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Q-Learning Fingerprint Representations Method for Matching Low Quality Fingerprint Features

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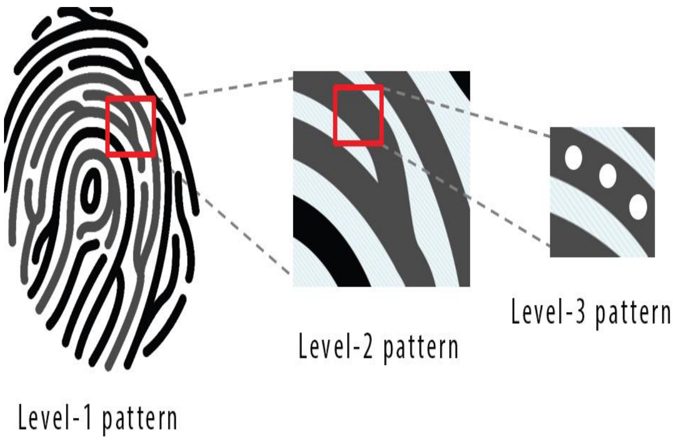
***Abstract*—Due to its non-invasiveness, high recognition accuracy and the use of fingerprints are one of the consistent biometric characteristics in the context of human recognition and identification. In this paper here they proposed a new machine learning method can be utilized for minutiae detection in low quality fingerprint images. Traditional methods have using initial preprocessing step but due to lack of robustness on highly sensitive to noise and image quality. We propose a more robust approach in which detects fingerprint images to recognize minutiae. Here they use machine learning to improve image quality an most advantageous policy. Multi-layer perceptions are used to large state space and select right reward structure and learning location to learn the assignment. One of the major problem is that the enhance minutiae points states are easily find and their learning job as well. An experimental result shows that our algorithm gives better results on both parameters.**

***Index Terms*— Fingerprint, Minutiae extraction, Convolution Neutral Network, Support Vector Machine, Principal Component Analysis**

I. INTRODUCTION

Fingerprint classification is single objective of the common accepted ways to accomplish [1] methods. Various fingerprints are started and the participation fingerprint images is classified aforementioned its identification. Conventionally, a proficient expert's manually tags every template fingerprint in the database. Then using this fingerprint patterns is classified is trained on the acquired labeled existing fingerprint image dataset with the endeavor of conveying to each input fingerprint the similar tag that was physically started for the corresponding pattern. This is a protracted and human-dependent process to focus on the classification robustness, which we characterize as the capacity of assigning the same class to different impressions of the same fingerprint, independently of the manual label. This enables the opportunity of additional increasing the presentation for fingerprints that reduce close to the frontier between classes. General fingerprint classification procedure is created of two main steps [1]: feature extraction and the classification itself. First step is to capture image of these features are repeatedly characterized in the structure of a numeric vector [1]. Another step is the feature vector is utilized to perform the classification either by a set of fixed policy or by training a model in a supervised manner

Fingerprints are physiological traits and can be viewed as texture patterns formed by ridge skin impressions on the surface of various materials. We can split patterns of fingerprints into 3 categories [2]. They differ in complexity of programmed classification and discrimination power in matching 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].

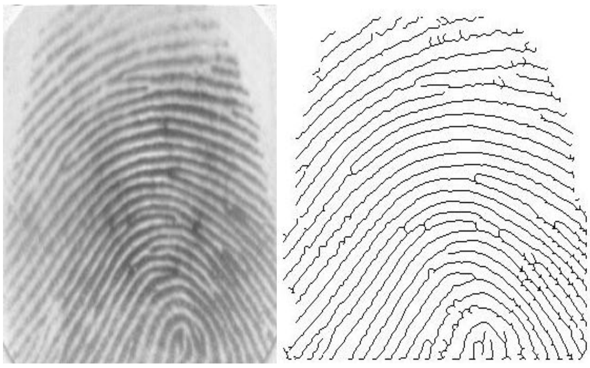
Level-2 features or minutiae are local ridge characteristics that make every fingerprint a unique pattern. The premise of fingerprint exceptionality has been usually recognized but still be deficient in proper scientific validation. Individuality of fingerprints based on Level-2 features in addition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

