Finger-vein Image Dual Contrast Enhancement and Edge Detection

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Summary
In this paper, we propose a novel scheme to get a pattern of Finger Veins from the original image. The central point of this paper is how to extract Finger-vein ridges from the background surface. For this purpose, we implement dual contrast limited adaptive histogram equalization (DCLAHE) method, which is used for enhancing the grayscale color intensity values. After improving the image contrast, we apply an Otsu thresholding algorithm in canny edge detection to obtain optimal edges for a Finger-vein. Investigational end results show a precise binary representation of the vein pattern.

Keywords:
Finger-veins, dual contrast limited adaptive histogram equalization, Otsu algorithm, edge detection.

1. Introduction

Biometrics authentication is a process of identification of a person using different biological features like Fingerprints, Palm prints, Facial recognition, Retina scans, Voice recognition, and the Finger-vein recognition system. These technologies are evolving the face of the person validation and identification of widespread, highly secure findings for personal data secrecy and confidential proceedings [1] [2] [24] [25]. Finger-vein authentication system has given a reliable solution for secure and precise authentication. The finger-vein system is fundamentally based on extricating the formation of the vascular pattern in the finger to get visible by implementing near-infrared (NIR) light on it. The finger-vein is present underneath the skin, which is not receptive to variances on the exterior of the skin (e.g. Wounds or scratch) gaining robustness regarding forgery [2] [3]. The finger-vein images are acquired by penetrating NIR light of a wavelength of 850-940nm on the finger dorsal side and we get veins images from the Palmer side of the finger to get visible from Charged Couple Device (CCD) camera. The arrangement of NIR light plays an important function for extracting a good quality finger-veins image and the arrangement of NIR lights is broadly classified into two kinds, such as:

a) Light penetration method
b) Light reflection method

Most of the popular finger-vein sensors are based on the penetration procedure that can yield sound quality finger-vein images when associated with the reflection method [2]. The finger-vein images are acquired from a database SDUMLA-HMT to implement proposed algorithms [4]. There are other datasets available such as HKPU-FV [5], UTFV [6], MMCBNU_6000[7], THU-FV [8], etc. [19].
After the finger-veins image acquisition than comes the image-preprocessing phase such as normalization, subtracting finger from the background, image enhancement, and Region of Interest (ROI) extraction to get veins and further enhancement on ROIused to get clear veins ridges for edge detection. The enhancement of finger-vein by applying Contrast-Limited Adaptive Histogram Equalization (CLAHE) on the image gives a better visualization. The CLAHEtechnique is widely applied by the researchers [9] [12]. This function is specified by the user and has not yet been automated, but the implementation of a dual CLAHE before and after ROI extracted from the acquired finger-vein image provides excellent results for the Finger-vein image enhancement. This is based on Adaptive Histogram Equalization (AHE) in which the histogram is determined for the area of a suitable pixel [9]. However, it is clear that CLAHE enhancement used finger-vein image sub-images or small patches with histogram clipping to enhance image contrast [10]. In this paper, with the CLAHE algorithm, the pixel intensity values are enhanced by the clipping limit up to an optimal value through experimental results. The methods for further improvement are discussed in the proposed method below.
The enhanced image is used for segmenting vein patterns from the selected ROI. Particularly, there are many algorithms purpose for extract the vein pattern after an optimal ROI selection and RIO enhancement. There are numbers of previous methods used to extract/segment the finger veins from the acquired images such as:

Manuscript received November 5, 2019
Manuscript revised November 20, 2019

a) Modified Hausdorff Distance (MHD) [3],
b) Personalized Best Bit Map (PBBM) [11],
c) Local Binary Pattern (LBP) [12][13],
d) discrete wavelet transforms (DWT),
e) Windowed Dynamic Mode decomposition (W-DMD) [13], and so forth.

