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IMAGE ENHANCEMENT FOR FINGERPRINTS WITH MODIFIED TEACHING LEARNING BASED OPTIMIZATION AND NEW TRANSFORMATION FUNCTION

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Abstract- Extracting minutiae features out of poor quality fingerprints is the most challenging problem. It becomes extremely difficult for the Automated Fingerprint Identification System to accurately locate the minutiae points in such fingerprint images. In the present work, an image enhancement technique is employed in order to obtain reliable estimates of minutiae locations prior to minutiae extraction. For the task of image enhancement a new parameterized transformation function is designed, which uses local and global information of the image. A new novel optimization technique, called Modified Teaching Learning Based Optimization (M-TLBO) is then implemented to control and change the parameters in the transformation function which is applied on the poor quality fingerprint images to remove noise. The best enhanced image is tried to achieve according to the objective criterion by optimizing the parameters used in the transformation function with the help of Teaching Learning Based Optimization (TLBO). So here Fingerprint image enhancement is considered as an optimization problem and TLBO is used to solve it. The work has been concluded with relevant findings based on improvements in Fingerprint Image Quality, Robustness Index and Verification Performance as three evaluation criterions. A comparative study between the proposed techniques with many other available models from the literature is done in order to establish the efficacy of the proposed enhancement techniques

Keywords- minutiae extraction, Transformation function, fingerprint image enhancement, TLBO, objective criterion

Introduction

In this post modern age, which is known as highly advancing digital world, the level of security is getting breached every day. Fraud, corruption and crime rate is on an increasing note and to provide security to the civilians, various biometric techniques came into existence. Though Fingerprint Authentication, Iris Scan, and Retinal Scan are some of the most reliable biometric technologies that are in regular use in the present digital world, the only possible biometric that might be available at a crime location is “Fingerprint”. This shows the importance of fingerprint based biometric systems.

It is believed that the first known example of biometrics in practice was a form of fingerprinting being used in china in the 14th century, as reported by explorer Barros [1]. Ever since, there has been a lot of emphasis for research on fingerprint related problems.

Fingerprint images are rarely of perfect quality. They are usually degraded and corrupted with elements of noise due to many factors including variations in skin and impression conditions. This degradation will result in a momentous number of spurious minutiae being created and genuine minutiae being ignored. Thus, it is necessary to employ image enhancement techniques prior to minutiae extraction to obtain a more reliable estimate of minutiae locations. The fingerprints that are acquired from digital scanners have relatively good quality where as the ones acquired from physical site of crime is poor in nature. Such images gathered from physical site first of all requires enhancement of image quality.

Fingerprints can be categorized into two types based on their method of acquisition.

- Tenprints
- Latent Fingerprints

Tenprints refer to the fingerprints that are directly captured by any digital scanner. Most of the Automatic fingerprint identification systems (AFIS) use these tenprints.

Latent Fingerprints are the ones that are captured from the physical location using some special equipment with some chemical processing. This type of process of acquiring a fingerprint image from the physical location is described by Galbally, et al. [2].

Latent Fingerprints are fingerprints that are most probably captured at crime scenes which are used as evidence in solving criminal cases. Unlike tenprints, which are captured in a relatively controlled environment for the known purpose of identification, crime scene fingerprints are accidentally left behind. They are often invisible to the human eye without some type of chemical processing or dusting. Because of this reason that they are traditionally called latent fingerprints.

Motivation and the Challenge

Extracting minutiae features out of these poor quality fingerprints is the most challenging problem faced during criminal investigation. On the other side the performance of a fingerprint feature extraction and matching algorithm depends heavily upon the quality of the input fingerprint image and the reliable extraction of minutiae.

Due to the poor quality of latent fingerprints, today's AFIS (Automatic Fingerprint Identification System) technology operates poorly when presented a latent fingerprint image. It is really difficult for an automated system to accurately classify latent fingerprints and reliably locate the minutiae in the fingerprint image. Consequently, human fingerprint experts, who are called latent examiners, must analyze and manually mark up each latent fingerprint in preparation for matching. This is a wearisome and blue-collar task.

Soft computing is one emerging area which can handle impressive data effectively. Teaching Learning Based Optimization (TLBO) is the latest optimization technique that has been experimented upon benchmark functions under linear, nonlinear, and quadratic constraints. Literature in soft computing reveal that this so-called efficient TLBO technique has not been experimented upon image enhancement related problems.

This context gave a motivation to investigate the application of TLBO for image enhancement on the poor quality fingerprint images and especially on the latent fingerprints for qualitative extraction of minutiae points.

Existing Techniques

Various contributions were made by different researchers in this area of fingerprint image enhancement, ranging from histogram based enhancement, frequency transformation based enhancement and Gabor filter based enhancement and its variants to composite enhancement technique [3]. Among all the fingerprint enhancement techniques, there is lot of emphasis on enhancing the ridge structures using Gabor, or Gabor-like filters. But, while the ridge structures are enhanced, these approaches have also shown to be less effective in enhancing areas containing minutiae points, which are the points of main interest [4].

There are various modifications proposed to the existing Gabor filter to enhance fingerprint image more effectively. But even Modified Gabor Filter (MGF) [5] along with Traditional Gabor Filter (TGF) also fails when fingerprint image regions are of heavy noise. In such a case, where ridge fields are contaminated with heavy noise, the orientation field can hardly be estimated and accurate computation of ridge width and valley width is excessively difficult. So it can be understood, how critical it is to eliminate noise from fingerprint image for qualitative extraction of minutiae. Fingerprint image enhancement techniques should be applied on fingerprint images prior to the minutiae extraction to get sure of less spurious and more accurate minutiae points. But Identifying and eliminating the noise from a fingerprint image is not a straight forward activity.

It may be concluded that despite decades of research in fingerprints, extracting reliable minutiae from poor quality fingerprints remained as a problem. Although many researchers, over the years have suggested various approaches to resolve, this problem, it still remained incomplete, challenging and seeking new contributions. Thus it has become very important for researchers experimenting with new methodologies for fingerprint image enhancement and reliable extraction of minutiae.

Proposed Methodology

In the proposed methodology, a new parameterized transformation function is designed, which uses local and global information of the image. A new fitness function '*Fit*(X)' is designed with entropy and other parameters. Peak Signal-to-Noise Ratio (PSNR), is also used as objective function to form a multi objective criterion for measuring the rate of enhancement. The best enhanced image was tried to achieve according to the objective criterion by optimizing the parameters used in the transformation function with the help of Modified Teaching Learning Based Optimization (M-TLBO). So here Fingerprint image enhancement is considered as an optimization problem and M-TLBO is used to solve it.

Design of New Transformation Function

In image processing, the simplest statistical measures of a random variable are its mean and variance [6]. These are the reasonable parameters to be considered to design an adaptive filter that can be based on these parameters because they are quantifiers closely related to the appearance of an image. The mean gives the measure of average gray level in the region in which the mean is computed, and the variance is the measure of average contrast or difference in that region.

