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On Forensic Use of Biometrics

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This chapter discusses the use of biometrics techniques within forensic science. It outlines the historic connections between the subjects and then examines face and ear biometrics as two case studies to demonstrate the application, the challenges and the acceptability of biometric features and techniques in forensics. The detailed examination starts with one of the most common and familiar biometric features, face, and then examines an emerging biometric feature, ear.

1.1 Introduction

Forensic science largely concerns the analysis of crime: its existence, the perpetrator(s) and the modus operandi. The science of biometrics has been developing approaches that can be used to automatically identify individuals by personal characteristics. The relationship of biometrics and forensics centers primarily on identifying people: the central question is whether a perpetrator can reliably be identified from scene-of-crime data or can reliably be excluded, wherein the reliability concerns reasonable doubt. The personal characteristics which can be used as biometrics include face, finger, iris, gait, ear, electroencephalogram (EEG), handwriting, voice and palm. Those which are suited to forensic use concern traces left at a scene-of-crime, such as latent fingerprints, palmprints or earprints, or traces which have been recorded, such as face, gait or ear in surveillance video.

Biometrics is generally concerned with the recognition of individuals based on their physical or behavioral attributes. So far, biometric techniques have primarily been used to assure identity (in immigration and commerce etc.). These techniques are largely automatic or semi-automatic approaches steeped in pattern recognition and computer vision. The main steps of a biometric recognition approach are: (1) acquisition of the biometric data; (2) localization and alignment of the data; (3) feature extraction; and (4) matching. Feature

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extraction is often the pivotal part of this workflow. The biometric studies are concerned with finding a set of features, which provides the least deviation between the different samples of one individual and most separability between the samples of one individual and the rest of the population. Such a feature set will provide the best chance for individualization. In fingerprint recognition, the most popular and widely used features are the minutiae-based feature. Such level of consensus, however, has not been reached for most of the biometrics traits and the best set of features is subject to constant examination.

One of the earliest attempts to use biometric data for identification dates back to the 1880s when the French criminologist Alphonse Bertillon proposed a method based on anthropometric measurements. Bertillon suggested this method as a means for classification and sorting of the records of individuals and searching among them (Bertillon 1893). In 1890, Bertillon set forth a set of standards for forensic photography. He also developed a taxonomy to describe some of the physiological features of the head, including: nose, forehead, and ear. He called this *portrait parlé* or *spoken portrait* (Bertillon 1890). The combination of the anthropometric measurements and the *spoken portrait* developed by Bertillon is called *Bertillonage* and was fast adopted by the police and the judicial systems. Around the same time, Hendry Faulds proposed the use of fingerprints for identification (Faulds 1880). Although fingerprints were first considered with scepticism, they gradually replaced Bertillonage as the main method of forensic identification, especially after the West v. West (1903) case concerning a pair of suspects who could not be disambiguated by the Bertillon's methods. Among the advantages of fingerprints over Bertillonage was their relative ease of use and that one could not find traces of Bertillonage's anthropometric measurements at the scene of crime while fingerprints were in abundance. The later developments in biometrics largely followed the development of computer vision techniques, enabling identification by other bodily attributes.

In Frye v. United States 1923, a federal court was faced with the question of expert evidence admissibility. The court concluded that the expert evidence could be admitted to court only if this expertise had gained *general acceptance* in the field in which it belongs. In 1993, in Daubert v. Merrell Dow Pharmaceuticals a new standard for expert evidence admissibility was introduced by the U.S. supreme court. In this, the proffered expert testimony must be shown to be based on reliable foundations. To show this, it is required to determine if the proffered science has been tested, if this testing was based on a sound methodology and also to take into account the results of this testing (see also the Daubert principle in Chapter 1). This new standard was considered as a paradigm shift (Saks and Koehler 2005) and it was suggested that fingerprints could be one of the first forensic identification methods to make this transition since the required large databases already exist in this field. In fact, the use of handwriting and fingerprint evidence has been challenged for use in court procedure in 1999, leading to a study of whether fingerprints are permanent and unique (Pankanti et al. 2002). This raised concerns in: the fallibility of fingerprint evidence; the performance in degraded imagery; the performance of available techniques and the need for its improvement. Such debate is not new in science since the development of any new technique must be justified in terms of societal use. Further, when it is to be deployed in serious crime investigations where punishment can be severe then error cannot be tolerated. Indeed, the need for individualisation as a forensic paradigm was later to be questioned (Cole 2009). The current state of the art of biometrics in forensics is more nascent than established. The first IEEE/IAPR International Workshop on

Biometrics and Forensics (IWBF) was held only recently in early 2013, arising from the EU-sponsored ICT COST Action IC1106 on Integrating Biometrics and Forensics for the Digital Age (http://www.cost.eu/domains_actions/ict/Actions/IC1106). Just earlier the first Workshop on Databases in Biometrics, Forensics and Security Applications (DBforBFS) was held as a satellite workshop of the 2013 BTW Conference (on database systems in Business, Technology and Web). The technical programs for these workshops considered face, hand-based, behavioural and other biometrics and forensics together with considerations of performance and database construction, especially for forensic deployment and analysis. There have been other previous conference sessions, and the successful emergence of conferences in new specialist topics generally underlines not only their contemporary nature, but also the importance of an emerging new subject.

When fingerprints were suggested by in 1880, little investigation had been performed over their individuality and there was no mention of the error rates for the identification predictions. In courts, other expertise were also being offered and admitted which seriously lacked the backing of proper scientific testing and statistical measures of performance. In this respect, many mistakes were made and are still being made. Saks and Koehler (2005) reported that in 86 DNA exoneration cases the error due to forensic science testing errors is ranked very high at 63% and that it is second only to the eyewitness errors with 71%. In terms of performance, the main aim of biometrics is to verify if a person has a claimed identity (a so called *one-to-one matching*) and identification (*one-to-many matching* where a subject is compared with a database). In forensics, the conclusion concerns likelihood between a suspect and evidence. In fingerprints evidence can lead to three conclusions: individualisation, exclusion or inconclusiveness (Champod 2000). The probability of matching can also be graded as impossible, possible, probable or very likely. In DNA analysis, the potential error rate is usually couched in terms of the likelihood of mismatch, which is another representation of probability.

In terms of the literature, the majority of approaches describe analysis of latent fingerprints. However, there is also use of voice for speaker identification, face identification, dental biometrics, DNA and handwriting, which are all established biometrics in their own right (Dessimoz and Champod 2008). In terms of emerging biometrics, so far there has been one deployment of gait biometrics for identification (Bouchrika et al. 2011; Guan and Li 2013; Guan et al. 2013) and there is now a system aimed at such use (Iwama et al. 2012). Soft biometrics is a more recent interest and can handle low quality surveillance data (Park and Jain 2010). Ears were considered in Bertillon's pioneering early study where the ear was described as the most identifying part of an individual and proposed a method for ear classification, and the length of the ear was one of the eleven measures that were used. One early forensics study (Spaun 2007) described interest in facial and ear individualization, adding the possibility of exploring additional biometrics including hands and gait and observing that additional ear analyses are needed; instead of databases of hundreds of ears, thousands of ears, or more.

In the remainder of this chapter, we will concentrate on two case studies discussing the forensic possibilities of face and ear as biometrics. Face is the natural means for human beings to recognise each other. However, currently no fully automatic face recognition system is accepted by the judicial system. Section 1.3 introduces the manual and computer-aided forensic face recognition; discusses the disparities between the behaviour of the current automatic face recognition systems and that which is needed for forensic application; and outlines the current progress towards addressing the challenges existing in face recognition. Section 1.4 examines an emerging biometric ear. The detailed examination shows the challenges that exist in introducing a new biometric feature into forensics. Ear biometrics has been chosen as the second case study as it is a potentially important biometric feature, yet its use is still under question. The current state of formal validation of ears as a forensic tool is discussed and a set of morphological features along with an analysis of their discriminatory powers are presented. These features are important in deciding whether there is enough information available for identification in case of missing features. The terminology associated with these features may also assist with communicating ear comparison results to juries, an important step in making such evidence effective at trial. But first, in section 1.2, we will give an overview of the general biometric system operation modes and performance metrics.

1.2 Biometrics Performance Metrics

A biometric system can be used as an assistant tool in the forensic scenarios for helping on queries against a large enrolled database. The query can be a *one-to-many search* to determine potential matches to a probe from the gallery, or a *one-to-one check* to verify the identity of an individual. These two tasks are referred to as *identification* and *verification* in the biometrics research community [1].

