ON USE OF BIOMETRICS IN FORENSICS: GAIT AND EAR

Mark S. Nixon, Imed Bouchrika, Banafshe Arbab-Zavar and John N. Carter

School of Electronics and Computer Science, University of Southampton
Southampton, SO17 1BJ, UK
tel: +44 (0) 2380593542, fax: +44 (0) 2380594498, [msn,ib04r,baz05r,jnc]@ecs.soton.ac.uk
web: http://www.isis.ecs.soton.ac.uk

ABSTRACT

We describe how gait and ear biometrics could be deployed for use in forensic identification. Biometrics has advanced considerably in recent years, largely by increase in computational power. This has been accompanied by developments in, and proliferation of, surveillance technology. To prevent identification, subjects use evasion, disguise or concealment. The human gait is a candidate for identification since other mechanisms can be completely concealed and only the gait might be perceivable. The advantage of use a human ear is its permanence with increase in age. As such, not only are biometrics ripe for deployment for forensic use, but also ears and gait offer distinct advantages over other biometric modalities.

1. BIOMETRICS AND FORENSIC DEVELOPMENT

The time is now ripe for biometrics to be employed for forensic investigations. Recognition techniques have matured considerably, and there is growing knowledge about covariate structure: not only on its influence on recognition capabilities, but also in ways to mitigate its effects. This paper will concentrate primarily on gait and on ear biometrics, and their potential for forensic use. These biometrics are a smaller research field than more established biometrics like face and finger, but are directly amenable to forensic use. Gait has already been used successfully in a number of criminal convictions. This has largely used photogrammetry or podiatry, and this paper will discuss how gait biometrics were used in a recent UK case. The ear has a more chequered use in forensics where it has been deployed for cadaver recognition (via the ear lobe) and in cases where an earprint was recovered from the scene. There is now re-emergent interest in earprints, and - as we shall describe - biometrics approaches may enable this approach to be better realised in forensic use.

In the chronology of identification technologies, in 1858 Herschel used a palm print on a contract document (and was later to study fingerprints). In his seminal works in the 1880s Bertillon considered anthropometry and identification and his studies included iris, face, and ear. Especially in the UK, Galton achieved some excellent work on fingerprints in 1888 And later in 1899 Henry was to achieve fingerprint classification. Fingerprints came to dominate identification at the expense of Bertillonage, especially after the West vs West case concerning a pair of suspects who could not be disambiguated by Bertillon's methods. There was then quite some delay in new techniques until 1951 when Crick and Watson discovered DNA, and as a means of identification also required developments in faster sequencing. In 1964 Iannarelli described a new method of ear identification and in 1987 Flom and Safir pioneered iris classification.

	Biometric Modalities	Technology; architecture	Deployment area	Database size
1960-	Finger, Voice	Manual	Forensic	
1970-	Palm, Face	Dec VAX; 7400	University dining	<100
1980-	Iris, Signature	PDP 11; TTL	Buildings	1000
1990-	Vein, *Gait*, *Ear*, Keystroke	<386; PAL	Buildings	100000
2000-	DNA, EEG, Dental, Shoe	Pentium/ mult-thread; FPGA	Immigration, laptops	10^7
2010-	!	Cloud computing	Health, forensics, media	$6*10^9$?

Table 1: Development of Biometric Modalities

As shown in Table 1, all of these identification approaches are candidates for biometric study. Daugman's work on iris followed directly Flom and Safir's work, though ear biometrics were to follow Iannarelli's work much later. Fingerprints were an early candidate for biometric study and largely followed the requirement for automated analysis which led to the AFIS system. The developments are largely due to the march of technology: in the 1960s on simple computing devices were available, with little storage, whereas now computers are much faster and with abundant storage. Some of the earliest approaches were studied on small databases only, whereas contemporaneous databases are considerably larger

Surveillance technology is now ubiquitous in modern society. This is due to the increasing number of crimes as well as the vital need to provide a safer environment. Because of the rapid growth of security cameras and difficulty of manpower to supervise them, the deployment of non-invasive biometric technologies becomes important for the development of automated visual surveillance systems as well as forensic investigations. Further, criminals are now habituated to surveillance deployment and are ready to use evasion or concealment – even disguise, to prevent identification. An example is shown in Figure (1) (and many more are available on the web) where the suspect is wearing a peaked cap, sunglasses and gloves. All of these conceal identity. However his ear can clearly be seen, albeit at very low resolution, and his gait is likely to be manifest in the recording as he had to walk in and most probably ran out. Note that each of the measures used to prevent identification is socially acceptable.