After a clear finger-vein enhancement there comes image edge detection by applying 'Canny' [18] with the Otsu's method for computing the optimal threshold to detect edges [14][18].
In our proposed method, we use Dual CLAHE first on the finger region and second on ROI to extract finger-vein patterns from the background image. After DCLAHE contrast enhancement for finger-vein segmentation utilizing the Otsu algorithm with Canny edge detection to achieve finger-vein pattern from the background image for pattern recognition.

2. System Model

In this model, the image selected and standardized from the database called SDUMLA-HMT [4] to speed up the algorithms applied to the finger-vein image in the blocks known as Image Read and Image Normalization. The surrounding area is manually subtracted from the finger-vein image in the block known as Finger Region Extraction after the block known as Image Normalization. The First CLAHE applied to the finger region, which has been cropped from the original image. With the finger region enhancement, ROI selected from the first CLAHE than the second CLAHE is implemented to enhance the ROI that is taken from the finger region.

2.1. Image Acquisition

Image acquisition is the primary step in the process of finger-vein recognition (FVR) where the finger-vein image is acquired using the NIR light penetration technique on the palm side of the finger via a CCD camera mounted under the dorsal side of the finger [2]. In this paper, the finger-vein images are collected from a database called SDUMLA-HMT [4].

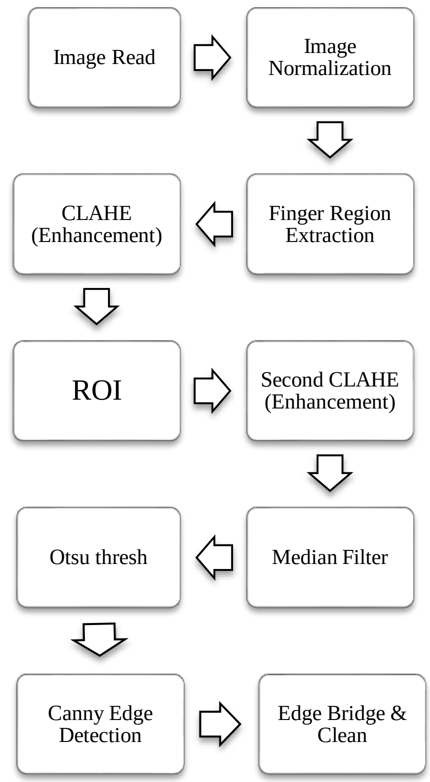

Fig. 1 Proposed System Model

Fig. 2 The Finger-veins capturing device [15].

Wuhan University, China's Joint Lab designed the capture device for Intelligent Computing and Intelligent System as shown above in fig. (2). The size of the finger-vein-image captured by the device is 320 × 240 ×3 [15]. The acquired image as shown in fig. (3) below:

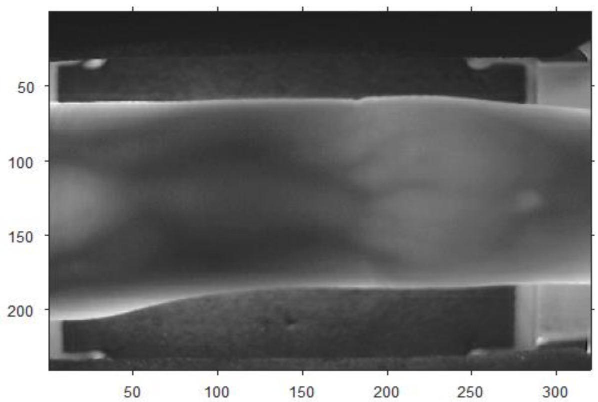

Fig. 3 Original Image from Database SDUMLA-HMT [4].

2.2. Database

To evaluate the algorithm, an image from a database known as SDUMLA-HMT [4] is utilized. It is a fact that the SDUMLA-HMT database is the generally rough finger vein database for preprocessing [4][16]. But with different enhancement techniques, it can be enhanced to the optimal level for Finger-veins edge detection.

2.3. Preprocessing Methodology

After the acquisition, Finger-vein needs enhancement for edge detection.

