Evidence Evaluation of Gait Biometrics for Forensic Investigation

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Abstract Due to the unprecedented growth of security cameras and impossibility of manpower to supervise them, the integration of biometric technologies into surveillance systems would be a critical factor for the automation of security and forensic analysis. The use of biometrics for people identification is considered as a vital tool during forensic investigation. Forensic biometrics concerns the use of biometric technologies to primarily determine whether the identity of the perpetrator recorded during the crime scene can be identified or exonerated via a matching process against a list of suspects. The suitability of gait recognition for forensic analysis emerges from the fact that gait can be perceived at distance from the camera even with poor resolution. The strength of gait recognition is its non-invasiveness nature and hence does not require the subject to cooperate with the acquisition system. This makes gait identification ideal for situations where direct contact with the perpetrator is not possible.

1 Introduction

Security has become a major concern in modern society. This is due to the proliferating number of crimes and terror attacks as well as the vital need to provide safer environment. Because of the rapid growth of security cameras and impossibility of manpower to supervise them, the integration of biometric technologies into surveillance systems would be a critical factor for the automation of security and forensic analysis. More importantly, by early recognition of suspicious individuals who may pose security threats via the use of biometrics, the system would be able to deter future crimes as it is a significant requirement to identify the perpetrator of a crime as soon as possible in order to prevent further offenses and to allow justice to be administered. Biometrics is concerned with deriving a descriptive measurement based on either the human behavioural or physiological characteristics which should distinguish a person uniquely among other people. Examples of physiological-based

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biometrics include face, ear, fingerprint and DNA whilst the behavioural features include gait, voice and signature. Apart from being unique, the biometric description should be universal and permanent. The universality condition implies that it can be taken from all the population meanwhile the permanentness signifies that biometric signature should stay the same over time. As opposed to traditional identification or verification methods such as passports, passwords or pin numbers, biometrics cannot be transferred, forgotten or stolen and should ideally be obtained non-intrusively. Biometrics can work either in verification or identification mode. For verification, the system performs a one-to-one match for the newly acquired person signature against a pre-recorded signature in the database to verify the claimed identity. For identification mode, a one-to-many matching process is conducted against all subjects already enrolled in the database to infer the subject identity. Biometrics is now emerging in regular use being deployed in various applications such immigration border control, forensic systems and payment authentication.

The use of biometrics for people identification is considered as a vital tool during forensic investigation. Forensic science can be defined as the method of gathering, analysing and interpreting past information related to criminal, civil or administrative law. This includes the perpetrator identity and the modus operandi [31]. Forensics involves several processes including: investigation, evaluation, forensic intelligence, automated surveillance and forensic identity management [40]. Forensic analysis is performed in order to conclude further evidence to exonerate the innocent and corroborate the identity of the perpetrator through producing a well-supported evidence. The term evidence spans to include physical evidence, scientific statement or expert witness testimony. Scientific statements are usually supported by hypothesis and experiments driven by statistical-based evidence and biometrics. Forensic biometrics is the scientific discipline that concerns the use of biometric technologies to primarily determine whether the identity of the perpetrator recorded during the crime scene can be identified or excluded via a matching process against a list of suspects.

Many biometric features can be used in forensic analysis such as face, ear [2], speech and gait [8]. However, the availability of biometric features for identification is limited to forensic experts depending on the nature of the crime scene and perpetrators. Expert witness is usually based on a body of knowledge or experience provided by an individual who is formally qualified and broadly experienced in a particular domain. There are considerable factors contributing to establish the credibility of an individual acting as an expert including educational qualifications and relevant experience. However, qualitative and descriptive-based expert opinions are argued to be insufficient and less credible [6, 18, 37] in contrast to empirical-based statements which are gaining wider acceptance.

The admissibility of forensic evidence is administered by the court juries or the legal system depending on the juridical framework of the country. In the United States, the Daubert standard was conceived in 1993 when the Supreme Court handed down the case of *Daubert v. Merrel Dow Pharmaceurticals, Inc*. The court insisted on the need for reliability into rule 702 of the *Federal Rules of Evidence* which governs the admission of scientific evidence [17]. The Daubert standard requires to show that the proffered science has been tested based on a sound methodology and whether it is published and peer-reviewed taking also into account that the technique has received general acceptance in the relevant scientific community. The Daubert standard has replaced Frye as the practiced *gate-keeping* standard, causing a paradigm shift in the way expert witness testimony is rigorously analysed and as a result, lowering the threshold for cutting-edge science and raising it for preceding expertise lacking scientific foundation [39]. Within the United Kingdom, the *Forensic Science on Trial* report [13] highlights known concerns for the admissibility of scientific evidence. In response, the Law Commission of England and Wales provisionally proposed a new statutory test in 2009 which determines the admissibility of expert evidence via a set of guidelines and stronger legislation, preventing unreliable expert opinion to be admitted in a court of law [13]. The recommendations build on the US Daubert standard, providing the judge with support to apply scientific scrutiny and an obligation to the party tendering expert evidence to demonstrate its reliability. Unfortunately, as of 2015, none of these recommendations have yet been acted on.

