Gait Recognition System: A Survey

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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. It also gives, a review of the available public gait datasets. The concluding discussions outline a number of research challenges and provide promising future directions for the field. In this article presents a survey of the work done in gait analysis for re-identification in the past decade, looking at the main approaches, datasets, and evaluation methodologies also discussed.*

Keywords: *Gait Recognition, Gait Classification, Gait Datasets, Image Processing, Feature Extraction.*

1. INTRODUCTION

With the increase in security and forensics concerns, as well as improved access to ultimedia technology, surveillance camera networks are proliferating in both public and private areas, including airports, railway stations, university campuses, shopping complexes, housing apartments, supermarkets, and workplaces.

Gait recognition system can be classified depending on the sensors used into three groups namely; motion vision based, wearable sensor based and floor sensor based. The motion vision can be divided into two groups namely; appearance-based methods and model-based methods. The appearance-based method can be also subdivided in two types; state space methods and spatio-temporal methods. Biometric gait recognition refers to verifying or identifying persons using their walking style. Human recognition based on gait is relatively recent compared to other biometric approaches such as fingerprint, iris, facial etc.[51]

Such technologies have been widely used in security fields. However, such biometrics techniques require hysiological and behavioral characteristics of different persons for identification. Using the human gait for identification is an unobtrusive technique that means no physical contact is necessary between the subjects and the measurement devices. Identification using the human gait does not require the cooperation or the attention of the subjects. Existing gait recognition approaches mostly use standard video cameras for capturing the movement of walking persons. However, their main challenge is the extraction of of characteristic features for identification of the human gait]. Gait recognition methods are broadly divided into two approaches, Model-based and Model-free. Model-free approaches use binary silhouette information to recognize human gait. Model based approaches use body information such as body joints for constructing a model. Using a standard camera, capturing body information is influenced by background color and intensity of the light for the gait recognition. Duo to this, these approaches require restricted ambience. With a depth camera, it is possible to capture the depth image which is able to track body information in the 3-dimension without the requirements in the standard camera[48].

Microsoft Kinect is a depth camera for the Microsoft Xbox gaming console, enabling players to control and play games with their body motion and gestures. The Kinect also enables body detection and tracking of people in real-time by an integrated depth camera using an SDK provided by Microsoft [8]. Color image, depth image, and human body data can be simply extracted from the Kinect device. Accordingly, several researchers already proposed these capabilities of Kinect to analysis for human gait recognition.

Gait is a behavioral biometric which can be perceived from a distance. It can be acquired without personal con- tact and cooperation. Iris and face biometrics have similar advantages but they need high resolution images and frontal view. However, it is possible to extract gait pat- terns from low resolution images. Human gait can vary over long durations due to many factors such as change in body weight, injuries and disease. However, studies have indicated that it still possesses sufficient discriminatory power for personal recognition [46]. Gait is a com plex function of skeletal structure, muscular activity, body weight, limb lengths, bone structures etc. This complexity of gait renders it difficult to imitate and hide if not impossible.

Human gait analysis can be used as a useful tool in a variety of applications. One such promising application is medical diagnostics of diseases that affect voluntary muscle activity such as walking. For example, Parkin-son's disease that affects nerve cells in part of the brain controlling muscle movements. People with Parkinson's often experience trembling, muscle rigidity, difficulty in walking, and problems with balance and coordination. Early detection of walking disorders by motion analysis can be very helpful for the treatment of such diseases. Gait can also be used to generate early warning for law enforcement agencies by detecting suspicious motion activity in airports or subway stations.

2. Work Done

From the last few years, a lot of research work has been done in this field but still a lot scope for improvement of results is there. Researchers and academicians are continuously contributing in this field using different available data sets. A few major contributions have been discussed in this review paper with required details which show the specification about the contribution of different individuals.

In this paper, a new patch distribution feature (referred to as DTCWT-PDF) for human gait view classification has been proposed. To extract DTCWT-PDF, we represent each GEI as a set of enhanced DTCWT features from which the distribution is estimated by exploiting a two-stage approach. Moreover, a multiview gait recognition approach referred to as LSDCCA has been developed by enforcing local sparsity constraints. UMLSDCCA is further proposed to extract uncorrelated discriminative features directly from tensorial data using the TVP of tensor objects. Comprehensive experiments on the USF Human ID database and CASIA-B database demonstrate the proposed method can achieve satisfactory results in covariate conditions across views[40].

