Efficient Night Gait Recognition Based on Template Matching

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Abstract

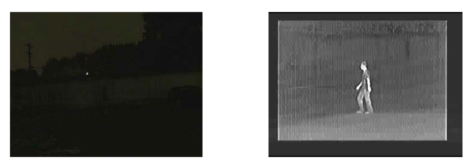
Gait is a useful biometric which can be used to recognize people at a distance when other biometrics are incapable. However, most work on gait recognition has been visible spectrum-oriented over the past decade, ignoring recognition at night which is in reality demand-imperative. This paper deals with the problem of night gait recognition via thermal infrared imagery. First of all, human detection is accomplished, based on the Gaussian mixture modeling of the background. Then, human silhouettes are extracted on the basis of preceding detection results. Moreover, a new gait representation called HTI is proposed to characterize gait signatures for recognition. An infrared night gait database was built to provide a foundation for night gait recognition. Experimental results on two gait datasets show the effectiveness of this method.

1. Introduction

Gait means the way one walks. The work by Murray et al. [11] seemed to support gait uniqueness to individuals. Gait recognition is aimed at recognizing the identity of people through the manner they walk. Currently a number of researchers active in the computer vision field have much interest in gait recognition, since gait has some advantages over fingerprint, face and iris, such as non-contact and unobtrusiveness. Furthermore, gait is the unique biometric which can be perceived at a distance.

There has been a great deal of work which considerably fertilizes the research field of vision-based gait recognition during the past years. Niyogi and Adelson [13] made an earliest attempt to identify people by virtue of their gait. Later, Little and Boyd [9] gained a set of moments from dense optical flow of a walker and individual recognition was accomplished by utilizing phase difference from these moments. In addition, Bobick et al. [3] selected a couple of compact distance signals which are static and activity-dependent to fulfill identity recognition while Collins et al. [4] chose some key frames in a gait cycle as feature templates to make a distinction between subjects. Further, Kale et al. [8] employed the width of the outmost profile of binary silhouettes and the whole binary silhouette of a pedestrian to identify him/her whereas Cunado et al. [5] made use of a pendulum of 3 degrees of freedom as the structural model of the thigh to discriminate subjects. In particular, Sarkar et al. [14] first established a large gait dataset composed of 122 subjects and aimed to provide a baseline for evaluation of gait recognition algorithms. Progress in automatic gait recognition was reported by Nixon et al. [12]. It should be pointed out that the commonly-used gait datasets in the literature are set up at daytime and that prior work on gait recognition is visible-spectrum-oriented.

However, for the problem of recognizing people at night from a distance, previous methods may be incompetent. Figure.1 (a) shows such an example. In the light of current vision techniques, it is difficult to accurately detect the human in Fig. 1(a) whereas it is relatively easier to finish the detection of the human in Fig. 1(b). The success in infrared-based face and iris recognition inspires us to exploit infrared imaging to conquer the problem of light dependence of gait recognition at night. More importantly, there is still a lack of work on infrared-based gait recognition, albeit Davis et al. [6] handled the problem of robust detection of people in thermal imagery and Han et al. [7] used infrared images to recognize human activities.



(a) (b)

Fig.1. Imagery in the visible light and thermal infrared spectra captured at the same scene. (a) Image in the visible light spectrum. (b) Image in the thermal infrared spectrum.

The motivation of this paper is to recognize people at night with low illumination. The fact that infrared imaging is light-irrelevant and shadow-immune, together with that gait is the only available biometric which can be used to recognize people at a distance at night, motivates us to take advantage of thermal infrared imagery of people's gait for their identity recognition. To the best of our knowledge, this is the first attempt in night gait recognition based on infrared images. In our opinion, night gait recognition, which combines infrared imaging with computer vision techniques, will be a novel, meaningful and promising research direction. This research work has practical implications from the perspective of night visual surveillance.

This paper will be organized as follows. Section 2 depicts the CASIA Infrared Night Gait Dataset established to recognize human beings at night. Our method is introduced in Section 3. Then, Section 4 presents experimental results on two gait datasets. Finally, Section 5 concludes this paper.

2. CASIA Infrared Night Gait Dataset

There have been many gait databases built for HumanID Research Project. However, there is still a lack of an infrared gait database which has a sufficient number of subjects and takes into consideration some significant factors affecting the performance of gait recognition algorithms. Bhanu and Han [2] exploited infrared sequences to analyze human motion, but their dataset has only one subject. Later, Han and Bhanu [7] used infrared images to recognize human activities; unfortunately, this dataset has the similar problem (just 5 subjects). Hence it is an inevitable necessity to establish an infrared gait database serving as a basis for infrared-based gait recognition and a theoretical preparation for night visual surveillance.

