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DESIGN OF NEW PARAMETERIZED TRANSFORMATION FUNCTIONS AND MULTI OBJECTIVE CRITERION FOR FINGERPRINT IMAGE ENHANCEMENT

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Abstract- Extracting minutiae features out of poor quality fingerprints is the most challenging problem and it is extremely difficult for the automated system to accurately classify poor quality fingerprints and reliably locate the minutiae in such fingerprint images. In the present work, some image enhancement techniques are employed in order to obtain reliable estimates of minutiae locations prior to minutiae extraction.

For the task of image enhancement some parameterized transformation functions were designed, which use local and global information of the image. Some novel optimization techniques like Modified Teaching Learning Based Optimization (M-TLBO), Modified Harmony Search (M-HS), Particle Swarm Optimization, Simple League Championship Algorithm (SLCA) were used to control and change the parameters in each transformation function which is applied on the poor quality fingerprint images to remove noise. A multi objective criterion is proposed to evaluate the rate of enhancement at each step in the enhancement process. The proposed technique outperforms the other existing noise elimination techniques.

Keywords- Image enhancement, Minutiae, Objective criterion, Optimization techniques, Transformation function

Introduction

The performance of any fingerprint extraction and matching algorithm depends upon the quality of the input image and qualitative extraction of minutiae. However, in practice, a fingerprint image is not always well defined due to elements of noise which may corrupt the clarity of the ridge structures. More so these images get degraded and corrupted due to variations in skin and impression conditions. Thus it is very important to employ image enhancement techniques prior to minutiae extraction in order to obtain a good number of reliable estimates of minutiae locations.

For fingerprint image enhancement task, a transformation function is needed that takes the intensity value of each pixel from the input fingerprint image and generates a new intensity value for the corresponding pixel to obtain the enhanced fingerprint image. And to evaluate the quality of enhanced fingerprint image automatically, an evaluation function is needed which tells about the quality of the enhanced fingerprint image.

In the present work some parameterized transformation functions are designed, which uses local and global information of the image and thereby enhance the image and facilitate qualitative extraction of minutiae. The best possible enhancement was attempted by using a multi-objective criterion. The enhancement is proposed by optimizing the parameters to be used in the transformation function with the help of a suitable optimization technique as examined in the present work.

Design of New Transformation Functions

Image enhancement, which is done on spatial domain uses a transform function that generates a new intensity value for each pixel of the M X N original image to generate the enhanced image, where M and N denotes the number of columns and the number of rows respectively. In other words, local enhancement model apply transformation functions that are based on the gray-level distribution in the neighborhood of each pixel in the given image.

In image processing, the simplest statistical measures of a random variable are its mean and variance [1]. These are the reasonable parameters to be considered to design an adaptive filter because they are the quantifiers that are closely related to the appearance of an image. The mean gives the measure of average gray level in the region over which it is computed, and the variance gives a measure of average contrast or difference in that region.

In the traditional enhancement technique, enhancement takes place at each pixel at location (*i, j*) using the following transformation function [2]:

$$g(i,j) = \left[\frac{G}{\sigma(i,j)}\right][f(i,j) - m(i,j)] \qquad (1)$$

where *m (i,j)* is the mean *(i,j)* is the centroid and σ (*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 [Eq-1] is modified by including four parameters a, b, c, d to convert into a parameterized transformation function. And the resultant transformation function looks as follows:

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

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]. And they are controlled by an optimization technique.

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

$$m(i,j) = \left[\frac{1}{n \times n}\right] \sum_{x=0}^{n-1} \sum_{y=0}^{n-1} f(x,y) \qquad (3)$$

σ(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:

$$\sigma(i,j) = \left[\frac{1}{M \times N}\right] \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i,j) \qquad (4)$$

Comparing [Eq-1] to [Eq-2], the transformation function in [Eq-1], the values of the parameters are taken as b=0, c=1, d=1 and the term 'm(i, j)a' is taken as 0. In [Eq-2], value of b is not '0', and this prevents the Not A Number (NAN) values. In the new transformation function, only a fraction of the mean is subtracted from the pixel's input gray-level intensity value because 'c' is not equal to '1', while the last term may have the effect of brightening and smoothing the image. This new transformation function broadens the spectrum of the transformation output range. This new transformation function in [Eq-2] is used with the optimization technique PSO.