For the history of biometrics, people have been identifying each other based on face, voice, appearance or gait for thousands of years. However, the first systematic and scientific basis for people identification dates back to 1858 when William Herschel recorded the handprint of each employee on the back of a contract whilst working for the civil service of India [5]. This was used as a way to distinguish employees from each other on payday. It was considered the first systematic capture of hand and fingerprints that was used primarily for identification purposes. For the use of forensic biometrics, Alphonse Bertillon who was a French police officer was the pioneer to employ the first biometric evidence into the judicial system presented as anthropometric measurements of the human body to counter against repeat offenders who could easily fake or change their names. He introduced the bertillonage system such that each person is identified through detailed records taken from their body anthropometric measurements and physical descriptions as they are impossible to spoof or change them. The system was adopted by the police authorities throughout the world. In 1903, the Bertillon system was challenged on the basis that anthropometric measurements are not adequate to differentiate reliably between people. This was fuelled by the case of identical twins who have almost the same measurements using the Bertillon system. In 1890s, Sir Francis Galton and Edward Henry described separately a classification system for people identification based on the person fingerprints taken from all ten fingers [2]. The characteristics that Galton described to recognize people are still used today. The Galton system was adopted by New York state prison where fingerprints were employed for the identification of apprehended inmates. Biometric systems are sold mainly for the following purposes: physical access control, logging attendance and personal identification [25].

The suitability of gait recognition for forensic analysis emerges from the fact that gait can be perceived at distance from the camera even with poor resolution as opposed to other biometric traits where their performance deteriorates severely.

Furthermore, the strength of gait recognition is its non-invasiveness nature and hence does not require the subject to cooperate with the acquisition system. This makes gait identification ideal for situations where direct contact with the perpetrator is not possible. Furthermore, as the purpose of any reliable biometric system is to be robust enough to reduce the possibility of signature forgery and spoofing attacks, the gait signature which is based on human motion is the only likely identification that can be taken in covert surveillance. Thus, gait analysis is more suited to forensic investigations as other biometric-based traits that could link to the presence in a crime scene can be obliterated and concealed as opposed to the gait pattern where the mobility of the perpetrator is a must as they have to walk or run to escape from the scene. In a recent empirical study conducted by Lucas and Henneberg [29], they argued that a combination of eight body measurements is sufficient to achieving a probability of finding a duplicate to the order of 10^{-20} comparing such findings to fingerprints analysis. Interestingly, in one of the high profile murder cases in the UK where a child was abducted and killed, the identity of the murderer could not be revealed directly from the surveillance video footage. The only inspiring solution that could be employed to determine the suspect's identity in this situation was gait recognition as proposed by researchers from the University of Southampton [33]. Gait analysis which is a well-established science in clinical and laboratory settings is becoming common as evidence in criminal trials with the advent of forensic podiatry which is concerned to examine foot-related evidence [16]. The notion that people can be recognized by the way they walk has gained an increasing popularity and produced impacts on public policy and forensic practice by its take up by researchers at the Serious Organized Crime Agency after its invention at Southampton in 1994 [33].

2 Gait Biometrics

Gait is defined as the manner of locomotion characterised by consecutive periods of loading and unloading the limbs. Gait includes running, walking and hopping. However the term gait is most frequently used to describe the walking pattern. The rhythmic pattern of human gait is performed in a repeatable and characteristic way [45] consisting for consecutive cycles. A gait cycle is defined as the time interval between successive instances of initial foot-to-floor contact for the same foot [14], and the way a human walks is marked by the movement of each leg such that each leg possesses two distinct phases. When the foot is in contact with the floor the leg is at the *stance phase*. The time when the foot is off the floor to the next step is defined as the *swing phase*. Each phase is marked by a start and an end; the stance phase begins with the *heel strike* of one foot when the leg strikes the ground. The locomotion process involves the interaction of many body systems working together to yield the most efficient walking pattern. The locomotion system consists of four main subtasks that are fulfilled at the same time to produce the walking pattern [46]. These four functions are: (i) initiation and termination of locomotor movements (ii) the generation of continuous movement to progress toward a destination (iii) adaptability to meet any changes in the environment or other concurrent tasks (iv) maintenance of the equilibrium during progression. Compared with quadrupeds, the maintenance of stability and balance for humans during walking is a particularly difficult task for the postural control system. This is mainly because for most of the gait cycle, the human body is supported by only a single leg with the centre of mass passing outside the base of support provided by the foot in contact with the floor.

Early medical investigations conducted by Murray [32] in 1964 produced a standard gait pattern for normal walking people aimed at studying the gait pattern for pathologically abnormal patients. The experiments were performed on sixty 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 [32] suggested that human gait consists of 24 different components which render the gait pattern unique for every person 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. Furthermore, Murray observed that the ankle rotation, pelvic motion and spatial displacements of the trunk embed the subject individuality due to their consistency at different trials. In 1977, Cutting et al. [15] published a paper confirming the possibility of recognizing people by gait via observing moving lights mounted on the joints positions. Although, there is a wealth of gait studies in the literature aimed for medical use with a few referring to the discriminatory nature of the gait pattern, none is concerned with the automated use of gait for biometrics and recognizing people. The gait measurements and results introduced by Murray are to be of benefit for the development of automated gait biometric systems. However, the extraction of the gait pattern is proven complex using computer vision methods.

