MODIFIED IMAGE ENHANCEMENT ALGORITHM FOR DORSAL HAND VEINS IMAGING

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MODIFIED IMAGE ENHANCEMENT ALGORITHM FOR DORSAL HAND VEINS IMAGING

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LIST OF ABBREVIATIONS

AHE	Adaptive Histogram Equalization
ANN	Artificial Neural Network
AO	Area Opening
BMF	Binary median filter
CDP	Cumulative Distribution Function
CLAHE	Contrast Limited Adaptive Histogram Equalization
FFNN	Feed-forward neural network
FN	False Negative
FP	False Positive
HE	Histogram equalization
IV	Intravenous
MLP	Multilayer perceptron
NIR	Near-infrared
TN	True Negative
TP	True Positive

PENAMBAHBAIKAN IMEJ ALGORITMA TERUBAH SUAI UNTUK PENGIMEJAN URAT DORSAL TANGAN

ABSTRAK

Akses kepada salur darah merupakan isu penting di hospital kerana ia amat biasa dalam perubatan. Walau bagaimanapun, corak salur darah tangan yang tidak jelas akan menyukarkan proses akses kepada salur darah. Corak salur darah yang tidak jelas akan menyebabkan kesilapan berlaku semasa suntikan dijalankan dan kesilapan tersebut akan menyebabkan kesakitan dan kecederaan salur darah yang tidak dapat dibaik pulih. Tiada kajian khusus yang menjustifikasikan kaedah pemprosesan yang berkesan ke atas imej corak salur darah tangan. Oleh itu, kajian ini dijalankan untuk membangunkan sistem pemprosesan imej corak salur darah tangan yang telah diubah suai. Permulaannya, imej salur darah tangan kelabu yang diperolehi daripada pengimejan NIR dengan menggunakan penyamaan histogram penyesuaian kontras terhad (CLAHE). Kemudian, corak salur darah tangan diruas berdasarkan nilai ambang tempatan. Selepas proses ini, imej bertukar kepada imej binari. Corak urat tangan dipertingkatkan dengan gabungan Pembetul Piksel Rangkaian Neural Buatan, pembukaan dan penapis binari median. Selepas itu, penilaian prestasi kaedah pemprosesan telah dibuat berdasarkan kepekaan, kekhususan dan ketepatan. Perbandingan dilakukan antara keputusan penilaian prestasi kaedah pemprosesan yang telah diubah suai dan kaedah yang telah wujud. Keputusan penilaian prestasi menunjukkan susunan AO-FFNN-BMF menghasilkan kepekaan, kekhususan dan ketepatan yang paling tinggi bagi kedua-dua jenis imej. Kaedah pemprosesan imej yang dicadangkan telah menghasilkan corak salur darah yang paling jelas apabila dibandingkan dengan kaedah lain-lain.

MODIFIED IMAGE ENHANCEMENT ALGORITHM FOR DORSAL HAND VEINS IMAGING

ABSTRACT

Peripheral intravenous (IV) access is an important issue in daily practice in hospital as it is a common practice in the medical field. However, it will be a difficult task if the dorsal hand veins are not clear or obvious for intravenous access. The poor visibility of dorsal vein may result in wrong puncturing which causes patient to suffer from pain and even will lead to permanent damage of vein. Hence, a number of imaging methods have been implemented to expose the veins. At present, there are limited literature regarding the specific study to justify the enhancement algorithm which can perform effectively for dorsal hand vein imaging. Therefore, this research is set-up to develop a modified image enhancement algorithm for dorsal hand vein. Firstly, the grayscale hand vein image obtained from NIR imaging with noise undergoes grayscale enhancement by applying Contrast Limited Adaptive Histogram Equalization (CLAHE). Then, the adaptive thresholding method is implemented on the filtered grayscale image for vein pattern segmentation purpose. After image segmentation, the input image is converted to binary image. The noisy binary vein pattern is then enhanced using a combination of Feed-Forward Neural Network (FFNN), Area Opening (AO) and Binary Median Filter (BMF). Finally, the enhanced image is evaluated by examining the image’s sensitivity, specificity and accuracy of the enhanced image through comparison with the ground truth images. The evaluation results between modified image enhancement algorithm are compared with the existed algorithm. The evaluation results shows that the AO-FFNN-BMF sequence produces the highest sensitivity, specificity and accuracy for both input images. The proposed technique has produced the clearest vein patterns in terms of connectivity and smoothness than the other binary enhancement techniques.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Peripheral IV access is a technique in which a cannula is placed inside a vein to provide venous access. The catheter is introduced into the vein by a needle and fixed to a patient's arm with adhesives and attached to a drip. There are 80% of the patients found in hospitals require intravenous access through needle insertion [1]. Venous access allows sampling of blood, as well as administration of fluids, medications, parental nutrition, chemotherapy, and blood products [2]. The ability to obtain IV access is an important issue in daily practice in hospital which is performed in a variety of settings by paramedics, nurses and physicians.

Intravenous access provides therapies that cannot be administered or are less effective if given by alternative routes. It can be carried out on hand, arm, neck, finger or legs of patients. The reason hand or finger is chosen because they reside very close to the surface of the skin and can be easily acquired. Furthermore, hands and fingers are directly observable with sufficient mobility. They created minimal acceptance issues from the individuals being scanned by a biometric system.

