Finger Vein Image Enhancement Technique based on Gabor filter and Discrete Cosine Transform

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***Abstract*— Biometrics is a global technique to establish the identity of a person by measuring one of their physical or behavioral characteristics such as fingerprint, signature, iris, voice and face. Compared to these biometric techniques, the finger vein technique has distinct advantages as it helps to protect privacy and anonymity in automated individual recognition. Many studies showed that the finger vein images were of a low quality because of the variation in the tissues and uneven illumination. Hence, there is a need for effective image enhancement techniques, which can improve the quality of the images. In this study, we proposed a novel technique, which enhances the image quality of the finger veins. This method includes contrast amelioration, use of Gabor filters and image fusion, which generates an image with highly connective patterns. We used three criteria to evaluate the quality of processed images, the mean of grey values, the image entropy, and the image contrast. The obtained result shows higher values when using our approach in comparison to the baseline methods considered in this work.**

***Index Terms*— Enhancement method; Finger-vein; Gabor filter; Image processing.**

I. INTRODUCTION

Owing to the rapid economic and social developments, there has been an increase in the need for an information security. However, many of the conventional authentication techniques, like the use of keys and passwords cannot satisfy all the expectations, as they can be stolen, lost or even forgotten. Since the novel authentication and identification-based techniques with biometric characteristics cannot be forgotten, lost or copied, these techniques have emerged as convenient, reliable and secure methods [1].

The vein-based image recognition techniques are non-invasive, convenient, and accurate; hence, they have garnered a lot of attention during the last few years. In comparison to the conventional biometric techniques such as face, iris, fingerprint and gait, the vein-based image recognition techniques are cost-effective, reliable and easy for data acquisition. The devices used for imaging purposes are small in size, and they are used in specific applications, which support small spaces like mobile phones and driver identification systems. Moreover, different fingers belonging to the same individual show a different vein pattern [2].

Vein pattern images acquired with the help of ultrasonic scanners (used in the medical imaging) or X-rays show a higher quality. However, these devices are not convenient for the users because of their slow acquisition; hence, they are not used for biometric purposes. Further, areas with a vein pattern display a dark intensity in comparison to the adjoining tissues when they are studied under an Infra Red (IR) light since the IR light is absorbed by the haemoglobin molecules present in the blood flowing through the veins. Therefore, IR imaging can be used in the biometric devices for a non-invasive and contact-less finger-vein image acquisition [3].

The details of finger vein patterns in the images, particularly thin ones are unclear. This fact is attributed to an uneven illumination or improper placement of the finger during image acquisition. Hence, finger vein images that have an uneven illumination and a low contrast are exposed to the nonlinear image enhancement techniques [4].

To improve the contrast in the finger vein images, researchers used the Point Spread Function (PSF) to address the blurring issues using a specific scattering model based on the optical properties of the skin on the fingers. However, there was a light scattering phenomena arising from the skin and the internal finger tissues such as the muscles, blood vessels and even bones. Due to these problems, the PSF is not sufficient to effectively enhance finger vein pattern visibility [5].

In this paper, we proposed a new technique to enhance finger vein image based on the fusion of two images from Histogram Equalization and Gabor filtering.

II. RELATED WORKS

The first problem that affects finger vein recognition performance is the quality of the images. Infrared images have a low contrast and blurry. Hence, before proceeding with the extraction of the characteristics, they must be pre-processed to improve their quality. Image pre-processing involves image enhancement, noise reduction, image segmentation and normalization [6].

Several methods have been proposed to improve the IR image. Zang et al. [7] proposed a multi-threshold fuzzy algorithm. Firstly, an improved threshold was derived by calculating the average of all the adjacent points, which is followed by counting the average to affiliate each point. Then, an inverse transformation was applied to obtain the images.

Cong-li et al.[8] proposed a method to extract finger-vein feature by detecting peak and valley using morphologic operation. This method is weak in finger-vein enhancement because IR image has low contrast. To improve the contrast, Zhao et al. [9] proposed an algorithm, which apply high-frequency emphasis filtering followed by histogram equalization.