2.3.1 Preprocessing Methodology

After the image acquisition, the finger-vein image is standardized from 240×320 to 168×224 because of the image size the processing time varies. It can be clearly observed that the size of an image is converted into a standard size for further filtration. All of the finger-vein images should be transformed into a standard image with the same mean and variance. As it is a three-dimension Red, Green, and Blue (RGB) color intensity image so for this, the image transformed into a grayscale image and it has pixel values from [0 255] or [0 1]. As shown in fig. (3), the image is in 320×240×3 format, which shows that image values have three RGB amounts. So, the image pixels are transformed into two-dimensional grayscale intensity values such as 240×320.
To drive out the illumination effect, a technique of grayscale normalization is adopted.

$$p(i,j) = \frac{p'(i,j) - G_1}{G_2 - G_1} \times 255, \quad (1)$$

Whereas G1 and G2 are the minima and maximum grayscale values of the original image$p'(i,j)$and$p(i,j)$is the converted grayscale value [3]. This process used to the downscale image to improve the processing time.

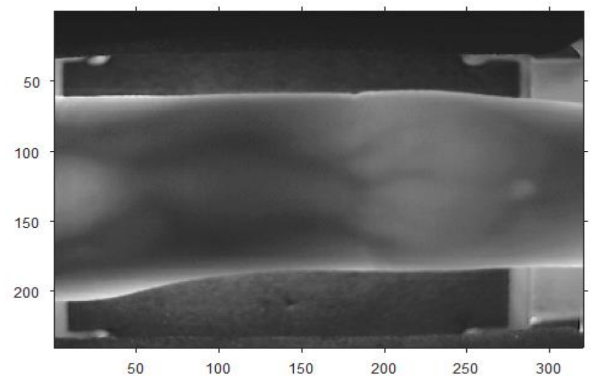

Fig. 4 (a) Original Image 240×320.

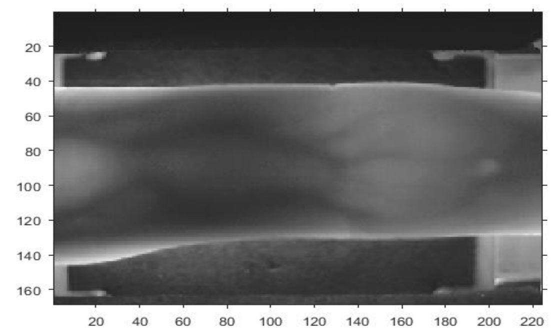

Fig. 4 (b) Normalized image 168×224.

2.3.2 Finger Region Extraction (FRE)

As it is observed from the database [4] the Finger-vein image has inappropriate distribution between finger area and overall image [16]. The image in fig. (2), shows an unsuitable allocation therefore the region of the finger is separate out from the entire image. The overall image has an additional area that needs to be removed. The object of interest is the Finger part and the rest is extracted from the overall image.

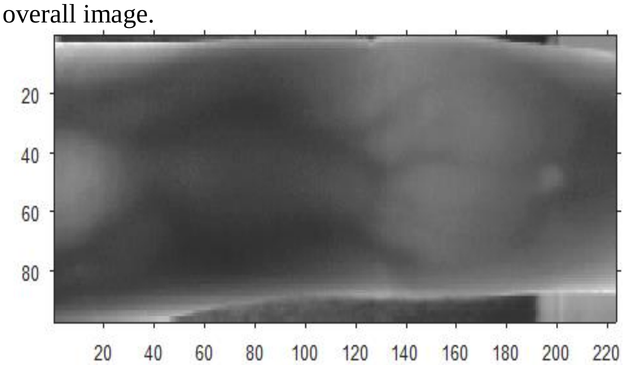

Figure4: Finger Region Extraction.