In identification, the biometric system searches an enrolled database for a gallery sample matching the probe sample. An ordered list of top *n* matches may be returned as the possible identities of the probe. The performance of the system in the identification task is measured in terms of *rank-n recognition rate* which is the rate at which the true association has been included in the top *n* matches to the probe. Recognition rate is the simplified term for rank-1 recognition rate where the system returns a single match, the best match, as the most probable association for the probe sample.

On the other hand, verification is the task where the biometric system attempts to confirm an individual's claimed identity by comparing the probe sample to the individual's previously enrolled sample. Verification is based on a decision threshold. This threshold is set by comparing all sample pairs in the gallery. The threshold is chosen to separate the genuine scores distribution from the impostor scores distribution and give the best performance based on one of the following metrics:

- *False acceptance rate* (FAR) is the rate at which the comparison between two different individuals' samples is erroneously accepted by the system as the true match. In other words, FAR is the percentage of the impostor scores which are higher than the decision threshold.
- *False rejection rate* (FRR) is the percentage of times when an individual is not matched to his/her own existing template. In other words, FRR is the percentage of the genuine scores which are lower than the decision threshold.
- *Equal error rate* (EER) is the rate at which both acceptance and rejection errors are equal (i.e., FAR=FRR). Generally, the lower the EER value, the higher the accuracy of the biometric system.

[1] Biometrics Glossary by National Science & Technology Council (NSTC) Subcommittee on Biometrics, 2013

Automated biometric techniques can be used to analyze and interpret biometric traces in the forensics scenarios such as in investigation of a criminal offense and the demonstration of the existence of an offense (Meuwly 2012). These tasks are usually interrelated with each other. Biometric techniques are used to help in the three main ways:

- *Decision.* In identity verification and identification, a decision needs to be made. Such applications include: criminal ID management, suspect or victim identification, etc.
- *Selection.* In forensics intelligence and investigation, biometrics techniques are used to link cases from biometric traces and generate short lists of candidates.
- *Description.* In forensic evaluation, biometrics are used to describe the evidential value of the biometric evidence.

1.3 Face: the Natural Means for Human Recognition

Since the advent of photography, both government agencies and private organizations have kept face photo collections of people (e.g., personal identification documents, passports, membership cards, etc.). With the wide use of digital cameras, smart phones and CCTVs, face images can be easily generated every day. In addition, nowadays these images can be rapidly transmitted and shared through the highly developed social network such as Facebook. So face is almost the most common and familiar biometric trait in our daily lives. There are more opportunities to acquire and analyze face images of a questioned person (e.g., suspect, witness or victim) for forensic investigation purposes.

Face recognition has a long history and receives research interests from neuroscientists, psychologists and computer scientists (Sinha et al. 2006). Compared with other biometric traits, face is not *perfect*. For example, it is generally less accurate than other forms of biometrics such as fingerprint and can potentially be affected by cosmetics more easily. However, face has its own advantages that make it one of the most preferred biometric traits for human recognition:

- *Biological nature*: Face is a very convenient biometric characteristic used by humans in the recognition of people, which makes it probably the most common biometric trait for authentication and authorization purposes. For example, in access control, it is easy for administrators to track and analyze the authorised person from his/her face data after authentication. The help from ordinary users (e.g., administrators in this case) can improve the reliability and applicability of the recognition systems. Whereas fingerprint or iris recognition systems require an expert with professional skills to provide reliable confirmation.
- *Non-intrusion*: Different from fingerprint and iris collections, facial images can be easily acquired from a distance without physical contact. People feel more comfortable for using face as identifier in daily lives. A face recognition system can collect biometric data in a user-friendly way, which is easily accepted by the public.
- *Less cooperation*: Compared with iris and fingerprint, face recognition has a lower requirement of user cooperation. In some particular applications such as surveillance, a face recognition system can identify a person without active participation from the subjects.

The first attempts we are aware of to identify a subject by comparing a pair of facial photographs was reported in a British court in 1871 (Porter and Doran 2000). Face recognition is one of the most important tasks in forensic investigations if there is any video or image material available from a crime scene. Forensic experts perform manual examination of facial images to match the images of a suspect's face. The use of automated facial recognition systems will not only improve the efficiency of forensic work performed but also standardize the comparison process.

1.3.1 Forensic face recognition

In the past, before the use of computers, face recognition was already widely used in forensics. The work of Bertillon (1893) was one of the first systematic approaches for face recognition in forensics as we mentioned in Section 1.1. Currently forensic face recognition is mainly performed manually by humans. In a typical forensic face recognition scenario, a forensic expert is given face images from a suspect (e.g., mug-shot images) and a questioned person (i.e., the perpetrator). The forensic expert will give a value which represents the degree to which the these images appear to come from the same person.

There are four main categories of approaches in forensic face recognition (Ali et al. 2010; Dessimoz and Champod 2008): holistic comparison, morphological analysis, anthropometry, and superimposition.

- *Holistic comparison*. In holistic comparison, faces are visually compared as a whole by the forensic experts. This is the simplest way and can be performed as a pre-step for other methods. Automatic face recognition systems can be designed to help for this not only on one-to-one comparison (i.e., verification) but also on one image compared to a large-scale gallery database (i.e., identification).
- *Morphological analysis*. In morphological analysis, the local features of the face will be analyzed and compared by the forensic experts who are trained in that discipline. They carry out an exhaustive analysis on the similarities and differences in observed faces, trait by trait on the nose, mouth, eyebrows, etc., even the soft traits such as marks, moles, wrinkles, etc. The location and distribution of local facial features are considered but not explicitly measured compared with anthropometry based approaches. One example of the examined facial features currently used by the Netherland's Forensic Institute[2] are summarised in Table 1.1 (Meuwly 2012). It can be seen from the table that both internal and external features of the face are considered. These features are usually fall into two categories (Spaun 2011): (1) *class characteristics* which can place an individual within a group (e.g., facial shape, shape of the nose, freckles, etc.) and (2) *individual characteristics* which are unique to distinguish the individual (e.g., skin marks, scars, creases, wrinkles, etc.). Generally, the forensic experts need to make the conclusion based on the following comparison criteria for these local features: (1) *Similar*: imaging conditions are not optimal, in a sense that differences might be invisible; (2) *No observation*: observation is not possible due to circumstances; and (3) *Different*: observed differences may be explained by differences in the imaging conditions.

[2]http://www.forensicinstitute.nl/

Table 1.1 Example of facial features examined

Feature	Characteristic
Face	Shape, proportions, hairline
Forehead	Shape, bumps, horizontal creases, eyebrows
Eyes	Distance, angle fissure, colour, eye slit shape, creases, bags, wrinkles
Nose	Length, width, prominence, symmetry, shape of tip and nostrils, septum
Mid part of face	Cheekbones, cheek line, cheek-eye groove, cheek-nose groove
Ear	Size, protrusion, shape of helix and antihelix, darwin's tubercle, earlobe
Mouth	Size, shape, upper lip, lower lip
Mouth area	Shape of philtrum, moustache and shadow, beard and shadow
Chin	Shape, groove between mouth and chin, dimple, double chin
Low jaw	shape
Throat	Adam's apple
Distinctive feature	Skin marks, scars, creases and wrinkles

- *Anthropometry*. Anthropometry refers to the measurement of the human individual, which can be used for human recognition. Different from morphological analysis, in face anthropometry, the quantification measurements (e.g., spatial distance and angles) between specific facial landmarks (e.g., the mid-line point between the eyebrows, the lowest point on the free margin of the ear lobe, the midpoint of the vermilion border of the lower lip, the most anterior midpoint of the chin, etc.) are used for comparison. However, usually blemishes on the face such as scars are not considered. When anthropometric measurements are taken from photographs rather than from the face of a living person, it is called *photo-anthropometry*. The face images being compared should be taken from the same angle and direction and has a high quality to be able to detect the facial landmarks. These requirements limit the use of anthropometry approaches in uncontrolled scenarios (e.g., surveillance situations). At present, anthropometry based methods are suitable to be used to exclude the questioned person rather than to make a positive identification.
- *Superimposition*. In superimposition, one face image is overlaid onto another and the forensic experts need to determine whether there is an alignment and correspondence of the facial features. These images should be captured under the same pose and be processed to the same scale. This category of approaches is not accurate due to their high requirement that the compared images should be taken under the same conditions. Generally, in forensics, superimposition can be performed not only between two face images but also between a face and a skull (Ibañez et al. 2011). In addition, superimposition is also widely used in forensic facial reconstruction (Aulsebrook et al. 1995) which aims to recreate the face of an individual (whose identity is often not known) for recognition purpose. Automatic face recognition system can be developed in the direction of modelling a 3D face/head model to compare with a 2D query image. In this way, the pose, angle and orientation of the face can be adjusted using the 3D models.

