A Genetic Algorithm for Creating a Set of Color Spaces for Ear Authentication

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Abstract - *An ensemble of 2D ear matchers is built by training each matcher using a set of Gabor filters and color spaces selected by a genetic algorithm (GA). First, using gray level images, we select the best Gabor filters applying Sequential Forward Floating Selection. Second, using the RGB images, several color spaces are obtained using a GA. Finally, an ensemble of 1-nearest neighbor matchers use the color spaces and filters for classification. The performance of the proposed approach is measured using the Notre-Dame EAR dataset. To create the color spaces, the dataset is divided into training and testing sets using ear samples from different individuals. System parameters are selected using samples of individuals that belong to the training set. The method is then tested on the testing set. In this way, we consider our protocol a reliable blind testing protocol. Our system obtains rank-1 of ~81% and rank-5 of ~92%.*

Keywords: Ear verification, Color space, Floating Search, Gabor Filters, Multimatchers.

1 Introduction

One promising biometric is the ear. Unlike face identification, ear characteristics are stable throughout the lifespan and are not altered by facial expressions. Unlike fingerprints and iris and retina identification, images of the ear are cheaper and easier to capture. Other advantages of ear identification include its use in identifying people in accidents, such as airplane crashes [1] and in crime scene investigations that provide video of the perpetrators [2]. Similar to face identification, problems involved in ear identification include hair and hat occlusions as well as changes due to ear adornments. One method for circumventing occlusion problems has been proposed by [3]: they use a sensor to measure the acoustic properties of the outer flap of the ear and the ear canal. For these reasons and more, ear recognition has been the focus of considerable research the last few years.

Although some researchers have used 3D images of ears in their classification experiments [4-7], most experiments extract features from 2D images (see [8], [9] and [10] for excellent surveys of the literature). The most commonly used 2D matchers are based on principal component analysis (PCA) [11-13]. However, PCA is very sensitive to pose variation and illumination conditions. In [14], Independent Component Analysis (ICA) coupled with a Radial Basis Function (RBF) network was shown to outperformed PCA. A graph matching technique based on a Voronoi diagram of curves, extracted from the Canny edge map of the ear, is proposed in [15], and in [16] a matcher based on a force field transformation, that treats the image as an array of mutually attracting particles that acts as the source of a Gaussian force field is proposed. This method outperforms the 2D based PCA matchers when the images are poorly registered since it does not need an explicit segmentation of the ear from the background. In [17-19], feature extraction is performed on selected subwindows of the whole image, and for each subwindow a different classifier is trained. In [19] this subwindow approach is improved using an ensemble of matchers that are each trained using a different color space and a different normalization procedure.

The use of different color spaces for improving classifier performance in other problem domains has been reported in [20-22]. Example color spaces include the R channel in RGB, and the V channel in HSV. Both have proven useful in face recognition [23]. A face recognition multi-matcher is proposed in [24], where each matcher is trained using one of the three components of the YIQ color space. In [25] a method is proposed that unifies the color image.

The ear authenticator proposed in this work is based on an ensemble of matchers, where each matcher is trained using a set of Gabor filters extracted from different images. We select the best Gabor filters by Sequential Forward Floating Selection using the gray level images. Then several color spaces are obtained using a genetic algorithm (GA), where the optimization function is the equal error rate obtained considering the previously selected filter. Each matcher in the ensemble, a simple 1-nearest neighbor classifier [26], is trained using the features extracted from the images transformed as follows: the new image is given by $\alpha\cdot R+\beta\cdot G+\gamma\cdot B$, where R, G, B are the channels of the RGB color space, respectively, and the values α, β, γ are selected by the GA. The set of matchers is combined by the sum rule [27]. The experimental results obtained in the well known Notre-Dame EAR dataset demonstrate that the proposed system is an effective method for building an ensemble of matchers.

