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Q-LFR METHOD FOR MATCHING MINUTIAE FINGERPRINT IDENTICAL FEATURES

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ABSTRACT

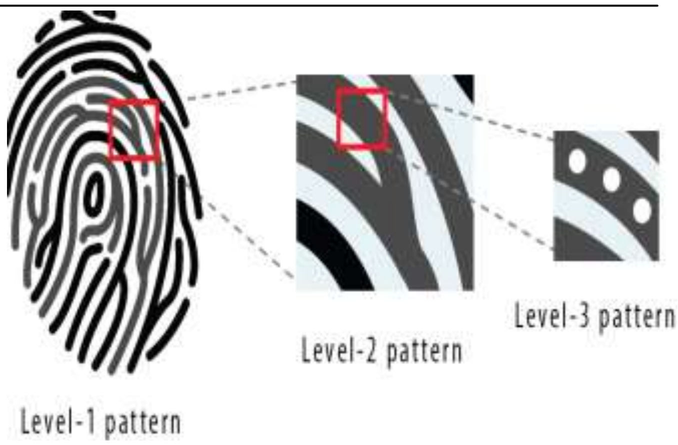
Because of its non-invasiveness, high precision recognition and the use of fingerprints are one of the most consistent biometric symbols in the context of human recognition and identification. In this paper here they suggested that a new method of machine learning can be used to find minutiae on low-resolution finger images. Traditional methods use the first step of preparation but due to the lack of intensity to be very sensitive to sound and image quality. We suggest a solid path where fingerprints are found to see the minutiae. Here they use machine learning to improve image quality and the most beneficial policy. Multi-layer ideas with in-depth learning strategies are used for a large area of the state and then select the appropriate reward structure and study area to learn the distribution. One of the major problems is that minutiae development facilities are easily accessible and their learning activity. The test result shows that our algorithm provides the best results in both parameters.

INDEX TERMS— ***Fingerprint, Minutiae extraction, Convolution Neutral Network, Support Vector Machine, Principal Component Analysis***

I. INTRODUCTION

The identification of fingerprints has become a very widespread method of applying biometric authentication [1], due to the desirable properties of fingerprints that include uniqueness, universality and consistency. Given a database of template fingers, identification consists of finding a template that matches the nature of the input fingerprints. The development of fingerprint samples can greatly improve the biometric use of finger samples. Deep learning-based development to improve performance on hidden finger samples, which can be considered very challenging. CNNs can even be trained directly to improve the biometric domain in terms of reliability and accuracy. Therefore, DL allows synchronization of improvements in data areas and feature extraction. Various fingerprints are activated and participatory fingerprint images are categorized above its identification. Typically, a professional marker manually marks all the template fingers in the database.

Fingerprints are a feature of the body and can be viewed as texture patterns formed by the brightness of the skin on the surface of various objects. We can divide finger patterns into 3 categories [2]. They differ in the complexity of systematic separation and the power of discrimination by comparing two fingerprints.



Level-1 pattern represents overall fingerprint ridge flow. These patterns are usually divided into 5 categories (left loop, right loop, whorl, arch and tented arch) [3]. Global ridge flow is a well-defined pattern and can be retrieved easily even when the image quality is not sufficient. After successfully resolving Level-1 pattern group the whole search freedom in fingerprint database is narrowed down to only specific fingerprint pattern subset what drastically reduces computation time [3].

Level-2 features or minutiae are local ridge characteristics that make every fingerprint a unique pattern. The premise of fingerprint exceptionality has been usually recognized but still be deficient in proper scientific validation. Individuality of

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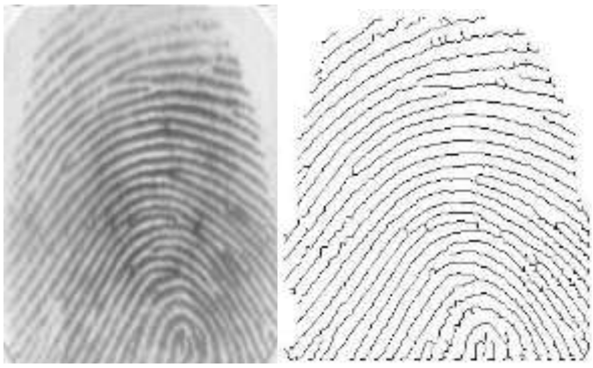
fingerprints based on Level-2 features in addition to probability of association of indiscriminate fingerprints is discussed in [4].

