

# Grayscale and binary image enhancement of hand vein images to aid peripheral intravenous access

Marlina Yakno, Junita Mohamad-Saleh, Bakhtiar Affendi Rosdi

**Abstract**—Difficulty in achieving a peripheral intravenous (IV) access in pediatric and some adult's patient is a clinical problem. The use of near-infrared imaging device to aid visualization of an IV access usually suffers from low contrast and noise due to non-illumination and thickness of hand skin. This further complicates subsequent processing such as image segmentation. In this work, two methods are proposed in two different stages; grayscale enhancement and binary enhancement for correction of low contrast and noisy images. For grayscale enhancement, a combination of histogram-based and fuzzy-based contrast enhancement algorithms are applied on hand vein images. For binary enhancement, a combination of three techniques; Artificial Neural Network pixel corrector, Binary Median Filter and Massive Noise Removal, are applied on the binary hand vein images. Comparative analysis on test images using different contrast enhancement methods has shown superior results from the proposed method in comparison to its counterparts.

**Keywords**—Image enhancement, neural network, fuzzy, hand vein imaging, peripheral intravenous access.

## I. INTRODUCTION

A peripheral IV access is a process of obtaining blood vessel for the purpose of blood drawing, intravenous fluid feeding or administration of medicine in patient's blood vessels by inserting a needle or catheter through the skin and into an underlying vein. It is often performed by medical laboratory scientists, medical practitioners, paramedics, phlebotomists and other nursing staff.

A catheter is a small tube, but is most often difficult to be placed into blood vessel, especially if a patient is at an extreme age, with chronic disease or has dark skin color [1-3, 5]. It was reported that worldwide, 10% (i.e. more than 1 million per year) of attempts to establish an IV line has failed [4]. The failure, although a small percentage, has led to various negative impacts during IV access such as fainting or feeling

lightheaded, hematoma (blood accumulating under the skin) and pain associated with multiple punctures to locate a vein. In addition, the frightful and stressful moments faced particularly by children patients during IV may lead to the development of severe psychological problems such as needle phobia or worse still, hospital phobia.

Near-infrared (NIR) imaging offers a solution for veins visualization as it can penetrate up to several millimeters into a tissue (i.e. skin) with a specific wavelength between 700 and 1000nm [5-7]. However, its image acquisition most often resulted in vein images with poor contrast, non-uniform gray level and noises because the acquisition is affected by luminous intensity and thickness of the back of hand skin. Several methods have been used to solve these imaging problems, focusing at grayscale or binary image enhancement.

Image enhancement process usually produces a better-quality image for the next imaging process such as separation or segmentation of vein from its background. A classical grayscale enhancement technique is based on histogram equalization (HE) [8]. Although HE is suitable for an overall contrast enhancement, practically HE usually causes level saturation, an effect which degrades the appearance of an image leading to loss of information [9]. To overcome this limitation, Kumar and Prathyusha have employed an extension of HE known as Contrast Limited Adaptive Histogram Equalization (CLAHE) into vein imaging [10]. By applying an appropriate value of clipping level, CLAHE method does not only enhance the contrast, but it is also able to solve the illumination problem. This method has been reported to be suitable for most medical imaging purposes [11-13]. However, if the chosen clipping level is inappropriate, CLAHE can degrade the quality of an image significantly.

Simplest methods such as unsharp masking (UM) [14-15] have also been proposed to enhance image contrast. Recently, Zhao et al. presented a method to enhance hand vein images based on Butterworth High Pass Filter and HE [16]. However, the methods may have poor performance at improving the contrast of some hand vein images due to the two main drawbacks. At first, it enhances high-contrast areas more than areas that do not exhibit high image dynamics. Second, the presence of linear highpass filter makes the system extremely sensitive to noise. Consequently, some unpleasant overshoot artifacts may appear in the output image.

Marlina Yakno. Author is with the Faculty of Electrical & Electronics Engineering, University Malaysia Pahang, Pahang, Malaysia (corresponding author to provide phone: 609-424 6032; fax: 609-424 6111; e-mail: marlinayakno@ump.edu.my).

Junita Mohamed-Saleh. Author, is with the School of Electrical & Electronics Engineering, University Sains Malaysia, Pulau Pinang, Malaysia. (e-mail: jms@usm.my).

