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Multi-View Neural Network Based Gait Recognition

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Abstract**—**Human identification at a distance has recently gained growing interest from computer vision researchers. Gait recognition aims essentially to address this problem by identifying people based on the way they walk [1]. Gait recognition has 3 steps. The first step is preprocessing, the second step is feature extraction and the third one is classification. This paper focuses on the classification step that is essential to increase the CCR (Correct Classification Rate). Multilayer Perceptron (MLP) is used in this work. Neural Networks imitate the human brain to perform intelligent tasks [3].They can represent complicated relationships between input and output and acquire knowledge about these relationships directly from the data [2]. In this paper we apply MLP NN for 11 views in our database and compare the CCR values for these views. Experiments are performed with the NLPR databases, and the effectiveness of the proposed method for gait recognition is demonstrated.

Keywords**—**Human motion analysis, biometrics, gait recognition, principal component analysis, MLP neural network.

I. INTRODUCTION

GAIT-based human identification aims to discriminate individuals by the way they walk [4].A unique advantage of gait as a biometric is that it requires no subject contact and is easily acquired at a distance, which stands in contrast to biometric techniques involving face, fingerprints, iris, etc.Gait also offers potential for recognition at low resolution when the human subject occupies too few image pixels for other biometrics to be perceivable. The recognition of a person from his (or her) gait is a relatively new research subject in biometrics and has been a recent focus in computer vision [2].

Gait recognition can be broadly classified into two types: model-based and model-free approach[5].Model based approaches purpose to explicitly model human body or motion and performs model matching in each frame of a walking sequence[6,7,8].The parameters such as trajectories are measured according to the model in the approach.The effectiveness of the model-based approaches, however, is still limited due to current imperfect vision techniques in body structure/motion modelling and parameter recovery from a walking image sequence involving individual walking movement and characterize the statistics of the walking patterns which captures both the static and dynamic properties of body shape[9,10,11].These approaches have high computational efficiency because they do not recover a structural model of human motion.Recently,tensor gait analysis has been reported to improve the model-free gait recognition performance [12,13,14,15].Two-dimensional gait image were represented as tensor data in [13,12] and tensor discriminate analysis(TDA) was combined with gabor feature and locally linear embedding (LLE) criterion in [14]and[15],respectively.Further,these are some hybrid works combining both model-based dynamic cues and model-free static cues, for example[16].

On the other hand, much research on neural networks has been conducted. The neural networks can construct nonlinear decision boundaries without prior assumptions about the statistics of input data. In particular, they have strong discriminatory and learning power and represent implicit knowledge of the given data [2].

This paper is organized as follows: In Section 2 we explain feature extraction that is the base of temporal changes of the walker`s silhouette. In Section 3 we pay attention to Principal Component Analysis (PCA) to represent the original gait features from a high-dimensional measurement space to a low-dimensional eigenspace. Section 4 represents the classification technique as the main contribution of this work. The proposed method is explained in section 5. Section 6 shows the experimental results in detail. Finally, conclusions form the last section.

II. FEATURE EXTRACTION

Before training and recognition, each image sequence including a walking figure is converted into an associated temporal sequence of distance signals at the preprocessing stage .An important cue in determining underlying motion of a walking figure is temporal changes of the walker's silhouette. To make the proposed method insensitive to changes of color and texture of clothes, we use only the binary silhouette. Additionally, for the sake of computational efficiency, we convert these 2D silhouette changes into an associated sequence of 1D signals to approximate temporal pattern of gait. This process is illustrated in Fig. 1. After the moving silhouette of a walking figure has been tracked, its outer contour can be easily obtained using a border following algorithm.

