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PAPER

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Imed Bouchrika,[1] Ph.D.; Michaela Goffredo,[2] Ph.D.; John Carter,[1] Ph.D.; and Mark Nixon,[1] Ph.D.

On Using Gait in Forensic Biometrics

ABSTRACT: Given the continuing advances in gait biometrics, it appears prudent to investigate the translation of these techniques for forensic use. We address the question as to the confidence that might be given between any two such measurements. We use the locations of ankle, knee, and hip to derive a measure of the match between walking subjects in image sequences. The Instantaneous Posture Match algorithm, using Harr templates, kinematics, and anthropomorphic knowledge is used to determine their location. This is demonstrated using real CCTV recorded at Gatwick International Airport, laboratory images from the multiview CASIA-B data set, and an example of real scene of crime video. To access the measurement confidence, we study the mean intra- and inter-match scores as a function of database size. These measures converge to constant and separate values, indicating that the match measure derived from individual comparisons is considerably smaller than the average match measure from a population.

KEYWORDS: forensic science, gait analysis, gait biometrics, posture matching, people identification, visual surveillance

Surveillance technology is now ubiquitous in modern society. This is attributable to the increasing number of crimes as well as the vital need to provide a safer environment. Because of the rapid growth in the number of security cameras and of the need for sufficient manpower to supervise them, the deployment of noninvasive biometric technologies becomes important for the development of automated visual surveillance systems and forensic investigation. Recently, the use of gait for people identification in surveillance applications has attracted researchers from the computer vision community (1). The suitability of gait recognition within surveillance systems emerges from the fact that gait can be perceived from a distance and no contact is made with the subject. Currently, as most biometric systems are still in their infancy (2), biometrics are deployed for identity verification and authentication. Gait is an emergent biometric which is increasingly attracting the interest of researchers and industry. Gait is defined as the manner of locomotion, that is, the way of walking. Although there is a wealth of gait studies in the literature aimed for medical use (1), none is concerned for the use of gait for biometrics within forensics.

Gait for Forensic Use

Early medical investigations conducted by Murray et al. (3) produced a standard gait pattern for normal walking people aimed at studying the gait patterns for pathologically abnormal patients. The experiments were performed on 60 people aged between 20 and 65 years old. Each subject was instructed to walk for a repeated number of trials. For the collection of gait data, special markers were attached on every subject. Murray et al. (3) suggested that gait is unique for every subject if all gait movements are considered. It was reported that the motion patterns of the pelvic and thorax regions are highly variable from one subject to another. Murray (4) observed that the ankle rotation, pelvic motion, and spatial displacements of the trunk embed the subject's individuality owing to their consistency at different trials. In one of the early experiments on gait recognition conducted by Kozlowski and Cutting (5) in 1978, it was demonstrated that people can recognize others just by gait cues. Interestingly, in one of Shakespeare's plays (The Tempest: Act 4, Scene 1), the following quote gives a clear indication that recognition by gait is not totally new:

> High'st Queen of state, Great Juno comes; I know her by her gait.

Identification systems will undoubtedly play a key role in aiding law enforcement officers in their forensic investigations. More important, by the early recognition of suspicious individuals who may pose security threats, the system would be able to reduce future crime. Gait recognition has the potential to overcome most of the limitations that other biometrics suffer from such as face, fingerprints, and iris recognition, which can be obscured in most situations where serious crimes are involved. Face recognition has in many cases been proven to be unreliable for visual surveillance systems; this is attributable to the fact that people can disguise or hide their faces as well as that the video data might be captured at too low resolution. Furthermore, another major drawback of face identification in security applications is the low recognition capability in poor illumination. This is because most of the facial features cannot be recovered at large distances even using night vision capability (6). Although fingerprint and iris recognition have proved to be robust for applications where authentication or verification are required, such biometrics are inapplicable for situations where the subject's consent and cooperation are impossible to obtain.

Recently Larsen and Simonsen (7) from the Institute of Forensic Medicine in Copenhagen, affirmed the usefulness of gait analysis in forensic investigations. They were able to identify a bank robber by matching surveillance footage from the crime scene against images of the suspect. This evidence was later used in conviction.

[1]School of Electronics and Computer Science, Building 1, University Road, University of Southampton, Southampton, U.K.
[2]Department of Applied Electronics, University Roma Tre, Rome, Italy.