Recently, the use of gait for people identification in surveillance applications has attracted researchers from the

Figure 1: An example of disguise in armed robbery.

computer vision community [25]. The suitability of gait recognition for surveillance systems emerges from the fact that gait can be perceived from a distance as well as its non-invasive nature. Currently, as most biometric systems are largely still in their infancy [17], the use of biometric technologies is limited to identity verification and authentication. Gait is an emergent biometric which is increasingly attracting the interests of researchers as well as the industry. Gait is defined as the manner of locomotion, i.e. the way of walking. Although, there is a wealth of gait studies in the literature aimed for medical and biometric use [25], none is concerned for the use of gait for identification within forensics.

Ear biometrics have yet to have any forensic deployment, though a major advantage of ears is that they age gracefully, unlike the human face or gait. There has been some forensic use of earprints, though this has been contested [18]. The ear lobe is actually part of the disaster identification system. As such, it would appear possible to match suspects after some time has passed, such as in war crimes cases, or when there is considerable natural disguise, such as the excessive growth of human hair.

2. GAIT AND EAR BIOMETRICS

2.1 Gait Biometrics

2.1.1 Approaches to Recognising People by Gait

Gait biometrics, which concerns recognizing individuals by the way they walk, is a particularly challenging research area. The potential for personal identification is supported by a rich literature, including medical and psychological studies [25, 17]. The completely unobtrusiveness without any subject cooperation or contact for data acquisition make gait particularly attractive for identification purposes. Gait recognition techniques at the state of the art can be divided into 3D and 2D approaches [25]. In the first group, identification relies on parameters extracted from the 3D limb movement. These methods use a large number of digital cameras and the 3D reconstruction is achieved after a camera calibration process. On the other hand, the 2D gait biometric approaches extract explicit features describing gait by means of human body models [10] or silhouette shape [13]. A rich variety of data has been collected for evaluation of 2D gait biometrics. The widely used and compared databases on gait recognition include: the HumanID Gait Challenge [27]; CASIA; and the University of Southampton [28] data. The majority of methods and databases found in the literature use a single camera positioned with a specific view of the subject's walking direction (generally capturing the walk from the lateral view) and a large number of papers describing gait recognition have been published.

In surveillance scenarios, we need a system that operates in an unconstrained environment where maybe there is no information regarding the camera [11] and where the subject walks freely. Recently we have developed approaches which can recognise subjects walking in intersecting camera views, by using our new approach which uses viewpoint invariant recognition. A novel reconstruction method has been employed to rectify and normalize gait features derived from different viewpoints into the side-view plane and therefore exploit such data for recognition. Initial evaluation of the method shows that a recognition rate of 73.6% is still achievable with an experiment carried out on a large gait data set with over 2000 video sequences consisting of different viewpoints.

Additionally, further experiments applied on CCTV footage has shown the potential of using gait to track people identities across different non-intersecting un-calibrated camera views based on gait analysis. This is an important step in translating gait biometrics into single view scenarios where calibration information cannot be recovered such as in surveillance and forensic applications.

2.1.2 On Gait in Forensics

Gait recognition has contributed to evidence for convictions in criminal cases like the case of the murderer of Swedish Foreign Minister Anna Lindh, a bank robber in Noerager (Denmark) and a burglar in Lancashire (United Kingdom) [5]. Lynnerup et al [21] affirmed the usefulness of gait analysis in forensics. They were able to identify the two bank robbers by matching surveillance images with images of the suspects.

In a recent case in the United Kingdom, a burglar was caught by police when his distinctive way of walking was analysed and identified by a podiatrist. The police officers observed the gait of the perpetrators captured from CCTV surveillance cameras, which shows similar gait pattern of a man pictured in CCTV shown in Figure (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. Gait-based analysis enabled the prosecution to use an important piece of evidence that would otherwise have had to be ignored due to the poor quality of the imagery data.

Figure 2: CCTV Footage of the burglary case in the United Kingdom. CCTV image of the robbery is shown on the left side whilst the right image was recorded in police custody.

We anticipate that video data wherein gait is likely to be of interest for recognition will be low quality and low resolution, of the form shown in Figure (3). For forensics, we have developed an approach which matches subjects on different occasions, with confidence assessed by analysis on a subject database. The approach aims to estimate the mean limbs' distance between different video sequences where subjects are walking by labelling joint positions. The matching process is based on the anatomical proportion of the human body within a window of frames.

Figure 3: Matching a walking subject with manually labelled features on different occasions.

Because we need to assess how such measure can scale up over a large population and quantify the confidence in the marching process, an automated marker-less gait extraction method [11] is being applied on a database with over 3000 video sequences having 100 different subjects.