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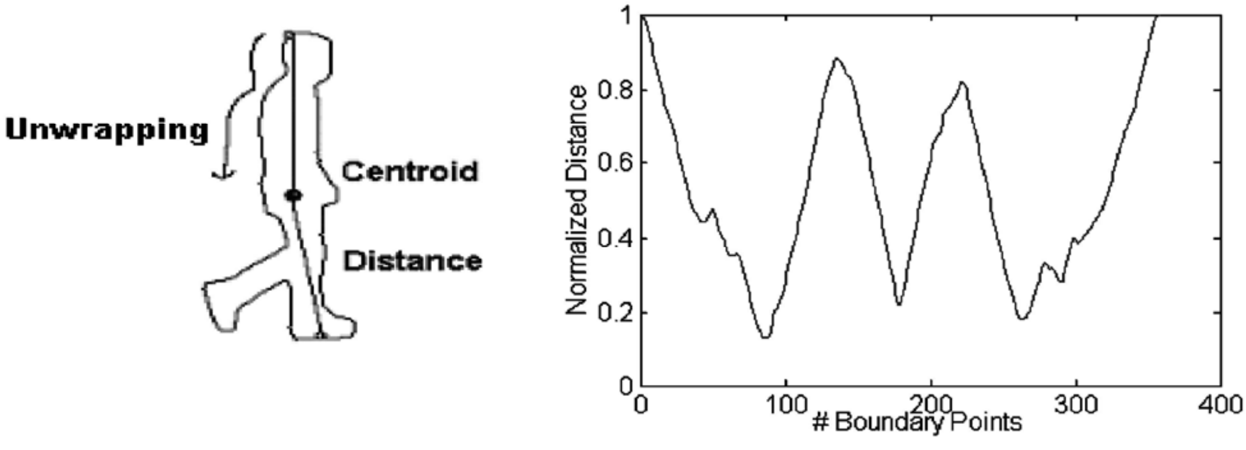

(a) (b)

Fig.1 Silhouette representation: (a) illustration of boundary extraction and counterclockwise unwrapping and (b) the normalized distance signal consisting of all distance between the centroid and the pixels on the boundary.

Then, we may compute its shape centroid(x_c,y_c).By choosing the centroid as a reference origin, we unwrap the outer contour counterclockwise to turn it into a distance signal $S=\{d_1,d_2,\ldots,d_i,\ldots,d_{Nb}\}$ that is composed of all distances d_i between each boundary pixel(x_i ,y_i)and the centroid

$$d_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \tag{1}$$

This signal indirectly represents the original 2D silhouette shape in the 1D space. To eliminate the influence of spatial scale and signal length, we normalize these distance signals with respect to magnitude and size. First, we normalize its signal magnitude through L1-norm. Then, equally spaced re-sampling is used to normalize its size into a fixed length (360 in our experiments). By converting such a sequence of silhouette images into an associated sequence of 1D signal patterns, we will no longer need to cope with those likely noisy silhouette data[1].

III. Training and Projection

PCA Training

The purpose of PCA training is to obtain several principal components to represent the original gait features from a high-dimensional measurement space to a low-dimensional eigenspace. The training process similar to [17] is illustrated as follows: Given s classes for training, and each class represents a sequence of distance signals of one subject's gait. Multiple sequences of each person can be freely added for training. Let $D_{i,j}$ be the jth distance signal in class i and N_i the number of such distance signals in the ith class. The total number of training samples is $N_t = N_1 + N_2 + \ldots + N_s$,and the whole training set can be represented by $[D_{1,1},D_{1,2},\ldots,D_{1,N1},D_{2,1},\ldots, D_{s,Ns}]$.We can easily obtain the mean m_d and the global covariance matrix $\sum$ of such a data set by

$$m_d = \frac{1}{N_t}\sum_{i=1}^{s}\sum_{j=1}^{N_i} D_{i,j} \tag{2}$$

$$\sum = \frac{1}{N_t}\sum_{i=1}^{s}\sum_{j=1}^{N_i}(D_{i,j} - m_d)(D_{i,j} - m_d)^T. \tag{3}$$

If the rank of the matrix $\sum$ is N, then we can compute N nonzero eigenvalues $\lambda_1,\lambda_2,..,\lambda_N$ and the associated eigenvectors e_1, e_2, …,e_N based on SVD (Singular Value Decomposition).

Generally speaking, the first few eigenvectors correspond to large changes in training patterns. Therefore, for the sake of memory efficiency in practical applications, we may ignore those small eigenvalues and their corresponding eigenvectors using a threshold value Ts

$$W_k = \sum_{i=1}^{k}\lambda_i \Big/ \sum_{i=1}^{N}\lambda_i > T_s. \tag{4}$$

where W_k is the accumulated variance of the first k largest eigenvalues with respect to all eigenvalues. In our experiments, T_S is chosen as 0.95 for obtaining steady results [1].

