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A RESEARCH ON EAR BASED BIOMETRIC SYSTEMS

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Abstract —, *A person's identity can be recognized automatically using Biometric based personal authentication with high confidence. This paper investigates different approaches of using ear as biometric in authentication systems. After studying many approaches we present another technique for the template generation of region of interest using hamming distance. We also investigate new feature extraction approach for ear identification using local gray- level phase information using complex log-Gabor filters. The experiments were performed on the publicly available database of 125 and 221 subjects of IIT (Delhi). We have also graphically represented our experimental results i.e. false positive identification verses false negative identification which suggests the superiority of the proposed approach.*

Keywords- *Ear Based Recognition); Segmentation; Fourier descriptors; Hamming distance; Localization.*

I. INTRODUCTION

In modern society, it has become very crucial to recognize or identify an individual depending upon conventional card based or password based systems. Because of their unreliability and inconvenience caused biometrics methods are used instead. With the rapid development of computing techniques, in the past several decades or so, researchers have exhaustively investigated a number of different biometric identifiers.

Ear is a relatively new member in the biometrics family and has recently received some significant attention due to its non-intrusiveness and ease of data collection. Also it is a rich and stable structure that is preserved since birth (which remains unchanged from 8 to 70 years of age as determined by Iannarelli in a study of 10,000 ears) [1] and is quite unique in individuals. As a biometric identifier, the ear is appealing and has some desirable properties such as relatively immune from anxiety, privacy, hygiene problems, uniqueness and permanence.

II. MAJOR TYPES OF EAR BASED SYSTEMS

To study every advances of biometric systems is beyond the scope of this paper; therefore, in this section only the major categories i.e. 2D and 3D approaches are comprehensively studied.

A. 2D EAR BASED SYSTEMS

In this approach the basic steps are - accurate segmentation of exact region of interest, from the acquired gray level ear images, success of the feature extractor, matching.

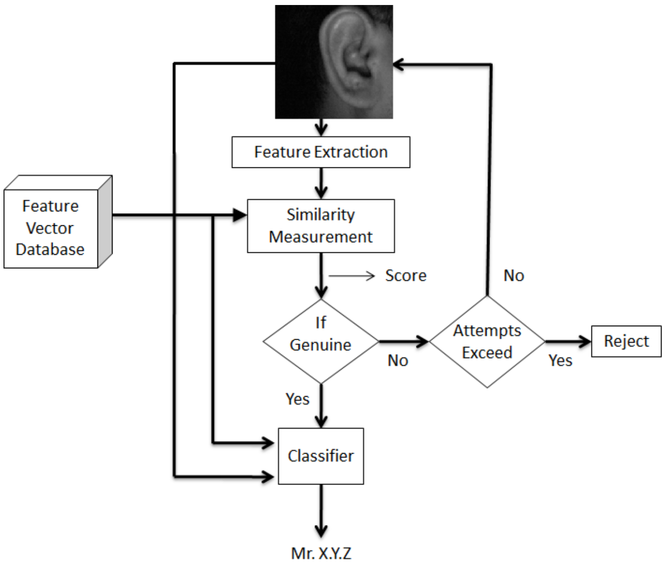

Figure 1. Typical 2D biometric system workflow

Different Methods available are:

- SIFT Feature detection and extraction [8]
- Local binary patterns and Hermetic Fourier descriptor [2]
- Best-Bin-First (BBF) method
- Our approach – Hamming distance calculation and Phase Encoding using multi-scale log-Gabor Filters

B. 3D EAR BASED SYSTEMS

Besides the traditional 2D ear sensing, there now also exists technologies to acquire 2D plus 3D ear data simultaneously. Different Methods available are:

- Hausdorff matching of depth edge images
- PCA (principal component analysis)
- ICP(iterative closest point) [4]
- SPARSE representation