Meanwhile, manual annotation is manipulated by individual issues consequential in incorrect classification. With the using improvement of deep learning technology to learn those discriminate features directly from original natural image without any image processing. In [6-7] convolutional neural network technology is for the first time to be used to detect the fingerprint liveness, and the detection result is satisfactory. Through the research and study of above paper, we think that the convolutional operation process is regarded as process of feature extraction. Then, the learned features based on CNN are fed into SVM classifier to obtain a classification result in this paper, and this is the main idea of our paper. Various paper is to improved CNN with PCA technique after convolutional and pooling process is proposed in this research paper. PCA process is to reduce the dimensionality of learnt characteristics between each convolutional and each pooling procedures. In addition another advantage based on ROI preprocessing operation to impact of invalid region. After above process high-level semantic features of fingerprint images have been automatically learnt from preprocessed labeled fingerprints images and then SVM classifier is utilized for the classification of these removed characteristics. Subsequently, a classifier model is created by using training fingerprint images.

After getting the thinned fingerprint image, the next step is to use the neural network to extracts the correct minutiae 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, this algorithm returns a degree of correspondence pattern between two fingerprint images which is a number in a given interval (i.e. 0 to 1). There are mainly two classes of fingerprint matching algorithms: minutiae based and non-minutiae based [8]. There are also hybrid methods which are a combination of them [9, 10] and applied in a case when the quality of a fingerprint is not enough for matching. In turn, non-minutiae based class of algorithms can be separated into 4 categories: image based, ridge feature based, 3rd Level features based and feature-point based. Mainly minutia based algorithms which are logically divided in local minutiae matching schemes and global minutiae matching schemes.

Non-minutiae based approach: Image-based algorithms compare an input image and an image from a database to find a similarity between two of them. The weakest side of this way of matching is that it is extremely responsive to alignment and non-linear deformations. Ridge feature based techniques use ridge point of reference and ridge occurrence which describe topological information of ridge patterns to make fingerprint matching. From one side they solve a non-linear deformation problem of Image-based techniques but from another side, they have their own weakness ridge information for matching. People often use Level 3 features [8, 11] together with ridge features which add such ridge details as sweat pores and dots, ridge contours. But as it was mentioned before, to apply level 3 features we must have images of very high resolution. Feature-point based methods usually used for object recognition and image matching but some scientists use this approach for fingerprint matching as well.

Minutiae-based approach: The first stage of each minutiae-based matching algorithm is a minutiae extraction. Minutiae are presented by their spatial location coordinates and the angle of rotation. A minutiae of a given image is considered to be matched with minutiae of an image from a database. By tolerance box, we understand a permissible variation from both coordinates and direction of certain minutiae to compensate image distortions and limitations of minutiae extractors.

Since in real-life tasks the correct alignment of two matched fingerprints is left unknown, it is obvious that they will vary in some way because of pose variations, scaling and physiological aspects. That is why to reach the highest number of matched pairs of minutiae it is crucial to make rotational alignment, scaling and bias.

As it was explained earlier, the minutia based techniques are classified as Local Minutiae Matching and Global Minutiae Matching.

- **Local Minutiae Matching** - These algorithms are taking into account confined arrangements of minutiae. By local structures, we should understand different relationships in groups of the closest minutiae. Such structures are invariant to global transformations of fingerprints which are undoubtedly the biggest advantage of using local matching. It also allows us to use only a part of information of a given fingerprint which is good for low-quality images and partial images which are usually not fully present in real-world tasks.

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- **Global Minutiae Matching -** In opposite, these algorithms consider the set of minutiae's under the general scope. These are required to make a proper alignment and since nearby are three restrictions by which we should align (both coordinates and rotation) global matching may be computationally costly. Sometimes it is useful to apply so-called pre-alignment techniques which are based mainly on singular points and orientation maps to reduce the computing costs.

Recent years minutiae-based matching algorithms tend to local matching techniques because of their invariance to distortion, ease and low computational power required.

Convolution Neutral Network: Convolution Neutral Network is also called as hierarchical neural network which modifies the convolutional layer with sub sampling layer. It has various additional layers called.

1) Image processing layers.
2) Convolutional layers.
3) Max-pooling layers.
4) Classification layer.