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FIG. 1—*CCTV images for the robbery case used for gait analysis (8). The perpetrator shown on the left side while the suspect is recorded walking outside the police station (right).*

Based on body features, gait, and anthropometric measures, Lynnerup and Vedel (8) argued that there was a strong resemblance between the suspect and a perpetrator. Figure 1 shows the perpetrator, on the left, and the suspect walking outside the police station, on the right. Lynnerup and Vedel (8) pointed that the features that give a strong confidence in the match between the suspect and the perpetrator are the outward rotated feet and inverted left ankle during the stance phase of their walking cycle, as well as the results of photogrammetric analysis.

In a recent case in the U.K., a burglar was caught by police when his distinctive way of walking was analyzed and identified by a podiatrist (9). The police officers observed the gait of the perpetrator captured from closed-circuit television (CCTV) surveillance cameras, which shows similar gait pattern of a man pictured in CCTV shown in Fig. 2. Based on gait analysis and posture assessment, strong evidence was provided by the podiatrist to suggest there is a significant similarity between the perpetrator and the suspect. The gait-based analysis of the CCTV footages formed a significant part of the evidence against the defendant. It enabled the prosecution to use an important piece of evidence that would otherwise have had to be ignored owing to the poor quality of the imagery data. When faced with the evidence against him, the defendant pleaded guilty and received a 9-year custodial sentence.

Main Contributions

There is considerable evidence in psychology, medicine, literature, biomechanics, and other areas that people can be recognized by the way they walk (1). Given that the surveillance video recorded in crime scenes is noninvasive (often recorded with the subject not being aware of its use) and that perpetrators of crimes often conceal more conventional identifying factors, it then appears prudent to determine whether a subject's identity can be determined by their gait by analyzing surveillance video. Using surveillance video from an actual crime scene, we show how we can use gait to match individuals and show how the confidence in that assessment can be derived.

We first describe the technique we have developed to determine features in surveillance video. These features are the positions of vertices of the human leg, namely the hips, knees, and ankle. Then, we describe how vertex features can be used to match subjects in video footage recorded at different times, by using a technique of instantaneous posture matching. Then, by using automated approaches from gait biometrics, we derive measures that demonstrate the confidence in our match procedure. In this way, we can analyze video footage recorded at different times to determine the match of the subject. As this is the first work of its kind, we conclude by considering a number of factors that will aid refinement of this analysis, together with suggestions for consideration in the placement and settings of surveillance systems.

Method

Markerless Extraction of Gait Features

Despite the recent outstanding advances in computer vision and pattern recognition, there are still major challenges to be overcome for the realization of automated visual surveillance based on the analysis of human motion. Accurate and robust segmentation as well as the tracking of multiple moving features in an unconstrained, dynamic, and cluttered environment are only a few of the numerous difficult challenges. Moreover, people detection and moving object classification using a single uncalibrated surveillance camera are an intricate task. The difficulties stem from a number of factors related either to the environment such as illumination changes, shadows, and occlusion or to the nature of human being

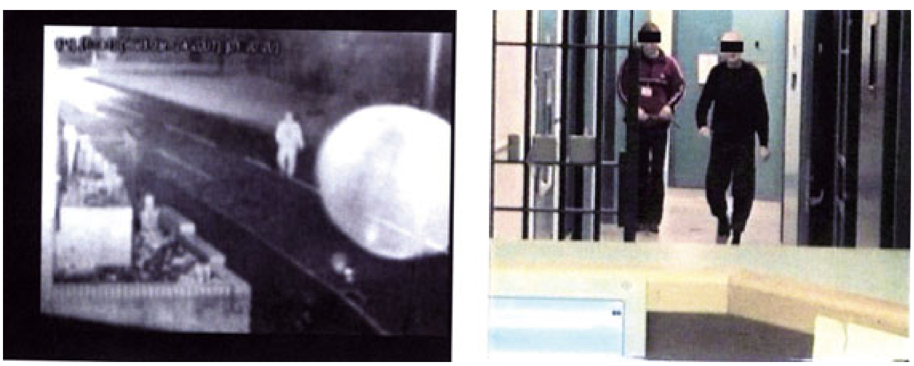


FIG. 2—*CCTV footage of the burglary case in the U.K. CCTV image of the robbery is shown on the left side while the right image is recorded in the police custody.*

such as self-occlusion, articulation, and appearance variation owing to the clothing type.

