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Kernel Fisher Discriminant Analysis for Natural Gait Cycle Based Gait Recognition

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Abstract

This paper studies a novel approach to natural gait cycles based gait recognition via kernel Fisher discriminant analysis (KFDA), which can effectively calculate the features from gait sequences and accelerate the recognition process. The proposed approach firstly extracts the gait silhouettes through moving object detection and segmentation from each gait videos. Secondly, gait energy images (GEIs) are calculated for each gait videos, and used as gait features. Thirdly, KFDA method is used to refine the extracted gait features, and low-dimensional feature vectors for each gait videos can be got. The last is the nearest neighbor classifier is applied to classify. The proposed method is evaluated on the CASIA and USF gait databases, and the results show that our proposed algorithm can get better recognition effect than other existing algorithms.

Keywords

Gait Energy Image, Gait Recognition, Kernel Fisher Discriminant Analysis, Natural Gait Cycle

1. Introduction

Gait recognition is one kind of gait identification technology, which can realize long-distance and hidden identity authentication and has been widely applied in the field of intelligent video surveillance. The existing gait recognition algorithms are mainly divided into two categories: methods based on appearance [1] and model-based methods [2]. The former is based on the spatiotemporal shape and motion characteristics of the gait sequence, and the latter adopts the structural model to measure the time varying gait characteristic parameters, such as gait cycle, frequency, direction of key point and so on. Different from biometrics of human faces [3] and fingerprint [4], gait features are a group of dynamic features and the significance and robustness of the features can be demonstrated in a running cycle [5]. How to extract the gait features which have significance and robustness and low data space from a set of gait image sequences is one of the research problems. GEI use a simple weighted average method to synthesize a periodic gait image into a better image. On the basis of the GEI method, the authors [6,7] proposed the two directional two-dimensional principal component analysis '(2D)²PCA' and weighted (2D)²PCA 'W(2D)²PCA' by the combination of the rows and the columns. Compared to traditional feature extraction methods such as the principal component analysis (PCA) and linear discriminant

analysis (LDA), (2D)^{2}PCA and W(2D)^{2}PCA have more resilient to change the angle of view. In order to extract local information better, Yang et al. [8] proposed the discriminant common vectors (DCV) method to solve small sample size problem and Liu et al. [9] used the local binary pattern (LBP) to extract the local feature of GEI and the DCV to reduce the LBP features, which explored the GEI information better than traditional methods. Atta et al. [10] proposed a spatio-temporal gait recognition method based on radon transform to overcome the limitations associated with the most existing temporal template approaches. To deal with a gait features directly as a matrix, the authors [11] suggested the concept of kernel cuboid, and proposed a new kernel-based image feature extraction method for recognition, which deal with a face image in a block-wise manner, and independently perform kernel discriminant analysis in every block set by using kernel cuboid instead of kernel matrix. Kernel Fisher discriminant analysis (KFDA) method [12] is another way to use the kernel function to map the nonlinear separable data to optimal feature space. In face recognition, KFDA has achieved better recognition results than other existing methods—such as PCA [13], LDA [14], and linear preserving projection (LPP) [15]. The experimental results in [16] show that the KFDA have the lower error rate than other methods (PCA, FLD).
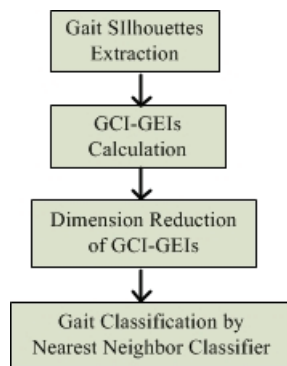

Fig. 1. Flow chart of the proposed gait recognition method.

The paper presents a new gait recognition method based on KFDA, as shown in Fig. 1. First, the GEI is calculated from gait cycle. Then KFDA can make use of the high correlation between different GEI for feature extraction by selecting the proper kernel function, and the nearest neighbor classifier is designed as the classifier. Finally, the algorithm is tested on CASIA and USF gait database. The results of experiment prove that our method is effective for gait recognition. The main contributions of this paper include (1) a new feature extraction algorithm is proposed based on natural gait cycles, and the observation vector set is constructed using the extracted features. In order to improve the algorithm robustness, the algorithm also adopts the feature combination of gait image and its region bounded by legs. (2) KFDA method is used to refine the extracted gait features, and low-dimensional feature vectors for each gait videos can be got. (3) Experimental results on CASIA and USF gait database show that even when human body have changed in walking at condition of carrying backpacks and other objects, the proposed method can still get better gait classification rates than other existing methods.

