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Research Article

A Survey of Gait Recognition Based on Skeleton Model for Human Identification

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Abstract: Biometric means the identification of persons by their traits or characteristics. We give in this study a simple survey and a general review of gait recognition based on a skeleton model for human identification of recent gait progresses. Every individual has features; therefore, a biometric means a unique feature of any person. The methods of the recognition currently, such as face recognition, iris recognition or fingerprint recognition based, require a physical contact or cooperative subject. So it is difficult to identify individuals by using these methods at a distance. However, gait as a feature of persons walk does not have these constraints. Gait is, in fact, a novel biometric feature. It attempts to distinguish people by the way of their walk. It has been increasingly taken the attentions of the research workers. Recent years, gait has become a hot topic in computer vision with great development accomplished.

Keywords: Biometric, gait, gait recognition approaches, skeleton model

INTRODUCTION

In recent years, there has been an increased attention on effectively recognizing personalities to prevent the terrorist attacks. Various biometric technologies have appeared for verifying and identifying individuals by analyzing fingerprint, face, iris, palm print, gait or a mixture of these characteristics (Xiao, 2007).

The systems of human recognition biometrics are derived from criminal and judicial real life that to be used. Within human recognition techniques, some methods such as fingerprints and face recognition have become extremely professional. The origin of the Biometrics terms is the Greek word "Bio" for "life" and "metrics" for "measure" (Singh and Jain, 2010). Briefly, biometrics is considered a tool and science uses biological data measuring and analyzing.

Comparing with other biometric methods, gait offers some unique features. The furthermost attractive characteristic is its unobtrusiveness, which does not need observed subjects' cooperation and attention. Furthermore, person gait can be taken at a far remoteness without requiring physical data from subjects. This favorable characteristic has an advantage, especially when individual information such as facial image is confidential (Wang *et al*., 2010).
Two groups are consisted the biometrics as follows:

- Behavioral Biometrics is the extraction of characteristics of the base of a person's action. The measure directs the human characteristics in a specific a behavioral biometric features, through which time as a metric is to be utilized. Thus, the techniques, keystroke scan and speech patterns, are included in this certain measure.
- **Physiological biometrics:** Refer to biometrics that originated from a direct measurement of particular parts in the individual body. In fact, fingerprints face recognition, remarks distinction, iris and hand scans are the most distinct and effective types of these measures.

Physiological characteristics are usually face, fingerprints, iris, palm print, DNA, etc. Behavioral characteristics are usually voice and gait. Gait recognition systems are usually applied in surveillance environments as well as human-machine interaction purposes. Recently, gait recognition has become interest in it of researchers. Although various gait recognition systems tend to be suggested by researchers, they are still far on the human's ability to recognize people by the way they walk. The factors that are must be improved in gait recognition studies are generally: Recognition rate, speed, accuracy and computational cost. Since, several characteristics can be achieved through the gait it is significant to discover

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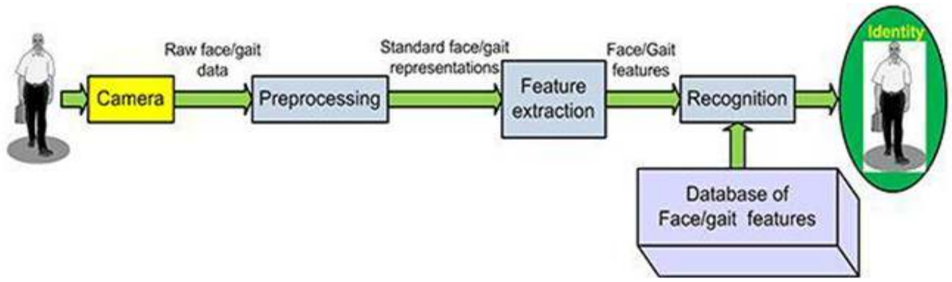


Fig. 1: Typical gait recognition system (Joshi *et al*., 2014)

which features or parts of our body are most effective in gait recognition. This study proposes an intelligent authentication of a human applying various feature extraction.

In commercial visual surveillance applications, gait has significantly a great utilize including the monitoring systems for public transportation, banks and car parks. Several applications were put into practice based on gait. Furthermore, specific information was extracted from human gait in order to produce helpful results.

