# Fingerprint Recognition Based on Compressive Sensing using Gabor Filters

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***ABSTRACT-*** Fingerprint Recognition is a widely used Biometric Identification mechanism. Up till now different techniques have been proposed for having satisfactory Fingerprint Identification. The widely used minutiae-based representation did not utilize a significant component of the rich discriminatory information available in the fingerprints. Local ridge structures could not be completely characterized by minutiae. The proposedcompressive sensing using Gaborfilter algorithm uses a bank of Gabor filters to capture both local and global details in a fingerprint and compress it produce a compact fixed length Finger Code. The proposed compressive sensing using Gaborfilter algorithmis more accurate than the minutiae based algorithm.

***Key Words:*** *fingerprints, Gabor filters, biometric identification , Minutiae Based Method*

## I.INTRODUCTION

Personal identification is to associate a particular individual with an identity. It plays a critical role in our society, in which questions related to identity of an individual in organizations like financial services, health care, electronic commerce, telecommunication, government. With the rapid evolution of information technology, people are becoming even more and more electronically connected. As a result, the ability to achieve highly accurate automatic personal identification is becoming more critical.

In the world of computer security, biometrics refers to authentication techniques that rely on measurable physiological and individual characteristics that can be automatically verified. In other words, we all have unique personal attributes that can be used for distinctive identification purposes, including a fingerprint, the pattern of a retina, and voice characteristics.

A biometric authentication is essentially a pattern-recognition that makes a personal identification by determining the authenticity of a specific physiological or behavioural characteristic possessed by the user.

A growing number of biometric technologies have been proposed over the past several years, but only in the past 5 years have the leading ones become more widely deployed.

Some technologies are better suited to specific applications than others, and some are more acceptable to users. We describe seven leading biometric technologies:

1. Facial Recognition
2. Fingerprint Recognition
3. Hand Geometry
4. Iris Recognition
5. Signature Recognition
6. Speaker Recognition

Fingerprint-based identification is one of the most important biometric technologies which has drawn a substantial amount of attention recently. Humans have used fingerprints for personal identification for centuries and the validity of fingerprint identification has been well established. In fact, fingerprint technology is so common in personal identification that it has almost become the synonym of biometrics. Fingerprints are believed to be unique across individuals and across fingers of same individual. Even identical twins having similar DNA, are believed to have different fingerprints. These observations have led to the increased use of automatic fingerprint based identification in both civilian and law-enforcement applications.

A fingerprint is the pattern of ridges and furrows on the surface of a fingertip. Ridges and valleys are often run in parallel and sometimes they bifurcate and sometimes they terminate. When fingerprint image is analysed at global level, the fingerprint pattern exhibits one or more regions where ridge lines assume distinctive shapes. These shapes are characterized by high curvature, terminations, bifurcations, cross-over etc. These regions are called singular regions or singularities. These singularities may be classified into three topologies; loop, delta and whorl. At local level, there are other important features known as minutiae can be found in the fingerprint patterns. Minutiae mean small details and this refers to the various ways that the ridges can be discontinuous. A ridge can suddenly come to an end which is called termination or it can divide into two ridges which is called bifurcations.

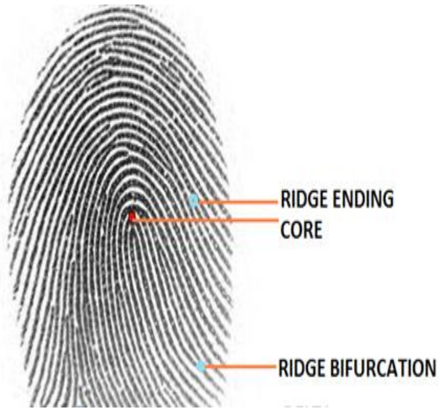


**Figure :1 Fingerprint**

## FINGERPRINT ALGORITHMS

### 2.1 Minutiae Based Method

Fingerprint based identification has been one of the most successful biometric techniques used for personal identification. Each individual has unique fingerprints. A fingerprint is the pattern of ridges and valleys on the finger tip. A fingerprint is thus defined by the uniqueness of the local ridge characteristics and their relationships. Minutiae points are these local ridge characteristics that occur either at a ridge ending or a ridge bifurcation.