As there have been many vision approaches aimed to extract limbs, and a dearth of approaches specifically aimed to determine vertices, we propose a new method to extract human joints by incorporating kinematics, anthropometric gait data, and prior knowledge. The method is background independent and therefore is not prone to background clutter, shadow, and other outdoor factors. A Haar-based template matching method is devised to derive the joint positions for subjects recorded using a single uncalibrated camera. Haar-based (10) methods (which concern evaluating the result of convolving selected families of binary templates with image data) are known for their simple and robust performance in real-time applications for pedestrian detection based on superimposing simple rectangular templates. Gait kinematical as well as anthropometric knowledge is used to refine the accuracy for the extraction of the joint positions and limit the search space. The proposed solution has capability to extract moving joints of human body with high accuracy for indoor data as well as outdoor data filmed in an unconstrained environment.

For the markerless extraction of gait features, we derive motion models based on medical data that describe the angular motion of the knee and hip at different states of the gait cycle. A gait cycle is defined as the time interval between successive instances of initial foot-to-floor contact for the same foot (3). The hip initially bends or flexes by approximately 20° throughout the terminal stance phase, and then it extends until it reaches approximately −10°. During the preswing and throughout most of swing phase, the hip flexes to nearly 20° and then starts to extend just before the next initial contact. The knee angular motion illustrated in Fig. 3 shows the knee is almost fully extended then during the first part of the mid-stance, it gradually begins to flex to its support phase peak which is about 20°. The knee extends again almost fully and then flexes to approximately 40° during the preswing phase. After toe-off, the knee flexes to reach a peak of 60–70° (measured relative to the thigh) at mid-swing and then extends again in preparation for the next initial contact.

The proposed algorithm derives the motion map image based on change detection by inter-frame differencing. Moving pixels for a walking subject are detected so as to emphasize edge information. A sample motion image is shown in Fig. 4*a* for a walking subject recorded from a CCTV surveillance camera inside a busy airport. The template shown in Fig. 4*b* is based on the outline of the leg. The templates are superimposed against the motion map image at candidate points, and computing a match score that describes how well the transformed template is superimposed on the motion map.

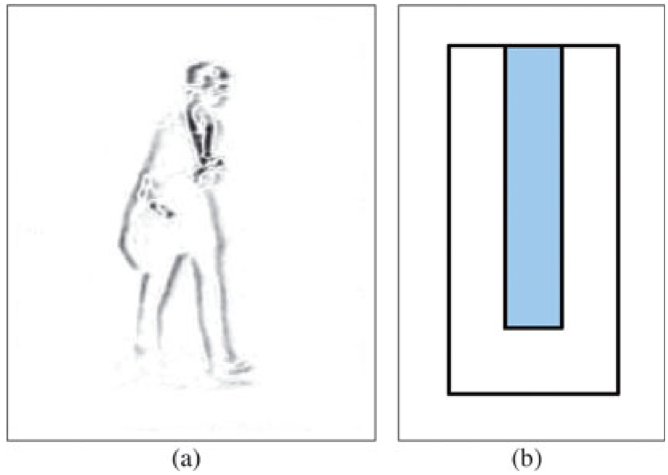


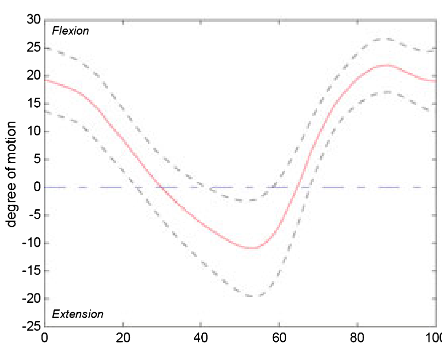
FIG. 4—*Markerless feature extraction. (a) Motion map image produced using frame differencing approach. (b) Haar template being used for the localization of the leg.*

To demonstrate the efficacy of the proposed markerless approach for extracting gait features for walking subjects, we have carried out a number of experiments on different scenarios including cases from real CCTV surveillance cameras. Figure 5 shows the markerless extraction results for a walking subject at Gatwick International Airport and the extracted vertices (hip, knees, and ankles) are highlighted in the image frames.