Level-3 features are microscopic level patterns that are almost exclusively used by forensic examiners. They consist of sweat pore locations, ridge geometric details, scars and other very small characteristics. Lately, their computer automated extraction has been seriously considered as more and more biometric system vendors begin to adopt 1000 PPI (pixels per inch) sensing resolution of fingerprint images in their recognition systems [5] Fingerprint authentication systems deeply settled in government, business and infrastructure institutions. However, most of the capturing systems depend on the condition of the finger's surface (i.e. humidity, dust, temperature, etc.), which can affect the identification accuracy.

II. RECOGNITION SYSTEM WITH MINUTIAE EXTRACTION

In the meantime, the manual annotation is caused by a series of problems with the wrong categories. With the rapid development of using in depth learning technology to learn those aspects of discrimination directly from the original image without the processing of the image. In [6-7] convolutional neural network technology, the technology is the first to be used to determine the life of fingerprints, and the result of discovery is satisfactory. By researching and studying the paper above, we assume that the process of convolutional operation is considered a process of exclusion. After that, the CNN-based study features are provided with the SVM segment to obtain segmentation results in this paper, and this is the main idea of our paper. Various papers should develop CNN through the PCA process after the recommendation of the resolution and integration process in this research paper. The PCA process reduces the magnitude of the symptoms learned between each discussion process and each integration process. In addition, another benefit based on ROI enhancement performance on the impact of the invalid region. After the above process, the advanced semantic features of fingerprint images were automatically read to pre-recorded fingerprints, and the SVM partition was used to separate these deleted features. After that, the separation model is created using fingerprint training.

After obtaining the fingerprint image, the next step is to use the neural network to extract the correct points from the fingerprint image. This neural network has an input layer, a hidden layer and an output layer.



(a) Original fingerprint image. (b) Thinning image of fingerprint.

- The input layer: The input layer consists of 9 neurons which is 3×3 pixel blocks from the fingerprint image.
- The hidden layer: The hidden layer consists 3×3 patterns of bifurcations and terminations.
- The output layer is a map which is the same size as the fingerprint image. In the map, 0 for non-minutiae points, 1 for termination point and 2 for bifurcation point.

III. FINGERPRINT MATCHING REGULARIZATION IN DEEP LEARNING ALGORITHMS

Simply put, this algorithm returns the connection pattern between two fingerprints which is the given interval number (e.g., 0 to 1). There are basically two classes of finger algorithm: the minutiae-based one, and the non-minutiae-based one [8]. There are also hybrid methods that are a combination of them [9, 10] and are used in cases where the quality of fingerprints is insufficient to compare. In recent years, minutiae-based algorithms have become accustomed to local matching techniques due to their flexibility, flexibility and low power consumption.

Convolution Neutral Network: The Convolution Neutral Network is also called the hierarchical neural network that converts a convolutional and sub sampling layer. It has various layers called.

1) Layers for image processing.
2) Variable layers.
3) Layers of integration.
4) Divide layer.

Image Processing Layer: It is not the obligation to redefine the obligation to define the set filters to be modified in the training process. If there is unexplained effort, more details can make it available in a system like edges, gradients. The output layer improves visibility.

Convolutional Layer: In this layer, they find the number of maps, missing items, character sizes and organization table. Each layer has maps of the same size namely (Mx, My). Kernel is transferred over the appropriate location for the input image. Pernel skip pixels in the X and y directories are defined by skipping intervals between consecutive interactions.