2 System description

Since it has been shown that different color spaces can be used for building a multimatcher system [28], in this study we explore the possibility of using an optimization algorithm to build an ensemble of matchers for creating a set of color spaces. The set of matchers is a set of 1-nearest neighbor classifiers. First, a set of Gabor features are extracted from each image. The set of Gabor filters are selected by Sequential Forward Floating Selection (SFFS[1]) using only the gray level images. Second, GA calculates k color spaces considering the set of Gabor filters selected. Finally, an ensemble of 1-nearest neighbor matchers use the color spaces and filters for classification. Using this system, the color spaces are optimized for the specific feature extractor and for the classifier used in the matchers.

2.1 Ear extraction

As in [18], we extract the ear from a given image using the landmarks, Triangular Fossa and the Incisure Intertragica (see Figure 1). Once the landmark positions are identified, a bounding box is inferred, and the ear image is extracted. The resulting images are then resized to 150 x 100 using nearest neighbor interpolation.[2] To improve image quality, we perform a contrast-limited adaptive histogram equalization[3] [29].

2.2 Filter selection

The features used to describe a given ear image are a bank of Gabor filters. As illustrated in Figure 2, different scales and orientations are applied on a regular grid that is superimposed on the image. By convolving the image with Gabor filters, features are extracted. In Table 1, we report the parameters used in filter selection.

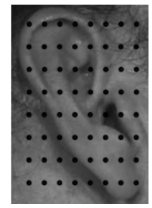
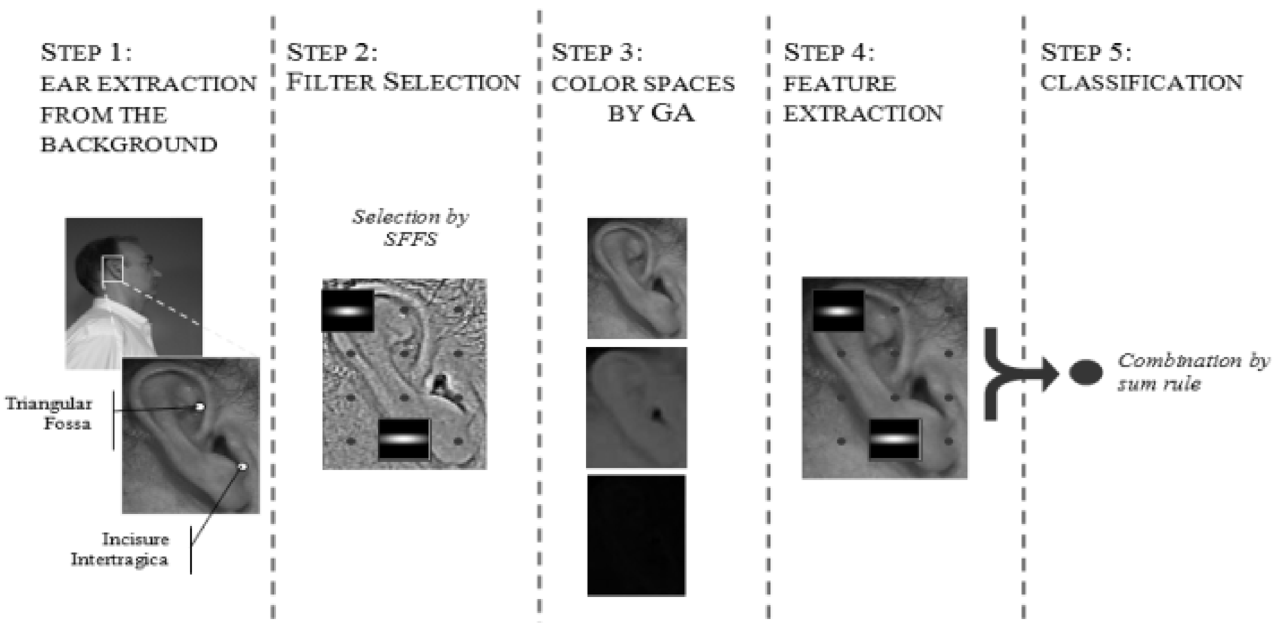


Figure 2. Square-meshed grid superimposed on an extracted ear image.

To improve performance and to reduce the computation time of the feature extraction step, only a subset of all the filters are used to describe a given image. In [17] it is demonstrated that a subset of filters selected by Sequential Forward Floating Selection (SFFS) obtains a set of Gabor filters that improves performance. In this work we use SFFS to select a set of filters starting from the gray level images of the ears. SFFS works in the following way: the best filter subset S_K of size K, is constructed by adding to the subset, S_{K-1}, the single

Figure 1. Block diagram of the proposed authentication system.



