ISSN:0975-9646
G. Venkata Narasimhulu et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 3 (3) , 2012,4015 - 4020

Fuzzy Principal Component Analysis based Gait Recognition

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***Abstract* - Gait recognition is a relatively new biometric identification technology for human identification. Gait recognition algorithm based on fuzzy principal component analysis (FPCA) for gait energy image(GEI) is proposed. Firstly, the original gait sequence is preprocessed and gait energy image is obtained. Secondly, the eigenvalues and eigenvectors are extracted by fuzzy principal component analysis, which are called fuzzy components. Then the eigenvectors are projected into lower-dimensional space. Finally, the NN classifier is utilized in feature classification. The method is tested on CASIA database. The experimental results show that this algorithm achieves higher recognition performance. Correct recognition rate (CRR) of 89.7% for FPCA algorithm and 83.1% for GEI algorithm. FPCA algorithm to achieve 100% recognition rate. The two component model, FPCA accounts for 91.7% of the total variance and PCA accounts only for 39.8%.**

***Keywords* - Gait Recognition, FPCA, PCA, GEI, RT, HMM.**

I. INTRODUCTION

Gait recognition is a relatively new biometric technology which aims to identify people at a distance by the way they walk. In comparison with other biometric characteristics such as fingerprint, iris and face. In recent years gait recognition has received more attention. Kale et al.[1] considered the width of the outer contour of the binarized silhouette of the walking person as the gait signature. In [11], Han and Bhanu extracted the GEI of the walking person. Huang et al.[12] proposed a template matching approach by combining transformation based on canonical analysis, with eigenspace transformation for feature selection. Wang et al.[13] extracted gait silhouettes of each image sequence and applied eigenspace transformation based on principal component analysis(PCA).

Gait recognition in recent years developed a long-range identification technology Surgery, it is mainly based on human walking posture identification. Gait recognition at home and abroad in recent years carried out extensive research.

[1] Lee Employing binary image of the side profile as the image features to identify the calculation. A gait sequence between each frame and the specimen FED (Frame to Exemplar Distance) vector, complete gait recognition using HMM. The FED vector captures both structural and dynamic traits of each individual. For compact and effective gait representation and recognition, the gait information in the FED vector sequences is captured in a hidden Markov model (HMM). In the first method, referred to as the indirect approach,

the high-dimensional image feature is transformed to a lower dimensional space by generating what we call the frame to exemplar (FED) distance**.** In the second method, referred to as the direct approach, we work with the feature vector directly (as opposed to computing the FED) and train an HMM. We estimate the HMM parameters based on the distance between the exemplars and the image features. Hidden Markov Model (HMM) is suitable for gait recognition because of its statistical feature and it can reflect the temporal state-transition nature of gait. HMM has been applied to human identification in [2-5]. In this paper, we propose a new HMM-based approach for gait representation and recognition. In next section, the Literature Review will be discussed briefly. The systems design is described in section 3, the results are discussed in section 4, conclusion are given in section 5.

II. LITERATURE REVIEW

Lee *et al.,* (2009) proposed for efficient gait recognition with carrying backpack. They have been constructed gait energy image (GEI) to apply recursive principle component analysis technique.

Shingh and Biswas (2009) are approached gait energy image (GEI) method for human identification. Gait recognition rate can be improved by applying GEI method. They selected large CASIA gait database for the experiment.

Ju and Bir (2006) proposed gait energy image (GEI) method for person recognition.

Okumura *et al*., (2010) described a large scale gait database that can use widely for vision based gait recognition.

Cheng *et al.,* (2006) proposed gait recognition based on PCA and LDA. PCA is mainly used for dimensional reduction technique and LDA is performed to optimize the pattern class.

Gait sequence in the database obtained through the pretreatment step State energy plans, energy plans will gait training samples FPCA transformation, and mapping To low-dimensional space, into the feature database.

III. SYSTEMS DESIGN

3.1 Gait Energy Image (GEI)

Gait Energy Image (GEI) is the sum of images of the walking silhouette divided by the number of images. GEI is a useful representation with superior selective power and strength against segmental errors (Miciak 2010). The equation (1) present the pre-processed binary gait silhouette images $B_t(x,y)$ at time t in a sequence, GEI is computed by

$$G(x,y)=1/N \sum_{t=1}^{N} B_t(x,y) \text{ ------------------------------(1)}$$

Where N is the number of frames in the full gait cycle and x and y are a value in the image coordinates (Miciak 2010). The Fig.1 shows the constructed sample of GEI from a sequence of silhouettes.

