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Automatic Gait Recognition and its Potential Role in Counter-Terrorism

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Abstract

Close circuit television (CCTV) footage can be used to assemble an often-complex picture of an incident and aid in the identification of suspects after a crime or terrorist attack has occurred. For example, such footage allowed the police to not only identify the 7/7 London bombers but also to piece together the details of the bombers' movements prior to the attack. In the case of the London bombers little attempt was made to disguise their identities but where such identities are concealed it is possible to identify suspects based on other unique biometric characteristics such as the style of walk referred to as gait. Gait feature-based individual identification has received increased attention from biometrics researchers. In this paper, we propose a novel gait biometric methodology which could contribute to the counter-terrorism effort and the identification of individuals involved in crime.

Introduction

Surveillance systems including CCTV have been used for a variety of purposes including the monitoring of traffic flow, in industrial processes, transport safety, in commercial premises and in home security.[1] Moreover, since they are widely deployed in public places, surveillance cameras can play an important role in countering terrorism and crime by supporting government and law enforcement agencies with the identification of threats and suspicious activities/individuals.[2] For instance, in the United Kingdom (UK) there are an estimated 6 million surveillance cameras nationwide, and 100,000 of these are publicly operated.[3] Whilst such coverage can be beneficial, in reality scanning such a large number of CCTV videos is not only time consuming, but also requires security officers for 24/7 CCTV workstation operations. As a result, it is nearly impossible to monitor every individual in the public arena using human operators.[4] Thus there is an essential immediate need for an automated person identification system for surveillance that can identify suspects in CCTV footage.

Increasingly, technologies such as biometrics are applied to automate verification.[5] The functionality of biometric-based individual identification systems rely on identifying unique biometric features to distinctively differentiate two individuals. Using biometric features for identification has several advantages; as is the case of biometrics, it is possible to identify individuals based on who they are, rather than by what they possess (e.g. ID card) or what they remembers (e.g. password).[6] Biometric systems measure and analyze physical and/or behavioral characteristics of humans for authentication, identification or screening purposes. Some commonly used physical characteristics are DNA, iris, fingerprints, and facial patterns. While the two most common behavioral characteristics are voice and human gait, face and fingerprint recognition are the conventional biometric technologies commonly used for identification.[7] A major limitation of face and fingerprint recognition is their requirement for subjects' co-operation and consent for identification. This is often difficult to acquire when the person is a suspect, when they appear at a distance, or when captured through CCTV cameras.

Recently, biometric technologies have moved towards more real-time, remote, distance-based, non-cooperative and non-invasive surveillance.[8] Gait analysis and recognition can form the basis of unobtrusive technologies for the detection of individuals who represent a security threat or behave suspiciously. A biometric surveillance solution would be advantageous to screen individuals in high-security civilian or military facilities and monitor potential targets for theft or terrorism.[9]

A person's gait is uniquely distinctive. The most attractive feature of gait as a biometric trait is its unobtrusiveness, i.e., the fact that, unlike other biometrics, it can be captured at a distance from low-resolution videos without requiring prior consent of the observed subject.[10] It offers non-invasive identification of threats at a distance where iris and/or face information is not visible, and provides long subject analysis time during gait recognition whilst remaining concealed to the suspect. For example, individual gait recognition at an airport could be compared to an existing database of CCTV footage, perhaps even before entering the airport concourse or during initial security checks. This data could be used to track suspected terrorists or criminals who may be disguised, wearing different clothing, carrying unknown objects or forged documents.

Gait biometrics is a recent biometrics system that works on the shape and gesture of an individual's walking style, and is categorized by behavioral biometric characteristics. From a given video sequence, the human body silhouette is extracted and a set of gait measurements that describe the individual's shape and movement are obtained. The gait signature of an individual has different components such as physical dimensions (cadence, stride length, and height parameters) and the trajectories of different body parts in motion, which are used for gait recognition.[11] Forensic gait analysis of public CCTV images has been admitted as evidence in British and Danish courts and helped secure convictions.[12]

A gait-based surveillance system is an intelligent CCTV solution that efficiently automates the recognition process. A high level architecture of a gait-based recognition system that can handle millions of hours of stored videos as well as the videos from real-time CCTV networked cameras is illustrated in Figure 1. A gait-based surveillance system can be centralized or distributed, and should scan huge amounts of data to compute gait similarity measurements using a heuristic search functionality.