However, the peripheral venous access is a painful procedure which will cause anxiety and stress indirectly. The process can be more difficult because of the patient's physical condition such as thick skin due to obesity, tanned skin, or at the extremes of age [3]. These factors make the dorsal hand veins become invisible and the peripheral venous access cannot be done. In addition, the number of high complex patients needing intravenous therapy is increasing [4]. It is essential to provide an optimal care to them.

Vein imaging on intravenous injection is of growing importance to help to ease the injection procedure [5]. The near-infrared (NIR) imaging is one of the best way for the image acquisition of hand vein. The deoxidized hemoglobin in the vein vessels absorb light having a wavelength in between 700 and 1000nm when the hand is exposed to NIR light. Thus, only the blood vessel pattern containing the deoxidized hemoglobin is visible as a series of dark lines in the NIR image [6]. In all these cases, visualizing the vein pattern by using a contrasting technique to separate them from the surrounding tissue can improve the success rate of the venipuncture [7, 8]. Since the image has more performance on low contrast and relative concentration of gray, a weak infrared light may cause the vein patterns to submerge in the image background. Hence, an appropriate image enhancement system is required in order to acquire more meaningful information from the image.

Image enhancement is an image processing technique which is used to enhance the appearance of an image to make it suitable for human visual perception. It has been an area of active research for decades. Most of the studies is targeted at improving the quality of image for better enhancement [9]. Noise as an unwanted information that contaminates an image is necessary being removed from the image. Although it is impossible to remove the noise totally without changing the original image, it is imperative to minimize the noise to a particular acceptable level for further analysis of the image. This can be achieved by proper image enhancement process depending on to different cases.

1.2 Problem Statement

Although a peripheral vein can be accessed on the first try, for a significant number of patients, the medical staff can need from 2 to 10 attempts for successful needle insertion [10, 11]. The causes of multiple attempts are determined by few factors, such as lack of venipuncture skills, lack of appropriate medical care or difficult peripheral venous access [3, 12]. Several attempts for intravenous cannulation will cause damage to vein and neighboring tissues.

Other than that, the characteristics of patients also make the IV process difficult. The prevalence of difficult venous access was 59.3% among complex patients and the gender, a history of vascular access complications and osteoarticular disease were significantly associated with difficult venous access [4]. Health condition such as tanned or burned skin, obesity, aging small vein and a lack of palpable veins will make the IV access becomes a challenging task [13].

In the medical field, there are a number of commercial implementations created to solve this problem, for example: VeinViewer [14], AccuVein [15], Veinsite [16], or VascuLuminator [17]. However, these commercial systems are often restrictive, with high acquisition costs and a proprietary interface that does not allow for adjusting acquisition values [7, 10].

NIR imaging is an alternative way to acquire hand vein image. However, the NIR imaging may result in low contrast, contain speckling noise and non-uniform gray-level due to non-uniform light and the fluctuant hand surface which will affect the quality of image acquired [6]. The information loss in image makes it becomes meaningless. Hence, a suitable image enhancement system is required to be developed to prevent the loss of information of image and provide a clear visualization of hand vein pattern.

1.3 Objectives of Research

This research is carried out to solve the problem of poor visibility of hand vein pattern by image enhancement techniques. The aim of the work is to develop a modified image enhancement algorithms for dorsal hand vein imaging. The objectives of the research are listed as below:

i. To obtain enhanced grayscale dorsal hand vein images based on optimal parameter.
ii. To obtain optimal binary dorsal hand vein images through investigation of segmentation process based on optimal parameters.
iii. To evaluate the performance of the modified enhancement algorithms based on various evaluation parameters of obtained binary images.
iv. To compare the modified enhancement algorithms with existing image enhancement algorithms based on the evaluation parameters of obtained binary images.

1.4 Scope of Research

This research focusses on image enhancement of dorsal hand vein image to aid peripheral intravenous access. The image enhancement algorithms are applied to solve the problem of unclear hand vein pattern of patients. Two different dorsal hand vein images from NIR imaging are used as input image in the research.

The input image undergoes three stages, which is grayscale enhancement, vein pattern segmentation and binary enhancement. For grayscale enhancement, CLAHE is applied since it is commonly used in medical field. Besides that, thresholding method is implemented for segmentation purpose. In final stage, intelligent technique Artificial Neural Network is introduced to do the binary image enhancement of image.

1.5 Thesis Outline

This thesis consists of five chapters. This chapter presents the overview of peripheral intravenous access. The problems encounter and effects brought to patients due to poor visibility of dorsal hand vein are discussed. The objectives to carry out this research are also stated.

Chapter Two presents the literature reviews that covers the previous works on image enhancement techniques which have been applied on hand vein images to eliminate the noise of image. The overview of dorsal hand image imaging and the system architecture are discussed in general. There are several sub-sections to discuss the types of algorithms implemented in different stage of image enhancement process and the evaluation parameters to evaluate the performance of the algorithm used.

Chapter Three explains the methodology that has been carried out in the research. The flow of the process, the algorithms applied in different stages and evaluation of the modified algorithm are explained in details. The modified algorithm involves three stages, which are grayscale enhancement, vein pattern segmentation and binary enhancement.

Chapter Four provides the results of the research. The evaluation results of the modified algorithm are presented in table form orderly and the discussions are made based on the result obtained. Comparison between the modified algorithm with existing techniques are made to determine the performance of the modified algorithm.

