International Journal of Soft Computing 8 (3): 154-162, 2013
ISSN: 1816-9503

Fuzzy Rule Based Neuro-Genetic Approach for Fingerprint Recognition

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Abstract: In this study, the accuracy of finger print recognition problem is been addressed. As per the literature the Back Propagation Network (BPN) for fingerprint recognition has resulted in inconsistent with unpredictable performance. This research has proposed the soft computing tool to images to overcome the low recognition rate and the low accuracy in fingerprint identification. Fuzzy logic is worn to eliminate the false minutiae from the fingerprint. Genetic algorithm has been incorporated to optimize the weights of neural network and the accuracy in the recognition process has been improved. The proposed method is implemented on the FVC 2004 DB1 database. The Laplacian based Pyramidal Model has strongly supported in fingerprint enhancement process which has increased the Peak Signal to Noise Ratio (PSNR) and decreased the Mean Square Error (MSE). The results have proven that the false minutiae have been eliminated by applying fuzzy rules and also the Equal Error Rate (EER) has been reduced. The increase in the recognition accuracy moreover in turn has reduced the training and the testing time.

Key words: Fuzzy rules, neuro-genetic algorithm, PSNR, MSE, EER

INTRODUCTION

Biometric Systems operate on behavioral and physiological biometric data to identify a person. The fingerprint is one of the popular biometric methods used to authenticate human being. Finger prints have been in use for biometric recognition because of their high acceptability, immutability and individuality. Fingerprints are the most widely used biometric feature for personal identification based on physiological and behavioral characteristics. Hence, fingerprint enhancement and extraction of fingerprint minutiae is one of the most important steps in automatic recognition of fingerprint. Many researchers are working on the enhancement of ridges on fingerprint. It is proved that most of the algorithms can efficiently develop ridges of the fingerprint when the fingerprint image is at quite high quality. In case of low quality fingerprint images the accuracy of fingerprint recognition is up to 12% (Hartwig *et al*., 2008). The performance of a fingerprint feature extraction and comparison algorithm relies heavily on the quality of the input fingerprint images. The first step is to enhance the fingerprint images. This is achieved by the Laplacian based pyramidal decomposition. The minutiae are extracted using the Crossing Number Method. The fuzzy rules are applied to remove the false minutiae. The minutiae are trained by the feed forward BPN algorithm. The accuracy of the recognition system is enhanced by optimizing the weight values of neural network with genetic approach.

LITERATURE REVIEW

For the success of biometric recognition, the processing of fingerprint images, two stages are of pivotal importance image enhancement and feature/minutiae extraction. Applied immediately after sensing but before feature extraction, an optional image enhancement can be performed to facilitate the feature extraction and the subsequent processing by de-noising the signal. In real world applications, the quality of a fingerprint image may suffer from various impairments, caused by scares and cuts, moist or dry skin, sensor noise/blur. The task of fingerprint enhancement is to counteract the aforesaid quality impairments and to reconstruct the actual fingerprint pattern as true to the original as possible.

For fingerprint enhancement many approaches have been introduced so far. These algorithms are classified in to two categories (Tung, 2006). They are spatial domain filtering enhancement techniques (Cheng and Tian, 2004; Huang and Qi, 2001; Wu *et al*., 2004) and frequency domain enhancement techniques (Pradenas, 1997; (Shalash and Abou-Chadi, 2006). Hong *et al.* (1998) proposed an algorithm based on Gabor filtering where all

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operations are performed in spatial domain. Gabor filters are usually band pass filters with both frequency and orientation features (Blotta and Moler, 2004). Yang *et al.* (2003) introduced the modified Gabor filtering technique. Sherlock *et al.* (1994) developed contextual filtering in Fourier domain. Hsieh *et al.* (2003) developed an enhancement algorithm based on Multi Resolution Analysis (MRA) using wavelets. Wahab *et al.* (1998) uses eight directional masks in spatial domain to find the local orientation of the ridges in fingerprint.

In constrained environments and in real world applications, fingerprint classification plus recognition are still a challenging problem. In fingerprint based classification and recognition, complexity and uncertainty are found because of the removal of true minutiae points. For appropriate recognition, this leads us into difficult situation in learning, teaching in addition to practicing the system. The proposed Fuzzy Rule based Neuro-Genetic algorithm is an appropriate method to model the range of uncertainties found in fingerprint classification and recognition systems.

