Gait Recognition Based on Energy Deviation Image Using Fuzzy Component Analysis

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***Abstract*—From past few years, Gait based recognition is one of the emerging new biometric identification technology for human identification, surveillance and other security applications. In some previous research articles GEI has been reported as a good feature robust to silhouette errors and image noise, but it ignores some gait motion information. So, this paper proposes a novel algorithm which uses Energy Deviation Image (EDI) and based on Fuzzy Principal Component Analysis (FPCA). Firstly, original gait sequences are preprocessed and Enhanced Energy Deviation Image is obtained. Secondly, using Fuzzy Principal Component Analysis eigenvalues and eigenvectors are formulated and which are finally termed as Fuzzy Components. Then, dimensional space is reduced by projecting eigenvectors into low dimensional space. At last, NN classifier is utilized in feature classification. The algorithm is tested on different datasets on CASIA database and the experimental results show that this algorithm achieves higher recognition performance.**

***Index Terms*—Energy deviation image, fuzzy principal component analysis, gait period, feature extraction, gait recognition.**

I. Introduction

More and more public areas and important working places have used cameras for surveillance and monitoring purpose. And gait has its unique advantages for this particular application in comparison with other biometrics such as iris, fingerprint, face and so on. Firstly, gait data collection is none contact and unobtrusive. Secondly, gait is perceivable at a distance. Therefore, gait analysis for recognition has received significant attention ever since it is studied.

The procedure of gait recognition includes subject segmentation (extract foreground subjects from video sequences), feature extraction (extract relevant gait features from segmented silhouette sequences), and classification (classify subjects using extracted gait features). Kale et al. [1] considered the width of the outer contour of the binarized silhouette of the walking person as the gait signature. The gait information in the FED vector sequences was captured in a hidden Markov model (HMM). Sarkar et al. [2] proposed the baseline algorithm; they estimated silhouettes by background subtraction and performed recognition by temporal correlation of silhouettes. In [3], Han and Bhanu extracted the gait energy image (GEI) of the walking person. A statistical feature extraction approach was used for learning effective features from real and synthetic templates. At the decision level, they applied a feature fusion strategy to improve recognition. Huang et al. [4] proposed a template matching approach by combining transformation based on canonical analysis, with eigenspace transformation for feature selection. Wang et al. [5] extracted gait silhouettes of each image sequence and applied eigenspace transformation based on principal component analysis (PCA). The silhouettes extracted from the videos collected with complex background at a relatively far distance are noisy, e.g., missing of body parts, small holes inside the objects, severe shadow around feet, and missing and adding some parts around the border of silhouettes due to background characteristics. Han et al. [3] propose a gait representation method, called Gait Energy Image (GEI), which has been reported as a good feature robust to silhouette errors and image noise. GEI represents the walking sequence of a subject as averaged image(s), so some motion gait features were ignored.

This paper proposes a new gait recognition algorithm. It represents subjects based on energy deviation image (EDI), which is a good complement of the GEI. Then, we apply fuzzy statistic on the PCA, using fuzzy set in the decision analysis stage. As, fuzzy principal component analysis (FPCA) improves the tradition PCA by diminishing the influence of outliers. Through FPCA, gait feature can keep the information of original data and reduce the dimension of the feature effectively. Firstly, the original gait sequence is preprocessed and EDI is obtained. Secondly, we extract the eigenvalues and associated eigenvectors called fuzzy components using FPCA. Then the eigenvectors are projected into lower-dimensional eigenspace. Finally, we utilize the nearest neighbor (NN) classifier to classify the gait feature. The rest of the paper is organized as follows. In Section II, we present the method of gait feature extraction using FPCA. Section III introduces the training and testing procedure. In Section IV, experimental results are presented. Finally, we conclude in Section V.

II. Feature Extraction

A. Image Sequences Preprocessing

The gait cycle of a person is a periodic activity and covering two strides—the left foot forward and right foot forward strides. Each stride spans the double-support stance to the legs-together stance and back to the double-support stance. We utilize the method proposed in [6] to estimate the gait period of a walking sequence.

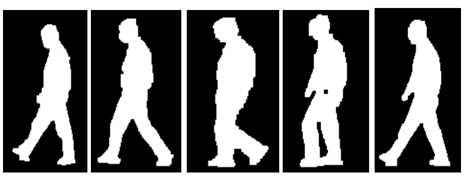

Fig. 1. Silhouette image sequences of a subject.