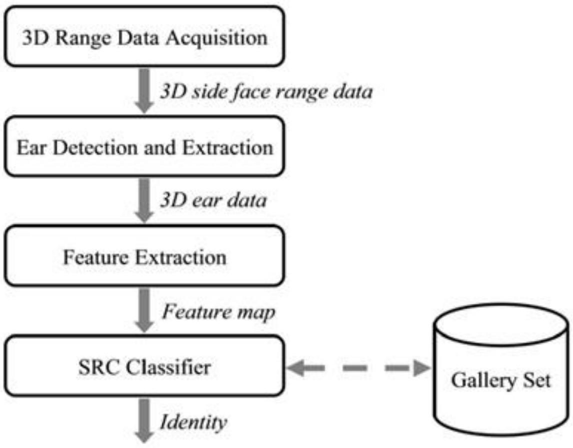

Figure 2. Typical 3D biometric system workflow

III. OUR APPROACH

In our approach, we make use of morphological operators and Fourier descriptors [5]. Every acquired image is subjected to pre processing that consists of smoothing with a Gaussian filter to suppress noise and then subjected to histogram equalization. The automated segmentation approach can also be used. After segmentation we created the templates of ear images for further stages. The two key points on the contour of this templates which achieve the maximum distance between them are selected as reference points. Gabor filters are used to efficiently encode gray level shape features and such details are employed to generate templates for matching.

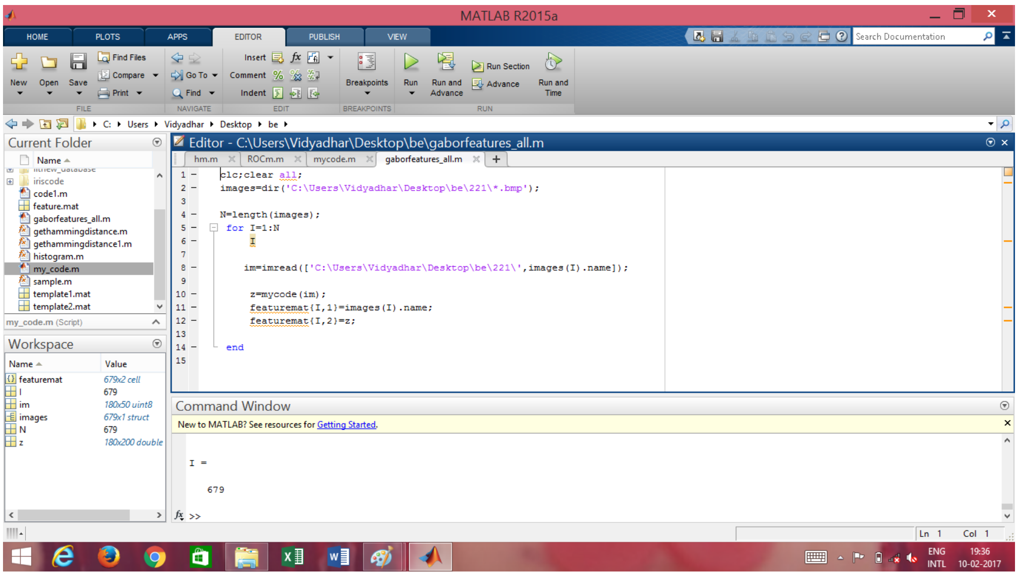

Figure 3. Illustration of MATLAB code of our approach

The experiments were performed on the publicly available database of 125 and 221 subjects of IIT (Delhi).

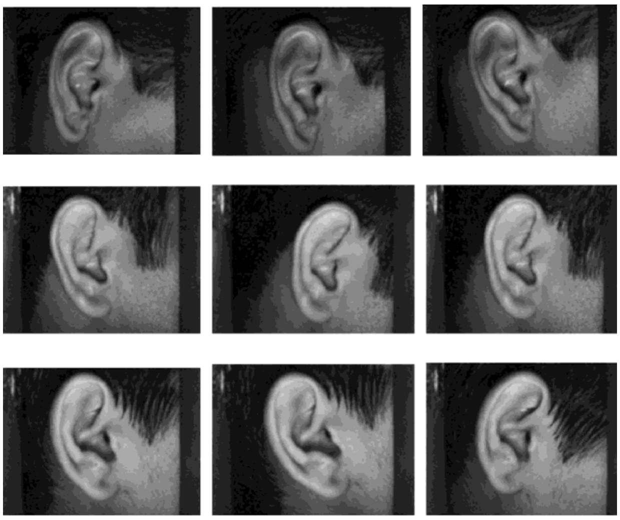

Figure 4. Typical image samples from our acquired database from the three subjects [7]

These log-Gabor filters always have null dc component and desirable high-pass characteristics

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

With fo as the central frequency and σf is the scaling factor of the radial bandwidth B.