Image Processing Layer: It is not obligatory preprocessing layer that has predefined filters which are reserved fixed in training process. Moderately than the unrefined effort the extra information can be making available to the arrangement like edges, gradients. The contrast extracting layer improves the recognition rate.

Convolutional Layer: In this layer, here they found number of maps, skipping factors, kernel sizes and the association table. Each and every layer has maps of same size i.e. (Mx, My). Kernel is transferred over the suitable area of the input image. The pixels skipped by kernel in x and y direction is defined by skipping issues which are between the successive convolutions.

Max Pooling Layer: The main difference between the implementation and CNN is the make use of of maximum pooling layer as an alternative of sub sampling layer. In this layer they leads to faster meeting and select better-quality invariant characteristics and recover simplification whereas the sub sampling layer hops the nearby pixels earlier to convolution as an alternative of collecting or averaging. Position invariance is permitted in max-pooling layer; it down illustrations the input fingerprint image by an aspect along each direction.

Classification Layer: In this layer convolutional filter max-pooling rectangles omitting features of kernel sizes are selected so that the amount produced maps of the previous convolution layer are down illustration to 1 pixel per map, or an entirely connected layer unites the outputs of the highest convolution layer into a 1-Dimensional feature vector. One amount produced unit per category label is joined with the top level.

The drawbacks of existing system are:

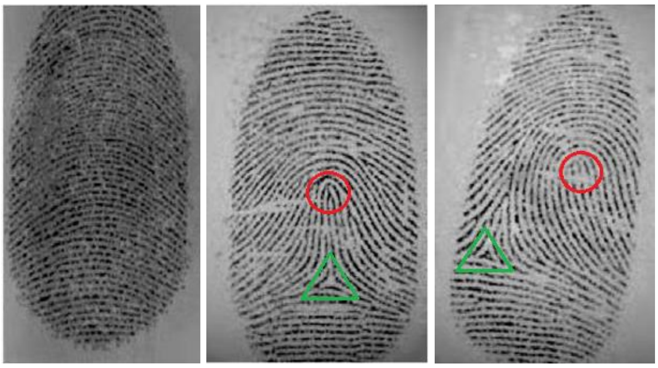
- Accuracy is less.
- It takes the decimal value as entire value and process.
- All the edges are not analyzed.

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.

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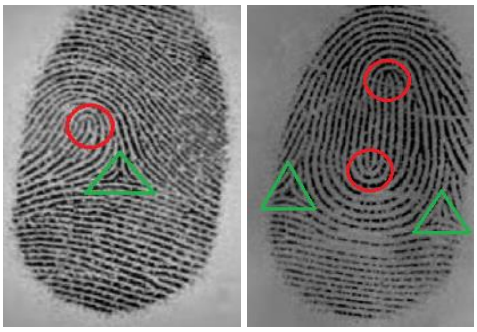

(d) Left Loop. (e) Whorl.
Image is taken from [12].

V. LITERATURE REVIEW

Similarly, a various research between six different enhancement techniques was recommended in [13]. The first one was based on Histogram Equalization. The second one was based on 2D Fourier transform and Butterworth filter. The third one was based on Gabor filters. The forth one was based on Gabor filters combined with Wavelet transforms. The fifth one was based on directional filters. The last one was based on Laplacian-based pyramidal decomposition (LPD). They computed the peak signal-to-noise ratio and Equal Error Rate (EER) for all the testing algorithms. The result showed that the LPD method and Wavelet based enhancement have been given a slight better result.

Another comparative study between three different enhancing algorithms was proposed in [14] to evaluate the effectiveness of fingerprint image enhancement. These algorithms included the use of FFT, smoothing on the spatial domain, and contextual filtering using Gabor filters. The result showed an improvement in enhancing reduced image quality fingerprint images in frequency domain. Although the FFT produced the best result in enhancing fingerprint images, it also introduced noise outside of the fingerprint representation as a side effect of the frequency domain process, which can be solved by using a better segmentation algorithm. The enhancement based on Gabor filters worked well in good and recoverable region of fingerprint image, but it leaved empty blocks in unrecoverable regions. Algorithms based on only the spatial domain could not enhance minutiae details in existing images.