Yang [10] employed a multi-channel Gabor filter

(MCGF) to extract information from a low quality finger vein image. This method was able to improve the image after applying reconstruction rule on vein information.

Another improvement of the image was proposed by Zhang et al. [11] who used circular Gabor filter with a grayscale group (GLG) algorithm. The circular Gabor filter was used after image processing by GLG to highlight the crests of the veins.

A method for extracting geometric information from the image has been proposed by Jianping et al. [12]. It is based on the non-subsampled contourlet transform. This technique makes it possible to distinguish noises from weak edges.

Enhancement filter bank that generates better performance was proposed by Truce et al. [13]. It was used for vessel enhancement with directional filter bank.

A succession of filtering operations has been proposed by Jinfeng [14] to illuminate the noise and improve the quality of the vein image. Firstly, an extraction operation of the region of interest was performed to erase the lights present in the background of the image, and then the image was filtered by a bank of directional filters. Afterwards, the directional image was filtered by Wiener adaptive filter and followed by the Frangi filter. Finally, a reconstruction rule was applied.

In their study, Park et al. proposed and developed an image quality improvement technique, which considered the thickness and the direction of the vein lines using an optimum Gabor filter [15]. In another study [16], the researchers proposed an image quality evaluation technique for finger vein images; however, they did not take into consideration the quality enhancement. They used a Modified Gaussian Filter (MGF) [17, 18] for improving the finger vein images.

III. Proposed Method

The method of Enhancement is presented in Figure1. Two operations were applied to the input image: the first operation applied Gabor filter and the second histogram equalization using Contrast-Limited Adaptive Histogram Equalization (Clache), which was followed by filtering with a median filter. The two images were merged by the DCT method. Finally, a contrast adjustment was made on the resulting image. The details of each step are described below.

A. Histogram Equalization

Researchers used to apply image histogram equalization technique for adjusting the dispersal of the grey levels in the images. However, this technique could not be applied to the finger vein images [19]. A novel technique, i.e., the Contrast Limited Adaptive Histogram Equalization (CLAHE) [20] method has been viewed to restrict the size of the local histograms. This method limits the noise amplification and increases the local contrast in the images.

The conventional histogram equalization techniques use the same transformation technique that is derived from image histograms for transforming all the pixels. This technique is appropriate if a similar pixel value distribution was used throughout the complete image. However, if the image consists of some regions, which are significantly darker or lighter than the remaining image, the contrast in such regions is not enhanced.

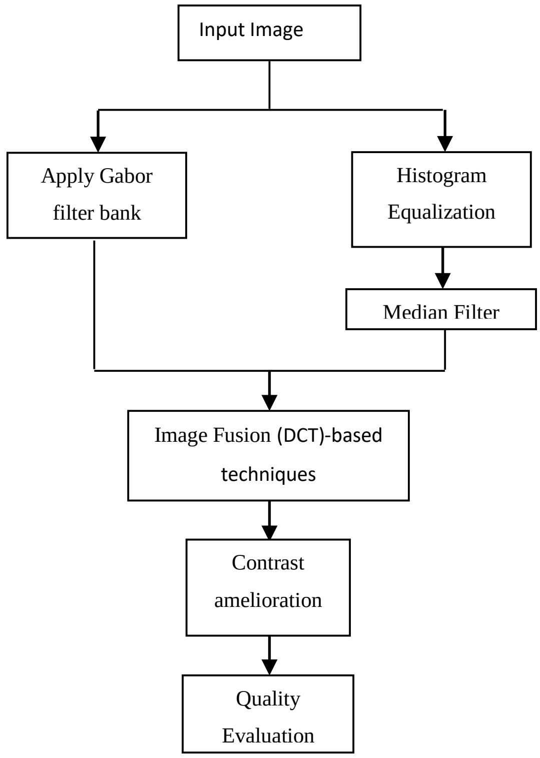

Figure 1: Proposed finger vein image enhancement

This technique operates on the smaller data regions (tiles), instead of the complete image. The contrast in every tile is improved, which matches the resultant region's histogram with the stipulated histogram. Thereafter, the neighboring tiles are combined based on the bilinear interpolation to eliminate the artificially-induced boundaries in the image [22].

