



Digital Vein Mapping Using Augmented Reality

Mohamed Taha^{1*} Mohamed Ibrahim¹ Hala H. Zayed¹

¹*Faculty of Computers & Artificial Intelligence, Computer Science Department, Benha University, Egypt*

* Corresponding author's Email: mohamed.taha@fci.bu.edu.eg

Abstract: Vein detection is an important issue for the medical field. There are some commercial devices for detecting veins using infrared radiation. However, most of these commercial solutions are cost-prohibitive. Recently, vein detection has attracted much attention from research teams. The main focus is on developing real-time systems with low-cost hardware. Systems developed to reduce costs suffer from low frame rates. This, in turn, makes these systems not suitable for real-world applications. On the other hand, systems that use powerful processors to produce high frame rates suffer from high costs and a lack of mobility. In this paper, a real-time vein mapping prototype using augmented reality is proposed. The proposed prototype provides a compromised solution to produce high frame rates with a low-cost system. It consists of a USB camera attached to an Android smartphone used for real-time detection. Infrared radiation is employed to differentiate the veins using 20 Infrared Light Emitting Diodes (LEDs). The captured frames are processed to enhance vein detection using light computational algorithms to improve real-time processing and increase frame rate. Finally, the enhanced view of veins appears on the smartphone screen. Portability and economic cost are taken into consideration while developing the proposed prototype. The proposed prototype is tested with people of different ages and gender, as well as using mobile devices of different specifications. The results show a high vein detection rate and a high frame rate compared to other existing systems.

Keywords: Vein mapping, Infrared, Mobile application, Image processing, Augmented reality.

1. Introduction

Biomedical imaging is the way for producing visual representations of a body's interior. It reveals the hidden structure of tissues and bones for clinical diagnosis and medical intervention. Biomedical imaging techniques have achieved significant progress in the vein detection field. However, in general, the solutions produced are high-cost end devices in addition to neglecting the portability of the device.

Intravenous puncture is the first step for any surgical procedure where the anesthetic is injected, and it is also the natural procedure for taking a blood sample. All physicians and nurses usually have trouble locating the vein accurately from the first trial [1]. This problem can occur due to unclear visibility of the blood vessels. Many medical situations require identifying the accurate location of blood vessels. This may include: receiving medicines intravenously,

contusions and tumefaction, kids and babies, and elders, among others [2]. Traditional techniques of locating veins such as slapping the skin or pressing the vein back and forth are not enough. They make the process of vein injection painful and uncomfortable [3]. AccuVein [4] and VeinViewer [5] are the most popular devices that come up to overcome these problems. However, they suffer from some issues such as their high cost, portability factor, ease of use, processing capability, or reliability [6]. Infrared imaging is a technique that guarantees to deliver systems with economic costs and precise results. The physicians have a severe problem in vein injection because of the veins are not noticeable under the ordinary conditions of visible light. Infrared radiation is the best solution to be used for detecting human veins. Imaging techniques have two different types: Far-Infrared (FIR) imaging technique and Near-Infrared (NIR) imaging technique.

These types of imaging techniques are used for detecting different parts of the hand's veins. FIR

imaging techniques are employed to distinguish the significant arteries of the hand. In the electromagnetic spectrum, the FIR range is 8-14 μ m. Still, it is so sensitive to external conditions that affect the quality of the image captured, so it does not offer an image of adequate quality. NIR imaging technique is used to detect the small veins on the wrist and palm. It has a range of 700-1000nm in the electromagnetic spectrum. It is not affected by external conditions, so it offers a perfect quality image [7].

Visible light has a very narrow range (400 - 700nm) of the electromagnetic wave range that can be observed by human eyes [8]. However, in other ranges of the electromagnetic wave, there are more details rejected by the objects of interest. Under the visible light in normal conditions, the visibility of human veins is not clear. Near-InfraRed (NIR) imaging techniques can be utilized to resolve this poor visibility because the vein vessels absorb all infrared radiation. This is due to the existence of Deoxidized Haemoglobin (Hb) in the vein vessels. The other parts of the hand appear transparent due to the presence of Oxidized Haemoglobin (HbO₂) in the arteries.

Subsequently, a part of a human body is exposed to infrared radiation with a particular wavelength. The veins will appear darker than the other parts. Fig. 1 shows the wavelength of NIR. The near-infrared radiation with the range extended from 700 to 1000 nm approximately is not visible.

Augmented Reality (AR) technology is one of the latest innovations that have a promising future. Applying the Augmented Reality technology opens up new possibilities in the healthcare sector. It has the potential to play a significant role in improving the healthcare industry. It is a technology that depends on the projection of virtual objects or information in the user's real-world to provide augmented information [9]. Users can deal with this augmented information or virtual objects through several devices, whether portable like smartphones or through devices that can be worn like glasses or lenses. AR is used for many fields such as education, gaming, medicine, etc. By integrating augmented reality techniques with biomedical imaging technologies, a new user-friendly system can be developed for vein mapping. In this paper, a real-time prototype for detecting and visualizing veins is proposed. The prototype integrates augmented reality technology and biomedical imaging techniques. It employs low-cost components: USB-Camera, 20 Infrared LEDs, and an Android smartphone for easy portability. Light computational algorithms are utilized to detect veins. It includes the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, the median filter,

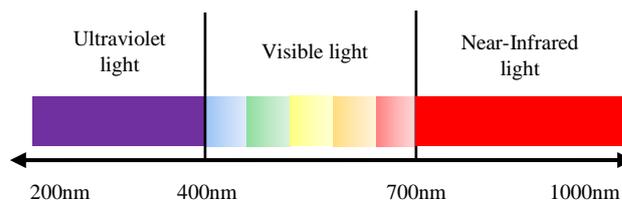


Figure. 1 The wavelength of near-infrared light

the adaptive threshold, and the Scan-Line Filling algorithm. The main characteristics of the proposed prototype in comparison with other existing work are as follows. First, it provides a high frame rate, making it suitable for real-time applications. Second, it uses low-cost components while providing a high vein detection rate. Finally, it employs light computational algorithms for vein detection. Thus, the smartphone processor can be relied upon to run these algorithms to benefit from the mobility advantage.