In comparison with other methods of biometric, gait offers many exclusive attributes. At the point of fact, the most obvious characteristic is essentially recognized by its unobtrusiveness in which the observation of subjects' interest and cooperation is not required. Figure 1 show a typical gait recognition system (Joshi *et al*., 2014).

This study collects some papers and works that conducted on gait recognition applications. The study shows some intelligent authentications of the application of a human being diverse features extraction.

Mainly human gait recognition is divided into two types: model-free and model-based approaches.

Model-free approach: The approach of the model-free expressed better performance of widespread databases. In fact, it utilizes as a compacted representation to describe the motion patterns of the human's body. Hence, appearance-based or model-free approaches include varied features, such as the complete silhouettes, silhouette width vectors, or Fourier descriptors that extracted firstly. Model-free approaches are insensitive to the quality of silhouettes and have the advantage of low computational costs comparing to model-based approaches (Singh and Jain, 2010). However, they are usually not robust to viewpoints and scale. Research examples of this approach are self-similarity Eigen gait, key frames analysis, spatial-temporal distribution characterization, kinematic features, unwrapped silhouette, higher order correlation, video oscillations and gait sequences.

Model-based approach: Model-based approaches obtain a series of dynamic or static body parameters via tracking or modeling body components such as legs, limbs, thighs and arms. Gait signatures derived from these parameters are then employed for recognizing or identifying a person. They have the advantage of view-invariant and scale-independent recognition. Though, model-based approaches have sensitivity to the quality of gait sequences and also suffer high computing costs due to parameters calculation. Model-based methods have an advantage of insensitivity to carrying variation and clothing (Li and Chen, 2013). Research examples of this approach are static body parameters, thigh joint trajectories, dual oscillator, articulated model and 2D stick figure.

MATERIALS AND METHODS

Currently, video is not the only technique to collect the gait any more. According to the techniques of data collection (Lu *et al*., 2014), gait methods are divided into three main types:

Video Sensor (VS): In this method, video cameras are used to collect the data of gait. In the absence of physical contact, this method is considered noninvasive and its work may limit to the walking of persons in the natural way. In addition, in our daily life, a video camera is used commonly. It is somewhat very easy to obtain the data of gait in different occasions. Yet, the processing of images is required and the images that resulted from cameras should preprocess to find the information of gait that may utilize in a straight.

Wearable Sensor (WS): This method requests the sensors to identify the wear and motion of the data collection that recorded by them. The single difference between the two methods VS and WS is that the motion data in WS could be obtained at once and the resulted data is the appropriate for the analysis of gaits. In fact, WS is commonly used in the analysis of gaits mainly in the medical fields. Yet, it is lacking the key feature of non-invasive. Therefore, it is not used in the remote monitoring. So, 2D has the capacity to indicate to the specific data of gaits. So, the data resulted from of 2D could be recognized by the sequence of images that used broadly in the past.

Walking surface Aging Illness

Fig. 2: Some examples of covariates factors in gait (Sivapalan, 2014)

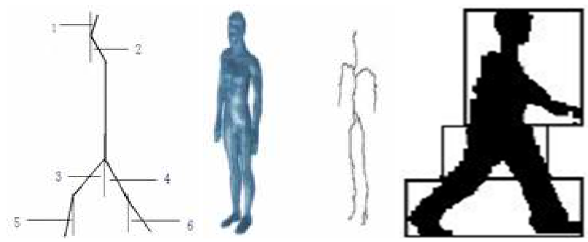
Floor Sensor (FS): This method called FS or footprint; it makes use of the sensors that put on the floor. The information on site and length of one's footprint are to be recorded for intending to be studied.

Covariate factors: Existing approaches connected with gait recognition systems that tend to be suggested by the researchers. Although the performance of these approaches is actually encouraging the gait recognition for the identification purpose of a particular person is still far from the practical applications. In fact, many factors that affect negatively on the method efficiency were definitely avoided by the assumption (Chai *et al*., 2011).
These factors include:

- Angles view, e.g., (side view, frontal view)
- Shooting environments, e.g., (outdoor/indoor, day/night)
- Apparel of subject, e.g., (clothes, shoe types, object carrying)
- Occlusions, e.g., (part or even the whole body of the human motion is covered provisionally)
- Moving objects segmentation, e.g., (the complex outdoor background)

As well as, there are some factors cause changes of the natural gait due to sickness (e.g., lower limb disorder, foot injury, Parkinson illness, etc.) or other physiological changes in the person's body due to aging, pregnancy, drunkenness, gaining or losing weight etc. (Prerna and Rajni, 2015). Figure 2 shows some examples of these factors.

