Ear Biometrics in Computer Vision

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Abstract

A class of biometrics based upon ear features is introduced for use in the development of passive identification systems. The viability of the proposed biometric is shown both theoretically in terms of the uniqueness and measurability over time of the ear, and in practice through the implementation of a computer vision based system. Each subject's ear is modeled as an adjacency graph built from the Voronoi diagram of its curve segments. We introduce a novel graph matching based algorithm for authentication which takes into account the erroneous curve segments which can occur due to changes (e.g., lighting, shadowing, and occlusion) in the ear image. This class of biometrics is ideal for passive identification because the features are robust and can be reliably extracted from a distance.

1 Introduction

Automating identification through biometrics [3] especially *face recognition* has been extensively studied in machine vision. Despite extensive research many problems in face recognition remain largely unsolved due to the inherent difficulty of extracting face biometrics. A wide variety of imaging problems (e.g., lighting, shadows, scale, and translation) plague the attempt for unconstrained face identification In addition to the many imaging problems, it is inherently difficult to collect consistent features from the face as it is arguably the most changing part of the body due to facial expressions, cosmetics, facial hair and hair styling. The combination of the typical imaging problems of feature extraction in an unconstrained environment, and the changeability of the face, explains the difficulty of automating face biometrics. Despite the attractiveness of face biometrics (e.g., they are easily verifiable by non-experts) other biometrics (e.g., fingerprint based) provide the basis for most commercial implementations.

Unlike facial biometrics, *fingerprint-based biometrics* have been shown to be highly amenable to automation by machine vision techniques The automation of fingerprint biometrics began in 1971 and has culminated in a number of commercial machine vision based systems. Fingerprint imaging is done within a controlled environment, usually with a specially designed scanner, which eliminates the problem of localization and artifacts from shadowing and lighting variations. Physical changes, a bane of facial biometrics, is a miniscule problem as the finger, baring surgery, remains comparatively constant over time. Machine vision techniques have been successfully applied to create highly accurate and robust commercial systems which are in use worldwide.

2 Passive Biometrics

Fingerprints are not the only successful example of the application of machine vision techniques to automated biometrics, both the three dimensional *shape of the hand* and *retinal patterns* have also been used. All of the biometrics which have been successfully automated using machine vision techniques are inherently *invasive*. They require the subject to participate actively in both enrolling into the system and during subsequent identification. The willing participation of the subject in the controlled environment of these systems is intrinsic in the success of the identification.

One class of *passive* physiological biometrics are those based upon *iris scans*. Unlike retinal scans, which require close contact with the scanner, iris-based recognition has been reported to be successful at distances of up to 46 cm [8]. The unique collection of striations, pits, and other observable features of the iris along with the ease of segmenting the iris from the white tissue of the eye which serves as its background, make iris based biometrics attractive. The decided disadvantage is the small size of the iris which makes image acquisition from a distance, and therefore passive usage, problematic.

To summarize the two classes of passive physiological biometrics which have been researched in machine vision up to now; face and iris-based techniques both have a number of drawbacks which make their usage in commercial applications limited. Facial biometrics fail due to the changes in features caused by expressions, cosmetics, hair styles, and the growth of facial hair as well as the difficulty of reliably extracting them in an unconstrained environment exhibiting imaging problems such as lighting and shadowing. Unlike facial biometrics, Iris biometrics remain relatively consistent over time and are easy to extract, but acquisition of the image at the necessary resolution from a distance is difficult. Therefore, we propose a new class of biometrics for passive identification based upon ears which have both reliable and robust features which are extractable from a distance.

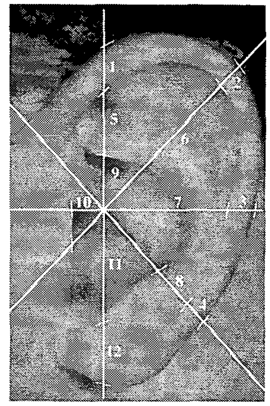


Figure 1. Anthropometric measurements used in the "Iannarelli System".