2.3.3 Steps for CLAHE

1. Partition the original intensity image into contextual regions that are not overlapping, these regions known as image tile of $M \times N$. The 8×8 is of excellent quality for preserving textural image data.
2. Calculate that textual region's histogram relying on the gray values in the image array.
3. Measurement of the contextual region's limited comparison by CL (clipped limit) value such as;

$$N_{avg} = \frac{(N_r X \times N_r Y)}{N_{gray}}, \quad (2)$$

Whereas N_{avg} is the average number of pixels, N_{gray} is the number of grayscales in the contextual region, pixel numbers in the X and Y direction of the context region are $N_r X$ and $N_r Y$.
We can express the actual CL as:

$$N_{CL} = N_{clip} \times N_{avg} \quad (3)$$

If N_{CL} is the real CL, the N_{clip} is the actual CL within the limit of [0, 1] array. The pixel will be clipped only when the number of pixels is higher than N_{CL}.The exact number of pixels clipped is determined as $N_{\Sigma clip}$, then the average of the remain pixels for each gray-level is distributed such as:

$$N_{avggray} = \frac{N_{\Sigma clip}}{N_{gray}} \quad (4)$$

The following statements set out the theory of trimming histograms:

$If\ H_{region}(i) = N_{CL}$ then

$$H_{region_{clip}}(i) = N_{CL} \quad (5)$$

$$Else\ if\,(H_{region}(i) + N_{avggray}) > N_{CL} \text{ then}$$

$$H_{region_{clip}}(i) = N_{CL} \quad (6)$$

$$Else\ H_{region\_clip}(i) + H_{region}(i) = N_{CL} \quad (7)$$

Whereas $H_{region}(i)$ and $H_{region\_clip}(i)$ are the original gray-level histograms and trimmed histograms of each region at i^{th} gray-level.

4. Rearrange the remaining pixels until all of the pixels have been allocated. The rearrangement of the pixel step is given by:

$$Step = N_{gray}/N_{remain} \quad (8)$$

The remaining number of clipped pixels is N_{remain}. Step is at least a positive integer 1. The program starts scanning from the minimum to the maximum gray level with the above point. When the number of pixels is less than N_{CL} in the grayscale, this will add one pixel to the gray level, until the pixels aren't all distributed and run according to Eq. (8), and new findings will go on until all remaining pixels are distributed [17].

The CLAHE contrast enhancement is implemented once again after a prominent selection of the vein where the ridges are visible and distinguishable to one another and considering it the ROI of Finger-vein image acquired from the sensor.

2.3.4 Median Filter

A median filter (MF) is far more efficient than convolution when the objective is to reduce noise and sustain boundaries simultaneously.

$$f'(x, y) = median_{(s,t)\in S_{xy}}\{g(s,t)\}\ [20] \quad (9)$$

For the 2D series, the MF is defined by a filter window $(2N + 1)$ x $(2N + 1)$ from which the median value is generated [21,20]. The main advantage of the MF (median filter) over the alternative class of linear filters is that impulsive noise is rejected in a series without smoothing "steps" or "boundaries" [21].

2.3.5 Otsu's Optimal Threshold

Thresholding produces binary images at a gray-level by transforming all pixels at a certain threshold to zero and above that threshold to one. The Otsu scheme is a form of global thresholding that depends only on the image's gray value. Scholar Otsu developed the Otsu model in 1979. It is a widely used threshold method, which is simple to find an optimal threshold for a grayscale finger-vein image. It gives a satisfactory segmentation result for the Finger-vein image combined with Canny Edge Detection.
This threshold technique requires a gray histogram to be measured earlier before the threshold is computed [14]. Suppose an image with gray level is L and can be defined by a function of 2D gray intensity $f(x, y)$, so the neighborhood pixel gray level is $g(x, y)$ and it is also represented as L. [23]

$$g(x, y) = \frac{1}{2k+1} \sum_{\Delta x=-k}^{k} \sum_{\Delta y=-k}^{k} \times f(x + \Delta x, y + \Delta y) \quad (10)$$

In this equation, k =1the probabilities of density function are:

$$\mathcal{P}_{ij} = \frac{f_{ij}}{M} \qquad (11)$$

Where$\mathcal{P}_{ij}$ is the probability and f_{ij} is the total number of incidences (frequency) of an array (*i*, *j*). *M* is the total number of pixels. Where 'i' is the grayscale value of every pixel *and 'j'* is the average grayscale value constitute a 2D-array *(i, j)*.

