Ear recognition based on Edge Potential Function

F. Battisti\textsuperscript{a}, M. Carli\textsuperscript{a}, F.G.B. De Natale\textsuperscript{b}, A. Neri\textsuperscript{a}

\textsuperscript{a} Applied Electronics Department, Universit\`{a} degli Studi Roma TRE, Roma, Italy;

\textsuperscript{b}University of Trento, Dip. Ingegneria e Scienza dell’Informazione, Trento, Italy.

1. ABSTRACT

The use of ear information for people identification has been under testing at least for 100 years. However, it is still an open issue if the ears can be considered unique or unique enough to be used as biometric feature. In this paper a biometric system for human identification based on ear recognition is presented. The ear is modeled as a set of contours extracted from the ear image with an edge potential function. The matching algorithm has been tested in presence of several image modifications. Two human ear databases have been used for the tests. The experimental results show the effectiveness of the proposed scheme.

Keywords: Biometrics, Human Identification, Image Analysis

2. INTRODUCTION

The worldwide adopted person authentication system is generally based on the comparison between the data stored into a paper ID (passport, driver license, ...) with features that a human controller can verify. Picture vs. face, sex, and human body measurements are parameters that can be easily estimated and verified by visual comparison. However, this authentication system is prone to several manipulations such as personal data tampering or picture substitution. To overcome these problems, there is an ongoing effort in coupling the traditional system with modern technologies as biometric-based authentication systems, to allow a more robust verification while respecting fundamental human rights including privacy.

Briefly, some human-depending features may be extracted, processed, and compared with the information stored in digital databases. These features are then combined with a password to create the secure key so that, two authentication factors, something you know and something you are, are jointly used to increase the overall security. Biometric feature based authentication systems are built on physical and behavioral characteristics (traits) of an individual such as DNA, face, fingerprint, hand geometry, iris, pupil dilatation and contraction, keystroke, signature, voice, gait, etc. Any characteristic can be used as a biometric identifier if it is:

- universal, every person should possess it,
- distinctive, the feature should be unique for every user,
- permanent, it should be time invariant,
- collectible, it can be measured manually or automatically.

Biometric traits are difficult to copy, share, and distribute, however the high variability in the extracted features due to the acquisition conditions and to the human variability factor (i.e. age, healthy problems, stress, injuries) can prevent an exact matching with the corresponding stored feature.

In this contribution we deal with human ear recognition. The ear can be described by many standard features (as helix, lobe, etc.); it is a unique feature of each human being, it is universal, it does not change too much with age, and its shape is usually not affected by facial expressions. Furthermore it can be acquired from distance, with low cost setup. Finally, its acceptability is higher than retina or iris scan since it does not require

Further author information: (Send correspondence to F. Battisti)

Federica Battisti: E-mail: federica.battisti@uniroma3.it
any scanner\textsuperscript{1}. The drawback is that it can be hidden by hair, caps, or earrings, and that the identification systems are prone to luminance changes and to head rotations. Ear identification systems can be classified according to the acquisition procedure: photographic, contact-based, and thermographic. In literature, most of the systems, are based on the first one. Preliminary studies about ear as a biometric feature have been presented in 1948 by A. Iannarelli. He collected and classified around 10,000 human ear images\textsuperscript{2}. Victor et al.\textsuperscript{3} apply Principal Component Analysis (PCA) and Face Recognition Technology (FERET) evaluation protocol to human ear classification. Moreno et al. in\textsuperscript{4} present a multiple identification method, which combines the results from several neural classifiers using features as outer ear points, shape and wrinkles, and macro features extracted by compression network. They also introduce three different classification techniques for outer ear or auricle identifying. In\textsuperscript{4} and\textsuperscript{5} Voronoi diagram of ear curve segments is applied. Their system is able to deal with lightning, shadowing, and partial occlusion by considering possible error curves in the matching algorithm. Hurley et al. in\textsuperscript{6} have used force field transformations. The image is modeled as an array of Gaussian attractors that act as source of a force field leading to a robust, reliable technique. More recent approaches are based on multimodality as in\textsuperscript{7–11}. Generally they focus first on image ear detection, followed by the ear recognition phase. Some authors shown that the use of databases containing the image of the profile, together with rotated version of that image, may improve the results. However the realization of such a database increases the complexity of the enrolled phase. It is therefore more feasible to design an ear-based biometric system considering only the 2D planar image of the ear. The use of databases containing both profile and rotated versions of ear image can be used for performance testing.