Projection

Taking only the K<N largest eigenvalues and their associated eigenvectors, the transform matrix E= [e_1, e_2, …,e_N] can be constructed to project an original distance signal into a point $P_{i,j}$ in the k-dimensional eigenspace.

$$P_{i,j=} [e_1, e_2, \dots, e_k]^T D_{i,j} \tag{5}$$

Accordingly, a sequential movement of gait can be mapped into a manifold trajectory in such a parametric eigenspace. It is well-known that k is usually much smaller than the original data dimension N. That is to say, eigenspace analysis can drastically reduce the dimensionality of input samples. For each training sequence, the projection centroid C_i in the eigenspace is accordingly given by averaging all single projections corresponding to each frame in the sequence [1].

$$C_i = \frac{1}{N_i} \sum_{j=1}^{N_i} P_{i,j} \tag{6}$$

IV. Classification

In this paper we try to improve the CCR to get better results than other existing methods [1]. In reference [1] classification process is carried out via two simple different classification methods, namely the nearest neighbour classifier (NN) and the nearest neighbour classifier with respect to class exemplars (ENN) derived from the mean projection centroid of those training sequences for a given subject [1]. As mentioned before, we focus on classification phase and use MLP classifier. The proposed network has 2 hidden layers with 38 and 20 nodes and default transfer function (tansig) for first and second hidden layers.

V. Proposed Method

The overview of the proposed algorithm is shown in Fig.2. It consists of two major modules, feature extraction and training or classification. The first module serves to extract the binary silhouette from each frame and map the 2D silhouette image into a 1D normalized distance signal by contour unwrapping with respect to the silhouette centroid. Accordingly, the shape changes of these silhouettes over time are transformed into a sequence of 1D distance signals to approximate temporal changes of gait pattern. The second module either applies PCA on those time-varying distance signals to compute the predominant components of gait signatures (training phase), or determines the person's identity using the standard nonparametric pattern classification techniques in the lower-dimensional eigenspace (classification phase).

As mentioned before, we focus on classification phase and use MLP classifier. The proposed network has 2 hidden layers with 38 and 20 nodes and default transfer function (tansig) for first and second hidden layers.

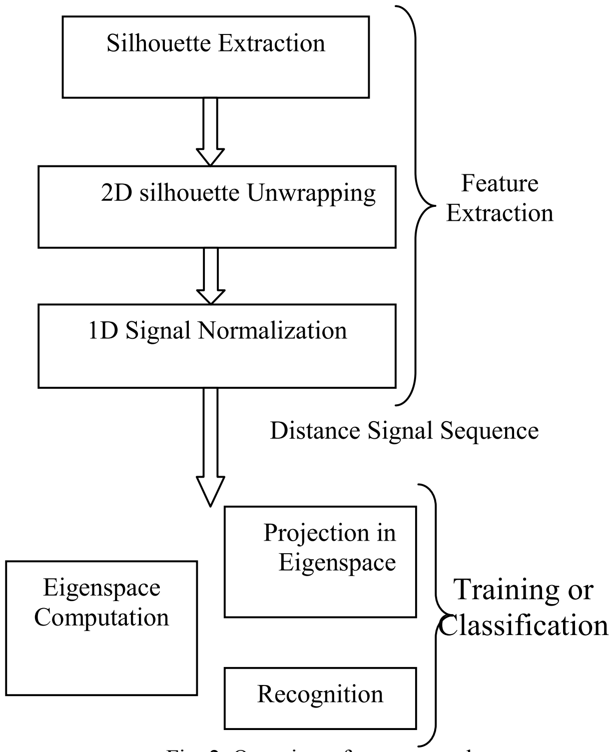

Fig. 2. Overview of our approach.

VI. Experimental Result

We conducted some experiments on the CASIA Gait Database (Dataset B) [18], currently one of the largest gait databases in the gait-research community. The database consists of 124 subjects aged between 20 and 30 years, of which 93 were male and 31 were female, and 123 were Asian and one was European. Each subject first walked naturally along a straight line six times, then put on his/her coat and walked twice, and finally walked twice carrying a bag (knapsack, satchel, or handbag). Each subject walked a total of 10 times in the scene (six normal two with a coat two with a bag). Eleven cameras were uniformly set on the left-hand side, with view angle interval of 18, so 11 video sequences from different views were captured simultaneously for every walking scenario (see Fig. 3). There are a total of 13,640 (124×10×1) video sequences in the database, with 2–3 gait cycles in each sequence. The frame size is 320-by-240 pixel, and the frame rate is 25 fps. We applied %11 of persons in this database to have the same scenario as of the work of L. Wang et al. The achieved results using the proposed method has better CCR compared the one of [1]. Based on the experimental

