Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 2, Issue. 1, January 2013, pg.11 – 21

RESEARCH ARTICLE

Comparative Study of Image Enhancement Techniques

Ms.Seema Rajput[1], *Prof.S.R.Suralkar*[2]

[1]**SSGBCOET, Bhusawal, Dist.Jalgaon** seema.rajput75@gmail.com

[2]**SSBTCOET, Bhambhori, Dist.Jalgaon** srsuralkar@rediffmail.com

Abstract— Fingerprints are the oldest and most widely used form of biometric identification. The performance of any fingerprint recognizer highly depends on the fingerprint image quality. Different types of noises in the fingerprint images pose greater difficulty for recognizers. However, fingerprint images are rarely of perfect quality. They may be degraded and corrupted due to variations in skin and impression conditions. Thus, image enhancement techniques are employed prior to minutiae extraction to obtain a more reliable estimation of minutiae locations. Most Automatic Fingerprint Identification Systems (AFIS) use some form of image enhancement. Therefore, this paper describes various techniques for fingerprint image enhancement.

Indexed Terms: - Contrast enhancement, Histogram equalization, PSNR, Spatial Domain method

I. INTRODUCTION

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide `better' input for other automated image processing techniques.

Image enhancement techniques can be divided into two broad categories:
1. Spatial domain methods, which operate directly on pixels.
2. Frequency domain methods, which operate on the Fourier transform of an image.

Unfortunately, there is no general theory for determining what good image enhancement is? When it comes to human perception. If it looks good, it is good! However, when image enhancement techniques are used as pre-processing tools for other image processing techniques, then quantitative measures can determine which techniques are most appropriate.

Apart from geometrical transformations some preliminary grey level adjustments may be indicated, to take into account imperfections in the acquisition system. This can be done pixel by pixel, calibrating with the output of an image with constant brightness. Frequently space-invariant grey value transformations are also done for contrast stretching, range compression, etc. The critical distribution is the relative frequency of each grey value, the *grey value histogram*.

The fingerprint images are rarely of perfect quality, due to the reasons like variations in impression condition, skin condition, scanning devices or may be due to non-co-operative attitude of the subject. This degraded quality of image can result in a significant number of spurious minutiae being created and genuine minutiae being ignored. A vital step in studying the statistics of fingerprint minutiae is to reliably extract the minutiae feature from fingerprint images. Thus it is important to employ image enhancement techniques prior to minutiae extraction to obtain a good number of reliable estimates of minutiae locations.

The main objective of fingerprint image enhancement is to improve the ridge characteristics of the image, as these ridges carry the information of characteristics features required for minutiae extraction. Ideally, in a well-defined fingerprint image, the ridges and valleys should alternate and row in a locally constant direction. This regularity facilitates the detection of ridges and consequently allows minutiae to be precisely extracted from the

© 2013, IJCSMC All Rights Reserved

thinned ridges [1]. Thus, the corruption or noise has to be reduced through image enhancement techniques to get enhanced definition of ridges against valleys in the fingerprint images.

II. IMAGE ENHANCEMENT

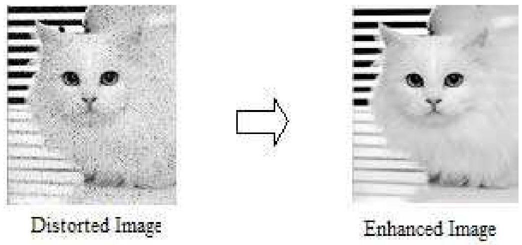


Fig.1. Showing the effect of Image Enhancement

Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task. Moreover, observer-specific factors, such as the human visual system and the observer's experience, will introduce a great deal of subjectivity into the choice of image enhancement methods. There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided in to the following two categories:

1. Spatial Domain Methods
2. Frequency Domain Methods

In spatial domain techniques [10] we directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values into image g using T. *(Where* T is the transformation. The values of pixels in images f and g are denoted by r and s, respectively. As said, the pixel values r and s are related by the expression,

$$s=T(r) \qquad (1)$$

Where T is a transformation that maps a pixel value r into a pixel value s. The results of this transformation are mapped into the grey scale range as we are dealing here only with grey scale digital images. So, the results are mapped back into the range [0, L-1], where L=2k, k being the number of bits in the image being considered. So, for instance, for an 8-bit image the range of pixel values will be [0, 255].

