Usefulness of Ear ang Gait Biometrics in forensics science

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ABSTRACT

Gait analysis is the systematic study of animal locomotion, more specific as a study of human motion, using the eye and the brain of observers, augmented by instrumentation for measuring body movements, body mechanics, and the activity of the muscles.[1] Gait analysis is used to assess, plan, and treat individuals with conditions affecting their ability to walk. It is also commonly used in sports biomechanics to help athletes run more efficiently and to identify posture-related or movement-related problems in people with injuries.

The study encompasses quantification, i.e. introduction and analysis of measurable parameters of gaits, as well as interpretation, i.e. drawing various conclusions about the animal (health, age, size, weight, speed, etc.) from its gait.

On a planet hosting 6.7 billion human beings, having proof you're unique is of tantamount importance. The ear, it turns out, may be the best identification yet. the outer ear may prove to be one of the most accurate and least intrusive ways to identify people.

I 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. Integrating Biometrics and Forensics for the Digital Age

Descriptions are provided by the Actions directly via e-COST.
"Forensics is the application of a broad spectrum of sciences to answer questions of interest to a legal system. This may be in relation to a crime or a civil action" . Since many such questions boil down to identifying, or verifying the identity, of people allegedly involved in some action, a clear relationship exists between forensics and biometrics. Biometrics developed a number of techniques which can clearly facilitate the identification of people involved in criminal actions or civil incidents. Thus, although the two communities have traditionally often operated in relative isolation, there are many scenarios where the synergic cooperation of multimodal biometrics and forensics can be successfully applied. To address such multifaceted areas it is important to develop an interdisciplinary network with complementary competences, to foster the birth of a new community which can develop novel technological solutions to crucial issues and new challenges in forensic science.

The Action will promote new partnerships, will provide education and training, will contribute to develop new standards and best practices, will produce awareness of the potential benefits of advanced technologies for evidence analysis in forensic cases and will stimulate improved mutual understanding of collaborative working models linking the academic and industrial sectors.

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 con-victions. This has largely used photogrammetric or podiatry, and this paper will discuss how gait biometrics Ire 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 ear print was recovered from the scene. There is now re-emergent interest in ear prints, and - as I shall describe - biometrics approaches may enable this approach to be better realized in forensic use.

In 1964 Iannarelli described a new method of ear identification and in 1987

	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*1o^9?

Table 1: Development of Biometric Modalities

Flom and Safir pioneered iris classification.

As shown in Table 1,. Surveillance technology is now ubiquitous in modern society. This is due to the increasing number of crimes as Ill 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 I b) 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. The suitability of gait recognition for surveillance systems emerge 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, 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 Ill 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 , 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 ear prints, though this has been contested . 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.

1. GAIT AND EAR BIOMETRICS

1.1 Gait Biometrics

Gait analysis is the systematic study of animal locomotion, more specific as a study of human motion, using the eye and the brain of observers, augmented by instrumentation for measuring body movements, body mechanics, and the activity of the muscles. Gait analysis is used to assess, plan, and treat individuals with conditions affecting their ability to walk. It is also commonly used in sports biomechanics to help athletes run more efficiently and to identify posture-related or movement-related problems in people with injuries. The study encompasses quantification, i.e. introduction and analysis of measurable parameters of gaits, as well as interpretation, i.e. drawing various conclusions about the animal (health, age, size, weight, speed, etc.) from its gait.

1.1.1 Approaches to Recognizing 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. 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 . 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 or silhouette shape . 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 Human ID Gait Challenge; CASIA; and the University of Southampton 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, I need a system that operates in an unconstrained environment where maybe there is no information regarding the camera and where the subject walks freely. Recently I have developed approaches which can recognize 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.

1.1.2 Gait in Forensics

Gait recognition has contributed to evidence for convictions in criminal cases like the case of the murderer of Sidish Foreign Minister Anna Lindh, a bank robber in Noerager (Denmark) and a burglar in Lancashire (United Kingdom)

Lynnerup affirmed the usefulness of gait analysis in forensics. They Ire 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 analyzed 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.