3 Ear Biometrics

In proposing the ear as the basis for a new class of biometrics, we need to show that it is viable (i.e., unique to each individual, and comparable over time). In the same way that no one can prove that fingerprints are unique, we can not show that each of us have an unique pair of ears. Instead, we will assert that this is probable and give supporting evidence by examining two studies from Iannarelli [6]. The first study compared over 10,000 ears drawn from a randomly selected sample in California, and the second study examined fraternal and identical twins, in which physiological features are known to be similar. The evidence from these studies supports the hypothesis that the ear contains unique physiological features, since in both studies all examined ears were found to be unique though identical twins were found to have similar, but not identical, ear structures especially in the Concha and lobe areas. Having shown uniqueness it remains to ascertain if the ear provides biometrics which are comparable over time.

It is obvious that the *structure* of the ear does not change radically over time. The medical literature reports [6] that ear growth after the first four months of birth is proportional. It turns out that even though ear growth is proportional, gravity can cause the ear to undergo stretching in the vertical direction. The effect of this stretching is most pronounced in the lobe of the ear, and measurements show that the change is non-linear. The rate of stretching is approximately five times greater than normal during the period from four months to the age of eight, after which it is constant until around 70 when it again increases.

We have shown that biometrics based upon the ear are viable in that the ear anatomy is probably unique to each individual and that features based upon measurements of that anatomy are comparable over time. Given that they are viable, identification by ear biometrics is promising because it is passive like face recognition, but instead of the difficult to extract face biometrics, robust and simply extracted biometrics like those in fingerprinting can be used.

4 Iannarelli's Ear Biometrics

An anthropometric technique of identification based upon ear biometrics was developed by A. Iannarelli [6] in 1949. The "Iannarelli System" is based upon 12 measurements illustrated in Figure 4. The locations shown are measured from specially aligned and normalized photographs of the right ear. To normalize and align the images, they are projected onto a standard "Iannarelli Inscribed" enlarging easel which is moved horizontally and vertically until the ear image projects into a prescribed space on the easel. The system requires the exact alignment and normalization of the ear photos.

Since each ear is aligned and scaled during development, the resulting photographs are normalized, enabling the extraction of comparable measurements directly from the photographs. The distance between each of the numbered areas in Figure 4 is measured in units of 3 mm and assigned an integer distance value. These twelve measurements, along with information on sex and race, are then used for identification. The system as stated provides for too small of a classification space as within each sex and race category a subject is classified into a single point in a 12 dimensional integer space where each unit on an axis represents a 3 mm measurement difference. Assuming an average standard deviation in the population of four units (i.e., 12 mm) then the 12 measurements provide for a space with *less* than 17 million distinct points.

Though simple remedies (e.g., the addition of more measurements or using a smaller metric) for increasing the size of the space are obvious, the method is additionally not suited for machine vision because of the difficultly of localizing the anatomical point which serves as the origin of the measurement system. All measurements are relative to this origin which if not exactly localized, results in all subsequent measurements being incorrect. In fact Iannarelli himself was aware of this weakness as he states on page 83, "This is the first step in aligning the ear image.... and it must be accurate or the entire classification of the ear will be inaccurate". In the next section we present a proof of concept implementation which avoids the problem of localizing anatomical points and the frailty of basing all subsequent feature measurements on a single such point.

5 Automating Ear Biometrics

The goal in *identification* is to verify that the biometric extracted from the subject sufficiently matches the previous acquired biometric for that subject. Let s' be the subject at the time of identification and s the subject at time of enrollment, further let $G_s = f(s)$ represent a function which extracts some biometric from a subject s as a graph G_s, and let $d(G_s, G_{s'})$ compute some previously defined distance metric between these two graphs. Identification is then the task of determining if $d(G_s, G_{s'}) < t$, where t is a given acceptance threshold.

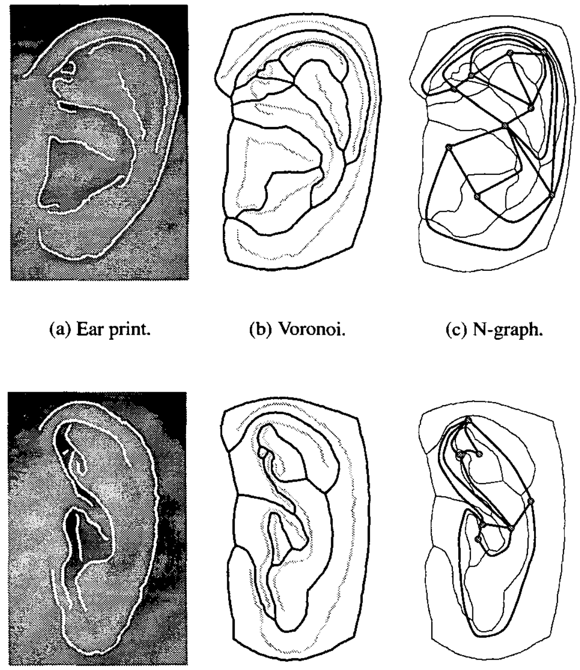
Since the subject and environment change over time, a certain tolerance in the matching criterion must be permited. This tolerance can be defined in terms of the *false reject rate* (FRR) and the *false acceptance rate* (FAR) exhibited by the system. A system is usually designed to be tunable to minimize either the FAR or the FRR (i.e., in the given formulation by lowering or raising t respectively) depending upon the type of security which is required.