Geometric distortion significantly reduces the match score value. These features prevent malicious users from hiding their identity, as well as reduce the inconvenience of using identification systems in authentication tasks. In this paper [15], here they try to extend existing work by a new rectification model based on a Deep Convolutional Neural Network (DCNN) to find accurate approximation alteration constraints from the input image. The experimental results shows that wide-ranging database of artificial indistinct models, the DCNN become skilled at precisely calculate approximately distortion to search techniques used to shown that the DCNN can estimate the non-linear distortions of samples more accurately from existing method.

In view of the fact that the finger pore extraction method is a vital step for AFRS high precision is essential for extraction process. Adaptive pore extraction, it is difficult problem to remove the finger pore information in the approved manner that the finger pore character depends on the human being, area, and finger pore category. To solve such kind of difficulty have accessible [16] a pore extraction technique using Deep CNN and pore intensity alteration. The deep networks are utilized to become aware of pores in aspect using a huge region of a fingerprint image. They try to improve the finger pore information by discovering local maxima to recognize finger pores with unusual intensities in the fingerprint image. Finally the experimental effects give you an idea about that their finger pore extraction technique achieves enhanced than the state-of-the-art methods.

In this paper [17] author has to present a CNN was used to differentiate the real and counterfeit fingerprint is significant for safety measures reason essentially for the apprehension of fingerprint protection in authentication arrangement. Using Ploy-Doh, silicon or other objects methods are used for constructing the counterfeit fingerprints. Using this fingerprint images but it is not rewarding the real world application problem. Using this CNN method they are providing the better optimization procedure for both feature extraction and classifier training. Local binary pattern and minutiae extractions are utilized as a quality descriptor. Using these texture descriptors is utilized to recognize the correctness on local binary pattern is making use of to alter the grey scale image into a binary image. Using this technique accuracy based on the 3x3 matrices model. Minutiae check the ridge and divergence by subsequent the procedure of binarization and thinning process. Afterward the fusion algorithm is utilized to combine both LBP and minutiae. This model produces the good accuracy on training sets. The histogram equalization method was utilized to get better the correctness of the images.

This paper mainly meeting pointes on how to apply CNN [18] to the research field of fingerprint liveness detection for fingerprint images is paying attention on the structure of composite handcrafted characteristics but these techniques generally devastate or are unable to find spatial information between pixels. Various method has use convolutional neural network (CNN) can produce high-level semantic demonstrations by learning and concatenating low-level edge and shape features from a enormous quantity of labeled information. Consequently, CNN is discovered to resolve the exceeding setback and distinguish accurate fingerprints from fake individuals. Here author has reflected that the convolutional process is observed as procedure of feature extraction. Therefore, the extracted characteristics based on CNN are fed into SVM classifier. PCA technique is also utilized to decrease the dimensionality structure of feature maps after each convolutional or pooling operation. Moreover, ROI preprocessing operation has been implemented in this paper to get free of the collision of anomalous region. Using above mentioned process they are utilized at without any human intervention to find out from basic preprocessing step of fingerprints images and then these feature extracted from using SVM classifier.

In this paper [19], here author has to present the new geometric distortion crisis of fingerprint recognition structures by proposing a quick and efficient distortion estimator which confines the non- linear properties of geometric distortion of fingerprints. While in recent times various recommended