Gait Energy Image (GEI) has constructed to apply Principal Component Analysis (PCA) with and without Radon Transform (RT). The Radon Transform is used to detect features within an image and PCA is used to reduce dimension of the images without much loss of information. The side view of slow walk; fast walk and carrying a ball walk have been selected from the CMU MoBo database for experimental purposes. The two techniques achieved equal error rates (EER) of 94.23%, 82.28%, and 90.38% for PCA only and 96.15%, 82.70% and 92.30% for PCA with RT for low walk, fast walk and carrying a ball walk respectively.

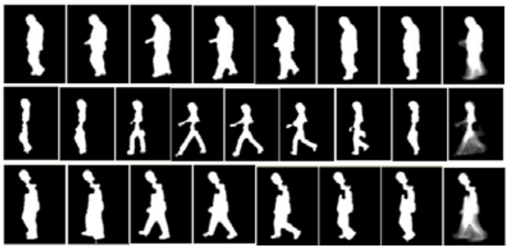

Fig. 1: The constructed sample of GEI from a Sequence of silhouettes

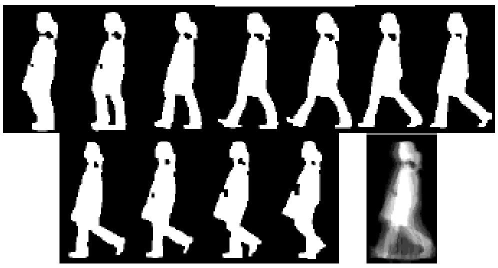

Fig 2: Sequence of the full cycle of gait energy diagram [FPCA]

3.2 HMM (Hidden Markov Model)

A new gait recognition algorithm using Hidden Markov Model (HMM) is proposed. The input binary silhouette images are preprocessed by morphological operations to fill the holes and remove noise regions. The width vector of the outer contour is used as the image feature. A HMM is trained iteratively using Viterbi algorithm and Baum-Welch algorithm and then used for recognition. HMM is suitable for gait recognition because of its statistical feature and it can reflect the temporal state-transition nature of gait. HMM has been applied to human identification in [2-5]. A new HMM based approach for gait representation and recognition.

3.3 HMM-Based Gait Recognition

We proposed a new HMM-based gait recognition method. An HMM is characterized by the following parameters.

(1) N , the number of states in the model. How to choose N is important and this is a classical problem of choosing the appropriate dimensionality of a model that will fit a given set of observations. For CMU MoBo database, N =5 is suggested [5]. The HMM states are denoted as $S=[S_1,S_2,...,S_N]$.

(2)M , the number of distinct observation symbols per state. For gait recognition, every frame's feature vector is treated as an observation symbol. The number M depends on the number of frames per cycle, the number of states in the model and how to divide one cycle into clusters. The frames in a gait cycle are a consecutive transition along with time. We divide each cycle into N clusters of approximately the same size of M . The observation symbols for one HMM state are denoted as $V = \{v_1,v_2,......,v_M\}$.

(3) A, the transition probability matrix. $A = \{a_{ij}\}$, and a_{ij} is defined as

$a_{ij} = P[q_{t+1} = S_j \mid q_t = S_i], 1 \le i, j \le N$ -------------- (2)

where qt is the state at time t . The values of a_{ij} will determine the type of the HMM. In this paper, the left-to-right model is chosen, which only allows the transition from the j^{th} state to either the j^{th} or the $(j+1)^{th}$ state. Also the last state can turn back to the first one.

(4) B , the observation symbol probability matrix. $B = \{b_j(k)\}$, where $b_i(k) = P[\,v_k$ at t | $q_t=S_J$ |, $1\le J\le N$, $1\le K\le M]$ .... (3)

(5) □, the initial probability. □ ={ □ i }

where □ i $= P[\,q_1 = S_i\,],\ 1 \le i \le N$ .... (4)

We always put the first frame into the first cluster, so the initial probability π_1 is set to be 1 and all other π_i are set to be 0.