Chapter Five presents the conclusion for the research based on the results and findings obtained. Suggestions on future work to further improve the system are also presented.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter briefly presents the overview of dorsal hand vein and the system architecture of dorsal hand vein imaging for peripheral IV access. A review of previous work of the image processing techniques in three different stages, which are grayscale enhancement, image segmentation and binary enhancement are introduced. The implementation of Artificial Neural Network used in previous work is also discussed. This is followed by discussing the evaluation parameters involved in evaluating the enhanced image.

2.2 Overview of Dorsal Hand Vein Imaging

The vein image can be used for biomedicine and personal identification, such as injecting vein and extracting Feature Points of Vein Pattern (FPVP) [18]. In this research, hand vein imaging for IV access will be focused. Figure 2.1 shows the veins usually can be seen on human skin for Peripheral intravenous cannulation purpose.

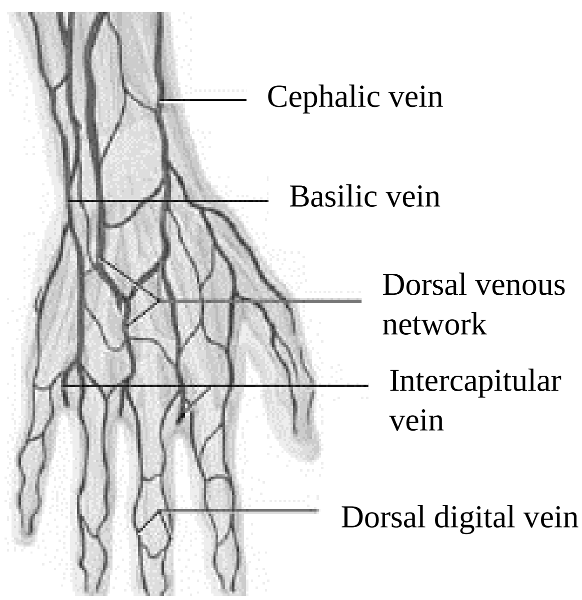


Figure 2. 1 :Vein of the dorsum

Peripheral intravenous cannulation is commonly used for medical purposes such as maintaining hydration, administering blood or blood components and administering drugs. It is done through intravenous catheters. In biomedicine, the dorsal hand vein image guides doctors to diagnose the vein diseases and helps nurses injecting vein.

Dorsal hand veins are visible under near infrared LEDs with a wavelength of 700-900mm [18]. NIR imaging works within the range of 700 to 1000nm and provides good quality images. This is because the medical spectral window is in the range of 700 to 900nm in which the light penetrates into biological tissues up to 3mm of depth. The reduced hemoglobin in blood vessels absorb more of this infrared radiation than the surrounding tissues. Due to NIR illumination, veins look darker than the surrounding tissues, which are captured by CCD camera in a darker environment [19]. The image acquisition which is affected by luminous intensity and thickness of the back of hand vein causes the image has differences in the gradation and some unwanted noise in the image.

In general, the system architecture of dorsal hand vein imaging is shown in Figure 2.2. This research will focus on image processing and evaluation of enhanced image.

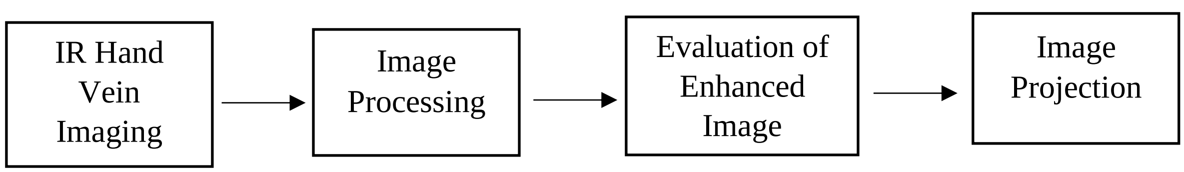


Figure 2.2: System architecture of dorsal hand vein imaging

2.3 Grayscale Image Enhancement

Grayscale image enhancement which is known as contrast enhancement as well has been taken full advantage to improve the image quality over the years. The image acquired from NIR hand vein imaging are usually low in contrast, which makes the visibility of the hand vein low and the hand veins are not clearly to be seen. The background information is taken as vein texture due to this drawback and this has led to false detection of hand vein [20]. Thus, contrast enhancement is essential to make the hand veins pattern prominent.

2.3.1 Histogram Equalization (HE)

Histogram equalization (HE) is one of the well-known method to enhance the quality of grayscale input images capturing from NIR imaging due to its simplicity and effectiveness [21]. It consists in applying a transformation function of the cumulative distribution of gray levels in order to obtain a new distribution that approximates the uniform distribution of the gray levels of the output image. It is suitable for overall enhancement of an image.

However, it may cause level saturation, which will lead to information loss [22]. The mean brightness of the output image is significantly different from the input image and this makes HE not the best method for contrast enhancement [23]. A result which is worse than original image might be produced since the histogram of the output image becomes approximately flat.

2.3.2 High Boost Filtering and Histogram Equalization

High Boost Filtering method is to give prominence to vein texture, and the HE is adopted to enlarge contrast of image. It overcomes the influence of luminous intensity and thickness of the back of hand skin [20].

Based on frequency domain processing technology in digital image processing, an image can be blurred by attenuating the high-frequency components of its Fourier Transform, the opposite process, edges and other abrupt changes in gray levels are associated with high-frequency components. Image sharpening can be achieved in the frequency domain by a high-pass filtering process, which attenuates the low-frequency components without disturbing high-frequency information in the Fourier transform. Zhao *et al*. have employed high-frequency emphasis filtering following by HE to overcome the abrupt change in gray level of hand vein image [20].