Bakhtiar Affendi Rosdi. Author is with the School of Electrical & Electronics Engineering, University Sains Malaysia. (e-mail: eebakhtiar@usm.my).

When dealing with binary images, the contrasts of vein patterns vary depending on the illumination of an image. A binary hand vein normally contains some noise and un-sharp edges. Thus, the quality of the image needs to be enhanced to expose the vein structures. Shahin et al. have employed Binary Median Filter (BMF) [17] and Kumar and Prathyusha applied Massive Noise Removal (MNR) [10] to eliminate noise regions with small amount of connectivity. Work by Ding et al. utilized the advantages of MNR and BMF into their work for the same purpose [18].

Image enhancement using fuzzy techniques have been used extensively in medical applications especially in digital mammogram [19-20]. Fuzzy Histogram Hyperbolization (FHH) is an example of fuzzy technique which promises good enhancement results in various applications. However, very few researchers have explored this approach for hand vein image enhancement. Also, to the best of our knowledge, no researchers have combined CLAHE with FHH for any application.

Aside from the conventional techniques, a more sophisticated technique like Artificial Neural Network (ANN) has also been employed in hand vein imaging. However, the ANN approach for hand vein imaging is mostly applied to vein recognition for biometric purposes [21-22]. To the best of our knowledge, no researcher has ever applied ANN technique onto binary hand vein image enhancement for medical purposes.

This paper proposes the application of CLAHE with FHH for grayscale enhancement of hand vein image. Then, using local threshold method the enhanced image is converted into binary. Finally, a combination of ANN pixel corrector, BMF and MNR techniques are applied in binary enhancement stage. With this method, the contrast of binary images can be increased and subsequently a more accurate hand vein patterns can be obtained to aid peripheral IV access. The proposed approach is compared with various existing image enhancement methods at exposing binary hand vein patterns.

## II. HAND VEIN IMAGE ACQUISITION

In this work, a Sony CCD TV camera is used to capture the vein patterns at the back of a hand. The subject's hand is illuminated by 48-near-infrared light emitting diodes (LEDs) with wavelength of 890nm. The LEDs are equi-distantly mounted around the camera lens to ensure an even illumination on the hand skin. The current level of the LEDs can be manually adjusted according to the environment. Subjects were asked to place their hands on a small platform with back of the hand facing the camera. The CCD TV camera was connected to a computer to capture the images as shown in Fig. 1. A captured hand vein image is then filtered from impulse noise [23] and extracted into a region of interest [24] based on modification on the image size at a pre-processing stage.

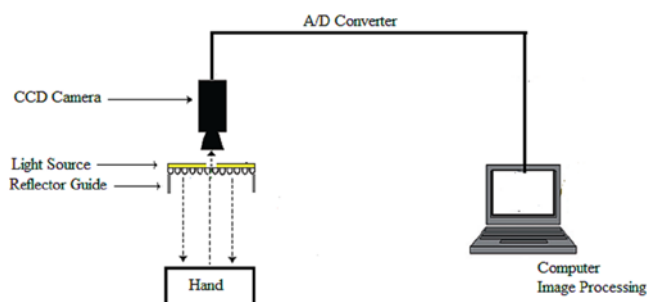


Fig. 1 Schematic of hand vein image acquisition

## III. HAND VEIN PATTERNS IMAGING

In general, the proposed enhancement method for hand vein imaging in this work consists of grayscale enhancement, segmentation, binary enhancement and image evaluation stages. This process is illustrated in Fig. 2. Each of these stages are discussed.

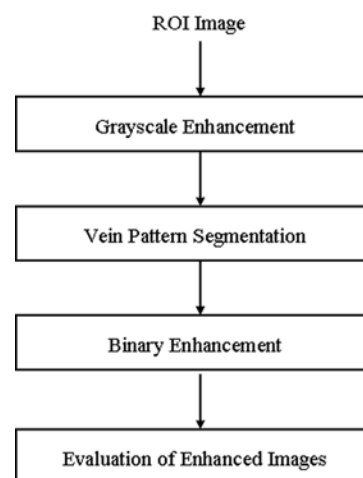


Fig. 2 Process flow diagram of proposed hand vein exposure system development

### A. Grayscale Enhancement

Grayscale enhancement is employed to simplify the separation of veins and its background within an image. This work considers CLAHE method to take advantages of its capability at enhancing image contrast. Then, it applies FHH to further sharpen the vein patterns. Image enhancement methods considered in this work are discussed.