FUZZY RULE BASED NEURO-GENETIC FINGERPRINT RECOGNITION (FN-GFR)

To overcome the low recognition rate and low accuracy of fingerprint recognition the Fuzzy Rule based Neuro-Genetic (FN-GFR) is proposed. The fingerprint recognition system consists of three different phases. They are:

- Fingerprint acquisition
- Minutiae extractor
    - Pre-processing
    - Minutiae extraction
    - Post-processing
- Minutiae Matcher

The fingerprint images acquired from sensors are not of perfect quality. Fingerprint image enhancement is always used to improve the image quality by a Fingerprint Recognition System. The main motivation of enhancement is to preserve the fingerprint features and remove noise and any irrelevant information. Hence, fingerprint enhancement techniques are used as pre-processing method. The above steps are shown in Fig. 1.

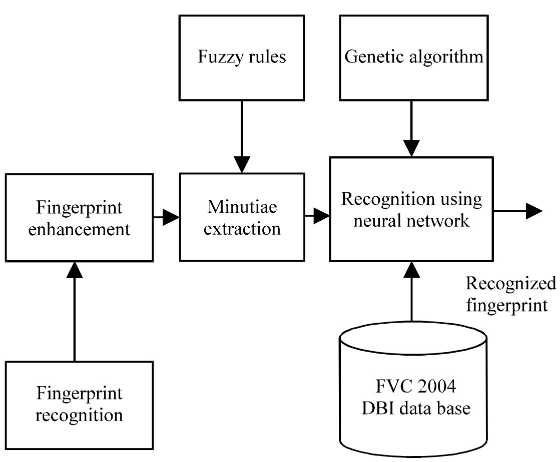

Fig. 1: Fuzzy rule based neuro-genetic fingerprint recognition

LAPLACIAN BASED PYRAMIDAL DECOMPOSITION

Fingerprint Recognition System depends on the quality of the input image. To improve the quality of the image and to increase the recognition rate and to ensure low error rate, the fingerprint is first subjected to enhancement technique. This study has incorporated Laplacian-based pyramidal decomposition for enhancement which is illustrated in Fig. 2.

Pyramid Decomposition (PD): Pyramid decomposition (Hartwig *et al.*, 2008) requires resizing (scaling or geometric transformation). In order to create the Gaussian and Laplacian-like pyramids, it is defined to reduce (I, f) and expand (I, f) operations which decrease and increase an image I in size by the factor f, respectively. On reducing, the image is initially low-pass filtered to prevent aliasing using a Gaussian kernel. The latter's standard deviation depends on the resizing factor which here

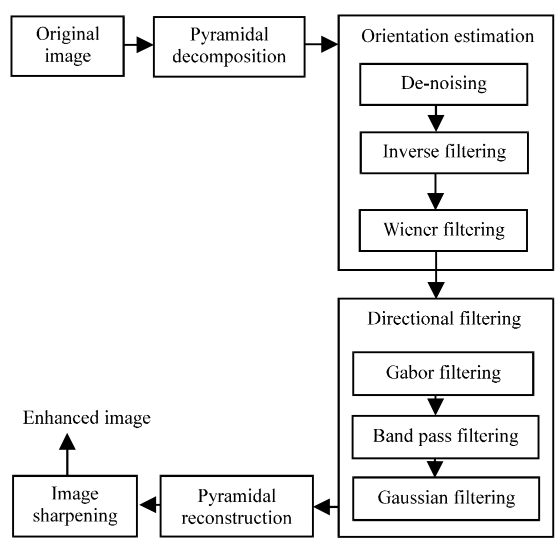

Fig. 2: Laplacian-based pyramidal decomposition

follows the lower bound approximation of the corresponding ideal low-pass filter, $\sigma = 0.75 \cdot f/2$ (Hsieh *et al*., 2003). Initially the original fingerprint image fp is reduced by a factor of $f_o \geq 1.5$ in order to exclude the highest frequencies. In further step the image size is reduced by a factor $f \leq 1.5$ for three times. To create images containing only band limited signals of the original image, one of the three original images is expanded, $g_{2\text{-}4}$ by factor f and subtract each of them from the next lower level, yielding $l_{1\text{-}3}$. The entire process is tabulated as shown in Table 1.