Here, we adopt a pattern recognition approach\textsuperscript{12} for ear recognition; more in detail, an Edge Potential Function (EPF) is proposed for modeling the attraction force generated by edge structures contained in an image over similar curves. The model, inspired to physics of electricity, has been designed for efficiently exploiting the joint effect of single edge points in complex structures (by considering edge position, strength, and continuity), in a unique powerful representation of the edge map. Good results in the correct matching are obtained even in presence of noise and partial occlusions. The representation of the ear in this domain allows the correct subject identification even if rotation, horizontal and vertical translation, and scale modification are affecting the image.

The paper is organized as follows. Section 3 briefly points out the previous work on EPF, highlighting the peculiarities of the model. Section 4 describes the proposed ear recognition system, while Section 5 presents the results of the performed simulations. In Section 6, the conclusions are drawn and further developments are discussed.

3. EDGE POTENTIAL FUNCTION (EPF)

In this Section the basics of the EPF are reported. Basically the model proposed by Dao et al. in\textsuperscript{12} resembles the behavior of the electric potential generated by a series of charged elements $Q_i$ in an homogeneous material. Its intensity depends on the distance between the charged points and the observation ones, and on the material permittivity $\epsilon$. Any $i^{th}$ pixel in an image contour $P(x_i, y_i)$, can be considered as a charged particle $Q_{eq}(x_i, y_i)$ which contributes to the potential of all the pixels in the image:

$$EPF(x, y) = \frac{1}{4\pi \epsilon_{eq}} \sum_i \frac{Q_{eq}(x_i, y_i)}{\sqrt{(x-x_i)^2 + (y-y_i)^2}},$$

where $\epsilon_{eq}$ is a constant that takes into account the equivalent permittivity of the background image. If each point has the same charge $Q_{eq}(x_i, y_i) = Q$, the Binary EPF (BEFP) is obtained.

We adopt this model as a representation for matching between a test image (the ear) and an image contained in a database. In real situations, the images in the database and the test image differ for rotation $\theta$, horizontal $t_x$ and vertical $t_y$ translation, and scale $s$. The goal is to find the value of $c = (\theta, t_x, t_y, s)$ giving the best match between the test image and the one contained in the database. To evaluate the similarity between the images that are compared, the energy EPF is computed as follows:

$$f(c_k) = \frac{1}{N(c_k)} \sum_{n^{(c_k)}=1}^{N(c_k)} \{EPF(x_n^{c_k}, y_n^{c_k})\},$$

where $N(c_k)$ is the number of images in the database, $n^{(c_k)}$ is the index of the image in the database, and $c_k$ is the transformation parameters. The energy EPF of the worst match is then used to determine the best match.
where $n^{(c_k)}$, is the $n^{th}$ pixel of the $c^{th}_k$ modified contour of length $N^{(c_k)}$ pixels. $f(c_k)$ represents the expected value of the EPF computed on the target image, calculated along a curve defined by the current instance of the sketch and it defines the average attractive energy generated by the target image when scaling, rotation, and translation distortions are applied to the sketch. The best match is obtained with the set of transformations corresponding to the maximum average potential along the contour among all possible transformations. One of the main features of the proposed algorithm is the robustness against noise and image cuts. The approach used for optimization is based on genetic algorithm even if any other optimization tool can be adopted for this purpose.

In Figure 1 the image of the EPF, computed on an ear image, is reported.

![Visualization of the EPF computed on a test ear image.](image)

**4. PROPOSED BIOMETRIC SYSTEM**

The proposed method can be used both for authentication (one to one comparison) and for recognition (one to many comparison) purposes. The authentication procedure shown in Figure 2, can be summarized as follows:

- a preprocessing step is performed to localize the Region Of Interest (ROI) in the test image. Several techniques can be applied for ear localization, based on skin color classification, multiple features detection, or contour extraction. In our system we apply an ear contour based matched filter;
- the image contours are extracted by using a Canny edge detector filter;
- the contour image is represented according to the EPF model previously described;
- the extracted template is compared to the template of the images stored in the database and a genetic algorithm is recursively run to translate, scale, and rotate the template until a fitness function returns a value greater than a selected threshold.