#### 1) Contrast Limited Adaptive Histogram Equalization

As already stated, CLAHE method is an improvement over standard HE. While HE considers the entire image, CLAHE algorithm operates by partitioning the image into a number of non-overlapping contextual regions. A histogram is calculated and constructed separately according to the size of contextual regions. Then, a clip limit value for clipping histograms is determined as a threshold. Next, the histogram is clipped according to the predefined clipping limit. The access clipped

pixels are then distributed back to the clipped histogram. Finally, the gray level mappings were combined using bilinear interpolation in order to assemble the final enhanced image .

### 2) Fuzzy Histogram Hyperbolization

It has been reported that CLAHE method may result in loss of image information [25]. Hence, after employing CLAHE, FHH is applied for further enhancement of the vein image. FHH combines the concepts of histogram hyperbolization and fuzzy hyperbolization [26]. Basically, the algorithm works in the following sequence:

- **Gray Level Fuzzification:** The image fuzzification transforms a gray level image into the range of [0, 1]. Here, a non-linear function is applied as a membership function [27]:

$$\mu(g_{ij}) = \frac{g_{ij} - g_{\min}}{g_{\max} - g_{\min}} \quad (1)$$

where  $g_{\min}$  and  $g_{\max}$  are the minimum and maximum value of the gray level in the image.

- **Modification of Membership Function:** A membership modification is carried out using [27]:

$$\mu'(g_{ij}) = [\mu(g_{ij})]^\beta \quad (2)$$

where fuzzifier,  $\beta$  is a parameter used to modify the meaning of a fuzzy set. Applying fuzzifier may result in either reducing image contrast or increasing image contrast, depending on the value of  $\beta$ , obtained based on trial-and-error.

- **Gray Level Defuzzification:** A new set of gray level is generated as follows [27]:

$$g'_{ij} = \left( \frac{L-1}{e^{-1}-1} \right) \times \left[ e^{-\mu'(g_{ij})^\beta} - 1 \right] \quad (3)$$

where  $\mu(g_{ij})$  is the gray level in the fuzzy membership values,  $\beta$  is the fuzzifier parameter,  $g'_{ij}$  is the new gray level values and  $L$  is the maximum number of gray levels in the original image.

### B. Segmentation

Segmentation is a process which partitions a digital image into multiple regions or sets of pixels that have similar characteristics to each other [28]. A simple segmentation process involves thresholding which can be categorized into global or local threshold. In global threshold, a distinct peak in the histogram is expected for determining the global threshold for the entire image. For hand vein images however, such peaks do not exist, and thus, it is unlikely that global thresholding can produce good results [19]. Therefore, local thresholding method is adopted in this work as it has been reported to perform better and produce more satisfactory results than global threshold [29].

To find local threshold value, the intensity values of the

local neighbourhood of each pixel are first statistically examined to determine the most suitable statistical function. This is necessary as suitable statistical function is dependent upon the input image. For hand vein images used in this work, mean of local intensity has been found to be the most appropriate statistical function. It is also simple in implementation and has fast execution.

For image window  $W(i,j)$  of size  $N \times N$ , the mean value is calculated as follows [30].

$$\mu = \frac{1}{N \times N} \sum_{i=0, j=0}^{i=N-1, j=N-1} W(i, j) \quad (4)$$

On the whole, mean of local area alone is not suitable as a threshold, because the range of intensity values within a local neighbourhood is very small and their mean values are close to the centre pixel [29]. The situation has been improved by employing a proposed threshold value ( $mean - C$ ), where  $C$  is a constant.  $C$  is determined based on trial-and-error as it is dependent upon the image.

The local threshold  $T_L(i,j)$  for each centre pixel of window  $W(i,j)$  is selected as [29].

$$T_L(i, j) = (\mu - C) \quad (5)$$

where  $\mu$  is a mean and  $C$  is a constant. Window  $W(i,j)$  is then thresholded as [30]:

$$W_L(i, j) = \begin{cases} 1 & \text{if } W(i, j) > T_L(i, j) \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

All pixels with value above the threshold,  $T_L$  are assumed to belong to the object of the interest while all pixels with values below the threshold level are assumed to be the background.