Orientation Estimation (OE): The next step is calculation of orientation of the image. Orientation calculation is critical for fingerprint image enhancement in both frequency and spatial domain. The orientation image is the local orientation of the ridges and is represented as a matrix of direction vectors. Most of the fingerprint classification and identification processes calculate the local ridge orientation of the fixed-block size instead of each pixel. The ridge-valley orientation for each of $l_{1\text{-}3}$ is estimated using the complex structure tensor approach. The latter tensor is built as in Eq. 1.

$$\begin{aligned} Z_i &= [(DxG(\sigma 1) + jDyG(\sigma 1)) * li]^2 \\ &= C.[(x.G(\sigma 1) + jy.G(\sigma 1)) * li]^2 \end{aligned} \tag{1}$$

where, $G(\sigma_1) = \exp(-(x^2 + y^2)\sigma/_1{}^2)$, $j = \sqrt{-1}$ and * denotes a 2D convolution. To obtain a robust estimation of the dominant direction (linear symmetry orientation) at a point, Z_i is averaged using a Gaussian $G(\sigma 2)$ where $\sigma 2 > \sigma 1$ to yield the complex image I_{20}. Likewise the magnitude of Z_i is averaged to yield I_{11}. To become independent of signal energy, calculate the $LSi = I_{20}/I_{11}$ for level i, encoding local orientation ($\angle$) and symmetry strength ($\|$). Also, by using LS, the magnitude of I_{20} is attenuated if the underlying linear symmetry is not well defined (Hartwig *et al*., 2008). It is worth mentioning that all convolutions are separable and only 1D Gaussian (derivative) filters have been used. When compared to a low-pass pyramid (e.g., Gaussian pyramid), the estimated orientation in band-pass pyramids (e.g., Laplacian pyramid) was found much more robust, in this context. Before determining the orientation of the fingerprint, it is subjected to three levels of filtering:

Table 1: Pyramidal Decomposition (PD)

Decomposition		
Gaussian-like	Laplacian-like	Reconstruction
g_1 = reduce (f_p, f_o)	l_1 = g_1-expand (g_2, f);	f_p = expand (., f_o)
g_2 = reduce (g_1,, f)	l_2 = g_2-expand (g_3, f);	expand (., f)+l_1
g_3 = reduce (g_2, f)	l_3 = g_3-expand (g_4, f);	expand (l_3, f)+l_2
g_4 = reduce (g_3, f)		

- De-noising
- Inverse filtering
- Wiener filtering

Fast Fourier Transform (FFT) of the original image is convoluted to remove white noise followed by the removal of additive noise by inverse filtering. The inverse filtering is a restoration technique for de-convolution, i.e., when the image is blurred by a known low pass filter, it is possible to recover the image by inverse filtering or generalized inverse filtering. However, inverse filtering is very sensitive to additive noise. The wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. The wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The wiener filtering is a linear estimation of the original image.

Directional Filter (DF): To enhance the SNR (Signal to Noise Ratio), i.e., to remove sweat pores, scars, etc., the directional averaging to all levels $l_{1\text{-}3}$ is applied independently. The local filtering direction within l_i is given by $\angle (LS_i)/2 - \pi/2$, thus it follows the ridges/valleys of the fingerprint. At every point, the neighboring pixels along a line having the same local direction are averaged with a (1D) Gaussian, yielding the new value. The possible number of different averaging directions is quantized (here 20). Additionally, the magnitudes of the complex pixels of LS_i are exploited. First, the pixels whose $LS_i < \tau 1$ are assigned as background, i.e., the pixel value are set to 0 (effectively amounting to a segmentation of the fingerprint from the background or the heavily noisy regions). Second, only if $LS_i| > 2$ filtering is done. Otherwise, the pixel is again set to 0. The resulting enhanced fingerprints exhibit a smooth ridge-valley flow yet preserving the discriminative local and global information.

Pyramidal Reconstruction (PR): By the use of filter levels $l_{1\text{-}3}$, the image is reconstructed to produce the enhanced image.

Image sharpening: The final enhanced version of the original fingerprint is generated using a Contrast Enhancement (CE) process called as image sharpening which produces a low PSNR image. Create a two-dimensional filter of a correlation kernel. Un-sharp contrast enhancement filter will enhance the contrast of the image. Special creates the un-sharp filter from the negative of the Laplacian filter with parameter alpha.

Alpha controls the shape of the Laplacian and must be in the range 0.0-1.0. The default value for alpha is 0.2. An un-sharp filter is an operator used to sharpen images. The created mask is subjected to multidimensional filtering according to the selected option namely replicate. Input array values outside the bounds of the array are assumed to be equal to the nearest array border value.

MINUTIAE EXTRACTION

The minutiae which are the local discontinuities in the ridge flow pattern, provide the features that are used for identification. The steps involved in extracting the minutiae points from the enhanced image are shown in Fig. 3. The steps given in Fig. 3 are explained.

