A New Technique to Fingerprint Recognition Based on Partial Window

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Abstract

Fingerprint verification is a well-researched problem, and automatic fingerprint verification techniques have been successfully adapted to both civilian and forensic applications for many years. This paper present a new technique to fingerprint recognition based a window that contain   core point this window will be input ANN system to be model we can recognize another fingerprint , so we will firstly,   A recognition algorithm needs to recover fingerprints pose transformation between the input reduce time computation. Our detection algorithm works in the field orientation of the adaptive smoothed with a varying area. The adaptive window is used to attenuate the noise effectively orientation field while maintaining the information of the detailed guidance in the area of high curvature. A new approach to the core point location that is proposed is based on hierarchical analysis orientation consistency. The proposed adaptation singular point detection method increases the accuracy of the algorithm. Experiments show that our algorithm developed consistently locates a reference point with high precision only for all fingerprints. And very faster for recognition process.

Keywords: Fingerprint recognition; field orientation; neural networks; core point, neural networks.

1. Introduction

Fingerprints are the most widely used biometric feature for user identification and verification in the field of biometric identification and security [1]. Fingerprint consists of ridges and furrows on the fingertips. It is widely used for personal identification due to its easy accessibility, uniqueness and reliability. Pose transformation samples normally exist in different fingerprints of the same finger. A popular solution is to locate a reference point that is used only for registration or alignment of the different samples. Since the singular points, i.e. central and delta points are landmarks unique fingerprint, which were used as reference points for fingerprint matching and classification [2].

However, some fingerprints contain only partial images with singular points are out of print, and not all have valid fingerprint singular points. To locate a single reference point consistent for all types of fingerprints. Central point is defined as the northernmost point of the innermost ridge line [3], which is usually located in the central area (see figure 1). Methods for detecting singular points operating in the field of orientation of the fingerprint. The Poincare index analysis is one of the commonly used methods and relates Karu Jain [2].

However, this method is sensitive to noise and orientation field does not work for arc fingerprint smooth, since there are no singular points in such a fingerprint. Koo and Kot [4] proposed a method of detecting a singular point based on searching the point with maximum curvature crest. It works well for low quality fingerprint, as calculated curvature is sensitive to noise of orientation field. A.K. Jain [5] proposed a robust method to locate a reference point with maximum curvature based on multi-resolution analysis of the sinusoidal component integration differences

between two defined regions of the field orientation. However, these two regions are sensitive to the rotation of fingerprints.
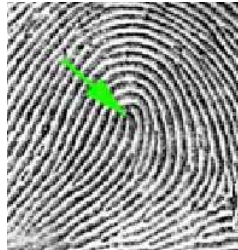

Figure 1 Example of core point.

In a fingerprint, all the ridges diverge out in the form of loops from the core point. They are generally elliptical in nature and grow in size as we move away from the core point. In general, the core point shows a discontinuity as far as the orientation of the ridges around it is concerned. In existing algorithms, we make use of this discontinuity to locate the core point. Finding the orientation of the ridges is the first step. Following this, various algorithms make use of different properties. The Detection of Curvature algorithm uses a global mask to locate the points which exhibit this discontinuity by considering the cosine and sine components of the orientation [6].

The Geometry of Region technique defines two sandwiched regions designed to capture the maximum curvature in concave ridges [7]. In these techniques, we use the micro features to locate the core point. However, the presence of discontinuities due to scars and wrinkles or faulty image acquisition, might lead to false detection of the core point. The proposed algorithm utilizes the global orientation features of the fingerprint. In any fingerprint, the ridges above the core point are almost horizontal, while those on its sides are almost vertical. Based on this property, we can make use of the vertical (sine) components of the orientations to locate the core point.