### C. Binary Enhancement

A segmentation result normally contains some noise and unsharp edges which affect the structure of vein images. Thus, the quality of an image needs to be enhanced to expose the vein structures. To achieve this, a proposed binary enhancement algorithm consisting of three stages; correction of selected pixels using ANN pixel corrector, smoothing of vein edges using BMF and elimination of unwanted noise using MNR, are tested. After a series of trial-and-error process, a sequence of the three components is employed.

#### 1) ANN Pixel Corrector

An ANN pixel corrector has been designed and trained to classify a pixel as background or vein based on the position of the pixel in a vein image. Outputs from the ANN pixel corrector are either 1 for vein or 0 for background.

For ANN training in general, it is necessary to gather sample data containing various features that can possibly appear in a vein image so that the ANN learns to map specially adapted parameters of these features. For this reason, a set of 3 x 3 window of binary image are used as training patterns for

binary vein image (see Figure 3), whereby  $x_1$  refers to the pixel of interest, and  $x_2$  until  $x_9$  are the neighbouring pixels. The window acts as a template to determine the correction for pixel  $x_1$ .

A total of 256 sets of training pattern have been generated from a hand vein image. These input patterns are then randomly divided into three subsets namely the training, validation, and test set with a ratio of 40:20:40 respectively. These datasets are used in ANN training.

In ANN training process, the binary values of each 3 x 3 window together with their corresponding desired binary output are fed into a Multilayer Perception (MLP), a variant of ANN model. The proposed MLP is a three layer feed-forward ANN with one hidden layer as shown in Figure 4. Each layer consists of a number of processing elements which do the computation. The feed-forward MLP neural network is trained by supervised learning using the Levenberg-Marquardt iterative back-propagation algorithm, from one to ten hidden layer neurons. For each specified number of hidden neurons, an MLP is trained 30 times to avoid local minima traps. After each iteration, the mean square errors (MSE) of the training and validation datasets are calculated. The training process terminates when there is no further reduction in the validation MSE for 5 consecutive training iterations. The best MLP is

$x_2$	$x_5$	$x_7$
$x_3$	$x_1$	$x_8$
$x_4$	$x_6$	$x_9$

Fig. 3 A 3 x 3 window of binary image pixels

selected from each of the 30 trains runs of each specified number of hidden neurons.

2) Binary Median Filter (BMF)

At this stage, the output of ANN pixel corrector is scanned uniformly using 5 x 5 sliding windows to eliminate burrs and make the vein edges smooth. This is done by using a median value. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replaces the value of the center pixel by the median value as given by:

$$m(i, j) = median(w(i, j)) \tag{7}$$

3) Massive Noise Removal (MNR)

Massive noise removal technique involves a conversion of the white pixel value of '1' (foreground) to black which is '0' (background) if the total value of white pixels in each object in an image is less than the minimum number of white pixels set for a connected component. The minimum number of the white

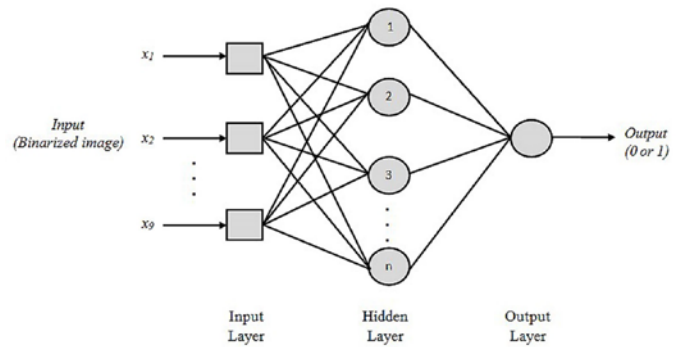


Fig. 4 Structure of a three-layer-feed-forward MLP-pixel corrector

pixels for connected components is also known as threshold value. In general, this technique is carried out based on four stages; connected component labeling area, component labeling area computation, threshold value determination and small objects removal.

It begins by assigning a unique label (i.e.  $L=1, 2, 3, \dots, n$ ) to each object (a group of connected pixels with intensity of 1) in a binary image by scanning the image pixel-by-pixel using 4-connectivity, from left to right and top to bottom. The area of each labeled component is then calculated. This is followed with the threshold value determination. Before the threshold value can be determined, the maximum size of connected components is defined using:

$$C_{Lmax} = \max(C_L) \tag{8}$$

where  $C_L$  is the connected components with a unique label and  $C_{Lmax}$  is the maximum size of connected components.

