Constructing Real Time Vein Imaging Device Utilizing Near Infrared Technology and Embedded System

Khoa Huu-Dang Nguyen, Anh Le-Trang Nguyen, and Hien Thi-Thu Pham

Abstract

This paper proposes an idea that utilizes near-infrared (NIR) imaging technique and embedded system to construct a low-cost device for detecting and visualizing veins of patients, who have problems with vein visibility, directly on the skin. The use of NIR light has received a considerable attention as it is non-invasive and can reveal much more information than visible one. By convention, biological materials of blood (hemoglobin, etc.) has larger attenuation coefficient than those of the skin (collagen, melanin, etc.), especially in the NIR region. Accordingly, vein patterns would appear darker, whereas skin would appear lighter. The embedded system then captures image of the interest area and conducts image processing in order to enhance contrast between veins and the surroundings. The experimental results show that, even in a preliminary implementation, images of vein pattern and location obtained by using the device exhibit promising consistency, accuracy and time-performance. It is anticipated that, with further investigation and optimization, the proposed system can develop and construct 3D depth image of veins.

Keywords

Near-infrared • Embedded system • Image processing

1 Introduction

Determining and extracting blood from veins is among the most frequent practiced procedures in any hospitals. However, there are various factors that cause difficulty even for experienced nurses or physicians such as alternation of subcutaneous fat distribution caused by obesity. There are more than 90% of hospitals require a peripheral cannula to deliver therapy, and more than 1 billion venipunctures per year are performed to obtain blood samples for testing [1]. Clinical statistics have shown that 25–50% of patients require multiple attempts to achieve intravenous access [2].

Several imaging technologies have been introduced to help improve the success rate, including transillumination, ultrasound and near-infrared imaging devices. Transillumination is a method that focusing light through tissues. The method has been limited to infants and small children as it tends not to penetrate through thicker tissues or be anatomically useful beyond the hand or wrist area [3]. Ultrasound is a method that utilizes high frequency sound waves to provide excellent resolution of vessels and tissue on a screen. However, the limitation of the method is that it requires users to hold a probe with one hand and perform the vascular puncture with the other hand, and the skill to think three dimensionally as one is looking at a two-dimensional image while attempting to place the needle in the center of the vessel [4].

The use of NIR imaging technique in vein detection is relatively less explored compared to other areas of imaging technique. However, it appears to have tremendous potential to deliver high-end result at low development cost. NIR imaging technique is safe, non-invasive, accurate, simple and fast.

K.H.-D. Nguyen · A.L.-T. Nguyen · H.T.-T. Pham (✉)
Biomedical Engineering Department, International University, Vietnam National University, Ho Chi Minh City, Vietnam
e-mail: ptthien@hcmiu.edu.vn

T. Vo Van et al. (eds.), *6th International Conference on the Development of Biomedical Engineering in Vietnam (BME6)*, IFMBE Proceedings 63, https://doi.org/10.1007/978-981-10-4361-1_95

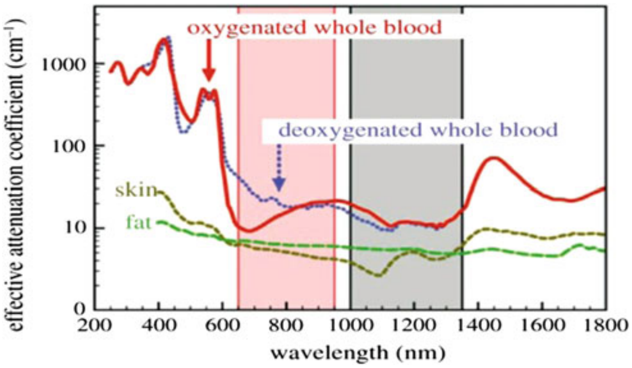

Fig. 1 The absorption coefficient as function of wavelength for specific biological materials