In this paper, a straightforward and effective memory-based method have been presented for automatic gait recognition. The extraction model on the basis of the labeled Parse dataset has been implemented. It takes less time and energy for us to adjust the joint extraction model and get the gait joint positions on experimental datasets. Though the extracted 2D joint positions are seriously noisy, so the MNN has been utilized to alleviate the problem, which can repair the damaged data based on the attractors. It is the first time that the memory mechanism used to solve the gait recognition issue. The network configuration is simple but the proposed method still achieved the relatively satisfactory and comparable results. Further, it is worth noting that the input features of MNN are human body joint tracking output, which may not be available under a more realistic setting to some extent. It must use the joint extraction model to get the necessary features and this is also a limitation of the paper. Thankfully, the process of joint extraction is not complicated[41].

This paper presented a method of gait recognition both by suppressing and using gait fluctuations. The inter-frame temporal misalignment has been suppressed because of temporal fluctuations using the phase-normalized image sequence, which was constructed in conjunction with phase estimation and morphing techniques. The phase fluctuation features were extracted as temporal fluctuation features as well as GFlucI, and trajectory fluctuation features as spatial fluctuations. Then two approaches using score-level fusion and/or a score-normalization framework using the gait fluctuation features have effectively combined as another score or as quality measures. The results of score-level fusion and quality dependent score normalization in large-scale databases showed greater performance improvement than solely using the phase normalized image. In future work, quality measures investigation has been planned to further improve gait recognition performance[42].

This paper has deliberated a CNN-based gait recognition method, with an extensive empirical evaluation in terms of different recognition tasks, preprocessing approaches and network architectures. With this method, we have updated the best recognition rates on three challenging datasets, showing its robustness to viewpoint and walking condition variations, and its generalization ability to large datasets and complex backgrounds[43].

A view-normalization approach for integrated tracking and recognition of people has been described. Our system combines face and gait recognition methods, and information from multiple views. An image-based visual hull is used for shape modeling and for trajectory tracking. Results were shown using view-dependent face and gait recognition modules, and were better than the unnormalized or single modality results. Each component of the system runs at real-time speeds. Currently the implementation uses monocular silhouettes based on color segmentation with static backgrounds, but could be extended to accommodate more sophisticated segmentation algorithms. This system works within the strict intersection of the field of view of all cameras, but it is expected that this to be relaxed as a more general visual hull algorithm is developed. Finally, the confidence integration method is clearly primitive in present form, and should be extended to an explicit probabilistic framework[44].

This paper described a method of gait recognition by deformable registration. The FFD with lattice-type control points and extracted the eigen FFD from a set of intra-subject deformation fields to constrain the deformation modes. Metric learning by LB, a recent deep learning framework, further improved the discrimination capability after the pre-processing deformable registration by the eigen FFD. Experiments with 1,334 subjects showed the effectiveness of the proposed method compared with direct matching without deformable registration[45].

One of future research avenue is consideration of not only the intra-subject deformations but also the inter-subject deformations to extract better deformation modes for discrimination. Moreover, the frame-by-frame deformation to cope with posture changes within one gait period.

In this research it is found that lower arm movement also played an important role in gait recognition. The results from the present work can be used for building a better feature selection process for a more robust recognition system. Lower leg is usually very noisy in the extracted silhouettes because of shadows and walking surface issues. A set of better discriminatory features may be extracted from lower arm motion avoiding noisy data from lower leg[46].

This study investigated the relative distance features for gait recognition with Kinect. Relative distance-based gait features were proposed, where the distances between particular skeleton points and their changes are used to characterize the gait. Random subspace method is also employed for feature selection to further improve the recognition accuracy. The experimental results showed that relative distance features' recognition accuracy reaches up to 85%, which was comparable with the anthropometric features. The two feature sets complement each other well. When relative distance features and anthropometric features were used together, recognition accuracy is at 95%. These results suggested that gait is of enough distinguishing ability. It showed that the relative distance features effectively were worthy of further study in a non-Kinect scenario[47].

It is also concluded that Future work should investigate relative distance features without Kinect, especially in the scenario where a single RGB camera is used. It is also a possible way to use deep learning method to extract the 2D skeleton model from the RGB image, and then apply our relative distance features method.