Then, threshold value  $T$  is calculated as follows:

$$T = C_{Lmax} / m \tag{9}$$

Where  $m$  is determined based on trial-on-error as it is dependent upon the image.

Finally, MNR is represented as:

$$Y(i, j) = \begin{cases} 0 & \text{if } C_L < T \\ 1 & \text{otherwise} \end{cases} \tag{10}$$

Based on Eq. (10), such connected component,  $C_L$  which is less than the minimum threshold value is converted to background and the others remained unchanged. This process ends the image enhancement process.

D. Evaluation of Enhancement Image

The performance of proposed grayscale and binary enhancement approaches have been quantitatively evaluated by examining an image's sensitivity. Sensitivity is often used to evaluate a clinical test [31]. For an enhanced binary image, sensitivity measures the proportion of positives or foregrounds (i.e. vein pixels) which are correctly identified against the entire region of the truth image. Each truth image is generated based on the grayscale image. In this case, background pixels are the false negatives. Sensitivity is calculated as follows

[31]:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (11)$$

where true positive is the number of foreground pixels correctly classified as foreground and false negative is the number of foreground pixels incorrectly classified as background. Sensitivity has a range of [0, 1]. Higher sensitivity values signify good accuracy of classification.

Sensitivity is used to evaluate the two proposed work stages, grayscale enhancement (i.e. CLAHE with FHH) against four commonly used contrast enhancement methods: LCS, HE, and CLAHE and binary enhancement compared to the existing binarization methods; BMF, MNR and a combination of both.

### I. RESULTS AND DISCUSSION

The performance of grayscale enhancement evaluates the ability of a method to provide high contrast between vein patterns and the background. Figure 5(b) to Figure 5(e) show the performance of the LCS, HE, CLAHE, and CLAHE with FHH over a low contrast hand vein image. Visually, it can be seen that the output image from CLAHE with FHH (Figure 5(e)) has the best enhancement throughout all vein regions as the contrast of vein texture and background is the largest. The

vein outlines are the clearest and continuous for the proposed method. By producing higher contrast fluctuation with minimum unwanted artifacts, the proposed method is capable of strong contrast enhancement around vein patterns present in the input image. Hence, it allows easier and more effective vein segmentation.

In order to verify effective segmentation from grayscale enhancement image, local threshold has been applied onto the images. As depicted in Figure 5(f) to Figure 5(i), it seems that vein patterns imaged by the proposed method (see Figure 5(i)) reveal clearest vein patterns. However, there is still much noise in these binarized images and thus, binary enhancement has been employed.

The performance of binary enhancement is analyzed both quantitatively and qualitatively, by comparing binarized image from the proposed method, ANN+BMF+MNR to BMF, MNR, BMF+MNR and MNR+BMF. The results are as shown in Figure 6. Based on visual perception, the proposed method produces the clearest vein patterns than other methods because it is able to reveal the vein patterns more accurately for most graylevel enhancement images.