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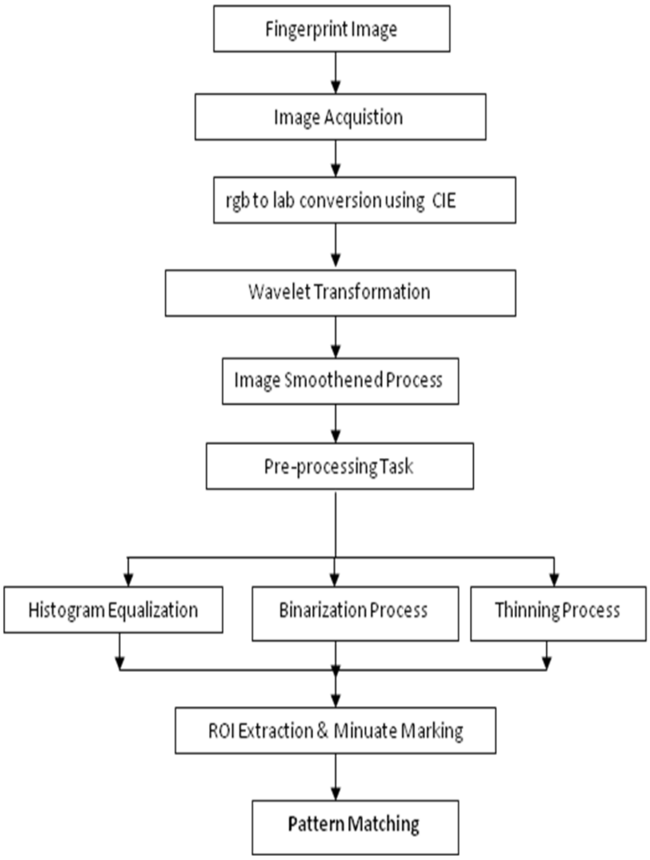
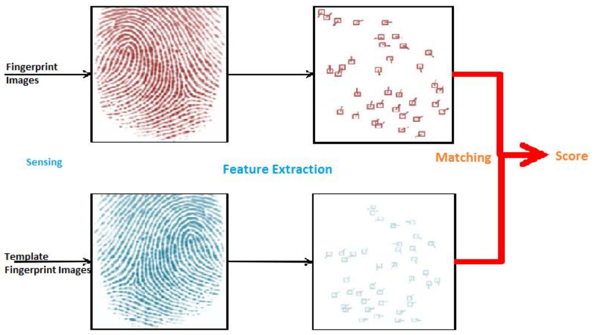
techniques hold distortion using a glossary of indistinct patterns for this effort here they utilize a DCNN to calculate approximately the principal distortion parts of input samples. It has the following contributions:

- There is no requirement to approximation the ridge occurrence and orientation maps of participation fingerprints.
- Distortion parameters are being calculated approximately continuously to accomplish extra precise alterations.
- A distinguished diminishes in rectification time due to embedding distortion patterns in network considerations.

VI. PROPOSED ARCHITECTURE





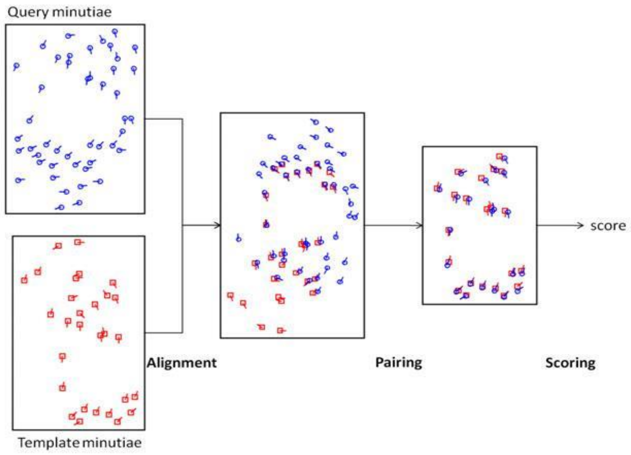


Figure: Proposed Architecture

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:

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

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: Subsequently pace is to use the Q-Learning methodology to extracts the accurate minutiae points from the fingerprint image. This neural network has an input layer, a hidden layer and an output layer.

- 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.

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- 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.

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

• ***Rule 1:*** if the distance between an execution and a bifurcation is less important than *D*1, then these two minutiae could be false minutiae. We should remove these two minutiae.

• ***Rule 2***: if the distance involving two terminations is smaller than *D*2, then these two minutiae could be false minutiae. We should remove these two minutiae.

