THE EAR AS A BIOMETRIC

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ABSTRACT

It is more than 10 years since the first tentative experiments in ear biometrics were conducted and it has now reached the "adolescence" of its development towards a mature biometric. Here we present a timely retrospective of the ensuing research since those early days. Whilst its detailed structure may not be as complex as the iris, we show that the ear has unique security advantages over other biometrics. It is most unusual, even unique, in that it supports not only visual and forensic recognition, but also acoustic recognition at the same time. This, together with its deep three-dimensional structure and its robust resistance to change with age will make it very difficult to counterfeit thus ensuring that the ear will occupy a special place in situations requiring a high degree of protection.

1. INTRODUCTION

The potential of the human ear for personal identification was recognized and advocated as long ago as 1890 by the French criminologist Alphonse Bertillon [4]. Ears have not proved popular in the past but they have been used in forensic science especially in the United States, where a manual classification system was developed by Iannarelli [20], although the reliability of ear-print evidence has recently been challenged [23,14] . Rutty et al. aim to extend this work [29] and a European initiative recently evaluated ear prints in forensics [24]. We will show in section 2 that the ear has many advantages to commend it as a biometric.

Burge et al. [7,8] were amongst the first to explore the ear's potential as a biometric using graph matching techniques on a Voroni diagram of curves extracted from the Canny edge map. Moreno et al. [26] using neural networks reported a recognition rate of 93% on a dataset of 168 images. Hurley et al. used force field feature extraction [16,15,19] to map the ear to an energy field which highlights "potential wells" and "channels" as features. By achieving a recognition rate of 99.2% on a dataset of 252 images [19], this method proved to yield a much better performance than PCA when the images were poorly registered. This approach is also very robust to noise [18]. Abdel-Mottaleb et al. [1] employed a technique based on surface curvature.

Principal Components Analysis (PCA) has proved the most popular technique. Victor et al. [32] applied PCA to both face and ear recognition and concluded that the face yields a better performance than the ear. However, Chang et al. [9] conducted a similar experiment and reached a different conclusion: no significant difference was observed between face and ear biometrics when using PCA. The image dataset in [32] had less control over earrings, hair, lighting etc. and as suggested by Chang et al., this may account for the discrepancy. Chang et al. also reported a recognition rate of 90.9% using an ear and face multimodal approach. Zhang et al. [40] developed a system combining Independent Components Analysis (ICA) with a Radial Basis Function (RBF) network showing that ICA outperforms PCA. However both PCA and ICA offer poor invariance requiring accurate registration for good results.

Yuizono et al.[39] used optimisation within a genetic local search but with poor invariance because there is no feature extraction. Some studies have focused on geometrical approaches [27,13]; Mu et al. [27] reported an 85% recognition rate using such an approach. Alvarez et al. [3] proposed and intend to implement an ovoid model for segmentation and normalization of the ear. Yan et al. [35,34] captured 3D ear images using a range scanner and used Iterative Closest Point (ICP) registration for recognition to achieve a 97.8% recognition rate. Chen et al. proposed a 3D ear detection and recognition system using a model ear for detection, and using ICP and a local surface descriptor for recognition, reporting a recognition rate of 90.4% [12,11,10,6].

Multimodal approaches have also been used [9,38,21,28]. Iwano et al. [21] combined PCA processed ear images with speech using a composite posterior probability demonstrating improved performance in noise. Chang et al. [9] and Rahman et al. [28] used multimodal PCA face and ear obtaining improved recognition rates of 90.9% and 94.4% respectively. Yan et al.[38] tested various combinations of 2D-PCA, 3D-PCA, and 3D-edges on a dataset of 203 images achieving best results with a fusion of all three. Table 1 shows the main results. For further details of ear, multimodal ear and face biometrics see [41].

Table 1

	2D/3D	Modality	Performance	Dataset
Moreno	2D	Neural Net	93%	168
Hurley	2D	Force Field	99.2%	252
Mu	2D	Geometric	85%	308
Yan	3D	ICP	97.8%	1386
Chen	3D	ICP	90.4%	104

Akkermans et al. [2] developed a biometric system which measures the acoustic transfer function of the ear by projecting a sound wave at the ear and observing the change in the reflected signal. Scandia patented a similar technique [30]. We proceed by making the case for the ear as a biometric and then touch on some representative case studies, followed by conclusions and future outlook.

2. EVIDENCE AND SUPPORT FOR EARS AS A BIOMETRIC

Figure 1 (right) shows the anatomy of the ear. In addition to the familiar rim or helix and ear lobe, the ear also has other prominent features such as the anti-helix which runs parallel to the helix, and a distinctive hairpin-bend shape just above the lobe called the intertragic notch. The central area or concha is named for its shell-like appearance. Figure 1(left) shows some examples of the human ear shape. Notice that helices, concha, intertragic notch, etc. are present in all the examples, but that some ears have so called attached lobes, which are poorly formed or are almost non-existent.