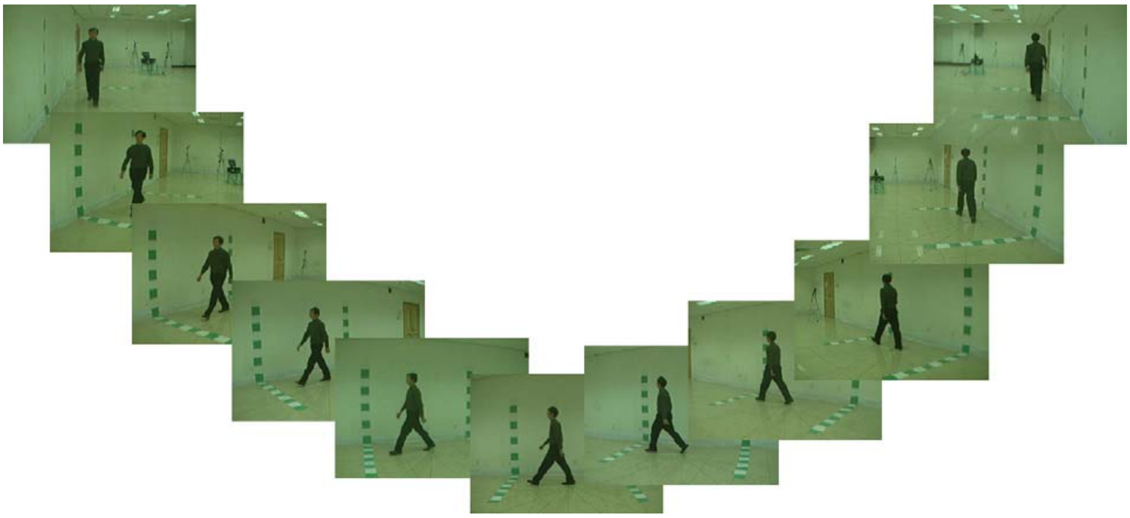

Fig. 3. The walking sequences captured from 11 different views.

results, fourth, fifth and sixth views (equal to 72, 90 and108 degrees) have better CCR results and the best one is 90 degree lateral view. The results are shown in the tables 1 and 2. Table 1 shows that the obtained results are better than [1] and the second table compares the results of different views. The database used in this work (database B) is a very large database, rarely used by researchers and the results show the effectiveness of the proposed method.

TABLE I COMPARED RESULTS FOR LATERAL VIEW

Method	Classifier	CCR
NED (L. Wang, T. Tan)	**NN** (Nearest Neighbour)	**65**
NED (L. Wang, T. Tan)	**ENN** (Euclidean Nearest Neighbour)	**75**
NED (In this paper)	**NN** (Neural Network)	**82**

VII. CONCLUSIONS

In this paper, we propose a novel method for efficient gait recognition using a MLP neural network. The proposed algorithm results in higher recognition accuracy. Based on the experimental results, fourth, fifth and sixth views (equal to 72, 90 and 108 degrees) have better CCR results and the best one is obtained for a 90 degree lateral view.

The results are shown in the tables 1 and 2. Table 1 shows that the obtained results are better than [1] (7% increase in CCR) and the second table shows the results for all views based on the proposed method and represents 5% to 25% increase in fourth and fifth views and 12% to32% increase in sixth view compared to the previous methods.

TABLE II THE RESULTS FOR ALL VIEWS BASED ON THE PROPOSED METHOD

View	Method	Classifier	CCR
0	NED	NN(Neural Network)	50
18	NED	NN(Neural Network)	57
36	NED	NN(Neural Network)	70
54	NED	NN(Neural Network)	75
72	NED	NN(Neural Network)	75
90	NED	NN(Neural Network)	82
108	NED	NN(Neural Network)	62
126	NED	NN(Neural Network)	60
144	NED	NN(Neural Network)	54
162	NED	NN(Neural Network)	50
180	NED	NN(Neural Network)	54

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