FINGERPRINT IMAGE ENHANCEMENT WITH A MODIFIED HARMONY SEARCH

M. JAMES STEPHEN

Research Scholar, Dept. of CS & SE, Andhra University, Visakhapatnam, India
jamesstephenm@yahoo.com

P.V.G.D PRASAD REDDY

Professor, Dept. of CS&SE, Andhra University, Visakhapatnam – 530 003, India
prof.prasadreddy@gmail.com

Abstract. Fingerprints that are gathered at crime location are obviously of very poor quality. This degradation can result in a significant number of spurious minutiae being created and genuine minutiae being ignored. And in other contexts also fingerprint images are rarely of perfect quality. They are degraded and corrupted with elements of noise due to many factors. Thus, it is necessary to employ image enhancement techniques prior to minutiae extraction to obtain a more reliable estimate of minutiae locations.

In this paper, a new methodology for fingerprint image enhancement is proposed where harmony search is implemented on a new parameterized transformation function. This new transformation function used local and global information of the image in the enhancement process. Entropy and Peak Signal-to-Noise Ratio (PSNR), are used as multi objective criterion for measuring the rate of enhancement at each step. 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 Harmony Search.

Keywords: minutiae extraction**,** Transformation function, fingerprint image enhancement, Harmony Search, objective criterion

1. Introduction

Fingerprint images are rarely of perfect quality. They may be degraded and corrupted with elements of noise due to many factors including variations in skin and impression conditions. This degradation can result in a significant 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 primary focus of this work is not on the fingerprints that are acquired from digital scanners. Such fingerprints are relatively of good quality. The focus of the present methods of enhancement is on poor quality fingerprints that are gathered from a physical location.

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 in [3]

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

2. The challenge & the motivation

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 extremely difficult for the automated system to accurately classify latent fingerprints and reliably locate the minutiae in the fingerprint image. Consequently, human fingerprint experts, called latent examiners, must analyze and manually mark up each latent fingerprint in preparation for matching. This is a tedious and labor intensive task.

This context gave a motivation to the present research work of enhancing poor quality fingerprint images and especially the latent fingerprints for qualitative extraction of minutiae points. It is very important to employ image enhancement techniques prior to minutiae extraction to obtain a good number of reliable estimates of minutiae locations.

3. Existing System

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 [5]. 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 [6].

There are various modifications proposed to the existing Gabor filter to enhance fingerprint image more effectively. But even Modified Gabor Filter (MGF) along with Traditional Gabor Filter (TGF) also fails when fingerprint image regions are of heavy noise [7]. 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 important 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. In fact extracting minutiae features out of the poor quality fingerprints is the most challenging problem faced in the area of fingerprint based authentication.

So, it can be concluded that in spite of decades of research in fingerprints, extracting reliable minutiae from poor quality fingerprint image has been remained as an open problem. Although many researchers, over the years have suggested various approaches to resolve this, still there are requirements for invention and improvements. Thus it has become a very important area for researchers experimenting with new methodologies for fingerprint image enhancement for reliable extraction of minutiae.

4. Proposed Methodology

In the proposed methodology, a new parameterized transformation function is designed, which uses local and global information of the image. Here Entropy and Peak Signal-to-Noise Ratio (PSNR), are used as objective criterion for measuring the rate of enhancement. Entropy value reveals the information content in the image, PSNR measures the difference between two images, i.e., between input image and enhanced image. 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 Harmony Search. So here Fingerprint image enhancement is considered as an optimization problem and Harmony Search is used to solve it.

4.1 Design of New Transformation Function

Image enhancement done on spatial domain uses a transform function which generates a new intensity value for each pixel of the MXN original image to generate the enhanced image, where M denotes the number of columns and N denotes the number of rows. 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 [8]. 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 over which the mean is computed, and the variance gives a 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 [9]:

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

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:

$$g(i,j) = [(d*G)/(\sigma(i,j)+b)][f(i,j) - c*m(i,j)] + m(i,j)^a \quad (2)$$

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 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

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

σ(i, j) are 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:

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

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

Comparing (1) to (2), in the transformation function (1), the values of the parameters are taken as constants (i.e., b=0, c=1, d=1) and the term m (i, j)^a is taken as 0. In (2), b is not equal to 0, prohibits the Not A Number (NAN) values, c is not equal to 1, allows only a fraction of the mean to be subtracted from the pixel's input gray-level intensity value, while the last term may have brighten and smooth the effects on the image. This new transformation function broadens the spectrum of the transformation output range by modifying the original equation.

4.1.1 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. So eliminating noise from a fingerprint image should be the 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 and edge enhancement are conflicting requests, thus it is difficult to realize these two requests at the same time. Zhang and Allebach [10] have proposed the adaptive bilateral filter (ABF) in order to realize the nose removing and edge enhancement at the same time. Bilateral filter (BF) combines range and domain filters based on Gaussian kernels. In ABF, range filter is changed depend on the output of

Laplacian of Gaussian (LoG) operation. Since, LoG operation can detect edges from noisy images; ABF can remove noise while enhancing edges. However, these filters work better for general image but not for fingerprint image enhancement task. Because increase in number of edges cannot be considered as if the fingerprint is enhanced, because the increase in number of edges might be the indication of spurious minutiae points in fingerprint image.

So in the present work, the aim of enhancement is 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 equation (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

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

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 equation (3)

$\sigma_L^2(i,j)$ is the local variance of (i, j) th pixel of the input fingerprint image over a *n*x*n* window

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

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

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

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. $\sigma_\eta{}^2$, 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. $\sigma_L{}^2$, the local variance of the pixels in *n*x*n* window

The behavior of the filter (transformation function) is supposed to be as follows:

- If $\sigma_\eta{}^2$ 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 $\sigma_\eta{}^2$, the filter should return a value close to f*(i, j)*. A high local variance typically associated with edges, and these should 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 is to be reduced simply by averaging.

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 $\sigma_\eta^2 <= \sigma_L^2$. The noise in this model is additive and position independent, so this is a reasonable assumption to make because *nxn* is a subset of *g(i, j)*. [8]

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 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 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.

Using the same constraints that are described above, a third transformation function is designed, which has been derived from the below traditional adaptive transformation function [8]

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

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.

The proposed enhancement model is derived from equation (9) and is applied to each pixel at location (i, j) using the following transformation:

$$g(i,j) = f(i,j) - d * ((\sigma_\eta^2 (i,j) / \sigma_L^2(i,j) + b))[f(i,j) - c * m(i,j)] + m (i,j)a \tag{10}$$

where all the terms in the above equation are same as described for the equation (3.8)

4.1.2 Objective criterion

While designing the objective function, there are certain important factors should be considered. The objective function that is used to evaluate the quality 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 weighted and must be effective in serving the purpose.

Keeping these factors into consideration, in the present work two objective functions namely ‘Entropy value’ and Peak Signal-to-Noise Ratio (PSNR) are used 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 Entropy and PSNR are calculated. If the fingerprint image is enhanced then both the Entropy value and PSNR value must have better values than before. Because two objective functions are used to evaluate the quality of fingerprint image, it is called Multi objective function or Multi objective criterion.

4.1.2.1 Entropy as objective function

It is mentioned in the 'User's Guide to NIST Biometric Image Software (NBIS)' [1] that 'A high quality region within a fingerprint image will have significant contrast that will cover the full grayscale spectrum'. So for evaluating the quality of the fingerprint image, Entropy is considered. Entropy value reveals the information content in the image. If the distribution of the intensities is uniform, then it indicates histogram is equalized and thus the entropy of the image will be more.

The entropy, $H(\mathrm{g}(\mathrm{i},\ \mathrm{j}))$ of the enhanced image g(i, j) is calculated based on histogram, as follows:

$$H(\mathrm{g}(\mathrm{i},\ \mathrm{j})) = -\sum_{i=0}^{255} e_{\mathrm{i}} \qquad (11)$$

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.