Here, the CLAHE was calculated as follows:

$$S = Hist(i) \times \frac{255}{M \times M} \quad (1)$$

wherein *Hist* refers to the cumulative distribution of the histogram. This also reflects the number of the grey levels, which appear in a specific region, *i* in the image. *S* refers to the new pixel values, while *M* denotes the size of the local window. Also, the median filter phase decreases the image noise and other image irregularities to improve the visual quality of the image. This result is described in Figure 2 [22].

B. Gabor Filters

Researchers applied the Gabor filters in many image analysis applications as these filters were tuneable in orientation and scale [18]. The 2-D Gabor filter is seen to be a function of the Gaussian-shaped functions along with a complex plane wave. This is estimated as follows:

$$G(x, y) = \frac{\gamma}{2\pi\sigma^2} exp\left\{-\frac{1}{2}\left(\frac{x_\theta^2+\gamma^2 y_\theta^2}{\sigma^2}\right)\right\} \exp(j2\pi f_0 x_\theta) \quad (2)$$

wherein;

$$\begin{bmatrix} x_\theta \\ y_\theta \end{bmatrix} = \begin{bmatrix} \cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (3)$$

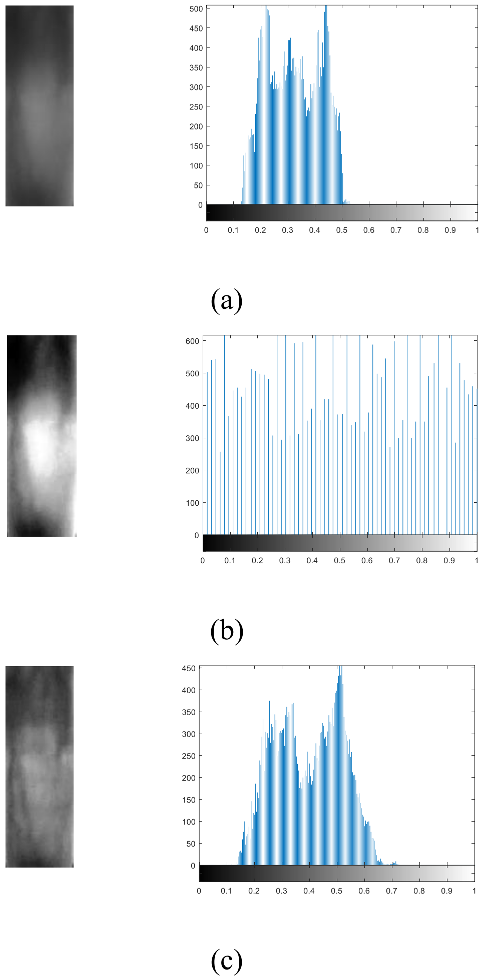

Figure 2: (a) original image and its Histogram, (b) the preprocessed image with Histogram equalization and its Histogram (c) the preprocessed image with CLAHE and its Histogram

Here, $j = \sqrt{-1}$, θ refers to the orientation of the Gabor filter, f0 is the filter centre frequency, σ and γ refer to the standard deviation (called as the scale) and the aspect ratio of an elliptical Gaussian envelope, respectively, and x_θ and y_θ represent two rotated forms of the x and y coordinates.

Based on the Euler formula, the Gabor filter was decomposed into real and imaginary components. The real component, known as the even-symmetric Gabor filter, was used for the ridge detection, whereas the imaginary component, known as the odd-symmetric, Gabor filter was used for edge detection. The orientation and the frequency of these Gabor filters are effective for enhancing the images. However, no method can replace the experience-based intuition for selecting the parameters. Hence, a trial-and-error based, heuristic search technique was used. Here, we set the frequency value as 4, while the orientation angle was set as 4π.

