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Digital Camera based Fingerprint Recognition

B.Y. Hiew, Andrew B.J. Teoh, *Member, IEEE* and Y.H. Pang

Abstract—**Touch-less fingerprint recognition deserves increasing attention as it lets off the problems of deformation, maintenance, latent fingerprint problems and so on that still exist in the touch-based fingerprint technology. However, problems such as the low ridges-valleys contrast in the fingerprint images, defocus and motion blurriness raise when developing a digital camera based fingerprint recognition system. The system comprises of preprocessing, feature extraction and matching stages. The proposed preprocessing stage presents the promising results in terms of segmentation, enhancement and core point detection. Feature extraction is done by Gabor filter followed by Principle Component Analysis (PCA) and the favorable verification results are attained with Cosine Angle.**

Index Terms—**touch-less fingerprint recognition, preprocessing, Gabor filter, Principle Component Analysis**

I. Introduction

TRADITIONALLY, fingerprint image acquisition was performed by using the so-called “ink-technique”. Today, most civil and criminal Automatic Fingerprint Identification Systems (AFIS) accept live-scan digital images acquired with an electronic fingerprint scanner where the finger surface is directly sensed [1]. Even so, touch-less fingerprint recognition has been gaining attention recently because it frees from the problems in terms of hygienic, maintenance, latent fingerprint problems and so forth that occur in the touch-based sensing technology. Most importantly, images captured with touch-less devices are distortion free and present no deformation since these images are exempted from the pressure of contact [2].

To date, several approaches for touch-less fingerprint recognition system have been reported. Application of fingerprint verification technology to mobile handsets is discussed in [3] and a novel method for fingerprint enhancement has been developed for that particular design[3, 4]. In [2], the authors proposed a preprocessing technique which included low pass filtering, segmentation and Gabor enhancement for their own-designed touch-less sensor. Later, [5] resolved the 3D to 2D image mapping problem that was introduced in [2] by a strong view difference image rejection method. Preprocessing of fingerprint images captured with mobile camera was suggested by [6]. Most lately, [7] introduced a new touch-less device - The Surround Imager^{TM}, which can acquire 3D rolled-equivalent fingerprints. To make 3D touch-less fingerprints interoperable with the current AFIS system, [8] proposed an unwrapping algorithm that unwraps the 3D touch-less fingerprint images into 2D representations that are comparable with the legacy rolled fingerprints.

In this paper, we opted for a the digital camera to acquire the fingerprint images owing to its affordable cost and the unique features such as zooming, auto-focusing, and high resolution that are suitable to capture high quality images. However, some challenging problems appear when developing a fingerprint recognition system that uses a digital camera. First, the contrast between the ridges and the valleys in the fingerprint images acquired with a digital camera is low. Second, the depth of the field of the camera is small, hence some part of the fingerprint regions are in focus but some parts are out of focus. Third, motion blurriness in the images is obtained.

Specifically, we propose an end to end resolution for the digital camera based fingerprint recognition system in which the raw images will be normalized, segmented, enhanced and followed by the core point detection. The normalized images will next be proposed by the Gabor filters. The Gabor features are compressed using PCA and finally the matching is done by the Cosine Angle.

The outline of the paper is as follows: Section 2 provides an overview of the proposed system and also describes the preprocessing, Gabor filter based feature extraction, PCA and fingerprint verification using Cosine Angle. Section 3 shows the experiment results of the preprocessing and verification. We end the paper with our conclusions.

II. Touch-less Fingerprint Recognition Algorithm

A. Proposed System Overview

The block diagram of the proposed touch-less fingerprint recognition system is shown in Fig.1. The main sub modules of the system comprise of:

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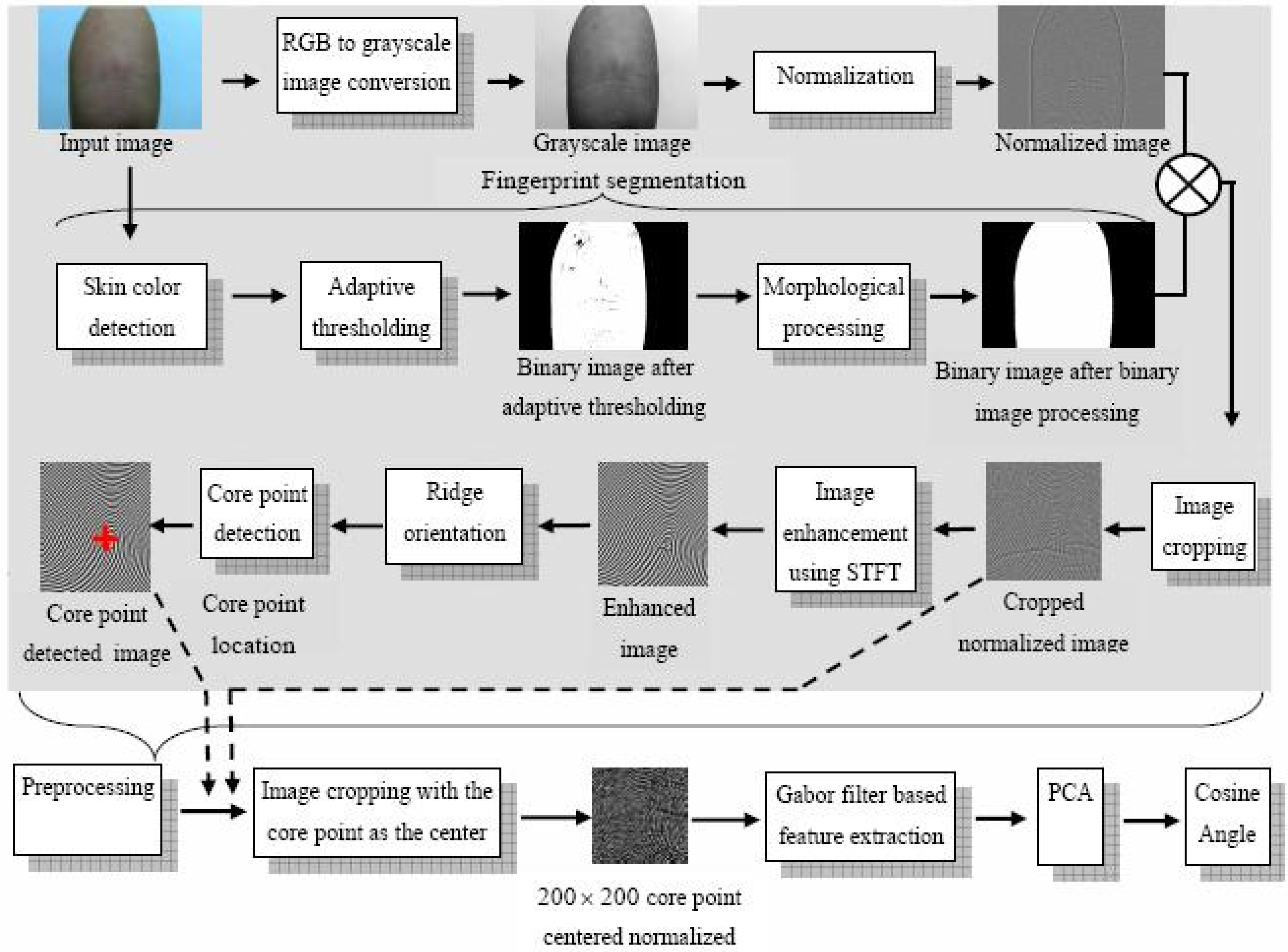


Fig. 1. Block diagram of the proposed touch-less fingerprint recognition

1) Preprocessing
   The fingerprint images are preprocessed using the proposed method which encompasses skin color detection, normalization, fingerprint segmentation, image enhancement and core point detection.
2) Gabor filter based feature extraction
   The feature vectors are extracted by Gabor filter from the images after preprocessing.
3) PCA
   The dimensionality of the Gabor feature vectors is reduced using PCA.
4) Matching
   The fingerprint verification is done by using the Cosine Angle.

B. Preprocessing

Fig. 1 depicts the preprocessing steps. Firstly, the RGB fingerprint image is converted to gray scale [0-255]. To reduce the degradation that is caused by the illumination, the image is then normalized by changing the dynamic range of the pixel intensity values. After the normalization, segmentation is done by the skin colour detection, adaptive thresholding and followed by the morphological processing. The fingerprint image is multiplied with the binary mask obtained from the segmentation later on. Consequently, the resulting image is cropped and enhanced by using the STFT analysis [9]. Finally, the core point is detected on the enhanced image. The detail description about the preprocessing can be obtained in [10].