4.1.2.2 PSNR as objective function

Along with Entropy value, 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

$$\mathrm{PSNR} = 10 * \log_{10}(b^2/\mathrm{MSE}) \qquad (12)$$

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

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

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 very common in image processing, probably 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 B, which remains constant and the enhanced image is considered as A, 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 after the enhancement process is over to evaluate how well the noise in the image is eliminated with respect to its original image. If the PSNR value is higher, that indicates that enhanced image has more quality.

But in this present work PSNR is used in other manner as it is used as objective function. To calculate PSNR, two images must be given but here only input image is given for enhancement. So after generating enhanced image in the 1st step / iteration then that image is 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. Again 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 more the image is enhanced then more the Mean Square Error (MSE) between enhanced image and input Image. And if the MSE value is high then the PSNR value will be less.

5. HARMONIC SEARCH

5.1 Introduction

An interesting connection between music and finding an optimal solution to a tough design problem is found by researcher. The resulted algorithm is called Harmony Search. Harmony Search (HS) was first developed by Zong Woo Geem et al. in 2001 [4]. It is a relatively new metaheuristic algorithm, but its effectiveness has been demonstrated in various applications. This algorithm was successfully applied to solve many optimization problems including function optimization, engineering optimization [11], water distribution networks [12], groundwater modeling, energy-saving dispatch, truss design, vehicle routing, and others.

Harmony search is a music-based meta heuristic optimization algorithm. It was inspired by the thought that the aim of music is to search for a perfect state of harmony. This harmony in music is considered to be analogous to find the optimality in an optimization process. The search process in optimization can be compared to a piano musician’s improvisation process. A piano musician always intends to produce music melody with perfect harmony. On the other hand, an optimal solution to an optimization problem must be the best available solution to the problem under the given objectives and constraints. Both processes aim to produce the best or optimum.

These similarities between two processes were used to develop a new algorithm by learning from each other. Harmony Search is just such a successful example by transforming the qualitative improvisation process into some quantitative rules by idealization, and thus turning the beauty and harmony of music into an optimization procedure through search for a perfect harmony, namely, the Harmony Search (HS) or Harmony Search algorithm.

5.2 Artistic Quality of Music

To understand the fundamentals of Harmonic Search algorithm, the aesthetic quality of music must be understood. So before proceeding to the introduction of the fundamentals of HS algorithm, first the aesthetic quality of music is briefly described. Then how the HS algorithm can be used for fingerprint image enhancement is demonstrated.

The creative quality of a musical instrument is essentially determined by three components, they are

- pitch (or frequency),
- tone (or sound quality), and
- amplitude (or loudness).

Tone is largely determined by the harmonic content that is in turn determined by the waveforms or modulations of the sound signal. But the harmonics that it can generate largely depends on the pitch or frequency range of the particular instrument.

Different notes on a piano have different frequencies. For example, the note A above middle C (or standard concert A4) has a fundamental frequency of $f_0=440$ Hz. As the speed of sound in dry air is about v=331+0.6T m/s where T is the temperature in degrees Celsius near T=0. So at room temperature T=20^{0}C, the A4 note has a wavelength $\lambda=v/f_0 \approx 0.7795$ m. When the pitch is being adjusted, in fact the frequency is tried to change. In music theory, pitch p_n in MIDI is often represented as a numerical scale (a linear pitch space) using the following formula [2]

$$P_n \quad = 69 + 12 \log_2 \left(\frac{f}{440Hz}\right), \tag{14}$$

or

$$f = 440 \text{ X } 2^{\,(P_n-69)/12} \tag{15}$$

which means that the A4 notes has a pitch number 69. On this scale, octaves correspond to size 12 while semitone corresponds to size 1, which leads to that the ratio of frequencies of two notes that are an octave apart is 2:1. Thus, the frequency of a note is doubled (halved) when it raised (lowered) an octave. For example, A2 has a frequency of 110Hz while A5 has a frequency of 880Hz.

The measurement of harmony where different pitches occur simultaneously, like any creative and artistic quality, is subjective to some extent. But at the same time, it is possible to use some standard estimation for harmony. The frequency ratio, pioneered by ancient Greek mathematician Pythagoras, is a good way for such estimation. For example, the octave with a ratio of 1:2 sounds pleasant when playing together, and same with a ratio of 2:3. However, it is quite unlikely that for any random notes played by a monkey to produce a pleasant harmony.

5.3 Improvisation Process by a skillful musician

In order to explain the Harmony Search in more detail, first one needs to idealize the improvisation process by a skilled musician. When a musician is improvising, he or she has three possible choices:

(1) Play any famous piece of music (a series of pitches in harmony) exactly from his or her memory;
(2) Play something similar to a known piece (thus adjusting the pitch slightly); or
(3) Compose new or random notes.

Zong Woo Geem et al. formalized these three options into quantitative optimization process in 2001, and the three corresponding components become: usage of harmony memory, pitch adjusting, and randomization [4].

The usage of harmony memory is similar to the choice of the best-fit individuals in genetic algorithms (GA). This ensures that the best harmonies are carried over to the new harmony memory. In order to use this memory more effectively, it is typically assigned as a parameter $r_{accept} \in [0, 1]$, called harmony memory accepting or considering rate. If this rate is too low, only some best harmonies are selected and it may take more time to converge. If this rate is extremely high (near 1), almost all the harmonies are used in the harmony memory, then other harmonies are not explored well, that leads to potentially wrong solutions.

Therefore, typically, r_{accept} is used with following range [2]

$$r_{accept} = 0.7 \sim 0.95.$$

The second component is the pitch adjustment determined by a pitch bandwidth b_{range} and a pitch adjusting rate r_{pa}. Even though in music, pitch adjustment implies to change the frequencies, it corresponds to generate a slightly different solution in the Harmony Search algorithm. This is similar to use the pitch band in a piano for slight variation in the present pitch frequency. In theory, the pitch can be adjusted linearly or nonlinearly, but in practice, linear adjustment is used. So the pitch can be adjusted to get a new pitch as follows [2]

$$x_{new} = x_{old} + b_{range} * \varepsilon \tag{16}$$

where x_{old} is the existing pitch or solution from the harmony memory, and x_{new} is the new pitch after the pitch adjusting action. This produces a new solution around the existing quality solution by varying the pitch slightly by a small random amount. Here 'ε' is a random number generator in the range of [-1, 1].

Pitch adjustment is something similar to the mutation operator in genetic algorithms. A pitch-adjusting rate (r_{pa}) is assigned to control the degree of the adjustment. A low pitch adjusting rate with a narrow bandwidth can slow down the convergence of HS because the limitation in the exploration of only a small subspace of the whole search space. On the other hand, a very high pitch-adjusting rate with a wide bandwidth may cause the solution to scatter around some potential optima as in a random search.

Thus, r_{pa} is generally used in most applications in the range [2]

$$r_{pa} = 0.1 \sim 0.5$$

The third component is the randomization, which is to increase the diversity of the solutions. Although adjusting pitch has a similar role, but it is limited to certain local pitch adjustment and thus corresponds to a local search. The use of randomization can drive the system further to explore various diverse solutions so as to find the global optimality.

The three components in harmony search can be summarized as shown in the algorithm. In the algorithm, it can be seen that probability of randomization is

$$P_{\text{random}} = 1 - r_{\text{accept}}\,, \tag{17}$$

and the actual probability of adjusting pitches is

$$P_{\text{pitch}} = r_{\text{accept}} * r_{\text{pa}} \tag{18}$$

The original Harmony search [4], which is presented in the below flowchart has been modified to suit the requirement of the purpose of fingerprint image enhancement. The modified harmony search for fingerprint image enhancement is presented.

5.4 Original Harmonic Search – Flowchart

As shown in the below flowchart, the steps in the harmony search are (i) initializing harmony memory (HM); (ii) improvising a new harmony, which is nothing but generating a new candidate solution vector; (iii) updating HM with new harmony if appropriate; next step is returning to step (ii) until some termination criteria are satisfied. The improvisation of new harmonies in step (ii) involves the following three options: harmony memory considering, pitch adjusting and random playing as described earlier.