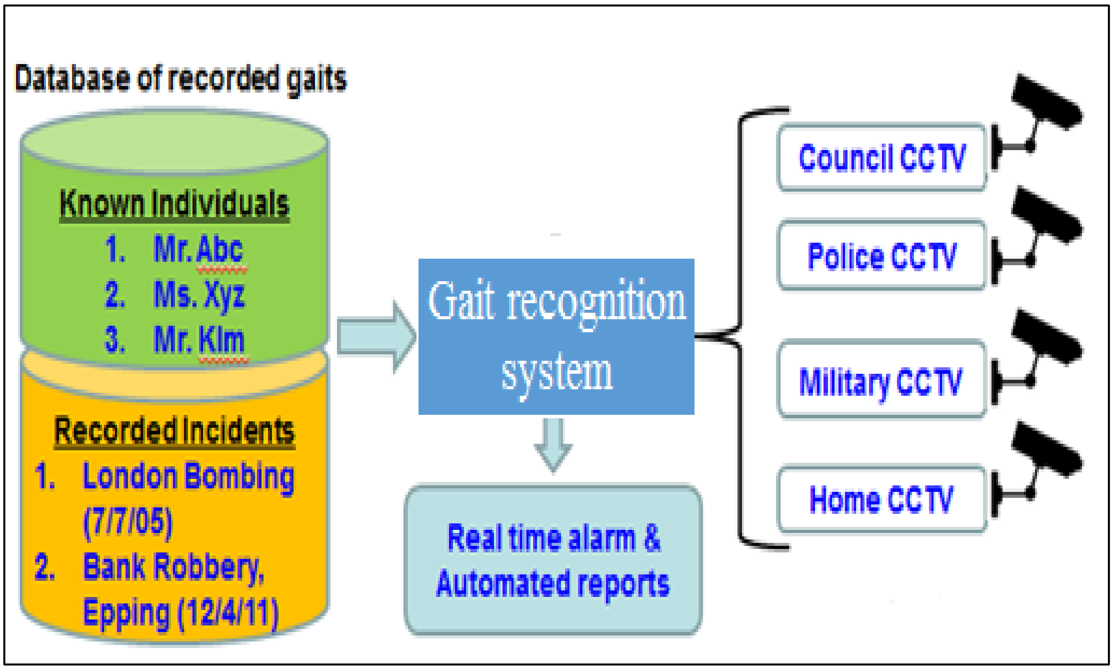

Figure 1: A gait-based surveillance system.

The functionality of a gait-based recognition system can be described by the following use-case. If a crime has happened at a scene and the CCTV footages are available, CCTV footage can be analyzed to extract gait information. The system searches its database of recorded gaits captured from individuals involved in previously recorded incidents from CCTV images. If any specific match is found among known individuals in the database then the unknown person is identified. If a match is found in multiple recorded incidents then the unknown person is not identified but ascertained to be involved in the recorded incidents. If any match is found in real-time CCTV footage then the system can find the unknown individual's current location and a real-time alert can be reported.

Gait recognition

Each person has unique gait features that are usually adhered to under normal conditions. Therefore it is possible to create a unique gait profile that distinguishes one individual from another. A gait recognition system is essentially a pattern recognition system[13] that analyzes training videos, extracts a set of gait features corresponding to different individuals, and stores it as reference templates. When a new video is given to the system, it extracts gait features and then evaluates the similarity between stored reference templates and probe template. Figure 2 illustrates the general structure of a gait-based recognition system. A person is analyzed through a CCTV cameras footage and processed to extract their walking human silhouette as shown in the last image of Figure 2(a). The Figure 2(b) illustrates different phases: data acquisition, pre-processing, feature extraction, and classification (matching and decision making), involved in the gait recognition process.

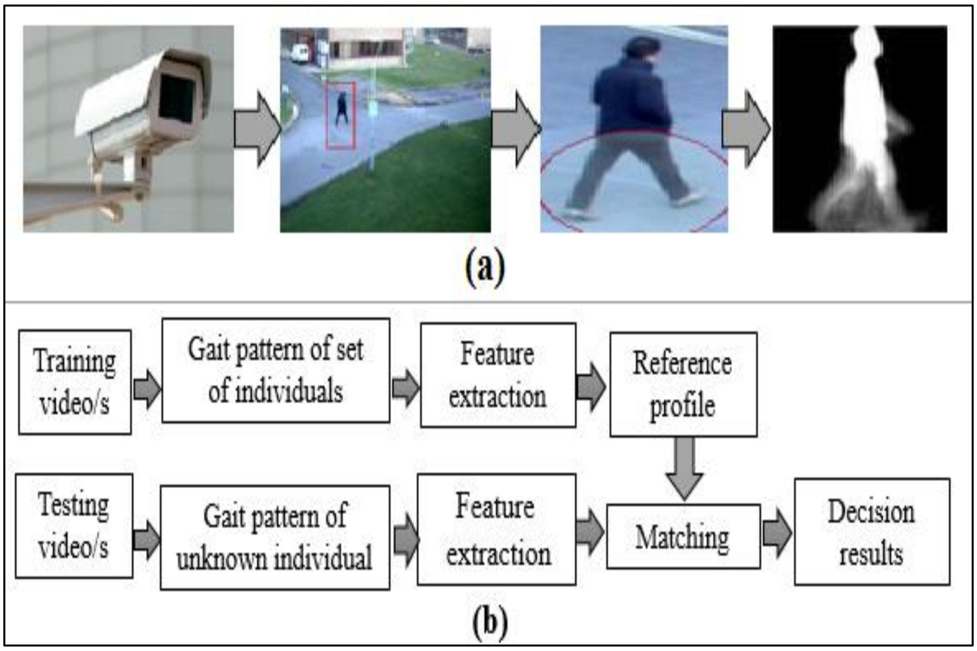

Figure 2: General structure of a gait-based recognition system: (a) Extraction of walking human (b) Different phases of gait recognition.

Unique gait features are extracted for each training and testing video. A person is identified by matching the unknown individual test gait features against the set of training gait features discovered in the classification phase (see Figure 2(b)).

Gait analysis techniques are categorised as model-based and appearance-based recognition. In model-based techniques, the body and overall shape of an individual are modelled whilst walking. [14] In appearance-based techniques, static (head and torso) [15] and dynamic (movement of arms and legs) information[16] are extracted from a sequence of walking human silhouettes.[17] Model-based techniques are more accurate; however the computational cost of building them is relatively high. Therefore, appearance-based techniques are more commonly used. [18] Additionally, we address gait recognition using appearance-based techniques.

Appearance-based gait recognition

Appearance-based gait recognition techniques extract the shape and dynamics of a person's gait. Gait shape refers to the structure of a person as they walk whereas gait dynamics captures the rate of transition during walking.[19] Wang et al. reported that a promising recognition rate can be achieved using static gait features.[20] Contrastingly, Cutting and Proffitt emphasised that dynamic gait features are more valuable for recognition.[21] More recent research suggests combining static and dynamic gait information to deliver better results than using each method in isolation.[22]

The process of appearance-based gait recognition begins by extracting a set of frames from a given video in the pre-processing stage.[23] These extracted frames are two-dimensional binary images (white pixel represented as 1 and black as 0) that represent a walking human and are referred to as binary silhouettes (see Figure 3).

