A Framework for Evaluating the Effect of View Angle, Clothing and Carrying Condition on Gait Recognition

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Abstract

Gait recognition has gained increasing interest from researchers, but there is still no standard evaluation method to compare the performance of different gait recognition algorithms. In this paper, a framework is proposed in an attempt to tackle this problem. The framework consists of a large gait database, a large set of well designed experiments and some evaluation metrics. There are 124 subjects in the database, and the gait data was captured from 11 views. Three variations, namely view angle, clothing and carrying condition changes, are separately considered in the database. The database is one of the largest database among the existing databases. Three sets of experiments, including a total of 363 experiments, are designed in the framework. Some metrics are proposed to evaluate gait recognition algorithms.

1. Introduction

Gait is an attractive biometric feature for human identification at a distance, and recently has gained much interest from computer vision researchers. Compared with those traditional biometric features, such as face, iris and fingerprint, gait has many unique advantages such as non-contact, non-invasive and perceivable at a distance. Hence gait has been considered as a suitable biometric feature for human identification at a distance in visual surveillance.

In recent years many gait recognition algorithms have been developed. Some of them are model-based approaches [9, 11], and some are appearance-based ones [7, 12, 13]. Even though many algorithms have been proposed, comparison of different algorithms and evaluation of robustness to some variations such as the variations of view angle, clothing, shoe types, surface types, carrying condition, illumination, and time are still hard and open problems. These variations should be fully studied to develop robust and accurate gait recognition algorithms.

The HumanID Gait Challenge Problem [1, 8], which consists of a large database, a baseline algorithm and twelve experiments, tried to handle these problems. The data in the HumanID Gait Challenge Problem was collected in an outdoor environment with complex background, so it is a little hard to extract good quality human silhouettes, and this will affect the analysis of other factors. The twelve experiments were designed to evaluate an algorithm's robustness to view, shoe, surface, time, clothing and carrying condition changes. However, for these factors twelve experiments are not enough. Besides, the subjects walked in an elliptical path, and then the view angle kept changing while the subjects was walking, so the relationship between view angle and algorithm's performance can not be obtained. In conclusion, a database that is more suitable for evaluation and some well designed experiments are needed.

A framework that consists of a large database, some experiments and metrics is proposed. In the database, data acquired from 11 views are included and also three most important factors, view angle, clothing and carrying condition changes, are separately considered. A total of 363 experiments were designed to thoroughly investigate these factors.

The organization of this paper is as follows. Section 2 describes the gait database. Experiment design is presented in Section 3, and metrics is in Section 4. Section 5 concludes this paper.

2. Database

2.1. Overview of other gait databases

In addition to the database in the HumanID Gait Challenge Problem [1, 8], there also exist many other gait databases, such as UCSD Database, CASIA Gait Database (Dataset A) [2], Georgia Tech Database [3], MIT AI Gait Data, CMU Mobo Database [4, 6], HID-UMD Database,

The 18th International Conference on Pattern Recognition (ICPR'06)
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and Soton Database [5, 10]. Among these gait databases used in recent work there are only two databases which contain more than 100 subjects: one is the Soton Large Database, and the other is the Gait Challenge Database. The Gait Challenge Database has been mentioned in the previous section. The Soton Large Database contains only side views of normal walking, and does not include many factors.

2.2. CASIA Gait Database: Dataset B

As the framework focuses on the effect of factors other than human detection or segmentation, simple background was used to simplify silhouette segmentation, and all the videos were captured in an indoor environment. We set up a lab specially for this data acquisition as illustrated in Figure 1. There were 11 USB cameras (Model: Fametech 318SC) around the left hand side of the subject when he/she was walking, and the angle between two nearest view directions is $18°$. Since many images would be taken from different positions, some geometry information of subjects could be reconstructed aided by some calibration equipments. Four calibration taps were placed to help reconstruct geometry information. There were $20cm \times 20cm$ white-green alternative blocks on these taps. Two taps were put on the vertical wall, and two were on the flow, as shown in Figure 1.