The complete parameter set of the HMM can be denoted as

$\lambda = (A,B, \pi)$..(5)

3.4 HMM (Hidden Markov Model) Training

Every gait sequence is divided into cycles. The feature vectors of each cycle are further divided into clusters with about the same size. Each cluster center is treated as an exemplar. An exemplar is defined as

$$e_n = 1/N_n \sum_{f_t \,\varepsilon\, c_n} f_t \quad \text{..} (6)$$

where f_t is the feature vector of the t^{th} frame, C_n represents the n^{th} cluster, N_n is the number of the frames in the n^{th} cluster. The exemplar set is denoted as $E = \{e_1,e_2,........,e_N\}$.

The initial exemplars of slow walk (a), fast walk (b) and walking with a ball (c) of the same person are shown in Fig.3. The similarities between (a) and (b) show the effectiveness of the feature extraction method, however, greater changes i.e. (c) cause the similarities decline.

For each feature vector f in a cycle, its distance from an exemplar e is measured by the inner product (IP) as defined in the following equation.

$$D(f,e) = 1-[\,f^T e / f_T\, f e^T e]^{1/2} \quad \text{..................................} (7)$$

The transition probability matrix A is initialized using trial and error method. The initial observation symbol probability matrix $B = \{b_j(k)\}$ is defined as

$$bn(f_t) = 0.01\, \delta n\, e^{-\delta n\, x D(f_t, e_n)} \quad \text{..................................} (8)$$

$$\delta_n = N_n / \sum_{f_t \,\varepsilon\, c_n} D(f_t, e_n) \quad \text{..} (9)$$

The parameter δ in equation (9) can reflect how much a feature vector belongs to the cluster C_n .

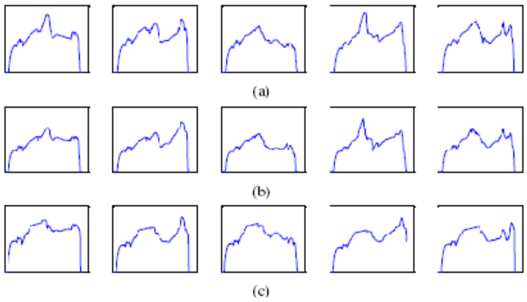

Fig.3. The initial exemplars of a person a) slow walk b) fast walk c) walking with a ball

The HMM is trained iteratively. Viterbi decoding is performed on the cycle to obtain the most probable path $q=[q_1^{(i)},q_2^{(i)},\ldots\ldots,q_T^{(i)}]$ where $q^{(i)}$ is the state at time t after i^{th} iteration. The new exemplars $E(i)$ can be obtained from the most probable path using equation (6) and $B^{(i)}$ can be calculated using equations (7)-(9). Next $A^{(i)}$ and $\pi^{(i)}$ are updated using the Baum-Welch algorithm. The training results consist of the exemplars and the HMM model parameters. It usually takes a few iterations to obtain a better estimate. The exemplars after training are shown in Fig.4. The similarities between Fig.3 and Fig.4 indicate the effect of the initial exemplar estimation.

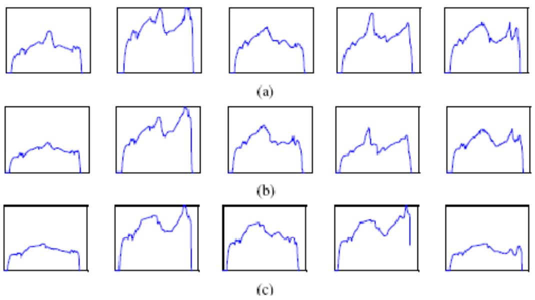

Fig.4. The exemplars estimated after training a person a) slow walk b) fast walk c) walking with a ball

3.5 Gait feature vector extraction

The background-subtracted silhouette image usually contains many holes, noise structure and shadows. One such image is shown in Fig. 5(a). The recognition performance may be degraded if the original silhouette is used directly. In this paper, some mathematical morphological operations are used to fill the holes, remove noise regions and extract the outer contour of the people. The image is cropped to remove the shadows and the result is depicted in Fig. 5(b). A one-dimensional signal, which is defined as the outer contour width of each image row, can be generated [Fig.5 (c)]. To further reduce influence of the remaining noise regions, the width signal is filtered using some specific rules. The smoothed width signal [Fig.5 (d)] is then used as the image feature. The one-dimensional feature vector fits the one-dimensional HMM well and has the advantages of noise insensitive and human location independent, thus we do not need to align the outer contour