Many different, often elementary and heuristic methods [11] are used to improve images in some sense. The problem is, of course, not well defined, as there is no objective measure for image quality. Here, we discuss a few recipes that have shown to be useful both for the human observer and/or for machine recognition. These methods are very problem-oriented: a method that works fine in one case may be completely inadequate for another problem. In this paper basic image enhancement techniques have been discussed with their mathematical understanding. This paper will provide an overview of underlying concepts, along with algorithms commonly used for image enhancement. The paper focuses on spatial domain techniques for image enhancement.

III. IMAGE ENHANCEMENT TECHNIQUES

A. *Spatial domain methods*

The value of a pixel with coordinates (x, y) in the enhanced image is the result of performing some operation on the pixels in the neighborhood of (x, y) in the input image, F. Neighborhoods can be any shape, but usually they are rectangular.

B. *Histogram Equalization*

Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. In histogram equalization we are trying to maximize the image contrast by applying a gray level transform which tries to flatten the resulting histogram. It turns out that the gray level transform that we are seeking is simply a scaled version of the original image's cumulative histogram. That is, the graylevel transform T is given by T[i] = (G-1)c(i), where G is the number of gray levels and c(i) is the normalized cumulative histogram of the original image.

When we want to specify a non-flat resulting histogram, we can use the following steps:

1. Specify the desired histogram g(z)
2. Obtain the transform which would equalize the specified histogram, Tg, and its inverse Tg^{-1}
3. Get the transform which would histogram equalize the original image, s=T[i]
4. Apply the inverse transform Tg^{-1} on the equalized image, that is $z=Tg^{-1}[s]$

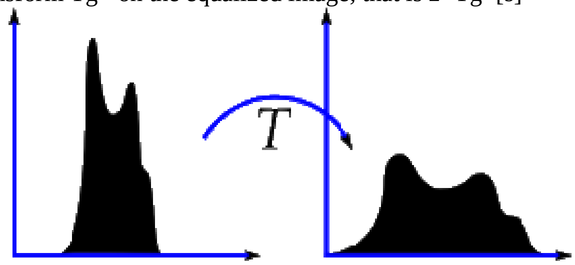


Fig. 2. Showing the effect of histogram

The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

In scientific imaging where spatial correlation is more important than intensity of signal (such as separating DNA fragments of quantized length), the small signal to noise ratio usually hampers visual detection.

Consider a discrete grayscale image $\{x\}$ and let n_i be the number of occurrences of gray level *i*. The probability of an occurrence of a pixel of level *i* in the image is

$$Px(i) = p(x=i) = \frac{ni}{n}, 0<i<L \quad (2)$$

L being the total number of gray levels in the image, *n* being the total number of pixels in the image, and being Px(i) in fact the image's histogram for pixel value i, normalized to [0,1].

Let us also define the *cumulative distribution function* corresponding to p_x as which is also the image's accumulated normalized histogram.

$$cdf_x(i) = \sum_{j=0}^{i} p_x(j) \quad (3)$$

We would like to create a transformation of the form $y = T(x)$ to produce a new image $\{y\}$, such that its CDF will be linearized across the value range, i.e.

$$cdf_y(i) = iK \quad (4)$$

For some constant *K*. The properties of the CDF (Cumulative *distribution function*) allow us to perform such a transform it is defined as

$$y = T(x) = cdf_x(x) \quad (5)$$

Notice that the T maps the levels into the range [0,1]. In order to map the values back into their original range, the following simple transformation needs to be applied on the result:

$$y' = y \cdot (\max\{x\} - \min\{x\}) + \min\{x\} \quad (6)$$

The cumulative distribution function (cdf) is shown below. Again, pixel values that do not contribute to an increase in the cdf are excluded for brevity.