Binarization: Binarization process converts the 8 bit gray fingerprint image to a 1 bit (either 0 or 1) binary image. The pixel represented by value 0 is for ridges and value 1 is for bifurcations. Ridges in the fingerprint are highlighted with black color while bifurcations are white after the operation. To binarize the fingerprint image a locally adaptive binarization method is performed.

De-noising/Direction: To locate the minutiae points and to find the direction of it a linear filter called Gabor filter is used. The impulse response of Gabor filter is defined by a harmonic function multiplied by a Gaussian function. 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:

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

Where:

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

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

In this equation, the wavelength of the cosine factor is represented by λ, the orientation of the normal to the parallel stripes of a Gabor function is represented by θ, ψ is the phase offset and γ is the spatial aspect ratio and specifies the ellipticity of the support of the Gabor function.

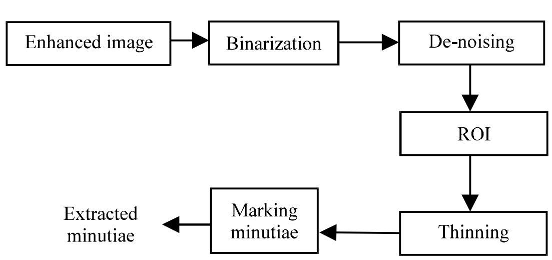

Fig. 3: Steps in minutiae extraction

Region of interest: Two morphological operations OPEN and CLOSE are adopted. The OPEN operation can expand the images and remove peaks introduced by background noise. The CLOSE operation can shrink images and eliminate small cavities. The algorithm throws away those leftmost, rightmost, uppermost and bottommost blocks out of the bound so as to get the tightly bounded region just containing the bound and the inner area.

Thinning: Ridge thinning is to eliminate the redundant pixels of ridges till the ridges are just one pixel wide (Tung, 2006). An iterative and parallel thinning algorithm is used. In each scan of the full fingerprint image, the algorithm marks down redundant pixels in each small image window (3×3) and finally removes all those marked pixels after several scans.

Minutiae marking: After the fingerprint ridge thinning, marking minutia points is relatively easy. For each 3×3 window if the central pixel is 1 and has exactly 3 one-value neighbors, then the central pixel is a ridge branch. If the central pixel is 1 and has only 1 one-value neighbor then the central pixel is a ridge ending. Suppose both the uppermost pixel with value 1 and the rightmost pixel with value 1 have another neighbor outside the 3×3 window, the two pixels will be marked as branches. Actually only one branch is located in the small region. Thus, a check routine is required to ensure that none of the neighbors of a branch or branches is added.

Crossing Number (CN) Method is used to extract minutiae. This method extracts the ridge endings and bifurcations from the skeleton image by examining the local neighborhood of each ridge pixel using 3*3 windows. The CN for a ridge pixel P is given by:

$$CN=0.5\sum_{i=1}^{8}|Pi-P_{i+1}|,\ \ P_9=P_1 \quad (3)$$

where, Pi is the pixel value in the neighborhood of P. For a pixel P, its eight neighboring pixels are scanned in an anti-clockwise direction as follows:

P3	P2	P1
P5	P	P1
P6	P7	P8

The CN for the ridge pixel is computed and then classified according to the property shown below:

- If CN = 1 then the central pixel is a ridge/termination
- If CN = 2 then the central pixel is a usual pixel
- If CN ≥3 then the central pixel is a bifurcation

For each extracted minutiae point, the following information is recorded:

- x and y coordinates.
- Orientation of the associated ridge segment, and
- Type of minutiae (ridge ending or bifurcation)

FUZZY RULE BASED FALSE MINUTIAE REMOVAL

In order to find the spurious minutiae points a new algorithm is developed based on fuzzy rules. This algorithm tests the validity of each minutiae point in thinned image and examines the local neighborhood around the point. The first step in this algorithm is to find the distance between termination and bifurcation. The Euclidian Method is used for calculating the distance. Fuzzy rules are framed to remove the false minutiae. The new algorithm is as follows:

Algorithm 1 (Elimination of false minutiae):
Input: Extracted minutiae points
Case 1: Between ridges and bifurcations

Step 1: Compute Euclidean distance between ridge and bifurcation points.
Step 2: Find the mean value (D1) for computed distances.
Step 3: Distance 1 = Euclidean distance (bifurcation, ridge).
Step 4: For entire size of the image, check for false minutiae using,
False minutiae = 1, for Distance 1 (i, j)<D1
= 0, Otherwise where (i, j) specifies rows and columns of an image.
Case 2: Between Bifurcations