The remaining part of this paper is organized as follows: Section 2 reviews the state-of-art of vein detection systems. The proposed vein mapping prototype is presented in Section 3. Section 4 discusses the experimental results to evaluate the proposed prototype. Finally, Section 5 draws conclusions and future work.

2. Related work

Recently, the improvement of subcutaneous vein detection has received much attention from many researchers. Due to the existence of commercial devices of vein detection at a high cost. Researchers focused only on developing real-time systems at a lower cost. This led to systems with low efficiency and low frame rate. Some researchers have relied on more powerful processors to improve real-time efficiency and to increase the frame rate. However, this increases the cost and produces unportable devices. Others tried to rely on smartphones for real-time processing to solve the problem of portability and high cost. Nevertheless, computationally intensive algorithms have been used for processing veins. This led to a low frame rate due to the limited computational power of the smartphone processors. Some others use ultrasound to detect veins and conduct venous cannula [10]. The related work is discussed here:

Mansoor *et al.* [2] presented a low-cost system that uses a USB-Camera modified with an infrared filter. The NIR LEDs are arranged in a ring shape to illuminate the desired part of the hand. Continuous frames are captured and sent to a computer from the camera through a USB cable for further processing. Some image pre-processing techniques are applied to enhance detected veins. Flood Filling algorithm is

used to fill enhanced veins with color for more visualization, but this algorithm has a disadvantage [11]. It is not efficient for large shapes and it has long computational time which affects the frame rate and real-time processing.

In [12], Juric and Zalik proposed a real-time prototype for vein visualization using mobile. Images are captured through a USB camera modified to be sensitive to infrared radiation. Four high-intensity IR LEDs (OIS-330-740-X-T) with a peak wavelength of 740 nm were used for illumination. Two algorithms are used: External Camera Management (EXCAM) for camera control and NIR Image Processing (NIP). The steps of the NIP algorithm are not mentioned to determine how detected veins are enhanced. To evaluate their system, they enrolled 20 trainees and 25 people and performed 500 attempts of vein detection. The results produced a failure rate of 35.2% in vein detection which can be improved.

Bawase and Apte [13] presented a vein detection system using a smartphone camera with a resolution of 6 megapixels and 36 IR LEDs with a wavelength of 850 nm. The image is taken by the mobile camera and sent to a personal computer for processing. Pre-processing is performed by CLAHE, median filter, and global thresholding. The main drawback is that global thresholding is not a recommended technique for NIR images. Some parts of the vein are removed because of the illumination variations [14].

Moreover, Dan *et al.* [15] combined anisotropic diffusion and multi-scale vessel enhancement filtering for the enhancement of the dorsal hand vein image. Their system includes two infrared LED light source of 850 nm, and two other infrared cameras used to capture veins. Every image is captured and sent to a microprocessor unit for processing. They tested their proposed technique against CLAHE on 40 samples. Half of which were obtained from a high-quality dorsal database called Bosphorus and the other half were captured from their system. The performance shows good results on the Bosphorus database in terms of enhancing quality. However, the results were supportive of the CLAHE method for their low-quality image collected from their system. CLAHE is more effective in low-cost systems. The main weakness of their study is that their system may not be practical in all situations. By inspecting the system hardware, it is rather costly and not portable. Also, the data captured from their system is offline, not in real-time.

The authors in [16] developed an add-on near-infrared illumination for hand veins recognition using mobile. Google Nexus 5 smartphone is used, and its camera is modified to be sensitive to infrared by EigenImaging Inc. It is a company specialized in

smartphone camera modification for applications of near-infrared imaging by detaching the original cut-off filter of near-infrared. The problem with this approach is that the modified smartphone price is nearly three times its original price. The control board (Arduino Nano Board) has 16 IR LEDs with a wavelength of 850 nm and is connected to the mobile via Bluetooth. The proposed algorithm started with the extraction of the Region of Interest (ROI) with a size of 512×512 pixels. CLAHE, Circular Gabor Filter (CGF), and High-Frequency Emphasis Filtering (HFE) are used for image enhancement before feature selection and comparison. Spatial domain filters have low time complexity over frequency domain like HFE and they are a good choice for real-time applications [17,18]. Although the combination of the spatial domain and the frequency domain produces good results, it is not suitable for real-time applications.

Furthermore, a standalone microcomputer for the dorsal hand vein imaging system is developed in [19]. It uses NIR imaging technology with two 850 nm IR (Edison-Opto and Taiwan) power LEDs to light the hand surface. A cut-off Kodak 87C Wratten filter is attached to an infrared camera connected to a Raspberry Pi 3 for processing. The system is developed for identification and authentication. To evaluate their system, the raw image is compared with images recorded in the database using 2D cross-correlation and pixel to pixel matching algorithm. Although the results were promising in matching, they have admitted that their system was processing in near real-time. They used algorithms with high computational time in segmentation like Niblack' threshold method [20]. This is in turn affected the frame rate and processing in real-time.