The cdf must be normalized to (0,255). The general histogram equalization formula is:

$$h(v) = \mathrm{round}\left(\frac{cdf(v) - cdf_{min}}{(M \times N) - cdf_{min}} \times (L-1)\right) \quad (7)$$

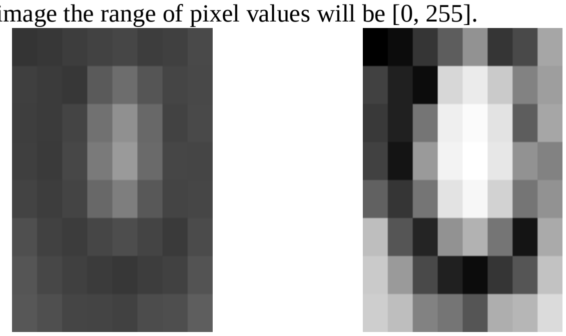
B. Negative Image Enhancement

Image enhancement is a very basic image processing task that defines us to have a better subjective judgment over the images and Image Enhancement in spatial domain (that is, performing operations directly on pixel values) is the very simplistic approach. Enhanced images provide better contrast of the details that images contain. Image enhancement is applied in every field where images are ought to be understood and analyzed. For example, Medical Image Analysis, Analysis of images from satellites, etc. Here I discuss some preliminary image enhancement techniques that are applicable for grey scale images.

Image enhancement simply means, transforming an image f into image g using T, Where T is the transformation. The values of pixels in images f and g are denoted by r and s, respectively. As said, the pixel values r and s are related by the expression,

$$s = T(r) \tag{8}$$

Where T is a transformation that maps a pixel value r into a pixel value s. The results of this transformation are mapped into the grey scale range as we are dealing here only with grey scale digital images. So, the results are mapped back into the range [0, L-1], where $L=2^k$, k being the number of bits in the image being considered. So, for instance, for an 8-bit image the range of pixel values will be [0, 255].



Original Equalized

Fig.3. Showing the histogram equalized

There are three basic types of functions (transformations) that are used frequently in image enhancement. They are,

- Linear
- Logarithmic
- Power-Law

The transformation map plot shown below depicts various curves that fall into the above three types of enhancement techniques.

The Identity and Negative curves fall under the category of linear functions. Identity curve simply indicates that input image is equal to the output image. The Log and Inverse-Log curves fall under the category of Logarithmic functions and nth root and nth power transformations fall under the category of Power-Law functions.

The negative of an image with grey levels in the range [0, L-1] is obtained by the negative transformation shown in figure above, which is given by the expression,

$$s = L - 1 - r \tag{9}$$

This expression results in reversing of the grey level intensities of the image thereby producing a negative like image. The output of this function can be directly mapped into the grey scale look-up table consisting values from 0 to L-1.

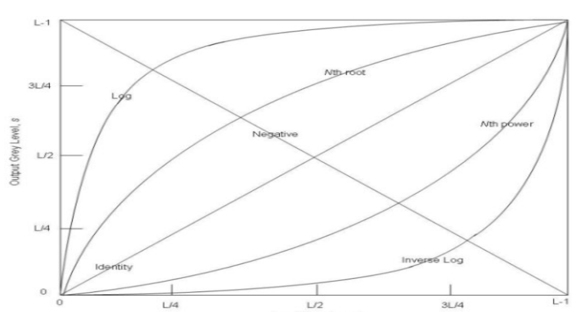


Fig.4. Plot of various transformation functions

© 2013, IJCSMC All Rights Reserved

a) Original digital mammogram b) Negative image

Fig.5. Note how much clearer the tissue is in the negative image of the mammogram

C. Contrast Stretching

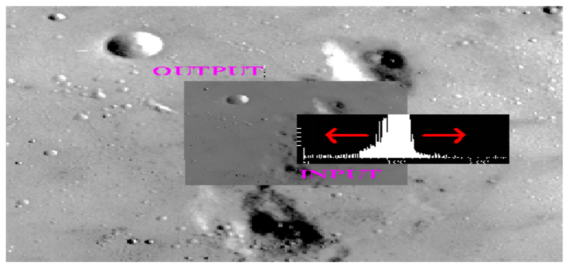


Fig.6.Contrast stretching of an image

Contrast stretching (often called normalization) is a simple image enhancement technique that attempts to improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values, *e.g.* the full range of pixel values that the image type concerned allows. It differs from the more sophisticated histogram equalization in that it can only apply a *linear* scaling function to the image pixel values. As a result the `enhancement' is less harsh. (Most implementations accept a gray level image as input and produce another gray level image as output.)