The sine of the orientation of the horizontal ridges will have a value close to zero, while that of the vertical ridges will have a value close to one. We make use of this property and apply a global (less than) threshold to the sine of the orientation of the ridges. The resulting image will have a component connected to the upper boundary of the fingerprint region. Ideally, there should be only one such component. However, there may be multiple components due to non-ideality. We choose the largest component and designate the lower most point of that component as the core point. Our proposed algorithm has major steps. Pre-processing, extracting core point, determined window surround   core point   , after extract the feature vectors of   the window it will be input to ANN to recognize fingerprints. Figure 2 show a diagram with the major steps of the proposed technique.
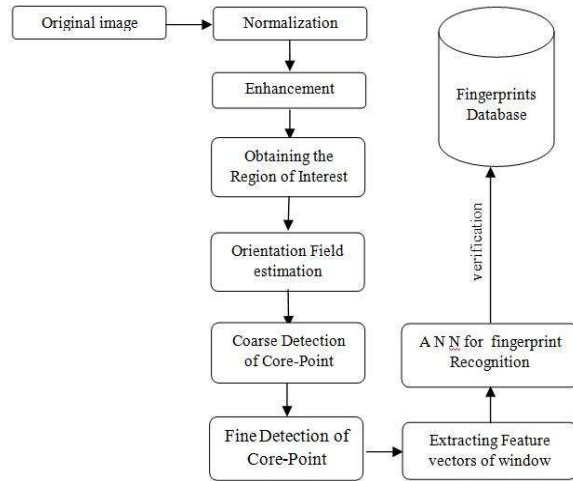
Figure 2 shows a diagram with the major steps of the proposed technique.

2. Pre-processing

In our algorithm, images are pre-processed with gray-level enhancement, followed by obtaining the bounding rectangle for the region of interest of the fingerprint and finally estimation of the orientation field in the region.

2.1 Normalization

Let l(x,y) represent the gray-level of the pixel at (x,y). The image is divided into a number of sectors of size w x w.

Let M_i and V_i denote the estimated mean and variance of the ith sector, $N_i(x, y)$ denote the normalized gray level value of the pixel at (x,y). Then for all the pixels in the ith sector, the normalized gray-level is defines as,

$$N_i(x,y) = \begin{cases} M_0 + \sqrt{\dfrac{V_0 \times (I(x,y) - M_i)^2}{V_i}} & , if\ I(x,y) > M_i \\ M_0 - \sqrt{\dfrac{V_0 \times (I(x,y) - M_i)^2}{V_i}} & , \quad otherwise \end{cases}$$

where M_0 and V_0 are the desired mean and variance values respectively. The result of normalization step is illustrated in Figure 3 where the first image is an original fingerprint image and the second one is the result of the normalization process.
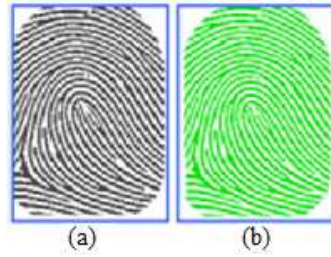
65

Figure 3 (a) Original fingerprint, (b) Normalization of (a)

2.2. Obtaining the region of interest

After normalization, the region of interest of the fingerprint has to be obtained. For our algorithm, it will be beneficial to find the bounding rectangle for the fingerprint (for subsequent steps). The gradients $G_x(i,j)$ and $G_y(i,j)$ at every pixel are computed, following which an overall gradient is computed as follows:

$$G(i,j) = \sqrt{G_x(i,j)^2 + G_y(i,j)^2}$$

$$\approx |G_x(i,j)| + |G_y(i,j)|$$

The overall gradient gives us the edge pixels in the fingerprint image. To this overall gradient G, a global threshold T_1 is applied. This threshold was empirically found to be in the range of 0.3 and 1.2.

$$E(i,j) = \begin{cases} 1, & if\ G(i,j) > T_1 \\ 0, & otherwise \end{cases}$$

We applying this threshold, we seek to eliminate noisy pixels and consider only the edges present in the fingerprint region. We then find the smallest bounding rectangle for the nonzero pixels in E. If (i_{min}, j_{min}) and (i_{max}, j_{max}) are the comer points of the bounding rectangle, $i_{min} \leq i \leq i_{max}$ and $j_{min} \leq j \leq j_{max}$, $\forall E(i,j) = 1$

Hence we obtain the bounding rectangle for the fingerprint region. A slightly liberal rectangular region of interest can also be found. If R be the Region of Interest (RoI) for the fingerprint in the image, then we have,

$$R(i,j) = N(i + i_{min}, j + j_{min})$$

$$\forall i = (0, 1, 2, \dots (i_{max} - i_{min})$$

$$j = (0, 1, 2, \dots (j_{max} - i_{min})$$

where $N(i,j)$ is the normalized image. We shall estimate the orientation field of the fingerprint only on this RoI, thus cutting down on a large number of unnecessary computations.

2.3 Orientation field estimation

One of the commonly used fingerprint representations, derived from the intensity images, is an orientation field. The fingerprint orientation field is a vector field, which assigns a vector along the direction of the prevailing ridge to each pixel of intensity image. One of the most important steps in core point detection as well as fingerprint matching and identification is the orientation field estimation. Let θ be defined as the orientation field of a fingerprint image.