C. Gabor Filter based Feature Extraction

A properly tuned Gabor filters are renowned in smoothing out noise, preserving the true ridge furrow structures in addition to capture both frequency and orientation information from a fingerprint image. Therefore, we used the Gabor filter based feature extractor to form the feature vectors.

The general form of a 2D Gabor filter is shown below:

$$h(x,y,\theta,f,\sigma_x,\sigma_y)=\exp\left[-\frac{1}{2}\left(\frac{x'^2}{\sigma_x^2}+\frac{y'^2}{\sigma_y^2}\right)\right]\times\exp(i2\pi fx') \quad (1)$$

$$x'=x\cos\theta+y\sin\theta\,,\; y'=-x\sin\theta+y\cos\theta \quad (2)$$

where

f : the frequency of the sinusoidal plane wave,

θ : the orientation of the Gabor filter,

σ_x and σ_y : the standard deviations of the Gaussian envelope along the x and y axes, respectively.

The feature extraction method that we use here is similar to the method described in [11]. After the core point detection, the cropped normalized image from the preprocessing is cropped again into the size of 200 x 200 with the core point as the center (the core point location is determined from the preprocessing). Those images are sampled by the Gabor filters. The filtered images are divided into a set of 8 x 8 non-overlapping blocks afterward, respectively. The resulting magnitude will be then converted to a scalar number by calculating its standard deviation value.

In our experiment, we applied a band of 6 Gabor filters (0°, 30°, 60°, 90°, 120°, 150°), and a frequency, f = 10 which corresponds to the reciprocal of the average inter-ridge distance. At last, a feature vector with $25 \times 25 \times 6$ = 3750 Gabor features are extracted from each image.

D. Principle Component Analysis

Due to the number of extracted Gabor features is huge, PCA is used here for reducing the dimensionality of the feature vectors while retaining those characteristics of the feature vectors that contribute most its variance by eliminating the later principal components. In the eigenspace method, our feature vector can be defined as a vector of dimension 3750, or, equivalently, a point in 3750-dimension space. Then, an ensemble of feature vectors map to collection of points in this huge space.

Feature vectors can be described by a relatively low dimensional subspace as it will not be randomly distributed in this huge space. Thus, PCA is to find the eigenfingers which is a set of eigenvectors derived from the covariance matrix of probability distribution of the high-dimensional vector space of possible fingerprints of the individual behavioral beings. Let the training set of Gabor feature vectors be $I_1, I_2, I_3, \ldots I_M$. The average feature vector of the set is

$$\bar{I} = \frac{1}{M} \sum_{n=1}^{M} I_n \tag{3}$$

Each feature vector differs from the average by the vector $\Phi_i = I_i - \bar{I}$. This set of large vectors is then subject to principal component analysis, which seeks a set of M (number of feature vectors in the training set) orthonormal vectors v_n and their associated eigenvalues λ_k which best describes the distribution of the data. The vectors v_n and scalars λ_k are the eigenvectors and eigenvalues respectively, of the covariance matrix

$$C = \frac{1}{M} A A^T \tag{4}$$

where

$$A = [\Phi_1, \Phi_2, \ldots, \Phi_M]$$

Apparently, the matrix C is of dimensions $N \times N$ where N is representing the number of Gabor features of a feature vector. It is clear that the eigenvectors of C can span an algebraic eigenspace and provide an optimal approximation for those training samples in terms of the mean-square error[12].

E. Matching

For the comparison purpose in verifying the identity of an individual through the feature matching, we have adopted three of the generally used distance measures which are Manhattan distance, Euclidean distance and Cosine Angle. Let x and y be two normalized feature vectors in n dimensional.

The Manhattan distance (L_1-norm) is just the sum of the absolute difference between the two feature vectors. It is calculated as follows:

$$d_{L1}(y, x) = \sum_{i=1}^{n} |x_i - y_i| \tag{5}$$

The Euclidean distance (L_2-norm) is the distance between feature vectors that is computed as a straight line. It is the most commonly used standard calculation defined as:

$$d_{L2}(y, x) = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \tag{6}$$

The Cosine Angle (Cosine similarity) which is defined as the cosine of the angle between them is formulated as:

$$d_{\cos}(y, x) = \frac{y \cdot x}{|y||x|} \tag{7}$$

Let d be the computed distance score from (5), (6) or (7), given a threshold T, the claim is accepted when $d < T$ and rejected when $d \geq T$.