Before the stretching can be performed it is necessary to specify the upper and lower pixel value limits over which the image is to be normalized. Often these limits will just be the minimum and maximum pixel values that the image type concerned allows. For example for 8-bit gray level images the lower and upper limits might be 0 and 255. Call the lower and the upper limits *a* and *b* respectively.

The simplest sort of normalization then scans the image to find the lowest and highest pixel values currently present in the image. Call these *c* and *d*. Then each pixel *P* is scaled using the following function:

$$P_{out} = (P_{in} - c)\left(\frac{b-a}{d-c}\right) + a \tag{10}$$

Values below 0 are set to 0 and values about 255 are set to 255.The problem with this is that a single outlying pixel with either a very high or very low value can severely affect the value of *c* or *d* and this could lead to very unrepresentative scaling. Therefore a more robust approach is to first take a histogram of the image, and then select *c* and *d* at, say, the 5th and 95th percentile in the histogram (that is, 5% of the pixel in the histogram will have values lower than *c*, and 5% of the pixels will have values higher than *d*). This prevents outliers affecting the scaling so much.

Normalization is commonly used to improve the contrast in an image without distorting relative gray level intensities too significantly.

We begin by considering an image which can easily be enhanced by the most simple of contrast stretching implementations because the intensity histogram forms a tight, narrow cluster between the gray level intensity values of 79 - 136

After contrast stretching, using a simple linear interpolation between $c = 79$ and $d = 136$

Compare the histogram of the original image with that of the contrast-stretched version

While this result is a significant improvement over the original, the enhanced image itself still appears somewhat flat. Histogram equalizing the image increases contrast dramatically, but yields an artificial-looking result.

In this case, we can achieve better results by contrast stretching the image over a more narrow range of gray level values from the original image. For example, by setting the cutoff fraction parameter to 0.03, we obtain the contrast-stretched image and its corresponding histogram

Note that this operation has effectively spread out the information contained in the original histogram peak (thus improving contrast in the interesting face regions) by pushing those intensity levels to the left of the peak down the histogram *x*-axis towards 0. Setting the cutoff fraction to a higher value, *e.g.* 0.125, yields the contrast stretched image as shown in the histogram most of the information to the left of the peak in the original image is mapped to 0 so that the peak can spread out even further and begin pushing values to its right up to 255.

As an example of an image which is more difficult to enhance, consider which shows a low contrast image of a lunar surface.

The image shows the intensity histogram of this image. Note that only part of the *y*-axis has been shown for clarity. The minimum and maximum values in this 8-bit image are 0 and 255 respectively, and so straightforward normalization to the range 0 - 255 produces absolutely no effect. However, we *can* enhance the picture by ignoring all pixel values outside the 1% and 99% percentiles, and only applying contrast stretching to those pixels in between. The outliers are simply forced to either 0 or 255 depending upon which side of the range they lie on.

Notice that the contrast has been significantly improved. Compare this with the corresponding enhancement achieved using histogram equalization.

Normalization can also be used when converting from one image type to another, for instance from floating point pixel values to 8-bit integer pixel values. As an example the pixel values in the floating point image might run from 0 to 5000. Normalizing this range to 0-255 allows easy conversion to 8-bit integers. Obviously some information might be lost in the compression process, but the relative intensities of the pixels will be preserved.

D. Adaptive Weighted Mean Filter (AWMF)

Filtering is a mathematical operation in which the intensity of one pixel is combined with the intensity of neighboring pixels. This neighborhood is defined by a box that has at least three pixels on a side. Perhaps the simplest filter is the mean filter, which sums the intensity of pixels in the box and determines the mean. The averaging of neighboring pixels will result the blurred image due to the random nature of pixels at the neighboring position. To avoid this blurring, this paper introduces Adaptive Weighted combination of pixel values I(i,j), I(i,j-1), I(i- 1,j-1), I(i-1,j), I(i-1,j+1), I(i+1,j+1), I(i+1,j-1), I(i,j+1) and I(i,j+1) is used to estimate the value for pixel I(i,j). This scheme has been considered as the four neighboring pixels of the current pixel which are most likely to be involved in the generation of the back reflection value in pixel position (i, j).The mask for this filter is shown in figure.