In holistic comparison, conclusions are generated by visually comparing images as a whole. Morphological analysis is the most applicable in modern forensics. Anthropometry

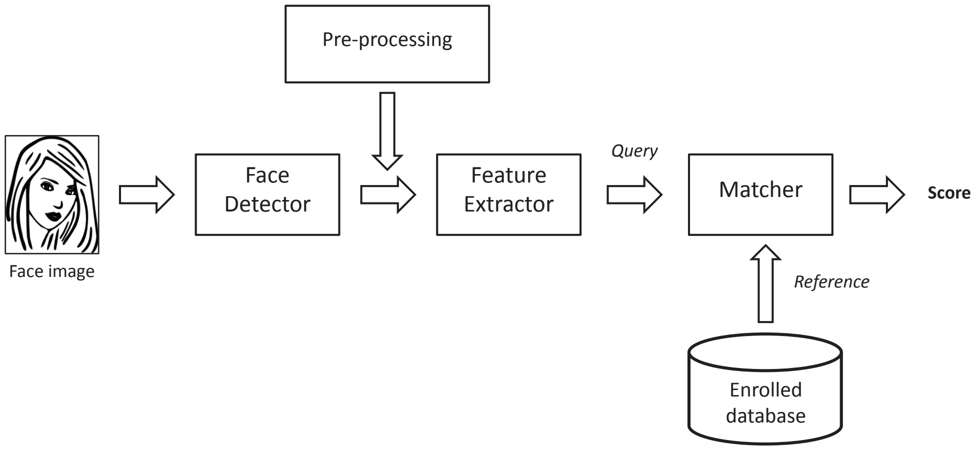


Figure 1.1 Framework of an automatic face recognition system.

and superimposition are practiced by jurisdictions, but the outcomes are highly sensitive to the subject's pose and thus may easily produce inaccurate results. The choice of a specific approach depends on the face images to be compared and generally a fusion of these methods is applied in the real case analysis scenarios.

Currently there is no standard procedure and agreed upon guideline among forensic researchers. Some working groups such as the Facial Identification Scientific Working Group (FISWG[3]) of FBI, the International Association for Identification (IAI[4]) and the European Network of Forensic Science Institutes (ENFSI[5]), as well as several international agencies such as the London Metropolitan Police are devoting to develop standards and guidelines for forensic face comparison.

Notice that in the aforementioned forensic face recognition methods, ears are also considered as an external feature of the face. The ear is an important emerging biometric trait and is stable throughout adulthood. We will discuss the use of ear biometrics in the forensic tasks later.

1.3.2 Automatic face recognition techniques

A general automatic face recognition system usually consists of the following modules: a face detector, a feature extractor and a matcher (Figure 1.1). The face detector crops the face area from the background of an image. The feature extractor then extracts effective information from face images for distinguishing different individuals. Usually pre-processing such as face alignment by the facial landmarks and face normalization (e.g., scale, illumination condition) will be performed before feature extraction. Then the matcher will compare two faces (e.g., one is from query and one is from the enrolled database) by the extracted features then

[3]https://www.fiswg.org/
[4]http://www.theiai.org/
[5]http://www.enfsi.eu/

a similarity score is calculated. Face recognition is based on the similarity scores and its performance highly relies on the extracted features and classification algorithms used to distinguish faces.

In the early time, the main recognition approaches are geometric feature-based methods which rely on measurements between specific facial landmarks. This is similar to the anthropometry based methods in the forensic face recognition. The first attempt to automatic face recognition started by Chan and Bledsoe (1965) in a semi-automated mode where a set of facial features were extracted from the photographs by humans. The first fully automatic face recognition system was presented by Kanade (1973), which was a milestone at that time. In 1990s, the linear subspace analysis approaches and statistical models became the mainstream. Turk and Pentland (1991) applied Principal Component Analysis (PCA) on face images, which was referred to as *Eigenface*. These eigenfaces were the eigenvectors associated to the largest eigenvalues of the covariance matrix of the training samples, which ensured the data variance was maintained while eliminating unnecessary existing correlations among the original features (i.e., dimensions). PCA based approaches greatly reduced the computational cost for high-dimensional data and inspired more active research in face recognition. Fisherface (Belhumeur et al. 1997), which was based on the Liner Discriminant Analysis (LDA), also performed dimensionality reduction while preserving as much of the class discriminatory information as possible. Other popular methods included Local Feature Analysis (LFA) (Penev and Atick 1996), Elastic Graph Matching (EGM) (Wiskott et al. 1997), etc. From the late 90s to present, the research of face recognition has focused on the uncontrolled and uncooperative scenarios (e.g., large pose changes, illumination and expression variations, low resolution, partially occluded faces, etc.). Locally Linear Embedding (LLE) (Roweis and Saul 2000), illumination core model (Georghiades et al. 2001), 3D Morphable Model (Romdhani et al. 2002), Local Binary Pattern (LBP) (Ahonen et al. 2006) and Sparse Representation based Classification (SRC) (Wright et al. 2009) are the representative methods in this period. A systematic survey of automatic face recognition can be found in the work of Zhao et al. (2003).

The performance of automatic face recognition techniques has been evaluated in a series of large-scale tests conducted by the National Institute of Standards and Technology (NIST[6]), such as the Facial Recognition Technology evaluation (FERET) (Phillips et al. 2000), the Face Recognition Vendor Test (FRVT) (Phillips et al. 2010) and the Face Recognition Grand Challenge (FRGC) (Phillips et al. 2005). Over the past decades, major advances occurred in automatic face recognition. The false reject rate (FRR) of the best performing face recognition algorithm has decreased from 79% in 1993 to 0.3% in 2010 at a false accept rate (FAR) of 0.1% (Phillips 2012). The automatic face recognition has been successfully used in the field of security (e.g., access control, video surveillance, etc.), but the performance in unconstrained environment is still unsatisfactory. A full and systematic assessment of the automatic face recognition technology must be conducted under realistic conditions before it can be utilised for forensic applications.

1.3.3 Challenges and trends of face recognition

Like in many biometric applications, the appearance variations caused by the unconstrained conditions are still challenges for face recognition in the context of forensic scenarios.

[6] http://www.nist.gov/

Currently automatic face recognition system is only regarded as an assistant tool in forensic tasks. This section will discuss several specific face recognition problems which may also be difficult even for forensic experts. These challenges should be addressed in the future research (Jain et al. 2011).

Partial/occluded face recognition

In the real-world environment, a face may be captured in arbitrary pose without the user's cooperation so it's very likely that the image only contains a partial face. Faces are easily occluded by facial accessories (e.g., sunglasses, scarf, hat, veil), objects in front of the face (e.g., hand, food, mobile phone), extreme illumination (e.g., shadow), self-occlusion (e.g., non-frontal pose) or poor image quality (e.g., blurring). In forensic face recognition, for example, it is needed to find a suspect in the crowd by matching a partially occluded face with enrolled database. The difficulty of occluded face recognition is twofold. Firstly, occlusion distorts the discriminative facial features and increases the distance between two face images of the same subject in the feature space. The intra-class variations are larger than the inter-class variations, which results in poorer recognition performance. Secondly, when facial landmarks are occluded, large alignment errors usually occur and degrade the recognition rate Ekenel and Stiefelhagen (2009).

An intuitive idea for handling occlusion in automatic face recognition is to detect the occluded region first and then perform recognition using only the unoccluded parts. However, the types of occlusions are unpredictable in practical scenarios. The location, size and shape of occlusion are unknown, hence increasing the difficulty in segmenting the occluded region from the face images. A more practical way is to perform recognition with the presence of occlusion. There are two main categories of approaches in this direction.

The first is the *reconstruction based approaches* which treat occluded face recognition as a reconstruction problem (He et al. 2011; Jia and Martínez 2008; Naseem et al. 2010; Wagner et al. 2012; Wei et al. 2012; Wright et al. 2009; Yang and Zhang 2010; Zhang et al. 2011). The sparse representation based classification (SRC) proposed by Wright et al. (2009) is a representative example. A clean image is reconstructed from an occluded probe image by a linear combination of gallery images and the basis vectors of an occlusion dictionary. Then the occluded image is assigned to the class with the minimal reconstruction error.

The second category is the *local matching based approaches*. Facial features are extracted from local areas of a face, for example, overlapping or non-overlapping patches of an image, so the affected and unaffected parts of the face can be analysed in isolation. In order to minimize matching errors due to occluded parts, different strategies such as weighting (Tan et al. 2009), warping (Wei et al. 2013a,b), voting (Wei and Li 2013), local space learning (Martínez 2002; Tan et al. 2005) or multi-task sparse representation learning (Liao et al. 2013) are performed.