$\theta(i,j)$ specifies the local orientation of the ridge at pixel(i,j). Since we have already obtained the bounding rectangle for the fingerprint in the image, we shall restrict our operation to the ROI only. There are numerous methods for estimating the orientation field [8] and [9]. However, in connection to the method outlined in this paper, the smoothed orientation field based on least mean square algorithm is used [6] and [7].

1) The RoI is divided into a set of non-overlapping blocks, each of size *w* x *w*.

2) The gradients $G_x(i,j)$ and $G_y(i,j)$ are computed at each pixel (i,j) which is at the center of a block. Since the gradients have already been computed in the previous step, they need not be recomputed.

3) The local orientation is estimated using the following equations [5].

$$V_x(i,j) = 2 \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} G_x(u,v) G_y(u,v)$$

$$V_y(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{j+\frac{w}{2}} G_x^2(u,v) G_y^2(u,v)$$

$$\theta(i,j) = \frac{1}{2} \tan^{-1}\left(\frac{V_y(i,j)}{V_x(i,j)}\right)$$

Here, $\theta(i,j)$ is the least square estimate of the local ridge orientation of the block centered at pixel (i,j).

4) The obtained orientation field contains discontinuities of ridges and valleys due to the presence of noise. We assume that local ridge orientation varies slowly in a local neighborhood where the core point does not appear. So the discontinuities could be softened by applying a low pass filter. However, to apply a low pass filter, the orientation field must be converted to a continuous vector field. The components of the continuous vector field are defined as follows

$$\emptyset_x(i,j) = \cos(2\theta(i,j))$$

$$\emptyset_y(i,j) = \sin(2\theta(i,j))$$

5) With the resulting vector field, a two dimensional low pass filter L of unit integral and size k x k is applied. As a result,

$$\emptyset'_x(i,j) = \sum_{u=-\frac{k}{2}}^{\frac{k}{2}} \sum_{v=-\frac{k}{2}}^{\frac{k}{2}} L(u,v) \emptyset_x(i-uw, j-vw)$$

$$\emptyset'_y(i,j) = \sum_{u=-\frac{k}{2}}^{\frac{k}{2}} \sum_{v=-\frac{k}{2}}^{\frac{k}{2}} L(u,v) \emptyset_y(i-uw, j-vw)$$

6) The smoothed orientation field can be computed as follows

$$\theta'(i,j) = \frac{1}{2} \tan^{-1}\left(\frac{\emptyset'_y(i,j)}{\emptyset'_x(i,j)}\right)$$

In our experiment, non-overlapping 3 x 3 pixel blocks were used to estimate the orientation field, smoothened with a 3 x 3 Gaussian Filter. Figure 4 show the result of orientation process.
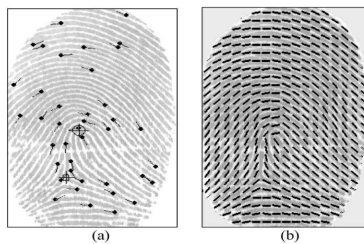
Figure 4   Orientation field estimation: (a) original image with minutiae and (b) orientation field of   (a).

3. Coarse Detection of Core Point

At this juncture, we have with us the rectangular region of interest for the fingerprint from the image and the smoothed orientation field of the same. The coarse detection of the core point is carried out in the following steps.

1)   The vertical component (sine) of the orientation field is computed

$$p(i,j) = \sin(\theta'(i,j))$$

2) A global inverse threshold T_2 is applied to $p(i,j)$.

$$Q(i,j) = \begin{cases} 1, P(i,j) < T_2 \\ 0, otherwise \end{cases}$$

The threshold T_2 is empirically found to vary between 0.2 and 0.6. As a result, we get a number of segments or components in the RoI.

3) Connected component labeling is performed over all the components, and as a result, the sizes of the components are also obtained.

4) The largest component C is chosen.

5) We check if the chosen component C is connected to the upper boundary of the RoI i.e.

$$min_{(i,j)\in C}(i) = i_{min}$$

where i_{min} is found while obtaining the bounding rectangle. If the above condition is valid, we move on to the next

step. If not, we discard this particular component and go back to Step 4.