Where$\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} f_{ij} = M \ and \ \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\mathcal{P}_{ij} = 1$.

Now suppose each pixel is partitioned into two classes C_o and C_1 with a threshold pair *(s, t)*, which represent objects and background, then probabilities of two cluster class incidence are denoted as:

$$\omega o = \sum_{i=0}^{s-1}\sum_{j=0}^{t-1}\mathcal{P}_{ij} \qquad (12)$$

$$\omega 1 = \sum_{s=0}^{L-1}\sum_{t=0}^{L-1}\mathcal{P}_{ij} \qquad (13)$$

Now for the mean C_o and C_1 vectors are:

$$\mu_0 = (\mu_{0i}, \mu_{0j})^T$$

$$= \left[\sum_{i=0}^{s-1}\sum_{j=0}^{t-1} i\mathcal{P}_{ij}\ , \quad \sum_{i=0}^{s-1}\sum_{j=0}^{t-1} j\mathcal{P}_{ij}\right]^T \ (14)$$

and

$$\mu_1 = (\mu_{1i}, \mu_{1j})^T$$

$$= \left[\sum_{i=s}^{L-1}\sum_{j=t}^{L-1} i\mathcal{P}_{ij}\ , \quad \sum_{i=s}^{L-1}\sum_{j=t}^{L-1} j\mathcal{P}_{ij}\right]^T \qquad (15)$$

The matrix of the global mean is:

$$\mu_t = (\mu_{ti}, \mu_{tj})^T$$

$$= \left[\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} i\mathcal{P}_{ij}\ , \quad \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} j\mathcal{P}_{ij}\right]^T \qquad (16)$$

The variance matrix of the interclass is defined as:

$$S = \sum_{k=0}^{1} \omega_k[(\mu_k - \mu_t)(\mu_k - \mu_t)^T]$$

$$= \omega_0[(\mu_0 - \mu_t)(\mu_0 - \mu_t)^T]$$

$$+\omega_1[(\mu_1 - \mu_t)(\mu_1 - \mu_t)^T] \qquad (17)$$

By using the trace of S as the inter-class variance calculation, there is:

$$r_{tr}(S) = \omega_0\left[(\mu_{0i} - \mu_{ti})^2 + (\mu_{0j} - \mu_{tj})^2\right]$$
$$+\omega_1\left[(\mu_{1i} - \mu_{ti})^2 + (\mu_{1j} - \mu_{tj})^2\right] \qquad (18)$$

By maximizing $r_{tr}(S)$, the optimal threshold vector (*s*, *t*) is obtained. The selection of thresholds is the most critical step in the object segmentation process [23] [22].

2.3.6 Canny Edge Detection

After sustaining boundaries and erasing noise after DCLAHE, the Canny Edge detection algorithm with the optimum determination of the threshold by the 2D histogram Otsu algorithm to achieve optimal edges [22].

John Canny proposed this function in 1986 and it is frequently used to detect the edges [18]. Methods for detecting the edge from Canny are:

1. Smoothing with Gaussian filter as:

$$H(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{(i)^2+(j)^2}{2\sigma^2}} \qquad (12)$$

Whereas *i*, *j*; is *x* and *y* filter co-ordinates and have a mean zero. For example, if the kernel size is 4, then *i* and *j* are within [-4, 4] and k is the kernel size. Whereas 'σ' is the standard deviation.

2. Computing the magnitude and orientation of gradients.

The path 'θ'and magnitude is determined by;

$$G = \sqrt{G_x^2 + G_y^2} \qquad (13)$$

and

$$\theta = \tan^{-1}\frac{\mathrm{Gy}}{\mathrm{Gx}} \qquad (14)$$

Where $G_x$the first derivative of horizontal component,$G_y$is the first derivative of vertical component and are calculated using the following matrices as masks for image gradient such as:

$$G_x = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}, G_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

3. Non-maximum elimination of unwanted pixels that are combined with edges and this is known as edge thinning.

It is achieved by matching the gradients of the pixel with their neighbors. If it is less than that of the neighbor, the edges will deduct the pixel. Its neighbor is the border pixel with the path ‘θ’, which is separated into four sections [18]. For separation of edges, Canny and 2D Otsu threshold functions are combined to achieve an optimal result to detect Finger-vein.