Klontz and Jain (2013) conducted a case study that used the photographs of the two suspects in the Boston Marathon bombings to match against a background set of mugshots. The suspects' photographs released by the FBI were captured under uncontrolled environment and their faces were partially occluded by sunglasses and hats (Comcowich 2013). The study showed that current commercial automatic face recognition system had the notable potential to assist law enforcement. But the matching accuracy was not high enough and more progress must be made to increase the utility in unconstrained face images.

Heterogeneous face recognition

Heterogeneous face recognition involves matching two face images from alternate imaging modalities. This is very practical in forensic scenarios. For instance, in the London riots in 2011, the police used face recognition system to help find the riot suspects involved in the unrest. The images of suspects are came from various sources, e.g., still images captured from closed-circuit cameras, pictures gathered by officers, footage taken by the police helicopters or images snapped by members of the public. These images are usually from various sources from different modalities. In addition, in some extreme situations, only a particular modality of a face image is available. For example, in night-time environments, infrared imaging may be the only modality for acquiring a useful face image of a suspect. But the stored mug-shots by the police are visible band images. Another example is the sketch-photograph matching. When no photograph of a suspect is available, a forensic sketch is often generated according to the description of an eye-witness. Matching sketches against face photographs is very important for forensic investigation.

There are three categories of approaches in current heterogeneous face recognition. The first one is the *feature based method* (Klare and Jain 2010; Klare et al. 2011; Lei and Li 2009) which represents face images with discriminative features that are invariant in different imaging modalities. The second one is the *synthesis based method* (Tang and Wang 2004; Wang and Tang 2009; Zhang et al. 2010) which converts a face image in one modality (e.g., sketch) into another (e.g., photograph). And the third one is the *prototype based method* (Klare and Jain 2013) which reduces the gap between two modalities by using a prototype as a bridge. 2D-3D face matching is a future research direction since face can be represented by heterogeneous features in the 3D and 2D modalities in the real-world cases.

Face recognition across aging

Facial aging is a complex process that affects both the shape and texture (e.g., skin tone or wrinkles) of a face. The typical application scenario of face recognition systems against aging effect is to detect if a particular person is present in a previous recorded database (e.g., missing children identification and suspect watch-list check). As the age between a query and a reference image of the same subject increases, the accuracy of recognition system generally decreases.

In automatic face recognition, aging effect in human faces has been studied in two directions: (1) developing *age estimation techniques* to classify face images based on age (Geng et al. 2007; Guo et al. 2008) and (2) developing *aging robust systems* to perform recognition. In the early time, researchers tried to simulate the aging effects by developing the aging function and then performing automatic age estimation based on that (Lanitis et al. 2002). But modeling the complex shape or texture variations of a face across aging is a very challenging task. Nowadays, researchers propose the generative aging model (Li et al. 2011) which learns a parametric aging model in the 3D domain to generate synthetic images and reduce the age gap between query and reference images. One most challenging aspect of face recognition across aging is that it must address all other unconstrained variations as well. Figure 1.2 shows the face samples of the same individual across aging. Pose, expression, illumination changes and occlusions can occur when images are taken years apart.

Figure 1.2 Face samples of the same individual across aging.

1.3.4 Summary

Face is the most natural way of recognition for human beings. A rich variety of approaches for face biometrics have been proposed and its basic patterns are well understood over past several decades. Face recognition technology has been considered as the next generation tool for human recognition [7]. Automatic face recognition is becoming an indispensable tool for modern forensic investigations.

However, currently there is no generally accepted standard for forensic face comparison. Many challenging problems related to forensic face recognition still exist. A full and systematic assessment of the automatic face recognition technology must be conducted under realistic conditions before it can be utilised for forensic applications.

Up to now, we have introduced the forensic use of face recognition and discussed some challenges needed to be addressed in the future. In the real forensic scenarios, usually a combination of information from different biometric traits is applied for case analysis. In the following sections, we will introduce one emerging biometrics - ear which is highly related to face but has its own advantages.

1.4 Ears as a Means of Forensic Identification

Although ears are an external part of the head, and are often visible they do not tend to attract human attention and a vocabulary to describe them is lacking. As for the latent prints, the common ones to be found in crime scenes are of fingertips, palms, and feet. Although

[7] see FBI's the Next Generation Identification (NGI) program, `http://www.fbi.gov/about-us/cjis/fingerprints_biometrics/ngi`

earprints may also be found in crime scenes fingerprints are much more abundant. The fact that the forensic use of ears and some of the other biometric traits were halted by the advent of fingerprints is partly due to this practical advantage. Dutch courts have admitted numerous cases of earprint related evidence (Van der Lugt C 2001). Earprints have also been used as a means of personal identification in other countries, such as the United States, UK, Germany and Switzerland. In Germany both earprints and ear images have been used for identification (Champod et al. 2001). In Switzerland, latent earprints have been used to assist in the early stages of investigation in burglary cases (R. v. Mark Dallagher 2002). While in a number of higher profile cases the reliability of earprint evidence has been challenged, been refused admittance or caused erroneous convictions. The evidence regarding earprints is mainly contested due to three main factors: (1) pressure deformation; and (2) the lack of generally accepted methodologies for comparison and (3) the lack of large scale testing.

A study of potential identification capabilities of ears was performed by Alfred Iannarelli who examined over 10,000 ear samples over 38 years (Iannarelli 1989). He developed the Iannarelli System of Ear Identification. His system essentially consists of taking a number of measurements from a set of landmark points on the ear. He concluded:

> ”Through 38 years of research and application in earology, the author has found that in literally thousands of ears that were examined by visual means, photographs, ear prints, and latent ear print impressions, no two ears were found to be identical.”

Despite his extensive experience with different forms of ear representation in forensics, in 1985 the Florida trial court of State v. Polite 1985 did not recognize him as an expert on earprint identification on the grounds that his ear identification method was not generally accepted in the scientific community. The court also raised concerns over the effects of pressure deformation on the appearance of earprints and also over the lack of studies concerning the comparison of earprints and refused to accept the earprint identification evidence altogether. The later development of ears as a biometric was to rely on the pioneering work of Iannarelli.

Ear biometric recognition has primarily been focused on automatic or semi-automatic methods for human identification or verification using 2D or 3D ear images. In comparison to the forensic references to the usage of ear morphology for recognition, the automated recognition of ear images in the context of machine vision is a recent development. Burge and Burger (1998) were amongst the first to investigate automated recognition of ears. Inspired by the earlier work of Iannarelli, they conducted a proof of concept study where the viability of the ear as a biometric was discussed theoretically, in terms of the uniqueness and measurability over time, and examined in practice through the implementation of a computer vision algorithm. Since then, there have been many ear biometric methods looking at 2D and 3D images of the ear while also attempting to overcome challenges such as occlusion, pose variation and illumination conditions.

The advantages that ear biometric studies can offer the field of ear forensic identification are twofold. Firstly, to advance and inform earprint recognition methods, and secondly, to introduce and facilitate the new emerging application of identification at a distance from surveillance footage. Pressure deformation is one of the main reasons why earprint evidence is contested. Being composed of malleable parts, the appearance of an earprint can be much influenced by the amount of pressure which is applied in making the print. A 3D model of the ear, as offered by 3D ear biometrics methods, may be useful in predicting the appearance of its earprint under different amounts of pressure. Another hindering factor for the application of earprints for identification is the missing features of the ear in an earprint. Due to the different elevations of the external ear parts, some of the ear components are commonly missing in earprints. Owing to the missing information, it can be debated that earprints present less variability than ear images. We will show that the insights offered by the ear biometric studies as to the degree of discrimination provided by different ear features can be used to evaluate the information content of earprints for identification.

Ear images from surveillance cameras have also been considered for forensic identification. Although this is considered a new development in the field of ear forensic identification, it is the core problem in ear biometrics. Thus the methodologies developed in ear biometrics may be readily transferable for use in this application. Automatic biometrics methods can also offer desirable properties for efficient processing of large datasets and attribute the performance and error rate directly to specific methodologies. Using automatic biometric methods can also provide reproducible results and eliminate operator bias.

Next, we will review earprint identification, its role as forensic evidence, its shortcomings and possible improvements. Since the forensic use of ear as a biometric is in a different stage of its life cycle compared to face, as well as looking at the methods of comparison, we will discuss the earlier question of admissibility in court. We will then look at specific automatic biometric methods and how they can be used for forensic identification from surveillance capturing. Finally, we will review the discriminant capabilities of individual ear features and how they can be used to infer the level of confidence in predictions from data which are prone to having missing features.