• ***Rule 3:*** if the distance involving two bifurcations is smaller than *D*3, then these two minutiae could be false minutiae. We should 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

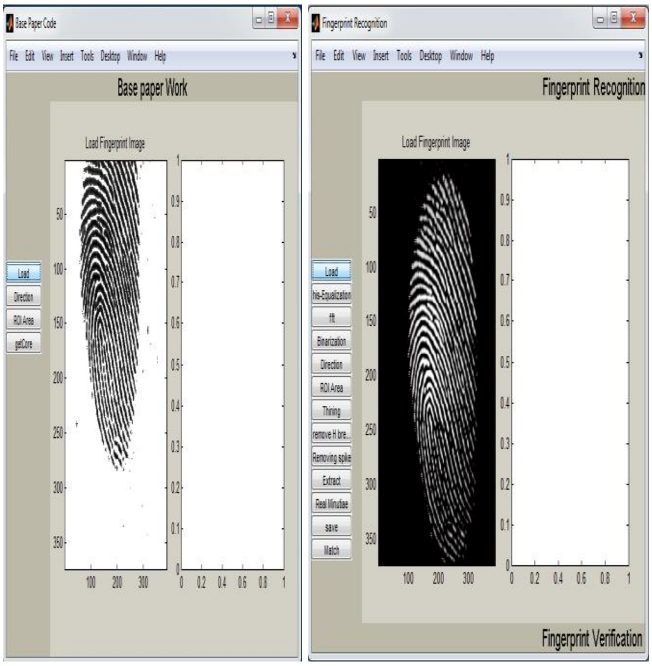
➢ **Step 4:** If the pixels are available then go to step 1 else return Minutiae.

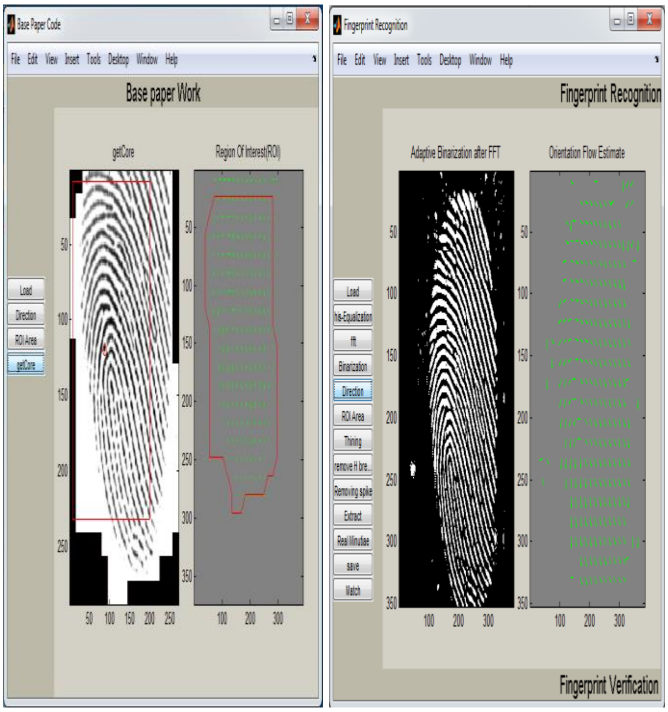
Proposed Algorithm:-

Q-Learning Algorithm:-

Input: Fuse Feature sets of MFP_I Fingerprint Input and MFP_{T1}, MFP_{T2}, MFP_{T3} ….. MFP_{Tn} Template Fingerprints
Output: The identified fingerprint.
Step 1: Divide MFP_I into L steps MFP_I^1, MFP ^{2} ……. MFP ^{N} each steps contain different feature set. (N= 6 set)
Step 2: Define threshold value at each level for comparison through histogram equalization.
Step 3: for i = 1
Step 4: for j = 1: L do
Step 5: T1 = Transform (MFP_I, L)
Step 6: T2 = Transform (MFP_T (i), L)
Step 7: S (i) = MatchingScore (T1, T2)
Step 8: if S (i) < Th
Step 9: break;
Step 10:else
Step 11:L= L+1;
Step 12:Repeat the step 5 and 6 and Compute the matching score using 7;
Step 13:if S (i) > Th then
Step 14:ID = i;
Step 15:Return;
Step 16end;
Step 17:end;
Step 18: end;
Step 19: end;