In [21], Garcia and Sanchez introduced a real-time biometric system for recognition of wrist veins. The hardware device consists of a modified USB webcam (Logitech® HD Webcam C525), light sources of 8 infrared LEDs (OSRAM® SFH 4715 A) with 850nm wavelength, and a small computer (Raspberry® Pi 4 B model). Their proposed software was divided into two parts: Firstly, Three-Guideline Software (TGS) was used for capturing images. This algorithm was used to create a database by guiding users to position their wrist within fixed three lines on the monitor. Secondly, Preprocessing and Identification Software (PIS) was used for user identification and verification purpose. It employs some pre-processing methods such as CLAHE, Gaussian, median and average filters of size 11×11 for enhancing images. Moreover, it uses a new scale-orientation-invariant algorithm, based on Oriented FAST and Rotated BRIEF (ORB), Speeded Up

Robust Features (SURF), and Scale-Invariant Feature Transform (SIFT) for feature extraction and matching. The result for recognition had a lower Equal Error Rate (EER) of 0.08% using SIFT over other methods but with the lowest frame rate per second 2 Fps because the algorithms take too much computational time which is not suitable for real-time applications.

The same authors used the same approach in [21], but with a modification. They use smartphones for capturing and processing their algorithms TGS and PIS in [22]. The smartphones used were Xiaomi Pocophone f1© and Xiaomi Mi 8©. These types of devices were selected because they had a built-in near-infrared camera and a near-infrared LED for facial recognition. The results showed that the recognition accuracy not the best from existing systems by EER of 18.72 % with a frame rate of 2-4 Fps. This is too low for real-time applications. Also, their developed system is limited to these two smartphones only.

3. The proposed prototype

The primary motivation for this research is to build a prototype that helps medical teams inject veins easily and accurately on the first attempt. Thus, it helps to reduce the pain that the patient may feel from repeated intravenous injection because the veins are not clear due to old age or excessive obesity. Most of the solutions presented in this regard suffer from

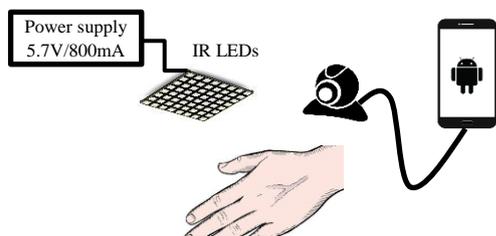


Figure. 2 The proposed prototype hardware

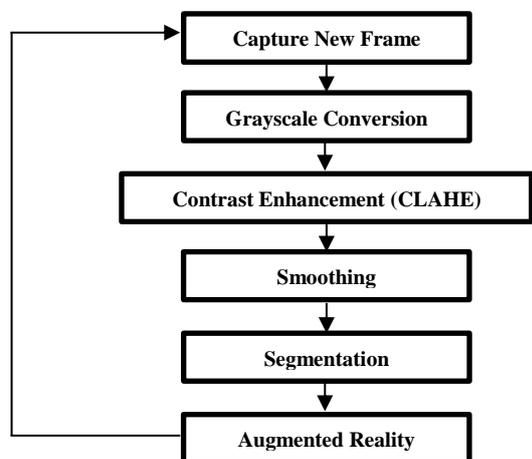


Figure. 3 Real-time vein mapping system diagram

high costs or lack of mobility. Besides, some of the presented solutions do not provide real-time processing and require complex computations, which make their application useless. Systems developed to reduce costs suffer from low frame rates.

Fig. 2 shows the hardware components of the proposed prototype. It is used to capture an image of the part to be injected and then augment the veins' image on this part to appear on the smartphone screen. The vein patterns are detected by converting the captured frame to a grayscale image. Then, contrast enhancement is applied to adjust the frame contrast. The noise is removed using median filtering. Then, the frame is segmented using adaptive thresholding. Finally, the extracted veins are colored. The real-time vein mapping system is shown in Fig. 3 and described in detail in the next subsection.

3.1 Frame acquisition

The proposed prototype consists of a USB camera attached to an Android smartphone used for real-time detection. Only the camera is directed towards the veins of the subject to take a snapshot. The USB-Camera captures the image of the vein under a source of infrared radiation at a specific wavelength. Actually, the captured image is affected by many physical phenomena as light propagates through human tissues. These phenomena include absorption, diffusion, and dispersion. The effects of light transmission become complicated by a large number of substances present in the human body, and the dynamics of the blood. All of these reasons made detecting veins from images captured in normal light extremely difficult. To overcome this issue, an array of Infrared LEDs is used. The veins appear in the IR image darker than the other human tissues because Haemoglobin strongly absorbs infrared wavelengths.

This process is done in real-time, as shown in Fig. 4. The camera captures a sequence of images. The processing of vein detection is done on every single frame. Practically, any part of the body can be examined to obtain an image of the vascular pattern, yet the hand and the fingers are usually preferred.