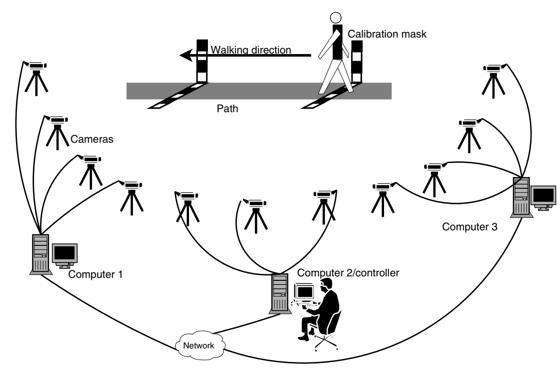

Figure 1. Set-up for gait data collection

When a subject walked in the scene, he/she was asked to walk naturally along a straight line 6 times first, and $11 \times 6 = 66$ normal walking video sequences were captured for each subject. Some normal walk examples are shown in Figure 2. After normal walk, the subjects were asked to put on their coats, and then walked twice along the straight line. We also recorded 2 sequences of each subject at each view when the subject carried a bag. The bag could be a knapsack, a satchel, or a handbag. The subjects could choose the bag that they liked. Figure 3 shows some sequences captured under these three conditions. The subjects' information, such as height, gender, was also recorded.

(a) Walking normally (b) Walking with a coat (c) Walking with a bag

Figure 3. Walking under different conditions

All the video sequences were stored as video files encoded with *mjpeg* codec. The frame size of the video files is 320×240, and the frame rate is 25 fps. There are 2 to 3 gait cycles in each sequence. Gait data of 124 subjects were captured at last. There were 93 males and 31 females, 123 Asians and 1 European among all subjects. Most subjects were young people and they aged between 20 and 30. Every subject walked 10 times in the scene (6 normal + 2 with a coat + 2 with a bag). There are a total of $10 \times 11 \times 124 = 13640$ video sequences in our database. The database is about $17G$ in size. It is a large gait database in terms of size or the number of subjects.

The CASIA Gait Database is provided free of charge at web site http://www.cbsr.ia.ac.cn/.

3. Experiments

We designed three sets of experiments (Experiment Set A, B and C) for gait recognition algorithm evaluation. Experiment Set A is for investigating how view angle affect the gait recognition performance and an algorithm's robustness to view variation. For each view of a subject, there are 6 normal walking sequences. In Experiment Set A the first 4 sequences are taken as gallery set, and the other 2 sequences are taken as probe set. There are $11 \times 11 = 121$ experiments in Experiment Set A as shown in Table 1. Experiment Set B is for investigating how clothing affect the performance and an algorithm's robustness to clothing change. Experiment Set C is for carrying condition change. The gallery sets of Experiment Set B and C are the same with A, but the probe sets are different. All the sequences of walking with a coat are put into the probe set of Experiment Set B, and all those of walking with a bag are put into the probe set of Experiment Set C. These three experiment set are used to evaluate an algorithm's robustness to view change, clothing change and carrying condition change.

In the following, a gait recognition algorithm is evaluated as an example by the metrics proposed in the paper. We take the well known average silhouette (also called Gait Energy Image, GEI) algorithm [7] as an example, which has been reported as a good feature robust to silhouette errors and image noise,

Given a fixed camera, the human silhouette can be ex-

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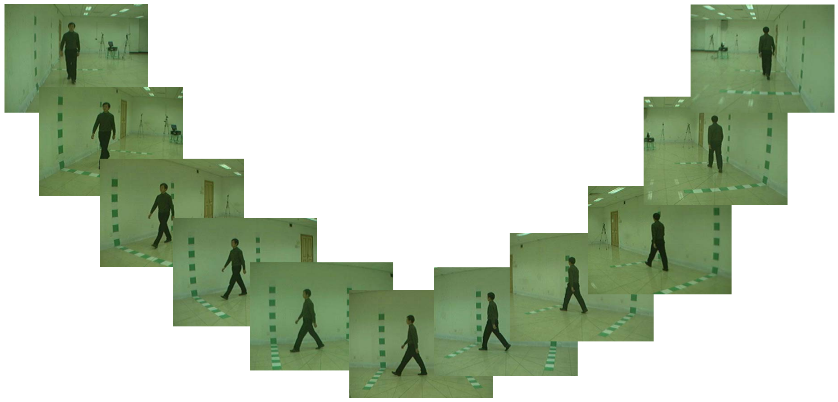

Figure 2. Normal walking sequences

tracted by background subtraction and thresholding. The method in [12] is used to segment human silhouette from image sequences. The sizes of the silhouettes are not unique, and the silhouettes need to be normalized to be the same size.