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. Though there are various filters that were proposed in the literature for fingerprint image enhancement for effective extraction of minutiae points, almost all the filters failed to work properly on the noisy fingerprint images. So eliminating noise from a fingerprint image should be prelude in fingerprint image enhancement.

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 [3,4] were proposed to address this problem. Zhang and Allebach [5] have proposed the Adaptive Bilateral Filter (ABF) in order to realize the noise removing and edge enhancement at the same time. The conventional Bilateral Filter (BF) combines range and domain filters based on Gaussian kernels. In ABF, range filter is changed depending on the output of Laplacian of Gaussian (LoG) operation. While, LoG operation detects edges from noisy images, ABF removes noise while enhancing 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

$$g(i,j) = \mathrm{d} \times ((\sigma_{\eta}^{2}(\mathrm{i},\mathrm{j}) / \sigma_{\mathrm{L}}^{2}(\mathrm{i},\mathrm{j}) + \mathrm{b}))[\mathrm{f}(\mathrm{i},\mathrm{j}) - \mathrm{c} \times \mathrm{m}(\mathrm{i},\mathrm{j})] + \mathrm{m}(\mathrm{i},\mathrm{j})\alpha \qquad (6)$$

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 an *nxn* window which is defined as in [Eq-3].

$\sigma_L^2(I,j)$ is the local variance of (i,j)th pixel of the input fingerprint image over an *nxn* window

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

and $\sigma_\eta^2(I,j)$, is the global variance of image and which is defined as:

$$\sigma_n(i,j) = \left[\frac{1}{M \times N}\right] \sum_{x=0}^{M} \sum_{y=0}^{N} (f(x,y) - m(i,j))^2 \qquad (8)$$

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 *nxn* 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 *nxn* at each location (i, j) on which the filter window is centered. A tacit assumption in the above equation is that $\sigma_\eta^2 \le \sigma_L^2$. The noise in this model is additive and position independent, so this is reasonable assumption to make because *nxn* is a subset of *g(i, j)* [1].

However having exact knowledge of σ_η^2 is very rare. Therefore it is possible for this condition to be violated in practice. For that reason, a test should be built into an implementation of the above equation 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 non-sensical 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. In the present work, this new transformation function in [Eq-6] is with Modified Teaching Learning Based Optimization (M-TLBO).

Using the same constraints that are described above, a third transformation function is designed, which has been derived from the traditional adaptive transformation function in [Eq-9] [1].

$$g(i,j) = f(i,j) - \frac{\sigma_\eta^2}{\sigma_L^2}[f(i,j) - m(i,j)] \qquad (9)$$

This is the traditional enhancement technique where the above equation is applied to each pixel at location (i, j). The mean and local variance are computed in a neighborhood centered at (i, j). Therefore they are dependent on the local information.

Four parameters have been introduced into [Eq-9] to transform the traditional adaptive transformation function into a parameterized transformation function. The proposed enhancement model is applied to each pixel at location *(i, j)*. This new transformation function looks as follows:

$$g(i,j) = f(i,j) - d \times ((\sigma_{\eta}^{2}(i,j) / \sigma_{L}^{2}(i,j) + b))[f(i,j) - c \times m(i,j)] + m(i,j)\alpha \quad (10)$$

where all the terms in the above equation are same as described for the [Eq-6]. The behavior of the traditional filter (transforma tion function) in [Eq-9] is supposed to be as follows:

- If σ_{η}^2 is zero, the filter should return simply the value of *f(i, j)*. This is the trivial, zero-noise case in which f*(i, j)* is equal to g*(i,j)*.
- If the local variance is high relative to σ_{η}^2, the filter should return a value close to f*(i, j)*. A high local variance typically associated with edges, and those edges need to be preserved.
- If the two variances are equal, then the filter will return the arithmetic mean value of the pixel in *nxn* window. This condition occurs when the local area has the same properties as the overall image, and local noise will be reduced simply by averaging.

But these points are not true with the modified transformation functions. First of all it is impossible to get the global variance zero with fingerprint image. The other two points are also not completely true with the new transformation function because of the new parameters that were introduced. But by controlling these parameters with an optimization technique, the new transformation function does produce more optimal enhancement result than the traditional method. This new transformation function in [Eq-10] is used with Modified Harmony Search (M-HS).

These three transformation functions are used to enhance the fingerprint image, with the help of different optimization techniques, which control the parameters values (a, b, c, d) to achieve optimal enhancement. Different optimization techniques that are investigated for the purpose are presented in the next two chapters.