Figure. 4 Frame acquisition of vein mapping prototype

3.2 Grayscale conversion

The captured frame is converted into a grayscale image to allow much quicker processing in the next steps than the color frame. The grayscale image is more suitable for certain applications, and it merely reduces the complexity. The OpenCV library always reads images or videos in BGR format. So BGR2Gray color space conversion is used to convert images into grayscale. Eq. (1) shows the conversion process to calculate luminance by multiplying R, G, and B color pixels values by constant-coefficient resulting in integer values between 0 and 255. The coefficients are standardized in ITU-R Recommendation BT.601-4 [23].

$$Y = 0.299 \times R + 0.587 \times G + 0.114 \times B \quad (1)$$

Where Y is the luminance, R, G and B are stand for Red, Green, and Blue color.

3.3 Contrast enhancement

The intensities on a given image should be accurately distributed. Histogram Equalization is used to adjust images contrast. In a biomedical imaging system, captured frames contain dark regions or low contrast of local regions. Therefore, Global Histogram Equalization is not the best method to be used [13]. The Contrast Limited Adaptive Histogram Equalization (CLAHE) technique depends on regional contrast [24]. However, if there is a noise in the image, it will be increased. Hence, contrast limiting is applied to fix this problem. This technique is used widely on biomedical images to both reduce noise and eliminate imperfections in the borders. CLAHE provides perfect results in a biomedical imaging system with low contrast[24, 25]. It depends on dividing each frame into small, separated regions called tiles. By default, the size of tiles is set to 8×8 , as it is a valid value to retain chromatic data [27]. For each region, the histogram is calculated. Then, each histogram bin is changed so that its height should not surpass a pre-determined threshold value called the clip limit. The pixels clipped will be distributed uniformly to other bins of the histogram, as illustrated in Eq. (2) [28].

$$g = (g_{max} - g_{min}) \times \rho(f) + g_{min} \quad (2)$$

Where g is the output pixel value, g_{max} is the maximum pixel value, g_{min} is the minimum pixel value, and $\rho(f)$ is the cumulative probability distribution. Finally, bilinear interpolation is applied for removing imperfections in the border.

3.4 Noise removal and smoothing

Smoothing filters are used to enhance noisy images. In the proposed prototype, the median filter is employed to reduce the noise and perform smoothing [29]. It has the advantage of preserving the details in the image. The median filter is less likely to generate new unrealistic pixel values, particularly when the filter operates in transition zones. It smooths images while maintaining the edges. The median value is calculated by sorting all the pixels values in ascending order (see Eq. (3)), then picking the middle pixel value to be replaced with the center pixel value.

$$y(m, n) = \text{median}\{x(i, j), (i, j) \in w\} \quad (3)$$

where $y(m, n)$ is the output pixel's value, and w is the window size of neighborhood pixels.

3.5 Segmentation

This step aims at carrying out a segmentation between veins and the background. Thresholding is a broadly known segmentation technique used for separating an object from its background. Global thresholding is not a satisfying technique as it depends on a single value for thresholding the whole image and produces poor results [14]. Hence, at any given threshold, some veins will be removed. In the proposed prototype, the adaptive threshold is employed to the different parts of the image, see Eq. (4).

$$dst(x, y) = \begin{cases} maxval & \text{if } src(x, y) > T(x, y) \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Where $dst(x, y)$ is the new pixel value after thresholding, $src(x, y)$ is the original pixel value, and $T(x, y)$ is a threshold value, which is calculated from the mean value of a window of block-size \times block-size neighborhood pixels. The block size should be an odd value. If the value of the threshold is less the center pixel, it is set to 0; else, it is set to $maxval$ which is 255. The dimension of the window is defined empirically and can be modified by the user from the settings in the Android app.

3.6 Augmented reality

In this step, the map of the detected veins is augmented and visualized on the mobile phone screen. Here, augmented reality uses a display (mobile phone screen) to overlay digital information (veins map) onto the real world (human body parts

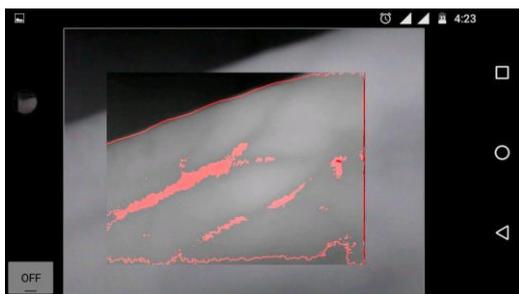


Figure. 5 A screenshot of a digital vein map of the wrist.

like hands). First, the contours of detected veins are extracted by the contour tracking algorithm used in [30]. Contours are consecutive points with the same color or intensity used for analyzing shapes and object detection. The technique depends on finding a change in value between two adjacent points. Second, a contour filling process is carried out using the Scan-Line filling algorithm [31]. Contour filling is one of the most widely recognized issues in image processing. The execution time of the contour filling is crucial, particularly for real-time applications. The Scan-Line filling algorithm depends on obtaining the intersections between the contour and scan line. The points of intersection are sorted in increasing order then the algorithm begins the process of filling inside the contour. The algorithm has a low computational time because it determines the intersections without the need to scan the whole image. This makes the algorithm more efficient than boundary fill and flood fill algorithms [11]. This feature made it a strong candidate for augmenting the vein network map. After completing this step, the physicians can see the augmented veins colored through the smartphone mobile screen, as shown in Fig. 5.

4. Experimental results

To verify the performance of the proposed prototype, a set of experiments are conducted. This section reports and discusses the experimental results.

