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A Review of Vision-based Gait Recognition Methods for Human Identification

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Abstract

Human identification by gait has created a great deal of interest in computer vision community due to its advantage of inconspicuous recognition at a relatively far distance. This paper provides a comprehensive survey of recent developments on gait recognition approaches. The survey emphasizes on three major issues involved in a general gait recognition system, namely gait image representation, feature dimensionality reduction and gait classification. Also, a review of the available public gait datasets is presented. The concluding discussions outline a number of research challenges and provide promising future directions for the field.

1. Introduction

In recent years, there has been an increased attention on effectively identifying individuals for prevention of terrorist attacks. Many biometric technologies have emerged for identifying and verifying individuals by analyzing face, fingerprint, palm print, iris, gait or a combination of these traits [1].

Compared to other biometric methods, gait recognition offers several unique characteristics. The most attractive characteristic is its unobtrusiveness, which does not require observed subjects' attention and cooperation. Also, human gait can be captured at a far distance without requiring physical information from subjects. This favorable characteristic has great advantages, especially when individual information such as face image is confidential [2] [3]. Moreover, gait recognition offers great potential for recognition of low-resolution videos, where other biometrics technologies may be invalid because of insufficient pixels to identify the human subjects [4]. Several review articles [2] [3] provide a general overview of gait recognition. However, a comprehensive survey of recent development of gait recognition can be rarely found.

The general framework of automatic gait recognition consists of subject detection, silhouette extraction, feature extraction, feature selection, and classification. Once moving subjects are captured, individuals will be detected and separated from the image background. The most widely used method is background subtraction, which attempts to separate objects from the difference between the modeled background and the current frame [5]. The initial detection of humans within images and the consequent separation from the background can be considered as a preprocessing step of gait recognition, which is beyond the focus of this review.

After individuals have been separated from the background, features that can be used for recognition are extracted from these segmented walking persons. There are mainly two kinds of gait features, i.e., model-based features and model-free features. Model-based features employ static and dynamic body parameters and are generally view and scale invariant [6] [7] [8]. One the other hand, model-free features usually only use binary silhouettes and do not need construction of a model for walking persons [9] [10] [11]. The model-based and model-free approaches are discussed in Section 2.

Features extracted from segmented video sequences are commonly not effective for classification and require too many training samples because of high dimensionality. Many dimensionality reduction methods have been proposed to solve this problem. Among them, principal component analysis (PCA) [10] [12] and linear discrimination analysis (LDA) [12] are widely used. In Section 3, several feature dimensionality reduction methods are reviewed.

The last step is to classify the test sequence to a particular individual based on the extracted features. The classification of gait features is mainly based on three categories of methods, namely, direct classification, similarity of temporal sequences and state-space model. The direct classification is usually used after single representation or key frames are extracted from a temporal sequence of gait frames. While the similarity of temporal sequences is used to measure the distance between two temporal sequences of gait, the state-space model such as Hidden Markov Model (HMM) [13] [14] [15] [16] [17] focuses on the pattern of state related to succession of stance. This stochastic approach explicitly employs both the similarity information between test and reference sequences, and probability of shapes appearance [2]. These three categories of classification methods are surveyed in

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Section 4. Several standard gait datasets are publically available as described in Section 5. This is followed by concluding remarks and future work in Section 6.

2. Gait Image Representations

2.1. Model-based Approaches

Model-based approaches obtain a series of static or dynamic body parameters via modeling or tracking body components such as limbs, legs, arms and thighs. Gait signatures derived from these model parameters are employed for identification and recognition of an individual. It is evident that model-based approaches are view-invariant and scale-independent. These advantages are significant for practical applications, because it is unlikely that reference sequences and test sequences are taken from the same viewpoint [2]. However, model-based approaches are sensitive to the quality of gait sequences. Thus, gait image sequences of high quality are required to achieve a high accuracy. Another disadvantage of the model-base approach is its large computation and relatively high time costs due to parameters calculations.