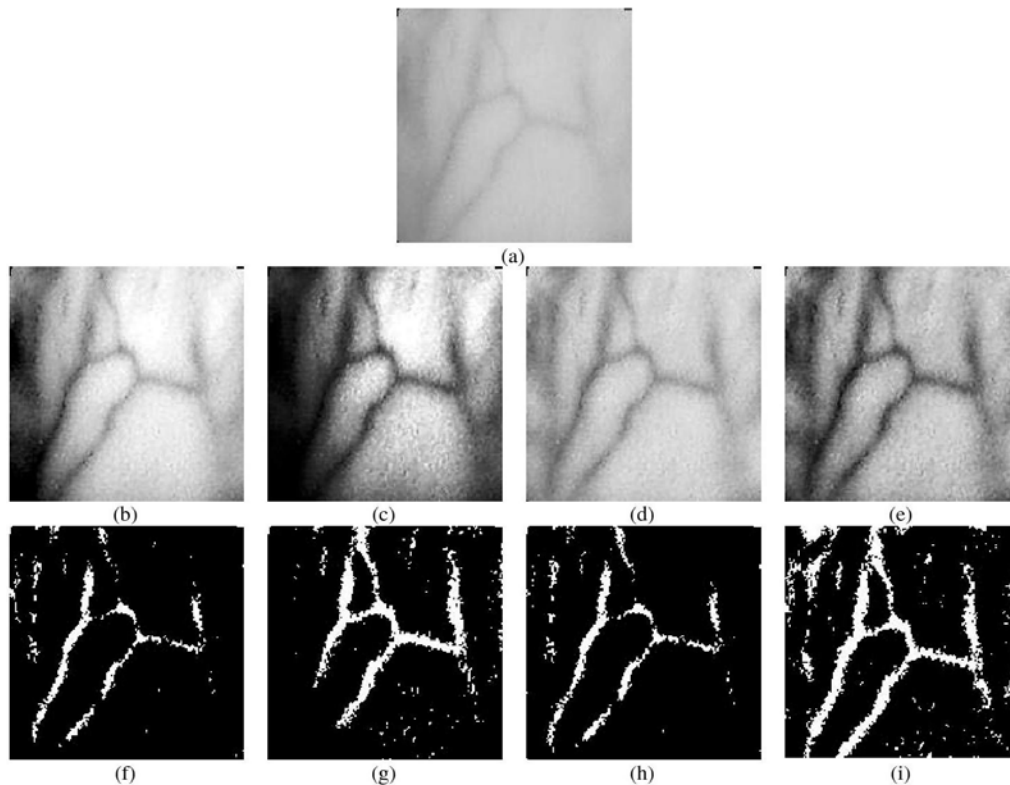


Fig. 5 Results of a grayscale image enhancement over (a) the original hand vein image using (b) LCS, (c) HE, (d) CLAHE and (e) proposed method, CLAHE with FHH. Binarized image using local threshold on the enhanced images of (f) LCS, (g) HE, (h) CLAHE and (i) proposed method, CLAHE with FHH

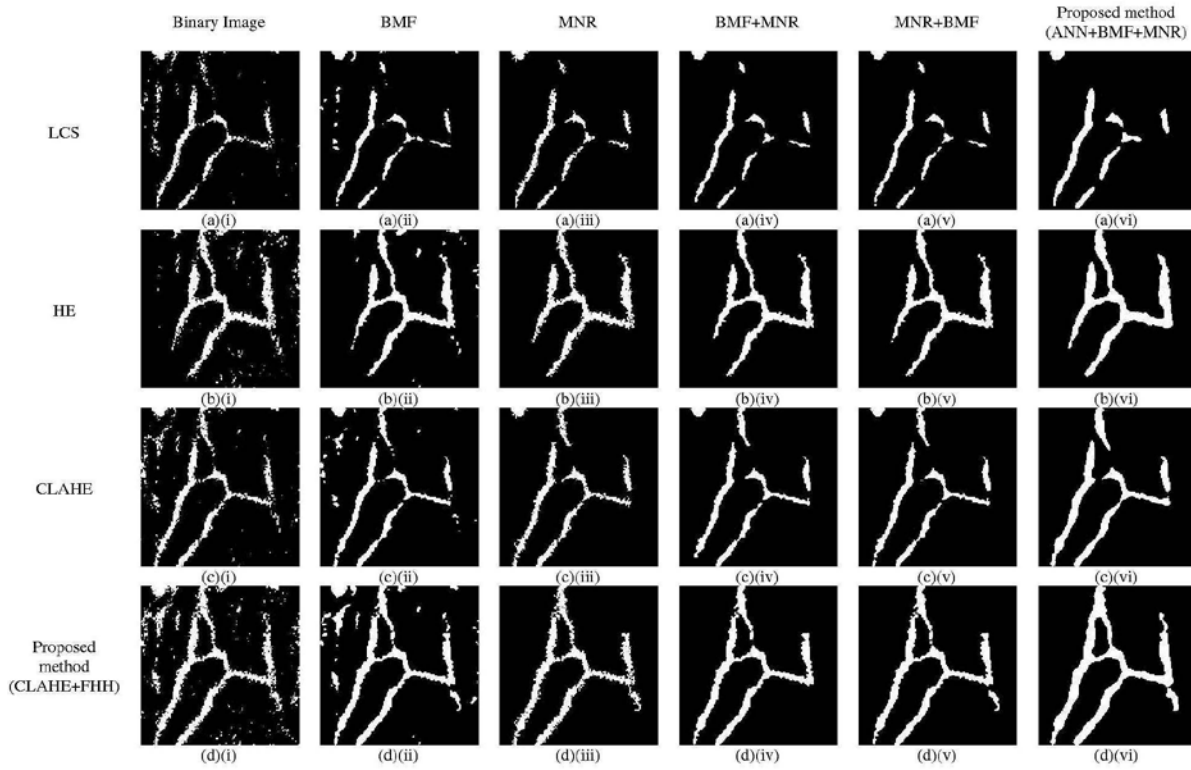


Fig. 6 Results of gray and binary image enhancement over (i) the original binary image on grayscale enhancement using (a) LCS, (b) HE, (c) CLAHE and (d) CLAHE +FHH and binary enhancement using (ii) BMF, (iii) MNR, (iv) BMF+MNR, (v) MNR+BMF and (vi) proposed method, ANN+BMF+MNR