I 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, I 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 labeling joint positions. The matching process is based on the anatomical proportion of the human body within a window of frames.

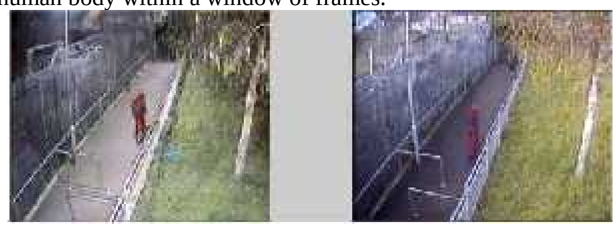

Figure 3: Matching a walking subject with manually labelled features on different occasions.

Because I 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 is being applied on a database with over 3000 video sequences having 100 different subjects.

Given a sample ***Si,h*** for the i^{th} subject of the k^{th} sample with a set of n point coordinates ***Si,h*** = (f,h,1, ***fi,h,***2***, , , , fi,h,n),*** I compute the matching distance D for all the match combinations of video sequences for the same subjects as Ill as different subjects as:

D(Si,h,Sj,e) = ∑(fi,h,s – fj.e,s)^2/N

The similarity scores Gv^{tra} and Gf^{ter} for all the match combinations of video sequences of the same subjects and different subjects respectively. The Gf^{tra} and $G^{i}v^{ter}$ 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 betIen 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 Ill 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 Tv 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:

$$\frac{\sqrt{(\sigma^{2}_{\ldots} + \sigma^{2}_{\ldots})}}{\|Gf^{er} - Gf^{ra}\|}$$

2.2 Ear Biometrics

On a planet hosting 6.7 billion human beings, having proof you're unique is of tantamount importance. The ear, it turns out, may be the best identification yet.

Through a new shape-finding algorithm called "image ray transform," which boasts 99.6 percent accuracy, according to a study presented at the IEEE Fourth International Conference on Biometrics Sept. 29, the outer ear may prove to be one of the most accurate and least intrusive ways to identify people.

Fingerprint databases of U.S. government agencies alone store the records of more than 100 million people, but prints can rub off or callous over during hard or repetitive labor. With the advent of computer vision, researchers and identification industries are seeking easier and more robust biometrics to get their hands on.

"When you're born your ear is fully formed. The lobe descends a little, but overall it stays the same. It's a great way to identify people," said Mark Nixon, a computer scientist at the University of Southampton. and leader of the research.

"There's real power in using the appearance of an ear for computer recognition, compared to facial recognition. It's roughly equivalent if not better," said computer scientist Kevin Bowyer of Notre Dame, who is pursuing his own ear-recognition technology and not involved with Nixon's work. "If you've got a profile image for someone, this is a great way to use it."

Recent technologies use computer vision to convert human features, such as faces and irises, even the gait of a person's walk, into reliable alternatives to fingerprints. Nixon and his team have pursued using ears as one biometric for years, and through what he called a "blue-sky research effort," his colleagues created the highly capable image-ray-transform algorithm.

The technology can identify an ear time after time with 99.6 percent accuracy. It works by unleashing a ray-producing algorithm on an image to seek out curved features. When a ray finds one, the software draws over the part and repeats the analysis. In a few hundred or thousand cycles, it cleanly paints the ear more than any other face structure.

"The rays fly around the image and get caught in tubular things. The helix, or outer edge, of an ear is a wonderful tube that rays keep hitting," said Alastair Cummings, the Southampton University computer scientist who developed the algorithm. "There are dozens of ways of doing ear biometrics, but this is a very good one."

From there, another program turns the curves into a unique set of numbers, something that could be used as an ear-based ID.

Nixon and Cummings acknowledged some limitations of the system, including hair covering the ears, less-than-ideal lighting conditions, and different IDs generated from different angles. And using the ear as a biometric isn't without critics.

"I have seen no scientific proof that the ear doesn't change significantly over time. People tend to believe notions like these, and they are repeated over time," said Anil Jain, a computer scientist at Michigan State University who was not involved in the study. "Fingerprinting has a history of 100 years showing that it works, unless you destroy your fingerprints or work in an industry that gives you calluses."