Primary model-based approaches employ static structure parameters of body as recognition features. BenAbdelkader et al. [18] present structural stride parameters consisting of stride and cadence. The cadence is estimated via the walking periodicity, and the stride length is calculated by the ration of travelled distance and walking steps. Bobick and Johnson [19] calculate four distances of human bodies, namely the distance between the head and foot, the distance between the head and pelvis, the distance between the foot and pelvis, and the distance between the left foot and right foot, as shown in Fig. 1. They use the four distances to form two groups of static body parameters and reveal that the second set of parameters are more view-invariant comparing to the first set of body parameters. More recently, Yoo and Hwang [20] extract nine coordinates from the human body contours based on human anatomical knowledge to construct a 2D stick figure, as shown in Fig. 2.

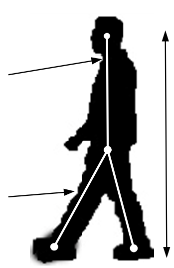


Fig. 1. Static parameters of four distances [19]

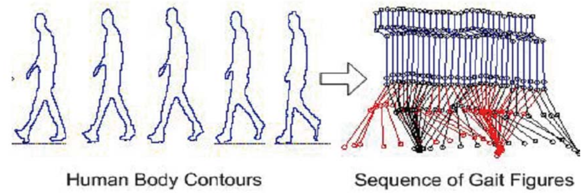


Fig. 2. Gait stick figures constructed from gait silhouettes [20]

Unlike some model-based approaches that utilize static structure parameters, Tanawongsuwan and Bobick [21] focus on the trajectories of joint angle from motion capture data. The joint angle trajectories are computed by estimating the offsets between the 3D marker and joints. Yam et al. [22] construct a structure and motion model of legs to analyze walking as well as running using biomechanics of human and pendular motion. A comparative higher recognition currency of running demonstrates that running may be more reliable for human identification due to more different gait pattern. Additionally, based on comprehensively analyzing the characteristics and description of human gait, Cunado et al. [8] implemented Velocity Hough transform (VHT) [23] to extract the structure model of the thighs and the motion model of the thighs. It is reported that the VHT achieved good performance of median noise immunity.

Some other methods model human body parts separately. In Wang et al. [24]'s work, human body is modeled as fourteen rigid parts connected to one another at the joints. The whole model has forty-eight degrees of freedoms (DOFs). The tracking results, namely joint-angle trajectories signals, are considered as gait dynamics for identification and verification. They also obtain static information of body based on Procrustes shape analysis of the change of moving silhouettes, which can be independently or combinatively applied to improve the recognition. More recently, Boulgouris and Chi [25] separate human body into different components and combine the result obtained from different body parts to form a common distance metric. Based on the study of each part's contribution to the recognition performance, the recognition rate is improved by using the most contributing parts. In addition, Li et al. [26] divide the average silhouettes over a gait cycle into seven different parts and summarize the impact of each part on gait recognition.

2.2. Model-Free Approaches

Model-free approaches focus on either shapes of silhouettes or the whole motion of human bodies, rather than modeling the whole human body or any parts of body. Model-free approaches are insensitive to the quality of silhouettes and have the advantage of low computational costs comparing to model-based approaches. However, they are usually not robust to viewpoints and scale.

The baseline algorithm proposed by Sarkar et al. [11] uses the silhouettes themselves as features, which are scaled and aligned before used. While the gait signature in the baseline algorithm is a sequence of gait silhouettes, Bobick and Davis [27] propose the motion-energy image (MEI) and motion-history image (MHI) to convert the temporal sequence of silhouettes to a 2D signal template. Han and Bhanu [9] employ the idea of MEI and propose the Gait Energy Image (GEI) for individual recognition, which is shown in Fig. 3. The left seven images in each row are silhouettes of walking sequences and the rightmost image is the corresponding gait energy image. GEI converts the spatial-temporal information during one walking cycle into a single 2D gait template, which avoids matching features in temporal sequences. GEI is comparatively robust to noise by averaging images of a gait cycle. However, it loses the dynamical variation between successive frames. Liu and Zheng [28] develop the Gait History Image (GHI) to retain temporal information as well as spatial information. Chen et al. [17] propose the frame difference energy image (FDEI) based on GEI and GHI to address the problem of silhouette incompleteness. They calculate the positive portion of frame difference as positive values of the subtraction between the current frame and the previous frame. FDEI is defined as the summation of GEI and the positive portion. Liu et al. [29] assess the quality of silhouette sequences to determine the contribution of each GEI for classification according the quality of GEI. Xue et al. [30] apply the wavelet decomposition of GEI to infrared gait recognition. The infrared gait sequences are robust to the covariates of holding a ball and loading packages.