2.3.7 Bridge and Clean Edge

Now, applying morphological bridge on unconnected pixels in a binary image that is, if they have two non-zero neighbors that are not linked, set 0-valued pixels to 1 such as:

$$\begin{bmatrix}1 & 0 & 0\\1 & 0 & 1\\0 & 0 & 1\end{bmatrix} \rightarrow \begin{bmatrix}1 & 1 & 0\\1 & 1 & 1\\0 & 1 & 1\end{bmatrix}$$

The morphological operation also used to clean the unwanted edges. These edges appear when the image has more illumination at the edges rather than the background. In this filter, the unknown edges are removed in a binary image to get a clear vein pattern of a binary image. The morphological operation removes isolated foreground pixels [20].

3. Proposed Image Enhancement Technique

To improve the level of contrast between the finger-vein images in a grayscale image, several procedures have been used to alter the intensity of a grayscale image. In these past few years, many enhancement algorithms were developed to increase the image contrast in a variety of applications. Image enhancement algorithms are broken down into two classifications.

1. Physical model-based image restoration,
2. Enhancement of the image utilizing image processing approaches [17].

The conventional approach for image enhancement is the histogram Equalization (HE) that works well on ordinary objects like human portraits or natural images. For relatively homogeneous regions, this suffers from noise amplification [12][17]. Adaptive Histogram Equalization (AHE) is an enhanced version of the conventional scheme of HE. Because the HE is applied to the complete input image, it would not have been possible to improve the local details with a lower probability. AHE instead of a whole image, it runs on small data regions (tiles) The AHE amplifies the small amount of noise in a large homogeneous region of image [12]. After analyzing these issues CLAHE compared to these perform well with finger-vein image enhancement.

Using Dual Contrast Limited Adaptive Histogram Equalization (DCLAHE) technique with a two-dimensional median filter to enhance the Finger-vein image to distinguish the background from the vein achieves an excellent result for Finger-vein image. The first CLAHE implementation is utilized to enhance the Finger region, which is extracted from the overall image matrix.

The initial implementation of CLAHE helps the image to increase the entire finger region contrast as shown in fig (5b). This approach consists of the processing of small finger areas (termed as tiles) and utilizing collective histogram necessity for each tile instead of operating on a complete image. The CLAHE restricts amplification by clipping the histogram before measuring the cumulative distribution function (CDF) to a predetermined value. It has two important bounds: Block Size (BS/tile), Clip Limit (CL) [17].

The fig.5(a) and (b) it can be clearly observed that contrast difference before the first CLAHE, after enhancing the contrast of the finger region with the tile size of 8×8 with clip limit of 0.03 and cumulative distribution 0.4. The initial CLAHE clip the limits of histogram and enhance the contrast by distributing histogram around the neighboring pixels of finger region. Distribution is a string that determines the desired shape for the tiles of the image. The distribution utilizes exponential shape for tile as it is clearly noticeable from histogram analyses that it needs an exponential shape for tiles because of veins ridges [20]. After the CLAHE now selecting the ROI where the character of the finger-vein looks dominant as compared to other areas.

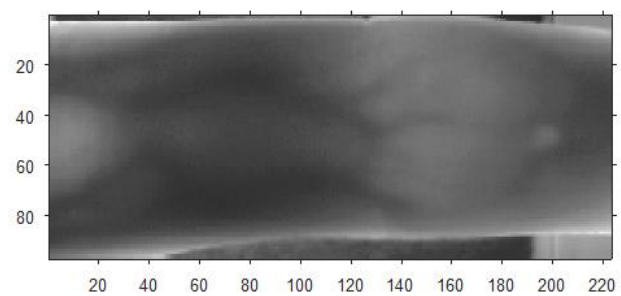

Fig. 5 (a) Enhanced Image from Finger Region.