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The swing distance *sw* of corresponding silhouette is obtained using this given formula:

$$sw = \sum_{y=y_b}^{y_t - \frac{(y_t - y_c)}{2}} \sum_{x=x_l}^{x_r} \left| (x - x_c) \times \frac{I(x,y)}{255} \right| \quad (1)$$

where (x_c, y_c) is the centroid of the silhouette, x_l and x_r denote the horizontal positions of the left-most and the right-most boundary pixels of the silhouette respectively, y_b and y_t denote the vertical positions of the bottom-most and the top-most boundary pixels of the silhouette respectively, and $I(x, y)$ denotes the intensity of the pixel (x, y).

As, periodicity of gait shown is analyzed by the variation of swing distance hence, the gait sequence with double support stance have the local maximum *sw* and similarly the sequences with legs together have local minimum *sw*. So, the frame with the local maximum is called maximum frame. The difference of frame number between every two adjacent odd maximum frame are calculated and sorted.

Let p_i be the i^{th} difference in the sorted list and let C be the number of differences in the sorted list i.e., the number of gait cycles in the video sequence. The gait period of a subject can be calculated as follows.

$$p = \frac{2}{C} \times \sum_{p_i = \frac{C}{4}}^{\frac{3C}{4}} p_i \quad (2)$$

On the basis of calculated gait period, deviation from gait energy image at the i^{th} frame in the C^{th} gait cycle is expressed as

$$diff_{hc} = |f_{hc}(x, y, i) - g_h(x, y)| \quad (3)$$

where, $f_{hc}(x, y, i)$ is the original silhouette image at the i^{th} frame in the C^{th} gait cycle and $g_h(x, y)$ is the gait energy image of the subject h, which is calculated by using the below formula.

$$g_h(x, y) = \frac{1}{m} \sum_{i=1}^{m} f_{hi}(x, y, i) \quad (4)$$

where, m is the number of frames contained in current gait cycle and $f_{hi}(x, y, i)$ is the i^{th} silhouette image sequence for the subject h.

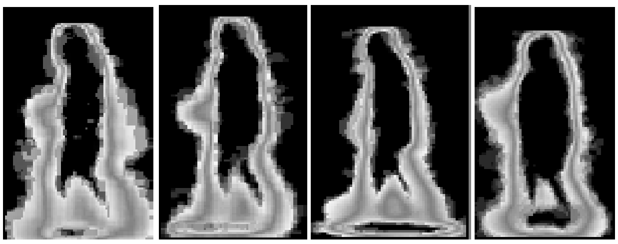

Fig. 2. Energy deviation image of each gait cycle of a subject.

The energy deviation image (EDI) of the c^{th} gait cycle is calculated recursively by using the following eq.

$$devf_{hc}(x, y, k) = \begin{cases} \max\left(devf_{hc}(x, y, k-1) - \frac{255}{p_h}, 0\right) \\ \quad if\ diff_{hc}(x, y, k) = 0 \\ \max\left(devf_{hc}(x, y, k-1), diff_{hc}(x, y, k)\right) \\ \quad else \end{cases} \quad (5)$$

where value of k ranges from 1 to s, that represents the sequence number of current gait silhouette in the c^{th} gait cycle. So, the result of the equation at the s^{th} step is the energy deviation image of c^{th} gait cycle. Finally, the energy deviation image is calculated as

$$devf_h(x, y, s) = \frac{1}{C_h} \sum_{c=1}^{C_h} devf_{hc}(x, y, s) \quad (6)$$

where C_h is the number of gait cycles in the current walking sequence of the subject h. In the above Fig. 2, the EDI corresponding to 4 gait cycles are expressed as a final EDI and in Fig. 3 final EDI i.e., the average of all EDIs mentioned in Fig. 2.

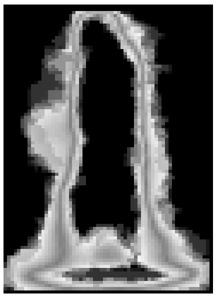

Fig. 3. Final energy deviation image.

B. Feature Extraction

FPCA, which is a combination of Fuzzy *C* Means (FCM) algorithm and Principal component analysis algorithm. As, FCM's main objective is to minimize the objective function and PCA is a kind of linear feature extraction method which projects the original data to principal axes for deducing their dimensions. Since, the gait feature space obtained from EDI is very high dimensional, so we transform it into low-dimensional eigenspace by FPCA. Thus, very few components are required to represent the o approach as follows.