Step 1: Compute Euclidean distance between detected bifurcation points.
Step 2: Find the mean value (D2) for computed distances.
Step 3: Distance 2 = Euclidean distance (bifurcations);
Step 4: For entire size of the image, check for false minutiae using,
False minutiae = 1 for Distance 2 (i, j) < D2
= 0, Otherwise, where (i, j) specifies rows and columns of an image.
Case 3: Between ridges

Step 1: Compute Euclidean distance between detected ridge points.
Step 2: Find the mean value (D3) for computed distances.
Step 3: Distance 3 = Euclidean distance (ridges);
Step 4: For entire size of the image, check for false minutiae using,
False minutiae = 1 for Distance 3 (i, j)<D3
= 0, Otherwise where (i, j) specifies rows and columns of an image.
Output: True minutiae points

NEURO-GENETIC APPROACH

In the proposed Neuro-Genetic approach for learning the neural network, Levenberg-Marquardt algorithms in the neural network trainer is used which is a Feed-Forward Back Propagation Network whose architecture is shown in Fig. 4 where the weights are optimized using GA. The algorithm used for this is given below:

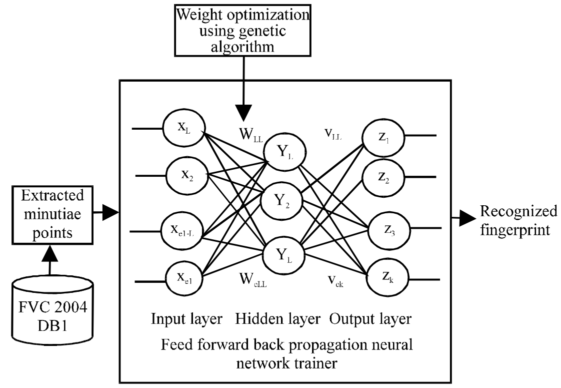

Fig. 4: Neuro-genetic recognition

Algorithm 2 (Neural network weights optimization using GA)
Input: Un-optimized weights

Step 1: Randomly initialize the values of parameters for {W_{ij} and b_i}.
Step 2: Generate initial random population.
Step 3:
- Calculate the fitness function of each individual in population.
- Record the best fitness.
- Evaluate the parameters {W_{ij} and b_i}.

Step 4:
- Train the neural network. (NN topology:Number of Neurons = 10)
- Adjust the final weights and thresholds.

Step 5: Calculate the net output and compute the error.
Step 6: Check for error acceptance
Case 1: If the error is not acceptable, perform GA operations like Selection, Cross over and Mutation to new generation and go to step 3.
Case 2: If the error is acceptable, Quit
Output: Optimized weights.

The weights of the BPN Neural Network are randomly initialized for better accuracy in learning and recognition process. Genetic approach is been incorporated to optimize the weight values so that the no. of epochs or iterations is highly reduced. Based on the weights, bias, and input and target outputs the MSE is reduced.

DISCUSSION

From FVC 2004 database, in the experiment, fingerprint images are used. For tougher benchmark, these are collected for state of the art recognition system than earlier fingerprint verification competitions. Using MATLAB V 7.9 on Windows 7 operating system the work is implemented. The performance of different stages of

Fig. 5: Original and enhanced fingerprints

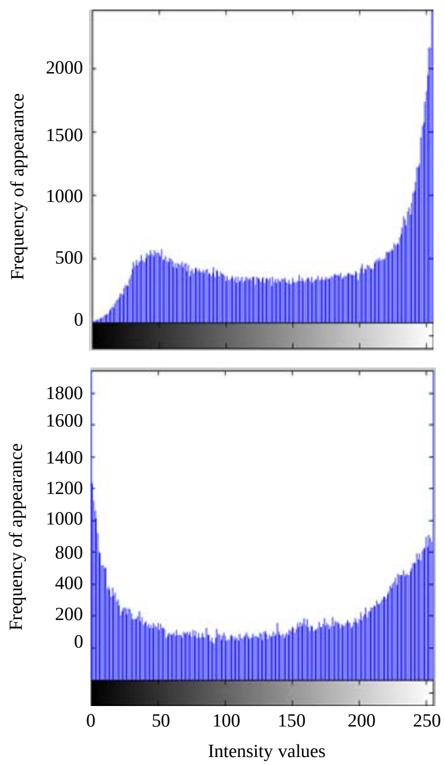

Fig. 6: Histogram of original and enhanced fingerprints

fuzzy based minutiae extraction along with the genetic algorithm for optimizing the neural parameters with recognition of images is evaluated.