III. Experiment Evaluation

A. Figures and Tables

As there is no standard database available for fingerprint images captured by digital camera at present, we collected the fingerprint images ourselves. Canon PowerShot Pro1, with 8 mega pixels of effective resolution and a 7x optical zoom Canon "L" series lens is used in the image acquisition. The “super macro mode” that permits close-focus to 1.2 inches enables us to get clearer foreground pattern and blurred background pattern while the L-series lens’ macro capabilities allow us to capture high resolution images. The setting of the digital camera is shown in Table I.

Table I. Digital Camera Setting for Fingerprint Image Acquisition

ISO Speed	400
Image Size/ Resolution	640x480
Image Quality	Superfine
Super Macro	On
Colour Space	RGB
Drive Mode	Continuous shooting (Speed priority)

As shown in Fig.2, all of the fingerprint images with the size of 640x480 are acquired and collected in a closed room. The white static light source from the table lamp is used as it is adequate to improve the clarity of the ridges and furrows of the captured fingerprint images. During the image acquisition process, the finger is put through the hole to decrease the motion blurriness.

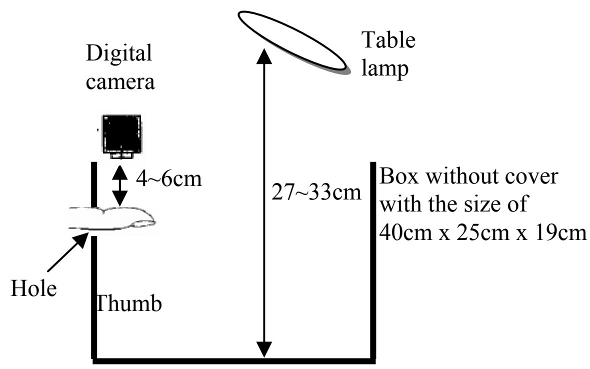


Fig. 2. Experiment Setup

B. Preprocessing Experiment Results

To conduct preprocessing experiments, a total of 1938 images are used and the results are assessed subjectively by the visual inspection.

By counting the number of false core point detection, it reveals that the proposed preprocessing algorithm can achieve an accuracy of 95.44% of core point detection whereas the false core point detection is only 4.56%. The causes of the failure of the core point detection are defocus, motion blurriness and deep wrinkle problems. Fig. 3 shows some samples of the false core point detection.

We observed that the proposed preprocessing provides pleasing results of the segmentation, enhancement and accurate core point detection as shown in Fig. 4. From the experiment results, it signifies that this approach is able to segment and enhance most of the fingerprint images successfully as well as detect the fingerprint's core point.

C. Verification Experiment Results

We observed that the proposed preprocessing provides pleasing results of the segmentation, enhancement and accurate core point detection as shown in Fig. 4. From the experiment results, it signifies that this approach is able to segment and enhance most of the fingerprint images successfully as well as detect the fingerprint's core point.

Verification experiments are conducted by using core point centered normalized fingerprint images with the size of 200 x 200 pixels. There are 1030 fingerprint images from 103 different fingers with 10 images for each finger. After the preprocessing, the features derived from the Gabor filter based feature extractor are compressed using PCA. One Gabor feature vector from each finger class is used as a training data for PCA analysis, the rest nine Gabor feature vectors are used as testing data. During the experiments, the eigenvectors are extracted from the Gabor feature vectors with the dimensionality varied from 10 to 100 in intervals of 10. Later on, the normalized eigen-based Gabor features are used for the subsequent verification. Three distance-based classifiers which are Euclidean Distance, Manhattan Distance and Cosine Angle have been adopted for verification comparison purpose.

In general, there are two types of errors in the verification system: false acceptance rate (FAR) and false reject rate (FRR). Our system performance is determined by using the Equal Error Rate (EER), i.e. FAR = FRR.