Let $X = \{x^1, x^2, \ldots, x^n\} \subset R^s$ represents a set of pattern space, $x_k^j = [x_1^j, x_2^j, \ldots, x_p^j]^T$ is feature vector of the test sample, which is a corresponding feature point in the eigenspace. s number of clusters represents different pattern classes and the clusters are characterized as the centroid $L = (L^1, L^2, \ldots, Ls)$. If we see the similar things in our context, then it is represented as following, n is the number of the original dimension of EDI feature vectors present in training dataset and p is the original dimension of EDI while the fuzzy partition space is represented as.

$$M_{fc} = \{P \in R^{sn} | A_i(x^j) \in [0,1], \forall\ i, j$$

$$\sum_{i=1}^{s} A_i(x^j) = 1, \forall j; 0 < \sum_{i=1}^{n} A_i(x^j) < n,\ \ \forall i\} \quad (7)$$

where $Ai(x^j) \in\ [0, 1]$ represents the membership value of EDI feature point to the centroid of cluster A_i . $P = [A_i(x^j)]_{s \times n}$ is the fuzzy partition of the EDI feature space. Since fuzzy clustering obtains the degree of uncertainty of samples belonging to each class and expresses the intermediate property of their memberships, it can more objectively reflect the real world [7].

C. Feature Extraction Using FPCA

Define the objective function of fuzzy clusters as follows:

$$\begin{cases} J(P,L) = \sum_{i=1}^{s}\sum_{j=1}^{n}(A_i(x^j))^2 d^2(x^j, L^i) \\ \quad s.t. P \epsilon M_{fc} \end{cases} \tag{8}$$

where $P = \{A_1, \ldots, A_s\}$ is the fuzzy partition of the EDI feature space, and $d(x^j, L^i)$ denotes the Euclidean distance from a feature point x^j to the centroid of the cluster A_i. The $d(x^j, L^i)$ can be calculated as follows:

$$(x^j, L^i) = \left[\sum_{k=1}^{p}(x_k^j - L_k^j)^2\right]^{\frac{1}{2}} \tag{9}$$

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

$$A_i(x^j) = \left[\sum_{k=1}^{s}\frac{d^2(x^j, L^i)}{d^2(x^j, L^k)}\right]^{-1}, \text{ i = 1,….., s} \tag{10}$$

For a given, we can obtain L^i.

$$L_i = \frac{\sum_{j=1}^{n}[A_i(x^j)]^2 x^j}{\sum_{j=1}^{n}[A_i(x^j)]^2}, \text{ i = 1,…., k} \tag{11}$$

An objective-function-based fuzzy clustering depends on the definition of prototypes, so we use the one dimensional linear cluster prototypes, defined as $L(u, V)$,where V is the center of the class and $u(\|u\|=1)$ is the main direction. We can obtain the fuzzy covariance matrix $\boldsymbol{C}$ from [8].

$$C_{kl} = \frac{\sum_{j=1}^{n}[A_i(x^j)]^2 (x_{jk} - \bar{x}_k)(x_{jl} - \bar{x}_l)}{\sum_{j=1}^{n}[A_i(x^j)]^2} \tag{12}$$

Define the objective function of FPCA:

$$J(A, L; \alpha) = \sum_{j=1}^{n}(A(x^j))^2 d^2(x^j, L^i) + \sum_{j=1}^{n}(\bar{A}(x^j))^2 \frac{\alpha}{1-\alpha} \tag{13}$$

where $\{A, \bar{A}\}$ is a fuzzy partition. The set A is characterized by its linear centroid. And set $\bar{A}$ is the complementary fuzzy set. $\alpha/(1-\alpha)$ 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). We determine α using the method in [8].

Centroid can be obtained by using following formula for FPCA.

$$v = \frac{\sum_{j=1}^{n}[A(x^j)]^2 x^j}{\sum_{j=1}^{n}[A(x^j)]^2} \tag{14}$$

where, $$A(x^j) = \frac{\frac{\alpha}{1-\alpha}}{\frac{\alpha}{1-\alpha} + d^2(x^j, L)} \tag{15}$$

We can transform x^j by

$$y^j = e^T(x^j - v) \tag{16}$$

where eigenvectors are $e = [e_1, e_2, e_3, \ldots\ldots, e_k]$.

The steps of FPCA algorithm are described below [9]:

Step1: Preprocess the EDI feature vectors.

Step2: Obtain the covariance matrix $\boldsymbol{C}$ with (12) and sort highest eigenvalues λ_1 and the corresponding eigenvector $\boldsymbol{e_1}$.

Step3: Determine the new fuzzy set A^{i+1} using (15).