6) The lower most point in component C is assigned as the core point, i.e.

$$If (i_{CP}, j_{CP}) \in C \ and \ i_{CP} = \max_{(i,j)\in C}(i),$$

$$then \ (i_{CP}, j_{CP}) \to Core\_point$$

Since the procedure makes use of a global threshold, it is extremely robust and gives satisfactory results even for poor quality images. However, there is a slight compromise as far as the precision of the location of the core point is concerned. A finer detection of the core point is carried out using the Geometry of Region technique. See figure 5.
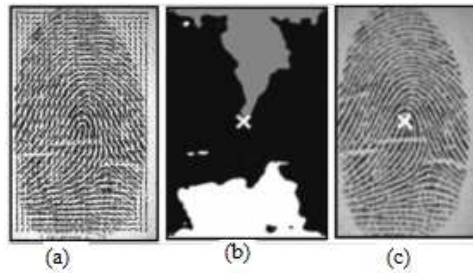

Figure 5 (a) estimated local orientation field, b) connected components obtained after applying threshold T_2 the

largest component is shown in gray. The lowest point in the largest component (i_{cr}, j_{cr}) is marked with 'X' and (c)

the location of the coarse core point shown on the fingerprint.

4. Accurate Detection of Core Point

Accurate detection of core point is carried out by using the existing geometry of region technique over a *m* x 2*m* window with the coarse core point lying at the center of the upper boundary of the window. In the previous step, we chose the largest component connected to the upper boundary of the ROI. So the method adopted for detecting the core point may be viewed as a top-to-bottom approach. So the actual core point can in no way lie above the coarse core point detected in the previous step. This is the reason for choosing the aforementioned search window. The process can be summarized as follows [5].

1) The smoothed orientation field $\theta'(i,j)$ is computed over the window

2) The sine component of $\theta'(i,j)$ is computed.

$$P(i,j) = \sin(\theta'(i,j)) \quad (18)$$

3) A label image A is initialized. This label image is used for indicating the core point.

4) The value of the difference in integrated pixel intensity of each region is assigned to the corresponding pixels in A.

$$A(i,j) = \sum_{RI} P(i,j) - \sum_{RII} P(i,j)$$

The regions RI and RII were determined empirically to capture the maximum curvature in concave ridges (See Figure 6). RI is sandwiched within R_{II} for our experiment; the radius of the region was taken to be 5 pixels.

5) The maximum value in A is found. Its corresponding point is the core point. The smoothed orientation field and the sine components need not be recomputed. For our experiment, we used a 50 x100 window see figure 7.
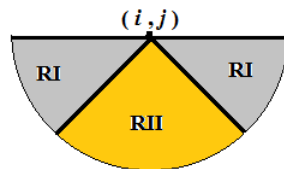
Figure 6 Regions used for integrating the pixel intensities of $P(i,j)$ for finding $A(i,j)$.
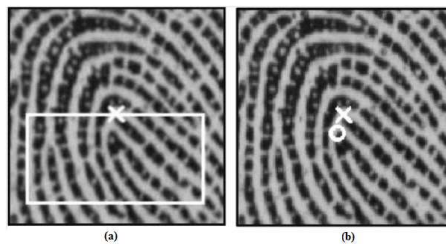

Figure 7   Results obtained by the proposed algorithm (a) coarse core point (marked by 'x') and the 50 x 100 search window for the next step and (b) the fine core point (marked by '0') obtained by the Geometry of Region technique applied over the search window

5. Artificial Neural Network for Fingerprint Recognition

After extract the feature vectors of fingerprint will be input to ANN to recognize fingerprints. Therefore, in the filtered images, a predetermined region of interest around the core point is tessellated into cells, as shown in Figure 8.

Figure 8   Core point (•) the region of interest, and window superimposed on a fingerprint

