Identity Recognition Algorithm Using Improved Gabor Feature Selection of Gait Energy Image

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Abstract. This paper describes an effective gait recognition approach based on Gabor features of gait energy image. In this paper, the kernel Fisher analysis combined with kernel matrix is proposed to select dominant features. The nearest neighbor classifier based on whitened cosine distance is used to discriminate different gait patterns. The approach proposed is tested on the CASIA and USF gait databases. The results show that our approach outperforms other state of gait recognition approaches in terms of recognition accuracy and robustness.

1. Introduction

Gait recognition [1] is the process of identifying and individual by the way they walk. This is less unobtrusive biometric, which offers the possibility to identify a person at a distance. Moreover, gait recognition offers great potential for recognition of low-resolution videos, where other biometrics technologies may be invalid because of insufficient pixels.

2. Previous Work

Since Han [2] proposed the gait energy image as a new spatio-temporal gait representation, a large number of improved approaches have emerged. Liang [3] present a novel approach to extract gait features based on gait energy image, and P Theekhanont [4] uses gait energy image transformed to a trace transform image for human identification. S Sivapalan [5] demonstrate the applicability of compressed sensing in the field of gait recognition as a very effective dimensionality reduction technique. And Xue H [6] apply PCA and LDA to extract the main vector of gait feature of GEI. In this paper, the Gabor magnitude of GEI and an innovative reduced dimensions method is proposed to select distinctive features.

3. The Gait Recognition System

The structure diagram of the gait recognition system based on GEI is shown in Figure 1.

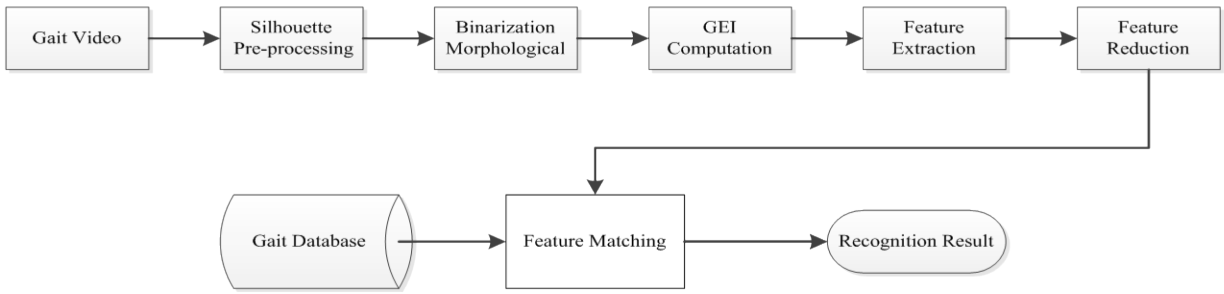

Figure 1. The flow chart of gait recognition system based on gait energy image

Given a size-normalized and horizontal-aligned human walking binary silhouette sequence B(x, y, t), the grey-level GEI A(x, y) is defined as follows

$$A(x,y)=\frac{1}{N}\sum_{i=1}^{N}B(x,y,t) \tag{1}$$

where N is the number of frames in complete cycles of the sequence, t is the frame number of the sequence, x and y are values in the 2D image coordinate. The examples of normalized and aligned silhouette frames in different human walking sequences and GEIs are shown in Figure 2.

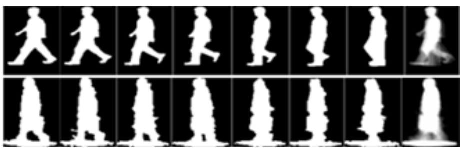

Figure 2. The average silhouette image over the whole sequence-Gait Energy Image (GEI)

3.1. Feature extraction algorithm based on the combination of gait energy map and Gabor wavelet

Gabor filters have proven themselves to be a powerful tool for gait feature extraction and robust gait recognition. They represent complex band-limited filters with an optimal localization in both the spatial as well as the frequency domain. In general, the family of 2D Gabor filters can be defined in the spatial domain as follows:

$$\psi(x,y)=\frac{f_u^2}{\pi k\eta}e^{-((f_u^2/k^2)x'^2+(f_u^2/\eta^2)y'^2)}e^{j2\pi f_u x'}\text{, u=0,1,…,scales-1, v=0,1,…,orientions-1} \tag{2}$$

where $x'=x\cos\theta_v+y\sin\theta_v$, $y'=-x\sin\theta_v+y\cos\theta_v$, $f_u=f_{\max}/2^{(u/2)}$ and $\theta_v=v\pi/8$.