The image was filtered using the real parts of Gabor filter with four orientations 22.5°, 67.5 °, 112.5 ° and 157.5 °. The reconstruction rule is defined as:

$$RI(x_i, y_i) = argmin([I_1(x_i, y_i), I_2(x_i, y_i), I_3(x_i, y_i), I_4(x_i, y_i)]) \quad (4)$$

where RI(x, y) represent reconstructed image and I(x, y) represent the filtered image. An example of image obtained by MCGF is shown in Figure 3.

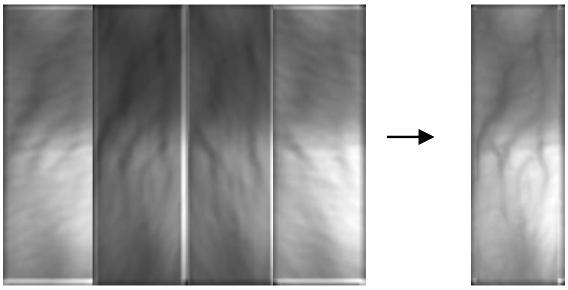

Figure 3: Filtered images with four orientations: 22.5°, 67.5 °, 112.5 ° and 157.5 °, and the reconstructed image

C. Image fusion

Image fusion combines all the relevant information obtained from the several images into one image. The Discrete Cosine Transform (DCT)-based techniques for image fusion are very effective and save a lot of time in the real-time systems, which use DCT-based standards for the still images. The 2-D DCT transform method for an N × N block in the image, x(m, n), can be defined as follows [23]:

$$d(k,l) = \frac{2\alpha(k)\alpha(l)}{N} . \sum_{m=0}^{N-1}\sum_{n=0}^{N-1} x(m,n) . \cos\left(\frac{(2m+1)\pi k}{2N}\right) . \cos\left(\frac{(2n+1)\pi k}{2N}\right) \quad (5)$$

Wherein k, l = 0, 1, . . . , N - 1 and

$$\alpha(k) = \begin{cases} \frac{1}{\sqrt{2}} & if\ k = 0 \\ 1 & otherwise \end{cases} \quad (6)$$

The Inverse DCT transform (IDCT) can be defined as follows:

$$x(m,n) = \sum_{k=0}^{N-1}\sum_{l=0}^{N-1} \frac{2\alpha(k)\alpha(l)}{N} . d(k,l) . \cos\left(\frac{(2m+1)\pi k}{2N}\right) . \cos\left(\frac{(2n+1)\pi k}{2N}\right) \quad (7)$$

Where m, n = 0, 1, . . . , N - 1.

In Equation (5), d(0, 0) refers to the DC coefficient, while d(k, l) is the AC coefficient in the block. Furthermore, the normalised transform coefficients can be calculated as:

$$\hat{d}(k,l) = \frac{d(k,l)}{N} \quad (8)$$

The average value, μ, and the variance, σ^2, for the N × N block within the spatial domain is estimated as follows:

$$\mu = \frac{1}{N^2} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} x(m,n) \quad (9)$$

$$\sigma^2 = \frac{1}{N^2} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} x^2(m,n) - \mu^2 \quad (10)$$

Also, the variance in the N × N block of pixels is estimated using its DCT coefficients after summing the normalised and squared AC coefficients in the DCT block.

$$\sigma^2 = \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} \frac{d^2(k,l)}{N^2} - \hat{d}^2(0,0) \quad (11)$$

The value of the variance is assumed to be a contrast measurement in the image processing applications. Furthermore, the fusion technique, which uses DCT, was based on the maximal information available for every pixel block for the 2 DCT images. All information used here was dependent on the values of the variance for every block [24].

The DCT fusion method is based on the principle of taking the block that contains the maximum information. So we made a comparison between the blocks of the two images (Histogram Equalization (HE) and Gabor filtering (GF)). The block containing the highest variance value was chosen and the other was discarded. From both processed DCT images, a final DCT image was obtained using equation (12) [21].

$$d_{fus}(i,j) = \begin{cases} d_{HE}(i,j) & if \quad var_{d_{HE}} > var_{d_{GF}} \\ d_{GF}(i,j) & if \quad var_{d_{HE}} < var_{d_{GF}} \end{cases} \tag{12}$$

IV. Quality Evaluation

To compare the quality of the improved images with the available finger-vein databases, we evaluated the mean grey values, image entropy, and the image contrast. The image contrast and the entropy were considered to be the representative criteria for evaluating the image quality [26].