A ridge ending is defined as the point where the ridge ends abruptly and the ridge bifurcation is the point where the ridge splits into two or more branches. Automatic minutiae detection becomes a difficult task in low quality fingerprint images where noise and contrast deficiency result in pixel configurations similar to that of minutiae. This is an important aspect that has been taken into consideration in this presentation for extraction of the minutiae with a minimum error in a particular location.

Minutiae based method mainly concentrates on local features of a fingerprint. In this method, matching is done by setting a threshold value.

#### 2.1.1 Algorithm

The main steps involved in minutiae based method for fingerprint recognitionare :

**Step 1:** Load the input fingerprint image.

**Step 2:** Enhance the fingerprint image.

**Step 3 :** After enhancement convert the image into binary image.

**Step 4:** Perform thinning operation on binary image.

**Step 5:** Extract minutiae from thinned image using crossing number concept and go to step 6 if input fingerprint image is processed for enrolment otherwise go to step 7 if it is processed for identification.

**Step 6:** If input fingerprint image is processed for enrolment then enrol it into database.

**Step 7:** Use minutiae based algorithm to match input fingerprint image with all template images stored in database if matching is successful then fingerprint is identified, display information related to matched fingerprint otherwise it is not identified.

### 2.2 Proposed Gabor filters Method

In image processing, a **Gabor filter**, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. Simple cells in the visual cortex of mammalian brains can be modelled by Gabor functions. Thus, image analysis with Gabor filters is thought to be similar to perception in the human visual system.

Its impulse response is defined by a sinusoidalwave (a plane wave for 2D Gabor filters) multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions.The two components may be formed into a complex number or used individually.

Complex

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\ \exp\left(\mathrm{I}\left(2\pi\frac{x'}{\lambda}+\psi\right)\right)$$

Real

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\ \cos\left(2\pi\frac{x'}{\lambda}+\psi\right)$$

Imaginary

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\ \sin\left(2\pi\frac{x'}{\lambda}+\psi\right)$$

Where

$$x' = x\ \cos\theta + y\ \sin\theta$$

and

$$y' = -x\ \sin\theta + y\ \cos\theta$$

In this equation, $\lambda$ represents the wavelength of the sinusoidal factor, $\theta$ represents the orientation of the normal to the parallel stripes of a Gabor function, $\psi$ is the phase offset, $\sigma$ is the sigma/standard deviation of the Gaussian envelope and $\gamma$ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function.

Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space. This process is closely related to processes in the primary visual cortex. Jones and Palmer showed that the real part of the complex Gabor function is a good fit to the receptive field weight functions found in simple cells in a cat's striate cortex.

### 2.3Gabor Filter Bank Based Feature Extraction

It is desirable to obtain representations for fingerprints which are scale, translation, and rotation invariant. Scale invariance is not a significant problem since most fingerprint images could be scaled as per the dpi specification of the sensors. The rotation and translation invariance could be accomplished by establishing a reference frame based on the intrinsic fingerprint characteristics which are rotation and translation invariant. The present implementation of feature extraction assumes that the fingerprints are vertically orientation. In reality, the fingerprints in our database are not exactly vertically oriented; the fingerprints may be oriented up to away from the assumed vertical orientation. This image rotation can be partially handled by a cyclic rotation of the feature values in the Finger Code in the matching stage; in future implementations.

The four main steps in our feature extraction algorithm are :

**1.** Determine a reference point and region of interest for the fingerprint image.

**2.** Tessellate the region of interest around the reference point.

**3.** Filter the region of interest in eight different directions using a bank of Gabor filters.

**4.** Compute the average absolute deviation from the mean (AAD) (9) of gray values in individualsectors in filtered images to define the feature vector or the Finger Code. In the current implementation.

**2.4Core Point Detection**

Two different methods are used to detect core point in a fingerprint image. The core point location is more accurately detected by using multiple techniques.

**Figure:2 Optimal Core Point Location**

**2.4.1 Using Poincare Index**

**1.** Estimate the orientation field O using the least square orientation estimation algorithm [10] . Orientation field O is defined as an M x N image, where O(i, j) represents the local ridge orientation at pixel (i, j). An image is divided into a set of w x w non-overlapping blocks and a single orientation is defined for each block.