Each of the enhanced ear images is encoded into a pair (or complex) of binary templates corresponding to number of bits of information using feature extraction [8]. Normalized Hamming distance between corresponding binarized templates is used to generate the matching scores between two ear images. The Hamming distance DPQ between two YxZ size complex bitwise ear templates, P and Q, is computed as follows:

$$D_{PQ} = \frac{\sum_{y=1}^{Y}\sum_{z=1}^{Z}\{P_r(y,z) \oplus Q_r(y,z) + P_i(y,z) \oplus Q_i(y,z)\}}{2 \times Y \times Z}$$

where $\oplus$represents bitwise XOR operation, Pr and Qr are the real part of the template while Pi and Qi are the imaginary part of the bitwise ear templates P and Q respectively.

During the matching, the bitwise shifting of bits in ear templates, i.e. left and right, is employed as it helps to account for the translational errors in during the image localization. The centre wavelength of 18 and the sf/f0 ratio of 0.55 is fixed for the log-Gabor filters.

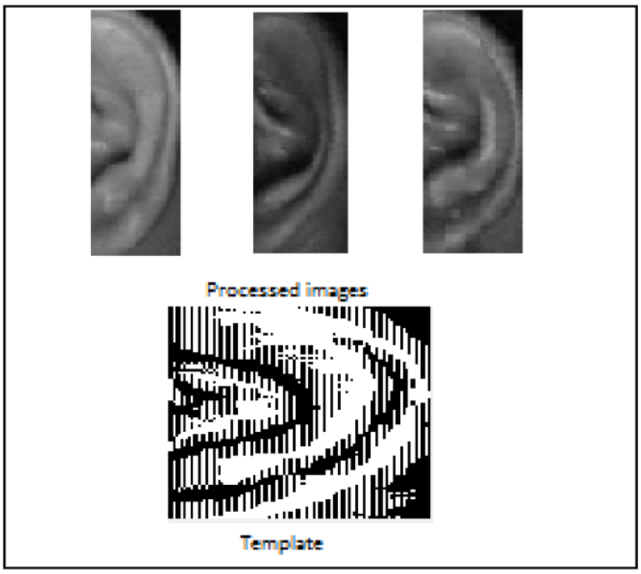

Figure.5 Illustration of template generated from processed image.

For finding the spatial orientation details of the curved ear shape a bank of even Gabor filters can be used. Each of the segmented and enhanced ear images are firstly convolved with a set of Gabor filters. The even Gabor filter is a product of Gaussian and sinusoid denoted as follows:

$$G_{\theta_n}(x,y) = \Gamma\ e^{-\pi(x^2+y^2/\sigma^2)}\cos(2\pi f(x\cos\theta_n + y\sin\theta_n))$$

Where τ represents the magnitude of the Gaussian envelope, σ corresponds to the standard deviation of Gaussian function, ϴn represents the orientation of the sinusoidal wave, and f is the frequency of the sinusoid.
The multiple responses from the O even Gabor filters are then compared to select a prominent orientation at every pixel in the normalized ear image as follows:

$$T(x,y) = \arg\{\max_{\forall n=1,2,..\Omega}\{G'_{\theta_n}(x,y)\otimes E(x,y)\}\}$$

Where G'ϴn(x,y) represents zero mean Gϴn(x,y) i.e. obtained by subtracting the mean values, ⊗ represent convolution operation, and E(x, y) is the normalized and enhanced ear image.
The binary encoded is done using three bits (for six orientations) and stored as representative feature for every pixel corresponding to E(x,y).The matching of two feature maps from two ear images, i.e. T and Q corresponding to the template and query ear images respectively, is ascertained from the angular distance
D (T,Q) as follows:

$$D(T,Q) = \frac{\sum_{y=1}^{Y}\sum_{z=1}^{Z}\sum_{k=0}^{3} T_k^b \oplus Q_k^b}{3\times Y\times Z}$$

The encoding of the phase information from the complex Gabor filters H(ϴ,F, σ) into the feature map F(x, y) is achieved as follows:

$$\begin{aligned}
F(x,y)_r &= 1 \quad \text{if} \quad Re\{H(\theta,f,\sigma)\otimes E(x,y)\} \geq 0\\
F(x,y)_r &= 0 \quad \text{if} \quad Re\{H(\theta,f,\sigma)\otimes E(x,y)\} < 0\\
F(x,y)_i &= 1 \quad \text{if} \quad Im\{H(\theta,f,\sigma)\otimes E(x,y)\} \geq 0\\
F(x,y)_i &= 0 \quad \text{if} \quad Im\{H(\theta,f,\sigma)\otimes E(x,y)\} < 0
\end{aligned}$$

The normalized Hamming distance between the query and the template feature map is computed. When the test and train images of same users are compared, the matching scores referred as *genuine* otherwise *imposter*. All the genuine and imposter scores are then subjected to the decision thresholds to generate ROC (Receiver Orientation Characteristic) curve. From ROC the best threshold providing a low FAR and high GAR can be chosen. This threshold is further used as a cut-off for online verification and identification.