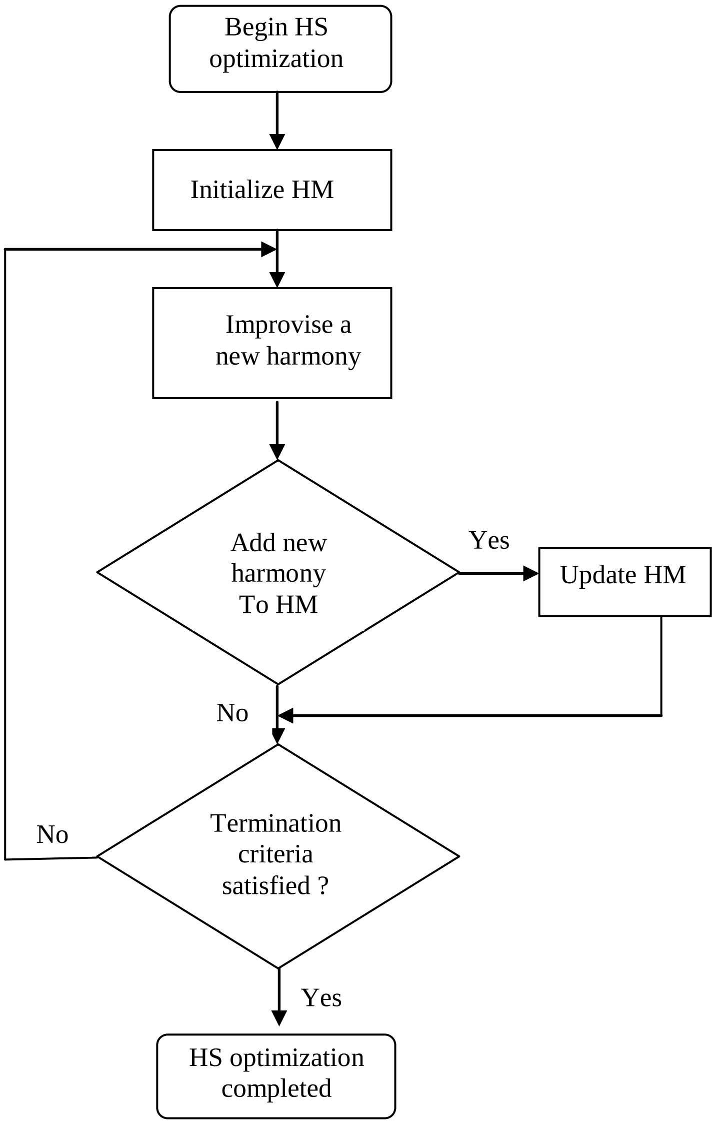

Figure 1 : Flowchart – original Harmony Search

6. Harmonic Search for Fingerprint image enhancement

The three components of the HS algorithm described in the above can easily be implemented for fingerprint image enhancement. The original HS algorithm has been tailored to suit for the purpose of fingerprint image enhancement. The initial harmonies are generated by initializing the Harmonic Memory. Here each harmony is considered as set of [a,b,c,d] values. In the present work, 24 initial harmonies are generated. The reason for generating 24 harmonies is that there are 24 different scales available in music (including major and minor scales). And these will be applied in the transformation function -3 to produce 24 enhanced images and the best will be selected based on the objective criterion. The harmonics are updated with the new harmonics as described in the below algorithm.

6.1 Harmonic Search Algorithm for Fingerprint image enhancement

Objective function – Entropy, PSNR

Step 1: Initialize Harmonic Memory (HM); Generate initial harmonics (generate 24 real number arrays in the range of [0, 1])

Step 2: Define pitch adjusting rate (r_{pa}), pitch limits and bandwidth (taken r_{pa}= 0.1 ~ 0.5)

Step 3: Define harmony memory accepting rate (r_{accept}) (taken r_{accept} = 0.7 ~ 0.95)

Step 4: while (t < Max number of iterations)

Step 5: Apply the harmonics (values of [a, b, c, d]) in the transformation function (equation (10)) to generate enhanced fingerprint images, select the best harmonics basing on the objective criterion (equations (11), (12). Generate new harmonics by accepting best harmonics

Step 6: Adjust pitch to get new harmonics (solutions) using equation (16), and generate enhanced image with this new harmonics,

Step 7: Select the best out of step 5 and step 6

Step 8: if (rand > r_{accept}), choose an existing harmonic randomly

Step 9: else if (rand > r_{pa}), adjust the pitch randomly within limits (go to step 6)

Step 10: else generate new harmonics via randomization

Step 11: Repeat step-5 to step-10 till the termination condition is reached.

In the above algorithm once the best enhanced fingerprint image is achieved through the objective criterion, and then pitch adjustment is done to change the parameters in the transformation function slightly to see that ever better enhancement can be obtained and at the same time randomization is used to search for the best in global space.

The major advantage with the proposed methodology with harmonic search algorithm is it balances both intensification and diversification. Through pitch adjustment, intensification is achieved and through randomization, diversification is achieved.

After performing this basic enhancement process with Harmonic search, the post processing steps, binarization, thinning are performed before extracting minutiae from the fingerprint image. In the present work, the crossing number method is used to extract minutiae.

7 Experimental Results

One of the highlights of the contributions in the present work is the assessment methodology and various experimental findings, are based on a large set of data from diverse subjects and acquisition conditions. Code has been developed for the above methodology on MATLAB Ver7, and implemented on Intel CORE i5 processor with 4G.B RAM.

7.1 Databases used for experiments:

The following two databases, collected from two major sources are used for various experiments in the present work.

1. "CASIA-FingerprintV5"
2. FVC 2004 from MSU

Initially the FVC 2004 databases (DB1_A , DB2_A, DB3_A, DB4_A) for various experiments to analyze and understand the performance of the proposed methodology but CASIA-FingerprintV5 is exhaustively used as this database suits well to the present work. Thus the results related to the work on this database are only presented. This database was created by the Chinese Academy of Sciences' Institute of Automation (CASIA)" - "CASIA-FingerprintV5", http://biometrics.idealtest.org/" [15], [3], [16]

A database of real and fake fingerprints was specifically created for each of the two scenarios namely: i) with a cooperative user, and ii) without the cooperation of the user. And the fingerprints were captured using three different sensors each belonging to one of the main technologies existing in the market: two flat (optical and capacitive), and one sweep sensor (thermal). The entire creation process of this database is explained in [15], [3], and [16].

Here these fake fingerprint images are considered as if they are gathered from the crime location. It is quite obvious that fingerprints that are gathered from the crime location are of very poor quality. So in this work those fake fingerprints are taken as the input to the proposed fingerprint image enhancement through HS. The advantage with this database is that the corresponding real fingerprints are also available. So the enhanced fake fingerprint's quality can be compared with the respective original fingerprint to evaluate the rate of enhancement achieved through the proposed method.

7.2 Evaluating the performance of Enhancement Technique

Various evaluation methods are used to validate the effectiveness of enhancement method that is discussed in this paper. The rate of enhancement in the enhanced image is evaluated using Robustness Index, Quality of the fingerprint image using NFIQ of NIST's BIS (NBIS). The results obtained in this work are compared with the results of various existing techniques / filters like Median Filter [18], Weiner Filter [19], Contrast Limited Adaptive Histogram Equalization (CLAHE)[20], Adaptive Bilateral Filter (ABF) [13].

7.2.1 Evaluation using NFIQ of NBIS Software of NIST:

In this section, results are presented for the proposed enhancement methodology using Harmonic Search Algorithm. First the quality labels of fingerprint images, before and after enhancement using NFIQ package of NBIS[1] are presented.

It can be observed from the below graphs that after applying the proposed Image Enhancement Algorithm, the quality of poor quality fingerprint images (input image) is considerably increased. Here again the results are presented only for 32 fingerprint images of the same sample set used for presenting various results in this work. More results presented at the end.