This paper proposed potential measurements for gait recognition to find a distinct difference based on the human gait. The measurements consist of a body length and an angle of hip/knee/ankle using 21 body frames captured by the Kinect device that provided RGB camera and an infrared sensor combination for inferring depths. Since the Kinect device captures body frames using the infrared sensor, it provided 3-dimensional body frame data without a process of recognizing subjects from background. All of the measurements were calculated by an individual cycle. A group of 5 people who have a similar body type participated in the experiment. As the result of the experiment, we revealed the distinct differences using the angle and body length measurements. However, because we experimented using a single Kinect device which can only capture body frames on single side, mis-capturing of body frames occurs when the body parts overlap each other, and it reduces an accuracy for gait recognition[48].

24@ In this work, two approaches to represent and recognize people were proposed by their gait. The width of the outer contour of the binarized silhouette as well as the silhouette itself were used as features to represent gait. In one approach, a low-dimensional observation sequence was derived from the silhouettes during a gait cycle and an HMM is trained for each person. Gait identification was performed by evaluating the probability that a given observation sequence was generated by a particular HMM model. In the second approach, the distance between an image feature and exemplar was used to estimate the observation probability. The performance of the methods was illustrated using different gait databases.

The paper extracted the length of skeleton as the static feature, and extracted the angle of swing legs and arms as the dynamic feature by Kinect. On the basis of this, a feature fusion and the feature vector were stored into the database which was established by ourselves. The paper proved the CCR is much higher after the feature fusion, reached 82%. The paper also compared with other two methods to prove the advantage of our feature extracted by Kinect[49].

In this research, a gait recognition style based on PCA with RT and only PCA techniques have been proposed. The proposed systems were presented adequate results while applying CMU MoBo gait database applied for the experiments. The best recognition above 95% is achieved for PCA with RT and PCA only for all three walking styles. The results were compared with other published papers and reported that the proposed system has given efficient result. Some of researchers presented better recognition rate of walking style in different gait database conditions[50].

Here a novel gait recognition method has been proposed based on statistical shape analysis. An improved background subtraction technique is used to segment silhouettes from the background. Shape changes of these silhouettes over time were then represented as the associated configurations in the common coordinate system, and were analyzed using the Procrustes shape analysis method to obtain eigen shape signatures representing implicitly the structural shape cue of the walking figure's appearance. The standard pattern classification technique was utilized for recognition. Experimental results have demonstrated the effectiveness and advantages of the proposed algorithm[51].

In this paper, a model based approach has been presented to gait recognition based on Microsoft Kinect. There are 13 different biometric features such as the height, the length of limbs, and the step length which are computed from the skeleton frames generated by Kinect. Based on test data from 9 different persons, the three basic classifiers Naive Bayes, 1R, and C4.5 were trained and evaluated concerning the success rate of their classification. Based on the features have been used of the decision tree C4.5, it is found that only four features, namely height, length of legs, length of torso, and length of the left upper arm, were sufficient to correctly identify a person in 91% of all cases using the complete video from the specific experiment and the Naive Bayes classifier. Classification based solely on step length and speed still yielded 55.2% success rate using either Naive Bayes or the decision tree[52].

In this research, a new PDF (referred to as Gabor-PDF) has been proposed for human gait recognition. To extract Gabor-PDF, each GEI has been presented as a set of local augmented Gabor features from which the distribution is estimated by exploiting a two-stage approach to learn an image-specific GMM. Moreover, a new classification method has been referred to as LGSR by enforcing both group sparsity and local smooth sparsity constraints, and it is also shown that the standard GSR-based method is a special case of LGSR. Comprehensive experiments on the benchmark USF Human ID database demonstrate the effectiveness of our newly proposed feature Gabor-PDF and the new classification method LGSR for human gait recognition[53].