(a) (b) (c)

Fig.2. Night infrared imagery under different weather conditions. (a) Image on a hot sunny day. (b) Image on a cloudy day. (c) Image with low contrast on a cloudy day.

We collected the gait data, called CASIA Infrared Night Gait Dataset, from 153 subjects: 130 males and 23 females. A thermal infrared camera was used to image night human gait (with the resolution of 320×240 and the rate of 25fps) from the side-view outdoors. In our experiments, each subject was asked to walk normally four times, walk with a bag two times, walk slowly two times and walk quickly two times, that is, each having ten sequences of gait data. As a result, this dataset has a total of 1530 sequences of gait data. Figure 2 illustrates some sample frames in this dataset. As far as current gait recognition is concerned, our dataset provides a platform for infrared-based gait recognition; at the same time, this database can be regarded as a meaningful complement of current gait databases from the viewpoint of visual surveillance. Moreover, it is obvious that more factors need to be taken into account by our dataset. This will be our future work.

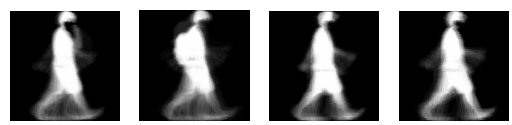
3. The Algorithm

3.1 Human Silhouette Extraction

Human detection is the cornerstone of gait recognition algorithms. Our detection module currently depends on a dynamic background model [15] to achieve the detection of subjects in each frame of infrared video with background subtraction. We first apply a 5×5 Gaussian filter to each frame for removal of the noise in that frame, and then acquire an initial detection image based on the above dynamic background image. Morphological operations and pyramid algorithms are further applied to segmented foreground images to remove erroneous pixels. At last, human silhouettes are obtained by the use of a simple threshold on the foreground images. It should be noted that every binary human silhouette image is normalized to the resolution of 129×130.

3.2 Gait Representation and Recognition

The representations for human gait obviously play a critical part in the final success of gait recognition. GEI [7] is a gait representation with good performance and robustness against segmental errors. It is worth noting that GEI is in essence equivalent to the representations of [10, 16]. Some sample GEI images are shown in Fig. 3.



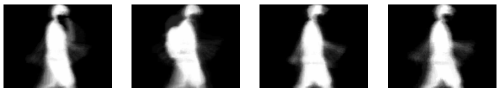
(a) (b) (c) (d)

Fig.3. GEI samples. (a) Walk normally. (b) Walk with a bag. (c) Walk slowly. (d) Walk quickly.

We can see from Fig. 3 that the lighter the pixels representing human body in the GEI are, the less drastic their movement is. For example, the fact that pixels in the area of head and torso are lighter than those in the lower legs indicates that when a person moves, the pose in the head and torso is more stable. Inspired by this observation (and the heuristic that we often identify our friends by the profile of their heads and torsos), we use the head-torso-thigh part of human silhouettes to represent human gait and refer to it as HTI. As far as HTI is concerned, it can be viewed to some extent as a first-order-statistic-based description of human gait from the structural point. Assume that $HT(x, y, t)$ is a set of images derived from human silhouettes with the part of crura (the leg from the knee to the foot) removed, then HTI is defined as

$$HTI = \frac{1}{N} \sum_{i=1}^{N=KT} HT(x, y, t) \tag{1}$$

where N is the number of frames in one sequence, T gait cycle and K = 1, 2, 3, …,. T can be determined using the method in [17]. Figure 4 displays some HTI images in correspondence to Fig. 3.



(a) (b) (c) (d)

Fig.4. HTI samples corresponding to Fig. 3. (a) Walk normally. (b) Walk with a bag. (c) Walk slowly. (d) Walk quickly.

At last, we use the nearest neighbor classifier to identify subjects with the aid of HTI. For an unknown gait representation U, it will be classified as the one from which U has the minimum L_1 distance:

$$ID = \arg\min_K Dis(U,K) \tag{2}$$

$$Dis(U,K) = \min_i Dis(U,K_i) \tag{3}$$

$$Dis(U,K_i) = \sum_{x,y} \left| U(x,y) - K_i(x,y) \right| \tag{4}$$

where K is the label of one subject, K_i is one of the gait templates of the subject with the label K.