The given image is passed through an edge detector and converted into a binary image. If the pixel of interest I (i,j) is an edge, the particular pixel is omitted. If the pixel of interest I(i,j) is not an edge, adaptive weighted mean filter omitting the edge pixel is applied.

1	2	1
2	4	2
1	2	1

Fig.7. Mask for Adaptive Weighted Mean Filter

E. Edge Adaptive Sigma Filter (EASF)

The sigma filter averages only those pixels within a box of predetermined size that do not deviate too much from the pixel that the box is centered on. To set the threshold value for a sigma filter, one must know the type of noise affecting the image and its standard deviation. To avoid this, this paper introduces another filter, namely edge adaptive sigma filter to enhance the contrast of a given image. The given image is passed through an edge detector and converted into a binary image. If the pixel of interest I (i, j) is an edge, a high pass filter mask is applied to sharpen the edge. If the pixel of interest I (i, j) is not an edge, a low pass mean filter omitting the edge pixel is applied.

F. Edge Adaptive Hybrid Filter (EAHF)

To improve the edges and fine details present in the given image, this paper proposes a new filter namely Edge Adaptive Hybrid filter which a combination of low pass and high pass filter. In this algorithm also, an edge detector is applied to the given image and converted into binary image. If the pixel of interest I (i, j) is an edge, a high pass filter mask is applied to sharpen the edge. If the pixel of interest I (i, j) is not an edge, a low pass mean filter is applied to improve the fine details.

IV. PERFORMANCE METRICS

A .Peak Signal to Noise Ratio (PSNR)

The phrase peak Signal-to-Noise Ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs it is used as an *approximation* to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content [1] [2]

It is most easily defined via the mean squared error (*MSE*). Given a noise-free $m \times n$ monochrome image I and its noisy approximation K, *MSE* is defined as:

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (11)$$

The PSNR is defined as:

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned} \qquad (12)$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is 2^B-1. For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space, e.g., YCbCr or HSL

B. Normalized Error

In statistics, the mean absolute error (MAE) / Normalized Error is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The mean absolute error is given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|. \qquad (13)$$

As the name suggests, the mean absolute error is an average of the absolute errors $e_i = |f_i - y_i|$, where f_i is the prediction and y_i the true value. Note that alternative formulations may include relative frequencies as weight factors.

The mean absolute error is a common measure of forecast error in time series analysis, where the terms "mean absolute deviation" is sometimes used in confusion with the more standard definition of mean absolute deviation. The same confusion exists more generally.

C. Correlation coefficient

The correlation is a measure of the strength and direction of a linear relationship between two variables. The correlation coefficient R is defined as

$$R = \frac{\langle x_m x_c\rangle - \langle x_m\rangle\langle x_c\rangle}{\sqrt{\langle x_m^2\rangle - \langle x_m\rangle^2}\sqrt{\langle x_c^2\rangle - \langle x_c\rangle^2}} \qquad (14)$$

© 2013, IJCSMC All Rights Reserved

A correlation of 1 indicates a perfect one-to-one linear relationship and -1 indicates a negative relationship. The square of the correlation coefficient describes how much of the variance between two variables is described by a linear fit.

D. Structural Similarity

The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric, in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean (MSE), which have proved to be inconsistent with human eye perception.

The difference with respect to other techniques mentioned previously such as MSE or PSNR, is that these approaches estimate *perceived errors* on the other hand SSIM considers image degradation as *perceived change in structural information*. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene.

The SSIM metric is calculated on various windows of an image. The measure between two windows x and y of common size *N*×*N* is:

$$\mathrm{SSIM}(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (15)$$

Where,

- μ_x the average of x;
- μ_y the average of y;
- σ_x^2 the variance of x;
- σ_y^2 the variance of y;
- σ_{xy} the covariance of x and y;
- $c_1=(k_1L)^2$, $c_2=(k_2L)^2$ two variables to stabilize the division with weak denominator;
- L the dynamic range of the pixel-values (typically this is $2^{\#bits\ per\ pixel}-1$);
- $k_1=0.01$ and $k_2=0.03$ by default.

