Ear Authentication using Log-Gabor Wavelets

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This paper investigates a new approach for human ear identification using holistic grey-level information. We employ Log-Gabor wavelets to extract the phase information, i.e. ear-codes, from the 1D gray-level signals. Thus each ear is represented by a unique ear code or (phase template). The query ear images are compared with those in the database using Hamming distance. The minimum Hamming distance obtained from the rotation of ear template is used to authenticate the user. Our experiments on two different public ear databases achieve promising results and suggest its utility in ear-based authentication. This paper also illustrates that the phase information extracted from ear images can achieve significant performance improvement as compared to appearance-based approach employed in the literature.

1. Introduction

Reliability in personal authentication is key to the stringent security requirements in many application domains ranging from airport surveillance to electronic banking. Many physiological characteristics of humans, *i.e*., biometrics, are typically invariant over time, easy to acquire, and unique to each individual. Most of the current research in biometrics is focussed on face, fingerprint, gait, signature, iris, palmprint or hand-geometry [11]. However, there have been very little efforts to investigate the human ear for personal authentication despite its significant role in forensic science. The ear is quite attractive biometric candidate mainly due to its (i) rich and stable structure which is preserved since birth, (ii) being invariable to the changes in pose and facial expression, and (iii) relatively immune from anxiety, privacy and hygiene problems with several other biometric candidates.

Table 1: A summary of prior work on 2D ear identification.

Authors	Approach	Classifier	Database Size
A. Ianarelli [1]	Manual Ear Measurements	-	10,000 images
Chang *et al*. [5]	PCA	Eucledian Distance, *k-NN*	197 subjects
Burge and Burger [2]	Voronoi Diagram	Graph Matching	-
Mottaleb and Zhou [8]	Differential Geometry	Hausdorff Distance	29 subjects
Zhang et al. [10]	ICA	RBF Network	60 subjects
Hurley et al. [4]	Force Field Transform, PCA	Eucledian Distance, *k-NN*	63 subjects
Kumar and Zhang	**Log-Gabor Wavelets**	**Hamming Distance, *k-NN***	**113 subjects**

1.1 Prior Work

Human ear has attracted several studies on its individuality and uniqueness. Ianarelli [1] has manually measured the distance between predicted points on human ear. He has extensively examined 10,000 ears and concluded their uniqueness. The ear image characterization using Voronoi diagram is illustrated in [2]. However, the work in [2] is largely conceptual and lacks experimental results on any ear database. Hurley *et al*. [4] have suggested a new method of localizing ear shape features using force field transformation. Authors have employed the database of 63 users to illustrate the appearance-based ear recognition. Table 1 presents a summary of prior work on the usage of 2D ear images for personal authentication. Researchers have also investigated the ear recognition using 3D imaging [6], [10] and acoustic characteristics [7].

2. Log-Gabor Filters

Ear identification using grey-level images requires simultaneous measurements in spatial and spatial-frequency domain. Gabor filters have invited lot of attention in biometrics research community, mainly due to its orientation selectivity, spatial localization and spatial-frequency characterization. However, these filters present a limitation in bandwidth where only filters with the bandwidth of one octave can be designed. Furthermore, large bandwidth Gabor filter introduces a significant dc component. Field [12] proposed Log-Gabor filters to overcome the bandwidth limitation in traditional Gabor filters. These Log-Gabor filters always have null dc component and desirable high-pass characteristics, *i.e*., fine details to be captured in high-frequency areas.

The frequency response of Log-Gabor filter in frequency domain is defined as follows:

$$G(f) = \exp\left(\frac{-(\log(f/f_o))^2}{2(\log(\sigma_f/f_o))^2} \right) \tag{1}$$

with f_0 is the central frequency and σ_f is the scaling factor of the radial bandwidth B. The radial bandwidth in octaves is expressed as follows:

$$B = 2\sqrt{2/\ln 2} * \left|\ln(\sigma_f / f_0\right| \tag{2}$$

Figure 1 shows the Log-Gabor filter spectrum on linear scale. This spectrum falls of at $1/f$ rate, which is similar to the natural image spectrum, and well adapted for encoding natural images.

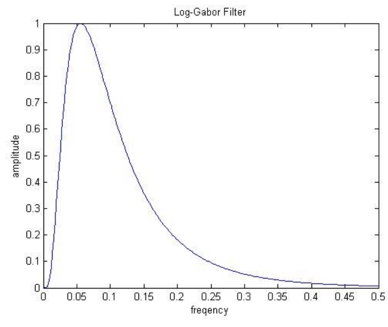

Figure 1: Amplitude spectrum of a typical Log-Gabor filter on linear scale.

2. Proposed Method

The accurate ear recognition requires the extraction of most discriminating information and exclusion (masking) of those regions that do not form the reliable features. Our approach extracts the reliable ear features using Log-Gabor filters and generates a phase template to characterize phase information. Figure 2 shows the block diagram of proposed approach for ear authentication. Small region of side face images having ear is extracted by using a fixed size masks. These elliptical size masks of 71 × 225 pixels were empirically selected from the localization of face images in the database [11]. The gray level masked images (rows) were unwrapped to generate 1D vector for feature extraction. These signals were convolved with Log-Gabor filters in frequency domain. The parameters of Log-Gabor filter were empirically selected as $f = 1/10$ and $\sigma_f = 0.25$. The resulting convolved form of the signal is complex valued. We then apply phase quantization [13] to extract binary phase templates which represents phase information. Thus each ear image is encoded to generate binary template corresponding to number of bits of information. The matching scores were generated using the Hamming distance. In order to correct the translational errors in the image localization, bit-wise shifting of ear templates, *i.e.* left and right, is employed. In our experiments, the best matching scores generated from the template shift of 20 bits (10 bits left and right each) are used.