The problem of *recognition* is harder than that of identification since the system must determine if the subject's identity can be verified against *any* previously enrolled subject. If the system's enrolled identities are the set $\mathcal{I} = \{G_0, G_1, \cdots, G_n\}$ then recognizing some subject s' is equivalent to finding the least member of the set $\{G_i | G_i \in \mathcal{I} \wedge d(G_{s'}, G_i) < t\}$. We have developed a machine vision system as a proof of concept of the viability of ear biometrics for passive and passive identification. The system implements $f(s')$ using the following steps:

1. *Acquisition:* A 300 by 500 grayscale image is taken of the subject's head in profile using a CCD camera.

   Next the location of the ear in the image must be found;

   since our goal was to construct a proof of concept system, we used a relatively simple method based on deformable contours.



(a) Ear print. (b) Voronoi. (c) N-graph.

(d) Ear print. (e) Voronoi. (f) N-graph.

Figure 2. Ear biometric graph model.

2. *Localization:* The the ear is located by using deformable contours [7] on a Gaussian pyramid representation of the image gradient.

3. *Edge extraction:* Edges are computed using the Canny operator (i.e., $\sigma = 3.0$) and thresholding with hysteresis using upper and lower thresholds of 46 and 20 (see Figure 2(b)).

4. *Curve extraction:* Edge relaxation is used to form larger curve segments, after which the remaining small curve segments (i.e., length less than 10) are removed.

   We could attempt to perform identification at this stage by trying to match features computed from the extracted curves to those computed from the model. Differences in lighting and positioning would render such a method very unreliabel. What is needed is to describe the relations between the curves in a way which is first invariant to Affine transformations and secondly invariant to small changes in the shape of the curves resulting from differences in illumination. To achieve invariance under affine transformations we turn to the neighboring relation, and construct a Voronoi neighborhood graph of the curves and use it as our model.

5. *Graph model:* A generalized Voronoi diagram [1] of the curves is built and a neighborhood graph is extracted (see Figure 2(c)).

Using the above steps results in a high FRR due to variations in the graph models due to underlying differences in the spatial relations of the extracted curves [2]. To improve the FRR rate we first eliminating some of the erronous curves and then develop a new matching process which takes into account broken curves.

5.1 Error Correcting Graph Matching

Let $G(V, E)$ denote the graph model with each vertex $v \in V$ containing unary features of a curve and edges $e \in E$ containing binary features between two neighboring curves. Matching is done by searching for subgraph isomorphisms between the subject's stored graph G_s and the extracted graph $G_{s'}$ and if the distance $d(G_{s'}, G_s)$ between them is less then the established acceptance threshold t then identification is verified.

In the case where G'_s and G_s belong to the same subject, erroneous curves can arise from differences in lighting and orientation. From our analysis [4] most of these false curves occur within the inner cavity of the ear. The main reasons are that areas of high specularity arising from oil and wax build up and shadowing caused by the Tragus and Antitragus create edges in Step 3 which are built into false curves in Step 4. These false curves are removed by first segmenting the inner cavity and then removing small, high curvature, and closed curves occuring within it.

This removes many of the false curves while preserving those arising from ear structures. Unfortunately due to imaging problems, many of the remaining curves may be broken even after Step 4. To compensate for this, we have developed Algorithm 1 for computing subgraph isomorphisms between G_s and $G_{s'}$ which considers the possibility of broken curves in $G_{s'}$. The idea is to merge neighboring curves in $G_{s'}$ if their Voronoi regions indicate that they are possibly part of the same underlying feature.