Gait energy image is defined in [7] as

$$G(x, y) = \frac{1}{N} \sum_{t=1}^{N} I(x, y, t) \qquad (1)$$

where N is the number of frames in the sequence $I(x, y, t)$, t is the frame number, x and y are the image coordinate.

Euclidian distance is employed to measure the similarity between two GEIs, and the nearest neighbor classifier is to recognition different subjects. The experimental results (correct classification rates) of Experiment Set A, B and C are listed in Table 1, 2 and 3.

		Probe angle θ_p (normal walking #5-6)										
		0°	**18°**	**36°**	**54°**	**72°**	**90°**	**108°**	**126°**	**144°**	**162°**	**180°**
Gallery angle θ_g (normal #1-4)	**0°**	99.2	31.9	9.3	4.0	3.2	3.2	2.0	2.0	4.8	12.9	37.9
	18°	23.8	99.6	39.9	8.9	4.4	3.6	3.6	5.2	13.7	33.5	10.9
	36°	4.4	37.9	97.6	29.8	11.7	6.9	8.1	13.3	23.4	13.3	2.0
	54°	2.4	3.6	29.0	97.2	23.0	16.5	21.4	29.0	21.4	4.8	1.2
	72°	0.8	4.4	7.3	21.8	97.2	81.5	68.1	21.0	5.6	3.6	1.6
	90°	0.4	2.4	4.8	17.7	82.3	97.6	82.3	15.3	5.2	3.6	1.2
	108°	1.6	1.6	2.0	16.9	71.4	87.9	95.6	37.1	6.0	2.0	2.0
	126°	1.2	2.8	6.0	37.5	33.5	22.2	48.0	96.8	26.6	4.4	2.0
	144°	3.6	5.2	28.2	18.5	4.4	1.6	3.2	43.1	96.4	5.6	2.8
	162°	12.1	39.1	15.7	2.4	1.6	0.8	0.8	2.4	5.2	98.4	28.6
	180°	41.1	19.8	8.1	3.2	2.0	0.8	1.6	3.6	12.5	51.2	99.6

Table 1. The experimental results of Set A (%)

4. Evaluation

The correct classification rates (CCRs) in Table 1, 2 and 3 can show the robustness of an algorithm to view, cloth-

		Probe angle θ_p (walking with a coat #1-2)										
		0°	**18°**	**36°**	**54°**	**72°**	**90°**	**108°**	**126°**	**144°**	**162°**	**180°**
Gallery angle θ_g (normal #1-4)	**0°**	24.6	6.9	3.2	1.6	0.8	0.8	0.8	0.8	1.6	5.6	8.1
	18°	4.4	27.0	18.5	6.9	0.8	0.8	0.8	2.4	5.6	11.7	2.8
	36°	1.6	8.5	30.2	16.5	1.2	1.2	1.6	6.9	9.3	3.6	0.8
	54°	0.8	2.4	10.1	30.6	5.6	4.4	7.7	14.1	5.6	2.4	0.8
	72°	0.0	2.4	5.6	7.7	31.0	21.8	14.9	8.9	2.8	2.4	0.4
	90°	1.2	2.4	4.0	6.0	20.6	32.7	16.5	6.0	3.6	3.2	0.8
	108°	1.6	2.0	2.4	4.8	17.7	27.8	30.2	9.3	4.8	2.0	1.6
	126°	1.6	1.6	1.6	4.4	10.1	10.1	18.5	26.2	8.9	1.6	1.6
	144°	2.4	2.8	4.0	12.5	4.4	2.4	4.4	18.1	30.6	1.2	2.0
	162°	2.8	7.7	9.7	2.0	0.4	0.8	0.8	1.6	4.0	27.0	6.5
	180°	9.3	6.0	3.2	0.8	1.2	0.0	0.0	1.6	5.6	12.5	27.4

Table 2. The experimental results of Set B (%)