4.1 Hardware Setup

When building the hardware for the proposed prototype, the Etrain CM-15-0 webcam is used as the USB-Camera connected to the Android smartphone. It has a resolution of 5 Megapixels with 480×640 dimensions, and its price is rather low. Most modern cameras come with an infrared cut-off filter behind the lens to get the maximum amount of visible light for high-resolution images. This filter blocks wavelength above 700 nm in the electromagnetic spectrum, and it must be replaced with a filter that allows infrared radiation to be visible to the camera [32]. Hence, the camera is modified by replacing the

infrared cut-off filter with another filter. This new filter is made of a magnetic film that came from a floppy disk to have access to the infrared light. The focus of the USB-Camera was also re-adjusted to gain more accurate results [33]. A USB cable called On-The-Go (OTG) is used to connect the USB-Camera with the mobile device. The IR LEDs are used for lightening with a wavelength of 940 nm. There are 20 IR LED's (TSAL6200) mounted on a small breadboard. It is provided with a power supply with an output: DC 5.7V/800mA. The target body part (such as a hand) is lighted with an infrared light source spotted on it, then the captured frames from USB-Camera are sent to mobile via (OTG) cable for further processing.

4.2 Mobile app development

In recent years, the use of smartphones has increased dramatically by millions of people. Smartphones are equipped with many sensors and processors of increasing power. These capabilities, along with signal processing algorithms, represent a growing platform for providing many smart solutions. If we take into account the advantage of mobility and portability with the continuous development in software and hardware, we find ourselves in front of a practical, low-cost, and accessible solution for many applications. Hence, we implemented our vein mapping system as a mobile app.

Currently, smartphones are equipped with high-resolution image sensors of 64 megapixels on some phones. These advances in camera sensors and the increased computational power of smartphones enable images to be captured with pinpoint accuracy that shows important image details. Thus, these images can be analyzed and used in various mobile applications.

In the proposed prototype, the vein mapping app is implemented optimally in Android using the Android Studio. Android is very flexible and provides a lot of application development tools. The (OpenCV4android) library is employed for developing the vein mapping app. It is a Computer Vision library integrated with Android Studio IDE for developing Android applications. This open-source library is used for computer vision applications as well as machine learning. It is the best choice for real-time processing. It has an advantage that it is an independent platform running on all operating systems. The OpenCV library contains a huge number of algorithms that can be used for augmented reality, image processing, face recognition, objects identifying, etc. [34]. Fig. 6 shows our developed Android app for the real-time

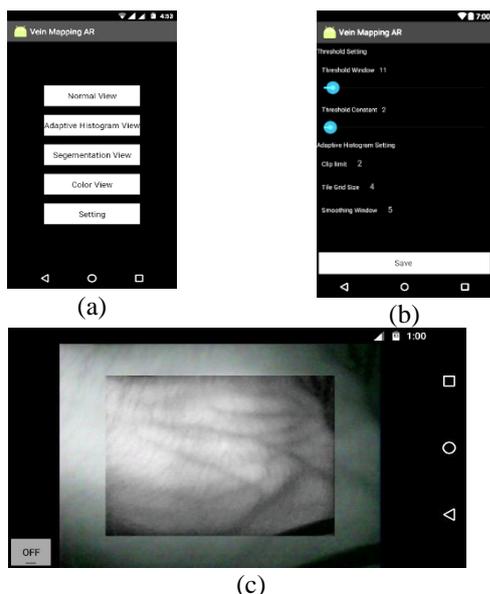


Figure. 6 Screenshots of the prototype android app: (a) main screen (b) setting screen, (d) view screen

vein mapping system. The app has only three screens. The main screen shown in Fig. 6 (a), contains the viewing options of detected veins, including normal view, CLAHE view, Segmentation view, and color view. The settings screen is shown in Fig. 6 (b), where users can adjust and control values to achieve the best results. In the view screen, enhanced veins on the hand are clearly shown in Fig. 6 (c).

4.3 System evaluation

To evaluate the proposed prototype, trials were conducted on 120 persons (64 females and 56 males), all from the same country, aged between 16 and 65 years with a standard deviation of 15.49 and an average age of 29.46. The sample data distribution is shown in Table 1. The trials were done in more than one session. The Success Detection Rate of the system is measured using Eq. (5). The result is reported in Table 2.

Table 1 Sample data distribution

Age	Male	Female
16-30	37	45
30-55	13	15
55-65	6	4

Table 2. Test results

	Trials	Successful Trials	Failure Trials
Male	56	37	19
Female	64	48	16
Total	120	85	35
Success Detection Rate (%)	70.8%		

$$Success\ Detection\ Rate(\%) = \frac{Successful\ Trials}{Total\ Trials} \tag{5}$$

Fig. 7 and Fig. 8 show the results of the proposed vein mapping system for the wrist and dorsal hand, respectively. The frame captured by USB-Camera is converted to a grayscale level. The grayscale conversion result is shown in Fig. 7 (a) and Fig. 8 (a). At the next step, CLAHE is applied to the grayscale image for contrast enhancement. The result of the contrast enhancement operation is shown in Fig. 7 (b) and Fig. 8 (b). Thus, the veins appear darker. Then, median filtering is applied to eliminate noise. After noise removal, the vein pattern is segmented by adaptive thresholding to discriminate veins from the background (see Fig. 7 (c) and Fig. 8 (c)). In Fig. 7 (d) and Fig. 8 (d), the result of the last step after coloring the veins.