Given a sample $S_{i,h}$ for the i^{th} subject of the h^{th} sample with a set of n point coordinates $S_{i,h} = (f_{i,h,1}, f_{i,h,2}, , , , f_{i,h,n})$, we compute the matching distance D for all the match combinations of video sequences for the same subjects as well as different subjects as:

$$D(S_{i,h}, S_{j,e}) = \frac{\sum_{s=1}^{N} (f_{i,h,s} - f_{j,e,s})^2}{N} \quad (1)$$

The similarity scores G_v^{intra} and G_v^{inter} for all the match combinations of video sequences of the same subjects and different subjects respectively. The G_v^{intra} and G_v^{inter} are the computed as the mean values for the intra- and inter-matching distance D computed for a dataset with v subjects. The scores are computed based on different experiments where the database size v is being increased gradually by adding more subjects. The experimental results are shown in Figure (4) which illustrates the observed relationship between the database size and the similarity match scores of the intra and inter classes computed using the proposed matching algorithm for the different 100 datasets being 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 to impact the analysis. The overlapping region shows the confusion between the similarities scores. A probability score T_v can be defined to provide a confidence measure that subjects are the same based on the size of the database v as defined in the following equation:

$$T_v = \frac{\sqrt{(\sigma^2_{G_v^{intra}} + \sigma^2_{G_v^{inter}})}}{\|G_v^{inter} - G_v^{intra}\|} \quad (2)$$

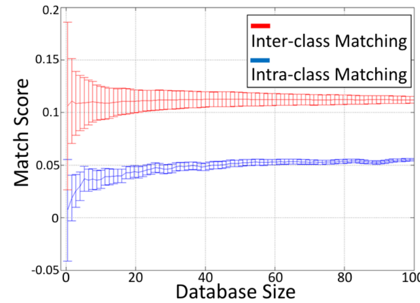


Figure 4: Analysis of intra (same subjects) and inter (different subjects) similarity scores for gait posture matching with respect to database size.

2.2 Ear Biometrics

2.2.1 Approaches to Recognising People by Ear

Most ear biometric approaches have exploited the ear's planar shape in 2D images. One of the first ear biometric works utilizing machine vision was introduced by Burge and Burger [6]. They modelled each individual ear with an adjacency graph which was calculated from a Voronoi diagram of the ear curves. However they did not provide an analysis of biometric potential. Hurley et al. [15] used force field feature extraction to map the ear to an energy field which highlights 'potential wells' and 'potential channels' as features. Achieving a recognition rate of 99.2% on a dataset of 252 images, this method proved to yield a much better performance than PCA when the images were poorly registered. The geometrical properties of ear curves have also been used for recognition [9, 16]. The most prominent example of these and arguably the first ear biometric method, proposed by Iannarelli [16], was based on measurements between a number of landmark points, determined manually. These methods are primarily reliant on accurate segmentation and positioning of the landmarks. Naseem et al. [24] have proposed the use of sparse representation, following its successful application in face recognition. The 3D structure of the ear has also been exploited, and good results have been obtained [30, 8]. Yan et al. [30] captured 3D ear images using a range scanner and having segmented the ear, they used Iterative Closest Point (ICP) registration for recognition to achieve a 97.8% recognition rate on a database of 415 individuals. Chen et al. [8] proposed a 3D ear detection and recognition system using a model ear for detection, and using a local surface descriptor and ICP for recognition. Though using 3D can improve the performance, using 2D images is consistent with deployment in surveillance or other planar image scenarios. In related studies Akkermans et al. [2] developed an ear biometric system based on the acoustic properties of the outer and middle ear. This introduces a unique opportunity for ear biometrics to combine the image-based information with acoustic data. A survey of ear biometrics has been recently provided by Hurley et al. [14].

2.2.2 On Ears in Forensics

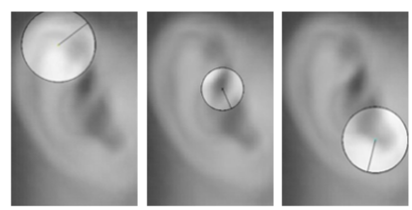
There has been some use of earprints in forensics, though there is certainly some debate. Earprints, which may be found in up to 15% of crime scenes [26], are latent prints left behind as a result of the ear touching a surface, for example while listening at a door. In Washington State in 1997 David Wayne Kunze was convicted of murder and was sentenced to life imprisonment on the basis of two expert witnesses testifying that a latent ear print found on a bedroom door could only have been made by Kunze. The murder conviction was subsequently appealed and the appeal court ruled [18] that the trial court erred by allowing the expert witnesses to testify that Kunze was the likely or probable maker of the latent print. A point of interest is that one of the two expert witnesses was a veteran Dutch ear print police officer who has pioneered ear print evidence in Holland where more than 250 ear print convictions are secured annually [20]. In response to the US appeals court ruling, a large scale study involving 10,000 subjects has been proposed to determine the variability of the ear across the population [23]. It is worth noting that this is earprint recognition, and that is largely why the evidence could be contested, but our biometrics approaches concern ear images only. Also note that the debate on the reliability of earprints is largely due to the effect of pressure deformation, which does not affect image-based biometric deployment. Hoogstrate et al. [12] have investigated whether forensically trained persons can identify individuals by ear from surveillance camera film, and presented positive results.