**2.** Initialize A, a label image used to indicate the core point.

**3.** For each pixel (i, j) in O, compute Poincare index [11] and assign the corresponding pixels in A the value of one if Poincare index is between 0.45 and 0.51.The Poincare index at pixel (i, j) enclosed by a digital curve, which consists of sequence of pixels that are on or within a distance of one pixel apart from the corresponding curve, is computed as follows:

$$\textbf{Poincare(I, j)} = {}^{1}/_{2\pi} \sum_{k=0}^{N_p-1} \Delta(k) \text{---------------}1$$

$$\Delta(\mathbf{k}) = \begin{cases} \boldsymbol{\delta}(\mathbf{k}) & \textbf{if } |\boldsymbol{\delta}(\mathbf{k})| < \frac{\pi}{2} \\ \boldsymbol{\pi} + \boldsymbol{\delta}(\mathbf{k}) & \textbf{if } \boldsymbol{\delta}(\mathbf{k}) < -\frac{\pi}{2} \\ \boldsymbol{\pi} - \boldsymbol{\delta}(\mathbf{k}) & \textbf{otherwise} \end{cases} \text{---------}2$$

$$\boldsymbol{\delta(k)} = \boldsymbol{\theta}(x_{(k+1) mod\, N_p,} y_{(k+1) mod\, N_p)} \text{-} \boldsymbol{\theta}(x_k, y_k) \quad \text{---------}\ 3$$

For our method, $N_p$ is selected as 8.

**4.**The center of block with the value of one is considered to be the center of fingerprint. If more than one block has value of one, then calculate the average of coordinates of these blocks.

**2.4.2 Using Slope**

**1.** Estimate the orientation field O using the least square orientation estimation algorithm [12].

**2.** Smooth the orientation field in local neighbourhood. Let the smoothed orientation field be represented as O'.

**3.** Initialize A, a label image used to indicate the core point.

**4.** In O'(i, j) , start from first row (0, 0), find the block whose angle is between 0 and π /2 and then trace down vertically until a block with a slope not within that range (0 and π /2) is encountered. That block is then marked [13] in A. This procedure is performed on all the rows of orientation field O'(i, j).

**5.** The center of block with the highest number of marks is considered to be the center of fingerprint.

**2.5Tessellation**

The spatial tessellation of fingerprint image which consists of the region of interest is defined by a collection of sectors. We consider Newdb14 database containing 14 TIFF Fingerprint images of size 256 x 256 with resolution 500dpi. We use four concentric bands around the core point. Each band is 20 pixels wide and segmented into sixteen sectors. Thus we have a total of 16 x 4 = 64 sectors and the region of interest is a circle of radius 100 pixels, centred at the core point.

Fingerprints have local parallel ridges and valleys, and well defined local frequency and orientation. Properly tuned Gabor filters [14][15], can remove noise, preserve the ridge and valley structures, and provide information contained in a particular orientation in the image. A minutia point can be viewed as an anomaly in locally parallel ridges and it is this information that we are attempting to capture using the Gabor filters. Before filtering the fingerprint image, we normalize the region of interest in each sector separately to a constant mean and variance.

**2.6Normalization**

Normalization is performed to remove the effects of sensor noise and gray level deformation due to finger pressure differences. Let I(x, y) denote the gray value at pixel (x, y), and $M_i$, $V_i$ the estimated mean and variance of sector Si, respectively, and Ni(x, y) the normalized gray-level value at pixel (x, y). For all the pixels in sector Si, the normalized image is defined as follows :

$$\mathbf{N_{i(x,y)}} = \begin{cases} \mathbf{M_0} + \sqrt{\frac{\mathbf{V_0 * (I(x,y) - M_i)^2}}{\mathbf{V_i}}} & \textbf{if } \mathbf{I(x,y)} > \mathbf{M_i} \\ \mathbf{M_0} - \sqrt{\frac{\mathbf{V_0 * (I(x,y) - M_i)^2}}{\mathbf{V_i}}} & \textbf{otherwise} \end{cases}$$

where $M_o$ and $V_o$ are the desired mean and variance values, respectively. Normalization is a pixel-wise operation which does not change the clarity of the ridge and valley structures. If normalization is performed on the entire image, then it cannot compensate for the intensity variations in different parts of the image due to the elastic nature of the finger. Separate normalization of each individual sector alleviates this problem.

**2.7Filtering**

Gabor filters optimally capture both local orientation and frequency information from a fingerprint image. By tuning a Gabor filter to specific frequency and direction, the local frequency and orientation information can be obtained .