1.4.1 Earprints in forensics

Earprints, which may be found in up to 15% of crime scenes (Rutty et al. 2005), are latent prints left behind as a result of the ear touching a surface, for example while listening at a door. In a legal context, the evidence regarding earprints could be utilized for various purposes including: dismissing a suspect, increasing evidence against a suspect or identifying possible suspects (Meijerman et al. 2004). Earprints have been used as a means of personal identification in different countries, however, in a number of cases the reliability of earprint evidence has been challenged. Figure 1.3 shows some sample earprints.

Earprint – a challenged forensic evidence

In the cases involving earprint evidence for positive identification, two issues have been the main source of dispute. One is the admissibility of this evidence and the other is its reliability. In the United States and under the Daubert standard, all forensic expertise is subjected to a scientific scrutiny over its reliability and accuracy. In this setting, the judge acts as a *gatekeeper* and determines whether the proffered forensic evidence accords to that standard. The forensic science in question does not need to be error free to be admissible; indeed there is always a level of error involved. However, a measure of this error should be made available through rigorous testing. This, however, is not a straightforward task while the question regarding the size of the dataset, which is needed to obtain the required reliability and the statistical evaluation of performance, has not been addressed.

Figure 1.3 Sample earprints (from Meijerman (2006)).

The admissibility of earprint evidence was a key issue in the case of State v. Wayne Kunze 1999. In Washington State in 1996, David Wayne Kunze was charged with aggravated murder amongst other charges. The key evidence against Kunze was a latent earprint found at the scene. Prior to the trial, Kunze moved for excluding any evidence of earprint identification. Subsequently, the trial court convened a Frye hearing on the matter and many ear experts and latent print experts were called. The hearing concluded that earprint identification has indeed gained general acceptance and thus the earprint evidence was admitted. However, later at the appeal court, after reviewing the evidence given at this pre-trial hearing, the appeal court concluded that general acceptance was not obtained ”if there is a significant dispute between qualified experts as to the validity of scientific evidence”, and since the hearing clearly showed such dispute, the appeal court ruled that the trial court erred by allowing the expert witnesses to testify and that a new trial was required. In the case of State v. Polite (US, Florida trial court) 1985, the court also refused to admit the earprint evidence. In excluding the earprint evidence the judge raised concerns over the unknown effect of pressure deformation and insufficient scientific background to establish reliability and validity of earprint identification.

Relevancy is another guideline for admissibility under Daubert. Relevancy is defined as (Rule 401, Federal Rules of Evidence): ”Evidence is relevant if: (1) it has any tendency to make a fact more or less probable than it would be without the evidence; and (2) the fact is of consequence in determining the action”.

In the United Kingdom, in the appeal court of Mark Dallagher 2002, the court examined the question of expert evidence admissibility. In 1998, in the Crown Court at Leeds, Mark Dallagher was convicted of murder and sentenced to life imprisonment. In this trial an earprint discovered at the scene of crime was one of the main pieces of the evidence against the defendant. Two expert witnesses testified that the defendant was the certain or highly likely maker of the latent earprints. No expert evidence was called on behalf of the defendant and the defence did not seek to exclude the evidence of the prosecution experts. Fresh evidence against the use of earprints for positive identification was offered as grounds for appeal. The appeal court subsequently refused the appellant's argument that if this expert evidence was available at the trial the prosecution's expert evidence should have been excluded. For this, references were made to other cases, such as R. v. Clarke 1995 on facial mapping expert evidence:

> ”It is essential that our criminal justice system should take into account modern methods of crime detection. It is no surprise, therefore, that tape recordings, photographs and films are regularly placed before juries. Sometimes that is done without expert evidence, but, of course, if that real evidence is not sufficiently intelligible to the jury without expert evidence, it has always been accepted that it is possible to place before the jury the opinion of an expert in order to assist them in their interpretation of the real evidence.”

And continuing:

> ”We are far from saying that such evidence may not be flawed. It is, of course, essential that expert evidence, going to issues of identity, should be carefully scrutinised. Such evidence could be flawed. It could be flawed just as much as the evidence of a fingerprint expert could be flawed. But it does not seem to us that there is any objection in principle.”

The appeal court concluded that the expert evidence could not possibly be considered irrelevant, or so unreliable that it should be excluded. Albeit, the appeal court eventually quashed the conviction and ordered a retrial on the grounds that it seemed that if the fresh evidence was given at the trial it might have affected the jury's approach toward the crucial earprint identification evidence.

In the appeal court of R. v. Mark Kempster 2008, the admissibility of the ear evidence was also a cause of debate. In 2001, Mark Kempster was convicted of multiple counts of burglary and attempted burglary at Southampton Crown Court. One of the main pieces of evidence against him was a positive identification of an earprint which was recovered from the scene of crime as his earprint. He appealed against the conviction twice and in 2008 the appeal was brought on the ground that relevant fresh evidence might have undermined the expert prosecution evidence, of positive earprint identification. In the court of appeal, the defence argued against the admissibility of earprint evidence. The defence also argued that while earprint evidence may be used for excluding a suspect, a positive identification cannot be obtained using earprint evidence. Both the prosecution and defence experts agreed that this area of science was in its infancy. However, they disagreed on the results of comparing the earprint found at the scene and the prints of the appellant. The appeal court eventually concluded that the earprint evidence was admissible, and could be used by the jury to decide if it was indeed the appellant who left the mark at the scene. The judge, thus, directed the jury:

> ”First of all consider the evidence of the earprint. Are you sure that the earprint was Mr Kempster's? If you are not sure then you must acquit Mr Kempster on Count 1.”

And the jury subsequently quashed the conviction on count 1 burglary. Thus, again, although the earprint evidence was admitted its reliability was challenged. Whether the earprint evidence is blocked out as an inadmissible expertise or is challenged on its reliability, it is apparent that it does not hold an assured status as a forensic method for positive identification. Next, we will look into the reasons for this and discuss as to how a more reliable earprint evidence maybe obtained.

Pressure deformation

Due to their different elevation and flexibility, ear ridges react differently to the changes in pressure and cause large intra-individual variations. The unknown effects of pressure deformation is one of the main reasons why earprint evidence is contested. To overcome this problem, it has been suggested that for each ear the control prints can be captured using different amounts of pressure and when comparing these control prints to a latent print only the best match would be considered. Junod et al. (2012) also proposed to combine the different earprint samples of an ear to build an earprint model. Hypothesising that in practise a perpetrator will be listening for a sound, Alberink and Ruifrok (2007) proposed that a more realistic dataset of control prints can be acquired by applying a *functional force*. In this, the donors were instructed to listen for a sound behind a glass surface.

A different and perhaps a more comprehensive approach may be offered using a 3D model or a 3D image of the donor ear. Combined with a model of external ear part-wise elasticity, the 3D model can be used to synthesize a set of possible earprints that can be generated by an individual ear. A 3D model of the ear can be acquired using a range scanner (Chen and Bhanu 2007; Yan and Bowyer 2007). There are also methods which use 2D ear images to infer the 3D model of the ear (Bustard and Nixon 2010a; Cadavid and Abdel-Mottaleb 2008).

Variability and missing features

The evidence regarding the variability of ear morphology is regarded as relevant but not directly usable in the field of earprint identification, since not all the parts of the ear leave a mark in an earprint. Due to the different elevations of the external ear parts, some of the ear components are commonly missing in earprints. The parts of the ear which are frequently seen in earprints are: helix; anti-helix; tragus; and anti-tragus, while lobe and crus of helix are not so common (Meijerman et al. 2004). Owing to the missing information, it can be debated that earprints present less variability than ear images (Dessimoz and Champod 2008). Also, the amount of pressure can affect the amount of information which has been left behind in the print.

Dessimoz and Champod (2008) hypothesises over the discrimination power of the features in different representations of ear morphology data due to the varying quality of the data. They referred to this discrimination power of the data as *selectivity* and discussed that the data with highest selectivity is of ear images captured under controlled conditions. The rest of the source data in order of diminishing selectivity are: ear image occluded by hair; reference earprint; ear image taken with a surveillance camera at a distance; and finally an earprint obtained from a crime scene. Note that the traditional biometrics and forensic applications of the ear morphology are at the either end of this selectivity spectrum. Dessimoz et al. did not explain how they arrived at this selectivity ranking. However, we suspect that, in this, the missing parts as well as the pressure deformation are the main reasons for the low selectivity of the earprints. Indeed, there is a concern that not all potentially discriminant parts of the ear are present in an earprint. This leads to the question of what features there are in an ear shape and just how discriminant they are. The findings of ear biometrics studies where occlusion and therefore missing part have been investigated may be useful to this discussion. Arbab-Zavar and Nixon (2011) have also investigated as to the origin of each part of the ear morphology and its discrimination powers. Ear parts are further discussed in section 1.4.3.