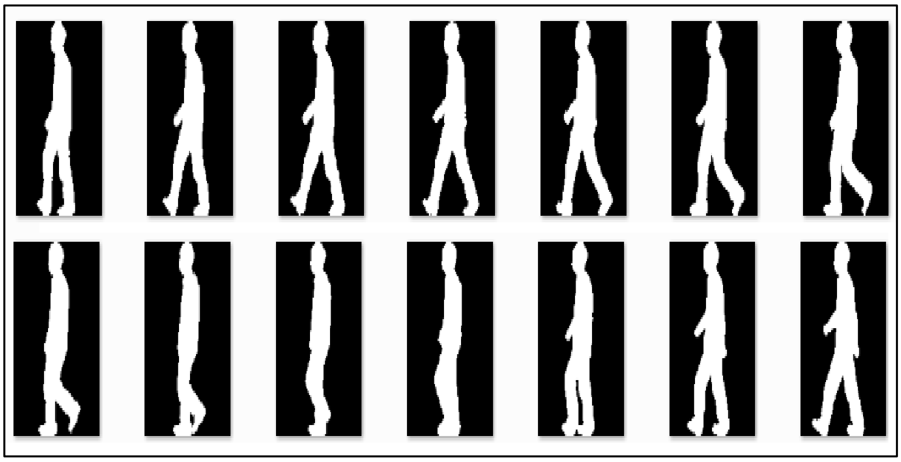

Figure 3: Sample of frames containing a walking human silhouette.

The following section describes the pre-processing steps carried out to extract the binary silhouettes.

Pre-processing

In the pre-processing stage, the subject is extracted from each video sequence frame by completing the pre-processing steps. In this paper, human silhouettes are extracted from each frame in a walking sequence using the method described by Stauffer and Grimson.[24] The extracted silhouette is resized to fit 128×100 pixels as shown in the last image of Figure 2(a). Resizing eliminates scaling that is caused by variations in camera depth. Thus video sequences captured for an individual at different instances will result in varying width and height.[25] Once scaling is complete, the horizontal alignment of each silhouette is resized with respect to its horizontal centroid. The result of applying these pre-processing steps is a set of binary silhouettes of an individual as shown in the Figure 3.

The number of frames in a given video varies based on its duration and recorded frame rate. Consequently, frames that are within one gait cycle are captured as a gait cycle. A gait cycle is considered as one complete walking sequence of an individual. A walking sequence is described as the movement of an individual from a mid-stance position (both legs closed) to a double-stance position (both legs far apart), again to the mid-stance position, followed by the double-stance position and finally back to the mid-stance position or vice-versa.[26] Figure 4 illustrates different phases in one complete walk sequence.

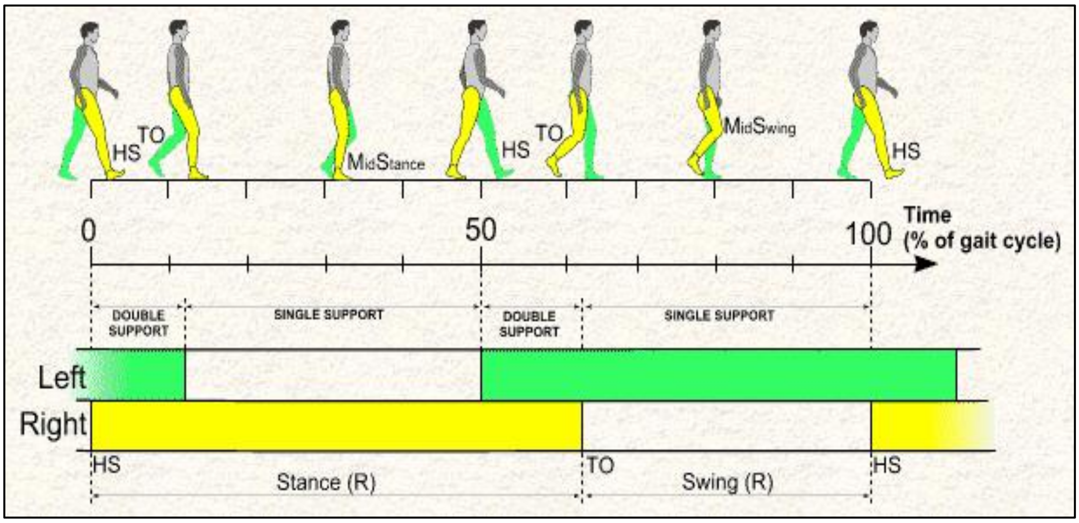

Figure 4: Different phases in one complete walk sequence.[27]

A gait cycle is estimated by computing the number of foreground pixels (white pixels) in the lower one-third of a binary silhouette image. The lower part of a mid-stance position silhouette image will have a minimum number of foreground pixels, whereas the double-stance silhouette image will have a maximum number of foreground pixels.[28] The gait cycle is calculated by considering the distance between three consecutive maxima or minima. Figure 5 illustrates the corresponding frames in a gait cycle computed using these three consecutive minima.