Figure 1 Left: a selection of ears. Right: anatomy of the ear.

The ear structure is rich, changes little with age, and is unaffected by facial expressions. It is firmly fixed on the side of the head so that the immediate background is predictable, unlike that of the face. Collection does not have an associated hygiene issue, unlike fingerprints, and will not cause anxiety as may happen with iris and retina measurements. The ear is large compared with the iris, retina, and fingerprint and therefore is more easily captured at a distance. It has roughly the same visual complexity as the face but unlike the face lacks any symmetry so that information is not duplicated. Its appearance is not altered by make-up, spectacles, or beards and moustaches, although of course it is often occluded by hair. As such, the ear is much less susceptible to covariate interference than many other biometrics, with particular invariance to age.

3. APPROACHES TO EAR BIOMETRICS

Iannarelli's manual classification system [20] developed around 1950 essentially consists of taking a number of measurements around the ear by placing a transparent compass with 8 spokes at 45 degree intervals over an enlarged photograph of the ear. The first part of registration is achieved by ensuring that a reference line touches the crus of helix at the top and touches the innermost point on the tragus at the bottom. Normalisation and the second step of registration are accomplished by adjusting the enlargement mechanism until a second reference line exactly spans the concha from top to bottom. Recent attempts have been made to automate Iannarelli's system [29].

Burge and Burger [7,8] were the first to investigate the human ear as a biometric, conducting a proof of concept study where the viability of the ear as a biometric was shown both theoretically in terms of the uniqueness and measurability over time, and in practice through the implementation of a computer vision based system. Each subject's ear was modelled as an adjacency graph built from the Voronoi diagram of its Canny extracted curve segments. They devised a novel graph matching algorithm for authentication which takes into account the erroneous curve segments which can occur in the ear image due to changes such as lighting, shadowing, and occlusion. They found that the features are robust and could be reliably extracted from a distance. Figure 2 shows the extracted curves, Voronoi diagram, and a neighbourhood graph for a typical ear. They identified the problem of occlusion by hair as a major obstacle and proposed the use of thermal imagery to overcome this obstacle.

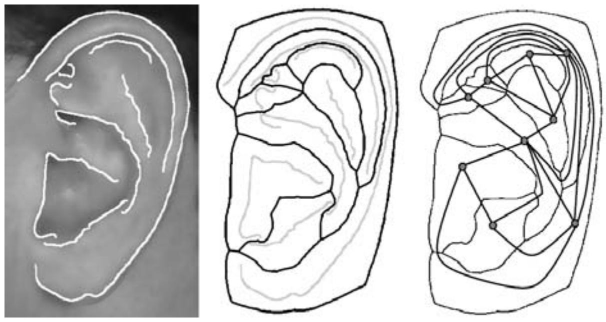

Figure 2 Stages in building the ear biometric graph model [7,8]. A generalized Voronoi diagram (centre) of the Canny extracted edge curves (left) is built and a neighbourhood graph (right) is extracted.

Principal Components Analysis, closely related to Singular Value Decomposition, has been one of the most popular approaches to ear recognition [32,9,19,21,33,28]. It is an elegant, easy to implement and easy to use technique, which produces excellent results providing that the images are accurately registered and closely cropped to exclude extraneous information. Unfortunately it suffers from very poor invariance. Hurley et al. used it on a subset of 252 ear images extracted from the XM2VTS face profiles database [25,41] to achieve a recognition rate of 98.4%. It works by exploiting the data compression advantage of SVD. A set of training images is processed to produce a special *projection matrix* which enables the computation a set of weights which when used to scale a set of special "picture-vectors" already encoded in the projection matrix produces a reasonable facsimile of the original image. These weights form convenient feature vectors representing each picture and are perfect for biometric comparison as they allow the calculation the a *distance* between pictures by doing a simple vector subtraction.

Force Field Transform. Hurley et al. [16,17,15,19] have developed an invertible linear transform which transforms an ear image into a force field by pretending that pixels have a mutual attraction proportional to their intensities and inversely to the square of the distance between them rather like Newton's Universal Law of Gravitation. Underlying this force field there is an associated energy field which in the case of an ear takes the form of a smooth surface with a number of peaks joined by ridges as shown in Figure 3. The peaks correspond to potential energy wells and to extend the analogy the ridges correspond to potential energy channels. Since the transform also turns out to be invertible, all of the original information is preserved and since the otherwise smooth surface is modulated by these peaks and ridges, it is argued that much of the information is transferred to these features and that therefore they should make good features.