VIII. Experimental Outcomes





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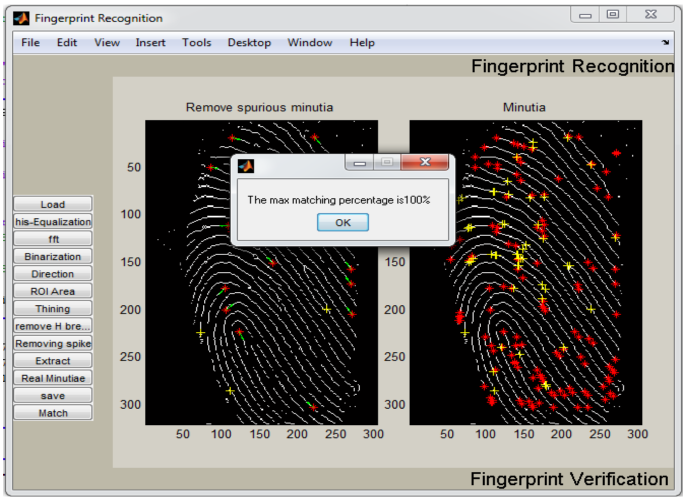

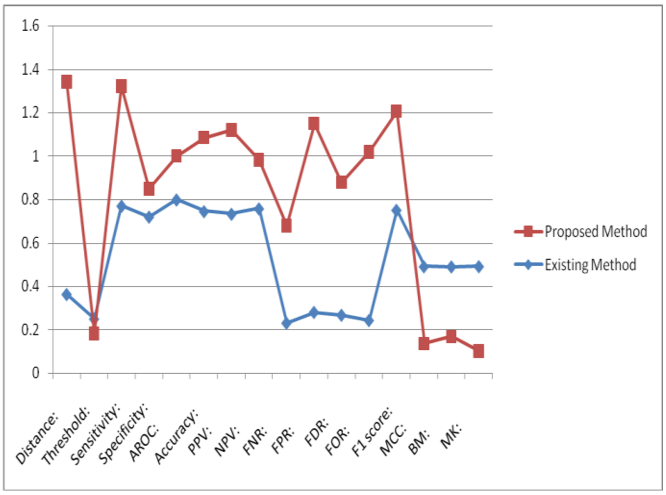

Figure: Overall Comparisons between existing method and proposed method by different parameters

IX. EXPERIMENTAL ANALYSIS

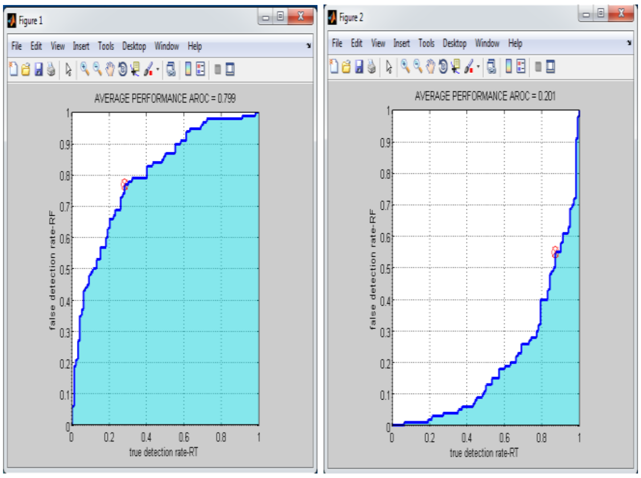

Table: Comparisons between Existing method and proposed method by different parameters

Parameters	Existing Method	Proposed Method
Distance:	0.3624	0.9795
Threshold:	0.249	-0.0637
Sensitivity:	0.77	0.55
Specificity:	0.72	0.13
AROC:	0.799	0.201
Accuracy:	0.745	0.34
PPV:	0.7333	0.3873
NPV:	0.7579	0.2241
FNR:	0.23	0.45
FPR:	0.28	0.87
FDR:	0.2667	0.6127
FOR:	0.2421	0.7759
F1 score:	0.7512	0.4545
MCC:	0.4906	-0.3526
BM:	0.49	-0.32
MK:	0.4912	-0.3885

X. CONCLUSION

All the algorithms that are discussed in this paper belong to quick fingerprint enhancement and fast minutiae extraction. The fingerprint enhancements to get better the feature of the ridge image and eliminate the noise in the fingerprint image, which helps to make up the disadvantages in the minutiae extraction. Minutiae extraction algorithms are quick since they use less patterns compared with some accurate image analysis algorithms. If the image is not processed i.e. low quality and noise may cause a lot of false minutiae and true minutiae missing. So the Q-Learning minutiae extraction method is a best for modern fingerprint recognition system.

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