3.2. Feature extraction of GEI using gabor filters

Let $I(x,y)$ stand for a grey-scale image of GEI and, moreover, let $\psi_{u,v}(x,y)$ denote a Gabor filter given by its center frequency f_u and orientation θ_v. The feature extraction procedure can then be defined as a filtering operation of the given GEI $I(x,y)$ with the Gabor filter $\psi_{u,v}(x,y)$ of size *u* and orientation *v*. In the Equation(3), $G_{u,v}(x,y)$ denotes the complex filtering output, that is

$$G_{u,v} = I(x,y) * \psi_{u,v}(x,y) \tag{3}$$

3.3. Gait feature dimension reduction based on Kernel Fisher Analysis

In this part, the improved kernel Fisher discriminant and Gabor feature based kernel Fisher analysis, which are main contributions of this paper. The idea of kernel Fisher discriminant analysis is to yield a nonlinear discriminant analysis in the higher space as F. In this paper, the F space for the Fisher method just as the Equation (4).

$$J(w) = \frac{w^T S_B^\Phi w}{w^T S_W^\Phi w} \tag{4}$$

where the S_B^Φ and S_W^Φ are the between and within class scatter matrices respectively. In this paper, the polynomial kernel is adopted. And then, the gait features of the training data in the kernel space is got by the Equation (5).

$$\arg\max(J(w)) \bullet \Phi(x) = \sum_{i=1}^{l} \alpha_i k(x_i, x) \tag{5}$$

Lastly, the features of test data are got by the following steps:

$$K = (X^T Y + 1)^2 \tag{6}$$

$$V = P^T * K \tag{7}$$

where the ***K*** denotes the kernel matrix, ***X***, ***Y*** are the test data and training data respectively. **P** is just the transformation matrix calculated by training data. ***V*** is just the features of test data.

3.4. Nearest neighbor classifier based on whitened cosine similarity measure

In this paper, the GEIs are normalized and aligned, so they can be clustered by the distance measure. According to related experimental results, the nearest neighbor classifier based on the white cosine similarity [7] is used to discriminate different gait patterns.

4. Experimental Results and Analysis

Our experiments are carried out on the CASIA DatasetB gait database and the USF HumanID gait database.

4.1. Experiment on CASIA gait database

On the CASIA gait database, a dataset consisting of 124 subjects in the 90° view is constructed. Each person has 10 GEIs with the resolution 240 * 240 and they are divided into training and test set with the ratio of 1:1. The parameters of Gabor filter banks are set as follows: nscales=6, norientions=8, k=η=$\sqrt{2}$, f_{max}=0.25. Give one gait energy image, the filter response is shown in Figure 3.

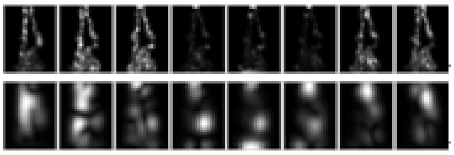

Figure 3. Filter response of GEI

To investigate the performance of gait recognition on the gait databases, the cumulative matching characteristic (CMC) and receiver operating characteristic (ROC) are used. On the CASIA, the experimental results as well as comparison with other approaches of individual recognition by gait are shown in Figure 4 ~5. The experimental data are shown in Table 1 and Table 2.

4.2. Experiment on USF gait database

A database consisting of 122 subjects based the USF HumanID database is constructed. For each individual, there are 12 gait energy images with a resolution of 88 x 128, in which the CALNB and CALBF are 6 respectively. They are divided into training and test set with the ratio of 1:1. The experimental results are shown in Figure 6 ~7, and the related data are shown in Table 3~4.