In the traditional enhancement technique, the original equation shown below is applied to each pixel at location (i, j) using the following transformation [6].

$$g(i, j) = \left[G/\text{ó}(i, j)\right]\left[f(i, j) - m(i, j)\right] \tag{1}$$

The $m(i, j)$ is the mean (i, j) is the centroid and $\sigma(i, j)$ is the standard deviation, which are computed in a neighborhood centered at (i, j). Therefore, they are dependent on the local information. $f(i, j)$ and $g(i, j)$ are the gray-level intensity of pixels in the input and output image, respectively, centered at location (i, j). And lastly, G is the global mean of the image.

The traditional enhancement model mentioned in "(1)" is modified by including the four parameters a,b,c,d to make it a parameterized transformation function. And this transformation function looks as follows:

$$g(i,j) = \left[\frac{d \times G}{\sigma(i,j) + b}\right]\left[f(i,j) - c \times m(i,j)\right] + m(i,j)\alpha \tag{2}$$

where $f(i, j)$ is the gray value of the $(i, j)^{th}$ pixel of the input fingerprint image and $g(i, j)$ is the gray value of the $(i, j)^{th}$ pixel of the enhanced fingerprint image. Four parameters are introduced in the transformation function, namely a, b, c, and d to produce large variations in the processed image. The parameters a, b, c and d are defined over the real positive numbers and their range is (0,1).

$m(i, j)$ is the local mean of the $(i, j)^{th}$ pixel of the input image over a n×n window which is defined as

$$m(i,j) = \frac{1}{n \times n}\sum_{x=0}^{n-1}\sum_{y=0}^{n-1} f(x,y) \tag{3}$$

$\sigma(i, j)$ is the local standard deviation of $(i, j)^{th}$ pixel of the input fingerprint image over a n×n window and G is the global mean of the image, which are defined as:

$$\sigma(i, j) = \sqrt{\frac{1}{n \times n}\sum_{x=0}^{n}\sum_{y=0}^{n}(f(x, y) - m(i, j))^2} \tag{4}$$

$$G = \frac{1}{M \times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} f(i, j) \tag{5}$$

This new transformation function broadens the spectrum of the transformation output range by modifying the original equation. This transformation function has been used with Particle Swarm Optimization (PSO) to enhance fingerprint image [7].

New Transformation Function

The focus of fingerprint image enhancement is not aimed at producing a good visual appearance of the image but focused at facilitating the subsequent feature detection like ridge detection and minutiae extraction and avoiding undesired side effects in the subsequent processing.

Removing noise while preserving and enhancing edges is one of the most challenging task in image enhancement. However, removing noise (smoothening) and edge enhancement (sharpening) are conflicting requests, thus it is difficult to process these two requests at the same time. Unsharp masking and its variants were proposed to address this problem. Zhang and Allebach, [8] have proposed the Adaptive Bilateral Filter (ABF) in order to realize the noise removing and edge enhancement at the same time. In ABF, range filter is changed depending on the output of Laplacian of Gaussian (LoG) operation. While, LoG operation can detect edges from noisy images, ABF can remove the noise while enhancing the edges. However, the experimental results have shown that these filters work better for images of general type but not for fingerprint image enhancement task. The increase in number of edges and intensity of edge pixels are not just enough to conclude that the fingerprint is enhanced, because high increase in number and intensities of edge pixels might result in fingerprint image that doesn't have a natural contrast.

The present work aims to eliminate the noise and enhance the region where the minutiae points are present, which is the region of interest. In such context, the transformation function in [Eq-2] is modified. Global variance is used in place of global mean and local variance is used in place of local standard deviation with certain constraints. The resulted proposed new transformation function looks as follows

$$g(i,j) = d \times ((\sigma_\eta^2(i,j)/\sigma_L^2(i,j) + b))\left[f(i,j) - c \times m(i,j)\right] + m(i,j)\alpha \qquad (6)$$

where f*(i, j)* is the gray value of the (i, j)th pixel of the input fingerprint image and *g(i, j)* is the gray value of the (i, j)th pixel of the enhanced fingerprint image. a, b, c, d are the four design variables.

m(i, j) is the local mean of the (i, j)th pixel of the input image over a *n*x*n* window which is defined as in [Eq-3].

σ_L^2(I,j) is the local variance of (i, j)th pixel of the input fingerprint image over a $n \times n$ window

$$\sigma_L^2 = \frac{1}{n \times n} \sum_{x=0}^{n} \sum_{y=0}^{n} (f(x,y) - m(i,j))^2 \qquad (7)$$

and σ_η^2, is the global variance of the image and , which is defined as:

$$\sigma_\eta^2 = \frac{1}{M \times N} \sum_{x=0}^{M} \sum_{y=0}^{N} (f(x,y) - m(i,j))^2 \qquad (8)$$

The response of the filter or transformation function at any point *(i, j)* on which the region is centered is to be based on four quantities.

1. *f(i, j)*, the value of the noisy image at *(i, j)*.
2. σ_η^2 , the variance of the noisy corrupted image to form *f(i, j)*.
3. *m(i, j)*, the local mean of the pixels of the input image over a *n*x*n* window.
4. σ_L^2 , the local variance of the pixels in $n \times n$ window.

Here the only quantity that needs to be known is the variance of the overall noise, σ_η^2. The other parameters are computed from the pixel in the $n \times n$ at each location (i, j) on which the filter window is centered. A tacit assumption in the above equation is that $\sigma_\eta^2 <= \sigma_L^2$. The noise in this model is additive and position independent, so this is a reasonable assumption to make because $n \times n$ is a subset of *g(i, j)*. However having exact knowledge of σ_η^2 is very rare. Therefore it is possible this condition to be violated in practice. For that reason, a test should be built into an implementation of the equation (6) so that the ratio is set to 1 if the condition $\sigma_L^2 > \sigma_\eta^2$ occurs. This makes this filter non linear. However, it prevents nonsensical results (i.e., negative gray levels, depending the value of *m (i, j)* due to potential lack of knowledge about the variance of the image noise.

Objective Criterion

During the process of fingerprint image enhancement with the above described transformation functions, the quality of an enhanced image should be evaluated without human intervention at each step / iteration. Because each proposed transformation function is used with a specific optimization technique, an objective function is required which will say all about the image quality at every step /iteration during the process of enhancement.

Objective function with Entropy and other parameters:

It can be noted from the literature that compared to the original image, an enhanced image should have more number of edges [6] and a higher intensity of the edges [9]. But the number of edges and intensity of edge pixels are not just enough to describe a valid fitness criterion for a better enhanced fingerprint image as one would expect. The setback is that a fingerprint image can sometimes have an excessive contrast with sharp transitions from white to black (or) on the contrary, from black to white, and with a relatively small number of gray levels. So a criterion that is proportional to number and intensities of edge pixels might give an outsized credit to an image that doesn't have a natural contrast.

The quantification of a number of gray-levels present in the fingerprint image is very much needed. It can be noted from the 'User's Guide to NIST Biometric Image Software (NBIS)' Watson, et al. [10,11] that 'A high quality region within a fingerprint image will have significant contrast that will cover the full grayscale spectrum'. The histogram of the fingerprint image should approach the uniform distribution, as in the case of histogram equalization techniques.