4. Experimental Results

In order to evaluate the effectiveness of HTI, we first perform night gait recognition experiments on a subset of 46 subjects in the CASIA Infrared Night Gait Dataset (the reason for the only use of a part of gait data is some challenges to the current detection module). In addition, results on the NLPR Database [17], which is a daytime dataset, further justify its efficacy in recognition capability.

4.1 Tests on the Infrared Night Gait Dataset

Four experiments designed for HTI are outlined in Table 1 to assess the power of our algorithm in night gait recognition. Experiment A is to evaluate the recognition power of HTI under the normal walking condition. In this experiment, we used the set of three normal-walking gait sequences of each subject as the training set and the remaining normal-walking gait sequences as the test set (with cross-validation). The factors including holding a bag and walking speed (walk slowly and walk quickly) are taken into account in the remaining experiments to evaluate their impact on the performance of our gait recognition algorithm. The corresponding recognition results are presented in Table 2.

It can be seen from Table 2 that both walking speed and carrying a bag deteriorate to some extent the performance of HTI and GEI. In particular, carrying a bag has much more impact on the recognition performance due to drastic differences in human silhouettes when one walks with a bag, compared with his/her normal walking. In addition, HTI is more robust against the variation in walking speed, in comparison with GEI. Figure 5 illustrates the identification performance measured in the cumulative match score (CMS). Table 2 and Fig. 5 show that the performance of the proposed HTI is comparable with that of GEI, but HTI has lower storage cost. This indicates that head, torso and thigh have much more important recognition information, which is in accordance with that in [16].

Table 1. Four experiments for infrared gait recognition on a subset of 46 subjects in the CASIA Infrared Night Gait Database

Experiment	Gallery Sequence	Probe Sequence	Gallery Set	Probe Set
A	138	46	Normal	Normal
B	184	92	Normal	Bag
C	184	92	Normal	Slow
D	184	92	Normal	Quick

Table 2. CCR Using HTI and GEI on the subset of 46 subjects in the CASIA Infrared Night Gait Database

Experiments	CCR(GEI) Rank=1	CCR(HTI)Rank =1
A	96%	94%
B	60%	51%
C	74%	85%
D	83%	88%

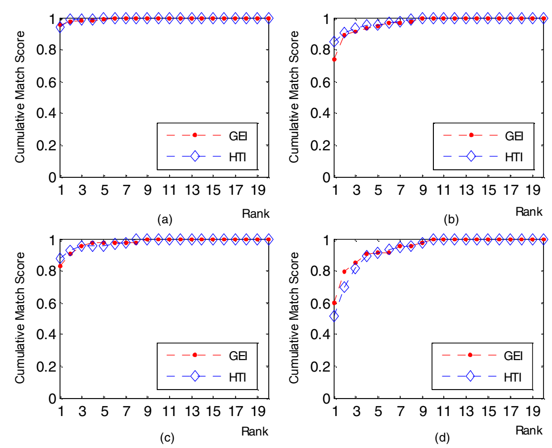


Fig.5. Recognition performance measured in the CMS. (a) Walk normally. (b) Walk slowly. (c) Walk quickly. (d) Walk with a bag.

4.2 Tests on the NLPR Gait Database

Figure 6 displays the CMS curves of HTI and the method of [17] on the NLPR Gait Database under the conditions specified by [17]. Recognition results demonstrate that HTI outperforms [17] which is better than [1, 4, 14].

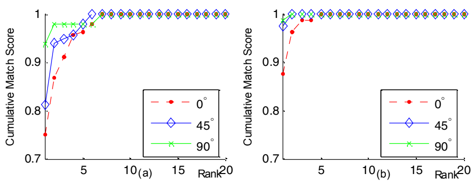


Fig.6. Performance comparison between HTI and the method of [17] on the NLPR Gait Database. (a) Performance of [17]. (b) Performance of HTI.

5. Conclusions and Future Work

This paper has addressed the problem of infrared-based gait recognition for the purpose of night visual surveillance. Our contributions currently lie in two folds. One is that we initially establish an infrared night gait database which constitutes mutual complement with the current gait datasets from the standpoint of visual surveillance (though it needs to be enlarged to consider more factors such as time difference and viewpoint). The other is that we propose HTI as a new gait representation whose performance is comparable to that of GEI on the night gait dataset and better than that of [1, 4, 17, 14] on the NLPR Gait Database. In addition, HTI is easy to compute and consequently very efficient, which stems from its straightforwardness and endows it with an important advantage over other computation-intensive techniques [1, 4, 17, 14]. The results indicate that the upper half body of a pedestrian carries important (shape-based) recognition information. But the problem with the current detection method is its missing detection induced by low contrast as shown in Fig. 2 (c).