Skeleton model: There are two types of methods for modeling: The first is modeling by human skeleton and the second is modeling by human body contour. These two types of methods have specific advantages and disadvantages. Skeleton model is hard to be obtained, but it can describe motion joints well and it is suitable for multi-view motion analysis. Contour information is relatively easy to be obtained, but it cannot represent



(a) (b) (c)

Fig. 3: (a) Skeleton model of 6 angles (Ming *et al*., 2009); (b) Skeleton branches (Xiao *et al*., 2010) and (c) Skeleton joints in running (Li and Yang, 2010)

motion details and deal with self-occlusion (Ming *et al*., 2009). Skeleton model is built in this way: some important points in the silhouette are selected to build a skeleton model which can produce the features representing a person's gait. Furthermore, shape skeletons have been effectively used for gait recognition. The strong point of these representation schemes is their insensitivity to visual transformations such as deformation and articulation as a result of their capability to capture hierarchy of parts (Xiao *et al*., 2010). Figure 3(a to c) shows some examples of skeleton model.

LITERATURE REVIEW

In (Tanawongsuwan and Bobick, 2001) studied the gait recognition by using tracks of the lowest parts of the body. The joint angles were projected into the walking plane. They specified these tracks in the 30 markers position as planned in the walking plane. The researchers were submitted a plain process to estimate the offsets place in the form of a plane lies between the markers. In addition, skeletons and joints were also underlined by the researchers. The given offsets that used by the researchers were used to compute the joint angle trajectories aiming at compensating the systematic temporal variations. Variations were in the same pattern with the next-predominantly space; the speed of walk was specified by the number of footsteps. Time was normalized the tracks by using a difference warping of the compensated instance. They examined this recognition on two walk databases for 18 people who made more than 150 walk spaces by using a plain nearest neighbor algorithm and Euclidean space as an evaluation measures. The researchers also exploited the predictable confusion metric as a way to estimate the effect of the well joint-angle signals that could be performed among a great number of persons.

According to Ming *et al*. (2009), the researchers discussed the silhouette that based on the descriptor characteristic. Human shape geometry is often generated by the limits pursuit approach for normalizing design purpose. On the other hand, Boundary centroid space was proposed in a way of describing the gait form. Ripples transform was applied to boundary centroid space and ripples descriptor extraction simultaneously, This centroid space could be attained by using a form of the human skeleton and body's active measurable factors that take out to be adapted in the gait from appearance. They carry out human identification that works in accordance with SVM in which two kinds of gait characteristics are used.

In Xiao *et al*. (2010), the study offered an approach relies on using skeletons for gait identification. The starchy structure of the skeleton depiction allows us to signify each gait. At first, the gait features are to extract from figure sequences. Subsequently, the gait recognition will be performed. Since this practice method was completely based on human gait, this approach is considered solid in varied types of the clothes that wear. Thus, a rate of recognition of 96.21% with MUMoBo dataset was reached through the adoption of the suggested approach.

In Li and Yang (2010), the researchers submitted a system of gait extraction and recognition that relies on geographical information of lower legs and ankles. According to the human knowledge, anatomy could be extracted from the lower legs and feet area. The location of ankle lies in the curve of lower legs and feet. It uses the least-square method to be suitable with the angle sequence of lower legs, by normalizing this information. Discrete Cosine Transform is to be transformed to the amplitude Angle sequences. The two kinds of optimal characteristics and findings will be processed through using the strategies of feature fusion. The experimented results in the NLPR gait database showed their acceptance.

New gait recognition algorithm techniques submitted by Xu and Zhang (2010). This technique is built on fuzzy principal component analysis of the gait energy image (FPCA). In the first step, the original gait sequence is to be preprocessed, after that, gait energy image is to be attained. In the second step, the eigen-vectors and eigen-values are taken out through the analysis of fuzzy principal components which known as fuzzy components. Subsequently, the eigenvectors are calculated through a space of lower dimension. In a final step, NN classifier is exploited in the classification feature. This method has been practiced on CASIA database. The investigational results prove that such algorithm attains an appropriate performance for recognition reaches 89.70%.