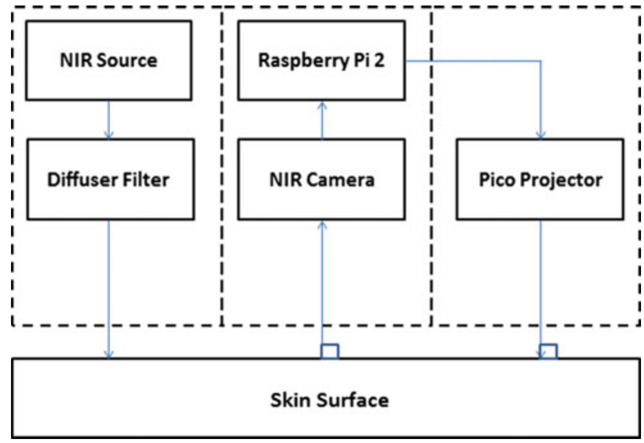

Fig. 2 Basic operating diagram

2 Background

The technique works based on the principle as follows. There are two types of hemoglobin in blood: oxyhemoglobin (HbO_2) which is bound to oxygen and deoxyhemoglobin (Hb) which is unbound to oxygen. They are the main absorber of NIR light. For illustrative purpose, Fig. 1 shows absorption coefficient of biological materials with respect to the NIR region of the electromagnetic spectrum. It can be seen that the absorption coefficient of blood is higher than those of the skin in general. Because of the different in absorption coefficient, areas with vessels underneath would have lower brightness intensity than those without. In addition, around the wavelength of 800 nm, the Hb has larger absorption coefficient than the HbO_2 which enable us to identify the veins, which contain more Hb.

Choosing the right wavelength is the important key to achieve good contrast between veins and surroundings. There are various experiments has been conducted to determine the best wavelength. Lin et al. and Zhang et al. state that vein image can be well distinguished from surrounding tissue by infrared camera when infrared spectrum is 720–1100 nm [5, 6] while Wang et al. claims that 850 nm NIR light produces better contrast between vein and surrounding tissue [7]. On the other hand, Li and Yuan [8] and Zharov et al. [9] consider 880 and 760–960 nm would result in the best contrast respectively.

3 Methodology

The proposed device is an embedded system which consists of a computer with MATLAB and Simulink software, a Raspberry Pi 2 (a credit card-sized single-board computer), a NIR light source and camera, an intensity diffuser filter and a pico projector. Figure 2 demonstrates the basic operation of the device. A cluster of 830 nm high power IR LEDs, which is the best available option economically, has been chosen as main illumination source. The light source emits NIR light into the area of interest. Before hitting the surface of the skin, the light passes through a diffuser filter so its intensity can be adjusted to reduce glare. When the adjusted light comes in contact with the skin surface, parts of it are reflected immediately; parts of it penetrate into deeper layers and then are reflected or completely absorbed.

Scientifically, human eyes cannot see light in the NIR region (wavelength from 700 to 2500 nm). Therefore, we cannot see the veins even when they are shone by NIR light and made more visible. This is where the proposed embedded system plays its important role: to enhance image quality and visualize the veins. An integrated IR camera captures analog signals reflect from the area of interest and convert them to digital signals. In other words, an image is digitized to form a 2D discrete-space signal $x[n_1, n_2]$. The digitized samples of an image are referred to as pixels. Most commonly, the value of the pixel $x[n_1, n_2]$ is interpreted as the light intensity of the image at the point (n_1, n_2). These pixels would then be transmitted to a Raspberry Pi 2 and be processed and enhanced. Simulink and MATLAB are used to construct the model and logics and then deploy into the Raspberry Pi 2 in order to make it operate as a standalone image processing unit.

Image enhancement refers to image processing that makes an image more suitable for inspection by human observer. Image enhancement is usually needed when an image is captured under bad lighting conditions. Since our light source is placed really near the target area of interest and device itself is not fixed, there would be glare and non-uniform brightness. Various techniques are applied to improve the quality, i.e. Median Filter, Histogram Equalization, Local Grey Level modification, Image Sharpening. In addition, Image Segmentation is being investigated to derive depth and other characteristics of the veins from digitized pixels.

Firstly, Median Filter is applied to eliminate impulsive noise (salt-and-pepper noise), which is characterized by large spikes in isolated pixels. The filter calculates the median value of all the neighborhood pixels, i.e. all the pixels in a specific window, and then replaces the pixels being considered with that value. The window scans through the entire image, pixel by pixel, to remove all the noise.

$$y[m,n] = median\{x[i,j],(i,j) \in \omega\}, \tag{1}$$

where w represents the neighborhood pixels.