The rest of the paper is organized as follows. In Section 2, the details of the proposed method are discussed. Section 3 presents the experimental methods and results analysis in detail. Finally, conclusions and future works are drawn in Section 4.

2. The Proposed Method

2.1 Gait Silhouettes Extraction

The proposed approach extracts the gait video silhouettes through moving object detection and segmentation from each gait videos. Since there are some influences of external factors in the process of real image acquisition, which can easily cause some problems such as noise and contrast, it is necessary to preprocess the image of gait recognition. Image preprocessing is the precondition of feature extraction and gait recognition. The paper mainly follows the steps to preprocess image.

- Background reconstruction: Since the scene is approximately stationary and the background information is corresponding to the low frequency part in the whole video sequence, the median of the corresponding pixels in the sequence image is used to estimate the static background.
- Moving object detection: Background subtraction is first used to eliminate moving foreground image, which is got by difference operation between the image sequence and the background image, and then the moving shadow of the foreground image is erased by HSV based color model [17]. At last, the binarization image is calculated by threshold value of OTSU algorithm [18].
- Binarization image noise removal and normalization: Since there are some small noises around the human body and background area in the process of threshold segmentation, the median filter method is used to remove the noise and redundant information. In addition, to deal with the problem of the inconsistency of the human silhouette size caused by the change of focal length in the shooting, the object image silhouettes is normalized and the image is scaled to the same size.
- Gait cycle detection: The change of gait is periodic and the center of gravity of the body is constantly changing in the process of walking. The center of gravity does not change with the hands and legs forward movement, but the vertical axis will change periodically. In the paper, the period of the gait is determined according to the change of the coordinate of the center of gravity.

2.2 Improving GEI Processing and Cycle Detection

The gait energy diagram adopts a simple weighted average method to synthesize a periodic gait silhouettes images into one image, which is defined as:

$$G(x, y) = \frac{1}{T} \sum_{t=1}^{T} B_t(x, y) \tag{1}$$

where T is the gait cycle length and $B_t(x, y)$ is the brightness values of pixel point (x, y) at time t. The brightness value of the background area is 0, and the target area is 255.

Since the method of gait video silhouettes extraction has been discussed in above section, this section will focus on subsequent gait description and identification and propose feature extraction algorithm based on natural video gait cycle. According to human leg characteristics, the key gait of normal walking can be classified three kinds:

State 1: The two legs are kept close together in the same plane of the body and there are three common postures, namely left foot being lifted by the side of the right foot, right foot being lifted by the side of the left foot and two feet normally standing, all together marked as $K1$;

State 2: The left foot being in front of the right foot, marked as $K2$;

State 3: The right foot being in front of the left foot, marked as *K3*.

We define the complete gait cycle as a process of *K1→K2→K1→K3→K1* or *K1→K3→K1→K2→K1*. Fig. 2 shows one example of complete gait cycle of *K1->K3->K1->K2->K1*. After the segmentation of a complete gait cycle, we will first continue to deal with all subsequent frames, find all complete gait cycles or gaits to evenly partition each gait cycle and extract NF key gait silhouettes images in turn. Then the GEI of a time domain is extracted based on center of each key gait silhouettes image to construct the observed state set. At last, the KFDA is used to reduce the dimensions of the observed state set and corresponding low dimensional eigenvectors would be got, which will be discussed in follow section.
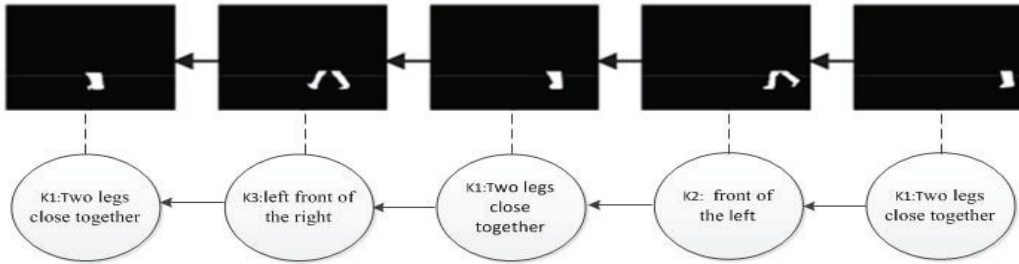

Fig. 2. An example of a complete gait cycle.