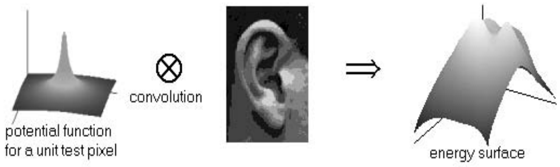

Figure 3 Left: Potential function. Right Potential surface [16,17]

$$Energy = \sqrt{MN}\left\{\Im^{-1}\left[\Im(potential\ \ function)\times\Im(image)\right]\right\} \qquad (1)$$

Two distinct methods of extracting these features are provided. The first method depicted in Figure 4 (left) is algorithmic, where test pixels seeded around the perimeter of the force field are allowed to follow the force direction joining together here and there to form channels which terminate in potential wells. The second method depicted in Figure 4 (centre) is analytical, and results from an analysis of the mechanism of the first method leading to a scalar function based on the divergence of the force direction. The second method was used to obtain a recognition rate of over 99% on a dataset of 252 ear images consisting of 4 time lapsed samples from each of 63 subjects, extracted from the XM2VTS face profiles database [25].

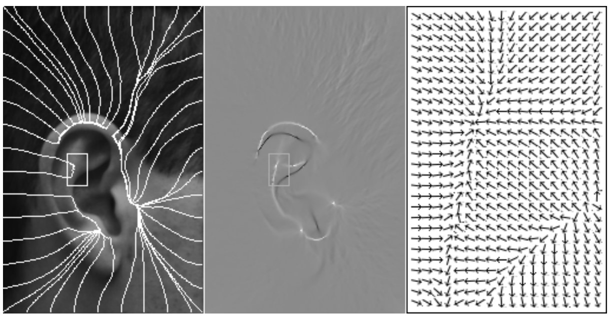

Figure 4 Force and convergence fields for an ear [18,19]. The force field for an ear (left) and its corresponding convergence field (centre). The force direction field (right) corresponds to the small rectangular inserts surrounding a potential well on the inner helix.

Equation 2 shows how the energy field is calculated at any point $\mathbf{r}$. This equation must be applied at every pixel position to generate the complete fields. The force field $\mathbf{F}$ is simply the derivative of the energy field. In practice for an M by N-pixel image this computation would be done in the frequency domain using Equation 1 where $\Im$ stands for FFT.

$$E(\mathbf{r}_j) = \sum_i \left\{ \frac{P(\mathbf{r}_i)}{\left|\mathbf{r}_i - \mathbf{r}_j\right|} \forall i \neq j \right\}, \quad 0 \forall i = j \qquad (2)$$

Convergence provides a more general description of channels and wells in the form of a mathematical function in which wells and channels are revealed to be peaks and ridges respectively in the function value. This function maps the force field $\mathbf{F(r)}$ to a scalar field $C(\mathbf{r})$, taking the force as input and returning the additive inverse of the divergence of the force direction and is defined by,

$$C(\mathbf{r}) = -\operatorname{div}\mathbf{f}(\mathbf{r}) = -\lim_{\Delta A \to 0} \frac{\oint \mathbf{f}(\mathbf{r})\cdot d\mathbf{l}}{\Delta A} = -\nabla\cdot\mathbf{f}(\mathbf{r}) = -\left(\frac{\partial f_x}{\partial x} + \frac{\partial f_y}{\partial y}\right) \qquad \mathbf{(3)}$$

where $\mathbf{f}(\mathbf{r}) = \frac{\mathbf{F}(\mathbf{r})}{\left|\mathbf{F}(\mathbf{r})\right|}$, ΔA is incremental area, and $d\mathbf{l}$ is its boundary outward normal. This function is real valued and takes negative values as well as positive ones where negative values correspond to force direction divergence. Note that the function is non-linear because it is based on force direction and therefore must be calculated in the given order.

Three Dimensional Ear Biometrics The auricle has a rich and deep three dimensional structure, so it is not surprising that a number of research groups have focused their attention in this direction. **Yan and Bowyer** [36,38,37,35,34] use a Minolta VIVID 910 range scanner to capture both depth and colour information. The device uses a laser to scan the ear, and depth is automatically calculated using triangulation. They have developed a fully automatic ear biometric system using ICP based 3D shape matching for recognition, and using both 2D appearance and 3D depth data for automatic ear extraction which not only extracts the ear image but also separates it from hair and earrings. They achieve almost 98% recognition on a time-lapse dataset of 1,386 images over 415 subjects, with an equal error rate of 1.2%. The 2D and 3D image datasets used in this work are available to other research groups.

Ear extraction uses a multistage process which uses both 2D and 3D data and curvature estimation to detect the ear pit which is then used to initialise an elliptical active contour to locate the ear outline and crop the 3D ear data. Ear pit detection includes: (i) geometric prepossessing to locate the nose tip to act as the hub of a sector which includes the ear with a high degree of confidence; (ii) skin detection to isolate the face and ear region from the hair and clothes; (iii) surface curvature estimation to detect the pit regions depicted in black in the image; (iv) surface segmentation and classification, and curvature information to select amongst possible multiple pit regions using a voting scheme to select the most likely candidate.