So for evaluating the quality of the fingerprint image, Entropy is considered as an important parameter in the objective function. Entropy value reveals the information content in the image. The uniform distribution of the intensities indicates that the histogram is equalized and thus the entropy of the image will be more. Having considered all these factors, the fitness function, which is given in [Eq-9], can be a good choice for an objective criterion:

$$Fit(X) = H(g(X)) + log(log(I(g_e(X)))) \times \frac{g_e}{M \times N} \qquad (9)$$

where, *Fit(X)* is the fitness function, *g(X)* denotes the enhanced fingerprint image (after transformation function is applied). $g_e(X)$ is the number of edge pixels as detected with the Sobel edge detector. The Sobel detector which is used in the fitness function is an automatic threshold detector. $I(g_e(X))$ is the intensity of the edges detected with a Sobel edge detector that is applied to the transformed image *g(x)*, M and N are the number of pixels in the horizontal and vertical direction respectively of the image. Finally, *H(g(X))* measures the entropy of the enhanced image *g(X)*. The entropy, *H (g(X))* of the enhanced image g(i, j) is calculated based on histogram, as follows:

$$H(g(X)) = -\sum_{i=0}^{255} e_i$$

where $e_i = h_i \log_2 h_i$ if $h_i \neq 0$ otherwise $e_i = 0$. And h_i is the probability occurrence of ith intensity value of g(i, j) image.

It can be noted in the fitness function in equation (9) that '*X*' in *g(X)*, represents the parameters *a, b, c, d* in the transformation function. So *g(X)* indicates the enhanced fingerprint image that is obtained through the transformation function that was applied on the input fingerprint image with a specific combination of *a, b, c, d* The optimization technique M-TLBO tries to find a solution '*X*' that maximizes the fitness value.

After many experiments on the huge fingerprint databases it is observed that large values for edge intensity had produced extreme contrast, and un-natural fingerprint images, so to reduce the over emphasis of this parameter in the fitness function, a log-log measure of the edge intensity is used in equation (9), whereas more emphasis is given to the entropy of the image because it is easy to extract minutiae points from a fingerprint image, where the gray levels are uniformly distributed. Some portion of the contributions from other parameters is added to the entropy value in the fitness function.

PSNR as objective function:

To make the objective criterion more powerful, along with *Fit(X)*, Peak Signal-to-Noise Ration' (PSNR) is also used as objective function. The PSNR computes the peak signal-to-noise ratio and represents a measure of the peak error in decibels, between two images. This ratio is often used as a quality measurement between the original and a reconstructed image. PSNR is expressed as

$$\mathrm{PSNR} = 10 \times \log_{10}(b^2/\mathrm{MSE}) \qquad (10)$$

where b is the largest possible value of the signal (typically 255 or 1), and MSE in the denominator represents the cumulative squared error between the reconstructed and the original image, and is computed as follows

$$MSE = \frac{\sum i \sum f \left| f(i,j) - y(i,j) \right|}{N} \qquad (11)$$

Where 'N' is the total number of pixels. The lower value of MSE represents the lower error in the enhanced image. It is the known fact that the greater the value of PSNR, the better the quality of the enhanced image.

In this present work, the PSNR is used as objective function as follows:

In the function PSNR (A, B), the input noisy image is considered as A, which remains constant and the enhanced image is considered as B, which keeps changing at every iteration. PSNR is used to measure the difference between input noisy images and enhanced images achieved after applying the transformation function. The best enhanced image is selected based on the PSNR value. To calculate it, two images must be given. But in this case, only input image is given for enhancement. So after generating enhanced image in the 1st step / iteration, it is then considered as the 2nd image. The input image is fixed at one side and at each step / iteration the enhanced images is considered as the second image. The usage of PSNR as objective function to evaluate the quality at each step / iteration is as follows.

During the enhancement process, at each step / iteration i, PSNR is calculated between enhanced image and input image and the value is stored. After enhancement in the next step / iteration i+1, the PSNR value is computed between new enhanced image and input image. The PSNR value at iteration i and i+1 are compared and the one with the lowest PSNR value must be selected. This is because the more the image is enhanced the more the Mean Square Error (MSE) between enhanced image and input Image. If the MSE value is high, the PSNR value will be less.

Using Fit(X) and PSNR as Multi Objective Function

The objective function should be simple and effective. Because the quality should be measured at each step / iteration in the run time, objective function should be computationally light in weight and must be effective in serving the purpose of evaluating the rate of enhancement and guide towards optimal enhancement.

Keeping these factors into consideration, two objective functions namely '*Fit(X)'* and Peak Signal-to-Noise Ratio (PSNR) are used in the present work to measure the quality of the enhanced fingerprint image. At each step when the enhanced fingerprint image is acquired after the transformation function is applied, the '*Fit(X)*' and 'PSNR' are calculated. If the fingerprint image is enhanced, then both '*Fit(X)*' and 'PSNR' value must have better values than before. Because two objective functions with different parameters are used to evaluate the quality of fingerprint image, it is called Multi objective function or Multi objective criterion.

During the fingerprint image enhancement process, at each step / iteration while a fingerprint image is enhanced, both '*Fit(X)*' value and 'PSNR' value are calculated. The best enhanced image is selected based on the better values of these two objective functions. Experimental results proved that the use of this multi objective criterion is more effective in evaluating the quality of fingerprint image than a single objective function.

Teaching Learning Based Optimization (TLBO)

Rao, et.al. [12], described the details about the Teaching Learning Based Optimization. Different constrained benchmark functions with different characteristics of objective functions and constraints (linear, nonlinear, and quadratic) were experimented upon and presented various results to show how TLBO works better than other optimization algorithms in soft computing.

The TLBO method is based on the effect of the influence of a teacher on the output of learners in a class room. Here, the output is considered in terms of results / grades. In general teacher is considered as a highly learned person who shares his or her knowledge with the learners. The quality of a teacher affects the outcome of the learners. It is obvious that a good teacher trains learners such that they can have better results in terms of their marks. Complete details of TLBO technique can be found in Rao, et.al. [12].

M-TLBO for Fingerprint Image Enhancement

In this work the Teaching Learning Based Optimization (TLBO) is used to enhance fingerprint image for effective extraction of minutiae. The Teaching Learning Based Optimization (TLBO) has been tailored to suit the purpose of enhancing fingerprint image and it is called Modified Teaching Learning Based Optimization (M-TLBO).

First the teaching-learning environment should be considered. So in the proposed methodology, ten learners are taken, and it implies ten vectors with the combination of (a,b,c,d) with random values. One combination of (a,b,c,d) is considered as one student /learner. The teacher is not taken explicitly, but the highly knowledgeable person among all the learners is considered as a teacher. Here the four parameters (a,b,c,d) in the transformation function are considered as four design variables (dimension), which are taken as four subjects in this Modified TLBO. This is fixed because only four parameters a,b,c,d are considered in the transformation function.