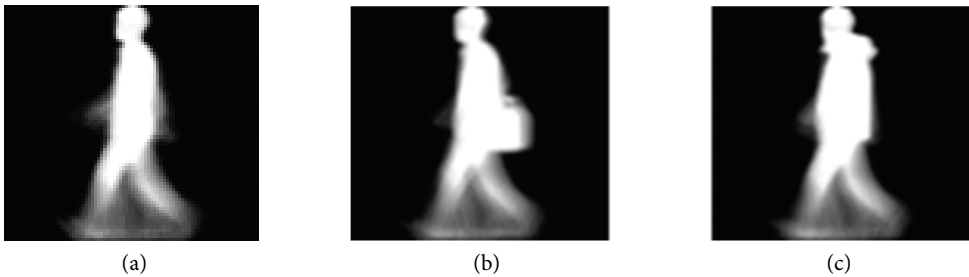|		
(a)	(b)	(c)

Fig. 3. GEIs of three different conditions at 90º: (a) normal condition, (b) carrying a bag, and (c) with a coat.

From Fig. 3, we can see the outermost outlines of the human body have changed when human is walking at condition of carrying backpacks and other objects, which can lead to poor gait recognition robustness [19]. Since changes on top part of the body is very little and lower part of the body (such as legs) has obvious change in normal, carrying and clothing conditions, the paper adopts the method in [20] to represent the gait feature by both gait silhouettes image and energy image in the local outline of the legs. Fig. 4 shows energy image in the local region of the legs (box tag).

Supposed using above feature extraction method to extract feature of whole video gait silhouettes image and the corresponding energy image in the local region of the legs for each gait video *G*, *G* can be expressed as

$$G = \left[\{F_1\}, \{F_2\} \right] \tag{2}$$

where F_1 and F_2 is extracted features from whole gait silhouettes images and from the local region of the legs respectively. The F_1 and F_2 can be calculated by eigenmatrix mapping method, which was discussed in detail in [20] and we're not going to analyze it.
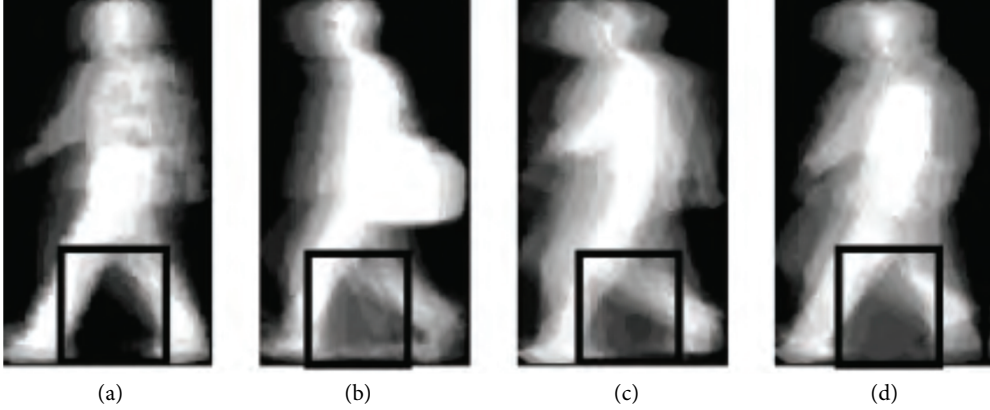
(a)   (b)   (c)   (d)

Fig. 4. Image in the local outline of the legs: (a) normal, (b) carrying a bag, (c) clothing, and (d) walking at night.

2.3 Kernel Fisher Discriminant Analysis

KFDA method is to map the input samples into a high dimensional feature space by a nonlinear mapping and find the projection space, which makes the inter-class scatter matrix biggest and the within-class scatter matrix smallest. The main idea of LDA algorithm is to find the optimal projection matrix W_{opt} by Fisher criterion, which objective is to determine the discriminant vectors by maximizing inter-class scatter matrix S_B^Φ while minimizing the within-class scatter matrix S_W^Φ.