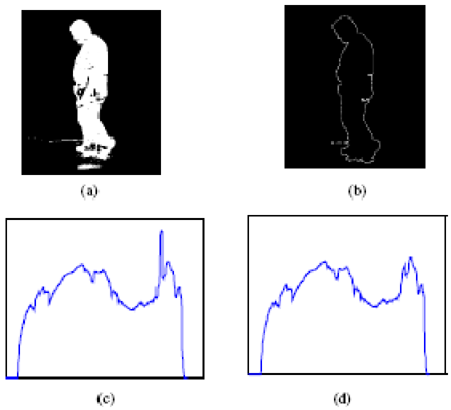

Fig.5. Use morphological operations to extract contour (b) from silhouette image (a), and the feature vector (d) can be obtained after filtering the width signal (c) of the contour

3.6 Principal Component Analysis

Principal component analysis is also known as eigenvector analysis. PCA is to represent in an economic way the location of the samples in a reduced coordinate system where instead of m axes only p (p<m) can usually be used to describe the data set with maximum possible information.

PCA practically transforms the original data matrix into product of two matrices, one of which contains the information about the samples and the other about the variables. The S matrix contains the scores of the n objects on m principal components. The V matrix is a square matrix and contains the loadings of the original variables on the principal components.

3.7 Fuzzy Principal Component Analysis

A fuzzy clustering algorithm with objective function can be formulated as follows: let $X=[x^1,x^2,....x^n] \subset R^s$ be a finite set of features, where n is the number of objects and p is the number of the original variables, $x_k^j=[x_1^j,x_2^j,.....,x_p^j]^T$ and $L=(L^1,L^2,....L^s)$ be s clusters, each of which characterizes one of the s clusters composing the cluster substructure of the data set: a partition of X into s fuzzy clusters will be performed by minimizing the objective function

$$J\,(P,L)=\sum_{i=1}^{S}\sum_{j=1}^{n}((A_i(x^j))^2\, d^2(x^j,L^i) \;\ldots\ldots\ldots\ldots\ldots(10)$$

where $P=[A_1,A_2,.........,A_s]$ is the fuzzy partition, of the GEI feature space, $A_i(x^j)\ \varepsilon\ [0,1]$ represents the membership degree of feature point x^j to cluster A_i,$d(x^j,L^i)$ is the distance from a feature point xj to the prototype of cluster A_i. The $d(x^j,L^i)$ can be calculated as follows

$$d(x^j,L^i)=\|x^j-L^i\|=[\sum_{k=1}^{p}(x_k^j-L_k^i)^2]^{1/2}\;\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

If L is given P, we get the fuzzy membership $A_i(x^j)$

$$A_i(x^j)=1/\sum_{K=1}^{s}d^2(x^j,L_i)/d^2(x^j,L_k)\quad i=1,2,\ldots.s\;\ldots\ldots.(12)$$

For a given P, we can obtain L^i

$$L^i=\sum_{J=1}^{n}[A_i(x^j)]^2\,x^j\,/\sum_{j=1}^{n}[A_i(x^j)]^2\quad i=1,2,\ldots.\,k\;\ldots\ldots..(13)$$

Fuzzy covariance matrix C

$$C_{kl}=\sum_{J=1}^{n}[A_i(x^j)]^2\,(x_{jk}-\overline{x_k})(x_{jl}-\overline{x_l})\,/\sum_{j=1}^{n}[A_i(x^j)]^2 \;........(14)$$

Define the objective function of FPCA

$$J(A,L;\alpha)=\sum_{J=1}^{n}[A(x^j)]^2\,d^2\,(x^j,L^i)+\sum_{j=1}^{n}[\bar{A}(x^j)]^2\;\alpha/1\text{-}\alpha \;....(15)$$

Where $[\bar{A}, A\ ]$ is a fuzzy partition. The set A is characterized by its linear centroid.

Set $\bar{A}$ is the complementary fuzzy set. $\alpha/1\text{-}\alpha$ is the difference between its hypothetical centroid and the GEI feature point x^j, where α is a real constant from the interval (0,1) .

$$\text{Centroid for FPCA}\quad v=\sum_{J=1}^{n}[A(x^j)]^2x^j\,/\sum_{j=1}^{n}[A(x^j)]^2$$

Where $A(x^j)=\underline{[\alpha/1\text{-}\alpha]/}\,[\alpha/1\text{-}\alpha]+d^2(x^j,L)$------(16)

We can transform x^j by

$y^j=e^T(x^j\text{-}v)$ where eigenvectors are $e=[e_1,e_2,.......e_k]$

3.8 FPCA training and testing

Fig. 7 shows the process of training and testing. In training phase, the sequences of database are preprocessed and the gait energy images are obtained. The samples of these GEIs are projected into the lower dimensional eigenspace by FPCA. These features construct the new GEI feature database. In testing phase, the test samples are preprocessed and eigenspace is achieved. Meanwhile the projection is compared with the projection in the feature database. We use the nearest neighbour (NN) classifier to determine the human's identity.