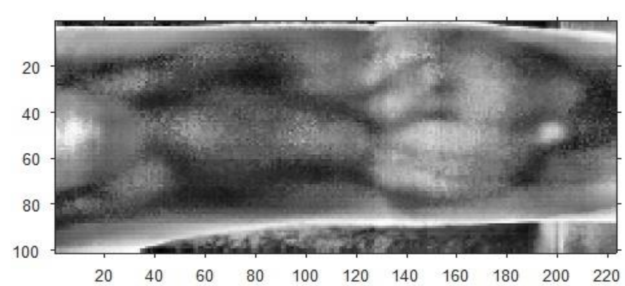

Fig. 5 (b) Enhanced Image from First CLAHE.

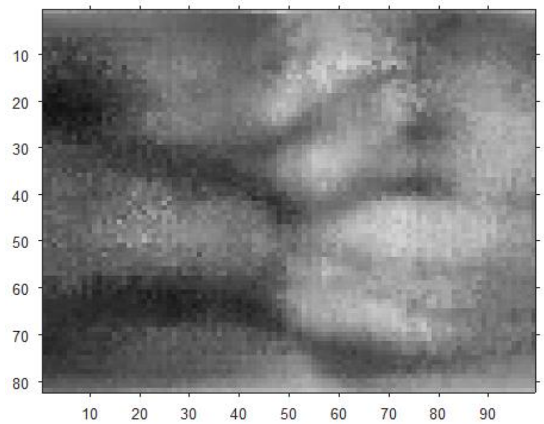

Fig. 5 (c) Enhanced Image from ROI.

With the ROI selection, another CLAHE contrast development method is implemented on the ROI image to utilize it for edge detection.
The fig.6b shows the result of dual CLAHE contrast

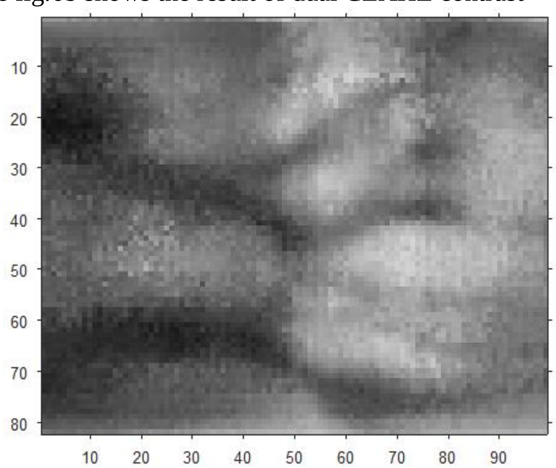

Fig. 6 (a) ROI.

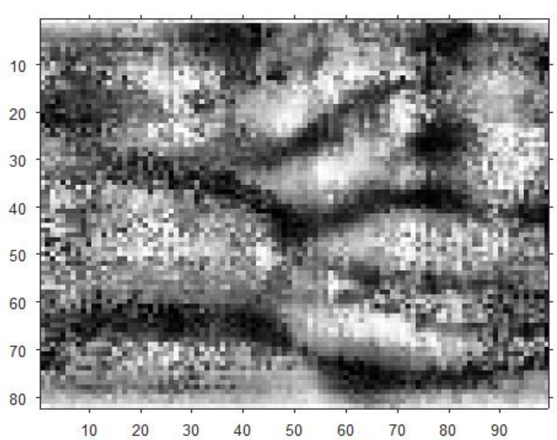

Fig. 6 (b) DCLAHE.

In the dual CLAHE, the image becomes blurred and unclear, so for that, we apply a median filter to smooth finger-vein image for edge detection.