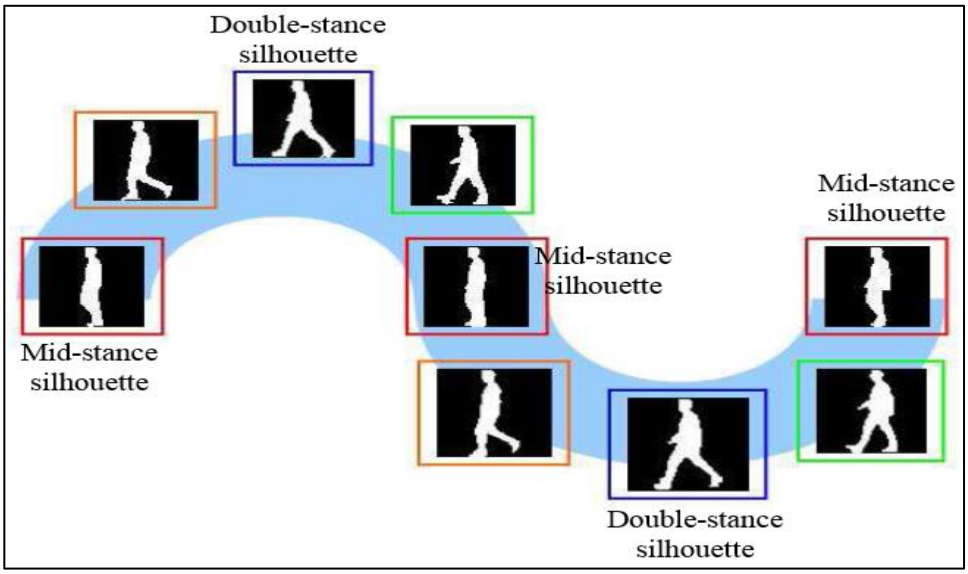

Figure 5: Individual’s silhouettes from one gait cycle.

Gait Energy Image

Following pre-processing, feature extraction is carried out to extract the unique gait features the can distinctively describe an individual. In appearance-based techniques, a commonly used approach is to symbolise all frames in a complete gait cycle as an averaged image, thus representing human motion sequence as a single gait feature image.[29] One of the commonly used gait representation methods is Gait Energy Image (GEI) in which all frames in one gait cycle are averaged to obtain a single grayscale image. The GEI gait feature is computed as[30]:

$$\mathrm{GEI}(i,j) = \frac{1}{N}\sum_{t=1}^{N} I(i,j,t) \tag{1}$$

where, *N* is the number of frames in a gait cycle, *i* and *j* are the image coordinates, *I* is the silhouette image and *t* is the frame number in the gait cycle. Figure 6 contains samples of extracted silhouettes and the computed GEI image. Figure 6 shows that the upper body of the subject remains almost static throughout the entire walk whereas the lower body captures the individual's walking motion. As a result in the GEI image, the upper body part has higher pixel intensity values i.e. more white pixels whereas the lower parts have lesser pixel intensity values i.e. more gray pixels. Therefore, the GEI image shown in the Figure 6 has similar upper body part in comparison to any of the binary silhouettes whereas the lower part reflects the varying motion of the different phases of gait motion.

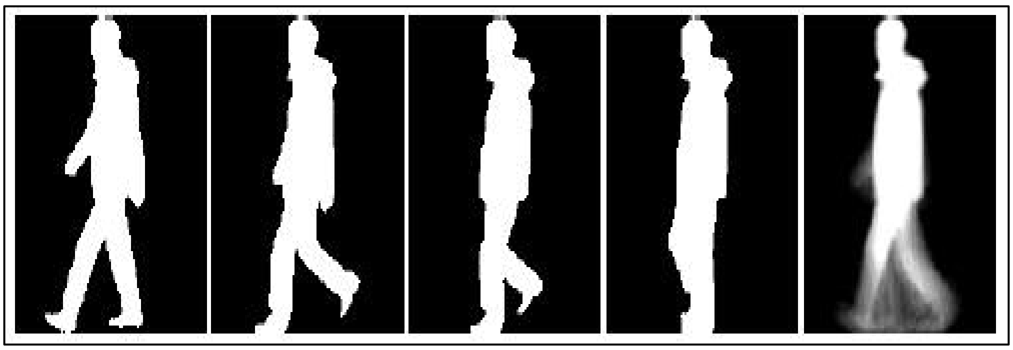

Figure 6: Sample of the extracted silhouettes and computed GEI (fifth image).

The computed GEI gait feature provides good recognition rates under normal gait sequences when a person is not carrying a bag or wearing heavy clothing.[31] However with a change in appearance i.e. under the effect of covariate factors, the resulting GEI is not similar to one recorded under normal conditions.[32] The variation in appearance can cause a dissimilarity in a person's gait and hence decrease recognition accuracy. Covariate factors may be either related to the subject itself, i.e. body related covariate factors, or external covariate factors such as different walking surfaces.[33] The work described in this paper addresses the problem of body related covariate factors and is described in the next section.

Body related covariate factors

The GEI in itself is a feature which can be directly used for matching. Under normal conditions, GEIs are unique, but a change in a subject's appearance can produce a GEI containing irrelevant information. As a result, even though the individual is known to the system under normal conditions i.e. the system is familiar with individual's normal GEI reference templates, when the individual appears with covariate factors the system cannot identify the individual.[34] Figure 7 shows an individual appearing with normal conditions, carrying a bag and with clothing conditions along with the corresponding GEIs.