In previous work [10], we got the results from which to recognize the fingerprints images of over 40% out of the original image size. So we can take the window size 40% of the original image so that core point is centered of this window, and extraction the features derived from the local ridge-line orientations and frequencies, this method descried in [11].ANN is the calculation model that is inspired by working principles of biological neural systems. It works as the principle of decision by learning. Multilayer ANN model is a kind of feed forward ANN which has input layer, hidden layer and output layer. Each layer is fully connected to the succeeding layer, as shown in Figure 9, the input layer neurons distribute the input signals to the hidden layer and the hidden layer neurons use the output of input layer as input. All input signals are added by multiplying by the weights of connecting neurons. The output value of neuron is calculated by passing the sum of these neurons through the transfer function. This process is repeated for all the neurons in this layer. The output layer neurons behave as hidden layer neurons and the output values of the network are calculated. The reason of using this kind of network is that lots of learning algorithm can be used in training of multilayer ANN such as Back propagation algorithm. The conjugate gradient algorithm is an improved method of multilayer perception training. It has better performance than Back propagation algorithm can be used for all the process as for this algorithm. It is suitable for the network which has huge number of output nodes and weights. In this work back propagation, batch back propagation; conjugate gradient training algorithms are used for training of multilayered ANN.
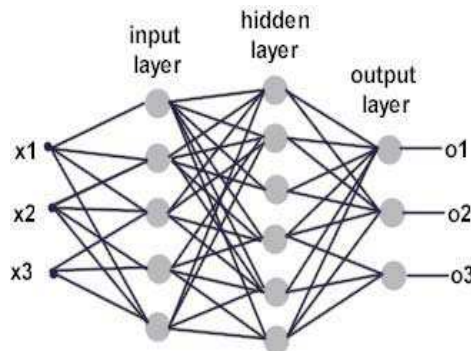

Figure 9 A scheme of feed forward back-propagation network

A feature vector is composed of an ordered enumeration of the features extracted from the (local) information contained in each sub image (window) specified by the tessellation. Thus, the feature elements capture the local information and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The local discriminatory information in each sector needs to be decomposed into separate components. Gabor filter banks are a well-known technique to capture useful information in specific band pass channels. In the matching process, we used feature vectors as an input of ANN.

6. Experiments

The proposed method has been evaluated on the public fingerprint databases of FVC2002 [12]. It is comprised of 800 fingerprints from 100 different fingers with 8 images captured from each finger using a low-cost capacitive sensor that produces many poor quality images. Since the location of the singular points is unknown. The experimental results were 93.2 % locating the core points with spurious and 6.8 % miss locating the core points. We applied the proposed algorithm on two Experiments of fingerprint complete image size and incomplete (partial) images and the results are described below. Experimental 1: Fig. 10(a) shows a set of complete fingerprints images.

The enhancement image of this image is shown in Fig. 6b. The proposed algorithm is applied on image Fig. 10(b) to get Fig. 10(c) which shows the extracted features superimposed on the original image and core pints assign with below circle. The performance of a biometric system can be measured by reporting its false accept rate (FAR) and false reject rate (FRR) at various thresholds [13]. These two error rates are brought together in a receiver operating characteristic (ROC) curve that plots the FRR against the FAR at different thresholds. Alternately, the genuine accept rate (GAR), which equals 1-FRR, may be plotted against the (FAR.) The FAR and FRR are computed by generating all possible genuine and impostor matching scores and then setting a threshold for deciding whether to accept or reject a match. A genuine matching score is obtained when two feature vectors corresponding to the same individual are compared, and an impostor matching score is obtained when feature vectors from two different individuals are compared. The ROC curves depicting the performances of the minutiae, ridge feature map. Figure 11 shows the average ROC curve of our approach.
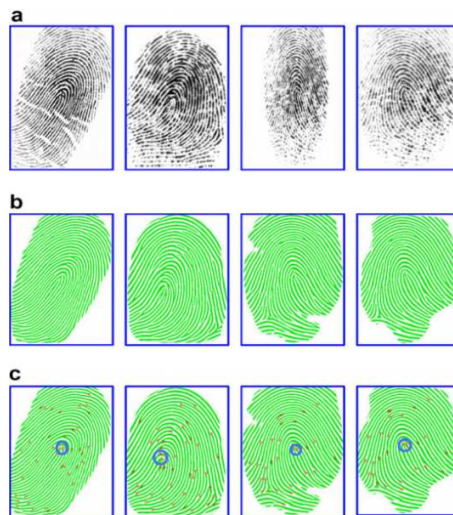

Figure 10 set of complete fingerprints images: (a) original image; (b) enhancement and (c) extracted core points and features superimposed on the original image.
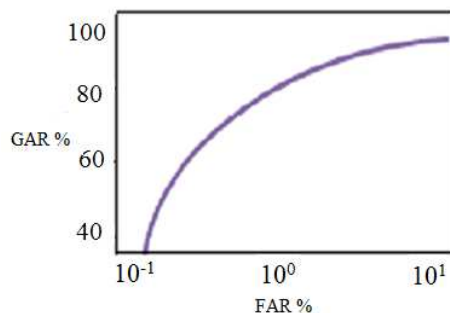