Suppose there are n samples $\{x_1, x_2, ..., x_n\}$ belonging to class $C\{X_1, X_2, ..., X_c\}$. According to Fisher LDA, non-linear function $\varphi(x)$ map n samples on the feature space F, and get the optimal subspace W_{opt}:

$$W_{opt} = \arg\max_w \frac{|W^T S_B^\Phi W|}{|W^T S_W^\Phi W|} = [w_1, \ w_2, ..., \ w_m] \tag{3}$$

Similarly, S_B^Φ and S_W^Φ represent the inter-class and within-class scatter matrix of feature space F.

$$S_B^\Phi = \sum_{i=1}^C n_i(u_i^\Phi - u^\Phi)(u_i^\Phi - u^\Phi)^T \tag{4}$$

$$S_W^\Phi = \sum_{i=1}^C \sum_{X_k \in X_i} (\Phi(x_k) - \mu_i^\Phi)(\Phi(x_k) - \mu_i^\Phi)^T \tag{5}$$

where $\mu_i^\Phi = \frac{1}{n}\sum_{x_k \in X_i} \Phi(x_k)$, $u^\Phi = \frac{1}{n}\sum_{i=1}^N \Phi(x_i)$, w_i is calculated by $S_B^\Phi w_i = \lambda_i S_W^\Phi w_i$.

In the kernel function theory, $w_i \in span\{\varphi(x_1), \varphi(x_2), \cdots, \varphi(x_n)\}$ is bound in the mapping function to generate space, which is, $w_i \in span\{\Phi(x_1), \Phi(x_2), ..., \Phi(x_n)\}$ can be linear represented as $w_i = \sum_{j=1}^n \alpha_i^j \cdot \Phi(x_j)$ by train samples. So molecular in (4) can be converted as:

$$w_i^T S_B^\Phi w_i = \alpha_i^T M \alpha_i \tag{6}$$

where $M = \sum\limits_{i=1}^{C} (M_i - \overline{M})(M_i - \overline{M})^T$, $\overline{M_j} = \frac{1}{n}\sum\limits_{i=1}^{n} k(x_j, x_i)$ and $\alpha_i = [\alpha_i^1, \alpha_i^2, ..., \alpha_i^n]^T$.

Similarly, the denominator in (3) can be converted as:

$$w_i^T S_W^{\Phi} w_i = \alpha_i^T L \alpha_i \tag{7}$$

where $L = \sum\limits_{j=1}^{C} K_j (I - I_{N_j}) K_j^T$, K_j is $n \times n_j$ matrix, $(K_j)_{nm} = k(x_n, x_m), x_m \in X_j$, I denotes a unit matrix, I_{Nj} represents a matrix formed by $1/n_i$.

Eq. (3) can also be simplified as:

$$\alpha_{opt} = \arg\max_{\alpha} \frac{|\alpha^T M \alpha|}{|\alpha^T L \alpha|} = [\alpha_1, \alpha_2, ..., \alpha_m] \tag{8}$$

The optimal subspace W_{opt} is:

$$W_{opt} = [w_1, w_2, ..., w_m] = [\sum\limits_{i=1}^{n} \alpha_1^i \Phi(x_i), \sum\limits_{i=1}^{n} \alpha_2^i \Phi(x_i), ..., \sum\limits_{i=1}^{n} \alpha_m^i \Phi(x_i)] \tag{9}$$

When given a non-linear mapping function $\Phi(x)$, the mapping result of sample x to the feature space F is:

$$\Phi(x) W_{opt} = [\sum\limits_{i=1}^{n} \alpha_1^i \Phi(x_i)\Phi(x), \sum\limits_{i=1}^{n} \alpha_2^i \Phi(x_i)\Phi(x), ...]$$
$$= [\sum\limits_{i=1}^{n} \alpha_1^i k(x_i, x), \sum\limits_{i=1}^{n} \alpha_2^i k(x_i, x), \sum\limits_{i=1}^{n} \alpha_m^i k(x_i, x)] \tag{10}$$

KFDA method can convert class X to $c-1$ dimension vector, and we can chose the feature vectors corresponding to the first $c-1$ eigenvectors to reduce the dimension of feature space and improve the processing speed. Since the dimension of samples usually is small in the recognition process, the number of training samples is smaller than the pixels of an image that may cause inter-class scatter matrix S_W singular matrix, that is say $rank(Q) = rank(S_w^{\Phi}) \leq n-1$, we cannot use generalized eigenvalue equation to solve Rayleigh's extremum problems. Aiming at this problem, we add μI (I represents a unit matrix and μ is a coefficient) to the Q matrix, and $Q\mu = Q + \mu I$, which can let Q become a nonsingular and use a generalized eigenvalue equation to solve.