Kale et al. [31] use the width of the outer contour of silhouette to encode the information of silhouettes. The width is defined as the horizontal distance between the leftmost pixel and the rightmost pixel of the contour. The width of the outer contour may be unreliable due to the poor quality of silhouettes. However, the silhouette itself as features may be more suitable for low quality and low resolution data. Later, Kale et al. [32] combine the entire silhouette and the width of outer contour silhouette as gait features. Wang et al. [10] unwrap the 2D contour of silhouette to a 1D signal using the distance between pixels along the contour and the shape centroid, as shown in Fig. 4. However, these 1D signals are easily affected by the quality of silhouettes. Dadashi et al. [33] apply wavelet transform to these 1D signals to extracted wavelet packets atoms coefficients as the gait signature. Instead of computing a distance between each pixel along the contour and the centroid, Boulgouris et al. [34] divide the silhouette into angular sectors and calculate the average distance between foreground pixels and the centroid in each angular sectors.

Some other algorithms pay attention to analyzing the whole shape of silhouettes. Wang et al. [35] apply the Procrustes shape analysis to silhouette shapes and extract a Procrustes mean shape from a sequence of silhouettes as gait signature. Boulgouris and Chi [36] perform Radon Transform on the binary silhouettes to get a template from gait sequences. Linear discriminate analysis (LDA) and subspace projection are used to extract Radon template coefficients to construct the feature vector.

3. Feature Dimensionality Reduction

The dimensionality of features extracted from gait sequences is usually higher than training data, which gives rise to the failure of conventional classification algorithms. This is well known as the undersample problem. Thus, a feature reduction algorithm is necessary to extract useful and informative features for classification. Principal component analysis (PCA) and linear discriminant analysis (LDA) [37] are traditional but widely used feature reduction methods. Wang et al. [10] apply PCA to time-varying distance signals derived from silhouette images sequence to reduce the dimensionality of feature space. Tan et al. [38] perform PCA and LDA together to improve the topological structure and reduce the dimensionality of the feature space. Han et al. [9] combine PCA and Multiple Discriminant Analysis (MDA) [37] to process Gait Energy Image (GEI).

PCA-based methods only preserve those features which contribute most to variance, which may be not optimal for classification. Tao et al. [39] develop a general GTDA to preserve discriminative information of Gabor features and use LDA for classification. More recently, Mu and Tao [40] utilize DLA to reduce dimensionality of biologically inspired features, while Hu et al. [41] apply a two-stage PCA+DLA to get Periodicity Feature Vector (PFV) and shape features. A two-dimensional LPP is used by Zhang et al. [42] to improve the discriminative power of features extracted based on active energy image (AEI). While most of the aforementioned approaches focus on feature dimensionality reduction, Guo and Nixon [43] [44] select gait feature subset by maximizing the mutual information of gait features.