Teacher's Phase

The actual Teacher's phase in this work begins with the population size of 10 (learners) and dimension of 4 (subjects). Because in the literature, no application of TLBO, even for image enhancement is found, so here with simple example, it is explained how TLBO can be used in image processing application. Once after selecting initial population and dimension, an initial matrix $X_{j,k,i}$ is generated using the function x(i,j) = rand(); in Matlab. The resulted matrix '$X_{j,k,I}$' is considered in terms of learners and subjects as shown in [Fig-1].

	a (subject-1)	b (subject-2)	c (subject-3)	d (subject-4)
Learner-1				
Learner-2				
Learner-3				
Learner-4				
Learner-5				
Learner-6				
Learner-7				
Learner-8				
Learner-9				
Learner-10				

Fig. 1- Structure of ten learners and four subjects in Modified TLBO

First the best learner for each subject is taken and the resulted vector is called K_{best} Later, the column wise mean is calculated (mean of each subject). Now the difference mean is calculated. For this, first the difference between the existing mean result of each subject and corresponding results of the learner in each subject is calculated and this result ($M_{j,i}$) is multiplied with Teaching Factor (T_F). The difference mean is calculated using the TLBO formula for difference mean

$$Difference\_Mean_{j,k,i} = r_i\,(X_{j,kbest,i} - T_F M_{j,i}) \quad (12)$$

where, $X_{j,kbest,i}$ is the result of the best learner (i.e. teacher) in subject *j*. T_F is the teaching factor which decides the value of mean to be changed, and r_i is the random number in the range (0,1).

The teaching factor T_F was calculated *as*

$$T_F = round\,[1+rand\,(0,1)\{2-1\}] \quad (13)$$

T_F is not a parameter of the TLBO algorithm. The value of T_F won't be given as an input to the algorithm and its value is randomly decided by the algorithm using [Eq-10]. Rao, et.al. [13,14] stated that 'after conducting number of experiments on many benchmark functions it is concluded that the algorithm performs better if the value of T_F is between 1 and 2'. Hence to simplify the algorithm, the teaching factor is suggested to take either 1or 2 depending on the rounding up criteria given by [Eq-13]. Based on the *Difference_Mean*$_{j,k,i}$, the existing solution is updated in the teacher phase.

Now this difference mean is added to the initially generated matrix $X_{j,k,i}$ to produce another matrix say $X'_{j,k,i}$

$$X'_{j,k,i} = X_{j,k,i} + Difference\_Mean_{j,k,I} \quad (14)$$

The values of each row are considered as values of a,b,c,d respectively and are applied in the transformation function in the [Eq-6], to produce output image.

As a result of the above process, as per the taken example, total of ten output images and ten fitness values are achieved, based on the fitness function value, the best output image is selected. Call it as Teacher-Best (I_{TB}).

Learning Phase

According to the original TLBO, which is proposed by Venkata and Patel [13], Rao, et al. [14] during Learner's Phase, randomly two learners *P* and *Q are* selected such that $X'_{total\text{-}P,i} \neq X'_{total\text{-}Q,i}$ (where, $X'_{total\text{-}P,i}$ and $X'_{total\text{-}Q,i}$ are the updated values of $X_{total\text{-}P,i}$ and $X_{total\text{-}Q,i}$ respectively at the end of teacher phase)

$$X''_{j,P,i} = X'_{j,P,i} + r_i\,(X'_{j,P,i} - X'_{j,Q,i}),\ \text{If } X'_{total\text{-}P,i} < X'_{total\text{-}Q,I} \quad (15)$$

$$X''_{j,P,i} = X'_{j,P,i} + r_i\,(X'_{j,Q,i} - X'_{j,P,i}),\ \text{If } X'_{total\text{-}Q,i} < X'_{total\text{-}P,I} \quad (16)$$

Modification to Learning Phase

The original concept of Learners phase in TLBO has been modified in the present work, because selecting two learners P and Q randomly for comparison may include comparison of the marks in one subject of a learner with the marks in another subject of another learner. This is practically not correct. A learner who is good at one subject need not be good at other subject and similarly a learner who is bad at one subject need not be bad at other subject. Most importantly updating the knowledge of a learner in one subject with the other learner's knowledge in some other subjects is practically incorrect. For example how can a learner who has more knowledge in microprocessor can help to improve the other learner's knowledge in Artificial Intelligence. So comparing the learners in the same subject is more appealing. So the learning phase in TLBO has been modified as follows.

Instead of selecting two learners randomly, Select one learner in a particular subject and compare with every other learner in the same subject (same column) and update the result accordingly with the formulas of TLBO, presented in [Eq-15] and [Eq-16].

Again the values of each rows are considered as values of a,b,c,d respectively and are applied in the transformation function (6) to produce output image. As a result total of ten output images and ten fitness values are achieved, based on the fitness function value, the best output image is selected and call that best output image as Learner-Best (I_{LB}). The best output image that is achieved in the teachers phase and the best output image that is achieved in the learners phase are compared and the best out of the two is saved and call that best image as Iteration-Best ($I_{B,i}$), this is the best image that is achieved so far. This completes one iteration. So for the next iteration $X''_{j,P,i}$ is considered as the initially generated matrix along with its fitness value and procedure continues until the termination condition is reached (number of iteration).

Fingerprint Image Enhancement Algorithm Using Modified Teaching Learning Based Optimization

Teachers Phase:

Step 1: Initialize population 'n' (rows), design variables 'm' (columns) and termination condition.

Step 2: Generate initial population $X_{j,k,i}$

Step 3: Calculate mean of each design variable (each subject).

Step 4: Select best solution as k_{best} (best learner in each subject).

Step 5: Calculate difference mean using the formula in [Eq-12].

Step 6: Add difference mean to the initially generated matrix $X_{j,k,i}$ to produce $X'_{j,k,I}$ as per [Eq-14].

Step 7: For each learner of $X'_{j,k,i}$, generate enhanced fingerprint image using [Eq-6].

Step 8: Calculate the fitness value for the images generated above using [Eq-9], [Eq-10].

Step 9: Select the best image based on the fitness value. Call it as Teacher-Best (I_{TB})

Learner Phase:

Step 10: Select a learner *P* and compare with every other leaner Q, subject wise. And update $X'_{j,k,I}$ using [Eq-15] or [Eq-16] to produce $X''_{j,P,i}$ (Repeat this process for every learner with every other learner)

Step11: For each learner of $X''_{j,P,i}$, generate enhanced fingerprint image using [Eq-6].

Step 12: Calculate the fitness value for images generated above using [Eq-9], [Eq-10].

Step 13: Select the best image based on the fitness value. Call it as Learner-Best (I_{LB})

Step 14: Compare the Teacher-Best (I_{TB}) and Learner-Best (I_{LB}) and the select the best and store it as Best Image (I_{Bi}) in i^{th} iteration.

Step 15: Now consider $X''_{j,P,i}$ as initially generated matrix and repeat step3 to step 14 till the termination condition is reached (no. of iterations). Select the best image among all the iterations.

During the learners phase, learners increase their knowledge by interaction among themselves. A learner interacts with every other learner for enhancing his or her knowledge. A learner gains new knowledge if the other learner has more knowledge than him or her. So the solution at teachers phase is updated using [Eq-15]/[Eq-16].

Preparation for Minutiae Extraction

After completing the above discussed enhancement method, in the current study the following steps need to be performed before the minutiae points are extracted [15,16].

- Segmentation
- Binarization
- Thinning
- Minutiae Extraction using Crossing Number (CN) technique

The minutiae that are extracted through the Crossing Number method is used to calculate the Robustness Index to evaluate the performance of the proposed methodology of fingerprint image enhancement.