2.3.3 Adaptive Histogram Equalization (AHE)

Adaptive Histogram Equalization (AHE) is an extension to HE technique. AHE is an excellent contrast enhancement method for both natural images and medical and other initially nonvisual images. Instead of enhancing the overall contrast of input image, it operates on small tiles of image.

The histogram equalization mapping is applied to each pixel in the image based on its neighbors of pixel, which means that each pixel is mapped to an intensity proportional to its rank in the pixels surrounding it [24]. This basic form of the technique was invented independently by Pizer [24]. This gives an equalization centered in the window and only the gray levels within the windows are allowed to get better enhancement of the portion of the image that is difficult visualize with a global equalization. Despite of that, AHE is associated with noise amplification, particularly visible in areas where there are homogenous gray levels.

2.3.4 Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) was employed by Kumar and Prathyusha to overcome the drawback of AHE by limiting the contrast enhancement in certain area [25]. CLAHE limits the number of pixels that can reach a certain gray level and it will correct the gray level peak associated to the homogenous regions. The pixels are redistributed in order to clip the peak. CLAHE was originally developed for medical imaging and it is reported to be appropriate for most medical imaging purposes now [26].

CLAHE proposed by Zuierveld *et al*. has two key parameters, which is block size (N) and clip limit (CL) [27]. These parameters are manipulated factors which are determined by user to control the image quality. The clip limit is defined as a multiple of the average histogram contents will limits the amplification, by which the CLAHE clips the histogram at a predefined value before computing the Cumulative Distribution Function (CDF) [28]. Increasing in block size will enlarge the dynamic range and the contrast of image is also increasing. Since the two parameters to control image quality is manipulated by user, it has the probability in which an inappropriate clipping value is chosen and degrade the quality of image significantly. In paper, a lower clip limit shows narrow enhancement of image, the behavior of CLAHE turns out to be similar to the AHE when a higher clip limit is used. Hence, an optimum clip limit has to be selected to produce an image with good quality.

2.4 Image Segmentation

Segmentation partitions an image into distinct regions containing pixels with similar attributes. Meaningful segmentation can transform a grayscale or colour image from low-level image processing into high-level image description in terms of features, objects, and scenes. A number of algorithms have been developed for segmentation, such as thresholding method, clustering method, edge detection method and region growing method [29]. Thresholding is reported to be the simplest non-contextual segmentation technique [30]. Thresholding will binarize the grayscale image by separating the pixels values of an input image into two pixel values such as black as background and white as foreground [31]. It can be done by two ways, which are global thresholding and local thresholding techniques.

Global method enhances contrast belong to the extensive group of methods to improve the contrast of the image. Smorawa and Kubanek have applied global method to improve the contrast of hand vein image [32]. In global threshold, a single threshold value is used in the whole image. Then each pixel is assigned to page foreground or background based on its gray value comparing with the threshold value. It is applicable when the intensity distribution of objects and background pixels are sufficiently distinct. Chen *et al*. and Kumar and Prathyusha have employed this method for hand region segmentation [33] [25]. Nevertheless, global thresholding is not preferable because thick veins provide higher response as compared to thin veins as the intensity not uniform throughout the image [34]. The thin veins will be detected as background pixel and it provide an inaccurate information of the vein structure.

Local thresholding can be used effectively when the gradient effect is small with respect to the chosen sub image. The threshold value depends on gray levels and some local image properties of neighboring pixels. This approach is effective if the region of interest (ROI) varies across the background of the image. For hand vein image, local thresholding is a better choice as the vein patterns vary across the background. Li *et al.* have used this technique in their researches for vein pattern segmentation [35]. Akram *et al.* has employed this method to separate the veins from the background and a binary image is obtained [34]. This thresholding method yields veins structure that is segmented having different thickness.

2.5 Binary Image Enhancement

When dealing with binary images, the contrasts of vein patterns vary depending on the illumination of an image. Binary image usually suffers from unsharp edges and some noise after segmentation. It is necessary to smooth out the segmented images before any statistical analysis is performed on the image. It can be done by Binary Median Filter (BMF). The output images have to be enhanced in order to make the hand vein pattern apparently clear by eliminating the small grains that recognized as background noise. Area Opening is commonly implemented for that purpose.

Binary Median Filter is an efficient method for both bipolar and unipolar impulse noise that sorts all values among the mask which chooses the middle gray-level value in the neighborhood to substitute center value. It has been proven that it can effectively suppress impulse noise while preserving edge information [36]. In general, the Median Filter allows a great deal of high spatial frequency detail to pass while remaining very effective at removing noise on images where less than half of the pixels in a smoothing neighborhood have been effected [37]. Wen *et al.* have used Median Filter algorithm to eliminate the small blocks and burr based on the area size to smoothen the edge of vein [38]. In Wen *et al.* research, a Median Filter of having 5x5 mask was implemented in order to obtain fair vein structure by removing outliers and to preserve the edges of an image [18].

After binarization process, there are some connected components which is known as unwanted noise appear in the image, the connected components in the segmented hand vein image are called block. The blocks can be eliminated by area opening operation. The bright connected components with area smaller than a threshold will be removed by this operation. The object edges are preserved and the data structure is low in memory requirements [39].

Wang *et al*. have employed area opening operations to remove those false block [40]. Wang *et al.* have applied opening operation to remove residual noise in image[37]. Lefki and Benziane have applied area opening on the binary image to eliminate the image noise because the method does not modify the pattern of veins [41].