The set of fake fingerprint images of the optical, thermal and capacitive sensors are taken, which are of very low quality and the proposed HS Fingerprint Image Enhancement Algorithm is applied. In the below table the results are presented only for 32 images because of the space constraint. Independent graphs have been plotted for the three types of scanners with 250 images for each of three sensors as input and results are presented in graphs.

Table 1: Quality levels of the input fake image before and after enhancement along with corresponding real image quality – NFIQ of NBIS.

Image From CASIA V5 (fake database)	File Name of the database	Type of Scanner	Scores before applying HS-FIE	Scores after HS-FIE	Scores of the corresponding real image (taken from real image database)
u01_f_fc_li_01	U01 Fake	Capacitive	5	5	3
u01_f_ft_rm_04	U01Fake	Thermal	5	5	2
u02_f_fo_li_03	U02Fake	Optical	5	3	1
u02_f_ft_ri_01	U02 Fake	Thermal	3	3	3
u03_f_fc_rm_04	U03 Fake	Capacitive	5	4	3
u03_f_ft_lm_04	U03Fake	Thermal	3	2	3
u04_f_fc_li_02	U04Fake	Capacitive	5	3	3
u04_f_fo_rm_02	U04Fake	Optical	5	4	1
u05_f_fc_ri_03	U05Fake	Capacitive	5	3	2
u05_f_ft_rm_01	U05Fake	Thermal	3	3	1
u06_f_fc_rm_03	U06 Fake	Capacitive	5	4	3
u06_f_fo_ri_04	U06 Fake	Optical	5	4	1
u07_f_fc_li_01	U07Fake	Capacitive	5	4	2
u07_f_ft_li_01	U07Fake	Thermal	3	2	1
u08_f_fc_lm_04	U08Fake	Capacitive	5	5	2
u08_f_ft_ri_04	U08 Fake	Thermal	3	3	1
u09_f_fo_rm_03	U09Fake	Optical	4	4	1
u09_f_ft_ri_03	U09 Fake	Thermal	5	4	2
u10_f_fc_lm_04	U10Fake	Capacitive	5	5	1
u10_f_ft_ri_02	U10Fake	Thermal	5	4	2
u11_f_fc_lm_02	U11Fake	Capacitive	5	5	1
u11_f_fo_li_04	U11Fake	Optical	3	3	1
u12_f_fc_rm_02	U12Fake	Capacitive	5	4	3
u12_f_ft_rm_02	U12 Fake	Thermal	4	4	2

u13_f_fo_rm_01	U13Fake	Optical	3	3	1
u13_f_ft_lm_04	U13Fake	Thermal	5	5	3
u15_f_fc_ri_04	U15Fake	Capacitive	5	4	3
u15_f_fo_ri_03	U15Fake	Optical	3	3	1
u16_f_fc_ri_04	U16Fake	Capacitive	5	5	2
u16_f_ft_rm_03	U16Fake	Thermal	5	5	2
u17_f_fo_lm_02	U17Fake	Optical	2	2	1
u17_f_ft_lm_04	U17Fake	Thermal	2	2	2

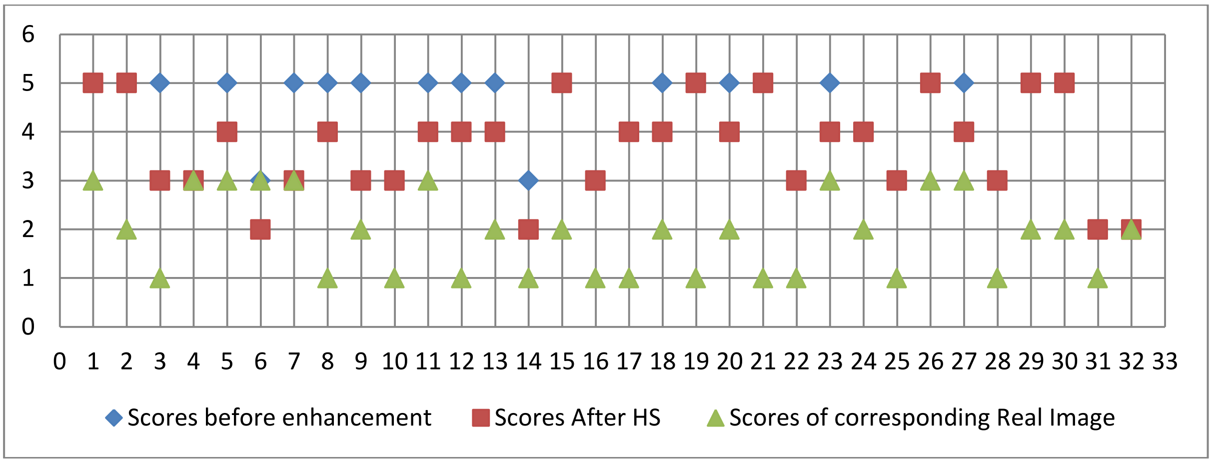

Figure 2 Quality levels of the input fake image before and after enhancement along with corresponding real image quality – NFIQ of NBIS.

It can be observed from the below graphs that after applying the HS Fingerprint Image Enhancement Algorithm, even the quality of poor fake images (input image) is considerably increased.

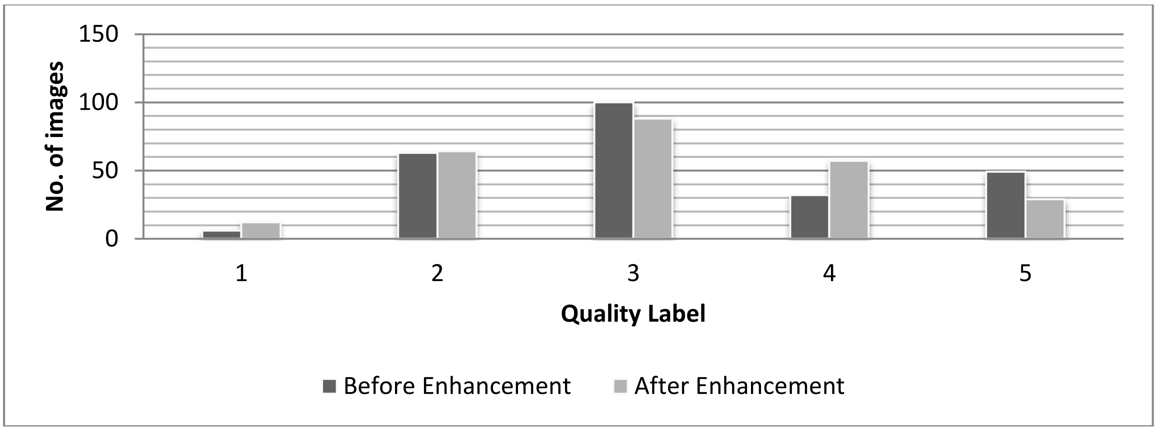

Figure 3: Quality levels of the input fake image before and after enhancement along with corresponding real image quality – NFIQ of NBIS. (Optical Sensor)

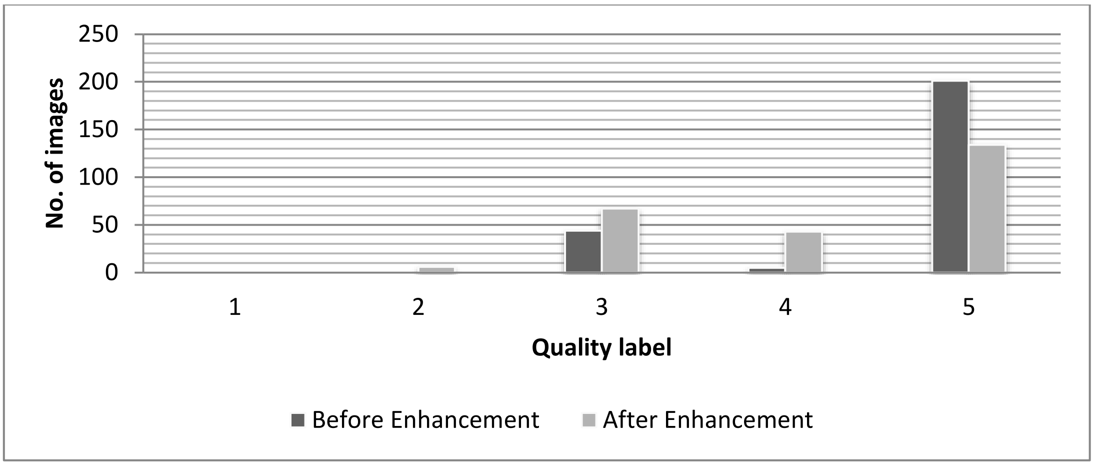

Figure 4 Quality levels of the input fake image before and after enhancement along with corresponding real image quality – NFIQ of NBIS. (Capacitive Sensor)