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Max Pooling Layer: The main difference between the startup and CNN is the use of the top layer as an alternative to the lower layer. In this layer they lead to faster assembling and select consistent features that are better quality and get simplified while the sample below strikes nearby pixels before assembling as another method of collection or measurement. Acquisition of a position is allowed on the basis of multiple integrations; reduce images by inserting a fingerprint with each element in each direction.

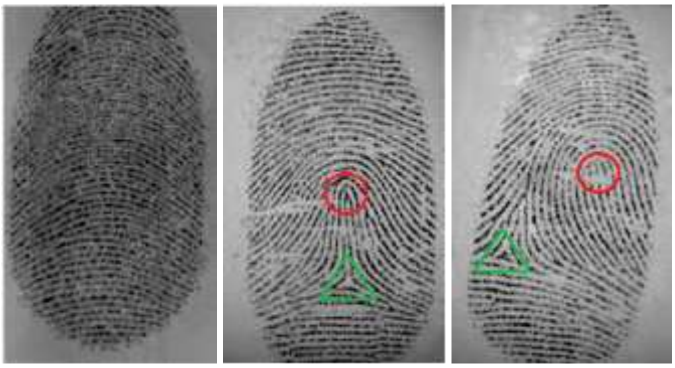
Classification Layer: In this layer of resolution, max-pooling rectangles leave kernel-sized features selected so that the output value of the previous convolution layer is less than 1 pixel per map, or a fully integrated layer incorporates the highest layer results. Convolution on the vector of a 1-Dimensional element. One value generated per label of the category is associated with a higher standard.

IV. TYPES OF FINGERPRINT MATCHING

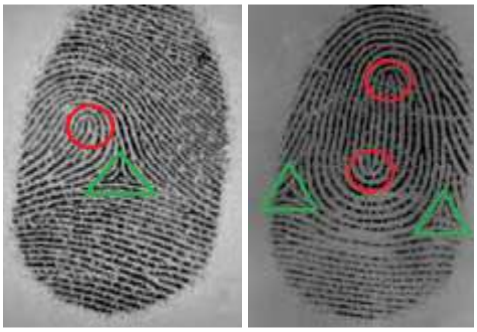
To reduce the computational needs of fingerprint matching task scientists categorize fingerprints in advance. Thus fingerprint identification can be done using not the whole database of finger images but using a subset of it. Among all features, only Level 1 features, the ones which describe the global direction of a ridge flow, are used for fingerprint classification. Features of Level 2 and 3 are too vary and too specific and used for fingerprint matching mostly. Therefore, fingerprints are classified into five major classes: Arch, Tented Arch, Left Loop, Right Loop, and Whorl. Level 1 feature hold the information of the global ridge orientation (represented in an Orientation Map) and crucial points location - Singular points. By Singular

Points we understand regions of a fingerprint with the highest variance, i.e. a place where ridges change their direction the most abruptly. Two types of such Singular Points can be distinguished: Core and Delta. Intuitively, cores are points where ridge flows flock into and deltas are points where ridge flows are diverging from.

- Arch: The only type of fingerprints which has no singular points. Ridges in Arch fingerprints flow from one part to another and form a small hump.
- Tented Arch: Has one central part and one delta singular points (the delta located below the core). Ridge flow is similar to arch but more pronounced and ridges have more strong curvature.
- Right Loop: Has one core and one delta singular points (the delta is below and to the left of the core). As a minimum one ridge starts on the left side, moves to a center, turn around and moves back to its start.
- Left Loop: Has one central part and one delta singular points (the delta is below and to the right of the core). As a minimum one ridge starts on the right side, moves to a center, turn around and moves back to its start.
- Whorl: Has two core and two delta singular points. One or more ridges make the complete turnaround the center.



(a) Arch. **(b) Tented Arch.** **(c) Right Loop.**



(d) Left Loop. **(e) Whorl.**

Image is taken from [12].