2.6 Artificial Neural Network for Image Enhancement

Artificial Neural Network (ANN) has been used to denoise and enhance an image that is corrupted by different noises such as Salt and Pepper, Gaussian and non-Gaussian noise. Most of the enhancement algorithms often utilize low level knowledge like gradient information to guide filtering parameters. However, in medical imaging it is often very essential that some features are preserved while others are suppressed. These required features usually cannot be distinguished by low level information. Thus, intelligent techniques are proposed to incorporate high level knowledge in the image enhancement process.

Artificial Neural Network is a computational system that attempts to simulate the structure and functional aspects of neural networks. The basic processing element of neural network are called neurons. They process information using connectionist approach to computation. ANN can be used to find patterns in data and to model complex relationships between inputs and outputs. The learning process of ANN can be supervised, unsupervised and recurrent [42]. The most widely used ANN are feed-forward and recurrent ANNs [43].

Artificial Neural Network have shown great strength in solving problem that are not governed by rules, or in which traditional techniques have failed or proved inadequate [44]. The inherent parallel architecture and the fault tolerant nature of the ANN is maximally utilized to address problems in variety of application areas relation to the imaging field [44]. ANN was implemented to generate a continuous parameter map that assigns specifically adjusted filter parameters to each pixel. Some sample pixels associated with the desired output act as input image and undergo training process to get the high level knowledge required for each pixel. Bhosale and Jadhav use multilayer perceptron (MLP) with the backpropagation algorithm to obtain the prior knowledge required for each pixel in their studies. They combine the concept of adaptive filters in general with neural network to achieve a better performance in image enhancement [45]. MLP is popular due to its simple implementation, finite parameterizations, stability and smaller structure size for a particular problem [46].

Pushpavalli *et al.* proposed a class of neural filter. The first step is to filter corrupted image by two special classes of decision based filter. The output is then combined with a

Feed Forward Neural Network [42]. Noisy image is given to the conventional filters like DBSMF and Nonlinear filter (NF). Then neural network assemble information to compute restored value of noisy image. When digital image consisting of higher level impulse noise, a FFNN with back-propagation learning algorithm is used. It eliminates noise and preserves edges and fine details [42].

Yakno *et al.* employed Multilayer Perceptron Artificial Neural Network (MLPANN) for binary image enhancement for hand vein. This approach is mostly applied to vein recognition for biometric purposes [47]. They proposed new algorithm by combining MLP pixel corrector, Binary Median Filter and Massive Noise Removal in binary enhancement stages for hand vein image.

For MLP neural network, one of the challenges is to determine the optimum number of hidden neurons to be used in hidden layer. Constructive or pruning technique can be used to solve this problem [48]. It is reported that constructive technique is better than pruning technique because constructive technique does not require prior knowledge [48]. The backpropagation algorithm is the learning method which is commonly used in MLP training [43]. However, it has slow learning speed. Numerical optimization techniques such as Conjugate Gradient and Leverberg-Marquardt algorithms are developed to improve the training speed. Leverberg-Marquardt is more effective than Conjugate Gradient and it has been proved to be the fastest training algorithm in most cases [43].

The activation function is the mathematical formula applied to hidden or output neuron to map its output value to within a specified bound. Sigmoid function is the mostly used activation function because they are differentiable [43]. This activation function scales the values in the range [0,1] by applying a threshold.

2.7 Evaluation Parameters on Vein Imaging

Sometimes it is difficult to determine which image enhancement algorithm shows the best performance by using naked eyes. Thus, evaluation parameters are required to evaluate the performance of the algorithms. Some researchers use quantitative measure to evaluate the algorithms they proposed.

Sensitivity, specificity, and accuracy are the evaluation parameters which are mostly used to evaluate binary image. In binary image, the pixels are classified into background pixel and foreground pixel. These parameters statistically measure the performance of the binary classification. Ponraj *et al*. have used the three parameters for classifier accuracy results of proposed binary textural patterns [49]. Thangaraj *et al*. have evaluated the segmented image in terms of sensitivity, specificity and accuracy by comparing it with ground truth image [50].

2.8 Summary

Vein pattern is not easy to observe in the visible light. This increases the level of difficulty of IV process. Hence, developing an appropriate image enhancement system to get a clear vein-pattern images is an important task. Overview of grayscale enhancement, image segmentation and binary image enhancement are presented. The comparison of the performance of different algorithms to enhance dorsal hand veins are reviewing. The implementation of intelligent techniques in image enhancement in previous work are discussed. Multilayer perceptron FFNN with backpropagation is reported can enhance an image effectively. Sensitivity, specificity and accuracy as evaluation parameters on vein imaging is discussed.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter describes the methodology in conducting the modified image enhancement algorithms on dorsal hand vein images. Firstly, the flow chart is drawn for simple visualization of the methodology. The next section explains the first step in flow chart, which is importing hand vein image as input image. Then, the modified image enhancement system is introduced one by one. The image enhancement system consists of grayscale enhancement, image segmentation and binary enhancement. Each stage is explained in detail in next sections. The following section discusses the evaluation method of the enhanced image.