An automated vision-based system for people identification via the way they walk, is designed to extract gait features without the need to use markers or special sensors to aid the extraction process. In fact, all that is required is an ordinary video camera linked to a special vision-based software. Marker-less motion capture systems are suited for applications where mounting sensors or markers on the subject is not an option as the case of forensic analysis. Typically, gait biometric system consists of two main components: (i) a hardware platform dedicated for data acquisition. This can be a single CCTV camera or distributed network of cameras. (ii) a software platform for data processing and recognition. The architecture of the software side for gait biometric system is composed broadly of three main components: (i) detection and tracking of the subject, (ii) feature extraction and (iii) classification stage. Figure 1 shows the flow diagram for gait identification outlining the different subsystems involved in the process of an automated people recognition.

- *Subject Detection and Tracking*: a walking subject is initially detected within a sequence of frames using either simple background subtraction techniques or other methods such as the Histogram of Oriented Gradients. Subsequently, intra-camera tracking is performed to establish the correspondence of the same person across consecutive frames. Tracking methods are supported by simple low-level features

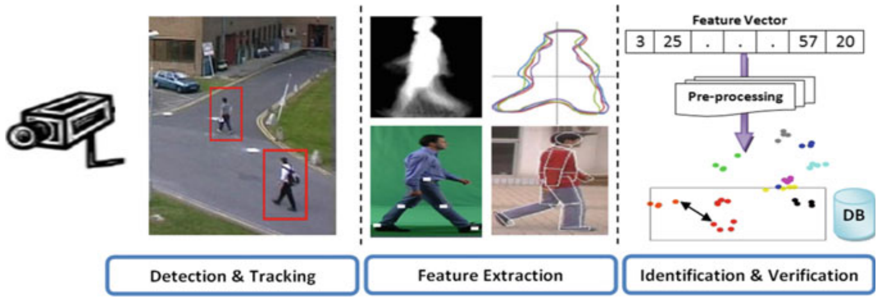

Fig. 1 Overview of gait biometric system

such as blob size, speed and color in addition to the use of prediction algorithms to estimate the parameters of moving objects in the next frame. This is based on motion models which describe how parameters change over time. The most popular predictive method used for tracking is the Kalman filter [44], the Condensation algorithm [22], and the mean shift tracker [12].

- *Feature Extraction*: this is the most important stage for automated marker-less capture systems whether for gait recognition, activity classification or other imaging application. This is because the crucial data required for the classification phase are derived at this stage. Feature extraction is the process of estimating a set of measurements either related to the configuration of the whole body or the configuration of the different body parts in a given scene and tracking them over a sequence of frames. The features should bear certain degree of the individuality of the subject. High-level features estimated at this level for gait recognition can be categorized into two types: static and dynamic features. Examples of static features include the subject height and other anthropometric measurements meanwhile dynamic or kinematic features are such joints angular measurements and displacement of the body trunk.
- *Identification or Verification Phase*: it is mainly a classification process which involves matching a test sequence with an unknown label against a group of labelled references considered as the gallery dataset. At this stage, a high-level description is produced from the features extracted at previous phases to infer or confirm the subject identity. The classification process is normally preceded by pre-processing stages such as data normalisation, feature selection and dimensionality reduction of the feature space through the use of statistical methods. A variety of pattern recognition methods are employed in vision-based systems for gait recognition, including Neural Networks, Support Vector Machines (SVM) and K-Nearest Neighbour classifier (KNN). The latter is the most popular method for classification due to its simplicity and fast computation.

2.1 Gait Datasets

As gait biometrics has gained an increasing interest in surveillance and forensic cases, the establishment of gait databases becomes vital for the evaluation and assessment of research theories and systems proposed for gait analysis, automated markerless extraction and gait recognition. There were two early gait databases which are the UCSD and Southampton datasets. The first database was collected by the Visual Computing Group at the University of California San Diego containing 6 people in the database filmed in outdoor environment. The Southampton database is recorded at indoor laboratory and consists of 16 video sequences for 4 subjects wearing special trousers [33]. Subsequently, several gait databases were developed primarily for the HumanID at a Distance research program [35] funded by the Defence Advanced Research Projects Agency (DARPA). The program was aimed to improve technologies for facial and gait recognition as well as new technologies for people identification. The HumanID project included the following research institutions: University of Southampton, University of Maryland, Georgia Institute of Technology and Massachusetts Institute of Technology. Within this program, the University of Southampton released publicly the largest dataset for over 100 people containing over 20,000 video sequences accounting for different conditions as footwear, clothing and walking speed. Recently, the Chinese Academy of Sciences released the CASIA Gait Database for gait recognition and analysis which is itself composed of three datasets. The Institute of Scientific and Industrial Research (ISIR) at Osaka