Using the ear is not about replacing existing biometrics such as fingerprints, Bowyer said. Rather, it's about supplementing them, especially when it comes to catching crooks.

"It's easy to say, 'Hey there's fingerprints, faces and irises, why do we need more?' For some applications that's a valid question," he said. "But when you're doing surveillance, where a person isn't being cooperative for obvious reasons, you want anything you can get. If you have images of ears, it's dumb to throw that away."

What's more, he says, there really aren't studies proving the agelessness of any human biometric — including fingerprints.

"Who over the age of 40 could think these things don't age?" Bowyer joked. "Some have said 'irises are for life,' but in some of our lab's work we've noticed degraded biometric performance even in those."

To address limitations of the approach, the team is looking to demonstrate that ears do hold up over time. In addition, the researchers hope to pair their new biometric with other computer-vision technologies, such as face recognition, to bolster its reliability. And if the algorithm can be made to work quickly in three dimensions, a fuzzy clip of a criminal walking by a security camera could be turned into grade-A courtroom evidence.

"We've shown we can use ears, but can we process data that comes from a sort of normal scenario? That's the real challenge," Nixon said.

2.2.1 Approaches to Recognizing People by Ear

If you've watched any spy movies, then you'll know that biometric security systems can recognize individuals based on physiological traits such as their fingerprints, handprints, faces and irises. Well, you may soon be able to add "ears" to that that list. Scientists from the University of Southampton's School of Electronics and Computer Science have used a program called image ray transform to achieve a 99.6 percent success rate in automatically locating and isolating ears in 252 photos of peoples' heads.

According to Southampton's Prof. Mark Nixon, ears are a good biometric indicator. Their unique structure doesn't change as the person gets older, they aren't affected by facial expressions, and they are always predictably displayed against the side of the head – complete faces, by contrast, can end up with all sorts of chaotic backgrounds behind them, making things more difficult for computer imaging systems.

The image ray transform used in this study utilizes a "pixel based ray tracing technique" and a subset of the laws of optics, analyzing the way that light reflects off of objects in pictures. It is able to identify and extract tubular and circular features from images, such As the helix (the curved outer rim) of someone's ear. The system then creates an isolated image of just the ear, even allowing for hair or spectacle arms covering part of it. The ear's owner could then be identified by matching that image to one in a database of ear images.

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 modeled 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. used force field feature extraction to map the ear to an energy field which highlights 'potential Ills' 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 Ire poorly registered. The geometrical properties of ear curves have also been used for recognition. The most prominent example of these and arguably the first ear biometric method, proposed by Iannarelli, 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. 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 . Yan et al. 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. 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. .

Ears in Forensics

There has been some use of ear prints in forensics, though there is certainly some debate. Ear prints, 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 Ill-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]. HoIver, 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.

I anticipate that I 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. HoIver, 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. HoIver, 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 vieId in profile as a subject passes through a gateway.

pears 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. I 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 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 key- points constitute the model parts [4]. I 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.

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

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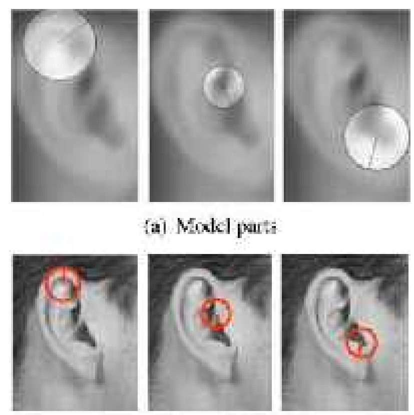

(b) Detected parts

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

3. DISCUSSION

In this paper I have taken steps to translate gait and ear biometric analysis for a potential use in forensics. I 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 betIen image samples, where the Euclidean distance betIen the corresponding points are computed and the mean distance represents the level of similarity betIen the samples. The advantage of automated identification of-

As such I anticipate that a point-based approach offered by biometric methods is apparent when large databases are to be analyzed. I 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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