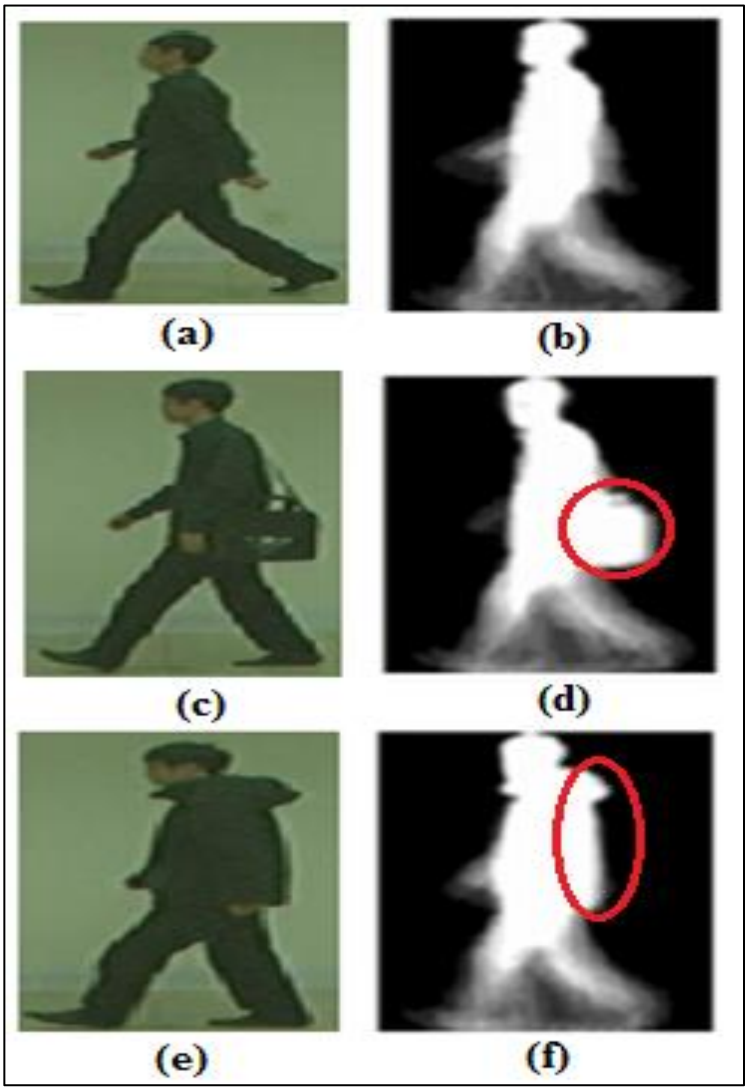

Figure 7: GEIs of an individual appearing in normal, and with clothing and carrying bag conditions.

Assuming the individual's GEI is known to the system under normal conditions (as shown in Figure 7(b)), and new GEIs (shown in Figure 7(d) and Figure 7(f)) contain extra irrelevant information (marked as a red circle in both images), the system will not detect a matching GEI. Body related parameters (head and torso) are affected by bags, clothing, and other factors, and this causes a system failure in identification.[35] The upper body part of a GEI contains irrelevant information that is not the part of the subject's gait and thus decreases overall recognition accuracy.

As a solution to this problem, this paper describes a methodology[36] that constructs a similar gait feature for an individual even though the individual's appearance may vary due to clothing and accessory changes. The solution is described in the following section.

Dynamic Static Silhouette Template

A binary silhouette can be divided into a static part that represents primarily the upper body parts (head and torso), and dynamic parts describing the human locomotive process that contains angular movement of legs and hands.[37] In our approach, the static part of the GEI is represented as a Static Silhouette Template (SST) and the dynamic part is represented as a Dynamic Silhouette Template (DST). The SST consists of upper body parts, which may be affected by body related covariate factors, so we propose a novel method that efficiently removes the covariate factors from the SST and gives a covariate free SST. The final gait feature template is obtained by combining the covariate free SST and the DST and is referred to as Dynamic Static Silhouette Template (DSST). The following sub-sections detail the process of extracting the SST and the DST from a given GEI.

Static Silhouette Template

The SST signifies the upper body characteristics such as the head and torso and as already discussed, the static part of GEI has higher pixel intensity values whereas the lower body part has lesser intensity values. Therefore, to obtain the SST and DST from the given GEI, a threshold value is used that separates the lower and higher pixel intensity values. The SST of GEI is given as:

$$\mathrm{SST}(i,j)=\begin{cases}\mathrm{GEI}(i,j) & \text{if} \quad \mathrm{GEI}(i,j)=\xi \\ 0 & \text{otherwise}\end{cases} \tag{2}$$

where ξ represents the maximum intensity value in the GEI. Figure 8 illustrates the obtained SST for an individual's GEI with a carrying bag covariate condition.

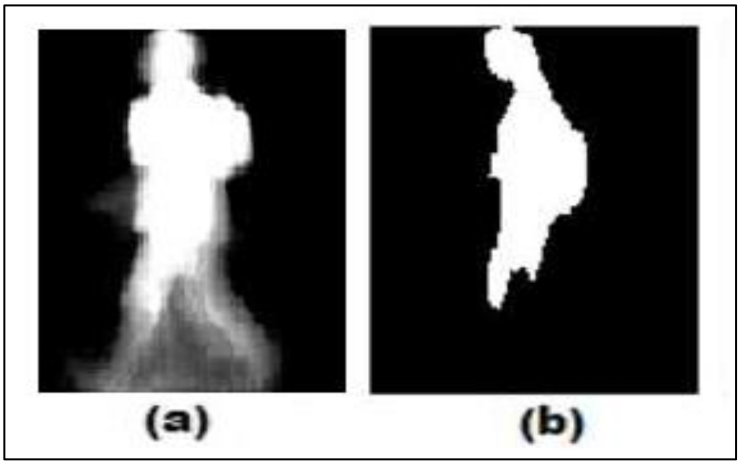

Figure 8: SST of carrying bag GEI: (a) individual's GEI with carrying bag (b) Obtained SST image.

Dynamic Silhouette Template

To extract the DST, first a base mask, $M(i, j)$, is calculated as $M(i, j) = \mathrm{GEI}(i, j) - \mathrm{SST}(i, j)$. The base mask, $M(i, j)$, separates the lower intensity values from the GEIs. In our approach, the hand swings are considered as the dynamic part; hence it should be included in the DST. Therefore a threshold value μ is required to keep the hand motion and ignore the rest of the upper body part. The DST of GEI is given as:

$$\mathrm{DST}(i,j)=\begin{cases}0 & \text{if} \quad (M(i,j)>\mu) \ \text{ and } \ (i<\frac{2}{3}*H) \\ M(i,j) & \text{otherwise}\end{cases} \tag{3}$$

where H is the height of the GEI image.