On another scale, the proposed prototype was tested on different mobile devices having different specifications in terms of RAM and CPU running on different Android versions and compared against the current state-of-the-art. The Android smartphones used in this test were the Meizu m5 (CPU 1.5Hz and RAM 2GB), Motorola G3 (CPU 1.4Hz and RAM 2GB), Huawei Honor V9 (CPU 2.4Hz and RAM 4GB), and Realme 5pro (CPU 2.3Hz and RAM 8GB). Table 3 shows the average frame rate (fps) after implementing the techniques used in previous work on the above-mentioned smartphones. In [15], the average frame rate was very low, approximately one fps. This is because it uses computationally intensive algorithms. It takes a long execution time which is not suitable for real-time applications. Also in [16], frequency domain filters (such as HFE) are used in the enhancement process. This resulted in a significant drop in the frame rate. In [19], the techniques used are similar to those used in the proposed prototype except the threshold method. They used a local threshold method called Niblack's method. It calculates the mean and the standard deviation to determine the threshold value within a window of size $w \times w$. Hence, it needs more time for calculation. This affects the frame rate (an average frame rate of 12.75 fps). Furthermore, the techniques used in [22] are CLAHE, median, Gaussian, average, feature selection, and feature matching. Only pre-processing was performed to be compared with other results. It achieved an average frame rate of 21 fps. The use of more than one filtering method with a window of size 11×11 size resulted in a slight increase in the execution time. Although we could not implement the algorithm presented in [12] because the details of the algorithm are not clearly explained,

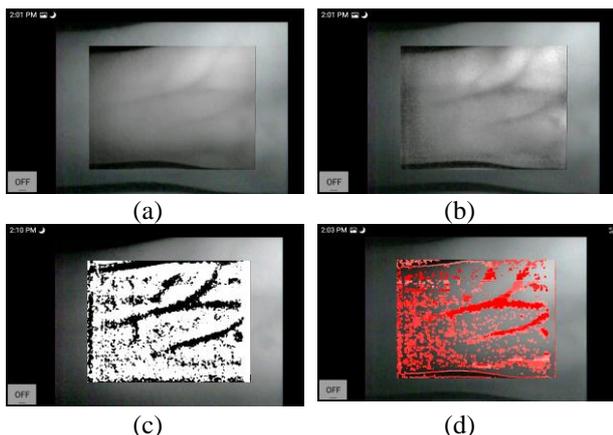


Figure 7. Sample results for a wrist: (a) grayscale frame (b) applying contrast enhancement CLAHE (c) adaptive thresholding, and (d) color veins

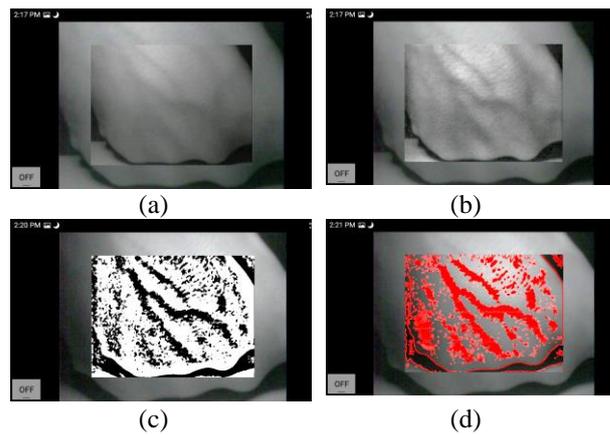


Figure 8. Sample results for a dorsal hand: (a) grayscale frame (b) after applying contrast enhancement CLAHE (c) adaptive thresholding, and (d) color veins

Table 3. Average frame rate of proposed prototype and previous systems in real-time processing

Study	Year	Methodology	Average Frame Rate (Fps)
Dan <i>et al.</i> [15]	2015	anisotropic diffusion+ multi-scale vessel enhancement filtering	1
Debiasi <i>et al.</i> [16]	2018	CLAHE+ Circular Gabor Filter+ High Frequency Emphasis Filtering	0.5
Yildiz and Boyraz [19]	2019	CLAHE+ Median filter+ Niblack’s local thresholding	12.75
Garcia and Sanchez [22]	2020	CLAHE+ Gaussian, median and average filter	21
Proposed	2020	CLAHE+ Median Filter+ Adaptive threshold+ Scan line fill algorithm	23

Table 4. Comparison between the proposed prototype with existing systems

Study	Year	Hardware	Samples Data	Sample Data Characteristics	Detection Rate (%)	Cost
Juric and Zalik [12]	2014	4 IR (OIS-330-740-X-T) high-intensity LEDs of 740 nm wavelength + USB-Camera connected to android tablet	25	N/A	64.8%	30-80 USD
Bawase and Apte [13]	2015	36 IR LEDs of 850nm + Mobile camera of 6 megapixel connected to a personal computer	55	25 males and 30 females	N/A	N/A
Debiasi <i>et al.</i> [16]	2018	16 IR LEDs of 850nm + Modified smartphone Nexus 5 + Arduino Nano Board	31	N/A	N/A	427.7 USD
Yildiz and Boyraz [19]	2019	Two light source of IR power LEDs of 850 nm + Kodak cut-off filter attached to mini Raspberry Pi IR camera	72	32 females and 40 males, age range from 18-65	N/A	75 USD
Garcia and Sanchez [22]	2020	Built-in near-infrared camera and the near-infrared LED in Xiaomi Pocophone F1 and Xiaomi Mi 8 smartphones	50	25 females and 25 males, age range 21-75, Europe (43), America (4), Africa (1) and Asia (2)	N/A	N/A
The Proposed Prototype	2020	20 IR LEDs of 940nm +USB-Camera of 5megapixel + connected to android smartphone	120	64 females and 56 males, age range from 16-65	70.8%	20 USD

they reported that their system achieves an average frame rate of 12.2 fps. It can be seen from Table 2 that the proposed prototype has the highest average frame rate of 23 fps due to its reliance on light and fast techniques: CLAHE for enhancing contrast, the median filter for smoothing with size 5×5, the adaptive threshold for isolating veins map, and the fast-fill algorithm scan-line for coloring the detected veins. All this makes the proposed prototype superior to the existing systems in terms of speed and real-time processing.