Another approach based on the identified issue in the lower limbs was adopted in a research submitted by Zhang *et al*. (2011). This new method of gait identification was proposed the use of lower limbs of a closed area as a vital feature of extraction. Firstly, the skeleton was applied aiming at obtaining body skeleton. Through the connection of left and right foot minor points, closed areas were formed as a feature of gait. At that time, the transform wavelet was also applied to evaluate the datum feature. Lastly, datum feature identification and classification were realized by the virtue of the established BP neural network. Such techniques have been practiced on Zero degrees Celsius camera angle of CASIA database.

Structural gait energy image is another gait recognition technique. It is suggested by Li and Chen (2013). This method combines the advantages of GEI and model-based methods. SGEI is reproduced by a fusion of foot and head energy images. Then a classifier fusion of both GEI and SGEI is carried out. In fact, this method is able to deal with the variations of clothing and carrying completely. They examined this technique on CASIA (B) database. The rate of recognition reached 89.29%, which consider good rate compared with results in the prior works.

Furthermore, Ali *et al*. (2013) presented human running joints (hip, knee and ankle) valuation recital based on the statistical computation techniques. They use the One-way ANOVA that of Less Significant Difference (LSD) test and Bartlett's test for equality of variances to determine which joint has more variation among others during the human running gait style. These three joints rotation the angle data were computed from the Bio Vision Hierarchical data (BVH) motion file for the reason that these joints provide the most important information on the joints of the human lower body (hip, knee and ankle) (Fig. 2 and 3). BVH file was used to estimate the participation and performance of the joints during the running gait which is considered a novel feature of our study.

In Lu *et al*. (2014) utilized another method that its work based on the joint distribution of motion angles. Motion angels were proposed for the recognition of gait. The motion angles of lower limbs new feature are extracted from either 2D video database or 3D motion capture databases. The equivalent angles of right and left legs bond together to work out the joint distribution spectrums. Through this process of joint distribution of those angles, the researcher builds a person specific feature of the histogram. In the distance measurement stage, three types of space vector were defined to be utilized in histograms' resemblance measurement. In this case, a classifier was built to carry out the classification procedure. Investigators have carried out the CMU motion capture and CASIA Gait databases by which the best recognition performance that achieved by the researcher's application.

In Mohan Kumar and Nagendraswamy (2014) conducted another way known Change Energy Images (CEI) for Gait Energy Image (GEI). CEI was produced for comprehensive dynamic and static data on person gait purpose. Radon transform was also used in CEI within four dissimilar directions, concerning horizontal, vertical and two contrary cross sections. The two opposite cross sections include four diverse angles use to calculate the values of discriminative characteristic. These reproduced features are clarified within the form of interval-valued type symbolic data. This technique was proficient in identifying a persons' distinctions through their gaits considering their unlike clothes they wear in varied situations or carrying a sack. In addition, a related measure used for the planned gait representation is investigated for signifying the similar match in gait recognition. Thus, experiments are conducted on CASIA database B. The results have demonstrated that a recognition performance reached 91.50%. This rate is considered valid in comparison with some previous works.

In addition, Dikovski *et al*. (2014) constructed and evaluated feature sets with the purpose of finding out the role of different types of features and body parts in the recognition process. The feature sets were constructed from skeletal images in three dimensions made with a Kinect sensor. The Kinect is a low-cost device that includes RGB, depth and audio sensors. In this study, automated gait cycle extraction algorithm was performed on the Kinect recordings. Metrics like angles and distances between joints were aggregated within a gait cycle and from those aggregations the different feature datasets were constructed. Multilayer perceptron, support vector machine with sequential minimal optimization and J48 algorithms were used for classification on these datasets.

Finally, Prathap and Sakkara (2015) presented a gait based human identification system using skeleton data acquired by using Microsoft Kinect sensor. The static and dynamic features of each individual are extracted using the skeleton information. Classification is performed using two different algorithms. First is the Levenberg-Marquardt back propagation algorithm, second is the correlation algorithm. 90% recognition rate is achieved with correlation algorithm where as for Levenberg-Marquardt back propagation algorithm proposed system is able to achieve a recognition rate of 94% for 5 persons with fixed Kinect sensor setup.