The mean grey values reflect the volatility of the grey values within the image. Assuming that $I(x, y) \in R_{m\times n}$ is the image, the mean grey values were determined as:

$$M = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} I(i,j)}{m\times n} \tag{13}$$

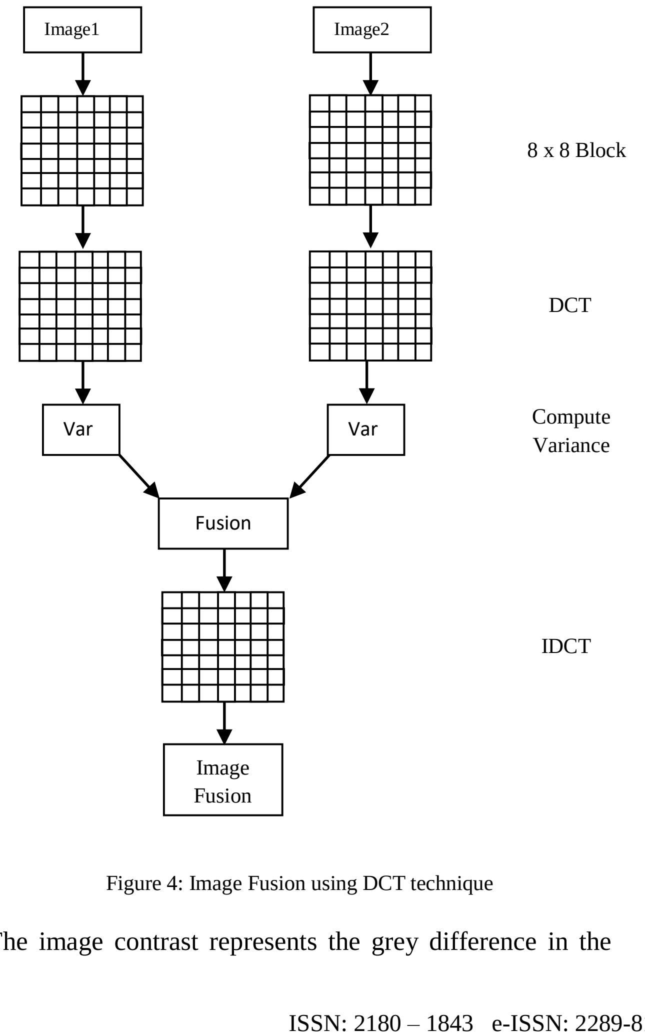

Figure 4: Image Fusion using DCT technique

The image contrast represents the grey difference in the image. To determine, we partitioned the image into t non-overlapping sub-images, which had an 8×8 resolution. The image contrast can be described as the mean contrast of the variance values for every block, which is determined as:

$$C_t = \sqrt{\frac{\sum_{k=1}^{64}(I_k - M_t)^2}{64}} \tag{14}$$

$$Contraste = \frac{1}{t}\sum_{i=1}^{t} C_t \tag{15}$$

Wherein, Mt and Ct refer to the mean grey values and the variance in the *th* sub-image, respectively. Also, I_k refers to one of the grey values within the 64 pixels.

The entropy denotes a statistical measurement for randomness, which characterises the image texture. The image entropy is calculated as:

$$Entropy = -\sum_{i=1}^{m}\sum_{j=1}^{n} I(i,j)\log(I(i,j)) \tag{16}$$

V. Experiment

Experiment was performed on two databases, the FV-USM [26] database and SDUMLA finger-vein database [27].

The images in the FV-USM database were composed from 123 persons. Every subject provided four fingers resulting in a total of 492 finger classes obtained with 6 images in each class, a total of 2952 finger-vein images. We used only the extracted ROI images provided in this database.