4. Gait Classification

4.1. Direct Classification

Direct gait classification methods do not pay attention to the temporal information of gait sequences. They are based on the single representation or key frames extracted from a sequence of gait frames. K-nearest neighbor classifier decides the class of test feature according to the number of the k closest training examples. The most common labeled class among the k closed training examples is chosen as the test feature's class. Collins et al. [45] extract key frames from a walking cycle to form a template, and then perform nearest neighbor classification to template scores. k-nearest

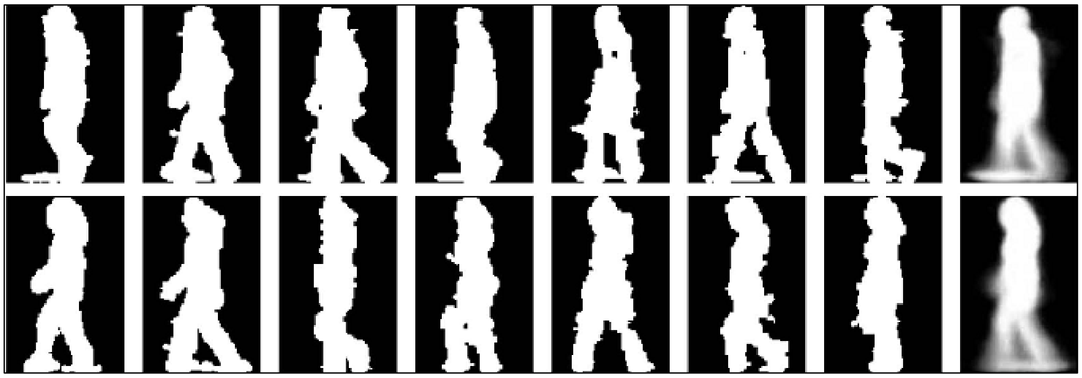
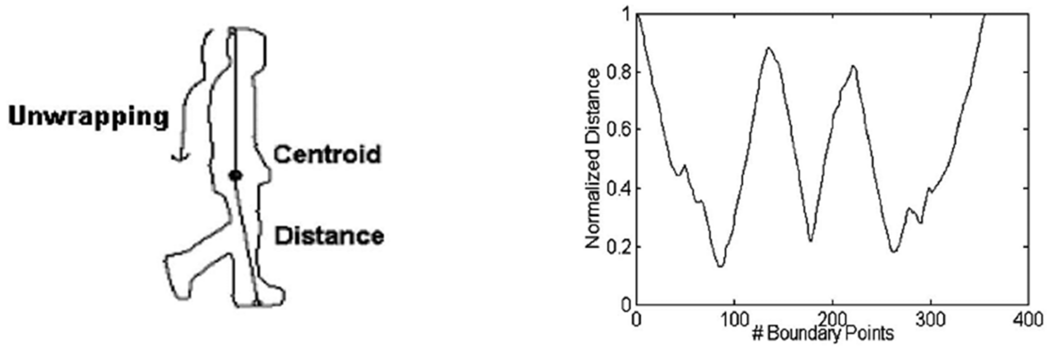


Fig. 3. Normalized and aligned silhouettes of two different walking sequences and the rightmost image is the corresponding GEI [9]



(a) (b)

Fig. 4. Unwrapping the 2D contour of silhouette: (a) counterclockwise unwrapping along contour, and (b) normalized 1D distance [10]

neighbor rule is applied by Cunado et al. [8] to frequency information of the hip motion for classification.

Additionally, some authors use various discriminative classifiers. Support vector machine (SVM) is used by Xue et al. [30] for wavelet decomposed features from gait energy image (GEI). SVM is considered as a generalized linear classifier and is a supervised learning method. Instead of using a supervised learning classifier, Dadashi et al. [33] employ transductive support vector machine (TSVM) to perform semi-supervised classification on gait signature extracted by wavelet packets. The TSVM take high-dimensional features as input and effectively investigate correlational structures of gait features.

4.2. Similarity of Temporal Sequences

Gait is a dynamic human activity. The signature of gait commonly contains a sequence of gait features, which makes classification perform measurement of the similarity of two gait temporal sequences. Some authors directly use cumulative distance over a gait cycle as the distance between two sequences. Phillips et al. [46] slide the test sequence over the reference sequence to find the position of minimum distance [2]. Sarkar et al. [11] use the ratio of the number of pixels in the intersection and union of two silhouette frames to measure the similarity between probe silhouette frames and gallery silhouette frames. The probe sequences are partitioned into several subsequences according to the gait period. Based on the similarity of frames, they calculate the correlations between each subsequence and the whole gallery sequences and choose the median values of the maximum correlation as similarity for robustness.