Among the various parts of the pinna, the ear lobe is more often used in forensic cases. The shape of the lobe can vary from well-formed to attached. Whether the lobe is attached or not is an international standard for identification in Disaster Victim Identification (DVI)[29]. Ear piercing, which often occurs on the lobe, is also a useful attribute for forensic identification [1]. However, the lobe seems to be the only part of the ear which continues to grow and change shape as the person grows older. Meijerman [22] looked at the lengthening of the auricle as the person ages and noted that the lobe appears to make up most of the increase. Thus this part of the ear does not offer a reliable attribute when samples with a considerable time lapse are compared.

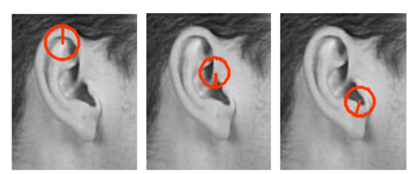
We anticipate that we are more likely to need capability to handle images of the form in Figure (5), rather than those of Figure (1). The resolution of Figure (1) is simply too low for any form of analysis. Perhaps this situation will increase as more digital cameras are deployed. However, it is still quite easy to conceal the human ear, such as by using a scarf. Clearly, if the ear is fully covered no analysis is possible. However, as it often happens with the cases where the subject is not actively interacting with the recognition system, the ear images might be partially occluded. It is more likely that the images will be of the form in Figure 5, or those derived when the human head is viewed in profile as a subject passes through a gateway.

Figure 5: A subject after a long period of concealment, and his ear structure.

As such we anticipate that a point-based approach appears the most suited to development. The advantages of a point-model include robustness in noise and occlusion. It also has a potential advantage in viewpoint invariance. Furthermore the model's explicit approach discards additional irrelevant elements, such as earrings, which are not part of the ear structure. We have therefore developed a model-based analysis of ear biometrics [4, 3]. Our model is a constellation of various ear components, which are learned using a stochastic clustering method and a training set of ear images. Further, the biological information of the morphology of the ear is used to guide and extend the choice of the model. The initial model parts are detected using the Scale Invariant Feature Transform (SIFT) [19]. The clusters of SIFT keypoints constitute the model parts [4]. We extend our model description, by a wavelet-based analysis with a specific aim of capturing information in the ear's outer structures [3]. In recognition, these parts are detected on every ear image; only the corresponding parts are then compared. Our model-based method obtains promising results recognizing occluded ears. Figure (6) shows three model parts detected on an ear image. Similar analysis to that which is shown in Figure (4) for gait samples, considering the effects of database size on recognition, was carried out for an 189-image database of ears and is shown in Figure (7). Bustard et al. [7] have recently developed a 3D model for the ear. This can be used in conjunction with the above point-model to handle the changes in viewpoint while the point-model gives robustness to occlusion [4, 3], to obtain a method more fit to handle images of the form in Figure 5.



(a) Model parts



(b) Detected parts

Figure 6: Three parts of our ear model and the same parts detected on an ear image

3. DISCUSSION

In this paper we have taken steps to translate gait and ear biometric analysis for a potential use in forensics. We have presented point-model based approaches to gait and ear recognition. These methods appear suitable for the task of forensic identification, since they have a proven capability in handling low quality samples, which is typical of surveillance type capturing, and occlusion. The point-model provides a basis for comparison between image samples, where the Euclidean distance between the corresponding points are computed and the mean distance represents the level of similarity between the samples. The advantage of automated identification of-

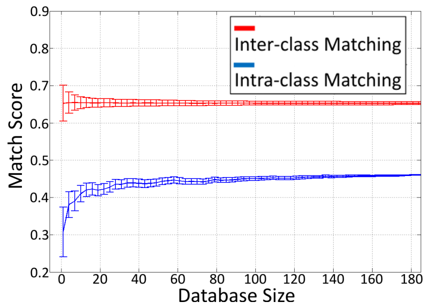


Figure 7: Intra (same subjects) and inter (different subjects) match scores for ear recognition with respect to dataset size.

fered by biometric methods is apparent when large databases are to be analyzed. We have also shown that our automatic marker-less gait and ear analysis are capable of handling the increase in the size of the database and the measure of biometric potential converges for the large datasets. This is an important step and a good start for translating gait and ear biometrics into real forensic scenarios.

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