Fingerprint enhancement: In this process, the original fingerprint is enhanced using Laplacian based pyramidal decomposition method. The original and the enhanced fingerprints are shown in Fig. 5.

The histograms of the original and the enhanced fingerprints are shown in Fig. 6. It is clear from the histogram that the intensities are uniformly distributed between the dark and the light pixels.

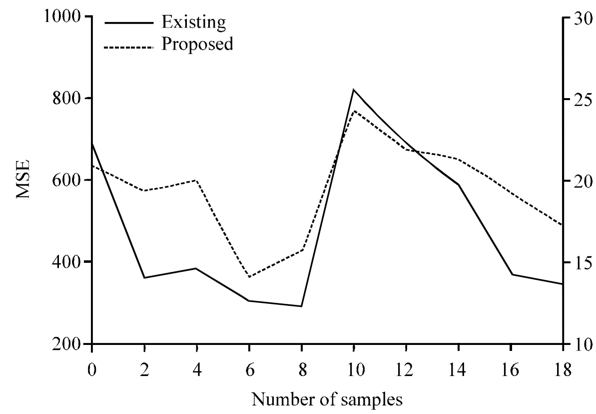

Fig. 7: The MSE values between existing and proposed method without sharpening

Table 2: MSE values of existing, proposed wih and without sharpening methods

MSE values		
Existing method	Proposed method (without sharpening)	Proposed method (with sharpening)
688.9	20.91	5.2940
364.8	19.33	5.1230
384.1	20.00	5.1940
302.9	14.10	3.5859
289.0	15.66	3.9010
822.3	24.25	5.9110
689.1	21.91	5.9710
588.3	21.27	5.0360
372.3	19.10	4.5410
344.1	17.17	4.3400

Table 3: PSNR values of existing, proposed with and without sharpening methods

PSNR values		
Existing method	Proposed method (without sharpening)	Proposed method (with sharpening)
19.74	34.98	40.89
22.50	35.26	41.08
22.28	35.13	40.97
23.31	36.63	42.58
23.52	36.18	42.21
18.98	34.28	40.41
19.74	34.72	40.37
20.43	34.85	41.10
22.42	35.31	41.55
22.76	35.78	41.75

Two metrics are used to measure the quality of the enhanced fingerprint image after applying the PD Model. They are Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE). Higher the value of the PSNR and lower the value of the MSE represents the better quality of the enhanced image. These values tabulated are shown in Table 2 and Table 3 and the corresponding plots are also shown in Fig. 7 and 8.