Secondly, Histogram Equalization is applied to enhance the image contrast. Plotting histogram of the image determines the distribution of its pixel values. When all the pixel values lie in a narrow range, the contrast is inadequate. The technique enhances contrast by changing the distribution of brightness. That is to say the original brightness levels are remapped to widen the distribution of intensities. As a result, a new image is formed. Let $f[m,n]$ is a given image with pixel intensity range $[0, L-1]$. L is the number of possible intensity value, often 256. Let p denote the normalized histogram of f with a bin for each possible intensity. So

$$Pn = \frac{\text{number of pixels with intensity n}}{\text{Total number of pixels}} \quad \mathrm{n} = 0, 1, \ldots, \mathrm{L} - 1 \tag{2}$$

The histogram equalized image g will be defined by

$$g_{i,j} = \text{floor}\left((L-1)\sum_{n=0}^{f_{i,j}}(p_n)\right) \tag{3}$$

This is equivalent to transforming the pixel intensity, k, of f by the function

$$T(k) = \text{floor}\left((L-1)\sum_{n=0}^{k}(p_n)\right) \tag{4}$$

Considering that the intensities of f and g are continuous random variables X, Y on $[0, L-1]$. Therefore the new intensities Y is defined by

$$Y = T(X) = (L-1)\int_0^X p_X(x)dx, \tag{5}$$

where p_X is the probability density function of f. T is the cumulative distributive function of X multiplied by (L − 1). By calculation, it can be shown that Y defined by T(X) is uniformly distributed on $[0, L-1]$, namely that $p_Y(y) = \frac{1}{\mathrm{L}-1}$.

However, because the image has non-uniform brightness, the brightness distribution is sufficiently broad and global gray scale modification will not provide any real enhancement. The solution is to apply a technique that adjusts the intensity of each pixel based on the intensity of its neighbors. The value of a pixel $x[n_1, n_2]$ is changed by the mean and variance of the brightness in the neighborhood of the pixel. As a neighborhood of ±M pixels, the mean and variance are:

$$\mu[n_1,n_2] = \frac{1}{(2M+1)^2}\sum_{k_1=-M}^{M}\sum_{k_2=-M}^{M} x[k_1,k_2] \tag{6}$$

$$\sigma^2[n_1,n_2] = \frac{1}{(2M+1)^2}\sum_{k_1=-M}^{M}\sum_{k_2=-M}^{M}(x[k_1,k_2]-\mu[k_1,k_2])^2 \tag{7}$$

Hence, the transformation to create a new image $y[n_1, n_2]$ is

$$y[n_1,n_2] = \frac{A}{\sigma[n_1,n_2]}(x[n_1,n_2]-\mu[n_1,n_2]) + g(\mu[n_1,n_2]) \tag{8}$$

The first part of the transformation increases or decreases the deviation of $x[n_1, n_2]$ from the local mean depending on whether the local variance is low or high. This has the effect of making the local contrast more uniform. The constant A is chosen. The second half of the transformation represents a gray scale remapping of the local mean with the function g(·).

Segmentation is being investigated to extract characteristics of the vein and create patterns. Segmentation is a process to dividing an image into multiple parts. It means that vein patterns can be extracted, mapped and trained for auto-recognition. Edge detection is a crucial process. Image sharpening make edges more detectable and vibrant by emphasizing them. To sharpen the image is simply to apply high-pass filter to the image.

4 Results and Discussion

The processed image was able to illuminate clearly most of superficial veins, especially cephalic veins (of limbs), superficial epigastric veins (of stomach) and jugular veins (of neck). Figure 3 illustrates the final results when examines a hand and a stomach.

Figure 4 shows the original image in comparison with their processed counterparts. It can be seen that vein patterns are much easier to notice after the image are processed. The figure also shows two displaying mode, i.e. normal gray-scale and inverting gray-scale.

The device is able to deliver high resolution with sufficient rate 10 fps. The processing time is also fast as the average time delay between original image and processed image is 0.032 s. However, the device has not been able to project the vein patterns back onto the skin of patients. It suffers great dislocation as the real position of veins and the image are not matched.