V. LITERATURE REVIEW

Khodadoust et al. is proposed to use triplets consisting of two minutiae and one as the corners [20]. This true approach depends on the reliable availability of fingerprint quantities. Discovery is especially challenging for poor-quality fingerprint samples. The plurals can be obtained at all with selected fingers or with fingers with a variety of patterns among other things, i.e., arches.

Xu et al. is proposed to use a complex representation of finger minutes [15]. Each minutia is represented by a complex dynamic in the image background. Minutia direction is included in the pressure section. By using the Fourier transformation and mapping to Polar links, this method is compatible with translation and rotation. Fourier modification enables unusual translation. Switching to an image background leads to translation into Polar links for the Fourier list. This translation can be controlled by using the combination between the two samples.

Feng et al. is proposed to calculate the so-called Ridge abnormalities from public buildings [11]. This method is related to minutiae-based methods as it defines ridges by minutiae in it. However, the focus here is on the ropes. Indices

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are generated on the lines, crossing the fingerprints. The edges are seen by the minute in it. This method mimics the method a human explorer can use when calculating the layers between the minutiae. This method can also deal well with the flexible distortion of the fingertips because that distortion cannot alter the river connections between the minutiae.

Jakubowski et al. is proposed to use the calculation of line crossings over multiple random lines [14]. This method describes not only the texture but also the direction found on finger samples. This method will require alignment. Otherwise, the path will fail because random lines will cross different lines. This method does not tolerate stretch ability.

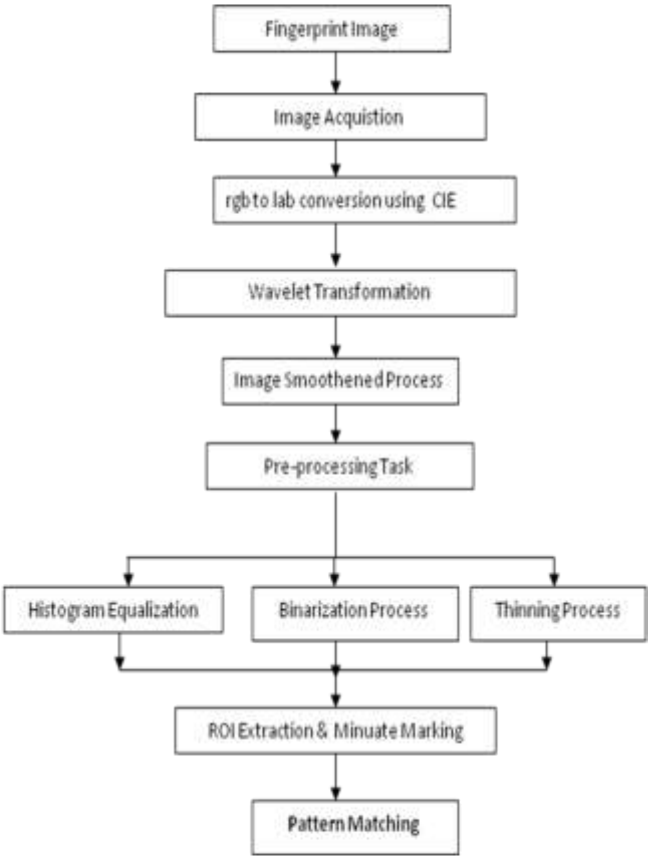
Considering the fact that the pore finger removal method is an important step in the high definition of AFRS, it is important in the extraction process. With the flexibility of the pore, it is difficult to extract the pore details with a finger in a way that allows the character of the pore finger to depend on the person's location, location, and finger class. To solve such a problem is reached [16] the pore extraction process using Deep CNN and pore power conversion. Deep networks are used to detect pores by element using a large finger image region. They try to improve the pores' knowledge of the finger by finding the local maxima to see the fingertips with superhuman strength in the image of the fingers. Finally, the test results give you the impression that their fingerprint process is more focused on improvement than modern methods.