In order to evaluate the image quality this formula is applied only on luma. The resultant SSIM index is a decimal value between -1 and 1, and value 1 is only reachable in the case of two identical sets of data. Typically it is calculated on window sizes of 8×8. The window can be displaced pixel-by-pixel on the image but the authors propose to use only a subgroup of the possible windows to reduce the complexity of the calculation.

V. RESULT

It is clearly seen that the **Edge Adaptive Hybrid Filter (EAHF**)Image enhancement method returns the best results when studied with all available database samples as compare with others for the four performance parameters like Peak Signal to Noise Ratio (PSNR), Normalized Error(MAE), Correlation coefficient(CC), **structural similarity** (SSIM) as, indicated in below figures .

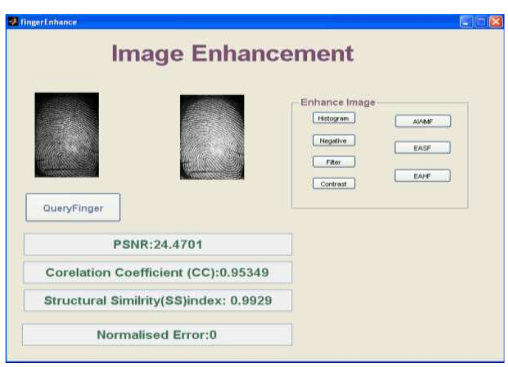


Fig.8.Result for Histogram

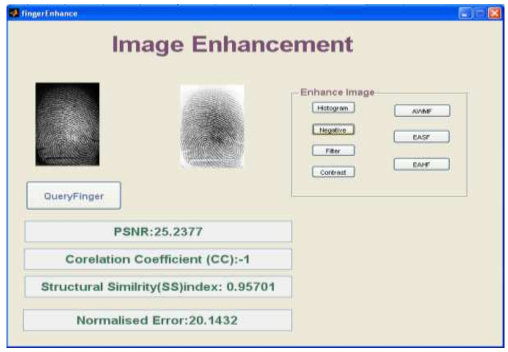


Fig.9. Result for Negative

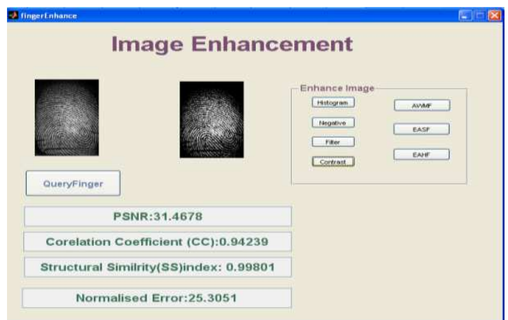


Fig.10. Result for Contrast

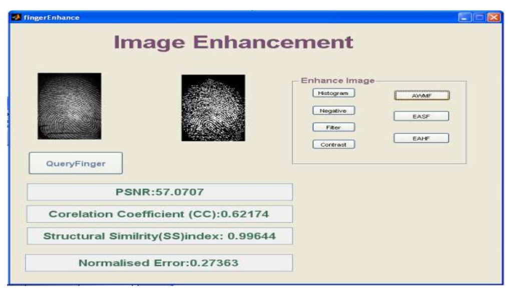


Fig.11 Result for AWMF

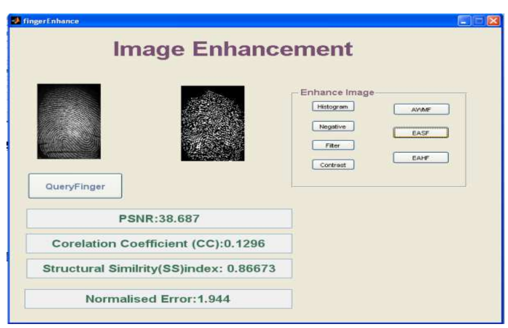


Fig.12 Result for EASF

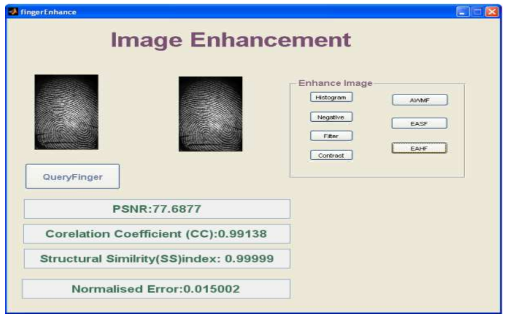


Fig13. Result for EAHF

Out of these studied methods we are in the position to conclude that the contrast Image enhancement is the one of the best method within the studied techniques as shown in Table 1below.

