A Survey of Advances in Biometric Gait Recognition

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Abstract. Biometric gait analysis is to acquire biometric information such as identity, gender, ethnicity and age from people walking patterns. In the walking process, the human body shows regular periodic motion, especially upper and lower limbs, which reflects the individual's unique movement pattern. Compared to other biometrics, gait can be obtained from distance and is difficult to hide and camouflage. During the past ten years, gait has been a hot topic in computer vision with great progress achieved. In this paper, we give a general review and a simple survey of recent gait progresses.

Keywords: Gait Analysis, Biometric, Recognition

1 Introduction

In the past ten years, terrorist attacks such as London subway bombings occur frequently, which make people clearly understand the importance of security monitoring and control in national defense and public safety. A large number of surveillance cameras have been installed in public places, but these security-sensitive early warning systems require intelligent approaches. Ideal intelligent monitoring system should be able to automatically analyze the collected video data, give out a early warning before the adverse event happens, and reduce injury and economic loss. For example, when the system detects abnormal behavior, it can immediately determine the identities of all persons in the scene, rapidly investigate their previous activities, and track the suspects across the regions. It requires the monitoring system can not only estimate the quantity, location and behavior, but also obtain the identity information.

Gait is the most suitable biometrics in the case of intelligent visual surveillance. In monitoring scenes, people are usually distant from cameras, which makes most of biometric features no longer available. Most of existing systems use face for identification. The shortcomings are obvious, for example, unexpected view angle and occlusion cause full faces can not be photographed, distance brings about low-resolution face image. Therefore, face can not always achieve acceptable results in practical. In contrast, gait is a behavioral biometric, including not only individual appearance, such as height, leg length, shoulder width, but also the dynamics of individual walking. Compared with other biometrics, gait is remote accessed and difficult to imitate or camouflage. Moreover, the capturing process does not require cooperation, contact with special equipment, or high image resolution.

Because of the urgent need for intelligent monitoring and the development of computer-related fields, video-based gait recognition research has gradually emerged since 1990s. Back in the 1960s, M. P. Murray et al. [1, 2] proved gait is a recognizable pattern of cyclical movement in medical experiments, and did a preliminary analysis of the impact of height, age and other factors on identity. H. J. Ralston et al. [3] decomposed the gait cycle into detailed synthetic movement of multiple joints and muscle, in which the parameters of factors include body weight, limb length, joint velocity, and bone structure. They pointed out the uniqueness of gait pattern, and did a performance evaluation of biometric gait. In the early psychological research on gait recognition, most work is based on the observation experiments. G. Johansson et al. [4] and C. D. Barclay et al. [5] equipped reflectors and moving lights in several joints, and made observations can not directly see pedestrians but only see these light points. Results are consistent with physiological measurements, the majority of observers are able to recognize their familiar friends with limited points of light. These experiments above proved that the gait pattern is personally unique, and can be used for biometric recognition.

2 Overview

By data source, the gait studies can be divided into two main categories, which are sensor-based and video-based.

In the studies of sensor-based gait, common used sensor devices are mainly tactile ones and wearable ones. Tactile sensors generally refers to multi-degree of freedom (angle) pressure sensor [6], usually installed in a particular road, to collect the pressure signal generated when walking. And wearable sensors [7] are attached to the key points of different body parts, selective collect the speed, acceleration, position and other information. Commonly used devices include light senses (such as reflectors, moving lights), acceleration sensors, magnetic sensors, gyroscopes, etc. Sensors can directly access to the motion information of specified parts. Although the sensor-based data can easily assure accuracy, but requires more complex equipment in collection. P. Vanitchatchavan [8] analyzed the angle pattern between joints. Three goniometers pasted at the pelvis, knee, and ankle joints, recording the joint change information during walking and stoping. C. D. Barclay et al. [9] and JECutting et al. [10] proposed the use of shoulder width, hip width, and other body parameters in identification and gender classification, and analyzed the recognition accuracy and feasibility. They become the cornerstone of a large number of of follow-up studies. However, most applications of these methods are limited in medical researches. They have been frequently used in the health status of diagnosis, such as Parkinson's disease diagnosis and feedback of treatment [11].

