contour feature design is 83.8%, which is 11.3%, 12.4% and 11.6% higher than the methods based on frequency domain attention space-time convolution network, dual flow gait network and multi-scale feature transfer learning. Based on the above results, the recognition results of each recognition method for normal walking gait are better, reaching more than 80%. Compared with general walking gait, dance gait recognition is still difficult, so the recognition rate of each method on dance video data set is relatively low. Compared with the three comparison methods, this design method has better recognition effect. Under the influence of complex movement and other factors, this method has a high accuracy for the recognition of dance gait features. Therefore, it also proves that the application of contour features for gait recognition has certain application value and feasibility.

6 CONCLUSION

Applying the gait dynamic recognition method to the study of Chinese dance can make the dance arrangement more efficient and play an auxiliary role in judgment or practice. In the dance movement sequence, the relationship mapping between gait and movement is established, and gait pattern analysis is completed through motion detection and feature extraction. According to the comparison between the dancer's movements and the standard dance steps, the dance steps are evaluated or corrected to improve the dance quality. Single feature recognition can not fully reflect the difference between dance gait information, resulting in low recognition rate of frame difference features. To solve this problem, this paper designs a dynamic gait recognition method of Chinese dance based on contour features. In this paper, the distance from the center of mass to the top of the head, hands and feet is selected as the contour distance feature, and the distance between hands and feet, the swing amplitude of the arm and the height span of the lower limb movement are selected as the width features. The key distance, width, wavelet features and gait energy map are fused and input into CNN model for classification and recognition. Under the influence of complex movement and other factors, this method has high accuracy and feasibility for the recognition of dance gait features. This paper mainly recognizes the gait of a single person, so it has limitations. Subsequently, we can carry out research on multi person gait dynamic recognition in real complex scenes, and enrich the research results in the field of moving object detection.

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