Covariate factor removal from SST

The obtained SST of GEI may be affected by body related covariate factors as shown in Figure 9. When compared to a normal SST, a SST including a bag accessory covariate factor has irrelevant information (marked as green circles in the Figure 9(b)) that need to be removed for accurate recognition. In this paper, we remove the covariate factors by exploiting the bilateral symmetry characteristic of the human body.[38] The bilateral symmetry characteristic is identified on the human body when it is divided by a midline (referred to as symmetric axis). The left part of the body becomes an approximate mirror image of the right part along the midline. Similarly, when a person is walking in normal conditions, the body can be divided into two equal halves using the symmetric axis. However when the person appears with covariate conditions, locating the symmetric axis is a difficult task.

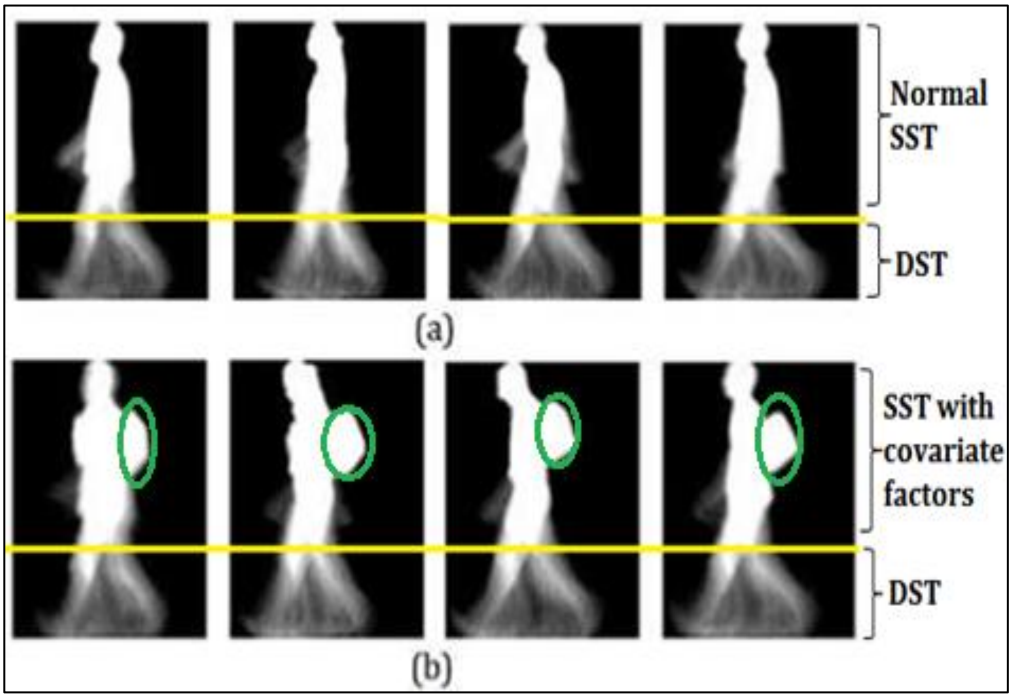

Figure 9: A comparative illustration of SSTs (a) SST of individuals in normal conditions (b) SST of the same individuals with carrying bag covariates.

Initially, to locate the symmetric axis in the case of covariate factors, a Distance Transform (DT) algorithm is applied. The DT is an important tool in image processing, computer vision and pattern recognition.[39] The DT approach gives the distance of each pixel from the background pixel when applied to a binary image. Figure 10 illustrates the DT matrix of a binary image.

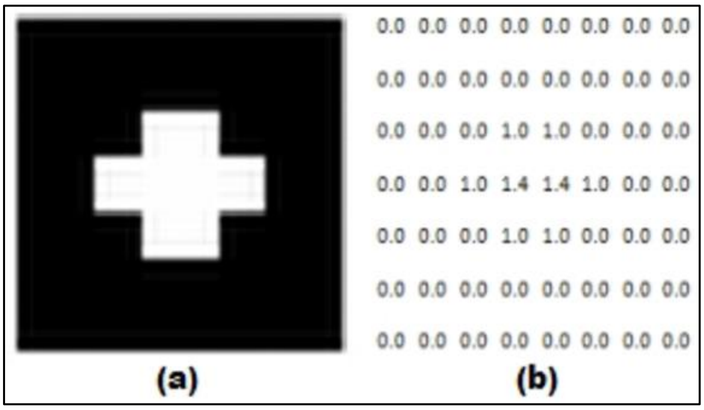

Figure 10: (a) Represents a binary image (b) Represents a corresponding DT matrix.

The DT algorithm is applied to the SST of GEI and the symmetry axis is located. Figure 11 shows the DT algorithm applied to the SST of a normal GEI and to the SST of a carrying bag GEI. The red line in the Figure 11(b) and Figure 11(d) represents the DT-based symmetry axis.

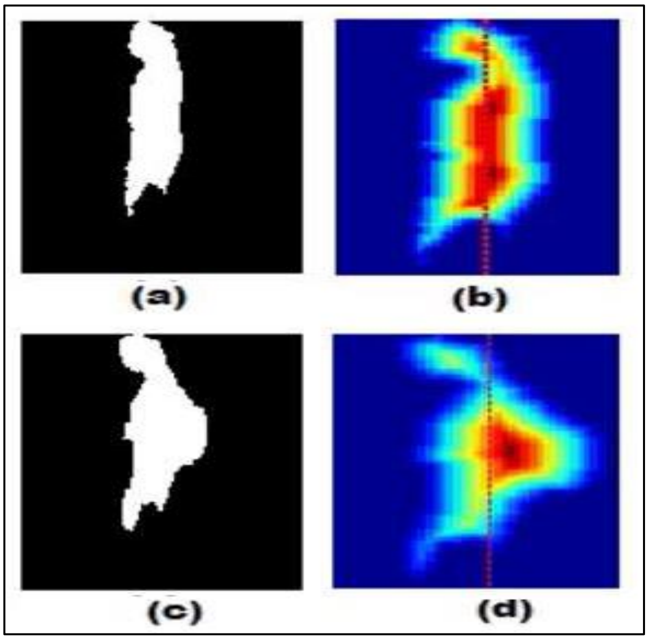

Figure 11: DT-based symmetry axis.