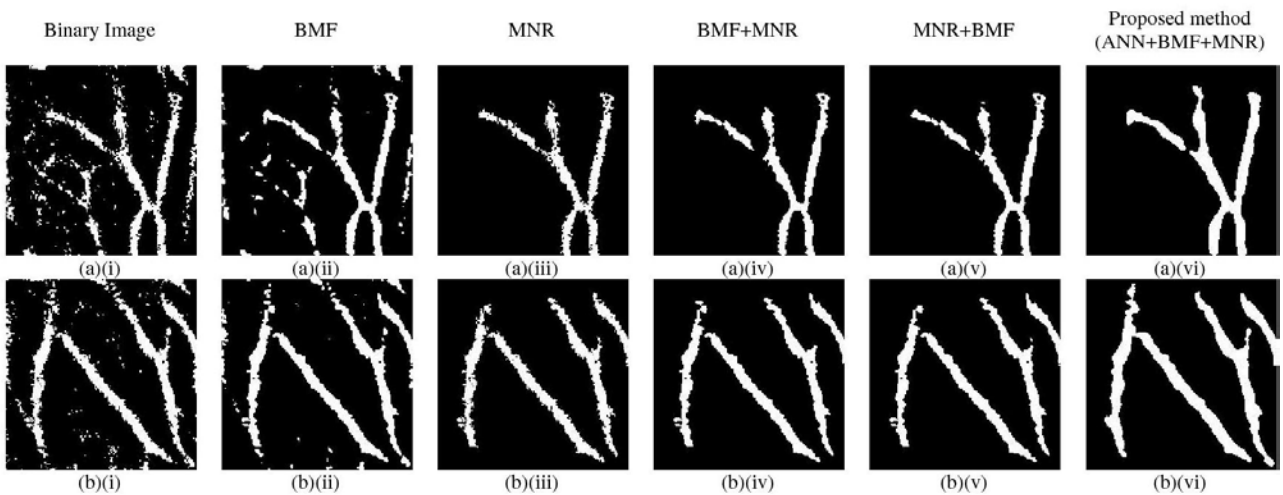


Fig. 7 Results of binary enhancement using (ii) BMF, (iii) MNR, (iv) BMF+MNR, (v) MNR+BMF and (vi) proposed method, ANN+BMF+MNR

The results of Figure 6 are also supported by the sensitivity values in Table 1. The sensitivity values for all binary enhancement methods show some increments after application of the proposed method compared to a binary image. Nevertheless, as can be seen, after applying the proposed three-level binary enhancement, CLAHE with FHH has the highest sensitivity value compared to the other enhancement methods. Figure 8 are additional result of CLAHE+FHH using different methods of binary enhancement.

**TABLE 1.** COMPARISON OF SENSITIVITY VALUE AMONG THE PROPOSED METHOD AND OTHER BINARY ENHANCEMENT METHODS

Binary	BMF	MNR	BMF+ MNR	MNR+ BMF	ANN+B MF+MNR	
LCS	0.4647	0.4336	0.4233	0.4131	0.4171	0.4976
HE	0.6762	0.6926	0.6553	0.6817	0.6824	0.7556
CLAHE	0.6700	0.6723	0.6396	0.6484	0.6572	0.7742
CLAHE+FHH	<b>0.8485</b>	<b>0.8899</b>	<b>0.8427</b>	<b>0.8584</b>	<b>0.8844</b>	<b>0.9627</b>

Table 2 shows the average sensitivity value obtained from 10 test images. This table clearly shows that the proposed method is able to produce highest sensitivity for all tested images as compared to the other binary enhancement methods. As can be observed also, the proposed method has increased the sensitivity value of the original image up to 10.66%. These results complement the findings obtained graphically in Figure 6.