3.2 Proposed Work

The flowchart of the proposed work of the modified image enhancement algorithm for dorsal hand vein imaging is shown in Figure 3.1. The work consists of four main stages, which is obtaining hand vein image, developing modified image enhancement, analysis for evaluation and comparison of performance. At the first stage, dorsal hand vein image from NIR imaging was imported to the system. Since it is capturing using NIR imaging, it is a grayscale image. At the second stage, a modified image enhancement method was developed. There are 3 stages for the modified enhancement process, which are grayscale enhancement, image segmentation and binary enhancement. Each algorithm applied in different stage is explained in detail. Next, the performance evaluation of the modified algorithm was analysed through some quantitative measures which are sensitivity, specificity and accuracy. After completing the image enhancement and evaluation process, the obtained results are compared with existing algorithm to determine the effectiveness of the modified image enhancement algorithm.

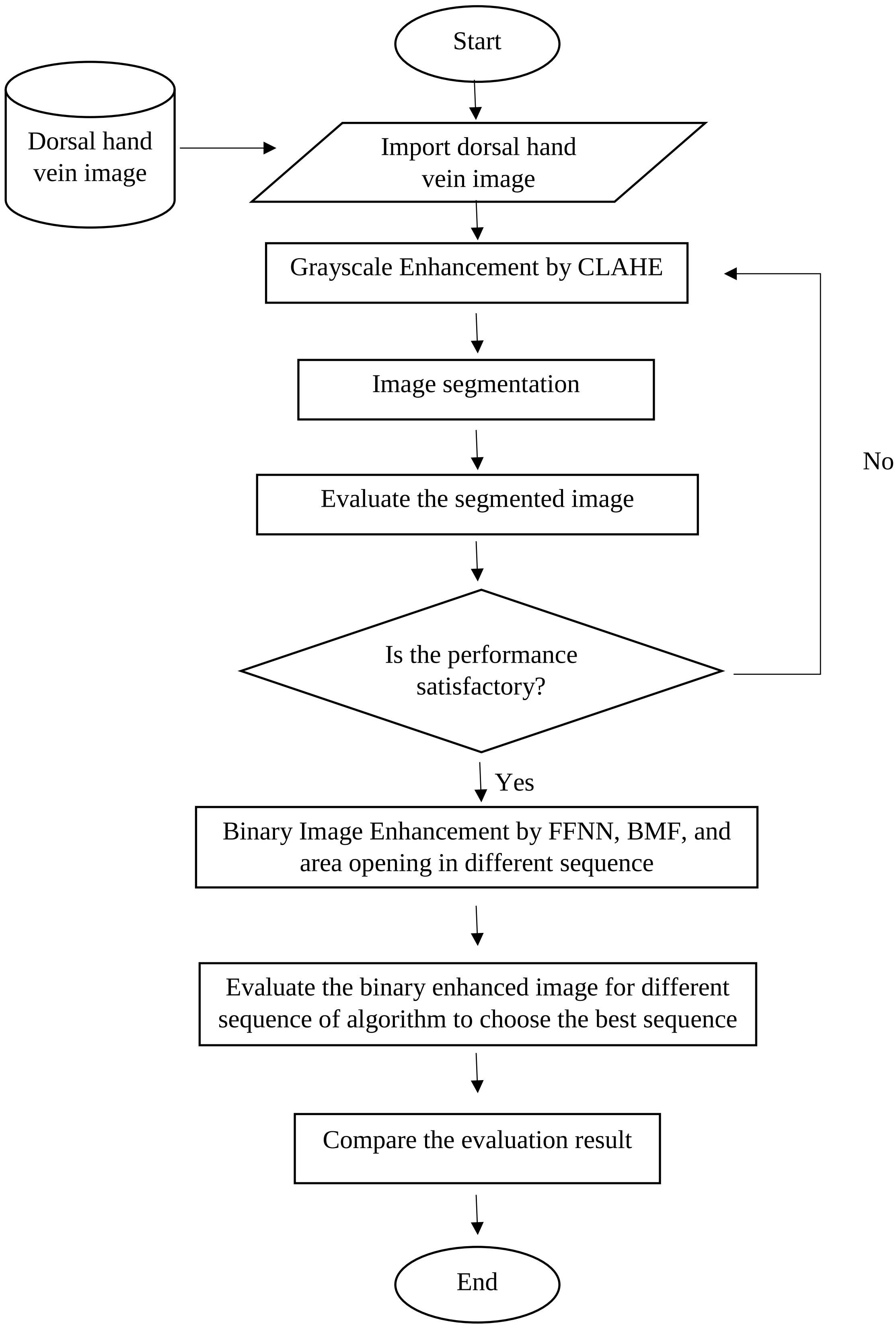


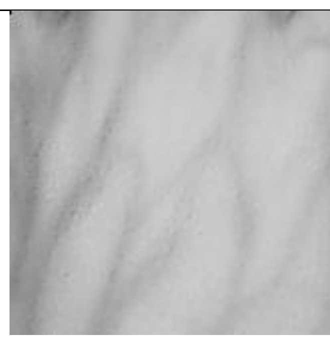
Figure 3 .1: Flowchart of the modified image enhancement process

3.3 Input Images

Vein patterns are not observable under the visible light. Veins can be detected using near infrared imaging technique (NIR). NIR image is presented as grayscale image due to its wavelength. Grayscale image is different from binary image which is with only two colours; black and white. Grayscale image is varying from black at the weakest intensity to white at the strongest. The intensity of pixel in grayscale image is expressed in a range of 8 bits which is from 0 to 255, where 0 represents black and 255 represents white.

Two dorsal hand vein images with different hand vein pattern captured using NIR imaging are used as the input image in this project. The hand vein image_1 has a more complex vein patterns as compared to hand vein image_2, while image_2 has higher contrast than image_1 since its entropy value is higher. The details of the two images are as listed in Table 3.1.