Our future work will consist of the following aspects. First, the infrared gait database needs to take into account more factors (such as time, view and weather conditions). Then, the performance of HTI in gait recognition needs to be further validated on the basis of much more subjects. In addition, HTI merely made use of shape cues to characterize night gait, ignoring rich dynamic hints in the crura part. Fusion of the two kinds of information will be promising. Finally, the detection of human beings in low-contrast infrared images will be one of our research focuses.

Acknowledgement

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References

[1] C. BenAbdelkader, R. Culter, H. Nanda and L. Davis. EigenGait: motion-based recognition of people using image self-similarity, in *Proc. of Intl. Conf. on Audio- and Video-based Biometric Person Authentication,* pp: 284-294, 2001.

[2] B. Bhanu and J. Han. Kinematic-based Human Motion Analysis in Infrared Sequeces. *Proc. the 6th IEEE Workshop on Applications of Computer Vision*, pp: 208- 212, 2002.

[3] A. Bobick and A. Johnson. Gait Recognition Using Static, Activity-specific Parameters. *Proc. Conference on Computer Vision and Pattern Recognition*, pp: 423-430, volume 1, 2001.

[4] R. Collins. Silhouette-based Human Identification from Body Shape and Gait. *Proc. the 5th IEEE International Conference on Automatic Face and Gesture Recognition*, pp: 351-356, 2002.

[5] D. Cunado, M. Nixon and J. Carter. Automatic Extraction and Description of Human Gait Model for Recognition Purposes. *Computer Vision and Image Understanding*, 90 (1): 1-41, 2003.

[6] J. Davis and V. Sharma. Robust Detection of People in Thermal Imagery. *Proc. the 17th International Conference on Pattern Recognition*, pp: 713- 716, Volume 4, 2004.

[7] J. Han and B. Bhanu. Human Activity Recognition in Thermal Infrared Imagery. *Proc. IEEE Workshop on Object Tracking and Classification Beyond the Visible Spectrum*, 2005.

[8] A. Kale, A. Sundaresan, A. Rajagopalan, N. Cuntoor, A. RoyChowdhury, V. Krueger. Identification of Humans Using Gait. *IEEE Transactions on Image Processing*, 13(9): 1163-1173, 2004.

[9] J.Little and J. Boyd. Recognizing People by Their Gait: The Shape of Motion. *Videre: Journal of Computer Vision Research*, 1(2):2-32, 1998.

[10] Z. Liu and S. Sarkar. Simplest Representation yet for Gait Recognition: Averaged Silhouette. *Proc. the 17th International Conference on Pattern Recognition*, pp: 211- 214, Volume 4, 2004.

[11] M. Murray, A. Drought and R. Kory. Walking Patterns of Normal Men. *Journal of Bone and Joint Surgery*, 46-A(2): 335-360, 1964.

[12] M. Nixon and J. Carter. Advances in Automatic Gait Recognition. *Proc. the 6th IEEE International Conference on Automatic Face and Gesture Recognition*, pp: 139-144, 2004.

[13] S. Niyogi and E. Adelson. Analyzing and Recognizing Walking Figures in XYT. *Proc. Conference on Computer Vision and Pattern Recognition*, pp: 469-474, 1994.

[14] S. Sarkar, P. Philips, Z. Liu, I. Vega, P. Grother and K.Bowyer. The Human Gait Challenge Problem: Data Sets, Performance and Analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(2): 162-177, 2005.

[15] C. Stauffer and W.E.L Grimson. Adaptive Background Mixture Models for Real-time Tracking. *Proc. Conference on Computer Vision and Pattern Recognition*, pp: 246-252, 1999.

[16] G. Veres, L. Gordon, J. Carter and M. Nixon. What Image Information is Important in Silhouette-based Gait Recognition. *Proc. Conference on Computer Vision and Pattern Recognition*, pp: 776-782, Volume 2, 2004.

[17] L. Wang, T. Tan, H. Ning and W. Hu. Silhouette Analysis-based Gait Recognition for Human Identification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(12): 1505-1518, 2003.