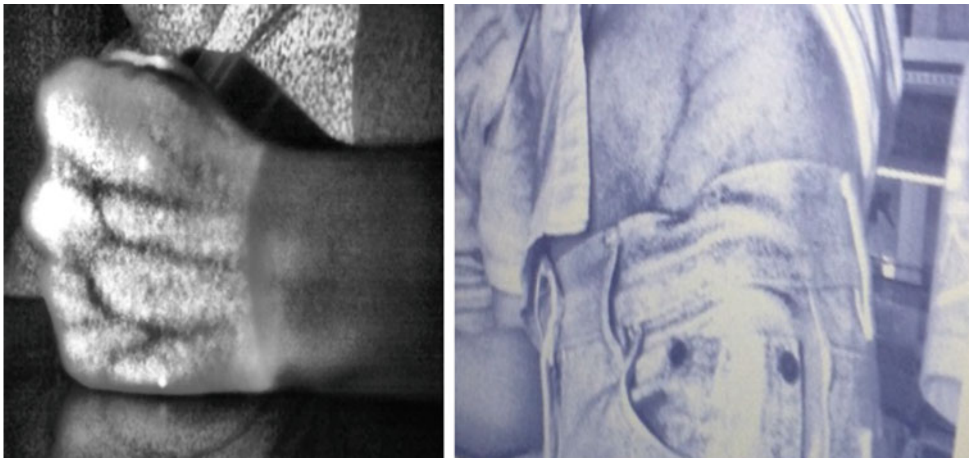

Fig. 3 Result images of cephalic vein (*left*) and superficial epigastric vein (*right*)

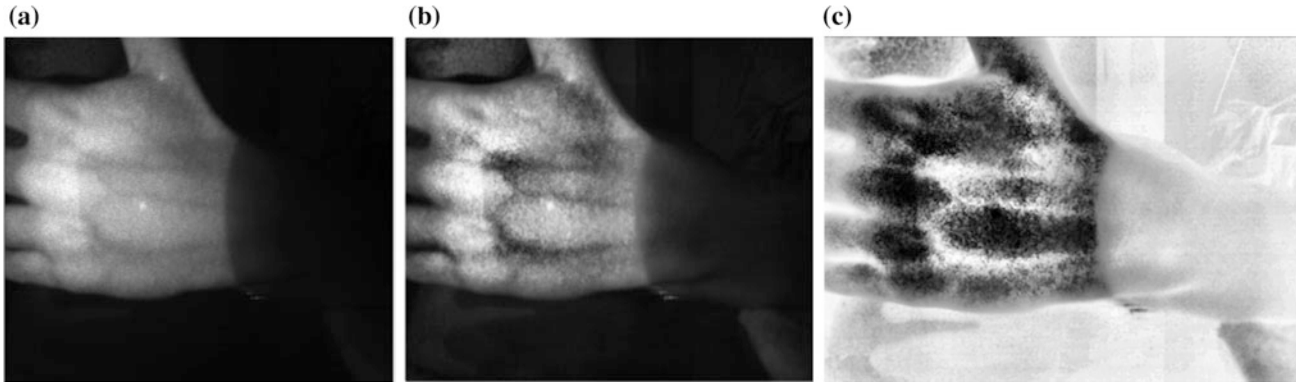

Fig. 4 Original image and their processed counterparts **a** Original image. **b** Normal gray-scale. **c** Inverting gray-scale

5 Conclusions

The work in this study provides the mean to limit difficulty in determining vein location and extracting blood from them. The device has been able to detect and display peripheral veins with sufficient rate and high resolution on screen.

Acknowledgements The authors gratefully acknowledge the financial support provided to this study by Vietnam National Universities—HCMC. Moreover, the devices of this work has been supported by grant No. 1161/QĐ-ĐHQG-KHCN of Vietnam National Universities-HCM City.

References

1. Ogden-Grable H, Gill GW (2005) Phlebotomy puncture juncture preventing phlebotomy errors—potential for harming your patients. Lab Med 36(7):430–433
2. Frey A (1998) Success rates for peripheral iv insertion in a children's hospital. Financial implications. J Intravenous Nurs Off Publ Intravenous Nurs Soc 21(3):160
3. Atalay H et al (2005) The use of transillumination for peripheral venous access in paediatric anaesthesia. Eur J Anaesthesiol 22 (04):317–318
4. de Caen A (2007) Venous access in the critically ill child: when the peripheral intravenous fails! Pediatr Emerg Care 23(6):422–424
5. Lin X, Zhuang B, Su X (2003) Measurement and matching of human vein pattern characteristics. J Tsinghua Univ 43(2):164–167
6. Zhang J-Y, Sun M-H (2007) Study on algorithm for skeleton features extraction of hand vein image. J Comput Appl 27(1):152–154 (Jisuanji Yingyong)
7. Wang K et al (2006) Hand vein recognition based on multi supplemental features of multi-classifier fusion decision. In: Proceedings of the IEEE international conference on mechatronics and automation
8. Li W, Yuan W (2011) Imaging quality analysis on palm vein under different wavelengths near-IR. Comput Eng Appl 47(30):15–18 (Jisuanji Gongcheng yu Yingyong)
9. Zharov VP et al (2004) Infrared imaging of subcutaneous veins. Lasers Surg Med 34(1):56–61