An even symmetric Gabor filter has the following general form in the spatial domain:

$$G( x, y ; f,\theta ) = \exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_{x'}^2} + \frac{y'^2}{\delta_{y'}^2}\right]\right\}\cos 2\pi f x^2$$

$$x' = x \sin\theta + y \cos\theta$$
$$y' = x \cos\theta - y \sin\theta$$

where f is the frequency of the sinusoidal plane wave along the direction from the x-axis, and x and y are the space constants of the Gaussian envelope along and axes, respectively. We keep value of f=average inter ridge distance i.e. 20 pixel and x and y as half of average distance 0.5.We perform the filtering in the spatial domain with a mask size of 33×33. However, to speed up the filtering process, we perform convolution in frequency domain. We have used eight different values for (0, 22.5, 45, 67.5, 90, 112.5, 135, and 157.5 degrees) with respect to the x-axis for Gabor filter. The normalized region of interest in a fingerprint image is convolved with each of these eight filters to produce a set of eight filtered images. A fingerprint convolved with a 00-oriented filter accentuates those ridges which are parallel to the x-axis and smoothes the ridges in the other directions. Filters tuned to other directions work in a similar way. These eight directional-sensitive filters capture most of the global ridge directionality information as well as the local ridge characteristics present fingerprint.

**2.8Feature Vector**

Let $F_{i\theta}$ be the θ-direction filtered image for sector Si. Now, and, the feature value $V_{i\theta}$, is the average absolute deviation from the mean $P_{i\theta}$, defined as

$$V_{i\theta} = \frac{1}{n_i}|F_{i\theta}(x,y) - P_{i\theta}$$

where is $n_i$the number of pixels in Si and $P_{i\theta}$, is the mean of pixel values of $F_{i\theta}$, in sector Si. The average absolute deviation of each sector in each of the eight filtered images defines the components of our feature vector. The rotation invariance is achieved by cyclically rotating the features in a feature vector itself. A single step cyclic rotation of the features corresponds to a feature vector which would be obtained if the image was rotated by 22.5 degrees. Fingerprint matching is based on finding the Euclidean distance between the corresponding feature vectors. This minimum score corresponds to the best alignment of the two fingerprints being matched. If the Euclidean distance between two feature vectors is less than a threshold, then the decision that “the two images come from the same finger” is made, otherwise a decision that “the two images come from different fingers” is made. Since the template generation for storage in the database is an off-line process, the verification time still depends on the time taken to generate a single template.

**2.9 CompressiveSensing**

Shannon’s Nyquist sampling theorem specifies that a signal should be sampled at a rate higher than twice the maximaAround 2004, Emmanuel Candès, Justin Romberg, Terence Tao, and David Donoho proved that given knowledge about a signal's sparsity, the signal may be reconstructed with even fewer samples than the sampling theorem requires.[4][5] This idea is the basis of compressed sensing. l frequency of the signal for fidelity of signal reconstruction. Around 2004, Emmanuel Candès, Justin Romberg, Terence Tao, and David Donoho proved that given knowledge about a signal's sparsity, the signal may be reconstructed with even fewer samples than the sampling theorem requires. This idea is the basis of compressive sensing. Orthogonal matching pursuit (OMP) algorithm is one of the most popular compressive sensing algorithms.It is used to compress the vectors generated from Gabor filters.

**2.10Fingerprint Matching**

The proposed scheme first detects the core point in a fingerprint image using two different techniques. Core point is defined as the north most point of inner-most ridge line. In practices, the core point corresponds to center of north most loop type singularity. Some fingerprints do not contain loop or whorl singularities, therefore it is difficult to define core. In that kind of images, core is normally associated with the maximum ridge line curvature. Detecting a core point is not a trivial task; therefore two different techniques have been used to detect optimal core point location. A circular region around the core point is located and tessellated into 128 sectors. The pixel intensities in each sector are normalized to a constant mean and variance. The circular region is filtered using a bank of sixteen Gabor filters to produce a set of sixteen filtered images.

Gabor filter-banks are a well-known technique to capture useful information in specific band pass channels.Two such techniques have been discussed in [20] and [21]. The average absolute deviation with in a sector quantifies the underlying ridge structure and is used as a feature. The feature vector (2048 values in length) is the collection of all the features, computed from all the 128 sectors, in every filtered image Orthogonal matching pursuit (OMP) algorithm is used to compress the vectors generated from Gabor filters. The feature vector captures the local information and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The matching stage computes the Euclidean distance between the two corresponding feature vectors.