Fig.5 depicts the comparative results of various distance-based classifiers using eigen-based Gabor features. For the Manhattan Distance and Euclidean Distance classifiers, we could see that the performance is becoming better till a certain point but turns to be worse after that. This shows that these two classifiers are not really stable and not effective enough to discriminate the principle components.

For Cosine Angle, the verification performance is better as the dimensionality is increasing. It is an evident that the dimensionality plays an important role in the matching process using Cosine Angle. Thus, this shows that Cosine Angle is the most effective and stable distance-based classifier among the three distance-based classifiers.

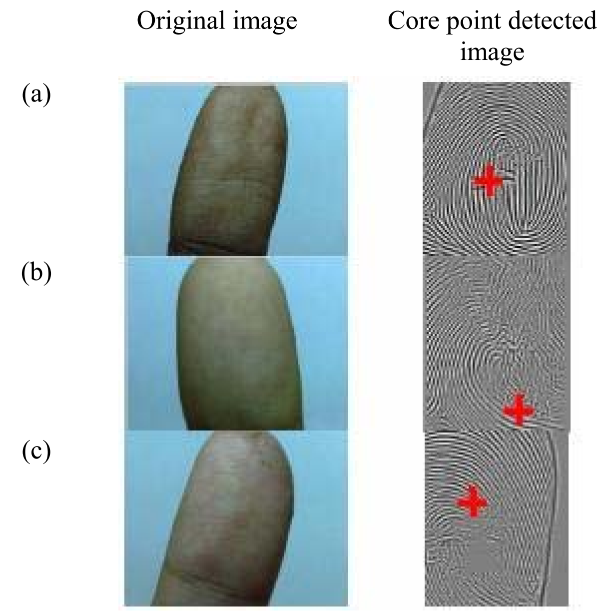


Fig. 1 Samples of false core point detection using proposed preprocessing for: (a) deep wrinkle image (b) motion blurriness image (c) defocus image

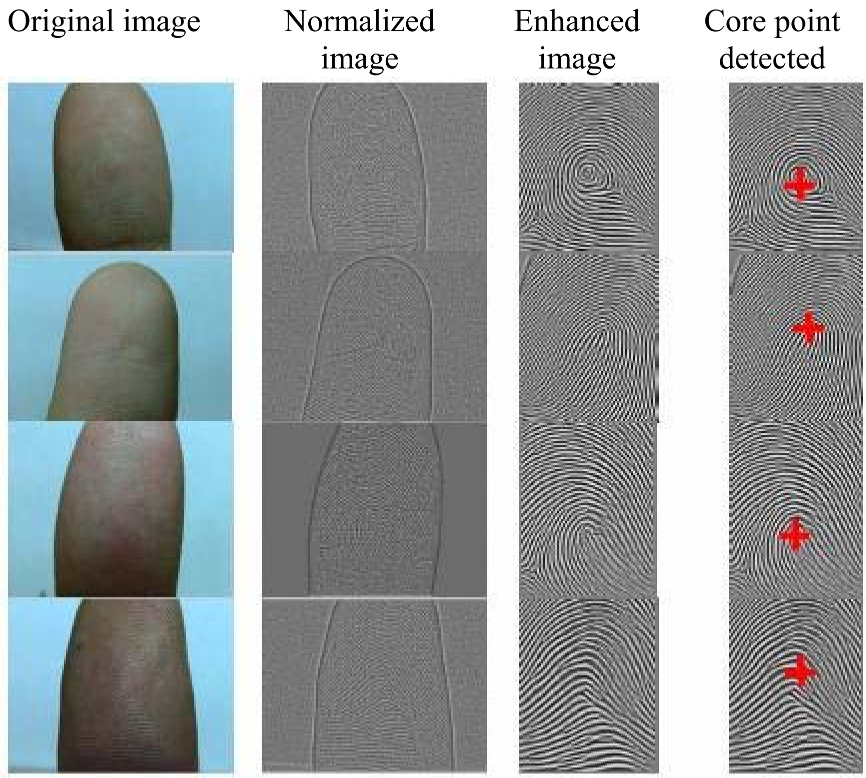
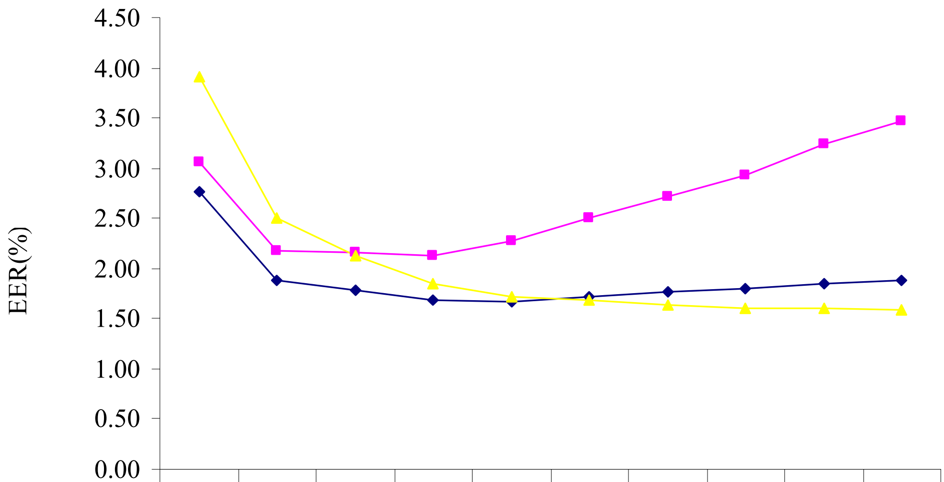