Experiments and Results

Databases used for experiments

Experiments were carried out on ATVS-Fake Fingerprint Database (ATVS-FFp DB) and FVC 2002 fingerprint database. “ATVS-Fake Fingerprint Database (ATVS-FFp DB)” is one of the bench marked databases that are made available at BIT website for researchers. In the present work this particular database is used for various experiments. The fake and the real / original portions of the databases are used. The fake fingerprint database contains the poorest quality fingerprints. The proposed Modified TLBO (M-TLBO) enhancement technique is applied on such poor quality fake fingerprints to improve their quality. Many experiments were also carried out on fingerprint dataset, collected from FVC 2002 of MSU.

Evaluating the Performance of Proposed Enhancement Technique

The performance of the proposed technique is verified through the following approaches as stated earlier.

- Quality measure using NFIQ package of NBIS
- Calculation of Robustness Index (R.I)
- Verification performance using Bozorth3 (fingerprint matcher) of NBIS

Evaluation of Fingerprint Quality Using NFIQ

‘NBIS’ which is ‘biometric image software’ was developed by the National Institute of Standards and Technology (NIST) for the Federal Bureau of Investigation (FBI) and Department of Homeland Security (DHS). The NBIS software is organized into two categories: non export controlled and export controlled. In the export controlled NBIS software, the third package NFIQ is used. In the export controlled NBIS software, BOZORTH3 is used. Bozorth3 is minutiae based fingerprint matching system. These packages in this software are made available as open source at NIST website: http://www.itl.nist.gov.

NFIQ Package

The third open source package, NFIQ, is a fingerprint image quality algorithm. It takes a fingerprint image and analyzes the overall quality of the image returning an image quality number ranging from 1 for highest to 5 for lowest. In the present work this package is used to validate quality of fingerprint images before and after the enhancement through proposed methodologies.

Table 1- NFIQ Quality labels of fingerprints - before and after M-TLBO enhancement

Sample Fingerprints-ATVS-FFp DB	Type of Scanner	NFIQ-Quality label before enhancement	NFIQ-Quality label after M-TLBO enhancement
u01_f_fc_li_01	Capacitive	5	4
u01_f_ft_rm_04	Thermal	5	4
u02_f_fo_li_03	Optical	5	3
u02_f_ft_ri_01	Thermal	3	3
u03_f_fc_rm_04	Capacitive	5	4
u03_f_ft_lm_04	Thermal	3	2
u04_f_fc_li_02	Capacitive	5	4
u04_f_fo_rm_02	Optical	5	3
u05_f_fc_ri_03	Capacitive	5	5
u05_f_ft_rm_01	Thermal	3	2
u06_f_fc_rm_03	Capacitive	5	4
u06_f_fo_ri_04	Optical	5	3
u07_f_fc_li_01	Capacitive	5	3
u07_f_ft_li_01	Thermal	3	2
u08_f_fc_lm_04	Capacitive	5	5
u08_f_ft_ri_04	Thermal	3	2
u09_f_fo_rm_03	Optical	4	3
u09_f_ft_ri_03	Thermal	5	3
u10_f_fc_lm_04	Capacitive	5	3
u10_f_ft_ri_02	Thermal	5	3
u11_f_fc_lm_02	Capacitive	5	5
u11_f_fo_li_04	Optical	3	2
u12_f_fc_rm_02	Capacitive	5	4
u12_f_ft_rm_02	Thermal	4	3
u13_f_fo_rm_01	Optical	3	2
u13_f_ft_lm_04	Thermal	5	4
u15_f_fc_ri_04	Capacitive	5	4
u15_f_fo_ri_03	Optical	3	2
u16_f_fc_ri_04	Capacitive	5	5
u16_f_ft_rm_03	Thermal	5	4
u17_f_fo_lm_02	Optical	2	1
u17_f_ft_lm_04	Thermal	2	2

The set of fake fingerprint images which are of optical, thermal and capacitive sensors are taken from “ATVS-Fake Fingerprint Database (ATVS-FFp DB)” [2]. The proposed M-TLBO Fingerprint Image Enhancement Algorithm is applied on these very low quality fingerprints. Many experiments are conducted to test the quality of the fingerprints before and after the enhancement. In [Table-1], the results are presented for 32 sample images and this same sample set is used for presenting various experimental findings throughout this paper.

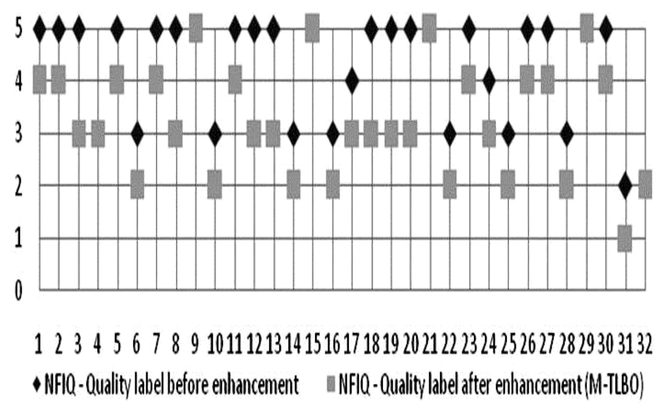

Fig. 2- NFIQ Quality labels of fingerprints - before and after M-TLBO enhancement

The improvement in the quality of fingerprint images after applying the proposed M-TLBO enhancement can be observed from [Table-1] and graph in [Fig-2]. In the graph, the X-axis shows the fingerprint images and Y-axis shows the quality label. Experiments are conducted on fingerprint images that are obtained from different scanners / sensors. Taking fingerprints from different sensors simulate different acquisition conditions at crime location. Independent graphs have been plotted for three types of scanners with 250 images for each of three sensors as input and results are plotted as graphs. It can be observed from the graphs in [Fig-3] to [Fig-5] that after applying the M-TLBO Fingerprint Image Enhancement Algorithm, even the quality of poor fake fingerprint images is also increased. After applying the proposed enhancement, the total number of fingerprint images with poor quality is decreased and the total number of fingerprint images with better quality is increased.

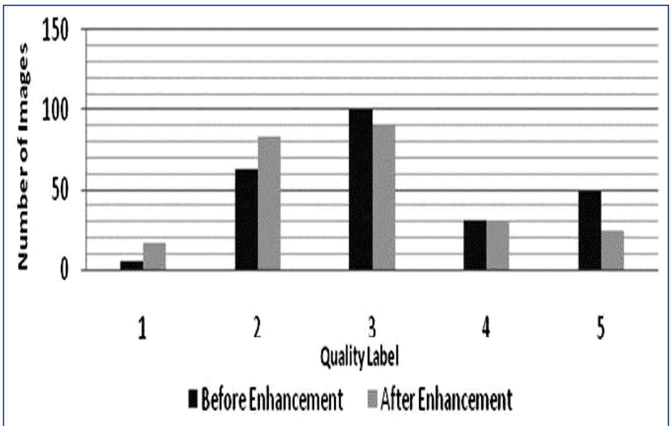

Fig. 3- NFIQ Quality labels of fingerprints (Optical Sensor) - before and after M-TLBO enhancement

The results obtained in this work are compared with the results of various existing image enhancement techniques in the literature such as Median Filter [17], Weiner Filter [18], Contrast Limited Adaptive Histogram Equalization (CLAHE) [19], adaptive bilateral filter (ABF) [8]. The results are presented in terms of quality improvement and Robustness Index on a same sample set of 32 fingerprint images of ATVS-FFp DB database. Most of the codes of these existing techniques are freely available at http://www.mathworks.in. In the present work, a lot of effort is invested to apply these codes (with required editing as per the need) on the huge fingerprint dataset for comparative result analysis.