GAIT DATASETS

Body's CMU Motion (MoBo) database: The Body's CMU Motion (MoBo) Database was introduced by the Robotics Institute, Carnegie Mellon University in Pittsburgh, Pennsylvania (MoBo) (Brook and Evans, 1972). They started to collect the CMU Motion (MoBo) database from the body on March 2001. The database included 25 persons who were practicing their walk on a treadmill in the unspecific area. The subject walking subject included four different styles of walking including unhurried, speedy, inclined and with the ball carrying.

The USF dataset: The dataset includes 122 individuals in 12 different Probe sets (different sessions, walking surfaces, different shoe type, carrying a briefcase, different camera orientations) (Sarkar and Liu, 2008). There are two cameras at left and right of the walking subjects and the subjects are walking on two different surfaces as grass and concrete.

The soton database: The Southampton Human ID at a distance gait database was another approach that introduced by Southampton University. It includes two major segments concerning a large database (~100) but basic, a small database but detailed. The small database was implemented for the purpose of investigating the robustness of the algorithms within a similar subject in a variety of general conditions, such carrying items database and wearing different clothing or footwear data bases (Nixon, 2001). The undersized database includes 12 subjects filmed walking with a green background. Through wearing a variety of shoes, clothes and carrying different sacks, each subject was filmed. With different speeds of walking, subjects were also filmed. Each digital video within the databases contains at least one completed gait cycle.

The CASIA dataset: The Automation Institution, Chinese Sciences Academy for Gait Studies and researches were provided new CASIA dataset (The Institute of Automation, 2001). This method includes four databases of gait in the CASIA including A, B, C and D databases. A Dataset was introduced on Dec 2001. It contains 20 subjects gait films. Each subject includes 12 gait sequences, 4 of these sequences are recorded for each three directions. The directions were parallel, 45 and 90 degrees were parallel to the image plane. The size of A Dataset was about 2.2 GB; it contains 19139 images. Dataset B is a gait of multiple view. It was firstly created in Jan of the year 2005. It contains 124 subjects. The subjects were filmed by using 11 different views. These subjects recorded with different clothing and carrying objects. Dataset C was recorded in Jul 2005 by an infrared camera. It includes 153 subjects which recorded within four dissimilar situations concerning standard, unhurried, speedy and regular walking during carrying of a sack. The gait sequences are recorded at night. Dataset D was recorded in Jul-Aug 2009. The gait sequences were collected by the camera and synchronously Rscan Footscan is applied. The dataset D contains 88 different subjects. All the subjects were Chinese and the videos were recorded indoor.

The TUM-IITKGP gait database: The TUM-IITKGP Database currently consists of 840 of different gait sequences from 35 subjects. It was gathered by the university of München Germany (Hofmann *et al*., 2011; Hosseini and Nordin, 2013). The subjects are walking in a narrow hallway and were as similar as the real surveillance cameras in the real world. The camera is located at the medium height of 1.85 m. The subjects walking began from left to right and right to left. Each subject's walking is recorded in six different conditions. The database contains 840 gait sequences. Each subject was recorded in a normal walking configuration followed by three degenerated configurations, including carrying a backpack; hands in pocket and having a gown.

DISCUSSION AND CONCLUSION

Human gait is simply a significant biometric feature uses for identification of people. This method has been applied for the latest decades. Several technologies on biometric have been appeared for recognizing and confirming persons by either analyzing their fingerprint, face, iris palm print, gait or a mixture of all these characteristics. In comparison with other methods of biometric, gait offers many exclusive attributes. In the point of fact, the most obvious characteristic is essentially recognized by its unobtrusiveness in which the observation of subjects' interest and cooperation is not required. Although the performance of these approaches is actually encouraging the gait recognition for the identification purpose of a particular person is still far from the practical applications. According to the related works, in gait recognition systems, variations of the subject's clothes, footwear and hair style add complexity to gait recognition and the subject's physical and mental conditions. Many approaches have been proposed for the description of the human gait. Human gait is an important biometric feature for identification of people that has been noticed for the last decade. In this survey study, we reviewed the approaches of gait recognition that gives an emphasis to the subject's shapes and skeleton model. Skeleton model of the shape that considers an uncomplicated gait representation technique is applied as the gait representation system. Gait recognition research need build larger real-world databases covering covariate factors such as clothes, environment, distance, object carrying and viewpoints as well as physiology factors like drunkenness and pregnancy *et al* to improve the robustness and practicality.

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