However, the direct cumulative distance is clearly not suitable for measuring gait temporal sequences, as it assumes that the test sequence and the reference sequence have an identical gait period [2]. This does not often the case in practical applications. Dynamic time warping (DTW) is a useful method to align two temporal signals with different length. Wang et al. [10] apply the dynamic time warping to measure the similarity between two sequences of distance signals. The parameters of DTW are determined by the relative stride frequency and phase difference. Vega et al. [47] adopt the DTW to temporally normalize two traces, which are projections of motion types in the Space of Probability Function (SoPF). More recently, Veeraraghavan et al. [48] improve the DTW based on Procrustes shape distances to compute distances between shape sequences.

Walking is a periodical activity, which means that frequency analysis of spatial-temporal gait signals can be a very appealing approach [2]. Lee and Grimson [6] divide gait silhouette into seven regions and use ellipses to fit each region. They apply Fourier Transform on the temporal signals from these ellipses and extract the magnitude components and phase components for classification. Yu et al. [49] compare Fourier descriptors and key Fourier descriptors as features for classification and achieve the conclusion that the key Fourier descriptors of human contours surpass the Fourier descriptors.

4.3. State-space Model: HMM

Hidden markov models (HMMs) have been successfully applied in speech recognition and hand gesture recognition [50] [51]. HMMs represent different phases of a gait as hidden states. They assume that the current state is only influenced by the previous state and is independent of the history state. Observation probabilities and transition probabilities are calculated via training input data. The subject corresponding to the highest posterior probability is chosen as the recognized result. The HMM-based approaches are generally preferable to other methodologies because they make use of both the similarity of shapes between test and reference sequences and the probabilities of shapes appearing and succeeding in a walking period [2].

Sundaresan et al. [13] construct a generic HMM based framework for individual gait recognition. The postures of subjects are regarded as the states of HMMs, and the HMM parameters are trained by binarized silhouette feature vectors. Kale et al. [31] use lower dimensional vector sequence extracted from key frames of a walk cycle to train a continuous HMM, while He and Debrunner [52] employ HMMs to recognize individuals from Hu moment feature vector sequence. The experimental recognition result demonstrates that the HMM has overall robustness due to its statistical nature.

More recently, Yin et al. [53] focus on the problem of extracting most discriminative feature for HMM. They proposed a new Segmentally Boosted HMM (SBHMM) to nonlinearly project original data to a new feature space, making the distribution of data more Gaussian. Chen et al. [15] take into account the problem of multiple gait feature fusion and extend HMM to construct a framework of factorial hidden Markov model (FHMM) and parallel HMM (PHMM). The FHMM and PHMM both have a multiple-layer structure. During the process of training, the FHMM and PHMM that get model parameters features are fused.

Several authors have used HMMs in combination with manifold learning. Wang and Suter [54] present a HMM to analyze learned motion manifolds by locality preserving projections (LPP), while Cheng et al. [14] [55] apply Gaussian process latent variable model (GP-LVM) to nonlinearly transform silhouette sequences into low-dimensional embedding and extract temporal dynamic information by a HMM.

Instead of employing HMM for recognition, Liu et al. [16] [56] [57] use a population HMM to model a set of persons. Gait stances over one gait cycle form the state space of the population HMM and the silhouettes of gait stances are the observations of the population HMM. After alignment of the silhouette sequences, the population HMM is trained on a group of manually specified silhouettes.

5. Public Gait Datasets

Standard publically available gait datasets are needed to fairly compare and evaluate the performance of gait recognition algorithms. Some popular publically available gait datasets are described below.

5.1. USF Dataset

The USF dataset was collected at the University of South Florida and contains 1870 sequences from 122 subjects. Each person walked around an ellipse in front of cameras. There are up to 5 covariates for each person: two different shoes types; with or without a briefcase; grass surface or concrete surface; left viewpoint and right viewpoint; and two different time instants [11]. An example frame from the USF gait dataset is shown in Fig. 5.