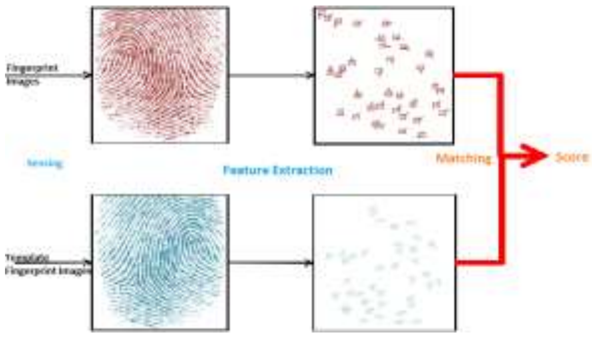
In this paper [17] the author must point out that CNN used to distinguish real and artificial fingerprints is important in security measures, the reason for concern with fingerprint protection in authentication systems. Ploy-Doh, silicon or other materials are used to create fake fingers. You are using these fingerprint images, but it does not cause any real application problems. Using this CNN approach, they provide a process to improve on both feature extraction and partition training. The local binary pattern and minutiae release is used as a quality adjective. Using these text definitions is used to determine the accuracy of a binary local pattern used to convert a gray scale image to a binary image. This method is used with precision based on the 3x3 matrix model. Minutiae look at the gap and divergence in terms of the process of diminishing the diminishing process. The fusion algorithm was then used to combine both LBP and minutiae. This model produces good accuracy in training sets. The histogram measurement method has been used to improve the accuracy of the images.

This paper mainly points out how to use CNN [18] in the field of fingerprint imaging detection research focusing on the structure of composite handmade features, but these methods are often destructive or unable to find location information between pixels. A variety of methods using the convolutional neural network (CNN) can produce high-quality demonstrations by reading and combining low-edge materials and structural features from a wide range of labeled information. As a result, CNN is found to solve extreme flaws and distinguish accurate fingerprints from false positives. Here the author has shown that the convolutional process is considered a process of elemental discharge. Therefore, extracted features based on CNN are included in the SVM separator. The PCA process is used to reduce the size of the feature map size after each pull or integration function. In addition, the ROI correction function has been implemented in this paper to detect undesirable regional conflicts. Using the above procedure they are used without any human intervention to obtain from the basic step of fingerprint correction, and these features are extracted using SVM partition..

- In this paper [19], here the author should introduce a new problem of geometric distortion of fingerprint recognition frameworks by proposing a rapid and efficient distortion measure that blocks non-linear fingerprint distortion structures. While in recent times various recommended techniques that capture distortions using a list of unconventional patterns have been used, in this attempt here we use DCNN to calculate approximately the main components of distortion of input samples. It has the following contributions:
- No need to guess maps of the emergence and rise of participating fingerprints.
- Distortion parameters are calculated almost continuously in order to achieve further change.
- Outstanding decrease decreases during adjustment due to embedding of distortion patterns in network thinking.

VI. PROPOSED ARCHITECTURE





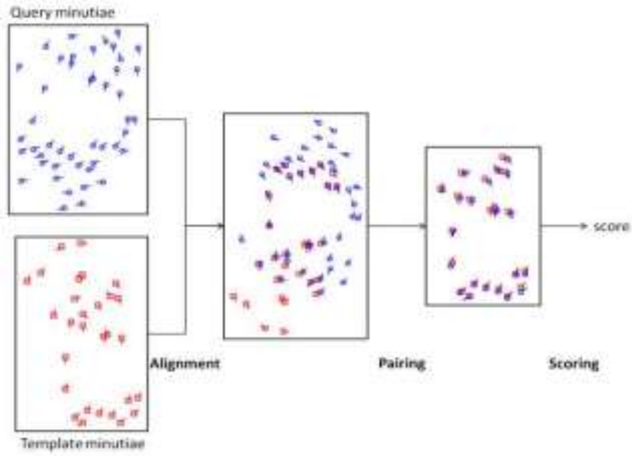


Figure: Proposed Architecture

VII. PROPOSED ALGORITHM

Algorithm for Minutiae Extraction:-

Step 1: After pre-process fingerprint image through binarization and thinning then working on pixel representation '1' or '0'. Find out the pixel value by two methods

A) First method, if the pixel value is '1' then Count Crossing Number importance on pixel value is '1' or P=1 and Mark Minutiae points.