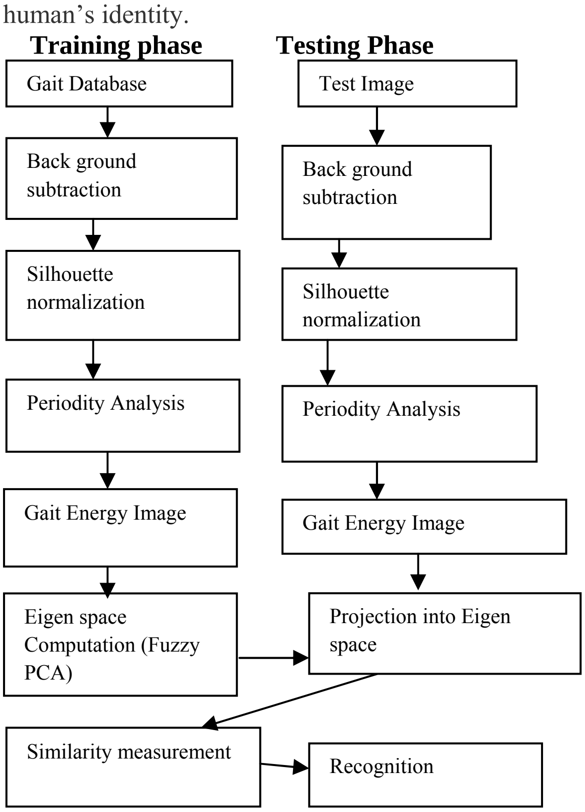

Fig 7. Block Diagram of testing and training phase

IV. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Database

We use CMU MoBo database [9] to evaluate our proposed method. This database has 25 people walking at a fast pace (2.82 miles/hr), slow pace (2.06 miles/hr),carrying a ball and walking in an incline. Fronto-parallel sequences are adopted and the image size is 640×480. Following experiments are done on this database:

(a) train on slow walk and test on slow walk.
(b) train on fast walk and test on fast walk.
(c) train on walk carrying a ball and test on walk carrying a ball.
(d) train on walk in a incline and test on walk in an incline.
(e) train on slow walk and test on fast walk.
(f) train on fast walk and test on slow walk.
(g) train on slow walk and test on walk carrying a ball.
(h) train on fast walk and test on walk carrying a ball.

For experiments (a-d), we use two cycles to train and two cycles to test. For experiments (e-h), we use four cycles to train and two cycles to test.

4.2 Experimental Results

We evaluate the paper method on the CASIA gait database. The CASIA database is obtained from 124 subjects and involves 10 gait sequences for 11 different views. Everyone has 10 sequences including 6 normal walking (Set A), 2 walking with a bag (set B) and 2 walking with a coat (set C).

Firstly, we choose 40 subjects from the database to train and test. The corresponding GEI is deduced the dimension respectively by FPCA and PCA. The accumulative contribution proportions are listed in Table 1. From table 1,the accumulative contribution proportion of first 5 components is 23.2% by PCA, which of first 10 components is 38.5%. The accumulative contribution proportion of first 5 components is 84.6% by FPCA.

Table 1.ACP through PCA and FPCA

Components	[ACP]Accumulative Contribution Proportion (%)	
	PCA	FPCA
First 5	**23.2**	**84.6**
First 10	**38.5**	**86.7**
First 15	**49.6**	**87.8**
First 20	**57.6**	**89.1**

Secondly, we choose 20 subjects of 90 view to test. The training set comprises the first 3 sequences of each subject and the testing set includes the rest sequences. We compare the recognition performance on Set A of the proposed algorithm. Algorithm in [6-8] of the algorithm CASIA database, the correct recognition rate for various methods is shown in Table 2.