Video-based gait recognition research generally refers to shot through the optical camera to get the video and identify biometric information, but not rely on special equipment. Currently, widely used large gait databases in academic research include CASIA Gait Database (Dataset B) [12], collected by National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, CMU Motion of Body Database [13], collected by Robotics Institute, Carnegie Mellon University, Southampton Human ID at a Distance Database [14], collected by Information: Signals, Images and Systems Research Group, School of Electronics and Computer Science, University of Southampton, and USF HumanID Gait Baseline Database [15], collected by Computer Vision and Pattern Recognition Group, Department of Computer Science and Engineering, University of South Florida. Even though some covariances such as viewing angle change, shoe type change, and carrying condition change etc. have been considered in these large databases, they were built for human identification. The obvious quantity difference between males and females can impact the performance of gender classification. Therefore, we have collected the BUAA-IRIP Gait Database [16]. The camera layout is shown as Figure 1. During the course of data collection, every participant was asked to walk along the straight line between camera C_1 and C_8, which are denoted by two black points in Figure 1, from left to right and then return, repeating five times. Thus, every camera recorded five left-to-right and five right-to-left walking video sequences for each person. Meanwhile, we label camera C_1 with the $0°$ view, C_2 with the $30°$ view, till C_8 with the $180°$ view. Camera C_4 and C_5 have the same view angle. Camera C9 records human face. Based on these databases, many related researches have been published, and most of them can accurately recognize the identity, gender, age, race, and other information in controlled environment and walking style. Related to the challenging factors, such as view angle, clothing, and walking speed, there are also some preliminary work. However, existing approaches are far from perfect. For example, it is difficult to track the pedestrian and extract gait sequences in the crowd, and gait feature may be extremely inaccurate if camera shakes or weather dramatic changes.

3 Recent progresses

Given several image sequences capturing human walking, the main researches of gait recognition lie in the analysis of spatial feature and temporal feature.

3.1 Spatial feature

This section describes the extraction of the body profile, joint position, or other information from videos, which has been used to represent the static state of body movement in each frame.

Two-dimensional model Yang Ran et al. [17] Combined edge detection and Hough Transform to extract the main leg angle, and categorized each frame into

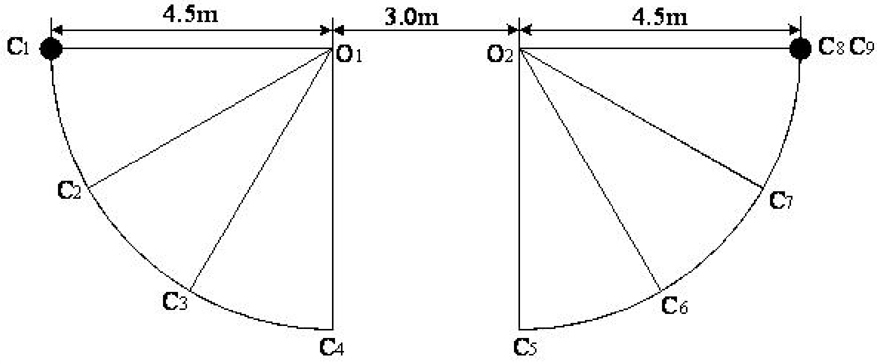

Fig. 1. Camera layout

positive and negative detection of Principle Gait Angle with Bayesian classifier. Frederic Jean et al. [18] proposed an efficient and promising features, which is the trajectories of the head and feet. The difficulties lie in the occlusion and other related issues caused by foot movement. They estimated the separation between feet in each frame, and determined whether the front foot changes. And then they keep on tracking in each half gait cycle by optical flow.

Three-dimensional model Junxia Gu et al. [19] proposed a method to automatically extract key points and pose parameters from the sequence of label-free three-dimensional volume data, and then estimated the multiple configuration (combination of joints) and movement features (position, orientation, and height of the body). A Hidden Markov Model (HMM) and an Exemplar-based HMM are then used to model the movement features and configuration features respectively. Based on these two features, actions are classified by a hierarchical classifier with sum and MAP (Maximum A Posteriori) rules. And identities are recognized from their gait sequences with the configuration features.