Step4: If $A^{(i+1)} - A^{(i)} < \varepsilon$ (we choose $\varepsilon = 10^{-5}$), then stop and go to step 6. Otherwise, increase i by 1 and go to the step 2.

Step5: Recomputed the covariance matrix $\boldsymbol{C}$ using (12) and determine its eigenvalues and eigenvectors.

Step6: Calculate the projections of test data with (16).

We sort the eigenvalues in decreasing order and select k number of highest eigenvalues. These eigenvectors are the fuzzy principal components. Usually k is much smaller than the original data dimension. The feature of EDI preprocessed is a 84×156 or 13104 dimensional vector, $k \ll 13104$. The k principal components adequately keep the original data of EDI. Thus, we obtain principal components which are projected into the lower dimension space through FPCA.

III. TRAINING AND TESTING

Fig. 4 shows the process of training and testing. In training phase, the sequences of database are preprocessed and the energy deviation images are obtained. The samples of these EDIs are projected into the lower-dimensional eigenspace by FPCA. These features construct the new EDI 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 neighbor (NN) classifier to determine the human's identity.

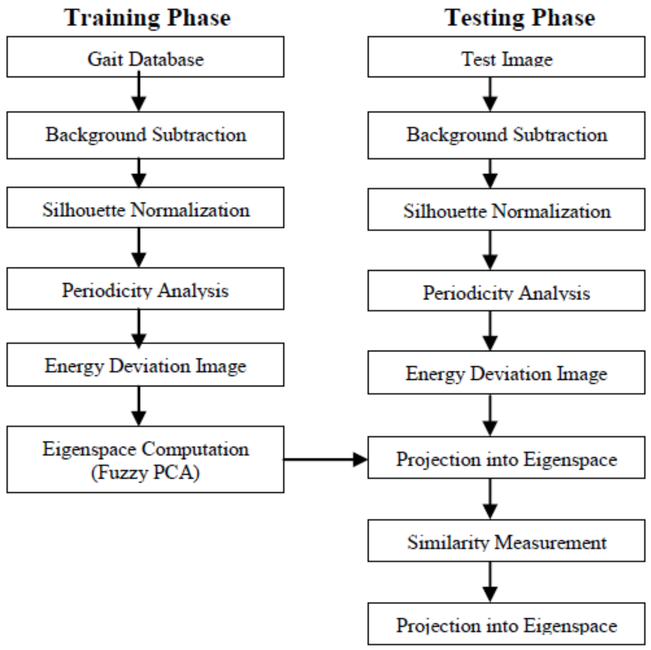

Fig. 4. Block diagram of training and testing phase.

IV. EXPERIMENTAL RESULTS

The method mentioned above is evaluated on the different datasets of CASIA database. The database consists of 124 subjects and involves 10 gait sequences recorded from 11 different views. In dataset A the normal walking, dataset B walking with bag and dataset C walking with coat is recorded.

For training the database, firstly we choose 45 subjects. The corresponding EDI is deuced the dimension by FPCA. In Table I accumulative contribution proportions are listed. As a consequence, in order to achieve the higher accumulative contribution proportion, it needs large number of the eigenvalues (principal components) through FPCA. The degree of deducing dimension is better through FPCA than PCA as FPCA preserves the principal information of the original data.

Finally, we evaluate the performance on set A, B and C of CASIA database using FPCA and compare the same with PCA and Radon Transformation algorithm respectively. The CMS using PCA and Radon Transformation is lower than FPCA. So, FPCA is one of the efficient way to represent the gait characteristics.

TABLE I: ACCUMULATIVE CONTRIBUTION PROPORTION THROUGH FPCA AND PCA.

Components	Accumulative Contribution Proportion (%)	
	PCA	FPCA
First 5	23.5	84.2
10	39.8	86.8
15	49.1	88.6
20	56.8	90.3

TABLE II: CCR OF SEVERAL METHODS MEASURED ON CASIA DATABASE.

Algorithms	CCR(%)
GEI	82.7%
RT	84.3%
EDI	86.2%
FPCA+EDI	90.1%

V. CONCLUSION

We present the novel approach of gait recognition using fuzzy principal component analysis (FPCA). The EDI is obtained after preprocessed. By FPCA, the k largest eigenvalues and associated eigenvectors are achieved while the components are projected into the lower dimension space. The NN classifier is adopted to identify the human. FPCA is insensitive to the outliers, the gait feature can keep the information of original data by FPCA compared with the traditional PCA. The experiment results show that the proposed method has better recognition performance than PCA and Radon transformation.

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