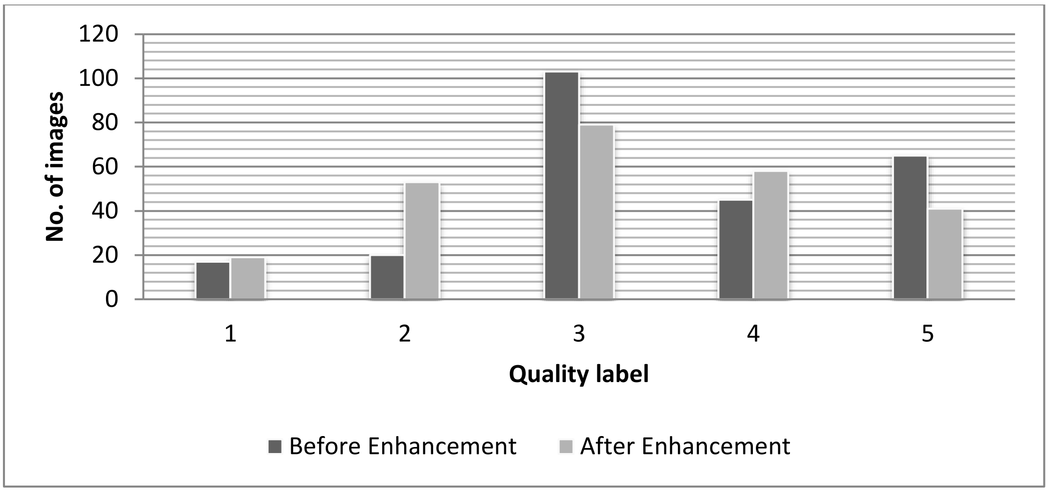

Figure 5 Quality levels of the input fake image before and after enhancement along with corresponding real image quality – NFIQ of NBIS. (Thermal Sensor)

Now some sample comparative results of Proposed Enhancement Technique with other enhancement techniques are presented on the same sample set of 32 fingerprint images which are taken above.

Table .2: Comparative Results - Quality levels of the input fake image and after various enhancement techniques along with corresponding real image quality – NFIQ of NBIS.

Image Name From CASIA (fake database)	Before Applying Enhancement	Median Filter	CLAHE	Weiner Filter	ABF	Proposed Enhancement Method	Corresponding real image (taken from real image database)
u01_f_fc_li_01	5	5	5	5	5	5	3
u01_f_ft_rm_04	5	5	5	5	4	5	2

u02_f_fo_li_03	5	5	5	5	4	3	1
u02_f_ft_ri_01	3	4	3	3	3	3	3
u03_f_fc_rm_04	5	5	4	5	5	4	3
u03_f_ft_lm_04	3	4	3	5	3	2	3
u04_f_fc_li_02	5	5	5	5	4	3	3
u04_f_fo_rm_02	5	5	5	5	4	4	1
u05_f_fc_ri_03	5	5	5	5	5	3	2
u05_f_ft_rm_01	3	5	3	3	3	3	1
u06_f_fc_rm_03	5	5	5	5	4	4	3
u06_f_fo_ri_04	5	5	4	5	3	4	1
u07_f_fc_li_01	5	5	4	5	5	4	2
u07_f_ft_li_01	3	3	3	3	3	2	1
u08_f_fc_lm_04	5	5	5	5	5	5	2
u08_f_ft_ri_04	3	4	3	5	3	3	1
u09_f_fo_rm_03	4	4	4	4	3	4	1
u09_f_ft_ri_03	5	5	5	5	4	4	2
u10_f_fc_lm_04	5	5	5	4	5	5	1
u10_f_ft_ri_02	5	5	5	5	5	4	2
u11_f_fc_lm_02	5	5	5	5	5	5	1
u11_f_fo_li_04	3	3	3	3	3	3	1
u12_f_fc_rm_02	5	5	5	5	5	4	3
u12_f_ft_rm_02	4	4	4	5	4	4	2
u13_f_fo_rm_01	3	4	3	3	3	3	1
u13_f_ft_lm_04	5	5	4	5	4	5	3
u15_f_fc_ri_04	5	5	5	5	5	4	3
u15_f_fo_ri_03	3	4	3	4	3	3	1
u16_f_fc_ri_04	5	5	5	5	5	5	2
u16_f_ft_rm_03	5	5	5	5	5	5	2
u17_f_fo_lm_02	2	5	2	4	2	2	1
u17_f_ft_lm_04	2	5	2	5	2	2	2

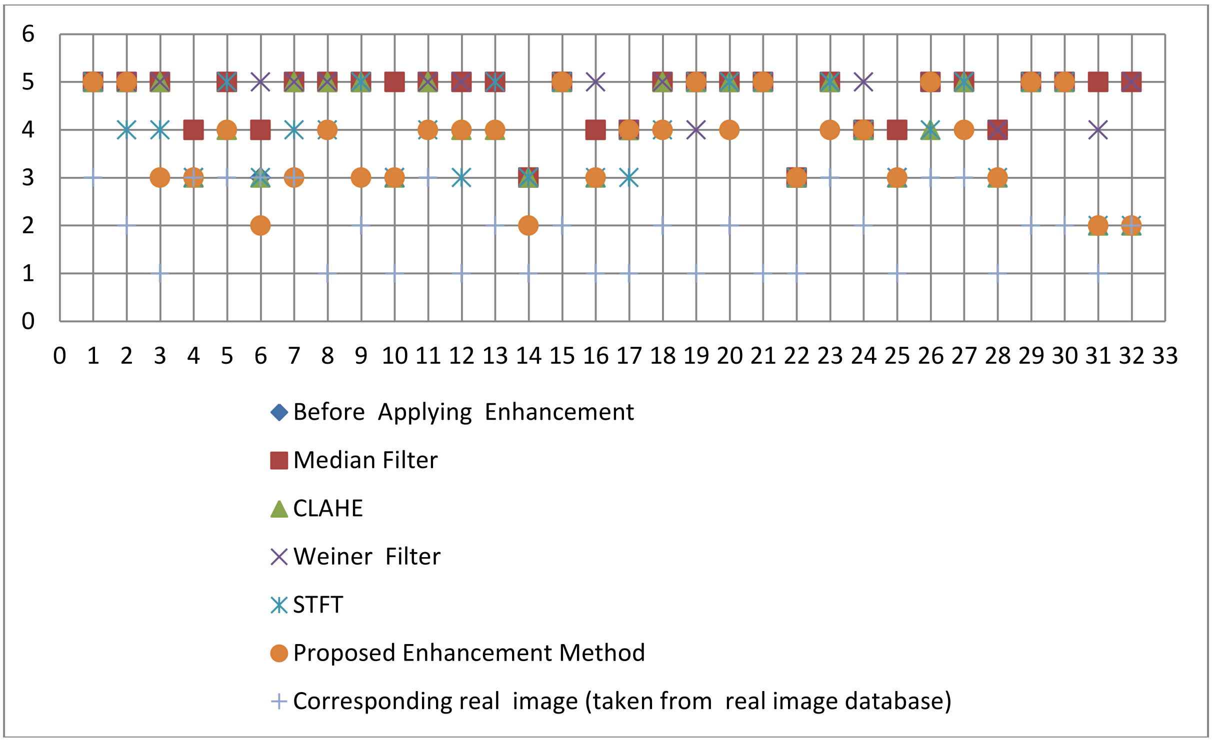

Figure 6 Comparative Results - Quality levels of the input fake image and after various enhancement techniques along with corresponding real image quality – NFIQ of NBIS. (Label-1 is the BEST and Label-5 is the WORST)

It can be observed from the above table and graph in Figure 6 that the proposed method out performs the existing techniques in eliminating the noise. Among all the techniques that are compared here, Adaptive Bilateral Filter (ABF) is of different approach; still it is observed that even it fails to work effectively when the fingerprint image is contaminated with heavy noise. This method does not conclude total fingerprint enhancement task but these results are presented to show, how the fingerprint quality is improved after eliminating the noise using proposed enhancement technique.