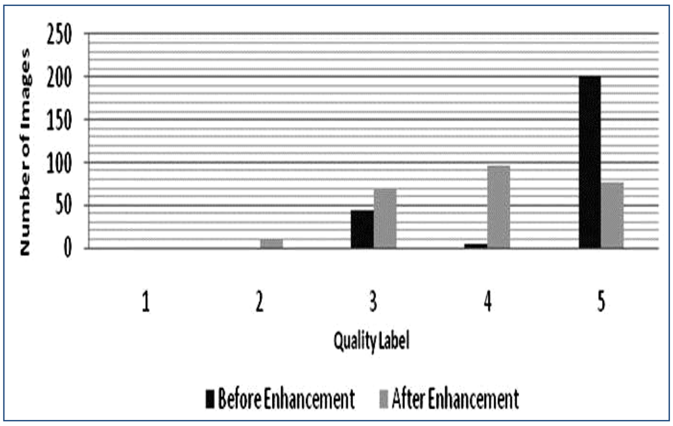

Fig. 4- NFIQ Quality labels of fingerprints (Capacitive Sensor) - before and after M-TLBO enhancement

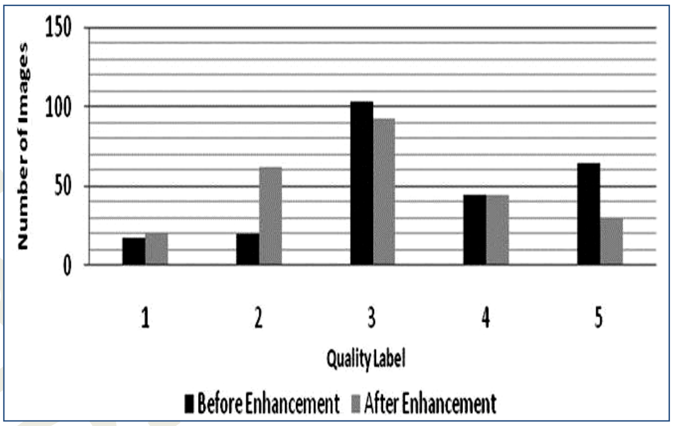

Fig. 5- NFIQ Quality labels of fingerprints (Thermal Sensor) - before and after M-TLBO enhancement

Table 2- Comparative Results of NFIQ Quality labels of fingerprints before and after enhancement (M-TLBO & other techniques)

Before Applying Enhancement	After Weiner Filter	After Median Filter	After CLAHE	After ABF	After M-TLBO Enhancement
5	5	5	5	5	4
5	5	5	5	5	4
5	5	5	5	4	3
3	3	3	3	3	3
5	5	5	4	4	4
3	3	3	3	3	2
5	5	5	5	4	4
5	5	5	5	4	3
5	5	5	5	5	5
3	3	3	3	3	2
5	5	5	5	5	4
5	5	5	4	4	3
5	5	5	5	5	3
3	3	3	3	3	2
5	5	5	5	5	5
3	3	3	3	3	2
4	4	4	4	4	3
5	5	5	4	4	3
5	5	5	5	5	3
5	5	5	5	5	3

Table 2- Continues

Before Applying Enhancement	After Weiner Filter	After Median Filter	After CLAHE	After ABF	After M-TLBO Enhancement
5	5	5	5	5	5
3	3	3	3	3	2
5	5	5	5	5	4
4	4	4	4	4	3
3	3	3	3	3	2
5	5	5	5	5	4
5	5	5	5	5	4
3	3	3	3	3	2
5	5	5	5	5	5
5	5	5	5	5	4
2	2	2	2	2	1
2	2	2	2	2	2

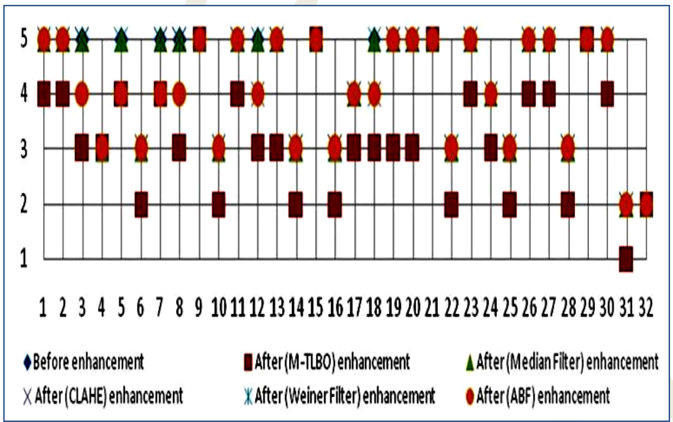

Fig. 6- Comparative Results of NFIQ Quality labels of fingerprints before and after enhancement (M-TLBO & other techniques)

Label-1 indicates the BEST and Label-5 indicates the WORST. It can be observed from the [Table-2] and graph in [Fig-6] that the proposed method out performs the existing techniques in eliminating the noise from the fingerprint image. This method does not conclude total fingerprint enhancement task but these results are presented to show, how the fingerprint quality can be improved after eliminating the noise using proposed enhancement technique. It is understandable that at this juncture the results of the proposed method are not compared with some of the typical fingerprint image enhancement techniques. The work that is presented in this paper is extended applying filtering operations.

Evaluation Using Robustness Index

The performance and effectiveness of the proposed Enhancement method is assessed using Robustness Index. Poor quality fake fingerprints and corresponding real fingerprints are taken from (ATVS-FFp DB) dataset. Two tests are carried out in calculating R.I. In the first test, R.I is calculated between unenhanced poor quality fake fingerprint and corresponding real (original) fingerprint image. In the second test, after enhancement, the Robustness Index (R.I) is calculated between enhanced fake fingerprint image and corresponding real fingerprint image.

Procedure to Calculate Robustness Index (R.I.)

Let $\{g^1, g^2 \ldots g^u\}$ be the set of minutiae detected in the fake fingerprint image before enhancement.

Let $\{h^1, h^2 \ldots h^u\}$ be the set of minutiae detected in the corresponding real / original fingerprint image.

Compute '*p*' as the number of paired minutiae between the two sets.

Minutiae $g^i = (i = 1,\ldots\ldots, u)$ and h^j $(j = 1,\ldots\ldots\ldots, v)$ are said to be paired if their distances in position and orientation are within a tolerance bound of 18 pixels and 30 degrees, respectively.

The robustness index (*RI*) is computed as

$$RI = \frac{P}{u + v - p}$$

where $u + v$ represents the total number of detected minutiae in both the sets.

The obtained value gives the R.I of the first test (between unenhanced fake fingerprint and corresponding real fingerprint image).