Statistical analysis of performance

So far there has been relatively little analysis of earprint performance for forensic identification. The statistical analysis of performance and error rates corresponding to earprint identification was the focus of the EU-funded project Forensic Ear Identification (FearID) in 2002-2005. In this project, an earprint dataset with 7364 prints from 1229 donors from three counties was acquired (Alberink and Ruifrok 2007). For this three left and three right earprints were gathered for each donor. Also, one or two simulated crime scene prints were taken for one out of 10 donors. A semi-automatic classification method was proposed to compare the prints, and each pair of prints was classified as matching or non-matching. In this, after the earprint was lifted from the surface, first a polyline is drawn manually following the earprint contour. This polyline gives a skeleton-like representation of the earprint. A set of features are then extracted for each earprint. These features are the width and the curvature of the print along this polyline. These features are each represented as a one dimensional signal where the horizontal axis is the position along the polyline and the vertical axis is the width or the curvature at that position respectively. A third feature vector is also extracted. This is a point pattern representing the distribution of specific anatomical locations which are manually marked by an expert. The comparison between each pair of prints is then performed by comparing the corresponding features in the two prints. A score is computed showing the similarity between the features of the two prints. An equal error rate (EER) of 3.9% for comparison of reference prints (per side) and an EER of 9.3% for the comparison of simulated crime scene prints with the reference prints are obtained using this method. Junod et al. (2012) have also experimented with this data. In this, the ear prints are manually segmented and pre-aligned. An earprint model is then computed for each ear (per side) by further aligning the input earprint images of that ear using a multi-resolution registration algorithm and obtaining the superposition of the aligned prints. The same alignment method is then used in testing to compute the similarity between a given earprint and a model earprint. Junod et al. report a 2.3% EER for the comparison of simulated crime scene prints with the reference prints and a 0.5% EER for the comparison of reference earprints. They also report hitlist results. For reference print comparisons, in over 99% of cases the true match is in the top three positions of the list and for the comparisons of simulated crime scene prints with the reference prints 88% of cases have the true match in the top three positions. In assessing the reproducibility of these results for real cases one should keep in mind that the FearID database is collected by applying a *functional force* by the print donor simulating a listening effort of a burglar. This minimizes the variability of pressure deformation in the different prints from the same donor. However, in real cases it is not practical to expect of a non-cooperative suspect to apply a *functional force*. Further evaluation of real case samples is required.

1.4.2 From earprints to ear images

The effects of deformation due to pressure and the fact that some components are missing, potentially, causes large intra-individual variation in earprints, resulting in a more challenging recognition problem than ear image recognition. In biometrics, 2D or 3D images of the ear are commonly used. These images are traditionally captured in controlled environments. More recent methods have looked into improving the robustness of the algorithms and easing the controls over the image capture procedures. With rapid deployment of surveillance cameras, the number of crimes recorded on surveillance footage is also growing fast. These footage are often characterized by poor quality while effects such as occlusion, shadows and noise are commonplace. With further development of biometric approaches towards more robust methods on one hand and the increase of crime scene surveillance footage, which calls for methods of recognition at a distance, on the other, it appears that the two fields are rapidly moving towards each other.

Compared to earprints, the use of ear images for identification has been explored and examined more frequently. Abaza et al. (2013) provides a list of available ear image databases which can be used for ear biometric studies. Some of the most commonly used among these databases are: the UND database (Yan and Bowyer 2005) which includes 2D and 3D images of 415 individuals; XM2VTS database (Messer et al. 1999) comprising of 2D ear images of 295 subjects taken in four time-lapsed sessions; and USTB database (UST 2005) with 500 subjects and with pose variation and partial occlusion.

The automatic recognition of ear images removes the operator bias, and so long as the probe images are comparable to the training and validation images in terms of overall quality, resolution, occlusion, illumination and pose variations the error rates reported for an algorithm are a good estimate of the reliability of the algorithm's predictions for new data. In this, the size of the validation set compared to the size of potential candidate set is also a factor which needs to be considered. However, determining the required size of the training and validation sets for each recognition problem is an open question. It should also be noted that these methods are often complex and unintuitive. Often it is not possible to point out the differences and similarities between two ear images explicitly. This is unfortunate as such descriptions can be useful for the jury.

Ear biometrics methods

Iannarelli (1989) proposed a method based on 12 measurements taken between a number of landmark points on an ear image. These landmark points were determined manually. An automated method based on similar measurements would primarily rely on accurate positioning and segmentation of the landmarks. This is a challenging task to perform automatically. On the other hand, an automatic analysis of samples can capture a more detailed signature, describing the sample, one which may not be viable to obtain manually. Also, there is the obvious benefit of being able to automatically search within a large dataset of samples. It is worth noting here that even the same ear would appear different, albeit slightly, in different images. Identification is possible when the intra-individual variations are smaller than the inter-individual variations. In other words, identification is possible when the samples from the same individual are more similar to each other than to the samples from other individuals. Also note that in biometrics, the focus is to design the most

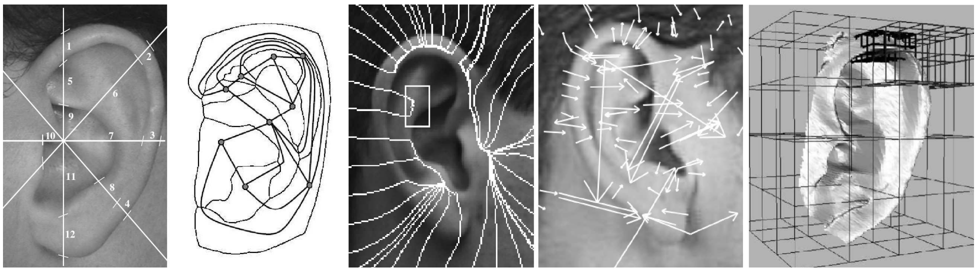


Figure 1.4 From left to right: the Iannarelli's manual measurement system; Burge and Burgers' adjacency graph; Hurley et al.s' force field; Arbab-Zavar and Nixons' keypoints; and Yan and Bowyers' 3D model.

effective and robust algorithms to perform identification. The experimental evaluation of a biometrics technique offers the error rates associated with that specific algorithm performing identification based on a particular biometric trait. Notice that this is not the same as the error rates pertaining to a biometric trait. In biometrics, the error rates are always associated with the algorithms and no upper limit is envisaged for the recognition performance of a specific biometric trait.

One of the first automatic ear biometric algorithms was introduced by Burge and Burger (1998). 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. (2005) 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 from 63 subjects. Naseem et al. (2008) have proposed the use of sparse representation, following its successful application in face recognition. Arbab-Zavar and Nixon (2011) proposed a parts-based model approach which was guided by the biological cues as to the independent parts of the external ear morphology. The ear model was derived by a stochastic clustering on a set of scale invariant features of a training set. The model description was extended by a wavelet-based analysis with a specific aim of capturing information in the ear's boundary structures. A recognition rate of 97.4% was achieved using this method on a dataset of 458 images from 150 individuals. Statistical methods such as principal component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA) have also been used in ear biometrics (Chang et al. 2003; Hurley et al. 2005; Zhang et al. 2005; Zhang and Jia 2007). These statistical methods can obtain satisfactory results in controlled environments. However they have almost no invariance properties, thus they rely on the acquisition and pre-processing stages to window and align the data.

The 3D structure of the ear has also been exploited, and good results have been obtained (Chen and Bhanu 2007; Passalis et al. 2007; Yan and Bowyer 2007). Yan and Bowyer (2007) captured and segmented the 3D ear images and used Iterative Closest Point (ICP) registration to achieve a 97.8% recognition rate on a database of 415 individuals. Chen and Bhanu (2007) proposed a 3D ear detection and recognition system. Using a local surface descriptor and ICP for recognition, they reported recognition rates of 96.8% and 96.4% on two different data sets. Although using 3D can improve the performance, using 2D images is consistent with deployment in surveillance or other planar image scenarios. Figure 1.4 shows the Iannarelli's manual measurements as well as Burge and Burgers' adjacency graph, Hurley et al.s' force field, Arbab-Zavar and Nixons' keypoints and Yan and Bowyers' 3D model. Hurley et al. (2008) described the steps required to implement a simple PCA-based ear biometric algorithm. A survey of ear biometrics has been recently provided by Abaza et al. (2013).