7.2.2 Evaluation using Robustness Index

The performance and effectiveness of the proposed Enhancement method is assessed using Robustness Index as mentioned in the below algorithm. Fake poor quality fingerprints are taken as input, after enhancement, the Robustness Index (R.I) is calculated between enhanced fingerprint image and corresponding real fingerprint image in the database of CASIA version5. The R.I is also calculated between unenhanced fake poor quality fingerprint and real fingerprint to assess the rate of enhancement.

Algorithm:

- Take the input image and apply enhancement function to get the enhanced image 'E'
- Detect Minutiae points from the enhanced image, Let A= $\{g^1, g^2 \dots g^u\}$ be the set of minutiae detected
- Detect Minutiae points from the corresponding original image, Let B= $\{h^1, h^2 \dots h^u\}$ be the set of minutiae detected
- Compute '*p*' as the number of paired minutiae in *A* and *B*:
- minutiae $g^i = (i = 1, \dots, u)$ and h^j $(j = 1, \dots, v)$ are said to be paired if their distances in position and orientation are within a tolerance bound of 10 pixels and 33 degrees, respectively.

The robustness index (*RI*) of a Fingerprint image is given by

$$RI = p / u + v - p$$

where ($u + v - p$) represents the total number of minutiae detected in both enhanced and original images.

A low *RI* value indicates large variance in the number of minutiae detected in two images and hence reflects poor image quality. On the contrary, high *RI* value indicates consistency in minutiae extraction in two images and consequently it reflects good image quality.

Same procedure is performed between Input image (before enhancement) and original image, so that we can evaluate proposed enhancement technique's performance. After enhancing the fingerprint image using proposed methodology in this paper, false minutiae is removed [14] before calculating robustness index.

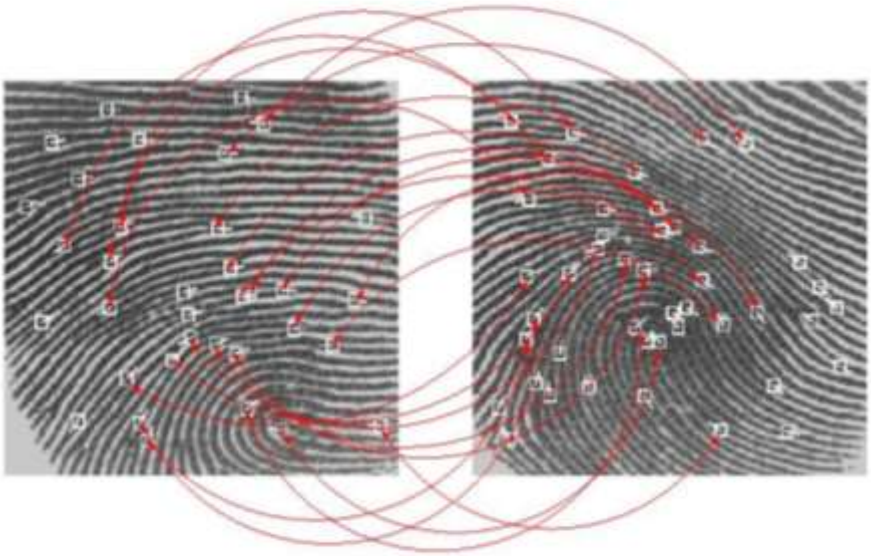

Figure 7 example: pairing of minutiae in two fingerprints to calculate R.I

These experiments are conducted on fake fingerprints data set of CASIA-FingerprintV5. The results are tabulated for randomly selected 32 sample images.

Table 3 Robustness Index: - Before and after the enhancement

Image Name	Robustness Index between Original & Unenhanced Image	Robustness Index between Original & Unenhanced Image
u01_f_fc_li_01	0.117	0.179
u01_f_ft_rm_04	0.129	0.198
u02_f_fo_li_03	0.198	0.252
u02_f_ft_ri_01	0.268	0.396
u03_f_fc_rm_04	0.128	0.259
u03_f_ft_lm_04	0.358	0.442

u04_f_fc_li_02	0.125	0.265
u04_f_fo_rm_02	0.211	0.316
u05_f_fc_ri_03	0.159	0.247
u05_f_ft_rm_01	0.347	0.396
u06_f_fc_rm_03	0.135	0.246
u06_f_fo_ri_04	0.218	0.357
u07_f_fc_li_01	0.159	0.274
u07_f_ft_li_01	0.327	0.509
u08_f_fc_lm_04	0.146	0.174
u08_f_ft_ri_04	0.338	0.362
u09_f_fo_rm_03	0.257	0.416
u09_f_ft_ri_03	0.137	0.253
u10_f_fc_lm_04	0.145	0.274
u10_f_ft_ri_02	0.135	0.283
u11_f_fc_lm_02	0.145	0.185
u11_f_fo_li_04	0.482	0.512
u12_f_fc_rm_02	0.129	0.257
u12_f_ft_rm_02	0.225	0.253
u13_f_fo_rm_01	0.509	0.518
u13_f_ft_lm_04	0.146	0.251
u15_f_fc_ri_04	0.139	0.258
u15_f_fo_ri_03	0.515	0.513
u16_f_fc_ri_04	0.145	0.169
u16_f_ft_rm_03	0.157	0.186
u17_f_fo_lm_02	0.645	0.659
u17_f_ft_lm_04	0.495	0.539

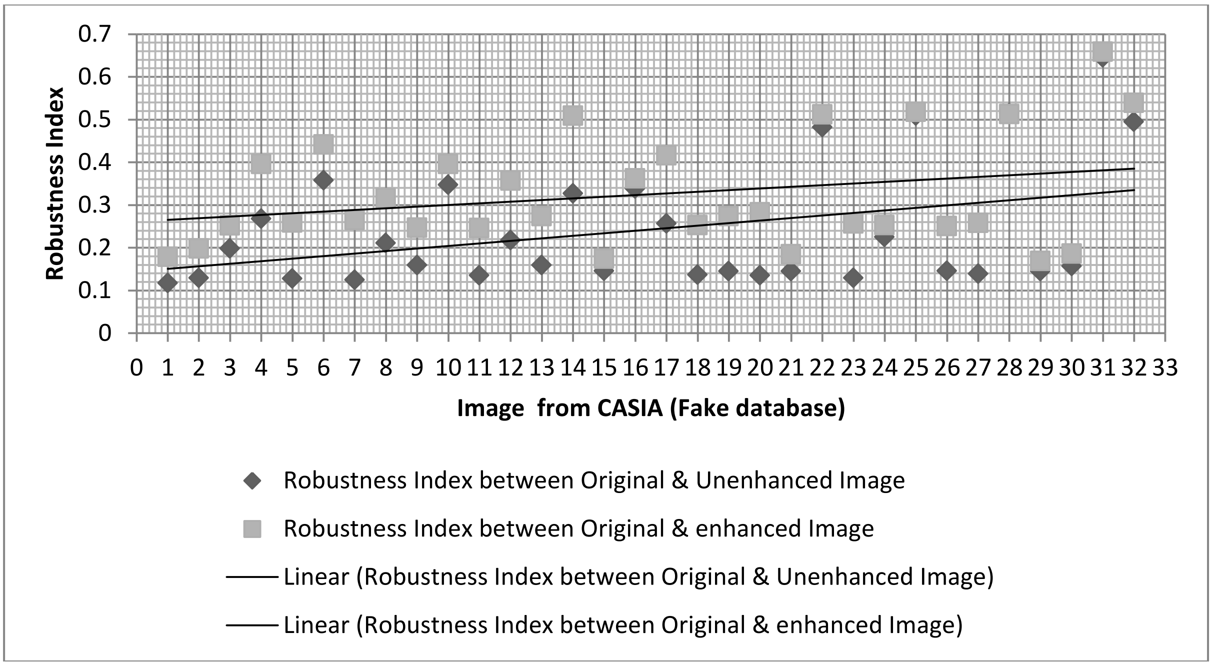

Figure 8 Robustness Index (R.I): - Before and after the enhancement

It can be clearly observed from the above graph that there is a significant increase in the Robustness Index after the enhancement of Fingerprint Image 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 for the purpose of result analysis.