Fig. 5. An example frame from the USF gait dataset [11].

5.2. CMU Mobo Dataset

The CMU Mobo dataset was constructed by the Robotics Institute, Carnegie Mellon University. The dataset contains 25 individuals walking on a treadmill in a 3D room. There are four different walking patterns for each individual: slow walk, fast walk, incline walk and walking with a ball. Six high resolution color cameras, distributed evenly around the treadmill, were used to capture all the subjects [32].

5.3. Southampton Dataset

There are two groups of datasets in the Southampton gait dataset, namely the small database and the large database. The small database consists of 12 subjects walking around an inside track at a different speed. Each person was captured wearing different shoes, clothes and without or within various bags. Subjects of the large database were filmed not only walking outside, inside track and inside treadmill, but also from six different views [3].

5.4. CASIA Gait Dataset

CASIA Gait Database is provided by The Institute of Automation Chinese Academy of Sciences. There are three datasets in the CASIA Gait Dataset (i.e., dataset A, dataset B, and dataset C). Dataset B is a large multi-view dataset containing 124 subjects from 11 views. 153 subjects walked in four different conditions: normal walking, slow walking, fast walking and normal walking with a bag [10].

6. Conclusions and Future work

6.1. Conclusions

This paper has presented a comprehensive review of the strategies in key stages and recent developments in gait recognition and identification. Three major issues of gait recognition including gait image representation, feature dimensionality reduction and gait classification are discussed. Features used to characterize gaits can be categorized into two major groups: model-based features and model-free features. Model-based features are extracted via modeling or tracking components of human bodies, while model-free approaches place more emphasis on shapes of silhouettes or the whole motion of human bodies. Inherently, the model-based features are more view-invariant and scale-independent comparing to the model-free features. However, model-based approaches require high quality of gait sequences to be captured and more computing time. In contrast, the model-free approaches are less sensitive to the quality of silhouettes and more efficient in computing. Reduction of feature dimensionality is essential to make classification more efficient and save precious computing time to satisfy the requirement of real-time applications. Linear and non-linear dimensionality reduction methods are prominently used in gait recognition. It is evident that linear dimensionality reduction methods such as PCA may be not optimal for classification of gaits and non-linear methods would be superior in this case [39] [42].

With regard to gait classifier design, direct classification methods and those methods based on measuring the similarity of temporal sequences are commonly seen in the literatures. The direct gait classification methods either lose the temporal variation of gait sequences or ignore the temporal order of gait sequences, though they normally have high computational efficiency. In contrast, the similarity-based methods take advantages of the temporal and dynamic information over sequences of images, thus, would be more suitable for gait classification. Unlike the direct classification methods and the methods of measuring the similarity of temporal sequences are based on a distance metric, the HMM-based methods model phases of a gait as hidden states. The HMM-based methods are generally preferable to the other methodologies because they utilize both the similarity information and the probability of shapes appearance [2].

6.2. Future Work

Although a considerable amount of research has been developed, gait recognition for individual identification is still far from practical applications. Promising directions for future research are outlined as follows.

1) Although the current state-of-the-art algorithms have achieved comparatively high recognition accuracies, the performances of these algorithms are affected in certain degree by covariates, especially by walking surface and capturing at different time [11]. Existing research has revealed that infrared images are robust to some covariates such as holding a ball and loading a package [30].
2) Most of gait recognition algorithms are restricted to fixed viewpoints and are sensitive to the view of sequences, which limited their applications. View-invariant methods are of importance to improve the performance of gait recognition algorithms. Combining different view sequences as training data may provide an effective way to solve this problem [58] [59].
3) Most of the existing gait recognition methods either assume silhouettes have already been segmented from videos or they can be estimated in simple background videos. However, in practice, humans may walk in a complex background, which means that the detection is a challenge for online gait recognition.
4) Combination of gait and other biometrics such as face and foot pressure may be more effective than only using single biometrics [2]. It is shown that fusion of gait and face achieves improved recognition performances comparing with only single biometric traits [60].

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