The same procedure is performed in the second test between fake fingerprint image after enhancement and corresponding real / original image. In both the tests, R.I is calculated once after the false minutiae are removed using modified fuzzy rules from the extracted minutiae [12]. The tolerance bound is taken higher than the normal case because the R.I calculation is done between poor quality fake fingerprints and corresponding real fingerprints. So it may be a reasonable consideration. A low R.I value indicates large variance in the number of minutiae detected in two images and hence reflects poor image quality. On the contrary, high R.I value indicates consistency in minutiae extraction in two images and consequently it reflects good image quality.

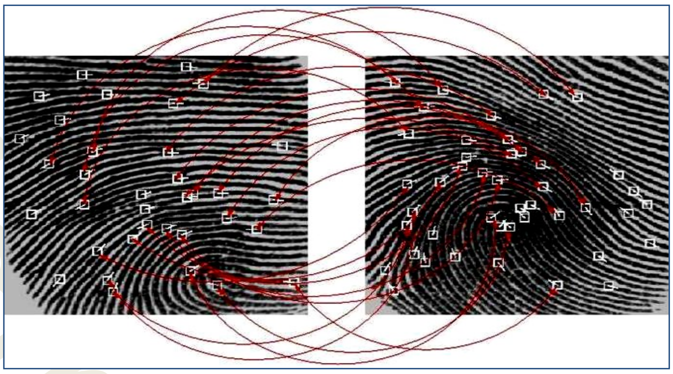

Fig. 7- Sample Picture: Pairing of Minutiae between Fingerprints

Various experiments are conducted on the fake and real fingerprint data set of ATVS-FakeFingerprint Database (ATVS-FFp DB). Some sample results are tabulated in [Table-3] and plotted on the graph in [Fig-8]. The same randomly selected 32 sample set is used in presenting various experimental findings in the present work to facilitate better results analysis.

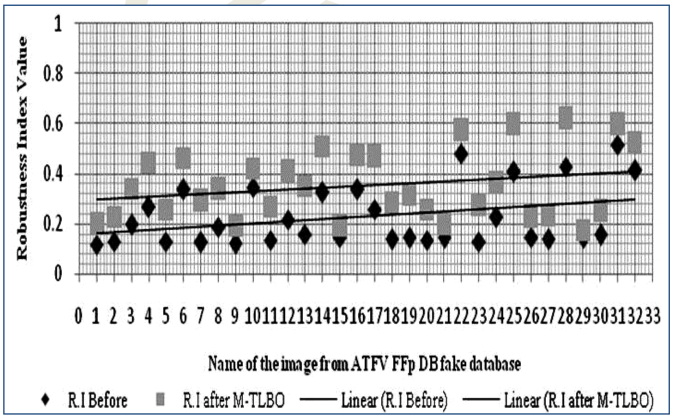

Fig. 8- Robustness Index (R.I): Before and after M-TLBO enhancement

Table 3- Robustness Index (R.I): Before and after M-TLBO enhancement

Sample Fingerprints of ATVS-FFp DB	Robustness Index between Original & Unenhanced Fake Image	Robustness Index between Original & Enhanced Fake Image
u01_f_fc_li_01	0.117	0.197
u01_f_ft_rm_04	0.129	0.228
u02_f_fo_li_03	0.198	0.339
u02_f_ft_ri_01	0.268	0.446
u03_f_fc_rm_04	0.128	0.257
u03_f_ft_lm_04	0.337	0.464
u04_f_fc_li_02	0.125	0.291
u04_f_fo_rm_02	0.187	0.337
u05_f_fc_ri_03	0.122	0.193
u05_f_ft_rm_01	0.347	0.423
u06_f_fc_rm_03	0.135	0.269
u06_f_fo_ri_04	0.218	0.406
u07_f_fc_li_01	0.159	0.353
u07_f_ft_li_01	0.327	0.511
u08_f_fc_lm_04	0.146	0.191
u08_f_ft_ri_04	0.338	0.476
u09_f_fo_rm_03	0.257	0.468
u09_f_ft_ri_03	0.137	0.287
u10_f_fc_lm_04	0.145	0.315
u10_f_ft_ri_02	0.135	0.258
u11_f_fc_lm_02	0.145	0.198
u11_f_fo_li_04	0.482	0.571
u12_f_fc_rm_02	0.129	0.276
u12_f_ft_rm_02	0.225	0.362
u13_f_fo_rm_01	0.409	0.594
u13_f_ft_lm_04	0.146	0.227
u15_f_fc_ri_04	0.139	0.231
u15_f_fo_ri_03	0.428	0.618
u16_f_fc_ri_04	0.145	0.175
u16_f_ft_rm_03	0.157	0.248
u17_f_fo_lm_02	0.515	0.597
u17_f_ft_lm_04	*0.414*	*0.528*

It can be clearly observed from the graph in [Table-3] and [Fig-8] that there is a significant increase in the Robustness Index after the enhancement of fingerprint images with the proposed enhancement methodology.

Some sample comparative results with respect to the Robustness Index of proposed enhancement technique with other enhancement techniques are presented on the same sample fingerprint data set of ATVS-FFp DB.

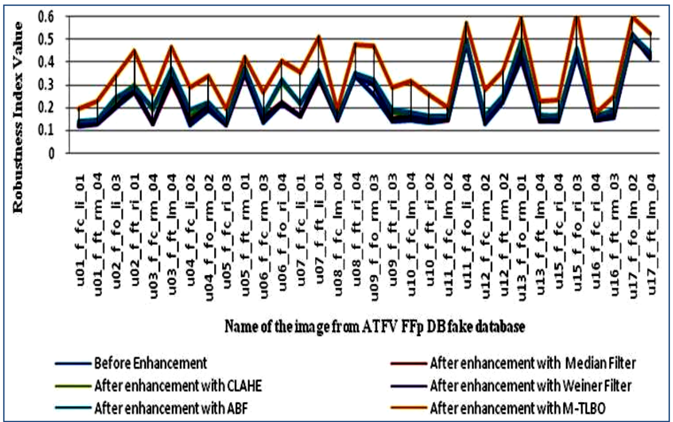

Fig. 9- Comparative results of Robustness Index: - before and after enhancement (M-TLBO & other existing techniques)

The results in [Fig-9], [Table-4] show that the Robustness Index after applying the proposed M-TLBO enhancement is always higher than the other existing image enhancement techniques. So it can be concluded that the proposed methodology of Fingerprint Image enhancement performs better than the existing techniques. A very important observation to be made here is that there is a clear correlation between the NFIQ quality labels of the fingerprint images and the calculated Robustness Index (R.I). This indicates that the verification performance highly depends on the quality of the input fingerprint image.