Instantaneous Posture Matching

The proposed method for gait analysis from video sequences acquired from CCTV cameras is based on instantaneous posture matching. Medical and psychological studies confirmed that the task of natural walking is executed in a different way for every person (1). Therefore, the limbs' position is unique in every instant of the movement, and the kinematic properties of the human body can be efficiently used for identity matching between different videos (11). Further, recent investigation by Lynnerup and Vedel (8) confirmed the usefulness of using anatomical and biomechanical knowledge to recognize other individuals for different types of court cases.

The instantaneous posture matching approach aims to estimate the mean limbs' distance between different video sequences wherein subjects are walking. The matching process is based on the anatomical proportion of the human body within a window of



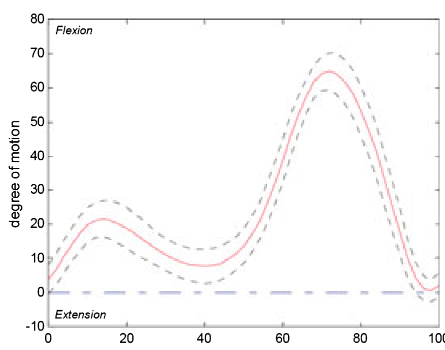


FIG. 3—*Gait angular motion. Hip (left), knee (right).*

FIG. 5—*Markerless feature extraction applied on the iLids data set recorded at Gatwick International Airport (U.K.).*

frames. We consider two different video sequences v_1 and v_2 recorded with the same frame rate. To compare the videos for identity-matching purposes, a set of reference frames from the first video are matched progressively against a window of frames from the other video sequence. Given the joint coordinates (x,y) for the hip x_{h1}, knee x_{k1}, and ankle x_{a1} (two of each are extracted for the left and right legs; both sides of the hips are extracted as we consider front-view video) of the human body of video v at frames/time t.

In order to define a position vector for the extracted joints for direct matching between subjects, we shift the extracted the joints to a new coordinate system whose origin point is set as the left ankle point. To alleviate the effects of different camera resolutions, the new shifted positions are normalized by the subject height. Therefore, a feature vector $P_v(t)$ of video v at frame t is defined as follows:

$$P_v(t) = \frac{\begin{bmatrix} x_{h1}(t)-x_{a1}(t) & x_{h2}(t)-x_{a1}(t) & x_{k1}(t)-x_{a1}(t) & x_{k2}(t)-x_{a1}(t) & x_{a2}(t)-x_{a1}(t) \\ y_{h1}(t)-y_{a1}(t) & y_{h2}(t)-y_{a1}(t) & y_{k1}(t)-y_{a1}(t) & y_{k2}(t)-y_{a1}(t) & y_{a2}(t)-y_{a1}(t) \end{bmatrix}}{L} \tag{1}$$

where L is the subject's height in pixels. The joint coordinates are referred to the image reference system, and it is assumed that the subjects in the v video sequences have the same walking direction without any loss of generality. The walking direction, in fact, can be easily extracted as the angle of inclination of the straight line, which approximates the heel-strike points (12).

The extraction of joint coordinates from the video sequences can be achieved with different approaches either manually or using the markerless approach described in the earlier section. After having extracted the normalized joints' position vector, the two subjects of different video sequences v_1 and v_2 are considered to have the same identity if the joints' distance D defined in Eq. 2 (as the mean distance of the Euclidian distances between the poses of subjects in different videos starting from frames t_1 and t_2, over a window of W consecutive frames) is less than a chosen factor:

$$D(v_1,v_2) = \min\{d(v_1,t_1,v_2,t_2) : 0 \le t_1 \le |v_1| - W, \\ 0 \le t_2 \le |v_2| - W\} \le \tau \tag{2}$$

where $|v_n|$ is the number of frames for video v_n and $d(v_1,t_1,v_2,t_2)$ is defined in Eq. (3) as:

$$d(v_1,t_1,v_2,t_2) = \left(\frac{\sum_{f=1}^{W} \| P_{v_1}(t_1+f) - P_{v_2}(t_2+f) \|}{W} \right) \tag{3}$$

The threshold value τ in Eq. (2) is chosen by analysis of intra- and inter-subject differences on a large gait database.

Crime Scene Description

In a recent case handled by the Metropolitan Police of London, a number of crimes included physical assaults and burglary against pedestrians walking on a short pathway near a subway in a London suburb. The same crime was reported to occur numerous times in the same fashion and at the same place. The police officers strongly suspected it was carried out by the same suspects, aged between 17 and 20 years old.