B) Second method, if the pixel value is '0' then Count Crossing Number value on pixel value is '0' or P=0 and Mark Minutiae points.

The Crossing Number estimate is based on formula:

$$CN = 0.5 \sum_{i=1}^{8} |Pi - P\,i + 1|, \text{ with } p9 = p1$$

where Pi is the pixel value in the neighborhood of P. For a pixel P its eight neighbouring pixels are examine in an anticlockwise direction as follows.

P4	P3	P2
P5	P	P1
P6	P7	P8

Step 2: After the CN for a ridge pixel has been calculated then pixel can be off the record according to the assets of its CN value. If CN = 1, End Point (EP) is acquired and if CN = 3, Bifurcation Point (BP) is obtained. Other values of CN are not applicable.

Properties of Crossing Number

CN	Property
0	Isolated point
1	Ending point
2	Connective point
3	Bifurcation point
4	Crossing point

Step 3: The next step is to use the Q-Learning method to extract precise minutiae points from a fingerprint image. This neural network has an input layer, a hidden layer and an output layer.

• Input layer: The input layer contains 9 neurons in 3 X 3 pixel blocks from a fingerprint image.

Hidden layer: The Hidden layer contains 3 X 3 patterns of split and cut.

• Map layout for the same size as photo fingerprint. On the map, 0 with non-minutiae points, 1 with a cross point and 2 with a split point.

This neural network is taught in off-line mode because the training lasts only for one loop. There is a well-known pattern of termination points and a few bifurcation points rules to ignore the false minutiae:

• Rule 1: if the distance between execution and bifurcation is less important than D1, these two minutiae can be false minutiae. We have to remove these two minutiae.

• Rule 2: if the distance involved in the two intersections is less than D2, then these two minutiae can be false minutiae. We have to remove these two minutiae.

• Rule 3: if the distance involved in the division into two is less than D3, then these small minutiae can be false minutiae.

We have to remove these two minutiae.

- Initialize Q[input layer, output layer]
- Initialize gamma Read image
- Thinning of image up to one pixel value
- Scan image by using 3×3 filter
- Find
- centerm= one neighbour of central
- centbif= two neighbour of central
- Calculate reward R= Euclidian distance (centerm, centbif)
- Take permutation of rows in R
- Repeat (for each occurrence up to all eight neighbouring pixels)
- select first state from the permutation
- For this state find all non-minutiae points in R
- Take permutation of non-minutiae points
- Select input layer from the permutation
- Q[input layer, output layer]= R[input layer, output layer]+ gamma*Qmax (output layer)
- input layer=output layer
- Until each occurrence up to all eight neighbouring pixels ends

➢ **Step 4:** If the pixels are available then go to step 1 else return Minutiae.