Model free Human body silhouette is the most frequently used initial feature, which can be easily obtained from background substraction. N.V.Boulgouris et al. [20] applied Radon transform on silhouette to extract the feature of each frame, and employed Linear Discriminant Analysis (LDA) to reduce the dimension of accumulated feature vector of one period. Shiqi Yu et al. [21] conducted psychology experiments on gait-based gender classification, and proposed a automatic gender classification approach based on the weighted sum of block features. Experiments show that human can recognize the gender by using the human gait, and upper and lower halves of the body have different contributions. The averaged body silhouette is divided into five parts, which are head, chest, back, hip, and leg. Support Vector Machine (SVM) is employed to train the classification weights of all the parts. The prior knowledge is combined with the automatic weighting method to improve the classification accuracy of psychology experiments. Maodi Hu et al. [22] took clothing and carrying conditions into account. They adopted Gabor filters to decompose body shape into local orientations and scales, and obtain low dimensional discriminative representation through the agency of Principal Components Analysis (PCA) and Maximization of Mutual Information (MMI). Gender related Gaussian Mixture Model-Hidden Markov Models are trained for classification and achieve the state of the art accuracy. Ibrahim Venkat et al. [23] also divided the averaged silhouette into several overlapped parts, including upper, middle, and lower parts as well as left and right parts. They trained a Bayesian network to evaluate the impact of these parts on identification, and achieved promising accuracy with backpack pedestrians. Outer contour is the outer boundary of human body silhouette. Kyung Su Kwon et al. [24] combined geodesic active contour models (GACMs) with mean-shift algorithm to extract and track human shape for gait recognition. Optical flow is the velocity field associated with image changes. Khalid Bashir et al. [25] divided flow filed into four parts in accordance with the direction and symbol, and use the weighted sum of these parts for gait recognition.

Fig. 2. Contrast enhanced images in gait sequences of CASIA Gait Database (Dataset B) [12]. Three samples from left to right show the gait patterns of normal walking, clothing and carrying condition changes.

3.2 Temporal feature

Spatial feature can be used in conjunction with time series analysis methods, such as HMM, Autoregressive Moving Average Model (ARMA), etc. for dynamics modeling and recognition.

Periodic Feature Yang Ran et al. [17] presented two methods of period estimation and used them for pedestrian detection. The first employ Fourier transform and periodogram to efficiently estimate gait frequency. The other marked cyclic pattern as a binary sequence by using Maximal Principal Gait Angle (MPGA) fitting. And cycle characteristics is expressed by a Phase-Locked Loop (PLL), whose operation is based on the detection of the phase difference between the input and output signals of a Voltage Controlled Oscillator (VCO). Meng-Fen Ho et al. [26] estimated gait cycle by using the cyclical swing. For each gait cycle, static information is extracted by analyzing the motion vector histogram, and dynamic information is extracted by Fourier descriptors. They used PCA and multiple discriminant analysis (MDA) projection to represent individual characteristics in a low-dimensional space, and trained a nearest neighbor classifier for identification. Changyou Chen et al. [27] proposed a tensor-based Riemannian manifold distance-approximating projection (TRIMAP), which is a two-stage projection method. It can quickly compute an approximately optimal projection for a given data set. In the first stage, they constructed a graph from data, whose distance preserves pairwise geodesic distances. In the second stage, they enhanced the discrimination ability. Finally, they extracted Gabor features of GEI (Gait Energy Image) to generate a third-order tensor data, and conducted gait identification experiments with TRIMAP projection. They reached better recognition rates than LDA methods.

Temporal Projection Vili Kellokumpu et al. [28] assume time as the third dimension other than XY axes in the image plane, so that consider the accumulation of gait sequence as XYT three-dimensional space. Three-dimensional local binary features (LBP) is used for XYT histogram extraction. To simulate the effect of multi-resolution analysis, they changed the radius of local binary features, and finally reached a better recognition rate. Yang Ran et al. [29] proposed a periodic pattern referred as double helical signature (DHS), which decomposes a video sequence into XT slices and generates DHS by iterative local curve embedding algorithm. It is used for segmentation and labeling of body parts in cluttered scenes and load-carrying conditions.

Temporal Modeling Alessandro Bissacco et al. [30] directly collected key points by special equipments, and proposed a hybrid dynamical model of human motion. Different from traditional autoregressive model, it uses a collection of self-regression function to represent the entire gait cycle. Between the autoregressive parameters and observation, an intermediate filter layer is embedded to estimate the most possible states. The weighted sum of these filters derives the posterior probability. They also discussed the problem of the distance between the autoregressive models, and calculated the similarities for identification. Xin Zhang et al. [31] presented a approach include two generative models, called the kinematic gait generative model (KGGM) and the visual gait generative model (VGGM), which represent the kinematics and appearances of a gait by a few latent variables, respectively. And a new particle filtering algorithm is proposed for dynamic gait estimation. Gracian Trivinoa et al. [32] divided a gait cycle into four approximately equal phases. Based on Computational Theory of Perceptions (CTP), the relationship among horizontal acceleration, vertical acceleration, and other indicators are learned by rule-based approach. Homogeneity, symmetry, and the four root model are extracted to represent the individual characteristics.