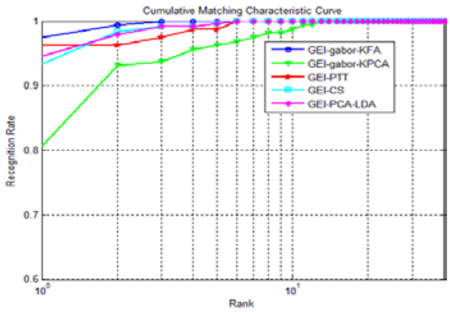

Figure 4. Recognition performance of CMC curves on CASIA

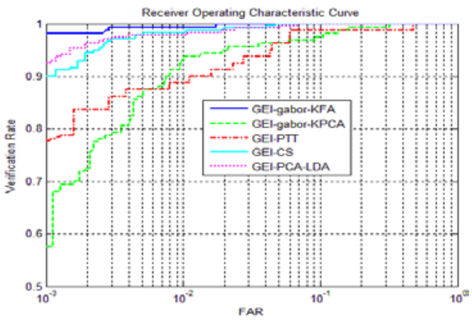

Figure 5. Verification performance of the ROC curve on CASIA

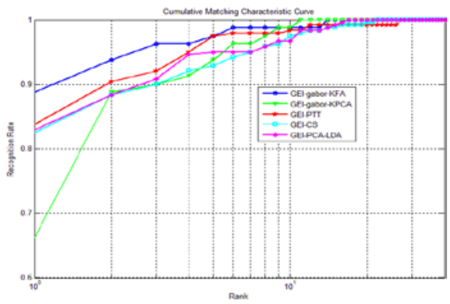

Figure 6. Recognition performance of CMC curves on USF

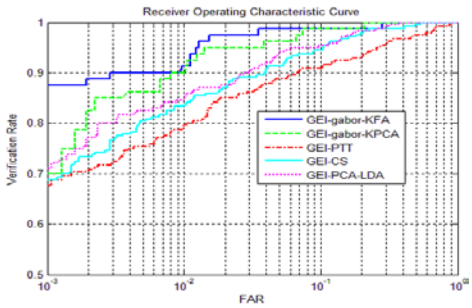

Figure 7. Verification performance of the ROC curve on USF

Table 1. CMC curve identification performance data on CASIA

Approach	GEI-gabor-KPCA[3]	GEI-PTT[4]	GEI-CS[5]	GEI-PCA-LDA[6]	Proposed
Rank1	80.63%	96.25%	93.33%	94.58%	97.50%
Rank5	96.25%	98.75%	99.58%	99.58%	100.00%

Table 2. ROC curve verification performance data on CASIA

Approach	GEI-gabor-KPCA[3]	GEI-PTT[4]	GEI-CS[5]	GEI-PCA-LDA[6]	Proposed
FAR=1%	93.13%	88.75%	98.33%	97.92%	99.38%
FAR=0.1%	56.88%	76.25%	89.17%	90.42%	98.13%

Table 3. CMC curve identification performance data on USF

Approach	GEI-gabor-KPCA[3]	GEI-PTT[4]	GEI-CS[5]	GEI-PCA-LDA[6]	Proposed
Rank1	66.25%	83.75%	82.50%	82.92%	88.75%
Rank5	93.75%	97.50%	92.92%	95.00%	97.50%

Table 4. ROC curve verification performance data on USF

Approach	GEI-gabor-KPCA[3]	GEI-PTT[4]	GEI-CS[5]	GEI-PCA-LDA[6]	Proposed
FAR=1%	90.00%	79.58%	83.33%	84.58%	91.25%
FAR=0.1%	66.25%	67.50%	68.75%	69.58%	87.50%

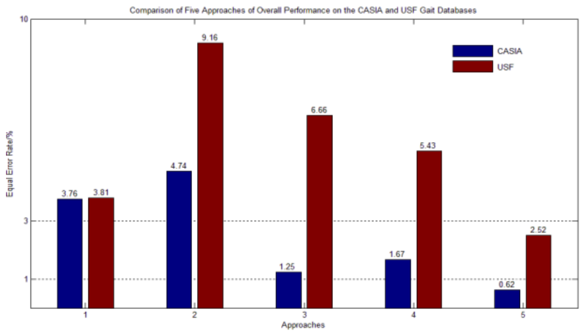

Figure 8. Equal error rate of five approaches on the CASIA and USF gait databases

In the CMC and ROC curves, the best performance of one approach should be close to the upper left corner as near as possible. As shown in Fig. 4~5 that our approach is closest to the upper left corner. The values of Rank1 and Rank5 of the proposed are the largest of the five approaches, and our approach is the only one converging to 1 in rank 5. The experimental data are shown in Table 1 ~2 as well as comparison with other approaches of individual recognition by gait.

It can be seen from the data in Table 2 that the recognition rate of the proposed approach is the highest when the false acceptance rate (FAR) is equal to 1% and 0.1%, and at the low FAR, the advantages of our approach are more prominent. With the decrease of false acceptance rate, the correct recognition rate just dropped by 6.25%, which is the smallest of the five approaches. This exhibits that the recognition performance of the proposed approach in this paper is relatively robust.

The same conclusions, as experiment on CASIA gait database, can be drawn from the experimental results on USF shown in Figure 6~ 7 and the related data in Table 3~ 4. The equal error rate in Figure 8 reflects the overall performance of one approach. The smaller the equal error rate, the better the performance of the algorithm.

5. Conclusions and Future Work

In this paper, the amplitude of Gabor of gait energy image is extracted and the kernel Fisher discriminant analysis is used to reduce the dimensionality of gait features of training set. The gait features of test set are selected in a novel way. According to the kernel matrix combined with transformation matrix, the features of test set are selected. Experimental results show that the approach proposed has the characteristics of high recognition rate and strong robustness. Further research will focus on the following aspects: a) explore more effective method to extract gait features; b) seek more effective method of similarity measurement; c) seek more effective classifier.

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