Table 4 reports the comparative results of the proposed prototype with other existing systems

presented in [12, 13, 16, 19, 22] in terms of hardware component used, the number of sample data, characteristics of sample data, and the total cost. The systems presented in [16, 19, 22] used the hardware components for collecting datasets for recognition purposes. These systems depend on an external processing unit for running their algorithms which leads to an increase in cost. Also, the work presented in [12] and [13] was mainly developed for vein detection. The system presented in [12] achieves a detection rate of 64.8%. on the other hand, the work presented in [13] depends on a personal computer in processing which limits its portability. As can be

seen from the table, the proposed prototype shows a high success rate of vein detection. The results obtained are broadly consistent with the prototype objective. It uses light computing algorithms with hardware components achieving reliable results at a low cost.

5. Conclusion

In this paper, a real-time vein mapping prototype has been introduced. The proposed prototype can help physicians in their work to give an intravenous injection to patients from the first trial. While developing the proposed prototype, the focus was on setting-up a low-cost and easily portable device for vein mapping. Augmented reality and biomedical imaging technologies are employed in the proposed prototype. A modified USB-Camera with an infrared filter manually added and an Android smartphone are integrated to take advantage of portability. The proposed vein mapping process involves six steps: frame acquisition, grayscale conversion, contrast enhancement, noise removal and smoothing, segmentation, and augmented reality. The prototype produces reliable imaging and augmented reality results in real-time. The performance has been evaluated for the frame rate, the successful detection rate, and the cost. The evaluation results show that the proposed prototype outperforms the other existing systems in a high average frame rate of 23 fps, a success detection rate of 70.8%, and with a low cost. In our future work, we intend to improve the details of the vein map produced by studying more the images details.

Conflicts of Interest

We declare no conflict of interest.

Author Contributions

All authors contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

References

- [1] H. K. Al Ghozali, Setiawardhana, and R. Sigit, "Vein detection system using infrared camera", In: *Proc. of International Conf. Electronics Symposium (IES), 2016*, pp. 122–127, 2016.
- [2] M. Mansoor, S. N. Sravani, S. Z. Naqvi, I. Badshah, and M. Saleem, "Real-time low cost infrared vein imaging system", In: *Proc. of International. Conf. Signal Processing Image Processing Pattern Recognition, ICSIPR 2013*, Vol. 1, pp. 1–5, 2013.
- [3] G. Cantor-peled, Ovadia-Blechman, and M. H. Zehava, "Peripheral vein locating techniques", *Imaging Med*, Vol. 8, No. 3, pp. 83–88, 2016.
- [4] K. W. Law, K. Ajib, F. Couture, C. Tholomier, H. D. Bondarenko, F. Preisser, P. I. karakiewicz, and K. C. Zorn, "Use of the AccuVein AV400 during RARP: An infrared augmented reality device to help reduce abdominal wall hematoma", *Can. J. Urol.*, Vol. 25, No. 4, pp. 9384–9388, 2018.
- [5] A. S. Saju, L. Prasad, M. Reghuraman, and I. K.Sampath, "Use of vein-viewing device to assist intravenous cannulation decreases the time and number of attempts for successful cannulation in pediatric patients", *Paediatr. Neonatal Pain*, Vol. 1, No. 2, pp. 39–44, 2019.
- [6] M. Lamperti and M. Pittiruti, "II. Difficult peripheral veins: Turn on the lights", *Br. J. Anaesth.*, Vol. 110, No. 6, pp. 888–891, 2013.
- [7] G. Leedham, L. Wang, G. Leedham, and S. Cho, "Infrared imaging of hand vein patterns for biometric purposes Infrared imaging of hand vein patterns for biometric purposes", *IET Computer Vision*, Vol. 1, No. 3, p. 113-122, 2007.
- [8] S. Crisan, I. G. Tarnovan, and T. E. Crişan, "A low cost vein detection system using near infrared radiation", In: *Proc. of 2007 IEEE Sensors Appl. Symp. SAS*, No. February, pp. 6–8, 2007.
- [9] M. Cowling, J. Tanenbaum, J. Birt, and K. Tanenbaum, "Augmenting reality for augmented reality", *Interactions*, Vol. 24, No. 1, pp. 42–45, 2017.
- [10] R. A. El -Aziz, "Effectiveness of AccuVein AV400 Device versus ultrasound-guided Cannulation of the Great Saphenous vein at the Ankle in Infants: A Randomized Controlled Trial", *Int. J. Anesthesiol. Res.*, Vol. 8, No. 3, pp. 594–599, 2020.
- [11] N. Nisha and S. Varshney, "A Review: Polygon Filling Algorithms Using Inside-Outside Test", *Int. J. Adv. Eng. Res. Sci.*, Vol. 4, No. 2, pp. 73–75, 2017.
- [12] S. Juric and B. Zalik, "An innovative approach to near-infrared spectroscopy using a standard mobile device and its clinical application in the real-time visualization of peripheral veins", *BMC Med. Inform. Decis. Mak.*, Vol. 14, No. 1, pp. 1–9, 2014.
- [13] A. B. Bawase and S. D. Apte, "Infrared Hand Vein Detection System", *IOSR J. Electron. Commun. Eng.*, pp. 2278–2834, 2015.
- [14] A. M. Badawi, "Hand vein biometric verification prototype: A testing performance