Table 1. Techniques and challenges in Gait reidentification

Reference	Input Type -dimension	View/gait direction	Feature/classification	Outcomes	Dataset
(Liu et al. 2015)	Single, 2D	Independent (11 different views)	Gait+appearance features (with PCA); Metric Learning to Rank	Short-term-based (appearance features incorporated)	CASIA
(John et al. 2013)	Single, Kinect 3D	Dependent (top-down/ lateral)	Frequency response of the height dynamics+ KL-Divergence (Feature selection); ML classifier	Long-term able (but not tested)	TUM-GAID + local studio datasets
(Chattopadhyay et al. 2015)	Multiple, Kinect 3D	Dependent (front and back)	Soft biometric cues for Re-ID and point cloud voxel-based width image for recognition; LMNN classifier	Long-term able (but not tested)	Local dataset
(Gala and Shah 2014)	Single, 2D	Independent (random directions in 8 cameras)	Gait feature (GEI/FDEI)+ colour (HSV histogram); combined similarity measure	Short-term (colour dependent)	local MCID Database + SAIVT SoftBio dataset
(Wei et al. 2015)	Single, 2D	Dependent (constrained poses were experi-mented)	Swiss-system-based cascade ranking; NN/SVM	Long-term able (better results verified w.r.to others)	Indoor CASIA, outdoor SOTON, local PKU datasets
(Kawai et al. 2012)	Single, 2D	Independent (near side view as the query)	Fusion of gait feature (STHOG) and colour information; Score-level fusion	Short term (colour dependent)	local dataset
(Nambiar et al. 2016)	Single, 2D	Dependent (frontal)	Histogram Of Flow Energy Image (HOFEI); NN classifier	Long-term able (but not test ed)	CASIA and HDA datasets
(Nambiar et al. 2017)	Single, Kinect 3D	Independent (Five different views)	Context-based ensemble fusion, SFS feature selection; NN classifier	Long-term able	Vislab KS20 dataset
(Wang et al. 2014, 2016)	Single, 2D	Independent (arbitrary viewpoints)	Appearance and space-time feature (ColHOG3D); DVR model for cross-view Re-ID	Short-term (colour is integrated)	PRID2011, iLIDS-VID and HDA+
(Bouchrika et al. 2016)	Single, 2D	Independent (arbitrary viewpoints)	Haar-like template for localization+ magnitude and phase of the Fourier components for gait signature; KNN classifier	Long term (but not tested)	i-LIDS
(Roy et al. 2012)	Single, 2D	Dependent (lateral)	Pose Energy Image (PEI)+phase of motion; graph-based path searching	Long-term able (but not tested)	local studio dataset
(Iwashita et al. 2010)	Single, 2D	Independent (arbitrary viewpoints)	Virtual 3D sequential model generation + affine moment invariance from virtual images; kNN classifier	Long-term able (but not tested)	Local dataset

To better understand the state-of-the-art techniques, as well as the challenges in Gait-based Re- ID, we categorize the paradigm into several dimensions (see Table 1) In this section, we address each of these dimensions in detail by conducting an extensive survey of various state-of-the-art approaches reported in the literature and discuss their strength and weakness.

Hence the field of gait recognition has been in existence for roughly a decade, the research community has long utilized publicly available databases for comparative performance evaluation.

3. Data Sets

Table 2 summarizes the most prominent gait recognition corpora. This table also shows the important features of the particular databases. The most important features of a database are the number of subjects (which should be high), as well as a good set of person variations. These variations include, but are not limited to, view angle, clothing, shoe types, surface types, carrying condition, illumination, and time.

The first available dataset was the 1998 UCSD Dataset [11], which contains merely 6 subjects. Most of the following early gait recognition databases were published in 2001 from various institutions [2][3][5][9][10][12]. Those datasets feature a medium number (about 25) of subjects. It was then found, that for meaningful evaluation, datasets should contain at least 30 subjects and possibly more.

The most comprehensive database to date, which features a large set of subjects as well as a substantial set of variations is probably the Human ID Gait Challenge [15]. Other databases such as CASIA (Dataset B) [1] also feature high numbers of subjects and a significant number of variations. CASIA additionally features an exhaustive number of views, which allows for precise 3D reconstruction.