Table 1 Human Gait Databases

Database Name	Subjects	Sequences	Environment	Description
Covariate SOTON	12	12,730	Indoor	Footwear, clothing, walking speed, viewpoint and carrying
CASIA Database A	20	240	Outdoor	4 Viewpoints
MIT AI Database	24	194	Indoor	Viewpoint, Time
Georgia Tech	20	188	Outdoor	Viewpoint, Speed
CMU Mobo DB	25	600	Indoor, Treadmill	Walking speed, viewpoint, surface and carrying conditions
Large SOTON	118	10,442	Indoor, Outdoor, Treadmill	Viewpoint
Gait Challenge	122	1,870	Outdoor	Viewpoint, surface, footwear, time and carrying conditions
CASIA Database B	124	13,640	Indoor	11 Viewpoints, clothing, carrying condition
CASIA Database C	153	1,530	Outdoor, Thermal	Speed, carrying condition
TUM-GAID DB	305	3,370	Indoor	Carrying, clothing, time
OU-ISIR Large Population	4,016	7,860	Indoor	Viewpoint

University constructed the OU-ISIR Gait Database to aid research studies related to developing, testing and evaluating algorithms for gait-based human recognition. Table 1 surveys the different gait databases made publicly available to the research community.

2.2 Gait Recognition Methods

Much of the interest in the field of human gait analysis was limited to physical therapy, orthopedics and rehabilitation practitioners for the diagnosis and treatment of patients with walking abnormalities. As gait has recently emerged as an attractive biometric, gait analysis has become a challenging computer vision problem. Many research studies have aimed to develop a system capable of overcoming the difficulties imposed by the extraction and tracking of biometric gait features. Various methods were surveyed in [33, 47]. Based on the procedure for extracting gait features, gait recognition methods can be divided into two main categories which are model-based and appearance-based (model-free) approaches.

2.2.1 Model-Based Approaches

For the model-based approach, a prior model is established to match real images to this predefined model, and thereby extracting the corresponding gait features once the best match is obtained. Usually, each frame containing a walking subject is fitted to a prior temporal or spatial model to explicitly extract gait features such as stride distance, angular measurements, joints trajectories or anthropometric measurements. Although model-based approaches tend to be complex requiring high computational cost, these approaches are the most popular for human motion analysis due to their advantages [47]. The main strength of model-based techniques is the ability to extract detailed and accurate gait motion data with better handling of occlusion, self-occlusion and other appearance factors as scaling and rotation. The model can be either a 2 or 3-dimensional structural model, motion model or a combined model. The structural model describes the topology of the human body parts as head, torso, hip, knee and ankle by measurements such as the length, width and positions. This model can be made up of primitive shapes based on matching against low-level features as edges. The stick and volumetric models are the most commonly used structural-based methods.

Akita [1] proposed a model consisting of six segments comprising of two arms, two legs, the torso and the head. Guo et al. [19] represented the human body structure by a stick figure model which had ten articulated sticks connected with six joints. Rohr [38] proposed a volumetric model for the analysis of human motion using 14 elliptical cylinders to model the human body. Karaulova et al. [26] used the stick figure to build a hierarchical model of human dynamics represented using Hidden Markov Models. For the deployment of structural model-based methods for gait recognition, Niyogi and Adelson [34] was perhaps the pioneer in 1994 to use a model-based method for gait recognition. Gait signature is derived from the spatio-temporal pattern of a walking subject using a five stick model. Using a database of 26 sequences containing 5 different subjects, a promising classification rate of 80 % was achieved.

The motion model describes the kinematics or dynamics of the body or its different parts throughout time. Motion models employ a number of constraints that aid the extraction process as the maximum range of the swinging for the low limbs. Cunado et al. [14] was the first to introduce motion model using the Velocity Hough Transform to extract the hip angular motion via modelling human gait as a moving pendulum. The gait signature is derived as the phase-weighted magnitudes of the Fourier components. A recognition rate of 90 % was achieved using the derived signature on a database containing 10 subjects. Yam et al. [48] modeled the human gait as a dynamic coupled oscillator which was used to extract the hip and knee angular motion via evidence gathering. The method was evaluated on a database of 20 walking and running subjects, achieving a recognition rate of 91 % based on gait signature derived from the Fourier analysis of the angular motion. Wagg and Nixon [42] proposed a new model-based method for gait recognition based on the biomechanical analysis of walking subjects. Mean model templates are adopted to fit individual subjects. Both the anatomical knowledge of human body and hierarchy of shapes are used to reduce the computational costs. The gait feature vector is weighted using statistical analysis methods to measure the discriminatory potency of each feature. On the evaluation of this method, a correct classification rate of 95 % is achieved on a large database of 2,163 video sequences of 115 different subjects. Bouchrika et al. [7, 9] proposed a motion-based model for the extraction of the joints via the use a parametric representation of the elliptic Fourier descriptors describing the spatial displacements. As most of the model-based are exploiting 2D images, there are recent work aimed for introducing 3-dimensional model for the extraction of gait features including the work of Ariyanto and Nixon [3] (Fig. 2).