Fig. 4 Results for the proposed preprocessing



	10	20	30	40	50	60	70	80	90	100
Euclidean Distance	2.77	1.88	1.79	1.68	1.68	1.73	1.77	1.80	1.85	1.88
Manhattan Distance	3.07	2.18	2.16	2.12	2.27	2.50	2.72	2.93	3.24	3.47
Cosine Angle	3.91	2.50	2.14	1.85	1.72	1.68	1.64	1.61	1.60	1.58

Feature Length

Fig. 5. Comparative results of various distance-based classifiers using eigen-based Gabor features of different dimensionality.

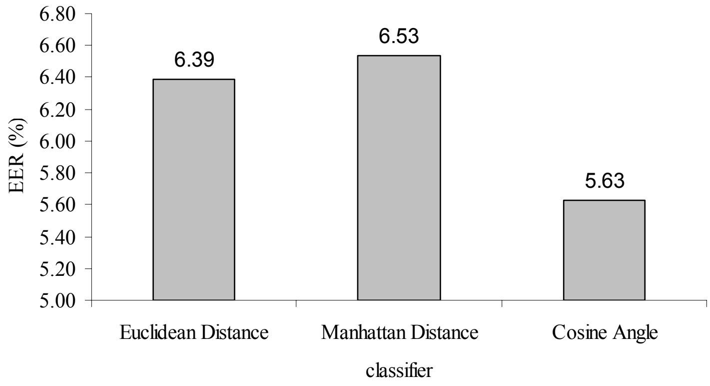


Fig. 6. Results of various distance-based classifiers using uncompressed Gabor features

The performance of Euclidean Distance, Manhattan Distance and Cosine Angle classifiers based on the uncompressed Gabor features, i.e. without going through PCA is presented in Fig.6. The result again justifies that Cosine Angle is the best classifier. Nevertheless, by comparing the best results of Cosine Angle for compressed (dimensionality = 100) and uncompressed Gabor features, we observe that the compressed features outperform the uncompressed features and this is shown in Fig. 7.

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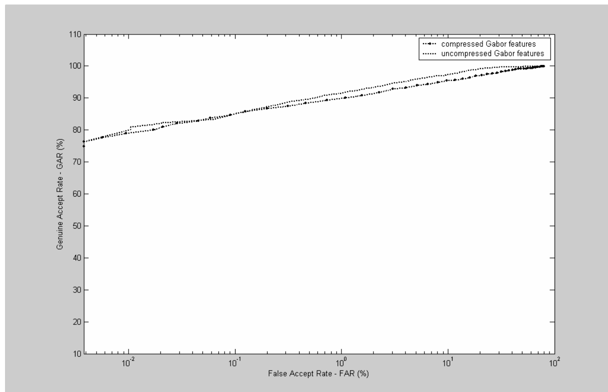

Fig. 7. Receiving Operating Characteristic (ROC) curve for compressed Gabor features (dimensionality =100) and uncompressed Gabor features with Cosine Angle as a classifier.