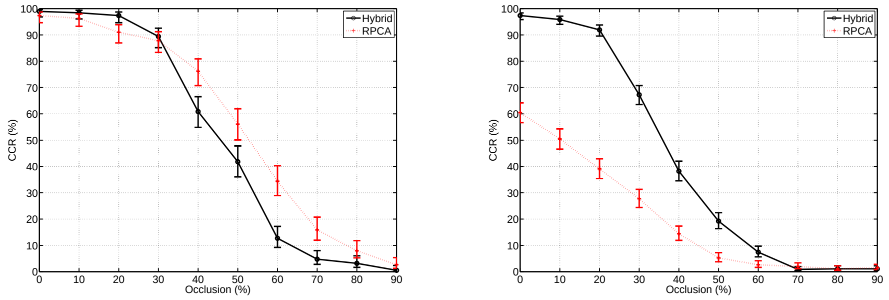
Are ear biometrics methods robust?

One of the main advantages of ear biometrics is that recognition may be made at a distance, such as in surveillance videos. The images captured by a surveillance system are generally of poor quality; they might be partially occluded; the pose might not be the most desired one for identification; while poor illumination and shadows may also deter the image quality. Therefore, the automatic processing of such images requires the use of robust methods.

Bustard and Nixon (2010b) pointed out that, presently, in order to obtain good recognition rates in the area of ear biometrics it is required that the samples be captured under controlled conditions. Moving toward an unconstrained ear recognition method was the main goal of (Bustard and Nixon 2010b). The proposed method includes a registration which computes a homography transform between the probe and gallery images using scale-invariant feature transform (SIFT) point matches. In recognition, a pixel-based distance measure is used to compare the registered and normalized images. The robustness of the method is then tested in presence of pose variation, occlusion, background clutter, resolution, and noise. It has been shown that this method can handle pose variations of up to $\pm 13^{\circ}$ and occlusions of up to 18%, while also showing good robustness properties in the other tested cases.

Model-based methods are generally more equipped to handle noise and occlusion. Using a localized description is another way of increasing robustness to occlusion. Inevitably, some of the information will be lost as a result of occlusion. However, other measurements can also be affected by the change in the overall appearance. It is these measurements which a localized approach can keep from being spoiled. Arbab-Zavar and Nixon (2011) demonstrated the performance advantages of their hybrid method, including a parts-based model extended by a wavelet-based analysis capturing information in the ears boundary structures, in occlusion. In this, they have compared the performance of their method with a robust PCA (RPCA) as a representative of holistic methods. Figure 1.5 shows the results of this comparison. On test set A, the hybrid method performs better than RPCA for as much as 30% of occlusion. The results on test set C exhibit the degrading effect of less accurate registration, which is obtained automatically, on RPCA. In contrast, the hybrid classification maintains good performance, and clearly outperforms RPCA on test set C. Test set C is also more challenging than test set A in terms of number of individuals and overall image quality. Yuan et al. (2010) proposed a localized approach with high redundancy between the local descriptions. They generated a set of 28 overlapping sub-windows for each image and used neighbourhood-preserving embedding to extract the features for each sub-window. In recognition, a weighted majority voting is used for fusion at decision level.

3D ear images have been used to overcome the difficulties encountered with variations in pose and lighting. Various recognition algorithms have been proposed (Chen and Bhanu 2007; Yan and Bowyer 2007) demonstrating high recognition performances. However, range scanners are required to capture the 3D images. Other methods have been proposed to extract



(a) Testset A (b) Testset C

Figure 1.5 The hybrid classifier versus RPCA in occlusion on testsets A and C (from Arbab-Zavar and Nixon (2011)).

the 3D information of the ear for recognition using a set of 2D images from different poses. Shape from shading (Cadavid and Abdel-Mottaleb 2008) and a B-Spline pose manifold (Zhang and Liu 2008) are two examples of these methods. Similar to the methods which work with range data, the data requirements of these methods also restricts their viability for surveillance scenarios. In a more promising approach, Bustard and Nixon (2010a) proposed a new technique for constructing a 3D morphable model of the face profile and the ear using a single image.

1.4.3 Ear morphology features

Perhaps one of the main questions which is encountered in the forensic identification is this question: “is there enough information available to make a positive identification?”. Hoogstrate et al. (2001) asked a similar question from two groups of operators: forensic experts and laymen. For this, multiple video captures using standard surveillance equipment were made from 22 subjects under different conditions. A mask was overlaid on the video showing only the ear part. Each participant was presented with 40 sets of paired videos and for each pair they were asked: (1) Is there enough information in the video for individualization or exclusion; and (2) Are the individuals in the two videos the same person? Hoogstrate et al. derived two main conclusions from their experiments: (1) the quality of the video influences the participant’s decision of whether they have enough information; and (2) the forensically trained persons were able to determine if they had sufficient information. Note that the dataset for this study was small and the experiment was conducted under closed set assumption. Albeit, this raises an important question of which are the ear’s discriminating features and how the performance accuracy and confidence levels are affected when different parts of the ear are not visible.

The significance of various parts of the ear for identification has been rarely studied in the field of ear biometrics. In our earlier work (Arbab-Zavar and Nixon 2011), we have looked into identifying the various parts of the ear morphology and investigate as to their discriminatory powers. This study was guided by accounts of embryonic development of the external ear. The study of ear embryology reveals that the external ear is the result of

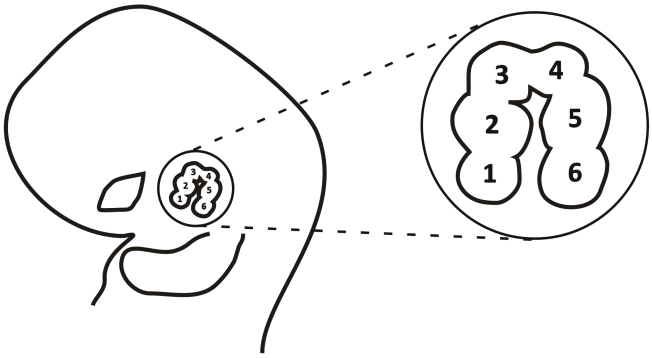


Figure 1.6 The six auricular hillocks and their location in a human embryo.

6 nodules whose unequal growth and coalescence give the final shape of the external ear. A conclusion was drawn that there should be a limited information redundancy between these parts since they are thought to be developed independently. Therefore missing the information of any of these parts could not be fully recovered by the other visible parts. Some of the information content is thereby lost and our capability to perform identification using this data is weakened.

The separability and variability of ear parts was investigated via two very different approaches. The first approach was based on statistical analysis of shape within a dataset of ears. In this, a part based model was learned from a dataset of ear images. The parts are arbitrary scaled circular neighbourhoods, called the keypoints, which are detected and described via the SIFT descriptor (Lowe 2004). A parts-based model was then built via clustering of the detected keypoints in different images. The second approach was based on embryonic development of the external ear and the embryological understanding of ear abnormalities. In this, cues from the ear abnormalities were used to hypothesise as to the independent parts of the ear. It was considered that the most variable parts of the ear are those which are most frequently the site of ear abnormalities. These parts also provide a valuable set of features that can be used to communicate with juries.

The initial appearance of the external ear in the human embryo is in the shape of six individual hillocks occurring in the fifth week of embryonic life (Streeter 1922). Figure 1.6 shows a drawing of an embryo with its auricular hillocks numbered. It is the unequal growth and coalescence of these six hillocks that gives the shape of the definitive auricle in a newborn baby. This is the reason for our interest in ear embryology – the premise of local and independent structures within the auricle is appealing to the classification purpose.

Streeter (1922), who provided one of the most extensive accounts of external ear embryology, argued against the individual development of the auricular hillocks and suggested that the external ear comes into existence as an intact and continuous structure which elaborates into its final form. However there is a wide range of defects which disturb the smooth continuity of the auricle. These can be best described as the failure of fusion or the lack of correct alignment of the various hillocks, which further insists on the role of separate structures in the formation of the definitive auricle (Davis 1987; Hunter and Yotsuyanagi 2005). Some other malformations can be described as excessive growth beyond,

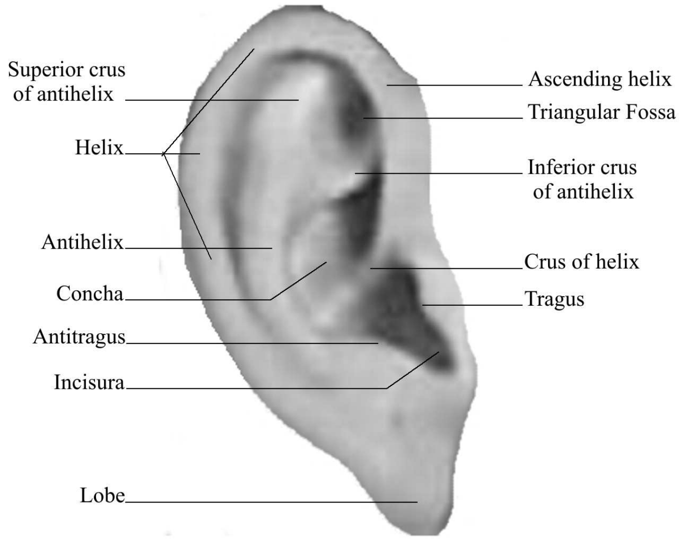


Figure 1.7 The terminology of the ear

or, underdevelopment beneath the thresholds of normality. Thereby the site of such anomaly is also where a considerable variation is introduced; it is unlikely that an abnormality will be observed in locations of more constant structures.