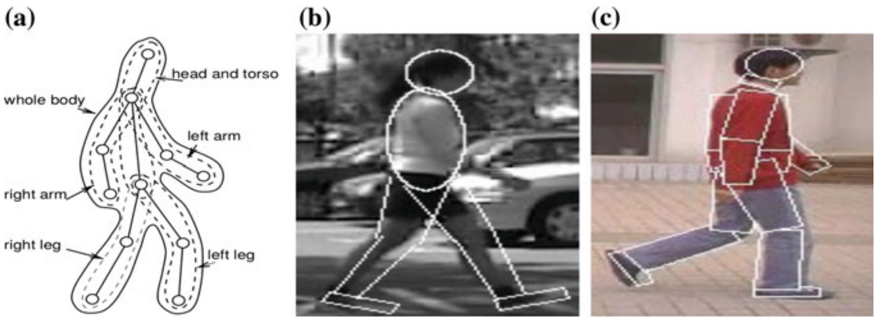

Fig. 2 Model-based approaches for gait feature extraction: **a** Karaulova et al. [26]. **b** Wagg and Nixon [42]. **c** Wang et al. [43]

2.2.2 Appearance-Based Approaches

Appearance-based or model-free approaches for gait recognition do not need a prior knowledge about the gait model. Instead, features are extracted from the whole body without the need to explicitly extract the body parts. The majority of appearance approaches depends on data derived from silhouettes which are obtained via background subtraction. The simplest method is called the Gait Energy Image (GEI) introduced by Han and Bhanu [20] in which gait signature is constructed through taking the average of silhouettes for one complete gait cycle. Experimental results confirmed that higher recognition rates can be attained to reach 94.24 % for a dataset of 3,141 subjects [24]. However, such method performs poorly when changing the appearance. Gait Entropy Image (GenI) is a silhouette-based representation introduced by Bashir et al. [4] which is computed by calculating the Shannon entropy for each pixel achieving a correct classification rate of 99.1 % on dataset of 116 subjects. The Shannon entropy estimates the uncertainty value associated with a random variable. Other similar representations include Motion Energy Image, Motion Silhouette Image, Gait History Image and Chrono-Gait Image. Hayfron-Acquah et al. [21] introduced a method for constructing a gait signature based on analysing the symmetry

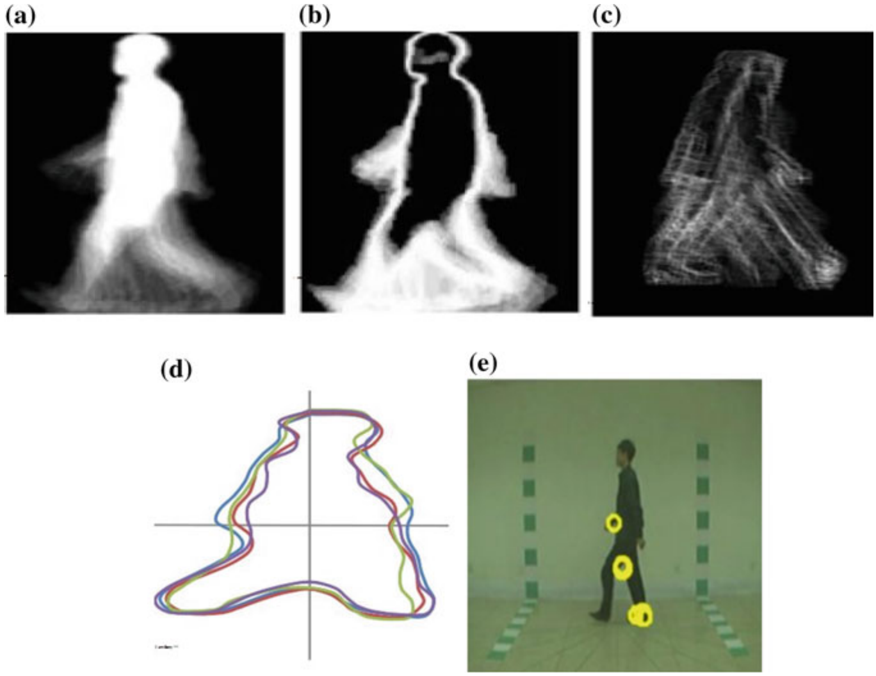

Fig. 3 Appearance-based methods for gait recognition: **a** Use gait energy image [20]. **b** Gait entropy image [4]. **c** Symmerty map [21]. **d** Procruste shape analysis [11]. **e** STIP descriptors

of human motion. The symmetry map is produced via applying the Sobel operator on the gait silhouettes followed by the Generalised Symmetry Operator (Fig. 3).

As the accuracy of silhouette-based methods depends on the background segmentation algorithm which is not reliable for the case of real surveillance footage in addition to the sensitivity issue to varied appearances, a number of appearance-based methods have emerged recently that use instead interest-point descriptors. Kusakunniran [27] proposed a framework to construct gait signature without the need to extract silhouettes. Features are extracted in both spatial and temporal domains using Space-Time Interest Points (STIPs) by considering large variations along both spatial and temporal directions at a local level. Appearance-based Method relies pivotally on statistical methods to reduce or optimize the dimensionality of feature space using methods such as Principal Component Analysis. In addition, advanced machine learning methods are usually applied as multi-class support vector machine and neural networks. Contentiously, recent investigations by Veres et al. [41] reported that most of the discriminative features for appearance-based approaches are extracted from static components of the top part of the human body whilst the dynamic components generated from the swinging of the legs are ignored as the least important information.