Suppose there are m individuals, each of which correspond the gait sequences of different view angles. The proposed algorithm extracts gait information contained in the each individual's GEI as an input vector samples. According to KFDA method, assuming that the number of gait sequences is m_i, $i = 1, 2, ..., q$, the sample set is $\{x_{1,1}, x_{1,2}, ..., x_{1,n1}, x_{2,1}, ..., x_{2,n2}, ..., x_{q,nq}\}$, the input samples is $n = n_1 + n_2 + ... + n_q$, if we want to classify the unknown class of gait sequences, the first we should do is to train the known classes of gait, find the optimal feature space W_{opt} and α_{opt}. Then the projection on α_{opt} and its projected trajectory are calculated. The detailed gait recognition algorithm is described in Algorithm 1.

Algorithm 1 The gait recognition algorithm based on combination of KFDA and GCI-GEIs

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Step 1: Calculate $K(x, y)$. Because the dimension of feature space F is high, in order to use Fisher LDA in the feature space F, the inner product kernel function is used to calculate approximately, which is $K(x, y) = \varphi(x) \cdot \varphi(y)$. That is, inner product of $\varphi(x)$ and $\varphi(y)$ vector in the feature

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space F can be replaced by the inner product of x and y.

Step 2: Calculate inter-class scatter matrix S_b and within-class scatter matrix S_W.

Step 3: Compute α_{opt}.

Step 4: Map the GEI of a gait sequence to the optimal feature space W_{opt}, and get the track of the gait sequence on W_{opt}.

Step 5: In training process, training features $\left(T_1, T_2, \ldots, T_u\right)$ are got by mapping GEI to W_{opt}.

Step 6: In testing process, testing features $\left(t_1, t_2, \ldots, t_y\right)$ are calculated by mapping the GEI of the gait sequence to the optimal feature space W_{opt}.

Step 7: Use the Euclidean distance to measure the similarity between the training and testing sequences and then classify. For the training set $T_x\ (x=1,2,\ldots,u)$ and the testing set $t_y\ (y=1,2,\ldots,v)$, the Euclidean distance is defined as $d_l^2 =\parallel T_x - t_y \parallel^2$, where the first l class that makes d_l minimum is the membership class of testing gait sequence. That is, it is classified into the class of its nearest sample.

Step 8: Calculate the recognition rate.

3. Experiments and Analysis

3.1 Experiment on CASIA Gait Database

The CASIA dataset A [21] is called NLPR gait database before, which contains 20 subjects and each subjects has 12 image sequences and 3 walking direction (0°, 45°, and 90°). There are 4 image sequences in each direction and 2 gait cycles in each sequence. Our experiments select 2 gait sequences and 4 gait cycles for training and another 2 gait sequences and 4 gait cycles for testing. We carried out 6 experiments on CASIA database A and calculate the average.

The CASIA Dataset B is a large multi-view gait dataset contains 124 subjects and data was captured from 11 views varying from 0° to 180° with 18° between each two nearest view directions. There are 10 sequences for each subject, 6 sequences of them for normal walking (normal), 2 for walking with bag (bag) and 2 for walking in coat. Our experiments use 60 subjects at 90° and normal conditions that is each subject has 6 sequences, each sequence contains 2 gait cycles and every sequence have 12 gait cycles. In the experiments, 2 gait sequences and 4 gait cycles are selected for training and another 4 gait sequences and 8 gait cycles for testing. We carried out 15 experiments on CASIA B and calculate the average.

Our main focuses are on feature extraction and identification of human silhouette image. The input samples of experiments are expansion of everyone's GEI by column vector. The training and testing set are divided with the ratio of 1:1. Then, the KFDA method is applied to train features, get α_{opt} and W_{opt}. Finally, the sample vectors are projected on the optimal feature space W_{opt} and the training features *Train _ Features* and testing features *Test _ Features* are got respectively.