In the case of a SST of a normal GEI, the DT-based symmetry axis is accurately located and the image is divided into two equal halves as shown in Figure 11(b). However in the case of a SST of a GEI with carrying bag, the appearance of the person has changed and accordingly the DT-based symmetry axis has shifted more towards the covariate condition as shown in the Figure 11(d). Therefore, an approach is required that could shift the obtained axis closer to the actual human body symmetry axis.

We developed our own algorithm that computes a new axis named as the *body major axis* that provides an improved calculation of the body major symmetrical axis. The *body major axis* is a line that passes through the DT image of a SST and contains the maximum number of foreground pixels.[40] Figure 12 shows a comparative illustration of the computed *body major axis* and the DT-based symmetry axis.

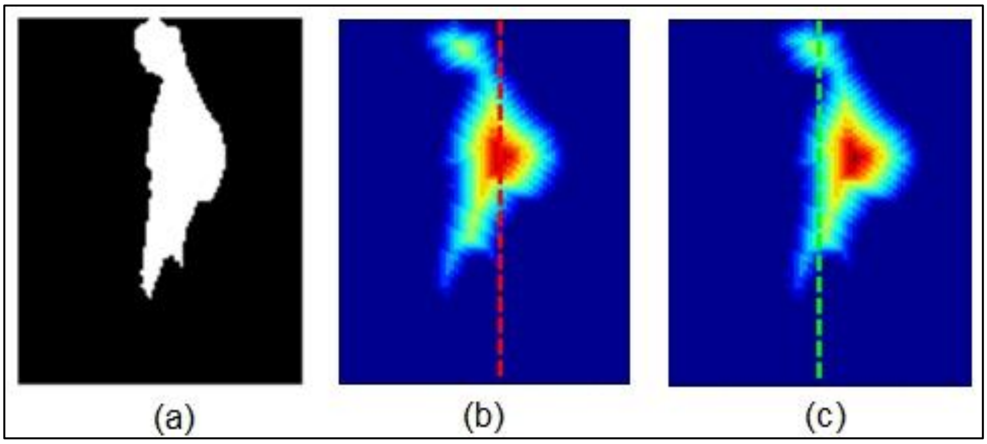

Figure 12: *Body major axis* approach on DT image: (a) represents the SST of a carrying bag GEI (b) represents the DT-based symmetric axis (c) represents the *body major axis.*

With the *body major axis* approach, the symmetrical axis has moved more towards the human body symmetry axis as shown in the Figure 12(c). However, the axis does not divide the body symmetrically. We combine the *body major axis* and the DT-based symmetry axis approach to obtain a more accurate axis. The final human body symmetry axis is calculated by taking the mean of the *body major axis* and the DT-based symmetry axis. Figure 13 illustrates the final human body symmetry axis obtained by taking the mean of the *body major axis* and the DT-based symmetric axis. The yellow line in Figure 13(d) represents the final human body symmetry axis. The final human body symmetry axis provides the desired results and accurately divides the human body into two equal parts.[41]

After accurately identifying the body symmetry axis, the left and the right width of the body are calculated to remove covariate factors. The left and right-most body vertical lines are calculated for each individual under normal clothing conditions from training sequences. Left width is calculated using the absolute difference between the left most vertical line and the final human body symmetry axis for each individual. The mean value of the left width is calculated by averaging the left width obtained for all individuals in the training phase. The right width is calculated with the same approach. For a given SST, any foreground pixels that are outside the left and right width are considered as part of covariate factors and are consequently removed.

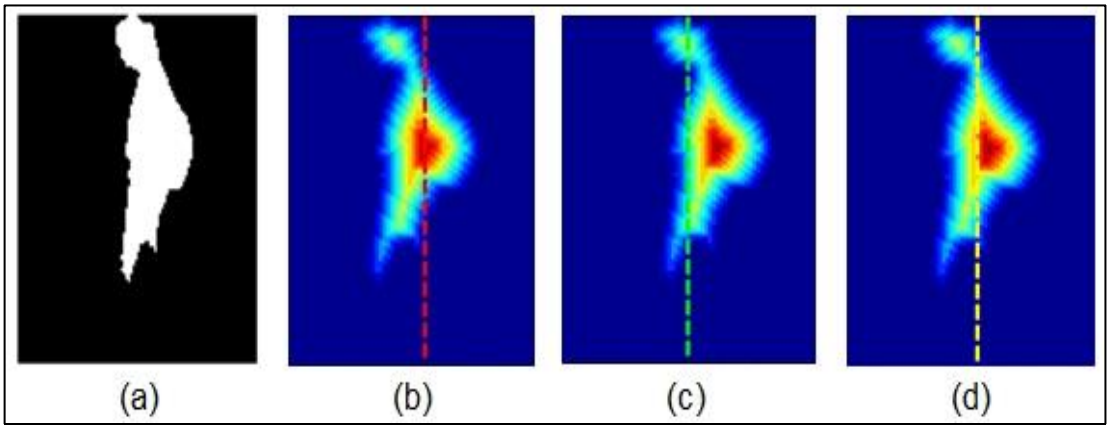

Figure 13: Final human body symmetry axis approach (a) represents the SST of a carrying bag GEI (b) represents the DT-based symmetric axis (c) represents the *body major axis* (d) the mean of DT-based symmetric axis and the *body major axis*.