Table 4: Comparative results of Proposed Method & Other existing Techniques in terms of Robustness Index

Image Name	Before	Median Filter	CLAHE	Weiner Filter	ABF	Proposed Method
u01_f_fc_li_01	0.117	0.146	0.123	0.174	0.165	0.179
u01_f_ft_rm_04	0.129	0.187	0.139	0.138	0.188	0.198
u02_f_fo_li_03	0.198	0.208	0.21	0.219	0.223	0.252
u02_f_ft_ri_01	0.268	0.213	0.357	0.375	0.321	0.396
u03_f_fc_rm_04	0.128	0.154	0.234	0.127	0.212	0.259
u03_f_ft_lm_04	0.358	0.253	0.385	0.158	0.378	0.442
u04_f_fc_li_02	0.125	0.148	0.139	0.175	0.247	0.265
u04_f_fo_rm_02	0.211	0.199	0.213	0.204	0.305	0.316
u05_f_fc_ri_03	0.159	0.165	0.162	0.185	0.194	0.247
u05_f_ft_rm_01	0.347	0.176	0.373	0.354	0.368	0.396

u06_f_fc_rm_03	0.135	0.157	0.136	0.172	0.234	0.246
u06_f_fo_ri_04	0.218	0.193	0.312	0.217	0.313	0.357
u07_f_fc_li_01	0.159	0.162	0.238	0.173	0.185	0.274
u07_f_ft_li_01	0.327	0.378	0.341	0.41	0.453	0.509
u08_f_fc_lm_04	0.146	0.157	0.143	0.163	0.167	0.174
u08_f_ft_ri_04	0.338	0.256	0.346	0.185	0.365	0.362
u09_f_fo_rm_03	0.257	0.306	0.297	0.319	0.398	0.416
u09_f_ft_ri_03	0.137	0.174	0.147	0.193	0.239	0.253
u10_f_fc_lm_04	0.145	0.177	0.154	0.264	0.186	0.274
u10_f_ft_ri_02	0.135	0.154	0.127	0.146	0.164	0.283
u11_f_fc_lm_02	0.145	0.147	0.156	0.166	0.171	0.185
u11_f_fo_li_04	0.482	0.503	0.495	0.479	0.48	0.512
u12_f_fc_rm_02	0.129	0.168	0.156	0.174	0.185	0.257
u12_f_ft_rm_02	0.225	0.253	0.235	0.159	0.247	0.253
u13_f_fo_rm_01	0.509	0.31	0.514	0.507	0.498	0.518
u13_f_ft_lm_04	0.146	0.136	0.247	0.154	0.229	0.251
u15_f_fc_ri_04	0.139	0.148	0.165	0.157	0.164	0.258
u15_f_fo_ri_03	0.515	0.298	0.507	0.312	0.497	0.513
u16_f_fc_ri_04	0.145	0.156	0.149	0.168	0.157	0.169
u16_f_ft_rm_03	0.157	0.167	0.154	0.175	0.173	0.186
u17_f_fo_lm_02	0.645	0.318	0.649	0.416	0.651	0.659
u17_f_ft_lm_04	0.495	0.154	0.467	0.163	0.485	0.539

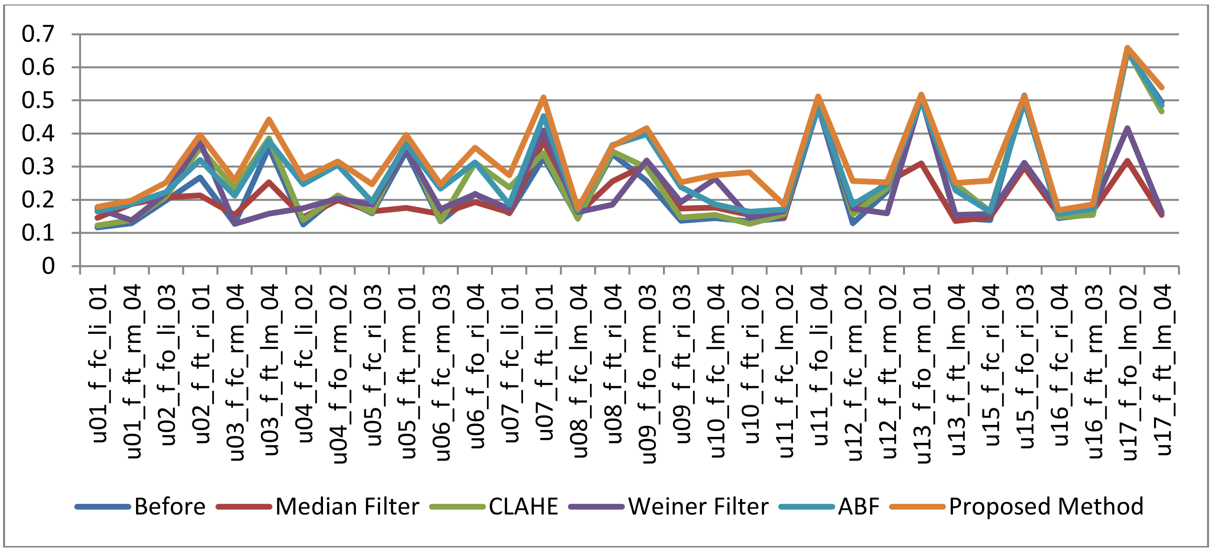

Figure 9 Comparative results – Robustness Index of proposed method and other existing methods

It can be observed from the above graph that the Robustness Index of the proposed system is always higher than the other existing techniques. So it can be concluded that the proposed methodology of Fingerprint Image enhancement works better than the existing techniques.

7.2.3 Evaluation using Verification performance:

The effectiveness of the enhancement process is also evaluated using the second export controlled package, BOZORTH3, which is a fingerprint matching system. It uses the minutiae to determine if two fingerprints are from the same person / same finger. It can analyze two fingers at a time or run in a batch mode comparing a single finger (probe) against a large database of fingerprints (gallery).

The verification process is done in the present work as described below:

The enrolment is achieved using real fingerprints, and tests are carried out with the fake fingerprints that were acquired as per the procedure mentioned in [16], [3], [15], the verification is done as follows

- All the ‘real fingerprints’ were enrolled into the system and try to access the application with the corresponding gummy fake fingerprints.
- First, the gummy fake fingerprint without applying the proposed enhancement technique was given for verification. The results are noted.
- Later, the gummy fake fingerprint after applying the proposed enhancement technique was given for verification. The results are noted.

The results are presented in terms of False Non Match Rate (FNMR) / False Rejection Rate (FRR) and Success Match Rate (SMR)

False Non Match Rate: This is also referred as False Acceptance Rate. It is the number of a fake images (out of total tested images) not being recognized by the system even when the corresponding real image is available in the database.

Success Match Rate: The number of the fake images accepted when it is verified against the corresponding real image on bozorth3 of NBIS.