3 Gait Analysis for Forensics

Forensic gait analysis has been recently applied in investigations at numerous criminal cases as law enforcement officers have no option to identify the perpetrator using well-established methods as facial recognition or fingerprints. This is partly due to the fact that key biometric features such as the perpetrator's face can be obscured or veiled and the CCTV footage is deemed unusable for direct recognition whilst the perpetrators are usually filmed at a distance walking or running away from the crime scene. Gait experienced specialists are consulted to assist with the identification process of an unknown person by their walking pattern through a qualitative or quantitative matching process. This would involve examining the unique and distinctive gait and posture features of an individual. Subsequently, a statement is written expressing an opinion or experimental results that can be used in a court of law. Meanwhile, the practice of forensic podiatry involves examining the human footprint, footwear and also the gait pattern using clinical podiatric knowledge [16]. However, gait analysis performed by a podiatrist involves the recognition and comparison of nominal and some ordinal data without quantitative analysis using numerical forms of data [16]. Because of the rising profile of gait biometrics and forensic podiatry, gait is used numerously as a form of evidence in criminal prosecutions with the inauguration of the American Society of Forensic Podiatry in 2003. Recently, Iwama et al. [23] developed a software with a graphical user interface in order to assist non-specialists to match video sequences based on gait analysis. For the methods used for forensic gait analysis, we can classify them into two major categories which are: *Descriptive-based* or *Metric-Based* approaches.

3.1 Descriptive-Based Methods

For descriptive-based methods, forensic gait specialists observe visually the gait pattern looking for abnormalities, irregularities or clues that can be exploited to confirm a match or mismatch. Abnormalities can include legs inversion, swinging range and flexion during stance. Larsen et al. [28] proposed a checklist for conducting gait analysis involving a number of semantic questions related to the gait pattern and posture of the individual that can be used to conclude the possibility of identification of the perpetrator by their walk. The checklist criteria include questions such as long or short steps, stiff or relaxed gait, outward or inverted feet rotation and forward or backward learning of the upper body. There were a number of concerns and critics for the admissibility of descriptive methods into criminal investigations as they are considered unreliable partly due to the fact that images are open to different interpretation by the forensic experts analysing them [6]. Biber [6], Porter [37] and Edmond et al. [18] argued that there are technical and contextual factors that can visually distort the relationship between the image and the actual object it represents. Furthermore, Vernon highlighted that cautions are required with descriptive-based evaluation [16] as subjectivity can be prone to errors.

An incident of a bank robbery in 2004 was handled by the Unit of Forensic Anthropology at the University of Copenhagen [30]. The police observed that the perpetrator has a special gait pattern with a need to consult gait practitioners to assist with the investigation. The police were instructed to have a covert recording of the suspect walking pattern within the same angle as the surveillance recordings for consistent comparison. The gait analysis revealed that there are several matches between the perpetrator and the suspect as an outward rotated feed and inverted left ankle during the stance phase. Further posture analysis using photogrammetry showed that there is a resemblance between the two recordings including a restless stance and anteriour head positioning. There were some incongruities observed during the analysis including wider stance and the trunk is slightly leaned forward with an elevated shoulders. This is suspected to be related by the anxiety when committing a crime [28]. Based on the conducted analysis, a statement was given to the police regarding the identity however such methods are argued that they do not constitute the same level of confidence as well-established methods such as fingerprints. The findings were subsequently presented in court and the suspect was convicted of robbery whilst the court stressed that gait analysis is a valuable tool [28]. In a similar case handled by the Unit of Forensic Anthropology, a bank robbery was committed by two masked people wearing white clothing. The bank was equipped with several cameras capturing most of the indoor area. One of the camera showed one of the perpetrator walking rapidly from the entrance. The frame rate was low which

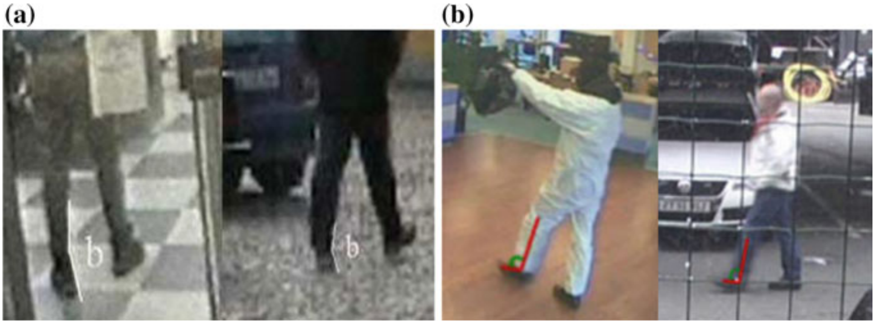

Fig. 4 Forensic gait cases for bank robbery [28, 49]: **a** 2004. **b** 2012

left only few useful images showing the perpetrator gait. Based on experimental results showing the most discriminatory potency for the joints angles, Yang et al. [49] argued about the possibility of identification based on certain instances of the gait cycle using the observed angular swinging of the legs. Figure 4 shows the two discussed cases of the bank robberies handled by the forensic unit.