Once the average absolute deviation is found out for the enquired image it is found out for the enquired image it is compared with average absolute deviation of the stored database by Euclidean Distance method, and the distance having minimum value will be considered as best match. In mathematics the Euclidean distance or Euclidean matrix is the ordinary distance between two point’s hat one should measure with a ruler, and is given by the Pythagorean formula. By using this formula as Euclidean space become a metric space. The Euclidean distance between points p & q is the length of line segment In Cartesian co-ordinates if p = ($p_1$,$p_2$,----$p_n$) and q= ($q_1$,$q_2$,-----$q_n$) are two points in Euclidean space then the distance from p to q is given by

$$\sqrt{(p_1 - q_1)\text{^}2 + (p_2 + q_2)\text{^}2 + \text{-----} + (p_n - q_n)\text{^}2}$$

It is desirable to obtain representations for fingerprints which are translation and rotation invariant. In the proposed scheme, translation is taken care of by a reference point which is core point during the feature extraction stage and the image rotation is handled by a cyclic rotation of the feature values in the feature vector. The features are cyclically rotated to generate feature vectors corresponding to different orientations to perform the matching. If the Euclidean distance between two feature vectors was less than a threshold, then the decision that " the two images come from the same finger " was made, otherwise a decision that " the two images come from different fingers " was made.

**2.11Comparison of Minutiae Based and Gabor Filter Methods**

**Advantage of Filter Bank Based Fingerprint Matching**

**1.** Both the global flow pattern of ridges and valleys and local characteristics (inter-ridge distances, ridge orientation) are used for feature extraction

**2.**They generate a short fixed length code, Finger Code (Feature vector) for fingerprint

**3.**Finger Code is suitable for fast matching (by Euclidean distance), storage on smartcard and indexing.

**4.**The obtained representation is scale, translation and rotation invariant.

5. Good finger print verification accuracy is achieved by the method.

**Disadvantages of Minutiae Based Approach for Fingerprint Matching**

**1.**A good quality fingerprint contains between 60 and 80 minutiae, but different fingerprints have different numbers.

**2.**Reliably extracting minutiae from poor quality fingerprints is very difficult.

**3.**Minutiae extraction is time consuming.

**4.**Variable sized minutiae based representation does not easily help in indexing fingerprint database.

**3 Results**

This chapter consists of the results generated by the GUI software, designed by using MATLAB.

First we created a database of 50 fingerprints. The steps involved in it are as follows:

**3.1Minutiae Based Method**

**1. Read an Input Image**

**Figure :3 Input Image**

**2. Applying Binarization Technique**

**Figure :4Binarization**

**3. Applying Thinning process**

**Figure :5 Thinning**

**4. Marking Minutiae Points**

**Figure:6Minutiae Extraction**

**5.** After creating the database, we match the fingerprints from it. The software takes a latent image as input and matches the minutiae points and orientation with the database and generates matching score. The following results were obtained:

| FVC Database | Input | Match Score |
|---|---|---|
| 101_1 | 101_1 | 1 |
| 101_2 | 101_1 | 0.77067 |
| 102_1 | 101_1 | 0.19739 |
| 102_2 | 101_1 | 0.24535 |
| 103_1 | 101_1 | 0.18019 |
| 103_2 | 101_1 | 0.2176 |
| 104_1 | 101_1 | 0.24772 |
| 104_2 | 101_1 | 0.22396 |