The findings of (Arbab-Zavar and Nixon 2011) have been revisited here with an eye towards earprint identification and the missing parts. Figure 1.7 shows the common terminology of the external ear.

Inferior crus of antihelix and the crus of helix

According to Streeter, the inferior crus of antihelix and the crus of helix are the least variant parts of the ear. Seemingly contradictory, these two parts are detected as the most significant parts of the parts-based model. It was discussed in (Arbab-Zavar and Nixon 2011) that this is caused by the models varying capability in detecting the parts. Automatic detection of parts is a task which precedes the comparison of parts and indeed not all the parts are detected in every ear image. The inferior crus of antihelix and the crus of helix are the most frequently and accurately detected parts in different ears, so much so that they become the most significant parts of the model for recognition. It is hypothesized that the comparative consistency of these parts helps with learning them via a clustering method. We suspect that a manual labelling of the parts, presuming that such labelling can be achieved accurately and consistently, would reveal a slightly different ranking of important parts. In the next section, we will describe how the inadequate representation of helix and antihelix in the parts model have motivated Arbab-Zavar and Nixon (2011) to extend the initial parts-based model and build a hybrid model. This emphasizes the importance of choosing the right algorithm for ear image, ear print and in fact any biometric comparison. Considering the earprints, it can perhaps be considered fortunate that two parts which often do not leave a print are actually the least varying parts of the ear. Thus their absence is least significant.

Helix, antihelix and scapha

The outer ear rim, the helix, may be attributed to as many as three out of six embryonic hillocks. Ascending helix, the portion of the helix immediately attached to the crus of helix, is assigned to an individual hillock by Streeter (1922) and Sulik (1995). An anomaly called the *lop ear* is the product of the absence of the ascending helix, while the rest of the parts have their normal shape (Hunter and Yotsuyanagi 2005). Two other defects exhibit conspicuous clefts separating the ascending helix from the rest of the helical components on either side (Davis 1987; Park and Roh 1999). The ascending helix is also detected by the parts model and is the third most significant part of the model. As for the rest of the helix, there are two major hypotheses regarding its formation: suggested by His, the upper and lower helical components, including the helix and antihelix, are derived from hillocks 4 and 5 respectively; while Streeter believes that a single hillock (5th) gave rise to the helix and the antihelix is the product of hillock 4. In accordance with the first hypothesis, the upper helical region appears to be subject to considerable growth variations. Cryptotia and Satyr ear are two anomalies exhibiting underdevelopment of this region (Hunter and Yotsuyanagi 2005). The upper and lower helical regions have been detected as separate parts in the parts model and are both among the 7 most significant parts of the model. On the other hand, the emergence of the scapha, the concave surface of free portion lying between the antihelix and the helix, provides a margin and allows the helix and antihelix to have some degree of independent development which is better described by Streeter's hypothesis. The antihelix, as mentioned above is subject to variations of the upper helical region, while the lower parts are more constant. Due to the limitation of the circular image descriptor which was the basis local area unit of the model parts, the elongated parts such as the helix and anti-helix were not captured adequately. A specialized representation and method was then applied to capture the variations of the two elongated structures of the helix and anti-helix separately. A recognition rate of 91.9% is achieved with helix and antihelix dominant representation on a dataset with 458 images from 150 individuals (Arbab-Zavar and Nixon 2011). In this the part model obtains an 89.1% recognition rate. The combination of these two methods, which is called the hybrid model, yields a significant improvement with a 97.4% recognition rate and further suggests that independent information content have been captured by these two methods. Also note that the helix and antihelix dominate the earprint mark. However, the upper antihelix region of the superior and the inferior cruses of antihelix are commonly missing in these prints.

The lobe

Lobe is one of the only parts of the ear which lends itself to categorical classification. Three types of lobe are: well-formed; attached; and no lobe. In forensics, ear lobes are used in international standards for identification in Disaster Victim Identification (DVI) 2008. Note also that ear piercing, which is a semi-permanent body modification, was reported by Abbas et al. to occur in 46% of their population sample of 400 adults (Abbas and Rutty 2005). They reported that, in about 95% of the cases with ear piercing, the piercing occurs on the lobe. They noted that the presence or absence of such piercing itself is a useful attribute for forensic identification. The ear lobe is the only part of the ear which is composed of fat rather than cartilage. This part continues to grow and change shape as the person grows older (Meijerman 2006). Albeit, it could exhibit a variety of shapes, and in a database with a small time lapse between the captured samples it can be comparatively discriminant.

Tragus and antitragus

In Otocephaly, which is a syndrome accompanied by an anomaly of the auricle, the tragus is missing. Other tragal anomalies may exhibit extensions or duplications of the tragus flesh (Hunter and Yotsuyanagi 2005), indicating a rich variation in the shape of this component. In contrast, antitragus has been little discussed in the analyses of ear anomalies. Tragus and antitragus are also commonly found on earprints.

Concha

Concha is the part of the external ear which will almost certainly be missing from the earprint. The depth of this cavity is the main feature of this component. The Mozart ear is characterized by its shallow concha and it was also discussed that there is a correlation between the depth of the concha and the sensitivity of the ear to hearing sounds. However, this feature is also absent in 2D ear images.

1.4.4 Summary

In the second case study, we have examined the application of the emerging field of ear biometrics for forensic identification. Human ear is an ideal contender for such a study since it is available both in images at a distance and in latent prints. Earprints and ear images are considered separately as two different representations of ear. The less familiar features of ear, along with their correlations and variability are also discussed. We have also addressed the question of admissibility in court.

Ear is an important emerging biometric. There is a clear expectation that ears do not change in structure from cradle to grave, only in size (except with surgical intervention). There is a known taxonomy for their description and it is accepted that people can be identified by their ears. There is a rich variety of approaches for ear biometrics and these are steeped in pattern recognition and computer vision. These show that using ears has similar performance to other biometrics, using similar methods, though the research is as yet not so deep or popular as that for the more established biometrics. As such, ears can then be deployed in scene of crime analysis where images of an ear are available, and the ear has actually already been deployed in this way. The notion that people can be recognised from a latent earprint has a more chequered history. This arises when a subject's ear makes contact with a surface, say for listening in purposes. Naturally, there are problems with image quality as there are for latent fingerprints and the problem is confounded by the absence of modelling of the change in print with ear deformation, though a combination of 3D shape analysis (which exists for ears) with a 3D plastic membrane could offer understanding in this direction. As it stands, the ear clearly has the potential to be one of the stock of biometrics in digital forensics both for imagery and for recorded prints - and given its proven identification capability it appears well worthy of future study in this respect.

1.5 Conclusions

Given that biometrics concerns automatically establishing identity and forensics requires confirmation of identity, it is perhaps surprising that the inclusion of biometrics is not further advanced within the forensic community. For this to be achieved, agreement standards for acceptability needed to be reached and these are relatively new to biometrics. Given its long history, it is no surprise there is a richer literature in identifying subjects from fingerprints and fingerprint biometrics is becoming well established for latent fingerprint recognition. The translation of other biometrics (such as face, gait, ear, voice) is considerably less advanced.

This chapter has outlined the historical connections between biometrics and forensics and examined the application of face and ear biometrics for forensic identification in detail. Given that face and ear are in different stages of deployment in forensics, various aspects of this deployment were discussed. The examination of ear forensic possibilities gave rise to the early questions of admissibility, mainly regarding the use of earprints. The morphological features of the ear were also examined in detail. Such insights are essential for evaluation of partially occluded data and further influential when communicating the findings of biometric comparisons to juries. More advanced in the forensic field, manual forensic face recognition methods and the deployment of automatic techniques were discussed. The challenges looming over both face and ear applications in forensics, mainly due to poor data quality which is common of forensic data, and the current state of automatic recognition performance and robustness were examined. This chapter has aimed at closing the gap between the forensics and biometrics experts understandings of the identification task. Although further study is needed within various fields of biometrics so that they are equipped for inclusion within forensics, given the prospects they offer this appears well worthy of the effort.

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