In SDUMLA dataset, every person was requested to submit images of their middle, index, and ring fingers for both hands. The images for the 6 fingers were collected 6 times, to generate a total of 36 images, which were compiled together. The finger vein dataset consisted of 3,816 images.

In each database, original images were compared with the proposed method, CLAHE method and MCGF method outputs.

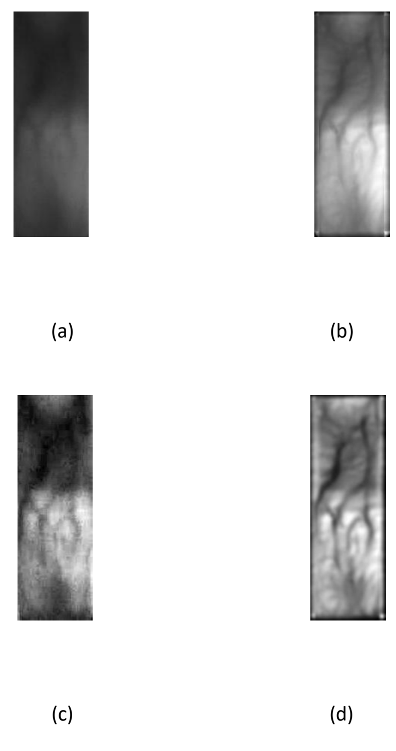

Figure 5: Sample Results using FV-USM images : a) Vein Images, b) Enhanced Images MCGF , c) Enhanced Images CLAHE , d) Enhanced Images Fusion

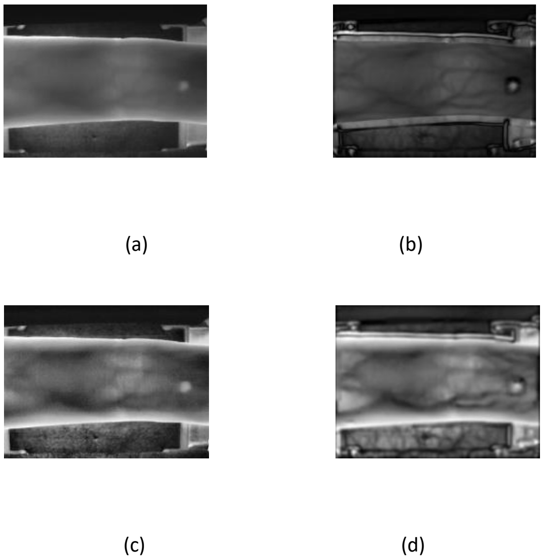

Figure 6: Sample Results using SDUMLA images : a) Vein Images, b) Enhanced Images MCGF , c) Enhanced Images CLAHE , d) Enhanced Images Fusion

Table 1
Average images mean value in FV-USM finger vein dataset

	Average gray value	Image contrast	Image entropy
Original Image	0,3353	0,0105	6,202
MCGF	0,5152	0,0407	7,1738
CLAHE	0,4028	0,0266	6,712
Fusion	0,5338	0,0447	7,0874

Table 2
Average images mean value in SDUMLA finger vein dataset

	Average gray value	Image contrast	Image entropy
Original Image	0,2184	0,0197	5,844
MCGF	0,2402	0,0392	6,5933
CLAHE	0,2914	0,038	6,7865
Fusion	0,3698	0,0575	7,5373

VI. RESULTS

The results on two images from both databases are shown in Figure 5 and Figure 9 for reference.

The good-quality images display higher values for mean grey, contrast and Entropy in comparison to the low-quality images. We compared the mean grey values, contrast and the image entropy for all images and the results are presented in Table 1 and Table 2.

From Figure 7, we noticed that the mean grey, contrast and Entropy become higher when we applied enhancement algorithms to the original images in both datasets.

For the SDUMLA database we noticed that the average value takes its maximum value for the images processed by our approach, whereas the AV takes the lowest value for CLACH and Fusion. But for the FV-USM database, the average value is equal to 0.4 for the CLAHE method and exceeds 0.5 for the two methods MCGF and Fusion.