Figure 11 shows the ROC curve of our approach method

Experimental 2. Figure 12 shows an example of a complete image size 100% and Fig. 13 shows a set of an incomplete fingerprint image of a partial fingerprint that contain the core point in center. The algorithm was applied to varying image sizes from 100% to 40%. The enhancement and the proposed method applied on images that show the extracted features superimposed on the original images as shown in Figure 14. In Figures. 15 and 16, we can

conclude that as image size decreases the system performance also decrease, but not the size but also the number of minutiae. The algorithm gives an error 17% for images size 60% of the original size for 100 choices from the database. These images must contain on at least 60 % of total number of minutiae.
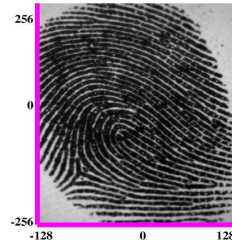

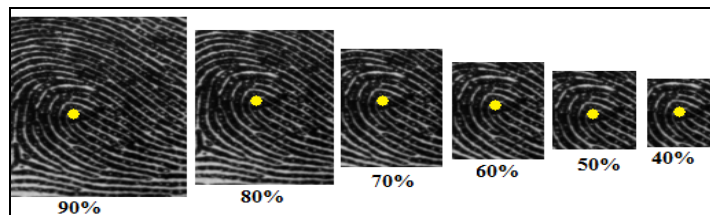Figure 12 an example of a complete fingerprint image size (i.e. 100%).

Figure 13 Partials images that contain the core point
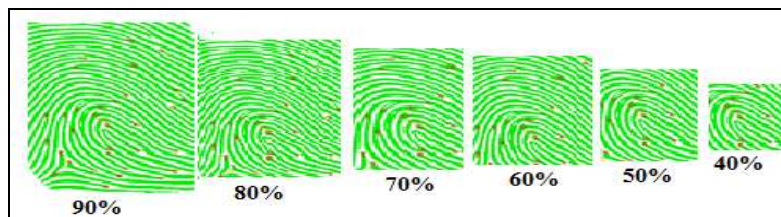

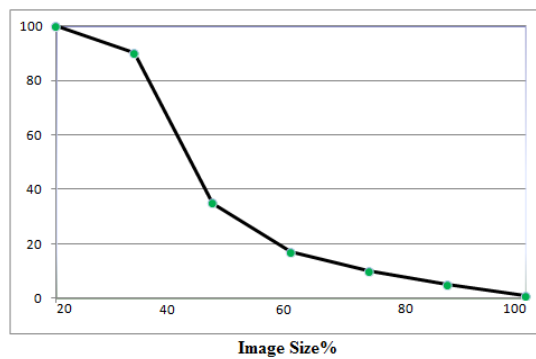Figure 14 Extracted features superimposed on the partials original images

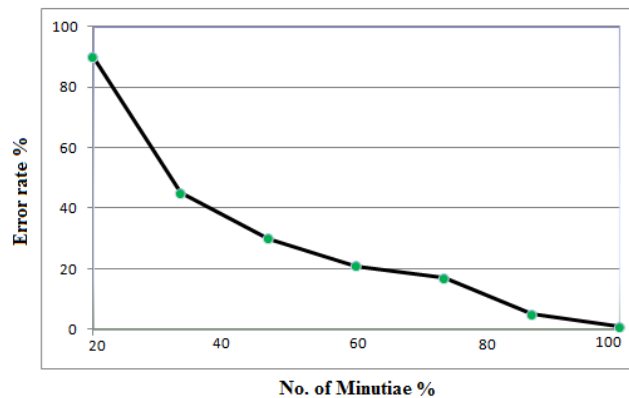Figure 15 illustrate the relation between image size and error rate.

Figure 16 illustrate the relation between number of minutiae in image and error rate

Conclusion

This is a robust method for locating the core point of a fingerprint. The global threshold reduces chances of falsely locating a core point due to presence of discontinuities like scars or wrinkles, which may occur in the existing processes. Since the detection is based on a global threshold, the method only gives us an approximate location of the core point. For exact detection of the core point, we use the geometry of region technique over a smaller search window using ANN. We show that as image size window that contain core point in center decreases the system performance also decrease but not the size but also the number of minutiae. The algorithm gives a error rate of 17% for images size 60% of the original size. Our proposed method is developed to get the best match with the original and demonstrate that the minutiae template of a user may be used to reconstruct fingerprint images.

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