There were a number of CCTV cameras in operation at the crime scene. Two of them were used to view the entrances of the subway as shown in Fig. 6 bottom. Two other cameras record views of the walkway adjacent to the subway as shown in Fig. 6 top. The CCTV video data were captured at a frame rate of 25 frames per second with a resolution of 704 × 576 pixels.

FIG. 6—*Sample frame images from the crime scene CCTV cameras.*

The police provided us with a set of videos in order to deploy Gait Analysis to find further information that would assist them in their investigation. CCTV footage from all cameras for the crime scene at two different days was made available to the ISIS Research group at the University of Southampton. The police provided another video of a suspect being recorded while was being held in police custody. The video was recorded at a frame rate of 2 frames per second and a resolution of 720×576 pixels.

In one of the videos recorded on April 4, 2008, two members of the gang wore helmets to cover their faces and drove a scooter. A female pedestrian walked through the subway where they followed her from behind, on the walkway. When she entered the subway, one of them walked toward her and then snatched her bag violently using physical assault, even dragging her down on the ground. Afterward they left on the scooter. In CCTV footage recorded on the following day, the same crime was carried out with apparently similar perpetrators, again riding a scooter motorbike, and recorded snatching the bag of another woman.

The police managed to trace the suspects, partly using a helmet found near the scene of crime. Facial recognition could not be applied because of the low resolution of imagery data in addition to the fact that the perpetrators' faces were obscured. In fact, gait was the only available biometric data as the irises could not be seen, the fingerprints were concealed, and the subject's DNA was withheld. Such a challenging case is common for police authorities, suggesting a need to explore innovative technologies in their investigation as gait biometrics.

Results and Discussion

Evaluation of the Match Score

The instantaneous posture matching approach has been tested on real data using the CASIA-B gait database (13) provided the Chinese Academy of Science. The gait database consists of 3718 video sequences with 101 subjects walking along straight lines with six different camera orientations (36°, 54°, 72°, 90°, 108°, and 126°). The 90° view corresponds to the sagittal walking direction, as shown in Fig. 7. The video sequences have a spatial resolution and frame rate of 320×240 pixels and 25 frames per second, respectively, with an approximate subject height of 90 pixels. Subjects were instructed to walk in three different scenarios: normal walking, wearing a coat, and carrying a bag. Therefore, this allows for the analysis of the covariate factors that are common in surveillance scenarios.

The markerless gait extraction method described earlier is applied to automate the extraction of the joints positions for all of the sequences from the CASIA-B gait database. Figure 8 shows an example of the extraction results for subjects walking at different view angles and carrying a bag or not.

A total of 101 different subjects from the CASIA-B data set were studied, with an average of 35 video sequences for every subject. The automated markerless extraction of the joints includes the hip, knees, and ankles. In the performance test, we defined a data set of $n \in \{2, 3 \ldots, N = 101\}$ subjects. We compute the similarity scores $\bar{S}_n^{\mathrm{Intra}}$ and $\bar{S}_n^{\mathrm{Inter}}$ for all the match combinations of video sequences of the same subjects and different subjects, respectively. The $\bar{S}_n^{\mathrm{Intra}}$ and $\bar{S}_n^{\mathrm{Inter}}$ are computed as the mean values for the intra- and inter-match scores computed using the instantaneous posture matching approach defined, respectively, as:

$$\bar{S}_n^{\mathrm{Intra}} = \frac{\sum_{a=1}^{n} \left(\frac{\sum_{i=1}^{L_a} \sum_{j=i+1}^{L_a} D(v_i^a, v_j^a)}{\frac{L_a(L_a-1)}{2}} \right)}{n} \quad (4)$$