Due to the small number of samples, to obtain the unbiased estimation of the correct recognition rate, leave-one-out cross-validation method is adopted to conduct the experiments. The paper adopts cumulative match score (CMS) [22] to evaluate the experiment results and presents recognition rates of Rank 1 and Rank 5. In order to evaluate the GCI-GEI feature extraction effect and the KFDA dimension reduction and classification ability, the recognition rate of our method is compared to other exiting algorithms, and the results are showed in Table 1.

Table 1. Recognition rate of Rank 1 and Rank 5

Algorithm	CASIA dataset A		CASIA dataset B	
	Rank 1 (%)	Rank 5 (%)	Rank 1 (%)	Rank 5 (%)
GEI+PCA [13]	88.04	92.37	85.41	90.31
GEI+LDA [14]	89.20	93.50	86.94	90.37
GEI+LPP [15]	90.12	94.37	87.07	91.53
GEI+DCV [8]	88.07	92.78	83.39	87.66
GEI+LBP+DCV [9]	86.16	90.38	82.44	87.53
GCI-GEI+KFDA (proposed algorithm)	93.08	100	90.78	93.98

As can be seen from Table 1, the average recognition rate of our algorithm is best. We can find that our proposed algorithm can get more than 90% recognition rate in Rank 1 and Rank 5, which testify that the method based on GCI-GEI and KFDA can identify better the different human gait and get better recognition effect than other algorithms in the small sample gait database. Furthermore, the experiment data shows the recognition rate of GEI+LBP+DCV is lower than GEI+PCA, which explains reducing the dimension by PCA will lose important gait recognition information after LBP feature extraction from GEI.

3.2 Experiments on USF Human ID Database

A database consisting of 1,870 sequences of the 122 subjects based the USF Human ID database [23] is divided into 1 set for training and 10 probes labeled from A to J for test, which based on 3 covariates: normal, walking, and carrying condition. Being different from experiment on CASIA, this experiment adopts weighted mean recognition rate to evaluate the experiment results. To demonstrate the advantages of KFDA, we choose the traditional algorithms LDA, PCA and DCV, and manifold earning algorithm LPP for comparison. Table 2 reports the recognition rates of this group of experiments on the 10 probes.

Table 2. Recognition rates (%) of different algorithms

Algorithm	A	B	C	D	E	F	G	H	I	J	Mean
GEI+PCA	80	87	72	26	22	11	13	47	40	37	39.25
GEI+LDA	88	89	74	25	25	15	20	52	53	56	45.93
GEI+LPP	88	91	76	29	32	21	23	53	52	53	47.49
GEI+DCV	87	93	76	30	35	21	23	53	57	53	48.33
GCI-GEI+KFDA (proposed algorithm)	90	87	80	41	48	27	28	72	63	63	55.64

As can be seen from Table 2, KFDA can achieve higher recognition rate than traditional GEI when using different dimensional reduction algorithms including PCA, LDA, LPP, and DCV. KFDA features present more discriminating power than original features. Comparing with other algorithms, the GCI-GEI+KFDA approaches can improve the recognition rate by about 6%. In addition, since the experiment is based on normal, walking and carrying condition, the experiment results demonstrate the proposed algorithm can eliminate effects of walking and carrying conditions and have great robustness.

4. Conclusion

The different walking conditions of human movement leaded gait recognition become more difficult. This paper proposes a new algorithm for gait recognition based on GEI and KFDA. The proposed algorithm firstly proposed a new feature extraction algorithm based on natural gait cycles, and the observation vector set is constructed using the extracted features by combination of gait image and its region bounded by legs. Then the expansion vector of the GEI by column is used as the input to get the optimal subspace W_{opt} and α_{opt}, the projection on α_{opt} is calculated by the GEI observation vectors. The third is to project sample vectors on W_{opt} to get training features and testing features. At last, the feasibility of the algorithm is verified by experiments on CASIA and USF. Comparing with other 5 existing algorithms, the results prove the proposed algorithm can get better recognition effect and have better robustness than other existing algorithms in the small sample gait database.

However, the limitation of the algorithm is that: first, only 5 other algorithms are used to compare with our proposed method in experiments; second, the experimental verification of the algorithm is only done on CASIA B and USF database. In the future work, we will try to use more other algorithms to compare and more publicly available databases to verify effectiveness and robustness of the proposed algorithm on a larger scale.

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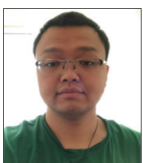
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