Table 2. Gait Recognition Databases with variations

Database, Ref.	#subjs.	Environment	Time	Variations
UCSD ID [11]	6	Outdoor, Wall background	1998	Time (minutes)
CMU Mobo [5]	25	Indoor, Tredmill	2001	Viewpoint, Walking speeds, Carrying conditions, Surface incline
Georgia Tech [9]	15	Outdoor	2001	Time(6 months), viewpoint
	18	Magnetic tracker	2001	Time(6 months)
HID-UMD Dataset 1 [10]	25	Outdoor	2001	
HID-UMD Dataset 2 [3]	55	Outside, Top mounted	2001	viewpoints (front, side), time
MIT, 2001 [2]	24	Indoor	2001	view, time (minutes)
Soton Small Database [12]	12	Indoor, green back-ground	2001	carrying condition, clothing, shoe, view
Soton Large Database [12]	115	Indoor, Outdoor, Tredmill	Summer 2001	view
HumanID Gait Chal-lenge [15]	122	Outdoor	May & Nov. 2002	viewpoint, surface, shoe, carry-ing condition, time (months)
CASIA Database A [1]	20	Outdoor	Dec. 2001	3 viewpoints
CASIA Database B [1]	124	Indoor	Jan 2005	11 viewpoints, clothing, carry-ing condition
CASIA Database C [1]	153	Outdoor, night, thermal camera	2005	speed, carrying condition
TUM-IITKGP	35	Indoor, Hallway, Occlusions	Apr. 2010	time (minutes), carrying condi-tion, occlusions

4. Data Acquisition Systems

The nature and characteristics of the data acquisition setup, i.e., number and type of cameras and dimensionality of the acquired imagery, clearly influence the algorithm to be employed toward Gait-based person reidentification. Re-ID systems exploit either two-dimensional (2D) or 3D information, depending on which image acquisition methods are employed. For example, depth sensors (e.g., Kinect) and motion capture systems

(MOCAP) can record directly 3D data of the environment (Josiński et al. 2014; Nambiar et al. 2017), albeit the 2D-based image sequence are the defacto standard in real scenarios (Gala and Shah 2014; Bouchrika et al. 2016).

A typical Re-ID scenario consists of many cameras (overlapping or non-overlapping) distributed across the surveillance network. Among them, some cameras are used for training, i.e., to create a gallery database, and some others are used for testing. Depending upon the number of the cameras used to acquire data and their coverage of the space (overlapping or not), the Re-ID systems differ. In the majority of cases, Re-ID systems consider networks composed of multiple cameras with non-overlapping fields of view. Thus, the basic unit of data for analysis is a short video snapshot, typically containing a few gait cycles, taken from a single view. For training the Re-ID system, many of the cameras can be used to collect a gallery of video snapshots that represent the identity of the subject from different views. Then, during runtime, a single camera is used to collect the probe image from which the subject will be re-identified. There exist many publicly available datasets composed of multiple non-overlapping cameras, e.g., CASIA, HDA+, SAIVT (see Table 3), so many works fall in this context of single-view multiple camera non-overlapping setup. For example, Gala and Shah (2014) applied a gait assisted Re-ID algorithm to the SAIVT dataset. This dataset contains views from eight non-overlapping cameras, but to simulate a real-world Re-ID scenario, they form gallery and probe sets from different cameras. During runtime a single camera is used for the probe set and the others are used for the gallery set. A similar approach was carried out in Wei et al. (2015) on the CASIA, SOTON, and PKU datasets, all containing multiple non-overlapping cameras. In Liu et al. (2015), they used 11 different views of the CASIA dataset. During the runtime, they matched individuals from any random viewpoint against the stored RGB images in the gallery database collected from any other viewpoint. Bouchrika et al. (2016) applied gait-based Re-ID methods in two different cameras of the i-LIDS datasets: one camera for gallery and the other for probe. Instead, Wang et al. (2016) randomly splits each sequence pair of the datasets8 into two subsets of equal size, one for training and one for testing. That work was tested on the i-LIDS-VID, PRID2011, and HDA+ datasets. Roy et al. (2012) and Kawai et al. (2012) employed single views for gait-based Re-ID locally created datasets of non-overlapping cameras. Roy et al. (2012) shows two camera and three camera topologies. In Kawai et al. (2012), seven non-overlapping views, from front to rear-oblique, have been collected. The lateral view is tested against the gallery set of all other views.

5. Conclusion

In this paper we have presented detailed survey on different Gait recognition available datasets with proper specifications have also been detailed over here like UCSD ID, CMU Mobo, Georgia Tech, HID-UMD dataset 1, HID UMD dataset2 and soton large dataset. .Besides we carried out a detailed survey of the various approaches on gait recognition system. To describe the topic in detail, we analyzed its various dimensions, i.e., input type, view/gait direction, Gait features/Classification and outcomes.

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