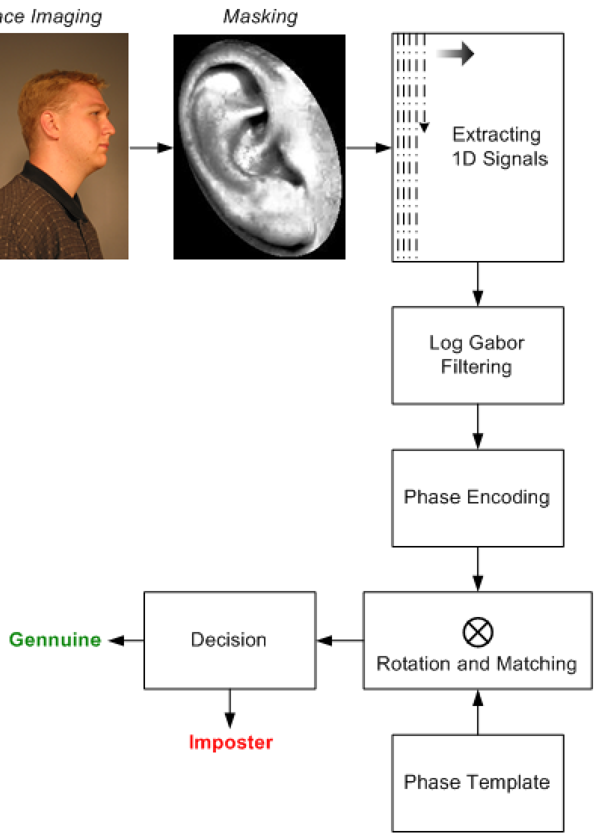

Figure 2: Ear authentication using Log-Gabor wavelets.

3. Experiments and Results

The experiments reported in this paper utilize the face database available at [5] [11]. The side face images of 113 subjects were used to extract the ROI using a fixed size mask as shown in figure 2 and detailed in previous section. Our experiments employed 265 images in the training set and 185 images in the test set. The receiver operating characteristics (ROC) from the test data is displayed in figure 3. This figure also illustrates the ROC when the *eigen-ear* approach [5] is used on the same training and test set. Thus the approach suggested in this paper using phase information extracted from Log-Gabor wavelets achieves significant performance improvement as compared to appearance-based approach using principal component analysis. Reference [3] also provides ear database from 17 subjects which have six 80 × 150 pixel ear images (only region of interest) of each subjects. We also performed the authentication experiments on these images, where masking to extract ear image was not required. The experiments employed first three images for training and rest three images for testing. The ROC for the test data is reported in figure 4. This figure also illustrates the results from the *eigen-ear* approach using the same training and test set. These results also confirm the significant performance gain achieved using the proposed method.

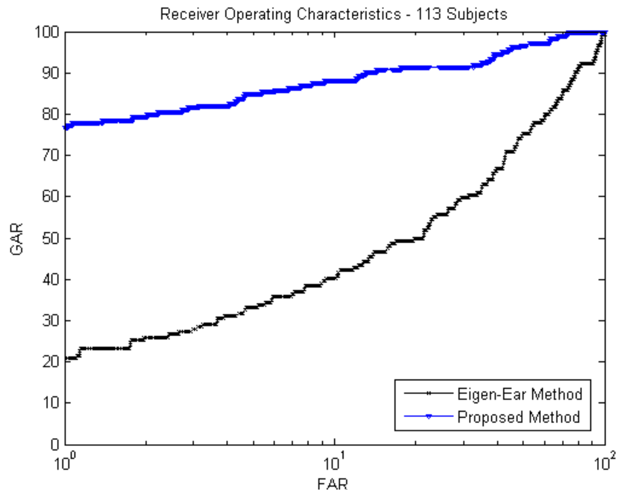

Figure 3: Receiver Operating Characteristics for the test data from 113 subjects database.

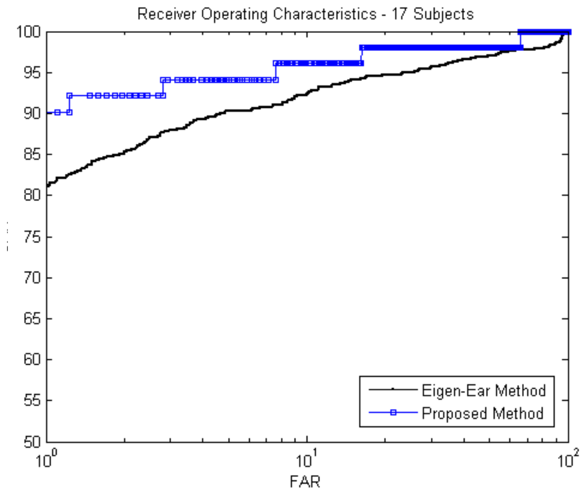

Figure 4: Receiver Operating Characteristics for the test data from 17 subjects database.

4. Conclusions

This paper has presented a new approach for ear authentication using phase information extracted from Log Gabor wavelets. The experimental results shown in this, on two different public databases, confirm the significant performance improvement using the proposed approach. The achieved results have suggested that the exploitation of Gabor phase information can achieve significant performance improvement as compared to the *eigen-ear* approach employed in [2] [5]. The achieved performance from the ear images can be further improved with the integration available information from the side face images. Our further efforts are directed to integrate matching scores generated from the side-face images with those from localized ear images employed in this work.

5. References

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