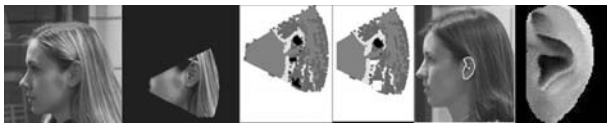

Figure 5 3D ear extraction [36,38]. From left to right, skin detection and most likely sector generation, pit detection and selection, ear outline location, 3D ear extraction

The detected ear pit is then used to initialise an active contour algorithm to find the ear outlines. Both 2D colour and 3D depth are used to drive the contour, as using either alone is inadequate since there are cases in which there is no clear colour or depth change around the ear contour.

Iterated Closest Point (ICP) [5] has been widely used for 3D shape matching due to its simplicity and accuracy, however it is computationally expensive. Yan et al. [36] have developed an efficient ICP registration method called "Pre-computed Voxel Closest Neighbours" which exploits the fact that subjects have to be enrolled beforehand for biometrics.

Chen and Bhanu [6,10,11,12] have also tackled 3D ear biometrics using a Minolta range scanner as the basis of a complete 3D recognition system on a dataset of 52 subjects consisting of two images per subject. The ears are detected using template matching of edge clusters against an ear model based on the helix and antihelix, and then a number of feature points are extracted based on local surface shape. A signature called a *Local Surface Patch* (LSP) based on local curvature is computed for each feature point and is used in combination with ICP to achieve a recognition rate of 90.4% Figure 6 depicts the LSP comprising of a characteristic signature consisting of a 2D histogram, a surface type, and a centroid.

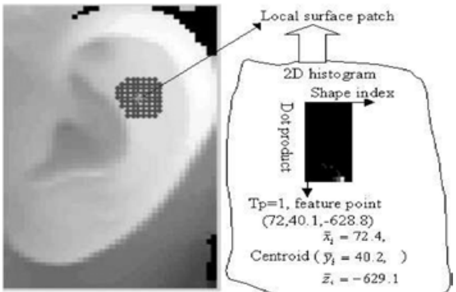

Figure 6 Local Surface Patch [6,10]. The LSP consists of a characteristic signature consisting of a 2D histogram, a surface type, and a centroid.

Acoustic Ear Recognition Akkermans et al. [2] have exploited the acoustic properties of the ear for recognition. It turns out that the ear by virtue of its special shape behaves like a filter so that a sound signal played into the ear is returned in a modified form.

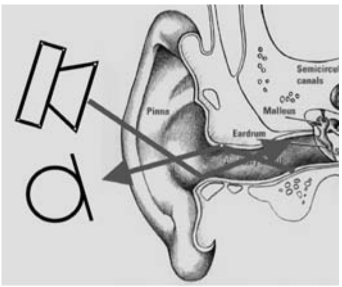

Figure 7 An ear signature is generated by probing the ear with a sound signal which is reflected and picked up by a small microphone [2]. The shape of the pinna and the ear canal determine the acoustic transfer function which forms the basis of the signature.

This acoustic transfer function forms the basis of the acoustic ear signature. An obvious commercial use is that a small microphone might be incorporated into the earpiece of a mobile phone to receive the reflected sound signal and the existing loudspeaker could be used to generate the test signal.

4. CONCLUSIONS AND OUTLOOK

The ear as a biometric is no longer in its infancy and it has shown encouraging progress so far - which is improving, especially with the interest created by the recent research into its 3D potential. It enjoys forensics support, its structure is well suited to biometrics, and it appears to have less variance with age than other biometrics. It is also most unusual, even unique, in that it supports not only visual recognition but also acoustic recognition at the same time. This, together with its deep 3-dimensional structure will make it very difficult to fake thus ensuring that the ear will occupy a special place in situations requiring a high degree of protection against impersonation.

The all important question of "just how good is the ear as a biometric" has only begun to be answered. The initial test results, even with quite small datasets, were disappointing, but now we have regular reports of recognition rates in the high 90's on more sizeable datasets. But there is clearly a need for much better intra-class testing, both in terms of the number of samples per subject and of variability over time. Most of the recent work has focused on the overall appearance or on the shape of the ear, whether it be PCA, force field, or ICP, but it may prove profitable to further investigate if different and particular parts of the ear are more important than others from a recognition perspective. There is also a need to develop techniques with better invariance, perhaps more model based, and to seek out high speed recognition techniques to cope with the very large datasets that are likely to be encountered in practice.

We must not forget that the inherent disadvantage of the occlusion of the ear by hair will always be a problem, but even this might be ameliorated by the development of thermal imaging schemes. But one thing is for certain, and that is that there are many questions to be answered, so we can look forward to many interesting research studies addressing these issues.

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