The contrast value in the SDUMLA database is the same for MCGF and CLAHE. However in the FV-USM base, the contrast reaches its minimum value. A higher contrast value is reached for the Fusion method for both databases.

In the Figure 7.c, we noticed that the entropy takes values close to 7 for all the methods in the two databases, a slight superiority was noted for the fusion method in the SDUMLA database and a slight superiority was thus noted for the MCGF method in the FC-USM database.

From this analysis, we found that the Fusion method and MCGF method takes the maximum values for contrast and entropy in both database, but the MCGF method seems more convenient for the FC-USM database.

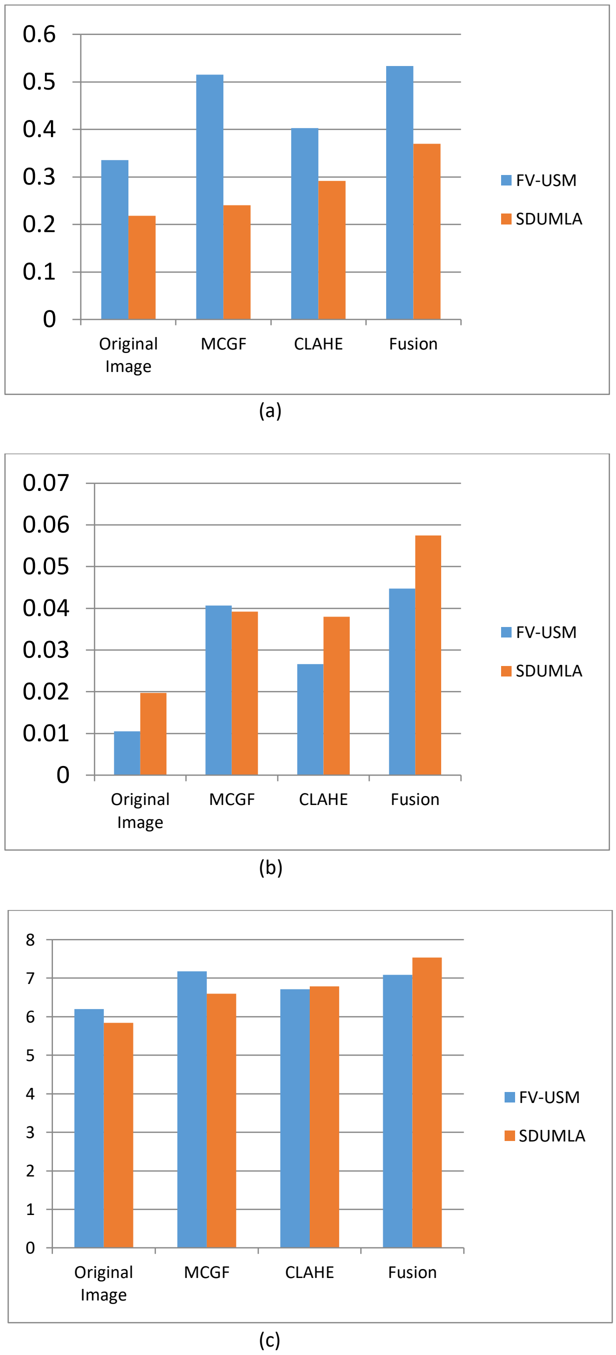

Figure 7: Results of: a) Average gray value, b) Image contrast, c) Image entropy

VII. CONCLUSION

In this paper, we proposed a novel blood vessel image enhancement method by applying various enhancement techniques on two-finger vein images database available in public domain. Fusion technique using DCT was implemented on the results acquired from Histogram Equalization and Gabor filtering. The use of Gabor filter and Adaptive Histogram Equalization prominently led to highlight and visualize as well as to enhance the vein pattern out of original image. Our approach shows good performance when it was used in the SDUMLA database. However, a similar performance can be obtained by the MCGF method when both methods have been tested with the FC-USM database. Another choice of parameters such as the orientations and the size of the mask should allow better results. This proposed method could produce clear veins images, thereby improving the performance of finger-vein recognition.

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