3.2 Metric-Based Methods

For this approach, a score value or a probability is produced based on a quantitative matching process of extracted measurements related to the human body parts or dynamics of the gait pattern. The extraction is done either manually or automatically through the use of vision-based marker-less methods. In forensics, it is desirable to use measurable characteristics for which matching probabilities can be estimated as it is more reliable for identification and evidence admissibility to be considered [29]. The Cumulative Match Score (CMS) is a useful measure for biometric systems which was introduced by Phillips et al. in the FERET protocol [36] for the evaluation of face recognition algorithm. The measure assesses the ranking capabilities of the recognition system by producing a list of scores that indicates the probabilities that the correct classification for a given test sample is within the top n matched class labels. The Receiver Operating Characteristics (ROC) plot is more suited for forensic analysis which expresses the verification result based on a decision threshold to confirm the claimed identity of an individual against a probe sample. The threshold which is usually experimentally defined through matching all sample pairs in a larger gallery dataset refers to the separation of the genuine score distributions from the imposter values. The following three metrics are produced for ROC analysis:

1. *False Acceptance Rate (FAR)* which is the rate of samples erroneously accepted by the system as a true match.
2. *False Reject Rate (FRR)* refers to the percentage for cases when an individual is not matched to their genuine identity.

3. *Equal Error Rate (ERR)* is the value where the two metrics FAR and FRR are equal. Biometric systems with lower ERR values are considered to be more accurate and reliable.

In a recent case handled by the Metropolitan Police of London [8], a number of crimes include physical assaults and burglary against pedestrians walking on a short pathway near a subway in one of the 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 members of an organized gang of youngsters aged between 17 and 20 years old. There are a number of CCTV cameras in operation at the crime scene. Two of them are pointing towards the entrances of the subway as shown in Fig. 5. Two other cameras are set to record both views of the walking pass next the subway as shown in Fig. 5. The police provided 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 Image Processing Research group at the University of Southampton. The police provided another video of a suspect member of the gang being recorded whilst was being held at the 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 that was recorded on 4th April 2008, two members of the gang wore helmets to cover their faces and drove a scooter motorbike. A female pedestrian came walking through the subway where they followed her from behind on the walking path. When she entered the subway, one of them walked and snatched her bag violently using physical assault and even dragging her down on the ground. Afterwards they left away on a scooter. In a different CCTV footage recorded on the following day, the same crime was carried out with apparently the same looking perpetrators riding a scooter motorbike seen snatching a bag of another woman. The police managed to trace the suspects, partly using a helmet found near the crime scene. Facial recognition cannot be applied in such cases due the low-resolution of imagery data in addition to the fact that the perpetrators where hiding their faces

Fig. 5 Sample frames from the crime scene CCTV cameras, 2008

completely. Such a challenging case is common for police authorities suggesting a need to explore innovative technologies in their investigation as gait biometrics.

The proposed method for gait analysis from video sequences acquired from CCTV cameras is based on Instantaneous Posture Matching (IPM). Medical and psychological studies confirmed that the task of natural walking is executed in a different way from every person [15, 32]. 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. Further, recent investigation by Larsen et al. [28, 30, 49] 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 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 since 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 normalised by the subject height. Therefore, a feature vector $P_v(t)$ of video v at frame t is defined as:

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

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 [7]. The extraction of joint coordinates from the video sequences can be achieved with different approaches either manually or using the marker-less approach. After having extracted the normalised 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:

$$d(v_1, t_1, v_2, t_2) = \left(\frac{\sum_{f=1}^{W} \parallel P_{v1}(t_1 + f) - P_{v2}(t_2 + f) \parallel}{W} \right) \tag{3}$$

The threshold value τ in Eq. (2) is chosen by analysis of intra- and inter-subject differences on a large gait database. f refers to the frame number. A statement was written to the police based on the achieved value of D confirming that the perpetrators on the processed videos are the same person. Other evidence gathered by the police was consistent with gait-based reported results. In fact, 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 [33]. Moreover, it is well known that the perception of a subject's gait varies with change in direction of camera relative to the subjects path. There are now techniques that provide for viewpoint-invariant gait recognition and which have been used to track subjects across nonintersecting camera views.

4 Evidence Evaluation and Challenges

Evaluation of biometric-based evidence in forensic investigation plays a pivotal role for its admissibility in court. This is because legal cases would involve serious punishment or recurrent further crimes on the basis of the produced evidence. The state of biometric-based forensics is still considered nascent rather than established. Saks et al. [39] argued that descriptive-based or observational methods for identification are being increasingly challenged in court as they can be subjective in addition to the recent development of metric-based evidence governed by statistical and empirical methods. Conversely, Saks [39] reported that 63 % of 86 DNA exoneration cases were due to testing errors recommending that the lack of reported error rates must be addressed through blind testing and external proficiency analysis. Champod et al. [10] described a uniform framework based on the Bayesian theorem that attempts to quantify the evidence with a likelihood-Ratio (LR). Within the *LR* approach, biometric technologies are used to assess statistically the evidential value for a biometric signature associated to a reference sample. The *LR* is defined as given in Eq. (4):

$$LR = \frac{Pr(E|S, I)}{Pr(E|\overline{S}, I)} \tag{4}$$

Such that E is the evidence value measured as the similarity score. S is the hypothesis supported by the prosecution asserting the perpetrator identity as the suspect. $\overline{S}$ is the defense proposition that biometric features correspond to another individual. I indicates relevant background information about the case [10].