The total images that are taken in the sample for verification is 200 fake images (without cooperation) against corresponding 200 real images. These sample images are taken from all the three types of scanners randomly. The results are presented in the below graph.

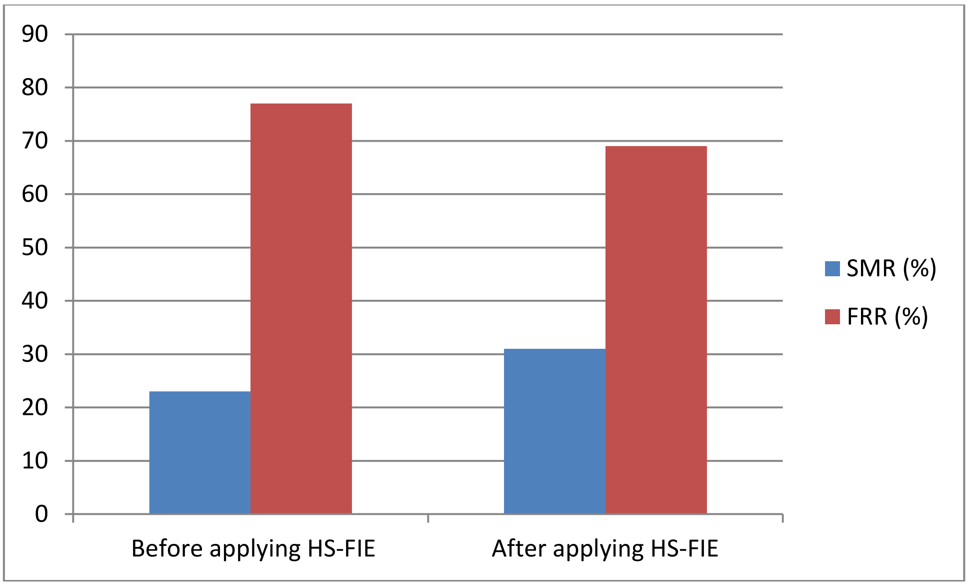

Figure 10: SMR, FRR (FNMR)-before and after enhancement
(using the database of Optical Sensor)

The verification of the fingerprint images in the present work is also done using the "fingerprint authentication system using traditional Euclidian distance and SVD algorithm".[17] , similar results are obtained so the results are commonly presented.

Conclusion and future scope:

A new methodology of fingerprint enhancement using harmony search on a new parameterized transformation function is proposed in this paper. The parameters in the transformation function are optimally controlled to get the best enhanced image. The experimental results have shown that this new methodology with harmony search performs better than the existing techniques for image enhancement.

The implementation of HS algorithm is easier. Furthermore, the HS algorithm is a population-based meta heuristic, so multiple harmonics groups can be used in parallel. Proper parallelism usually leads to better implantation with higher efficiency. The good combination of parallelism with elitism as well as a fine balance of intensification and diversification is the key to the success of the HS algorithm, and in fact, to the success of any meta heuristic algorithms. These advantages make it very versatile to combine HS with other meta heuristic algorithms such as PSO to produce hybrid meta heuristics and to apply HS in various applications.

References:

[1] Watson, G. I., Garris, M. D., et al. (2004). *User's guide to NIST fingerprint image software 2 (NFIS2).* National Institute of Standards and Technology.

[2]X.-S. Yang, “Harmony Search as a Metaheuristic Algorithm”, in: *Music-Inspired Harmony Search Algorithm: Theory and Applications* (Editor Z. W. Geem), Studies in Computational Intelligence, Springer Berlin, vol. **191**, pp. 1-14 (2009).

[3] J. Galbally, J. Fierrez, F. Alonso-Fernandez and M. Martinez-Diaz, "Evaluation of Direct Attacks to Fingerprint Verification Systems",Telecommunication Systems, Special Issue on Biometrics, Vol. 47, n. 3, pp. 243-254, January 2011.

[4] Geem ZW, Kim JH and Loganathan GV (2001) A new heuristic optimization algorithm: Harmony search. Simulation, 76:60-68

[5] Kumud Arora, Dr.Poonam Garg “A Quantitative Survey of various Fingerprint Enhancement techniques” , International Journal of Computer Applications (0975 – 8887) Volume 28– No.5, August 2011.

[6] R. Thai. Fingerprint Image Enhancement and Minutiae Extraction, thesis, School of Computer Science and Software Engineering, 2003.

[7] Jianwei Yang, Lifeng Liu, Tianzi Jiang , Yong Fan, A modified Gabor filter design method for fingerprint image enhancement, Pattern Recognition Letters 24 (2003) 1805–1817.

[8] R.C.Gonzales, R.E. woods, Digital Image Processing. Newyork: Addison-wesley, 1987 & R.C.Gonzalez and R.E.Woods, Digital Image Processing (Second Edition), Prentice Hall, 2001.

[9] R. Gonzalez, R. Woods, and S. Eddins, *Digital Image Processing using* matlab. Upper Saddle River, NJ Jensen: Prentice Hall,2nd Edition, 2004.

[10] B.Zhang and J.P.Allebach, "Adaptive bilateral filter for sharpness enhancement and noise removal," IEEE Trans. on Image Processing, vol.17, no.5, pp.664-678, May 2008.

[11] Lee KS and Geem ZW (2005) A new meta-heuristic algorithm for continuous engineering optimization: harmony search theory and practice. Comput. Methods Appl. Mech. Engrg., 194:3902-3933.

[12] Geem ZW (2006) Optimal cost design of water distribution networks using harmony search. Engineering Optimization 38:259-280

[13] B.Zhang and J.P.Allebach, "Adaptive bilateral filter for sharpness enhancement and noise removal," IEEE Trans. on Image Processing, vol.17, no.5, pp.664-678, May 2008

[14] M.James Stephen, P.V.G.D. Prasad Reddy, et al./ Removal of False Minutiae with Fuzzy Rules from the Extracted Minutiae of Fingerprint Image, *Advances in Intelligent and Soft Computing*,Jan 2012, vol 132/2012, pp. 853-860, 2012.

[15] J. Galbally-Herrero, J. Fierrez-Aguilar, J. D. Rodriguez-Gonzalez, F. Alonso-Fernandez, J. Ortega-Garcia and M. Tapiador, "On the vulnerability of fingerprint verification systems to fake fingerprint attacks", in *Proc. IEEE Intl. Carnahan Conf. on Security Technology, ICCST*, pp. 130-136, Lexington, USA, October 2006.

[16] J. Galbally, F. Alonso-Fernandez, J. Fierrez and J. Ortega-Garcia, "A High Performance Fingerprint Liveness Detection Method Based on Quality Related Features", *Future Generation Computer Systems,* Vol. 28, pp. 311-321, January 2012.

[17] M.James Stephen, P.V.G.D Prasad Reddy, "Implementation of Easy Fingerprint Image Authentication with Traditional Euclidean and Singular Value Decomposition Algorithms" Int. J. Advance. Soft Comput. Appl., Vol. 3, No. 2, July 2011, ISSN 2074-8523; Copyright © ICSRS Publication, 2011.

[18] Dr.E.Chandra, K.Kanagalakshmi, Noise Elimination in Fingerprint Image Using Median Filter, Int. J. Advanced Networking and Applications, Volume: 02, Issue: 06, Pages: 950-955 (2011)

[19] Shlomo Greenberg, Mayer Aladjem and Daniel KoganFingerprint Image Enhancement using Filtering Techniques, Real-Time Imaging 8, 227–236 (2002), doi:10.1006/rtim.2001.0283, available online at http://www.idealibrary.com

[20] M. Sepasian, W. Balachandran and C. Mares Image Enhancement for Fingerprint Minutiae-Based Algorithms Using CLAHE, Standard Deviation Analysis and Sliding Neighborhood, Proceedings of the World Congress on Engineering and Computer Science 2008, WCECS 2008, October 22 - 24, 2008, San Francisco, USA.