**TABLE 2.** COMPARISON OF SENSITIVITY VALUE AMONG THE PROPOSED METHOD AND OTHER BINARY ENHANCEMENT METHODS

Original Binary image	BMF	MNR	BMF+ MNR	MNR+ BMF	ANN+B MF+MNR	
1	0.8485	0.8899	0.8427	0.8584	0.8844	<b>0.9627</b>
2	0.7704	0.7973	0.7447	0.7761	0.7752	<b>0.8832</b>
3	0.7422	0.7479	0.7002	0.7163	0.7151	<b>0.8278</b>
4	0.7004	0.6990	0.6634	0.6737	0.6718	<b>0.8097</b>
5	0.6730	0.6899	0.6263	0.6477	0.6492	<b>0.8151</b>
6	0.7807	0.7988	0.7552	0.7751	0.7551	<b>0.9171</b>
7	0.7715	0.7749	0.7152	0.7273	0.7239	<b>0.8674</b>
8	0.7644	0.7781	0.7464	0.7650	0.7650	<b>0.8407</b>
9	0.7317	0.7297	0.7593	0.7159	0.7798	<b>0.8273</b>
10	0.6585	0.6566	0.6069	0.5745	0.6196	<b>0.7567</b>
Average	0.7441	0.7562	0.7158	0.7230	0.7339	<b>0.8508</b>

Table 3 shows the average standard deviation values obtained from 10 test images. This table shows that all binary enhancement methods are able to maintain the standard deviation values closer to the truth image. However, the proposed method produced the lowest average of standard deviation values. This means that the proposed method does not deviate far from the truth image.

**TABLE 3.** COMPARISON OF STANDARD DEVIATION VALUES AMONG THE PROPOSED METHOD AND OTHER BINARY ENHANCEMENT METHODS

	Truth image	BMF	MNR	BMF+ MNR	MNR+ BMF	ANN+BM F+MNR
1	0.3088	0.3440	0.3099	0.3060	0.3107	0.3480
2	0.2936	0.3262	0.2728	0.2733	0.2731	0.3099
3	0.3759	0.3586	0.3370	0.3371	0.3366	0.3735
4	0.2929	0.2818	0.2736	0.2712	0.2712	0.2913
5	0.3508	0.3793	0.3221	0.3227	0.3229	0.3624
6	0.3275	0.3561	0.3022	0.3034	0.3034	0.3384
7	0.3549	0.3603	0.3381	0.3301	0.3369	0.3620
8	0.2458	0.3000	0.2825	0.2817	0.2817	0.3197
9	0.2818	0.2905	0.2973	0.2757	0.2950	0.3101
10	0.4276	0.3927	0.3700	0.3587	0.3690	0.4128
Average						
Difference (%)		2.5200	2.652	2.7600	2.7470	<b>2.0160</b>

I. CONCLUSION

This paper presents a CLAHE with FHH method for grayscale vein image enhancement. It also presents a combination of three approaches; ANN pixel corrector, BMF and MNR, for binary image enhancement. The numerical results explicate that the proposed grayscale image enhancement and binary image enhancement methods are able to successfully increase the binary hand vein image contrast. The clearly exposed vein patterns, when projected back onto patient’s hand is able to aid peripheral IV access.

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**Marlina Yakno** received her BEng in Electrical and Electronic Engineering from the Universiti Tenaga Nasional, Malaysia in 2007 and MSc from the Universiti Sains Malaysia in 2013. She is currently a lecturer in the Faculty of Electrical and Electronic Engineering, Universiti Malaysia Pahang. Her research interests include image processing and computational intelligence.

**Junita Mohamad-Saleh** received her BSc in Computer Engineering from the Case Western Reserve University, Ohio, USA in 1994, MSc from the University of Sheffield, UK, in 1996, and PhD from the University of Leeds, UK, in 2002. She is currently an associate professor in the School of Electrical and Electronic Engineering, Universiti Sains Malaysia. Her research interests include computational intelligence, tomographic imaging, and soft computing.

**Bakhtiar Affendi Rosdi** received his BEng, MEng, and DEng in Electrical and Electronic Engineering from Tokyo Institute of Technology, Tokyo, Japan in 1999, 2004, and 2007, respectively. He is currently a senior lecturer in the School of Electrical and Electronic Engineering, Universiti Sains Malaysia. His research interests are LSI implementation of pattern recognition and image processing algorithms.