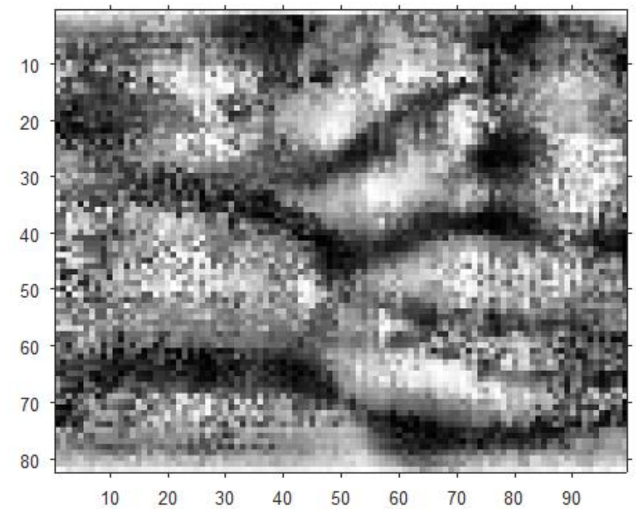

Fig. 7 (a) Result of DCLAHE.

5. Utilization of Canny Edge Detection and Otsu Thresholding

After the proposed finger region and ROI enhancement technique, the optimize threshold required Canny Edge Detection to extract the finger-vein pattern. For this Otsu thresholding with two-dimensional histogram count of a grayscale image is utilized to convert gray values into [0 1]. The result as shown below in the fig. (8).

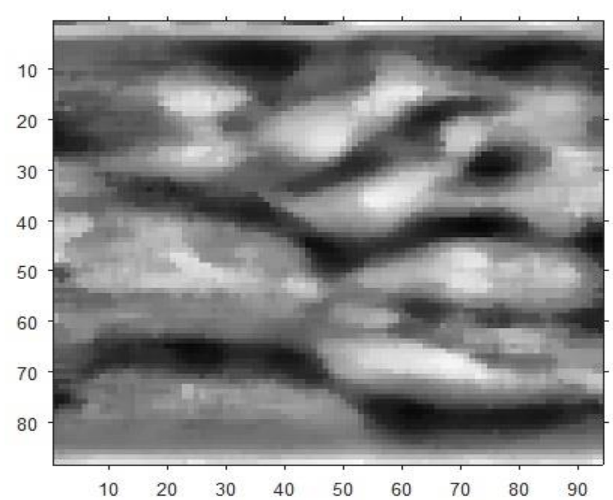

Fig. 7 (b) Result of Median Filter.

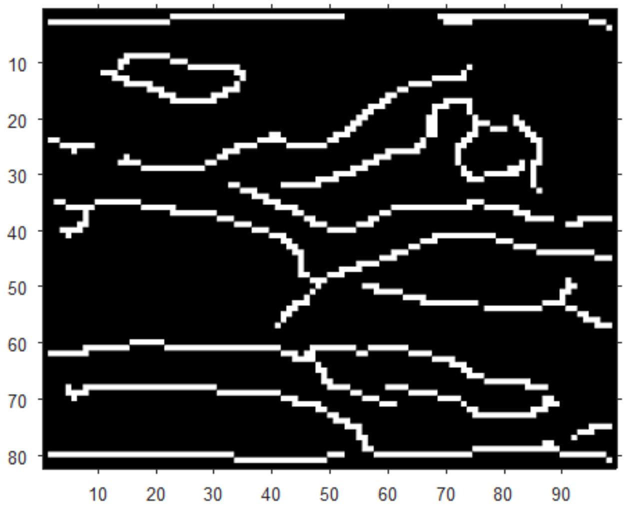

Fig. 8 Canny Edge Detection Result.

6. Conclusion

We have applied Dual CLAHE to enhance image contrast of a low intensity finger-vein image for a clear extraction of finger-vein edges from background. We used these algorithms in MATLAB to examine the result as shown in the above figures. The goal of these algorithms is to segment finger-vein image correctly from the background for pattern recognition. Using Otsu's threshold choice and Canny edge detection, an excellent result can be obtained, as shown in the figures above. After achieving the finger pattern through edge detection, some of the non-edges remain visible because of illumination effect and NIR light intensity so for this we apply a morphological binary filter to bridge edges and remove non-edges from canny edge detection.

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