Evaluation 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. There are few objective functions presented in the literature [6,7,8,9] that describe the quality of an image but limited literature is available about the objective function to evaluate the quality of an image at the run time during the enhancement process. In this present work, two objective functions are used to form a multi objective criterion in order to evaluate the rate of enhancement at each step / iteration during the enhancement process.

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 [1] and a higher intensity of the edges [6]. 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, because having more number of edges and high intensity of edges simply does not guaranty high quality of fingerprint image. 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)' [10] 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-11], can be a good choice for an objective criterion:

$$Fit(X) = H(g(X) + \log(\log(I(g_e(X))))) \times \frac{g_e(X)}{MXN} \quad (11)$$

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 [11]. $I(g_e(X))$ is the intensity of the edges detected with a Sobel edge detector that is applied to the transformed image *g(X)* [12], 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:

$$H(g(X)) = -\sum_{i=0}^{225} e_i$$

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 i^{th} intensity value of g(i, j) image.

It can be noted in the fitness function in [Eq-11] 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 techniques try to find a solution '*X*' that maximizes the fitness value.

After many experiments on the huge fingerprint databases collected from "Biometrics Ideal Test (BIT)" [13] and FVC 2002 of MSU [14], 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 [Eq-11], 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 Ratio (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

$$PSNR = 10 \times \log_{10}(b^2/MSE) \quad (12)$$

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

$$MSE = \frac{\sum i \sum j \left| f(i,j) - y(i,j) \right|}{N} \quad (13)$$

where 'N' is the total number of pixels. The lower value of MSE represents the lower error in the enhanced image. There are many versions of signal-to-noise ratios, but the PSNR is common in image processing, maybe because it gives better-sounding numbers than other measures. It may be noted that the greater the value of PSNR, the better the quality of the output 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.

Usually, PSNR value is calculated once the enhancement process is done to evaluate how well the noise in the image is eliminated with respect to its original image. If the PSNR value is higher, it indicates that enhanced image has more quality.

But in this present work PSNR is used as an objective function at run time. 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.

The 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.

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. The objective of the fingerprint image enhancement is to enhance fingerprint image such that enhanced fingerprint images should be suitable for qualitative extraction of minutiae. 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.

Optimization Techniques

To apply the new transformation functions on the fingerprint images, some optimization techniques are needed to control and change the parameters in the transformation functions. Three optimization techniques, namely Modified Teaching Learning Based Optimization (M-TLBO), Modified Harmony Search (M-HS) and Particle Swarm Optimization Technique (PSO) are used in the present work. Initially, PSO is used with transformation function in [Eq-2] [16], M-HS is used with transformation function in [Eq-6] and M-TLBO is used with transformation function in [Eq-10]. Later a novel optimization technique by name SLCA [15] is used with an objective of deriving combined advantages of individual techniques. All the three transformation functions and three optimization techniques were used with various combinations to get the optimal results.

Experiments and Results

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 publicly available at BIT website [13]. 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 creation of this fingerprint database is described in [17]. The fake fingerprint database contains the poorest quality fingerprints. The proposed SLCA 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 [14].

The third open source package of NBIS [10], NFIQ, is a fingerprint image quality algorithm. A fingerprint image is taken and it 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 methodology. Results were presented only for 32 sample fingerprints.

The graph in [Fig-1] shows quality labels (NFIQ) of fingerprints before and after enhancement. The quality scores of the new methodology using all the three transformation functions and three optimization techniques in various combinations with the help of Simple League Championship Algorithm as well as the scores with the application of individual optimization techniques / transformation functions are presented. It can be observed from the resulted data that the proposed new methodology always performs better than the other techniques that are used independently.