**5. EXPERIMENTAL RESULTS**

To verify the effectiveness of the proposed method, it has been tested on two ear images databases:

- the USTB Ear Image Database\textsuperscript{13}, which contains 780 color images taken from 78 users. The images size is 384 * 288 pixels. The images of each subject are taken under two conditions: illumination variation and orientation variation and individuals were asked to be seated 2 meters from the camera and change their face orientation.
• the UMIST Face Database\textsuperscript{14} containing 86 gray-scale images taken from 14 users. For each person 6 photos are taken in five different positions (profile image, and rotation of 5, 10, and 15 degrees). In this database there are users wearing glasses and earrings. A set of images is shown in Figure 3.

![Figure 3. UMIST database: color images of size 384 * 288 pixels. Different profile rotations are provided.](image)

In our test the size of the ROI is 80 * 60 pixels. The chosen parameters for the genetic algorithm are: population dimension of 200, repetition number equal to 30, mutation probability of 0.1, and unitary crossover probability.

To evaluate the performances of the proposed method the False Rejection Rate (FRR) and the False Acceptance Rate (FAR) have been computed. The FRR corresponds to the likelihood that the biometric system incorrectly rejects an access of an authorized user, while the FAR corresponds to the percentage of occurrence when a non-authorized user is accepted by the system. The Equal Error Rate (EER) corresponds to the rate at which the FRR equals the FAR rate. It is usually adopted as a performance measure. Another indicator of the system performances is the Receiver Operating Characteristic (ROC) curve, which depicts the behavior of Genuine Acceptance Rate (GAR=1-FRR) versus the FAR.

In Figure 4 the FRR and the FAR curves obtained by varying the fitness threshold values $\sigma$, for the USTB and for the UMIST databases respectively, are presented. The parameter $\sigma$ is used in the genetic algorithm for stopping the system evolution when the best fitness in the current population becomes less than the user-specified fitness threshold. The choice of the threshold impacts on both accuracy of the retrieved solution and on the computational cost. In the USTB case, the EER value of 2.1\% is obtained for a threshold value of 440. Similar results are obtained for the UMIST database.

In Figure 5 the ROC curve versus different threshold values is depicted.
The Cumulative Match Characteristic (CMC) has been computed and the proposed method presents a rank-1 recognition rate of 98% (Figure 6).

To verify the performances of the system when noisy images are presented to the detector, additive gaussian noise with different intensities, 5 dB, 10 dB, and 15 dB, has been applied to the test image. The corresponding degraded images present respectively PSNR values of 41 dB, 37 dB, and 31 dB. The FAR and FRR curves obtained are shown in Figure 7(a). The ERR point for all the 3 cases is below the 8%. Figure 7(b) shows the ROC curve for the three different cases. To verify the robustness of the proposed method to rotations, the test image has been rotated of 16 and 20 degrees in a counter clockwise direction. The FAR and FRR curves are shown in Figure 8. The resulting ERR is around 8% in the first case and below 15% in the second one.

6. CONCLUSIONS

In this paper a biometric identification system, based on the human ear matching, has been proposed. The ear, used as a biometric feature, when not totally occluded by hair or hat, allows a reasonable identification accuracy even in presence of noise and without requiring the complete subject cooperation. Furthermore, it does not require direct contact (as finger-palm prints) increasing the acceptability of this biometric system. The
proposed method, based on a matching function computed in the edge potential function domain, is effective. Experimental results, show the effectiveness of the proposed method.

REFERENCES


Figure 7. (a) FAR vs FRR when additive gaussian noise of different intensities is applied to the test image. (b) ROC curve when additive gaussian noise of different intensities is applied to the test image. (c) detail of the ROC curve in (b) for FRR values in the interval $[0,25]$.

Figure 8. FAR vs FRR when the test image is rotated.