Proposed Algorithm:-

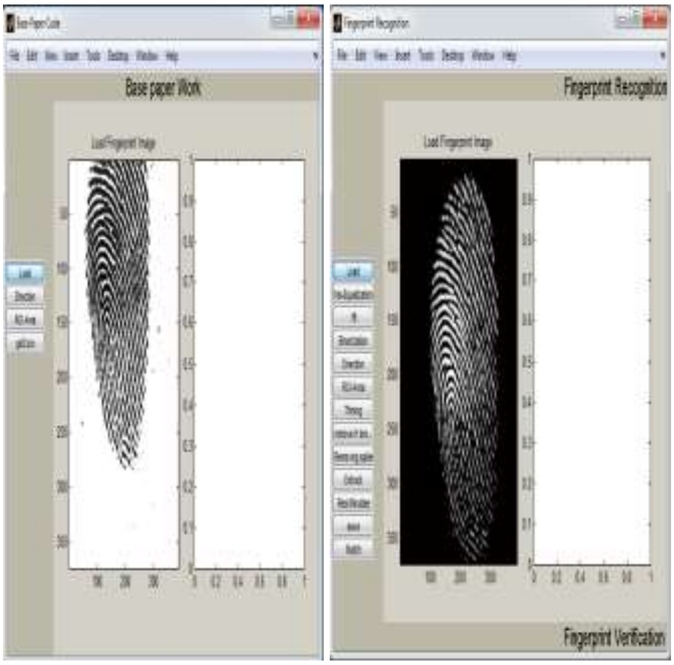
Q-Learning Algorithm:-

Input: Fuse Feature sets of MFP_I Fingerprint Input and Q (s_1, a1), Q (s_2, a2), Q (s_3, a3) ….. Q (s_n, an) Template Fingerprints

Output: The identified fingerprint.

Q-Learning Algorithm
Initialize Q(s, a) arbitrarily
Repeat (For each episode):
Initialize s
Repeat (For each step of episode):
Choose a from s using policy derived from a
Take action a,observe r,s'
$Q(s,a) \leftarrow Q(s,a) + \alpha\,(r + \gamma\ \max(Q(s',a') - Q(s,a))$
$s \leftarrow s'$:
Until s is terminal ;

VIII. EXPERIMENTAL OUTCOMES



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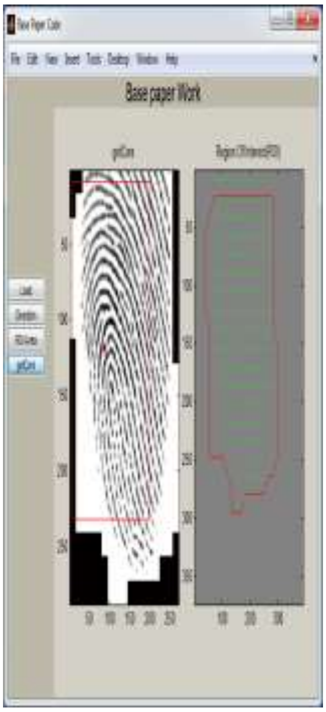
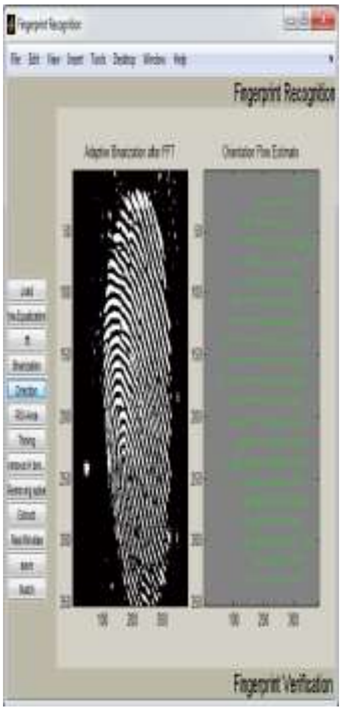
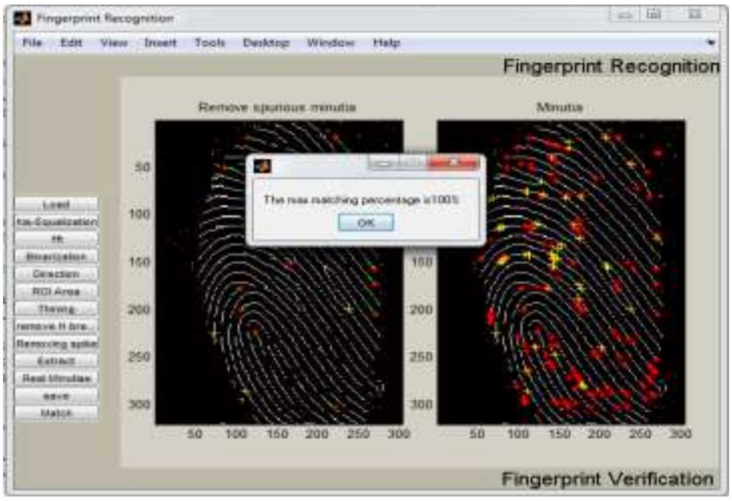
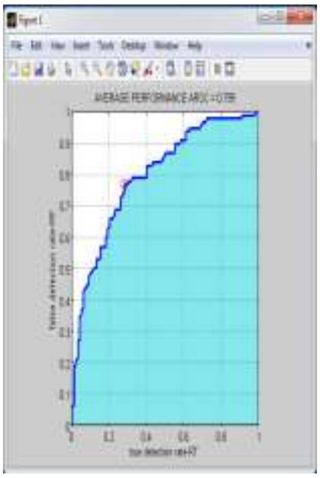