- and patterns similarity”, In: *Proc. of International Conf. Image Processing Computer Vision, Pattern Recognition, IPCV'06*, Vol. 1, pp. 3–9, 2006.
- [15] G. Dan, Z. Guo, H. Ding, and Y. Zhou, “Enhancement of dorsal hand vein image with a low-cost binocular vein viewer system”, *J. Med. Imaging Heal. Informatics*, Vol. 5, No. 2, pp. 359–365, 2015.
- [16] L. Debiasi, C. Kauba, B. Prommegger, and A. Uhl, “Near-infrared illumination add-on for mobile hand-vein acquisition”, In: *Proc. of International Conf. Biometrics Theory, Appl. Syst. BTAS 2018*, pp. 1–9, 2018.
- [17] C. Chaudhary and M. K. Patil, “Review of Image Enhancement Techniques Using Histogram”, *Int. J. Appl. or Innov. Eng. Manag.*, Vol. 2, No. 5, pp. 343–349, 2013.
- [18] S. Dewangan and A. K. Sharma, “Image Smoothing and Sharpening using Frequency Domain Filtering Technique”, *Int. J. Emerg. Technol. Eng. Res.*, Vol. 5, No. 4, pp. 169–174, 2017.
- [19] M. Z. Yildiz and Ö. F. Boyraz, “Development of a low-cost microcomputer based vein imaging system”, *Infrared Phys. Technol.*, Vol. 98, No. February, pp. 27–35, 2019.
- [20] L. P. Saxena, “Niblack’s binarization method and its modifications to real-time applications: a review”, *Artif. Intell. Rev.*, Vol. 51, No. 4, pp. 673–705, 2019, doi: 10.1007/s10462-017-9574-2.
- [21] R. Garcia-Martin and R. Sanchez-Reillo, “Wrist vascular biometric recognition using a portable contactless system”, *Sensors (Switzerland)*, Vol. 20, No. 5, 2020.
- [22] R. Garcia-Martin and R. Sanchez-Reillo, “Vein Biometric Recognition on a Smartphone”, *IEEE Access*, Vol. 8, pp. 104801–104813, 2020.
- [23] ITU-R BT.601-7, “Studio encoding parameters of digital television for standard 4:3 and wide screen 16:9 aspect ratios”, *Recomm. ITU-R BT.601-7*, Vol. 7, pp. 1–18, 2017.
- [24] K. Zuiderveld, *Contrast Limited Adaptive Histogram Equalization*. Academic Press, Graphics Gems, 1994.
- [25] A. M. Reza, “Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement”, *J. VLSI Signal Process. Syst. Signal Image. Video Technol.*, Vol. 38, No. 1, pp. 35–44, 2004.
- [26] S. Gupta and S. Singh, “Curvelet based Rayleigh CLAHE Medical Image Enhancement”, *Int. J. Comput. Appl.*, Vol. 182, No. 6, pp. 19–23, 2018.
- [27] J. Ma, X. Fan, S. X. Yang, X. Zhang, and X. Zhu, “Contrast Limited Adaptive Histogram Equalization-Based Fusion in YIQ and HSI Color Spaces for Underwater Image Enhancement”, *Int. J. Pattern Recognit. Artif. Intell.*, Vol. 32, No. 7, pp. 1–26, 2018.
- [28] B. B. Singh and S. Patel, “Efficient Medical Image Enhancement using CLAHE Enhancement and Wavelet Fusion”, Vol. 167, No. 5, pp. 1–5, 2017.
- [29] D. Mulyono and H. S. Jinn, “A study of finger vein biometric for personal identification”, *IEEE- Int. Symp. Biometrics Secur. Technol. ISBAST'08*, 2008.
- [30] P. Tan, X. Li, J. Xu, J. Ma, F. Wang, J. Ding, Y. Fang, and Y. Ning, “Catenary insulator defect detection based on contour features and gray similarity matching”, *J. Zhejiang Univ. Sci. A*, Vol. 21, No. 1, pp. 64–73, 2020.
- [31] F. Zeng and W. Feng, “Hole filling algorithm based on contours information”, In: *Proc. of the 2nd Int. Conf. Inf. Sci. Eng. ICISE2010*, pp. 3741–3743, 2010.
- [32] G. Verhoeven, “Imaging the invisible using modified digital still cameras for straightforward and low-cost archaeological near-infrared photography”, *J. Archaeol. Sci.*, Vol. 35, No. 12, pp. 3087–3100, 2008.
- [33] S. Crisan, T. Crisan, and C. Curta, “Near infrared vein pattern recognition for medical applications. Qualitative aspects and implementations”, In: *Proc. of International Conf. Adv. Med. Heal. Care through Technol. MediTech 2007*, pp. 27–29, 2007.
- [34] S. N. Sravani, S. Z. Naqiv, N. Sriraam, M. Mansoor, I. Badshah, M. Saleem and G. Kumaravelu, “Portable Subcutaneous Vein Imaging System”, *International Journal of Biomedical and Clinical Engineering*, Vol. 2, No. 2, pp. 11–22, 2013.