3.3 Other issues

It is worth notice that, there is also a number of interesting work related to gait recognition under view changes, speed changes, and other intractable conditions. For example, Maodi Hu et al. [33] proposed a multi-view multi-stance gait identification method using unified multi-view population HMMs (pHMMs). Hence, the gait dynamics in each view can be normalized into fixed-length stances by Viterbi decoding, whose results are exemplified in Figure 3. To optimize the view-independent and stance-independent identity vector, a multi-linear projection model is learned from tensor decomposition.

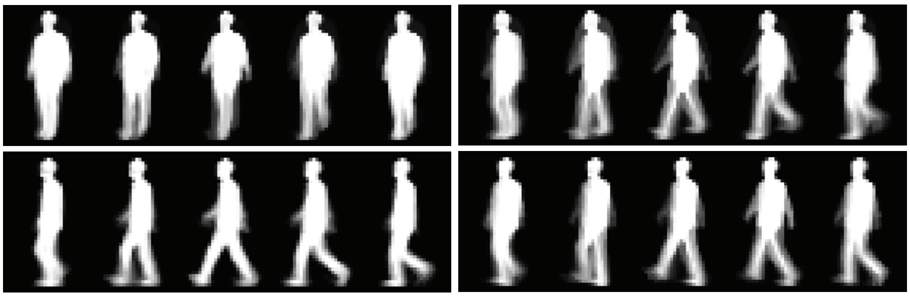

Fig. 3. Normalized dynamics of 18°, 54°, 90° and 126° views, which are extracted from CASIA Gait Database (Dataset B) [12]

4 Conclusions

This paper briefly reviews the main approaches in gait recognition, and recent progress in spatial and temporal modeling. The further trends of gait biometrics should be more robust features extracted; more accurate modeling of spatial and temporal information and improve the practicability of gait in real surveillance systems

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References

1. M. P. Murray, A. B. Drought, and R. C. Kory, "Walking patterns of normal men," *Journal of Bone Join Surgery*, vol. 46, no. 2, pp. 335–360, 1964.
2. M. P. Murray, "Gait as a total pattern of movement," *American Journal of Physical Medicine*, vol. 46, no. 1, pp. 290–333, Feb 1967.
3. H. J. Ralston, V. Inman, and E. TTod, *Human walking.* Williams and Wilkins, 1981.
4. G. Johansson, "Visual perception of biological motion and a model for its analysis," *Perception and Psychophysics*, vol. 14, no. 2, pp. 201–211, 1977.
5. J. E. Cutting and L. T. Kozlowski, "Recognizing friends by their walk: gait perception without familiarity cues," *Bulletin of the Psychonomic Society*, vol. 9, no. 5, pp. 353–356, May 1977.
6. J. van Doornikc and T. Sinkjaer, "Robotic platform for human gait analysis," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 9, pp. 1696–1702, October 2007.
7. S.W.Lee, K.Mase, and K.Kogure, "Detection of spatio-temporal gait parameters by using wearable motion sensors," in *Proc. IEEE Conf. Eng. Med. Biol. Soc.*, 2005, pp. 6836–6839.
8. P. Vanitchatchavan, "Patterns of joint angles during termination of human gait," in *Proc. IEEE Conf. Syst., Man, Cybern.*, 2000, pp. 1226–1230.
9. C. D. Barclay, J. E. Cutting, and L. T. Kozlowski, "Temporal and spatial factors in gait perception that influence gender recognition," *Perception and Psychophysics*, vol. 23, no. 2, pp. 145–152, 1978.
10. J. E. Cutting, D. R. Proffitt, and L. T. Kozlowski, "A biochemical invariant for gait perception," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 4, pp. 357–372, 1978.
11. M. Field, D. Stirling, F. Naghdy, and Z. Pan, "Mixture model segmentation for gait recognition," in *ECSIS Symposium on Learning and Adaptive Behaviors for Robotic Systems*, 2008, pp. 3–8.
12. S. Yu, D. Tan, and T. Tan, "A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition," in *Proc. IEEE/IAPR Int. Conf. Pattern Recog.*, vol. 4, 2006, pp. 441–444.
13. R. Gross and J. Shi, "The cmu motion of body (mobo) database," Robotics Institute, Pittsburgh, PA, Tech. Rep. CMU-RI-TR-01-18, June 2001.
14. J.D.Shutler, M.G.Grant, M.S.Nixon, and J.N.Carter, "On a large sequence-based human gait database," in *Proc. Int. Conf. Recent Advances Soft Comput.*, 2002, pp. 66–72.
15. S.Sarkar, P.J.Phillips, Z.Liu, I.R.Vega, P.Grother, and K.W.Bowyer, "The human id gait challenge problem: Data sets, performance, and analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 2, pp. 162–177, February 2005.
16. D. Zhang and Y. Wang, "Investigating the separability of features from different views for gait based gender classification," in *Proc. IEEE/IAPR Int. Conf. Pattern Recog.*, 2008, pp. 1–4.
17. Y. Ran, I. Weiss, Q. Zheng, and L. S. Davis, "Pedestrian detection via periodic motion analysis," *Int. J. Comput. Vis.*, vol. 2, no. 71, pp. 143–160, May 2007.
18. F. Jean, A. B. Albu, and R. Bergevin, "Towards view-invariant gait modeling: Computing view-normalized body part trajectories," *Pattern Recog.*, vol. 42, no. 11, pp. 2936–2949, November 2009.
19. J. Gu, X. Ding, S. Wang, and Y. Wu, "Action and gait recognition from recovered 3-d human joints," *IEEE Trans. Syst., Man, Cybern. B*, vol. 40, no. 4, pp. 1021–1033, August 2010.