Table 3.1: Input images of dorsal hand veins used

	Image_1	Image_2
Image		
Width	162 pixels	166 pixels
Height	162 pixels	157 pixels
Entropy	5.6504	6.0208

3.4 Grayscale Enhancement

Grayscale enhancement is applied to make the vein pattern clearer and obvious from the background. The captured image from NIR imaging has poor contrast and the vein patterns are not clearly distinguishable from background. The purpose of grayscale enhancement is to extract the vein features from the image captured. In this stage, CLAHE is employed to improve the image contrast.

3.4.1 Contrast Limited Adaptive Histogram Equalization (CLAHE)

The steps to carry out CLAHE algorithm for grayscale enhancement are listed as below:

i. The input image was divided into a number of non-overlapping contextual regions equal sizes, the size was set to be at its default (8x8 window size) in MATLAB.

ii. The probability of an occurrence of grey level i for each contextual region was computed by using Equation 3.1:

$$p(i) = \frac{number\ of\ pixels\ with\ intensity, n_i}{total\ number\ of\ pixels, n} \tag{3.1}$$

iii. Different clip limit range from 0.01 to 0.10 were applied on the image.

iv. The probability occurrence which is higher than the clip limit were summed up and distributed equally to all histogram bins as shown in Figure 3.2.

v. By using bilinear interpolation, the new values of grey level are mapped to all contextual regions.

vi. The results were tabulated in a table, the most appropriate clip limit was chosen based on the visual quality of the output image.

vii. The CLAHE function was repeated with the clip limit ranges from 0.01 to 0.02 to further enhance the contrast of the image, the results were tabulated in a table and the most suitable clip limit was chosen based on the result.

viii. Two results were compared to determine how many iteration CLAHE should be applied to get a better result.

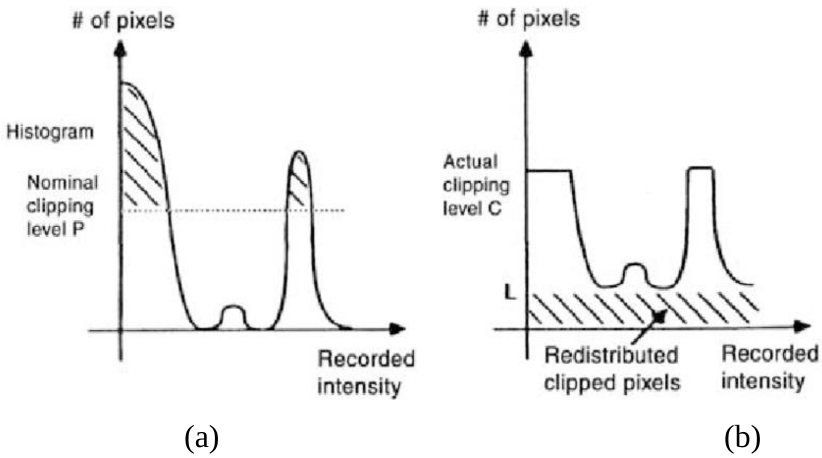


Figure 3.2: Histogram for CLAHE method (a) The histogram is clipped at clipping level P, (b) Excess is equally distributed to all histogram bins

3.5 Image Segmentation

Local thresholding was implemented to achieve the vein pattern segmentation to transform the grayscale image to binary image.

In local thresholding, a threshold *T(x,y)* was calculated for each pixel based on some local statistics of the neighborhood pixels such as range, variance, or surface-fitting parameters within a local block of size *N* x *N*. Mean was used as the statistical function because for hand vein images, mean of local intensity has been found to be the most appropriate statistical function. For image with window *w(k,l)* of size *NxN*, the mean was computed using Equation 3.2:

$$\mu = \frac{1}{N\text{x}N} \sum_{k=0,l=0}^{k=N-1,l=N-1} w(k,l) \tag{3.2}$$

However, it is reported that local area's mean alone is not suitable as a threshold, since the range of intensity values within a local neighborhood is very small and their mean values are close to centre pixel [31]. To improve the algorithm, a threshold value (mean-*C*) was employed. The *C* value was determined through trial-and-error. The local threshold $T_1(i,j)$ for each center pixel of window *W(k,l)* is chosen as shown in Equation 3.3:

$$T_1(i,j) = (\mu - C) \tag{3.3}$$

Then the window $W(k,l)$ is threshold as

$$W_1(i,j) = \begin{cases} 1, & W(k,l) > T_1(i,j) \\ 0 & \text{otherwise} \end{cases} \quad (3.4)$$

By doing this, the pixels with values more than threshold are belong to the object of interest while pixels with values below the threshold level will categorized as background. An analysis on different value *C* value is carried out to find out the most suitable *C* value that will expose a clear vein structure with less noise.