		Probe angle θ_p (walking with a bag #1-2)										
		0°	**18°**	**36°**	**54°**	**72°**	**90°**	**108°**	**126°**	**144°**	**162°**	**180°**
Gallery angle θ_g (normal #1-4)	**0°**	80.2	20.2	5.2	2.4	2.4	2.0	2.0	2.0	4.4	14.5	25.8
	18°	16.9	76.2	36.7	7.3	3.6	2.8	2.8	4.8	10.9	18.1	8.1
	36°	3.6	23.0	74.6	24.2	9.3	8.1	7.3	10.5	15.3	6.5	1.6
	54°	0.8	2.8	19.4	66.5	19.0	13.3	14.5	18.5	7.3	4.0	1.6
	72°	0.4	4.8	6.5	8.9	60.5	31.0	22.2	11.7	4.0	3.6	1.2
	90°	0.4	2.8	5.2	8.5	42.3	52.0	31.9	9.7	6.0	3.2	2.0
	108°	1.6	1.2	3.6	7.3	39.9	44.0	57.3	23.4	6.5	3.6	1.6
	126°	0.8	2.8	4.0	17.3	25.4	14.9	27.8	65.7	14.5	2.0	1.6
	144°	2.0	4.8	15.3	11.7	6.9	2.0	4.4	31.9	64.1	2.4	1.2
	162°	7.7	23.8	13.7	3.6	2.4	2.0	2.4	4.4	6.0	68.1	19.0
	180°	30.2	12.9	6.5	2.0	2.0	2.0	1.2	2.8	7.7	31.5	80.2

Table 3. The experimental results of Set C (%)

ing and carrying condition change. But it is not straightforward to compare two algorithms or evaluate an algorithm's robustness using these values in the three tables. Two metrics (C_Δ and σ) are designed for each experiment set. C_Δ^A, which is the average of the CCRs on the diagonal ($\theta_g = \theta_p$) of Table 1, is defined as

$$C_\Delta^A = \frac{1}{11}\sum_{n=0}^{10} C_{n\cdot n}^A \tag{2}$$

where $C_{n\cdot n}^A$ is the CCR in Experiment Set A when the gallery and probe angles are all $n \cdot 18°$. C_Δ^B and C_Δ^C are defined similarly. C_Δ^A can be used to indicate the algorithm's accuracy of recognition when there is no great variation, and C_Δ^B and C_Δ^C can be used to indicate the algorithm's robustness to clothing and carrying condition changes respectively.

The standard deviation is a statistic that tells how tightly all the various examples are clustered around the mean. So the standard deviations of the three experiment set, σ^A, σ^B and σ^C, are used as metrics. σ^A can indicate the algorithm's robustness to view angle change. σ^B and σ^C are slightly different from σ^A. They indicate the algorithm's robustness not only to view angle change, but also respectively to clothing and carrying condition changes.

All these metrics values for the GEI algorithm are listed in Table 4. A better gait recognition algorithm should has larger C_Δ and smaller σ.

Metrics	Exp. Set A	Exp. Set B	Exp. Set C
C_Δ	0.977	0.289	0.678
σ	0.302	0.086	0.195

Table 4. Evaluation metrics for the GEI algorithm

5. Conclusions and Future Work

In the framework proposed in the paper there are a large gait database, three experiment sets and some evaluation metrics. The gait database, which has 124 subjects and 11 views, is one of the largest databases. The database can be used for not only gait recognition, but also human body tracking, human body reconstruction, human motion analysis, etc. The framework provides a platform to evaluate gait recognition algorithms. It can promote the development of gait recognition. In future we will enlarge the database to include more data of different time, outdoor environment, other sensors (infrared camera) etc. In addition, a more systematic evaluation for gait recognition as FRVT in face recognition is also our goal.

Acknowledgement

We would like to thank Stan Z. Li, Liangsheng Wang, Wenhai Chen, Lun Xin, Zhang Zhang, Wenfeng Jin and other members in CASIA for their help on setting up the capture lab. We would also like to thank all volunteers taking part in the data collection.

This work is partly supported by National Natural Science Foundation of China (Grant No. 60335010), National Basic Research Program of China (Grant No. 2004CB318100) and International Cooperation Program of Ministry of Science and Technology of China (Grant No. 2004DFA06900).

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