and

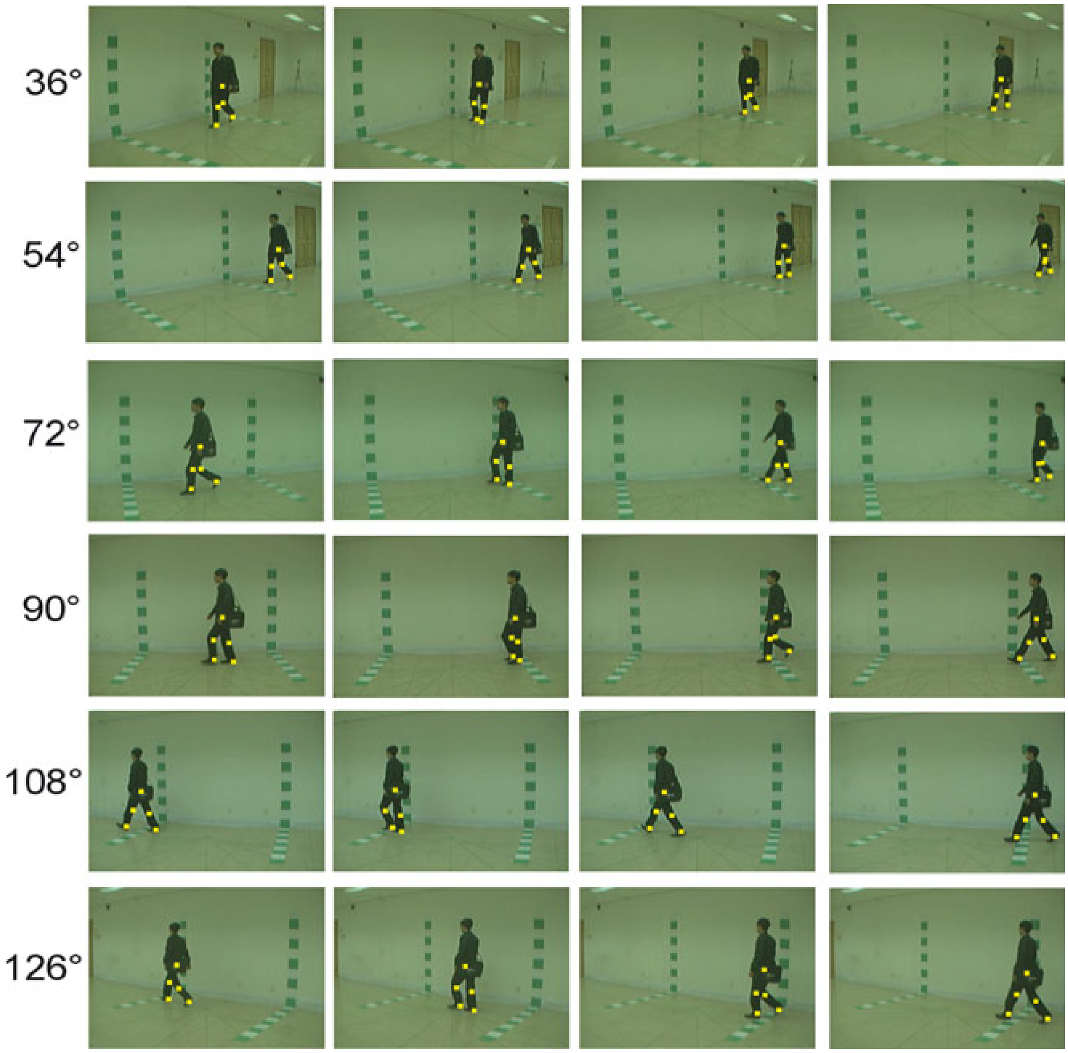


FIG. 7—*Markerless extraction of the joint positions for walking subjects applied on the CASIA-B data set with different viewpoints.*

$$\bar{S}_n^{\text{Inter}} = \frac{\sum_{a=1}^{n} \sum_{b=a+1}^{n} \left(\frac{\sum_{i=1}^{L_a} \sum_{j=1}^{L_b} D(v_i^a, v_j^b)}{L_a \times L_b} \right)}{n(n-1)} \quad (5)$$

where v_i^a is the ith video sequence of subject a. L_a is the number of video sequences belonging to subject a. D is the distance computed as defined in Eq. (2).

The general framework for performance analysis is outlined by starting with an initial data set of size $n = 2$ and then the database size was progressively increased by including more (different) subjects in the experimental test. The selection of new subjects into the data set is carried out at random. To avoid bias owing to which initial $n = 2$ subjects are selected, the similarity scores $\bar{S}_n^{\text{Intra}}$ and $\bar{S}_n^{\text{Inter}}$ are computed for 100 different initial data sets selected at random. The experimental results are shown in Fig. 8, which illustrates the observed relationship between the database size and the similarity match scores of the intra- and inter-classes ($\bar{S}_n^{\text{Intra}}$, $\bar{S}_n^{\text{Inter}}$) computed using the proposed instantaneous posture matching algorithm for the different 100 data sets taken at random.