[1]Implemented as in PrTools 3.1.7 ftp://ftp.ph.tn.tudelft.nl/ pub/bob/ prtools/ prtools3.1.7
[2] This method is implemented as in the function imresize.m of Matlab 7.0
[3] Implemented as in adapthisteq.m of the Matlab 7.0 Image Processing Toolbox

filter that, combined with the others in S_{K-1}, gives the best performance for the new subset. At this point, each filter in S_K is iteratively excluded, and each new set S'_{K-1} is compared with S_{K-1}. If one S'_{K-1} outperforms S_{K-1}, then it replaces S_{K-1}. The first set S_0 is initially empty. The fitness function is the equal error rate obtained by a set of matchers, in this case, a set of 1-nearest neighbor[1] matchers. Each matcher is trained using a single filter and combined using the sum rule [26].

Table 1. The values of the main parameters used in filter selection.

Parameter	Value
Number of grid nodes	5×10
Gabor filter size	50
Gabor filters standard deviation σ	5, 10, 15, 20
Gabor filters orientations	$0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3}{4}\pi$

2.3 Color spaces by GA[4]

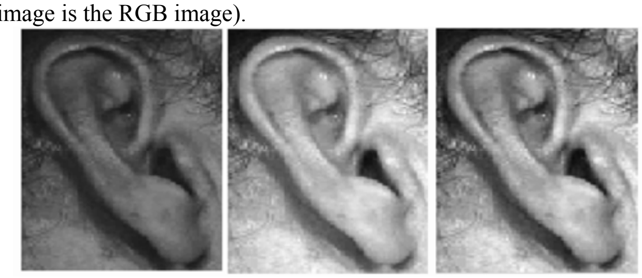
Starting from the RGB space, a color model is defined as $\alpha \cdot R+\beta \cdot G+\gamma \cdot B$ where the three parameters α, β, γ are selected using a GA. Chromosome **C** of length 3 contains the numerical values (between 0 and 1) for α, β, and γ. The basic operators (selection, crossover and mutation) used to guide this search are defined as follows:

Selection: Our selection strategy is cross generational. Assuming a population of size D=50, the offspring double the size of the population. The best D individuals from the combined parent-offspring population are then selected.

Crossover: Uniform crossover is applied with the crossover probability 0.96.

Mutation: The mutation probability used here is 0.02.

Figure 3. Some examples of color spaces obtained by GA (the left image is the RGB image).



[4] Implemented as in GAOT MATLAB TOOLBOX www.ie.ncsu.edu/mirage/GAToolBox/gaot/

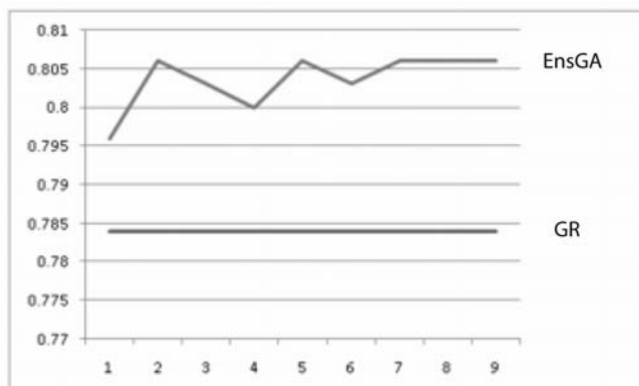
In this step, k GAs select k color spaces. The fitness function of the GA is the equal error rate obtained by a set of 1-nearest neighbor matchers. In Figure 3, we show examples of color spaces found using GA.

2.4 Feature extraction and classification

Each color space is used for extracting features from the set of filters, and an ensemble of 1-nearest neighbor matchers use the color spaces and filters for classification. The matchers are combined using the sum rule.