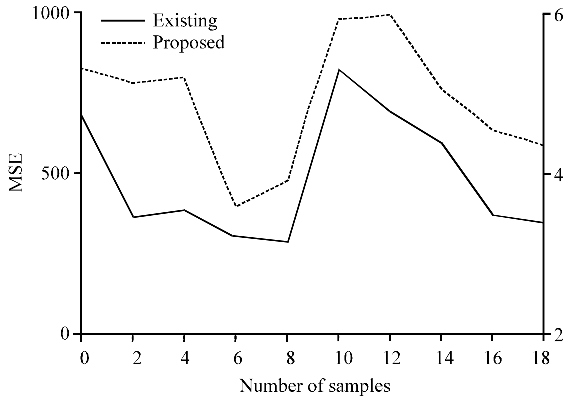

Fig. 8: The MSE values between existing and proposed method with sharpening

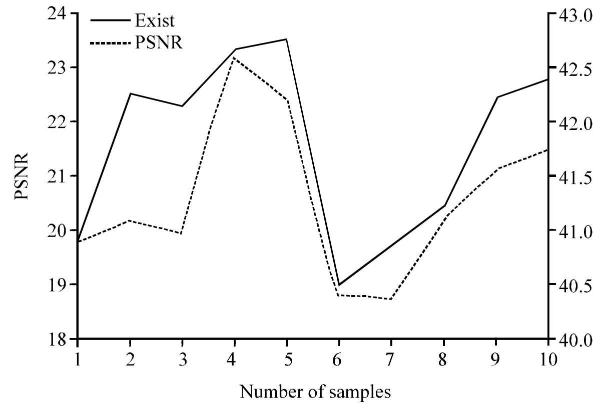

Fig. 10: The PSNR values between existing and proposed method with sharpening

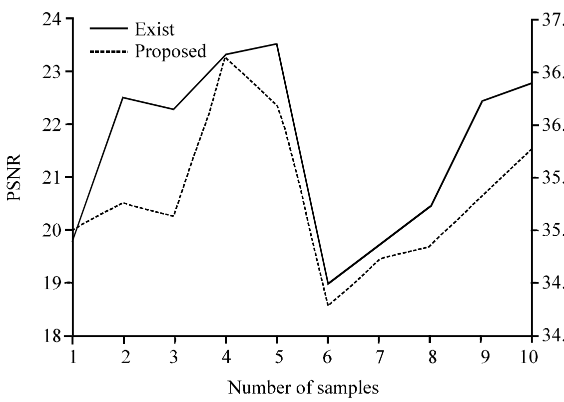

Fig. 9: The PSNR values between existing and proposed method without sharpening

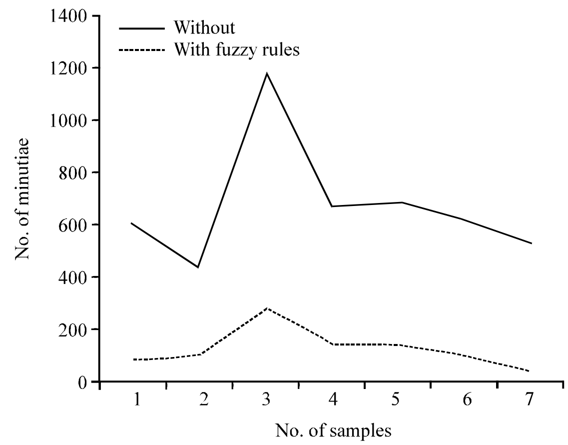

Fig. 11: False mintiae elimination

Table 4: No. of minutiae points before and after applying fuzzy rules

Before elimination	After elimination
595	79
438	102
1176	290
669	142
685	139
616	99
527	43

From the Table 2 and 3 and Fig. 7-10, it is clear that the MSE values are reduced considerably than the existing method and also the PSNR values are incresed than the existing method.

Fuzzy rule based false minutiae removal: The minutiae points that are extracted using CN Method consists of both true and false/spurious minutiae points. By applying the appropriate Fuzzy Rule to the entire set, the false minutiae points are removed and the true minutiae points are given as output and are are tabulated as shown in Table 4 and the corresponding plot is shown in Fig. 11.

Table 5: Training and testing time values

	Training time		Testing time	
No. of sample	NN	NN-GA	NN	N-GA
20	0.276	0.2714	0.013	0.0026
40	0.2712	0.2679	0.0119	0.0021
60	0.3036	0.3012	0.0104	0.0011

It is well known from the Fig. 11 that considerable false minutiae points are removed after applying the algorithm which is an added advantage for improving the performance of recognition.

Neuro-genetic approach: A Feed Forward Back Propagation Neural Network is a learning algorithm where the weight correction is done by propagating the error backward from the output layer towards the input layer. Genetic algorithm is used to optimize the weights thereby improving the recognition rate and reducing the error rate. For varying number of samples the neural network is trained and tested and the values are tabulated in Table 5 and plotted as shown in Fig. 12.