The covariate-free SST is established after covariate factors are removed from the SST. The final gait feature template called the DSST is obtained by combining the SST and the DST as follows:

$$\text{DSST}(i, j) = \text{covariate free SST}(i, j) + \text{DST}(i, j) \quad (4)$$

where i and j are the image coordinates. Figure 14 shows the final DSST that has the upper body part as the covariate free SST and lower body part as DST.

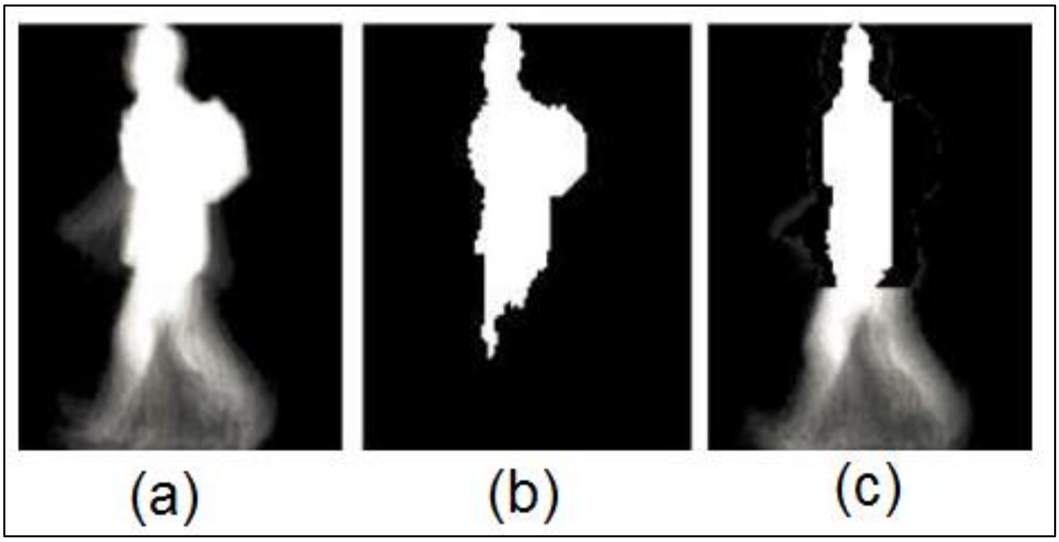

Figure 14: (a) GEI of an individual with carrying bag. (b) Corresponding SST image (c) Final gait feature template, DSST.

Evaluation of DSST approach

Referring back to Figure 2(b), the feature extraction phase results in the generation of a DSST gait feature template. Once obtained, the next phase of gait recognition involves matching and decision making. The probe DSST template of an unknown individual is matched against the set of reference DSST templates of known individuals from the database of the gait recognition system. The proposed DSST gait feature is examined for accuracy in detecting individuals through an evaluation process. We used a gait database that has the walking sequence of individuals with body-related covariate factors such as carrying a bag and different clothing. The two most standard gait datasets with covariate factors available in the public domain are (1) the Southampton Human ID gait database[42] and (2) the CASIA dataset.[43]

The Southampton Human ID gait database referred to as SOTON dataset was developed by the University of Southampton.[44] The dataset is collected for 10 subjects with normal walking and with covariate conditions. A set of normal sequences i.e. with no carrying bag or clothing is used for training (90 training videos) and a set of sequences with covariate conditions is used for testing (90 test videos). Figure 15 shows a sample of training and test sequences from the SOTON dataset.

Figure 15: SOTON database (a) Training sequences with normal clothing (b) Test sequences with different clothing and carrying objects.[45]

The DSST approach is proposed to handle body-related covariate conditions; therefore the CASIA Dataset-B covariate dataset collected for 124 subjects consisting of different clothing and carrying bag condition is used in our work. Figure 16 shows a sample of training and test sequences from the CASIA Dataset-B.

Figure 16: CASIA Dataset-B (a) Training sequences with normal clothing (b) Test sequences with different clothing and carrying objects.[46]

For both datasets, we evaluated the DSST gait feature template and as a benchmark of comparison, we examined results using the GEI gait feature template. On the SOTON dataset, 77.8% accuracy was obtained using the GEI feature. The DSST feature achieved 88.9% accuracy. On the CASIA Dataset-B dataset, 71.3% accuracy was obtained using the GEI feature. The DSST feature achieved 84.6% accuracy. Results demonstrate our proposed DSST approach worked favourably for individual identification under body related covariate factors. Thus with the reduced effect of body related covariate factors, more accurate recognition can be obtained and hence increase the performance of the surveillance system in individual identification.

Conclusion

This paper has considered a unique behavioral biometric using gait. Gait features have distinctive characteristics that can be used in surveillance systems and applications; however successful identification can be affected by the covariate factors problem such as an individual wearing different clothing and/or carrying objects such as a bag or backpack. By overcoming these issues, gait can be used as a biometric feature for individual identification in surveillance systems. This work proposed a methodology to perform individual identification from surveillance videos using gait-based features even after a change in a subject's appearance. A novel hybrid appearance-based covariate free gait feature template, DSST, which consists of the covariate free SST and the DST is developed. SST is comprised of upper body parts of the gait and static parts such as the head and torso. DST contains motion features from a gait including bodily motion such as that captured during walking from the legs. In this paper, the main objective was to increase gait recognition rates with different clothing and carrying bag covariate gait sequences. The covariate factors are removed from the SST using our developed algorithm. The advantage of using the DSST gait feature is demonstrated on two different gait datasets available in the public domain. The results obtained using the proposed DSST gait feature are significant in identifying individuals when they appear with different clothing and carrying bag conditions. The proposed methodology could provide a real-time, remote, distance-based, non-cooperative and non-invasive surveillance tool for use in the counter-terrorism effort.

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