The results show that when increasing the database size, the similarity scores tend to converge to fixed values that are well separated. This suggests that for larger population, gait analysis can be still deployed and the size of the database should not be a factor impacting on the analysis. The overlapping region shows the confusion between the similarity scores. A probability score $T(n)$ can be defined to provide a confidence measure that subjects are the same based on the size of the database n as defined in the following equation:

$$T_{variance}(n) = \frac{\sqrt{\sigma^2_{\bar{S}_n^{\text{Intra}}} + \sigma^2_{\bar{S}_n^{\text{Inter}}}}}{\left\| \bar{S}_n^{\text{Intra}} - \bar{S}_n^{\text{Inter}} \right\|} \quad (6)$$

Additionally, the receiver operating characteristic curves are plotted in Fig. 9 to express the verification results applied on the CASIA-B data set. In the verification process, subjects from the database are verified against other subjects to check whether their identities match. In order to plot the false acceptance rate versus the false rejection rate, different score thresholds are used for the instantaneous posture matching method. The system achieved equal error rates of 11.6% for the first experiments involving all the candidate subjects. The result is based on posture matching, and it is likely that fusing additional features in the identity signature would improve the observed error rate.

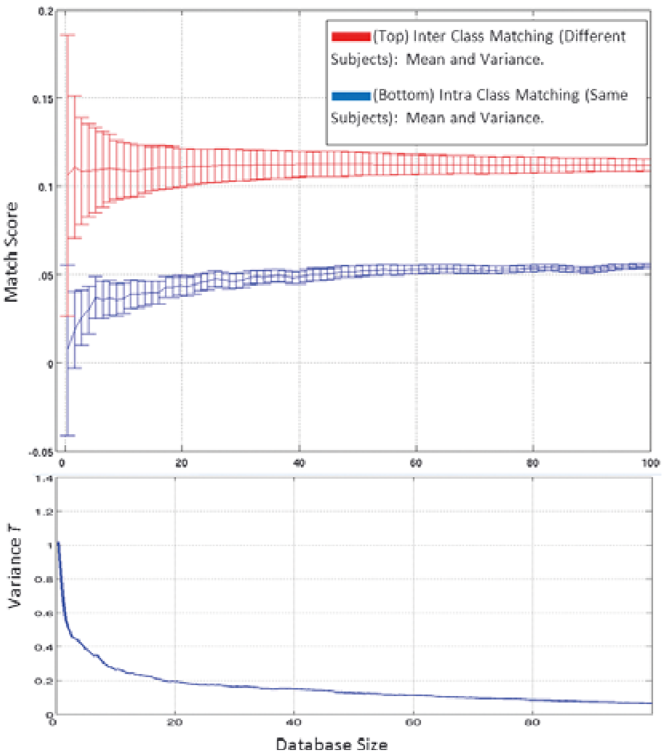


FIG. 8—*Relationship of instantaneous posture match versus the size of database. (Top) Plots of inter-class (nonmatching) and intra-class (matching) results with relation to the database size. (Bottom) Variance between the intra and inter matching results.*

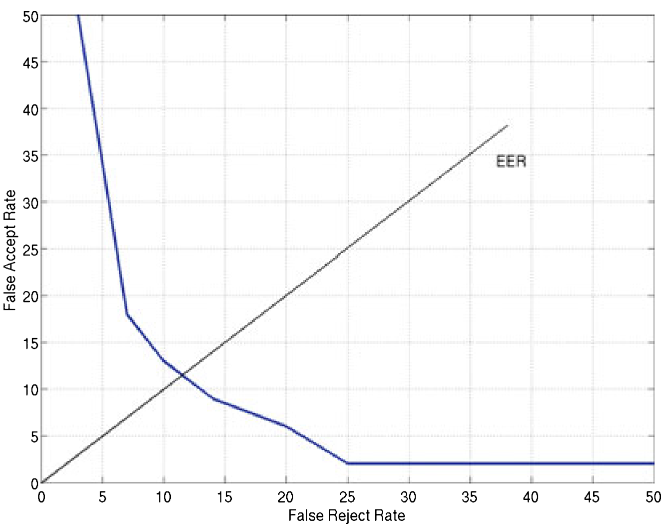


FIG. 9—*The receiver operating characteristics curve for identity matching applied on the CASIA-B data set.*

Matching Suspects in the Crime Scene

Two sets of video sequences recorded at different days were provided by the Metropolitan Police to analyze and provide a statement whether the perpetrators in both videos are the same people. The videos were sampled at the same rate of 25 frames per second. An additional video footage with low frame rate of 2 frames per second (for a suspect held in police custody) was provided for further analysis and to provide any cues that may link them to the perpetrators based on gait analysis. Because of the accuracy issue, gait labeling software is used to manually extract the joint positions of the perpetrators in both scene-of-crime videos. For every frame, we choose to manually label 10 joint positions from the human body including the head, shoulders, hips, knees, and ankles.