20. N. V. Boulgouris and Z. X. Chi, "Gait recognition using radon transform and linear discriminant analysis," *IEEE Trans. Image Process.*, vol. 16, no. 3, pp. 857–860, March 2007.
21. S. Yu, T. Tan, K. Huang, K. Jia, and X. Wu, "A study on gait-based gender classification," *IEEE Trans. Image Process.*, vol. 18, no. 8, pp. 1905–1910, August 2009.
22. M. Hu, Y. Wang, Z. Zhang, and Y. Wang, "Combining spatial and temporal information for gait based gender classification," in *Proc. IEEE/IAPR Int. Conf. Pattern Recog.*, August 2010, pp. 3679–3682.
23. I. Venkat and P. DeWilde, "Robust gait recognition by learning and exploiting sub-gait characteristics," *Int. J. Comput. Vis.*, vol. 91, no. 1, pp. 7–23, January 2011.
24. K. S. Kwon, S. H. Park, E. Y. Kim, and H. J. Kim, "Human shape tracking for gait recognition using active contours with mean shift," in *Proc. Int. Conf. Human-Comput. Interaction.*, 2007, pp. 690–699.
25. K. Bashir, T. Xiang, and S. Gong, "Gait representation using flow fields," in *Proc. British Mach. Vis. Conf.*, 2009.
26. M.-F. Ho, K.-Z. Chen, and C.-L. Huang, "Gait analysis for human walking paths and identities recognition," in *Proc. Int. Conf. Multimedia Expo*, 2009, pp. 1054–1057.
27. C. Chen, J. Zhang, and R. Fleischer, "Distance approximating dimension reduction of riemannian manifolds," *IEEE Trans. Syst., Man, Cybern. B*, vol. 40, no. 1, pp. 208–217, August 2010.
28. V. Kellokumpu, G. Zhao, S. Z. Li, and M. Pietikainen, "Dynamic texture based gait recognition," in *Proc. IAPR/IEEE Int. Conf. Biometrics*, 2009, pp. 1000–1009.
29. Y. Ran, Q. Zheng, R. Chellappa, and T. M. Strat, "Applications of a simple characterization of human gait in surveillance," *IEEE Trans. Syst., Man, Cybern. B*, vol. 40, no. 4, pp. 1009–1020, August 2010.
30. A. Bissacco and S. Soatto, "Hybrid dynamical models of human motion for the recognition of human gaits," *Int. J. Comput. Vis.*, vol. 85, no. 1, p. 101C114, March 2009.
31. X. Zhang and G. Fan, "Dual gait generative models for human motion estimation from a single camera," *IEEE Trans. Syst., Man, Cybern. B*, vol. 40, no. 4, pp. 1034–1049, August 2010.
32. G. Trivinoa, A. Alvarez-Alvareza, and G. Bailadorb, "Application of the computational theory of perceptions to human gait pattern recognition," *Pattern Recog.*, vol. 43, no. 7, pp. 2572–2581, July 2010.
33. M. Hu, Y. Wang, Z. Zhang, and D. Zhang, "Multi-view multi-stance gait identification," in *Proc. IEEE Int. Conf. Image Process.*, 2011.