IX. EXPERIMENTAL ANALYSIS



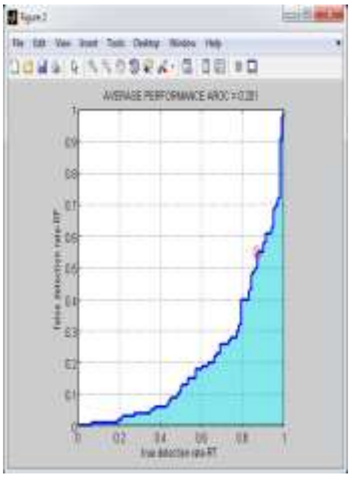


Table: Comparisons between Existing method and proposed method by different parameters

Parameters	Existing Method	Proposed Method
Distance:	0.4161	0.8134
Threshold:	0.249	-0.0637
Sensitivity:	0.58	0.41
Specificity:	0.68	0.24
AROC:	0.654	0.378
Accuracy:	0.512	0.201
PPV:	0.7333	0.3873
NPV:	0.7579	0.2241
FNR:	0.23	0.35
FPR:	0.28	0.45
FDR:	0.2667	0.6127
FOR:	0.2421	0.7759
F1 score:	0.6245	0.2187
MCC:	0.3267	-0.1034
BM:	0.49	-0.32
MK:	0.4912	-0.3885

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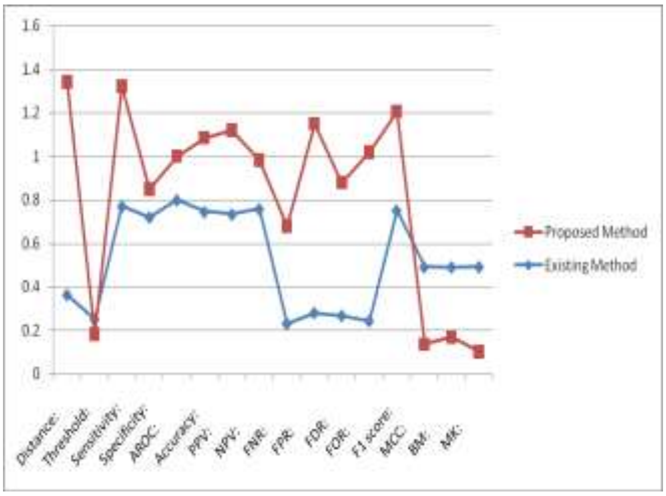

Figure: Overall Comparisons between existing method and proposed method by different parameters

X. CONCLUSION

All of the algorithms discussed in this paper are subject to rapid fingerprint development and rapid minutiae release. Fingerprint enhancers to improve the image of the ridge image and remove noise from the fingerprint image, which helps to make the minutiae removal error. Minutiae algorithms are faster because they use smaller patterns compared to other more accurate image analysis algorithms. If the image is not processed, i.e., low quality and sound can create many false minutiae and real minutiae do not exist. So how to extract Q-Learning minutiae is the best way of modern finger recognition system.

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