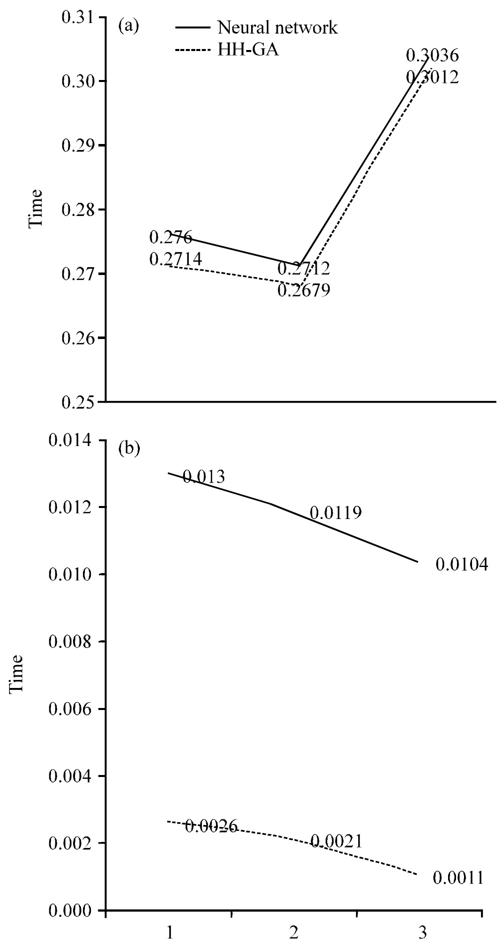

Fig. 12: Training and testing time values. a) NN and b) NN-GA

Training the neural network depends on various parameters like learning rate, initial weight, number of epochs and the number of input and output neurons. The weights are optimized using genetic algorithm and the neural network is trained with that of optimized weights. The performance plots of mean square error versus number of epochs under the testing models reveal the achieve exactness, in classification of the data set models. The performance plot for the neural network with and without Genetic algorithm is shown in Fig. 13 with Low MSE value for NN with GA when compared with NN without GA.

The ROC (Receiver Operating Characteristics) plot is a visual characterization of the trade-off between the FAR and the FRR which is depicted in Fig. 14.

Equal Error Rate (EER) is the rate at which both False Acceptance Rate (FAR) and False Rejection Rate (FRR) are equal. EER is a quick way to compare the accuracy. Normally the values of EER are directly obtained from the ROC curve and it is tabulated as shown in Table 6.

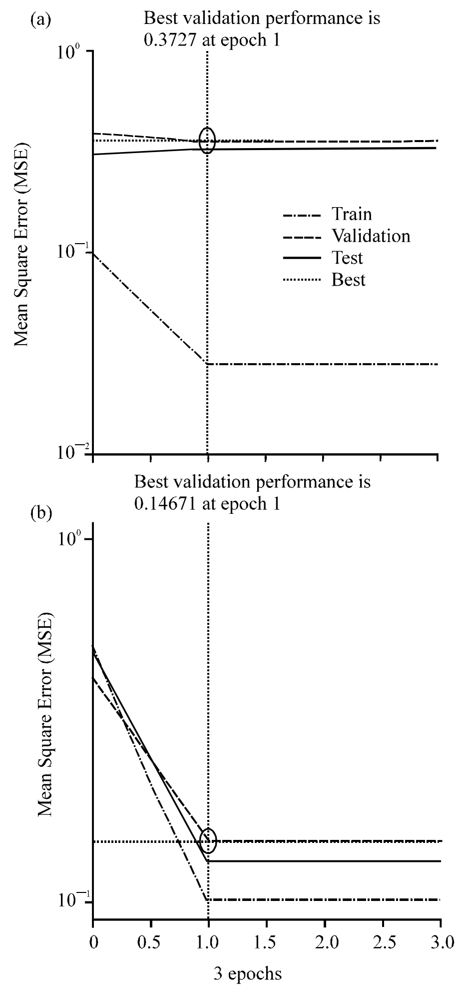

Fig. 13: Performance plot. a) MSE = 0.37327 NN; b) MSE = 0.14671 NN-GA

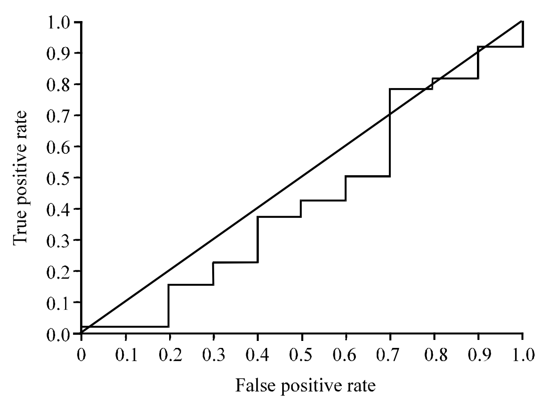

Fig. 14: Receiver operating characteristics

Table 6: EER values

Enhancement method	EER (%)
No pre-enhancement	14.5
Existing system	12.0
Proposed system	5.5

From the comparative evaluations as shown in Table 5 and Fig. 12-14, it is clear that the proposed method produces low error rate, less training and testing time with reasonable recognition rate.

CONCLUSION

Fingerprint image enhancement is presented as a novel procedure where the enhancement is done in a pyramidal manner in the spatial domain. Spurious minutiae points are removed using the proposed reliable fuzzy rule based algorithm. At last in the fingerprint recognition phase for learning the neural network, the weights are optimized using genetic algorithm. The simulation results show that the proposed Fuzzy Rule based Neuro-Genetic approach for fingerprint recognition increases the recognition rate and decreases the error rate and training and testing time.

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