To apply to the instantaneous posture matching algorithm, videos captured from the CCTV pointing at the pathway are matched. Figure 10 shows the labeling of the suspects running after attacking the victim. It was found for a window size of $W = 1$ frame that the error rate is 2.5% between the two videos at frames 27 and 67. For an increased frame window size of 15 frames, the value d of the instantaneous posture matching decreased to 1.3%. This leads us to believe that perpetrators who carried out the assaults in the different videos sequences are the same person, with confidence based in the inter- and intra-subject variation described earlier.

It was not possible to compare the video footage of the suspect in custody with that of the crime scene owing to different frame rates between videos acquired at each site. Further, gait motion could not be captured from the custody data owing to its low frame rate.

Conclusions and Future Work

We have demonstrated how it is possible to determine the match between subjects recorded performing the same motion, in video footage recorded at different times. This match is achieved by instantaneous posture matching, which determines the difference between the positions of a set of human vertices. In order to determine the confidence in that matching procedure, we have deployed automated video analysis derived from biometrics. A new technique is described for automatic vertex location in surveillance imagery, and this technique is deployed to analyze human gait in a standard biometrics database. This technique allows for the automated analysis of the video images and thus allows us to determine how the match measure between different subjects varies as a function of database size. This analysis demonstrates that the match measure derived from the scene of crime footage is considerably smaller than the average match measure across the different subjects in the database. Further, the size of the database appears sufficient for this purpose, because the variance of the match measure decreases with increased size of the database and at the database size used here shows that within-class match is considerably different from the between-class match, thus assuring of confidence in our new match procedure.

As this is the first study that translates gait biometrics to forensic use, there are many factors arising from this research, which are worthy of future study. First, the procedure concerned video wherein the subjects were running along the same trajectory. Biometrics approaches have shown that people can be recognized by the way they walk or run. These two motions differ in that there is a double-float (where neither foot is in contact with the ground) in running which does not occur when walking. As such, there is a need for the assessment of the nature of the transition from walking to running (a transform that has previously demonstrated to be as unique as the walk or running style) and how this can be used to match between the two styles. Although many of the factors between different scenes can be normalized (by calibration or photogrammetry), it is well known that the perception of a subject's gait varies with change in direction of camera relative to the subject's path. There are now techniques that provide for viewpoint-invariant gait recognition and which have been used to track subjects across nonintersecting camera views, but which have yet to be translated for use in a surveillance environment. There are

FIG. 10—*Matching process between different videos.*

many approaches to determining a match between subjects, other than the use of vertex location. We believe that the use of vertex location is more favorable in forensic procedure because this can be more readily communicated to those without a technical background, but there are other approaches that might derive a better performance (14,15).

Clearly, video footage recording a side view of a subject (wherein the path of a subject is perpendicular to the camera view) is preferred to analyze gait in surveillance video by using vertex position. In contrast, many surveillance systems use installation and settings that are directed more to the analysis by human observers, rather than automated means. As such, surveillance cameras often use front-view imagery (in part because a greater volume of data recording a subject approaching a camera can be derived in this way). Further, time lapse imagery can be used to reduce the volume of stored video information. Accordingly, the requirements of automated analysis appear to differ from those of human analysis. In terms of biometrics, this motivates research in analysis of front-view imagery and of analysis that can predict movement between video frames, and these works have already started. Given that subjects can easily conceal identity in a socially acceptable manner, and in a way which does not give rise to suspicious behavior, it would appear prudent to consider not just the optimization of installation and operation of surveillance systems but also the refinement of automated measures to determine identity in surveillance video footage.

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Additional information—reprints not available from author:
Imed Bouchrika, Ph.D.
School of Electronics and Computer Science
Building 1, University Road
University of Southampton
Southampton
U.K.
E-mail: imed@imed.ws