In forensic biometrics, one of the key issues is what are the chances that another individual has the same biometric measurements. In other words, evidence can be challenged around the certainty that there exist no other people having the same signatures as the perpetrator at any one given time. As we are limited to screen the entire population, the certainty of finding a possible duplicate is supported using statistical probabilities based on research performed on relatively smaller datasets. For gait forensic analysis, a dataset of 101 subjects are taken from the CASIA-B dataset with an average of 35 video sequences for every subject. Automated marker-less extraction is applied to obtain the joints positions including the hip, knees and ankles. In the performance test, we defined a dataset of incremental size $n \in \{2, 3, 4...N = 101\}$ subjects. We compute the similarity scores S_n^{Intra} and S_n^{Inter} for all the match combinations of video sequences of the same subjects and different subjects. The S_n^{Intra} and S_n^{Inter} are computed as the mean values for the intra- and inter-match scores computed using the Instantaneous Posture Matching approach defined earlier as expressed in Eqs. (5) and (6):

$$S_n^{Intra} = \sum_{a=1}^{n} \frac{\sum_{i=1}^{L_a} \sum_{j=i+1}^{L_a} D(v_i^a, v_j^a)}{\frac{L_a(L_a-1)}{2}} \Big/ n \tag{5}$$

and

$$S_n^{Inter} = \sum_{a=1}^{n} \sum_{b=a+1}^{n} \frac{\sum_{i=1}^{L_a} \sum_{j=i+1}^{L_a} D(v_i^a, v_j^a)}{L_a \times L_b} \Big/ n(n-1) \tag{6}$$

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 dataset of size $n = 2$ and then the database size is progressively increased by including more (different) subjects in the experimental test. The selection of new subjects into the dataset is done at random. To avoid bias when selecting subjects, the similarity scores S_n^{Intra} and S_n^{Inter} are computed as the average for up to 100 different initial datasets selected at random. The experimental results are shown in Fig. 6 which illustrates the observed relationship between the database size and the similarity match scores of the intra- and inter-classes computed using the proposed Instantaneous Posture Matching algorithm for the different 100 subsets 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.

Compared to other well-established and widely used biometrics in forensic science as fingerprints and DNA, gait analysis is reported to be influenced by a number of external covariate factors that can affect the gait pattern and therefore undermine evidence credibility. Factors can be related to the appearance of the subject as clothing, footwear or psychological factors as anxiety state and medical conditions in

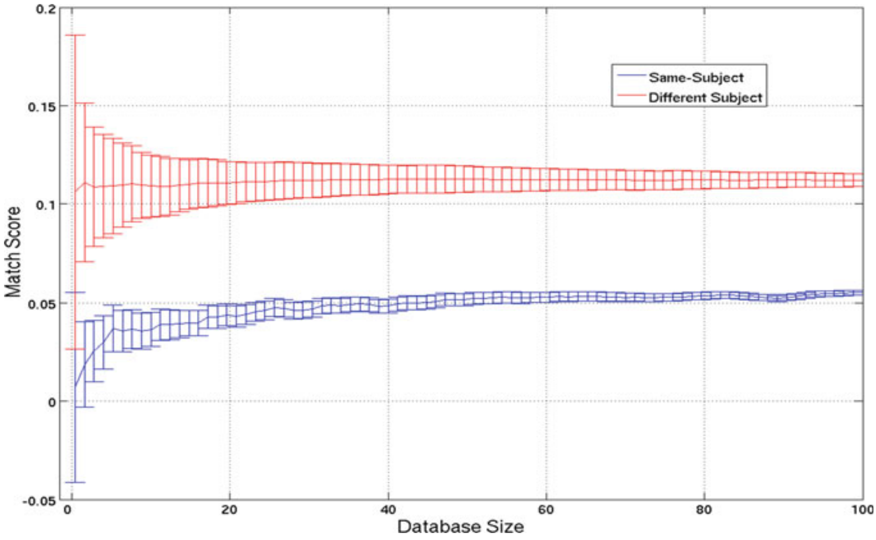

Fig. 6 Sample frames from the crime scene CCTV cameras, 2008

addition to the acquisition environment as viewpoint and illumination. A number of studies emerged recently addressing such issues with promising identification rates of gait recognition under several covariate factors.

5 Conclusions

The notion that people can be recognized by the way they walk has gained an increasing popularity and produced impacts on public policy and forensic practice by its take up by researchers at the Serious Organized Crime Agency with numerous forensic cases where gait is used as a form of evidence in successful criminal prosecutions. This chapter outlines the different methods used for the automated extraction of gait features and recognition. We discuss the deployment of gait analysis into forensic investigation with detailed study of both descriptive and metric-based approaches. The chapter finally examines the evaluation of biometric-based evidence in forensics due to its pivotal role for the admissibility in criminal proceedings.

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