Table 1: The comparative study of Performance parameter of Image enhancement techniques

Image Enhancement Techniques	PSNR	MSE	CC	SSIM
Histogram	24.3443	0	0.96855	0.99379
Negative	25.519	23.35	1	0.95245
Contrast	30.5928	20.41	0.9471	0.99832
AWMF	57.503	0.255	0.7087	0.99643
EASF	38.9922	1.810	0.166	0.87787
EAHF	78.258	0.013	0.9931	0.999

VI. CONCLUSION

Image enhancement is the improvement of digital image quality (wanted e.g. for visual inspection or for machine analysis), without knowledge about the source of degradation. Different image enhancement techniques are compared by taking parameters Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), and Correlation Coefficient (CC), SSIM. This paper conclude that Use of the edge adaptive hybrid filter gives some better results compared to histogram processing, negative enhancement, contrast stretching, filtering, AWMF,EASF.

VII. FUTURE SCOPE

The fingerprint images are rarely of perfect quality, due to the reasons like variations in impression condition, skin condition, scanning devices or may be due to non-co-operative attitude of the subject. This degraded quality of image can result in a significant number of spurious minutiae being created and genuine minutiae being ignored. A vital step in studying the statistics of fingerprint minutiae is to reliably extract the minutiae feature from fingerprint images. Thus it is important to employ image enhancement techniques prior to minutiae extraction to obtain a good number of reliable estimates of minutiae locations.

The main objective of fingerprint image enhancement is to improve the ridge characteristics of the image, as these ridges carry the information of characteristics features required for minutiae extraction. Ideally, in a well-defined fingerprint image, the ridges and valleys should alternate and °ow in a locally constant direction. This regularity facilitates the detection of ridges and consequently allows minutiae to be precisely extracted from the thinned ridges. Thus, the corruption or noise has to be reduced through image enhancement techniques to get enhanced definition of ridges against valleys in the fingerprint images.

REFERENCES

[1] Feng Xiao, Mingquan Zhou, and Guohua Geng, “Detail Enhancement and Noise Reduction with Color Image Detection Based on Wavelet Multi-scale,” 2011, pp. 1061-1064.

[2] L. Hong, Y. Wan, and A. Jain. “Fingerprint image enhancement: Algorithm and performance evaluation”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(8):777–789, August 1998.

[3] Y. He, J. Tang, X. Luo, and T. Zhang, "Image enhancement and minutiae matching in fingerprint verification," Pattern Recognition Letters, 24, 2003.

[4] Maltoni, D., Maio, D., Jain, A. K., and Prabhakar, S. *Handbook of Fingerprint Recognition*. Springer, 2003.

[5] Chaohong Wu, Zhixin Shi _ and Venu Govindaraju "Fingerprint Image Enhancement Method Using Directional Median Filter "

[6] Salil Prabhakar, "Fingerprint classification and matching using filterbank", Ph. D. Thesis, 2001

[7] Xia,X. and O'Gorman, L.: Innovations in fingerprint capturedevices. Journal of Pattern Recognition, Pergamon Press,Vol. 36, No. 2, pp. 361-370, 2002

[8] Jain,A., Hong,L. and Bolle,R.: On-Line Fingerprint Verification. IEEE-PAMI, Vol.19, No.4,pp. 302-314, Apr.1997.

[9] Zhou Wang ,Alan Conrad Bovik'sJain,A., "Image Quality Assessment :from error visibility to structure similarity IEEE transaction On image processing" Vol.13 No4 April2004]

[10] D. Maltoni, Dmaio, A.K. Jain, S. prabhakar, "Hand book of Fingerprint ecognition", springer, 2003

[11] Bhabatosh Chanda and Dwijest Dutta Majumder, 2002, Digital Image Processing and Analysis.

[12] R.W.Jr. Weeks, (1996). Fundamental of Electronic ImageProcessingBellingham:SPIEPress