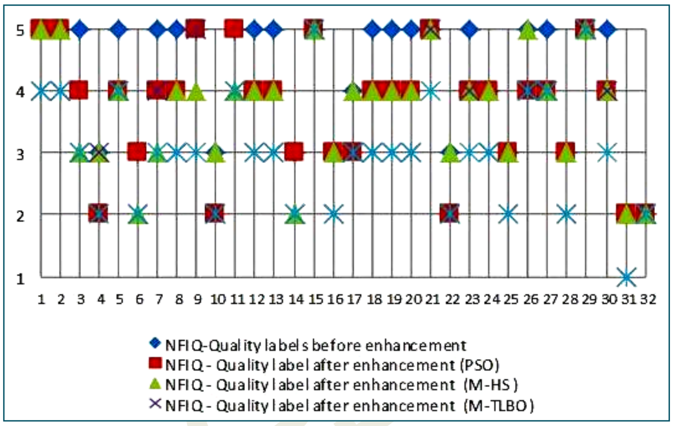

Fig. 1- Comparative Results of NFIQ Quality Labels- before and after enhancement through M-TLBO, PSO, M-HS & SLCA

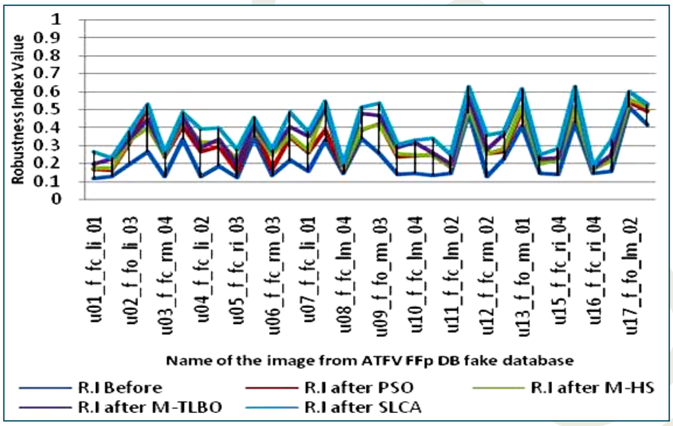

Fig. 2- Comparative results of Robustness Index: - before and after enhancement with PSO, M-TLBO, M-HS & SLCA

Some sample comparative results with respect to the Robustness Index of Proposed Enhancement Technique with SLCA and other enhancement techniques independently are presented in figure 2. The results are presented for the same sample fingerprint data set as in [15,16] for better result analysis. It can be observed from the graph in figure 2 that the Robustness Index that is obtained through the proposed SLCA technique is always higher than the other techniques. So it can be concluded that the proposed methodology of fingerprint image enhancement with SLCA works better than the various techniques independently. These results establish the efficacy of the newly proposed method of using multiple optimization techniques to solve a single optimization problem.

The experimental findings with respect to the verification performance on the standard fingerprint dataset, collected from FVC 2002 of MSU [14] are presented in [Fig-3]. The proposed enhancement technique is evaluated on a set of 800 images (100 fingers, 8 images each from DB3_A) derived from FVC2002. The total number of genuine and impostor comparisons are 2800 and 4950 respectively. Two tests are carried out. In the first test, verification is performed on the fingerprints before applying enhancement and in the second test verification is done on the fingerprints after enhancement. ROC graph can be seen in [Fig-3], where genuine acceptance rate is plotted against the false acceptance rate at different operating points.

From these experimental results, it can be observed that the performance of the verification system is further improved with the proposed image enhancement technique. The results of individual techniques with each transformation function and an optimization technique are presented and the combination of all three techniques with different optimization techniques through SLCA are also presented. It can be noted that at this stage, image enhancement is done basically to remove noise from the fingerprint image but other typical fingerprint filtering techniques have not been applied. As such, the results obtained demonstrate that verification performance can be increased by effectively eliminating the noise from fingerprint images.

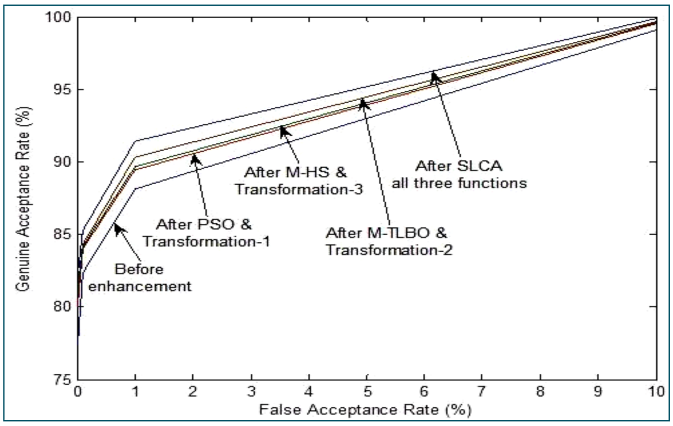

Fig. 3- ROC curves before and after enhancement on FVC 2002 DB

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