3.6 Binary Enhancement

The unsharp edges and noises in the images from the segmentation result will affect the pattern of hand veins. The binary images have to be further enhanced to improve the quality of the image. In this section, Binary Median Filter (BMF), Feed Forward Neural Network (FFNN) Pixel Corrector, and Area Opening (AO) are employed. These three algorithms have been combined in different sequences and the performance for each sequence is evaluated to find out the best sequence which present the best performance. The sequences are as follows:

i. FFNN-BMF-AO
ii. FFNN-AO-BMF
iii. BMF-FFNN-AO
iv. BMF-AO-FFNN
v. AO-FFNN-BMF
vi. AO-BMF-FFNN

3.6.1 Binary Median Filter

Median filtering algorithm smoothens the vein edge effectively. It can filter the noises in the image while preserving the edge information. The pixels of the image are scanned one by one from left to right and from top to bottom. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into ascending order and then replaces the value of the center pixel $m(i,j)$ by the median value $w(i,j)$ as shown in Figure 3.3. The center pixel value is computed as shown in Equation 3.5.

$$m(i,j)=\text{median}(w(i,j)) \tag{3.5}$$

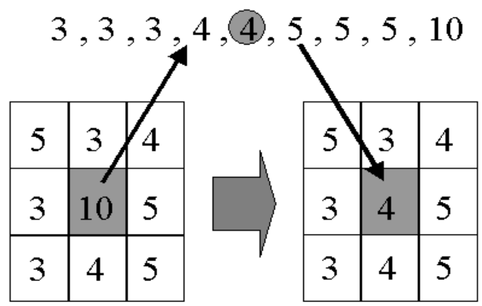


Figure 3.3 Operations to calculate the median pixel value

The window size of sliding window to apply the median filter will affect the quality of the image. An analysis on three different window size, which are 3x3, 5x5 and 7x7 is carried out to identify which window size will give the best result.

3.6.2 Area Opening Operations

The binary images, X are subsets of a connected compact set M called the mask. Let $X \subset M$ and $\lambda \geq 0$. The area opening of parameter of λ of X is given by

$$\gamma_{\lambda}^{a}(X) = \{\, x \in X \mid Area\big(C_x(X)\big) \geq \lambda \,\} \tag{3.6}$$

It will filter the bright connected components having a smaller surface area than the parameter λ in binary image. Different value of λ are applied to investigate the optimum λ that will can filter out the noises effectively for both images.

3.6.3 FFNN Pixel Corrector

Multi-Layer Perceptron (MLP) which is categorized as feed-forward neural network (FFNN) was applied in this study for enhancing the connectivity of the vein patterns. The structure of MLP is illustrated in Figure 3.4, it consists of input layer, hidden layer and output layer.

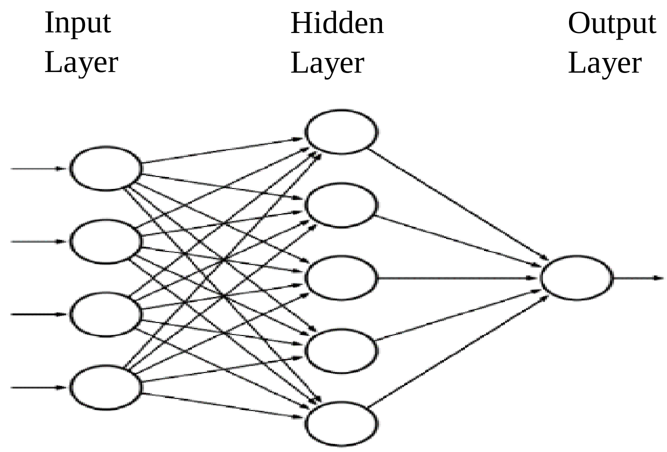


Figure 3.4: The structure of a MLP consists of three layers

The FFNN Pixel Corrector was employed to identify a pixel as a background pixel or foreground pixel based on the corrected pixel's local neighborhood within a sliding window. A 3x3 window was used as sliding window as shown in Figure 3.5. The x_1 indicates the pixel to be corrected. However, if x_1 has value of '1', it will remain unchanged. It is to prevent the vein pixels change to background pixels since the purpose of applying FFNN Pixel Corrector is to enhance connectivity of vein pixels. The sliding window will be evenly superimposed throughout a hand vein image for image enhancement purpose.

x_2	x_3	x_4
x_5	x_1	x_6
x_7	x_8	x_9

Figure 3.5 A 3x3 window used as sliding window for FFNN pixel corrector

There were nine pixels in total for a 3x3 windows. Thus, 512 sets of training patterns can be generated. Three different sets of data were generated with same input data set but three different output data set. Each set has 512 sets of training patterns. The three different data sets were labeled as Set A, Set B and Set C as below:

- Set A: The center pixel '0' will be corrected to 1 if the number of pixel '1' in the 3x3 window is equal or more than 5, center pixel '1' remains unchanged

- Set B: The center pixel ‘0’ will be corrected to 1 if the number of pixel ‘1’ in the 3x3 window is equal or more than 4, center pixel ‘1’ remains unchanged
- Set C: The center pixel ‘0’ will be corrected to 1 if the number of pixel ‘1’ in the 3x3 window is equal or more than 3, center pixel ‘1’ remains unchanged

Figure 3.6 to 3.8 shows some samples of a 3x3 window from various binary images of hand vein for different data sets are used as the training patterns for the FFNN.

Input			Target Output
1	0	1	
1	0	1	1
1	1	0	
1	0	0	
1	0	0	1
1	1	1	
1	0	0	
1	1	0	1
0	1	1	
1	0	0	
1	0	0	0
1	0	1	
1	0	0	
0	1	1	1
0	1	0	

Figure 3.6: Samples of inputs patterns and their corresponding target output for Set A.

Input			Target Output
1	0	1	
0	0	1	1
1	1	0	
1	0	0	
0	0	1	1
1	1	0	
1	0	0	
1	1	1	1
0	0	0	
1	0	0	
0	0	1	0
1	0	0	
1	0	0	
0	1	1	1
0	0	0	

Figure 3.7: Samples of inputs patterns and their corresponding target output for Set B