Table 4- Comparative results of Robustness Index: before and after enhancement (M-TLBO & other existing techniques)

Sample Fingerprints - ATVS-FFp DB	Before	Weiner Filter	Median Filter	CLAHE	ABF	M-TLBO
u01_f_fc_li_01	0.117	0.122	0.128	0.13	0.139	0.197
u01_f_ft_rm_04	0.129	0.129	0.131	0.139	0.146	0.228
u02_f_fo_li_03	0.198	0.201	0.208	0.232	0.243	0.339
u02_f_ft_ri_01	0.268	0.29	0.279	0.301	0.291	0.446
u03_f_fc_rm_04	0.128	0.127	0.131	0.191	0.198	0.257
u03_f_ft_lm_04	0.337	0.329	0.313	0.356	0.369	0.464
u04_f_fc_li_02	0.125	0.142	0.148	0.159	0.191	0.291
u04_f_fo_rm_02	0.187	0.204	0.209	0.213	0.221	0.337
u05_f_fc_ri_03	0.122	0.13	0.131	0.139	0.142	0.193
u05_f_ft_rm_01	0.347	0.354	0.349	0.373	0.378	0.423
u06_f_fc_rm_03	0.135	0.151	0.157	0.166	0.171	0.269
u06_f_fo_ri_04	0.218	0.219	0.223	0.312	0.319	0.406
u07_f_fc_li_01	0.159	0.163	0.162	0.218	0.215	0.353
u07_f_ft_li_01	0.327	0.349	0.331	0.341	0.359	0.511
u08_f_fc_lm_04	0.146	0.147	0.15	0.153	0.158	0.191
u08_f_ft_ri_04	0.338	0.343	0.341	0.347	0.351	0.476
u09_f_fo_rm_03	0.257	0.298	0.306	0.317	0.321	0.468
u09_f_ft_ri_03	0.137	0.143	0.151	0.177	0.191	0.287
u10_f_fc_lm_04	0.145	0.158	0.165	0.171	0.178	0.315
u10_f_ft_ri_02	0.135	0.146	0.154	0.159	0.164	0.258
u11_f_fc_lm_02	0.145	0.148	0.144	0.157	0.161	0.198
u11_f_fo_li_04	0.482	0.489	0.493	0.495	0.499	0.571
u12_f_fc_rm_02	0.129	0.148	0.154	0.161	0.163	0.276
u12_f_ft_rm_02	0.225	0.231	0.238	0.245	0.252	0.362
u13_f_fo_rm_01	0.409	0.422	0.441	0.497	0.488	0.594
u13_f_ft_lm_04	0.146	0.137	0.146	0.156	0.167	0.227
u15_f_fc_ri_04	0.139	0.147	0.151	0.165	0.164	0.231
u15_f_fo_ri_03	0.428	0.435	0.448	0.457	0.461	0.618
u16_f_fc_ri_04	0.145	0.147	0.154	0.159	0.161	0.175
u16_f_ft_rm_03	0.157	0.161	0.167	0.174	0.189	0.248
u17_f_fo_lm_02	0.515	0.521	0.505	0.519	0.512	0.597
u17_f_ft_lm_04	*0.414*	*0.423*	*0.432*	*0.439*	*0.445*	*0.528*

Evaluation based on Verification performance

The effectiveness of the enhancement process is also evaluated using BOZORTH3, a fingerprint matching system, which is the second export controlled package of NBIS (available at http://fingerprint.nist.gov). It uses the minutiae detected by MINDTCT (a minutiae detection system of NBIS) to determine if two fingerprints are from the same finger. The BOZORTH3 matcher uses only the location (x,y) and orientation (theta) of the minutia points to match the fingerprints. The matcher is rotation and translation invariant.

During experiments a lot of effort is spent to examine the efficacy of the proposed enhancement technique in terms of verification performance. The experimental findings with respect to the verification performance on the standard fingerprint dataset, collected from FVC 2002 of MSU are presented. The proposed enhancement technique is evaluated on a set of 800 images (100 fingers, 8 images each from DB3_A) derived from FVC2002.

The following two matching attempts have been made:

Genuine Recognition attempts: The template of each impression is matched against the remaining impressions of the same finger, but avoiding symmetric matches (i.e. if the template of impression *'i'* was matched against impression *'j'* then template *'j'* was not matched against impression 'i').

Impostor Recognition Attempts: the template of the first impression of each finger is matched against the first impressions of the remaining fingers, but symmetric matches were avoided. (This is done as per the test protocol of FVC 2002).

During genuine matching attempt, each fingerprint impression is matched against the remaining impressions of the same finger (symmetric matches were avoided). So the total number of genuine comparisons are 2800. Similarly during impostor matching attempt, the first impression of each finger is matched against the first impression of remaining fingers (avoided symmetric matches). So the total number of impostor matching attempts are 4950.

The overall matching performance is presented by the ROC curve, which is presented in [Fig-10]. The improvements in the verification performance after applying the proposed enhancement technique can be observed. The verification performance through PSO with the transformation function in equation (2) [7] is also presented. The results prove M-TLBO performs better than existing techniques.

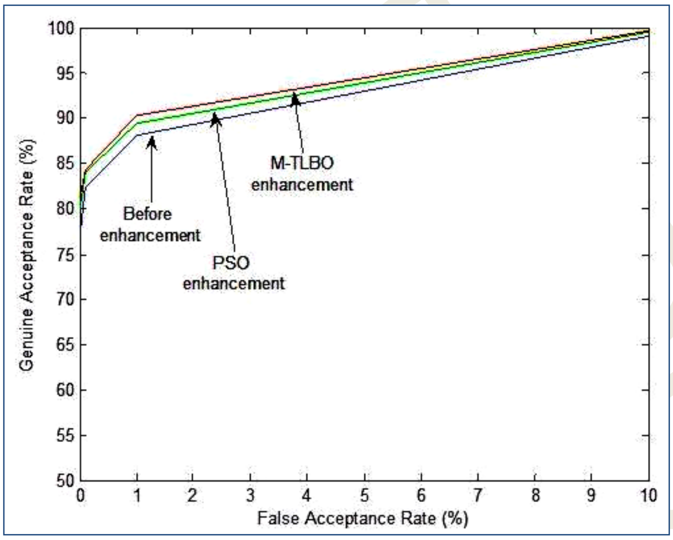

Fig. 10- ROC curves before and after M-TLBO enhancement

It can be noted that in this paper only image enhancement is done to remove noise from the fingerprint image but filtering operations can be performed on these enhanced images to further enhancement. The results obtained at this stage of experimentations demonstrate that verification performance can be increased by eliminating the noise from the fingerprint image. Initially in the present work, the verification performance is evaluated using, "fingerprint authentication system using traditional Euclidian distance and SVD algorithm" [20] which was developed by the researcher. But because Bozorth3 is a standard matching system of reputed international organization, NIST, the final results are verified using Bozorth3 of NBIS and reported.

Conclusions

A new parameterized Transformation Function is designed and applied on the Fingerprint Image. The latest Teaching Learning Based Optimization has been implemented as M-TLBO for optimizing the transformation function for effective enhancement of fingerprint Image. With the achieved results it can be concluded that M-TLBO can also be used to enhance the fingerprint image effectively. By increasing the number of learners and number of iterations, even better results may be achieved. The newly designed transformation function has also been proved to work effectively for enhancing poor quality fingerprint image. The enhanced fingerprint image can be further enhanced through filtering techniques that includes ridge orientation and frequency estimation. This completes the entire fingerprint enhancement process. Filtering is not included in the present work, because the objective is to show the improvement in the quality of fingerprint image, just by eliminating noise.

Conflicts of Interest: None declared.

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