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An effective method for detecting dorsal hand veins utilising near-infrared imaging technology

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Abstract:

Intravenous access for blood collection and other related therapies is one of the most frequently practiced procedures in the modern medical system. The procedure requires complex training and experience, as it might cause dangerous nerve damage and subcutaneous bleeding. This paper proposes a dorsal hand vein detection method utilising the near-infrared (NIR) imaging device to segment and visualise the subcutaneous vein patterns on the skin directly. Applying NIR light has received substantial attention because of its non-invasive and revealing substantially more information than the visible one. The proposed method is divided into the low- and high-level processes. The captured image is smoothed and enhanced to make the vein patterns clearer in the low-level process. The pre-processed image is then segmented step by step to extract the vein features and eliminate the pseudo-vein regions precisely. Lastly, the detected veins are thinned to reduce the thickness and projected back onto the acquired image in the high-level process. The proposed method performs effectively in detecting the clear dorsal hand veins through the experiment with a processing time of 0.61s for the high-resolution image.

Keywords: **adaptive thresholding, feature extraction, image processing, near-infrared, vein detection.**

Classification number: **2.3**

Introduction

Venipuncture is an invasive procedure to obtain intravenous access for blood collection and other intravenous therapies. One of the most frequently practiced procedures in modern medicine, over one billion cases are performed annually by 90% of hospitals worldwide [1]. It causes mild pain, and subsequent nerve damage and subcutaneous bleeding are not uncommon. Extreme internal bleeding, trauma, and chronic pain such as complex regional pain syndrome resulting from damage to the peripheral and central nervous system have been reported across decades [2-4]. Venipuncture is difficult even for experienced medical practitioners as a result of many factors such as the size and depth of a patient's vein, non-uniform fat distribution. or skin color. Clinical studies have indicated that 25 to 50% of patients necessitate multiple attempts to obtain peripheral venous access [5].

Several imaging modalities have recently been proposed to improve the success rate of the procedure attempt, including transillumination, ultrasound, and NIR imaging devices. Transillumination is a technique in which light is focused through tissues. The method is limited to infants and small children because the light intensity decreases by absorption in thicker, denser tissues and cannot penetrate through the hand or wrist area [6]. Ultrasound utilises high-frequency acoustic waves to image vessels and tissues, but its probe requires haptic control and occupies the attention of one hand; the procedure itself requires skills and experience to attempt placing the needle precisely in a three-dimensional structure with only its two-dimensional projection to work on [7]. The NIR light vein-viewing device has the advantages of offering a quick, cost-effective solution to intravenous access in critically ill children [8].

Applications of NIR imaging technique in vein detection have not been exhaustively explored relative to those of other imaging techniques. This non-invasive imaging technique can rapidly deliver high-end results at a low

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cost. Pham, et al. (2015) developed a device using six NIR light-emitting diodes (LEDs) and a webcam to construct a finger-vein database. This database provided training data sets to distinguish real fingers from fake fingers [9]. They also incorporated in their image recognition algorithm a convolutional neural network for vein feature extraction, principal component analysis for dimensionality reduction, and a support vector machine for classification [10]. Li, et al. (2015) developed a method to extract the dorsal hand vein by first registering the region of interest on the back of the hand and then detecting the veins with a thickness of one pixel through normalisation, morphological operators, and refinement [11]. Additionally, Crisan, et al. (2018) presented a system to detect the liveness of the hand vein by embedding the temperature, pressure, and humidity sensors in the developed biometric module. However, the accuracy of this system could depend on the calibration step of the sensors [12].

The previous study proposed an imaging 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, a visible light filter, and a Pico projector [13]. The imaging system will examine the area of interest by flooding it with NIR light of 940 nm wavelength. The reflected light passes through the plastic filter to remove visible light before being captured by the camera board and converted into digital signals. This system can quickly capture and process a high-resolution image of a hand but has yet to mark the position of vein patterns on the original image. This study is intended to improve upon the previous result by changing the programming language from MATLAB to Python to reduce processing time, modifying and integrating some techniques to extract vein patterns and project them back onto the original image.

Materials and methods

The NIR imaging system has been used to collect a dataset of dorsal left- and right-hand 1280×720-pixel images from 12 males and 10 females between the ages of 9 and 66 years (with an average age of 28.1 years). These images are twice the size of the previous ones we used [13]. Figs. 1 and 2 depict the dorsal right-hand of female and male subjects.

Fig. 1. Dorsal hand of female of 40 years.

Fig. 2. Dorsal hand of male of 21 years.

Figure 3 illustrates the 10-step procedure of the proposed method. This method is divided into two types of computerising processes: low- and high-level. The low-level process involves basic image pre-processing to smoothen the image and enhance contrast. High-level processing involves partitioning an image into regions or objects (segmentation), removing objects that are not the cephalic veins, also called pseudo-vein objects (simplification), and vein refinement. Low-level processing involves pre-processing an image for effective vein extraction by the high-level process. Image pre-processing improves the quality of images captured under poor lighting conditions so that cephalic veins can be easily segmented in the next step. The high-level process segmented and simplified the image to extract branching patterns, edges of vessel walls, and other characteristics of the veins.