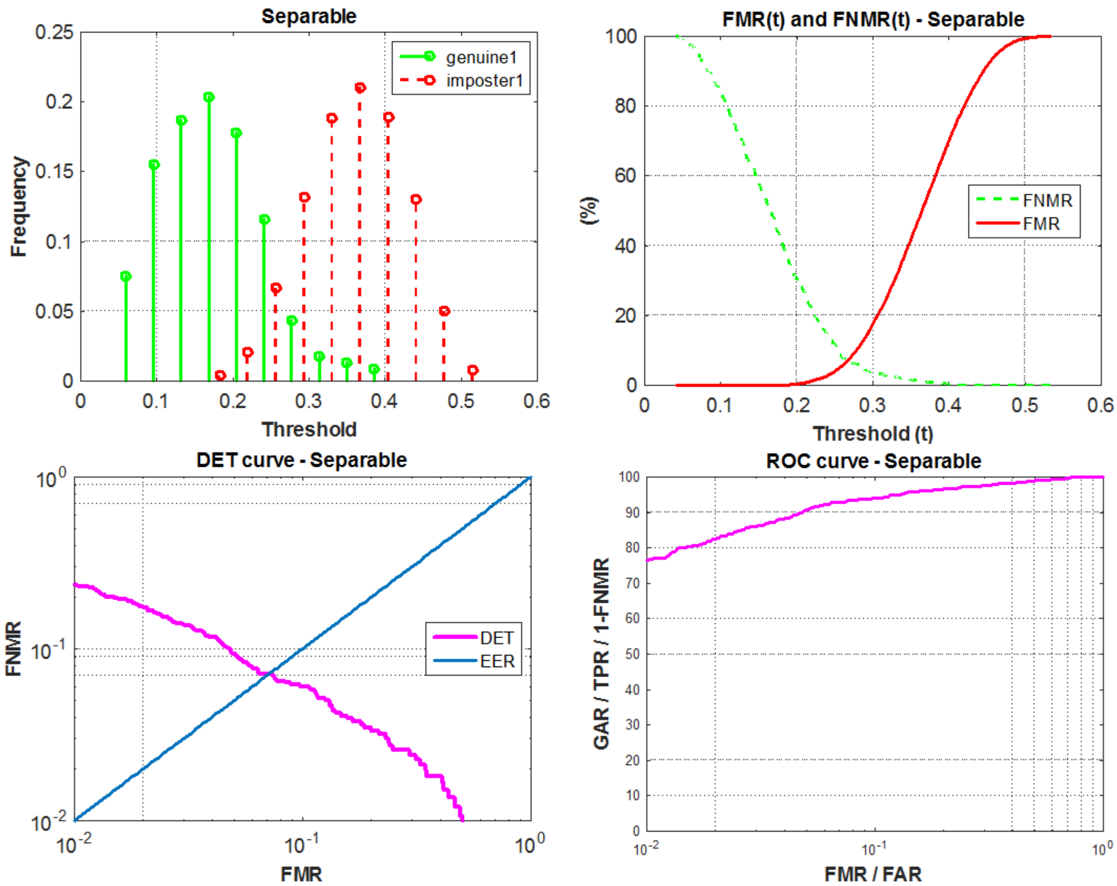

Figure 6.

IV. RESULTS & CONCLUSION

Our approach provides decidability of 50% and EER i.e. Equal Error Rate of 0.0708 and the threshold value for critical applications is 0.1, with the scale of 0.4919.

From the literature review we found that 3D approach is more efficient over 2D in terms of accuracy but for 3D method we require an expensive scanner for proper capturing and segmentation of the image, while 2D method I comparatively cheap and thus can be used for less crucial applications. Also ear is an effective biometric when used in multimodal system with other alternatives thus one should go for a technique which is suitable according to the requirements of their applications.

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