**Table :1Results after comparing similarities between input with other fingerprints in database FVC2002**

### 3.2 Proposed Gabor Filter Method

**1. Image to the Software**

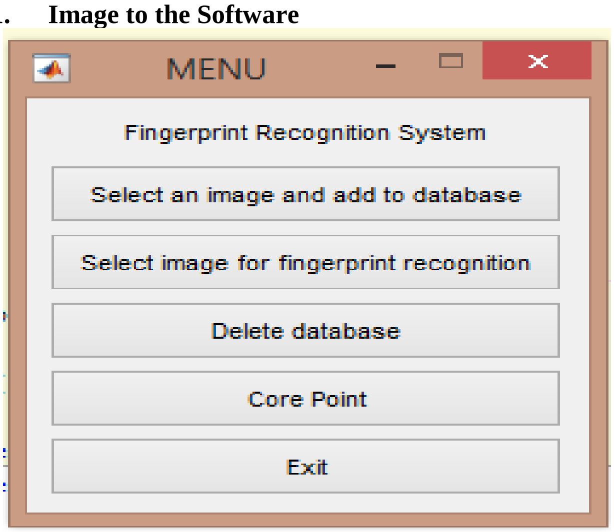


**Figure7 : Graphical User Interface (GUI) for Input Image**

**2. Addition of Database**

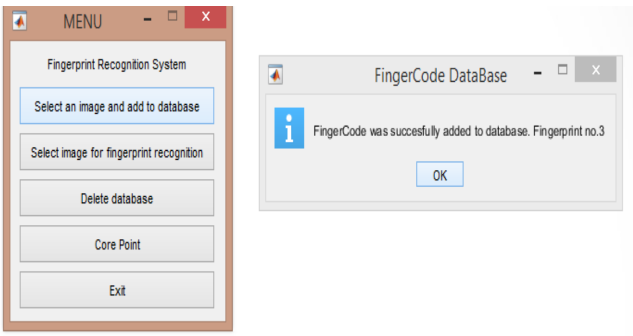


**Figure :8 Database Addition**

**3. Finding Core Point**

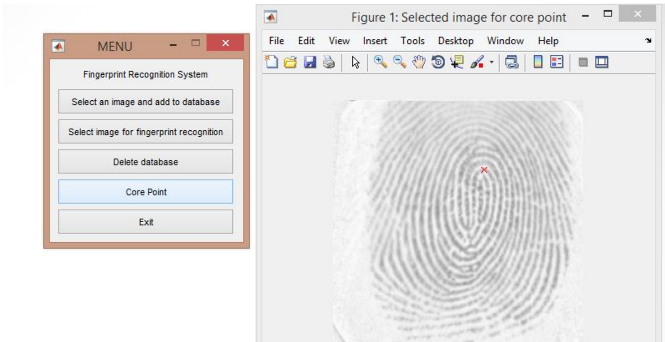


**Figure:9Core Point Recognition**

**4. Finding Similar Fingerprint**

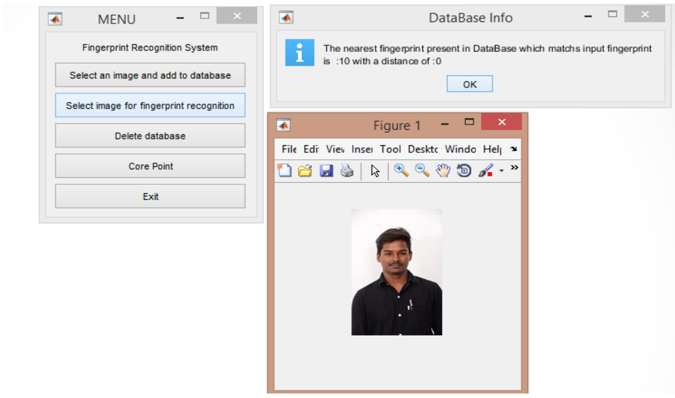


**Figure :10 Similar Fingerprint Recognition**

**5. Finding Non-Similar Fingerprint**

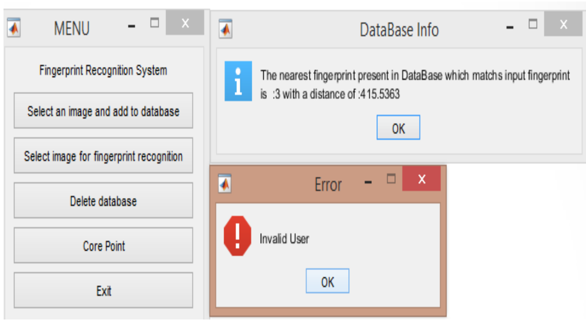


**Figure :11 Non-Similar Fingerprint Recognition**

### 4.CONCLUSION

Fingerprint Recognition is used in many applications like biometric measurements, solving crime investigation and security systems. From minutiae extraction to minutiae matching all stages are included in this implementation which generates a match score.The proposedGabor filter based method is implemented for Fingerprint Recognition which consider global and local features to gives more accuracy.

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