Table 2. CCR of several methods

Database	Algorithm	(CCR) Correct recognition rate (%)
CASIA	**GEI[6]**	**83.1**
	GHI+TM[7]	**75.0**
	IDTW[8]	**83.5**
	GMI[6]	**60.4**
	FPCA	**89.7**

Algorithms were used PCA, FPCA algorithm and Radon algorithm the test. FPCA algorithms to identify rate of 89.7%, PCA count Law and Radon algorithm were 83% and 80%. FPCA algorithm to achieve 100% recognition rate. PCA and Radon algorithm of Order Recognition rates are lower than the FPCA algorithm.

The cumulative match characteristics (CMC) curves for the eight experiments are given in Fig.6. In order to show the results clearly, the CMC curves for experiment (a-h) are showed in Fig.6.

For experiments (a-d), the training and the testing data set are of the same motion style. All of experiments (a), (b) and (d) hit 100% and (c) matches more than 95% at the top match. For experiments (e-f), the training and the testing data set are of the different motion styles. Experiments (e) and (f) also achieve very high recognition rate. The CMC of experiment (g) goes beyond 90% at rank three. The CMC of experiment (h) goes beyond 90% at rank six. The results show that the proposed method is robust to speed. But the drastic changes may cause the recognition performance drop slightly.

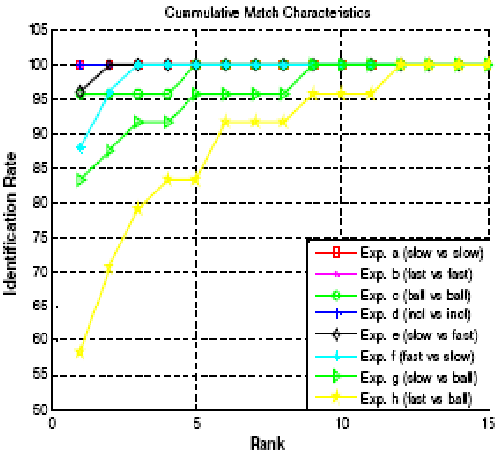

Fig.6. CMC curves for experiments (a-h)

We compare our results with that of Maryland [5] and Rutgers [10]. The details are shown in Table.3, where P is the identification rate and P values at rank 1, 5 and 10 are listed. It can be seen that our results are much better than that of [5] and [10].

Table3. Comparison with other methods

Train vs Probe	Maryland[5]			Rutgers[10]			Our method		
	P(%) at rank			P(%) at rank			P(%) at rank		
	1	5	10	1	5	10	1	5	10
Slow vs Slow	72	96	100	100	100	100	100	100	100
Fast vs Fast	68	92	96	96	100	100	100	100	100
Ball vs Ball	91.7	100	100	100	100	100	95.8	100	100
Incline vs Incline	---	---	---	95.8	100	100	100	100	100
Slow vs Fast	32	72	88	---	---	---	96	100	100
Fast vs Slow	56	80	88	---	---	---	88	100	100
Slow vs Ball	---	---	---	52.2	69.6	91.3	83.3	95.8	100
Fast vs Ball	---	---	---	---	---	---	58.3	83.3	95.8

V. CONCLUSION

This paper presents a new fuzzy principal component analysis based gait recognition party Law. First, according to the original image capture gait energy contour map, and then use fuzzy Principal component analysis to extract the first k eigenvalues larger eigenvector corresponding to gait, and mapped to the low-dimensional space, the last of using the nearest neighbour gait characteristics Classification. PCA algorithm for extreme values and missing data is sensitive, the use of FPCA Will fuzzified data matrix can reduce the impact of extreme values.This algorithm will Experiments on the CASIA database, and with the PCA algorithm, Radon transform of comparison, The results show that FPCA algorithm has better recognition performance. In the future consider using fuzzy neighbour classifier Gait classification.

We propose a HMM-based framework to represent and recognize human gait. We use the outer contour width to construct a one-dimensional feature vector from the two dimensional silhouette image. The feature extraction method is robust to noise and independent of human location in the image, thus does not need to align the images. For each gait sequence cycle, a HMM is trained using the inner product distances of each frame to a set of exemplars and then the HMM is used for gait recognition. We evaluate the proposed method on CMU MoBo database and the results show its efficiency and advantages.The algorithm is proved robust to speed changing and the performance is better when the HMM is training using cycles from slow walk and testing using cycles from fast walk than that training and testing are reversed. This conclusion is not agreed with that in [5]. Great changes, such as walk carrying a ball or changing in viewing angle beyond ten degrees, will bring the performance decline, so more robust feature extraction method should be developed in the future work.

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