Algorithm 1 Calculate $d(G_s, G_{s'})$

while $d(G_s, G_{s'}) \cdot c < t$ and $|V| \leq |V'|$ **do**
  for all $v \in V'$ **do**
    for all a adjacent to v **do**
      if $d_v(v, a) < \gamma$ **then** {see Equation 1}
        contract(v, a)
      end if
    end for
  end for
  increase t_1 and decrease c
end while

Figure 3. Ear curve widths.

Let the boundary of the Voronoi region of a curve c_j be represented by $\partial V(c_j)$ such that $\partial V(c_j) = \{p | d(p, c_j) = d(p, c_k), j \neq k\}$ where $d(p, c_j)$ is the distance $\min_{q \in c_j} d(p, q)$ between a point p and any point on the curve c_j. Then the adjacent vertices v and a are contracted (i.e., all incident edges of a are added to v and self-loops removed) when

$$d_v(v, a) = \frac{|\partial V(c_a) \cap \partial V(c_v)|}{|\partial V(c_a)| + |\partial V(c_v)|} \quad (1)$$

is less than some threshold, γ, the contraction threshold. We continue in this way to change the topology of $G_{s'}$ until either we have a match or the number of vertices in $G_{s'}$ is less then that in G_s and since curves may be erroneously merged we decrease our confidence in the match each time by a factor c.

5.2 Decreasing the FAR

As only the topological relations between the extracted curve segments are used during the matching process, their is the possibility of a false acceptance since there exists a set of ears having the same topology. By measuring physical features of the ear curves we can significantly decrease the FAR. We have found that measurements based on the length of the ear curves are not reliable since small changes occur due to lighting. More reliable is the width of an ear curve, in particular we have found that the width of the curve corresponding to the upper Helix rim (See Figure 5.2) can be reliably extracted and normalized against the height of the ear (i.e., the distance from the top of the upper Helix rim to the lowest point on the Lobule as found during the Localization step.

5.3 Thermograms and Occlusion by Hair

The main drawback of ear biometrics is that they are not usable when the ear of the subject is covered. In the case of active identification systems this is not a drawback as the subject can pull their hair back and proceed with the authentication process. The problem arises during passive identification as in this case no assistance on the part of the subject can be assumed.

In the case of the ear being only partially occluded by hair then it is possible to recognize the hair and segment it out of the image. This can be done using texture and color segmentation, or as we have implemented it, using thermogram images. A thermogram image is one in which the surface heat (i.e., infrared light) of the subject is used to form an image. Figure 6 is a thermogram of the external ear. The subjects hair in this case has an ambient temperature between 27.2 and 29.7 degrees Celsius, while the pinna (i.e., the external anatomy of the ear) ranges from 30.0 to 37.2 degrees Celsius. Removing partially occluding hair is done by segmenting out the low temperature areas which lie within the pinna.

The Meatus (i.e., the passage leading into the inner ear) of the ear is easily localizable using thermogram imagery. In a profile image of a subject, if the ear is visible, then the Meatus will be the hottest part of the image, with an expected 8 degree Celsius temperature differential between it and the surrounding hair. In Figure 6 the Meatus is the clearly visible section in the temperature range of 34.8 to 37.2 degrees Celsius. By searching for this high temperature area it is possible to detect and localize ears using thermograms.

Figure 4. Thermogram of an ear. Image provided by Brent Griffith, Infrared Thermography Laboratory, Lawrence Berkeley, National Laboratory.

6 Conclusions

The proof of concept system discussed lends support to the theoretical evidence that ear biometrics are a viable and promising new passive approach to automated human identification. They are especially useful when used to supplement [5] existing automated methods. Though ear biometrics appear promising, additional research needs to be conducted to answer important questions like:

- *Feature or appearance based:* can primitives (e.g., curves) be extracted under varying imaging conditions with sufficient reliability for a feature based approach or will appearance based approaches (e.g., eigenimages) be necessary, and

- *Occlusion by hair:* in the case of the ear being completely occluded by hair there is no possibility of identification using ear biometrics, it remains to be seen with what degree of partial occlusion is identification possible and if thermogram imagery can resolve this problem.

In conclusion we have shown that ear biometrics can be used for passive identification and for the further development, testing, and comparison of ear biometric algorithms the creation of an imagebase of ear-images and a set of standardized tests must be the next step.

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