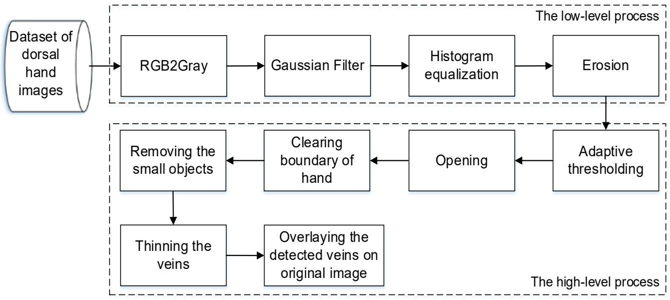

Fig. 3. The 10-step procedure of the proposed method.

Low-level process

A Gaussian filter is applied after the colour-to-grayscale conversion step. This filter attenuates the high-frequency noise of glare and non-uniform brightness resulting from the close proximity of the light source to the region of interest and the device's variable positioning. This filter blurs an image based on a weighted average of each pixel's neighbourhood; therefore, it can preserve edges better than the median filter used in the previous study. The histogram equalisation was maintained to keep the local contrast consistent. Because hemoglobin in the blood has higher absorption coefficient around NIR frequencies than collagen or melanin, vein patterns would appear darker, whereas skin would appear lighter; therefore, a morphological erosion operator was used to thicken the veins by adding more pixels to dark regions. Figs. 4B, 4C, 4D illustrate the result of the three above steps applied to the grayscale image in Fig. 4A. These pre-processing steps rendered cephalic veins clearly visible and easy to identify and segment in the subsequent step.

High-level process

Segmentation is the most crucial step in this process to extract the characteristics of the vein, create patterns, and clear the other remaining objects. The adaptive thresholding technique for segmentation is suitable where illumination change affects the image and vein size is minor relative to the skin area and image background. Bradley, et al. (2011) developed an adaptive thresholding method to set a pixel to black or white based on the average of its neighbourhood in the $s\times s$ window [14]. This study has optimised the sensitivity and computational intensiveness of Bradley's method by reducing the threshold value from 15 to 4% and the neighbourhood size s by half. The value of the current pixel can be completely calculated by T(x,y), as given in Equation 1.

$$T(x,y)=\begin{cases}0 & if\left(f(x,y)\mathrm{x}N_{sxs}\right)>sumA\mathrm{x}(100\mathrm{x}t)/100\\ 1 & otherwise\end{cases} \qquad (1)$$

where, $T(x,y)$ is the binary image, $f(x,y)$ is the preprocessed image, $N_{s\times s}$ is number of pixels in the $s\times s$ window, and $sumA$ is the sum of intensity of all pixels in the $s\times s$ window.