3 Experiments

In our experiments, we used the Notre-Dame EAR dataset of 464 images of ears obtained from 114 individuals [30]. Each individual in this dataset is represented by a set of 3 to 9 ear samples taken on different days and under different lighting conditions. Using images of 64 individuals, we randomly extracted one ear sample from each individual to be included in the testing set, and then we selected another sample at random to be included in the training set [30]. A validation set containing images of the 50 remaining individuals was also randomly extracted from the dataset. The fitness function was calculated for the validation test and results were averaged over 20 experiments.



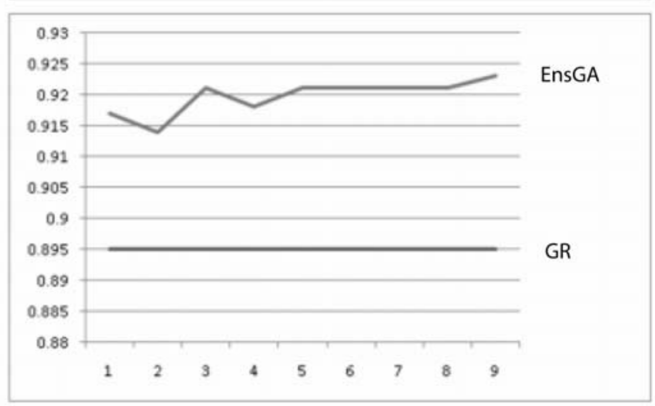


Figure 4. Rank-1 (top) and Rank-5 (bottom) obtained by the proposed ensemble (ENSGA), and by a stand-alone matcher (GR).

The RANK-R performance parameter was used for the comparison of the approaches described in this paper. The RANK-R answers the question *Is the right answer in the top R matches?* In this work, R=1 or R=5. In Figure 4, we present the results of the average RANK-1 and RANK-5 obtained by varying the number of color spaces created by the GA (ENSGA). We also report the performance obtained considering only the gray level image (GR). It should be noted that in our system the number of combined color spaces is selected using the validation set.

To select the parameters of our method, i.e., the color models and dimensions of the ensemble, we used as a performance indicator the equal error rate. This is a robust indicator that maximizes rank-1 and rank-5. It is likely that a better performance could be obtained if the parameters were separately selected for rank-1 and rank-5, but the computational complexity would be drastically increased. An example, using one validation set reporting the parameters α, β, and γ selected by the GA, is shown in Table 2.

In Table 3, we compared the performance of our proposed authentication system, as illustrated in Figure 1 and which we label NEW, with the following state-of-the-art approaches:

- PCA-*X*, the well known PCA approach [12] trained using gray-level pixels and where the first *X* (0 and 5) eigenfeatures are discarded;
- SFFS-Color, the method proposed in [19], where only the preprocessing method described in this paper is used.

Table 2. Example of a set of parameters α, β, and γ selected by GA.

α	β	γ
0.2789	0.7513	0.0879
0.0934	0.8557	0.1581
0.2451	0.8352	0.1013
0.2809	0.5862	0.1986
0.0721	0.9138	0.2299
0.5518	0.7809	0.0080
0.1304	0.9709	0.0097
0.0363	0.7724	0.3021
0.2676	0.6699	0.0520

Table 3. Performance comparison of our method.

Method	RANK-1	RANK-5
PCA-0	66	70
PCA-5	70	82
SFFS-Color	77	87
NEW	80	92

The results of Table 3 show the great effectiveness of using color images for ear authentication. This advantage is clearly visible by comparing the performance of the well known PCA approach on the gray level image vs. color images (as reported in [19]). The main advantage of the proposed system is that the color spaces are directly created by a GA. By varying the objective function, it is possible to obtain a set of color spaces that are well suited for a given feature extraction method and for a given matcher.

4 Conclusion

In this paper we propose a system for creating a set of color spaces that were then used in building an ensemble of matchers for personal authentication using ear matchers. The multi-matcher is based on the fusion of several 1-nearest neighbor classifiers trained using the Gabor filters extracted from different images.

The proposed system obtained a RANK-1 of 80% and a RANK-5 of 92%. These show that performance of the 2D matchers is improved by using a set of different color representations of the ear. By using different color components, it is possible to partially overcome the imaging conditions.

5 Acknowledgment

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