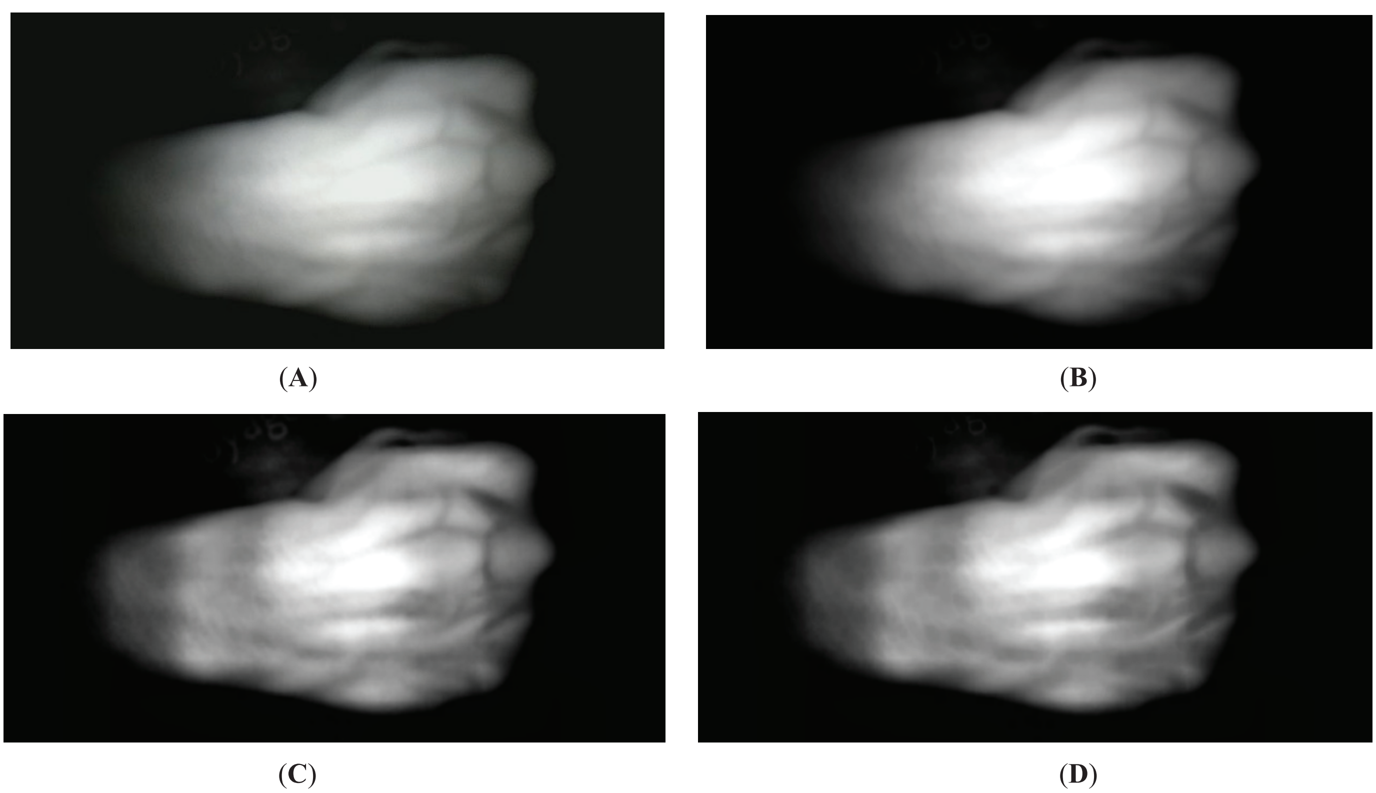

Fig. 4. Result images in low-level process. (**A, B**) Grayscale image is applied Gaussian filter with σ=2.5; (**C**) Histogram equalisation; (**D**) Erosion operator with the structure element size 7×7.

The vein patterns were then determined, the other objects were removed during post-processing. Objects' boundaries were curved from smoothening with circular structuring element. This operator removed some of the small objects inside and separated them from the border (Fig. 5). The clear_border function was used to remove any object that touches the border within a 0÷50 pixels range (Fig. 6) [15]. Any object less than 100 pixels in length was eliminated based on the characteristics of the vein patterns in the dataset (Fig. 7). The erosion step during pre-processing can alter the thickness of the detected veins; therefore, a thinning algorithm and morphological dilation operator is applied for better depiction of vein thickness. Fig. 8 illustrates the thinned line and boundary of the dilated veins. Finally, these veins were projected back onto the original image (Fig. 9).

Fig. 5. Opening image.
Note: the circular structuring element has a diameter of nine pixels. The input image is Fig. 4B.

Fig. 6. Cleared border image.

Fig. 7. Image of removed short objects in horizontal axis.

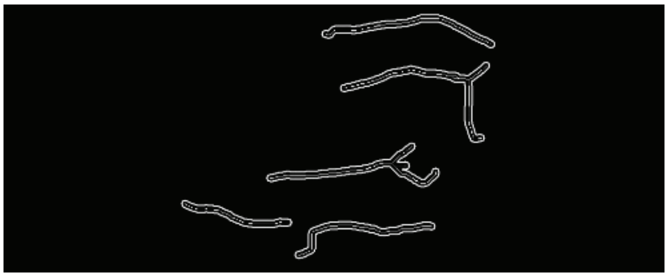

Fig. 8. Thinned and bounded vein image.
Note: after applying the thinning technique, the dilation operator is used with the circular structuring element of five pixels. The input image is Fig. 7.

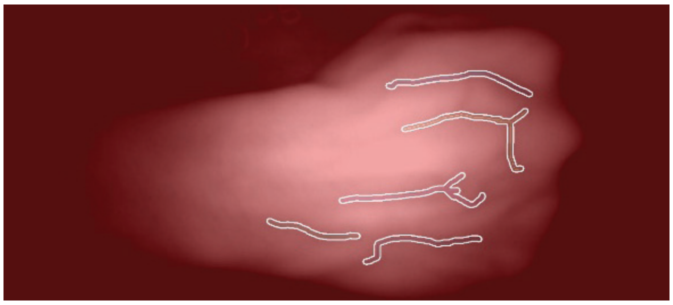

Fig. 9. Coloured veins on the original image.
Note: the segmented vein patterns (colors) overlaid on Fig. 4A.

Results and discussion

It was proven that the adaptive thresholding algorithm with modified parameters could better segment the veins. Fig. 10 illustrates the results of the original adaptive thresholding and the modified technique. The processing time of the modified algorithm in Cython was 0.025s, approximately 37% faster than the threshold_local algorithm in scikit-image library, suitable for any real-time application [15, 16]. The proposed method was written with Python and scikit-image library and processed the high-resolution image with the computational time of 0.61s. Figs. 11 and 12 illustrate vein segmentation results of the left- and right-hand of female and male from the dataset, respectively. For a simpler and more straightforward method, the performance was comparable to Li, et al.'s (2015) approach, and even the detected veins were more apparent when projected back onto the original image [11].

Since no skill was required to operate the NIR imaging system, the captured image could impose some problems, as suggested in Figs. 11 and 12. Nonetheless, the segmentation results clearly indicated the effectiveness and stability of the proposed method. Any exception to this high performance, which prevents the extraction of the vein patterns, may be the result of the over-illumination of an area in some images (Figs. 11B and 12B), or inadequate contrast and an object's size disproportion during the adaptive thresholding step (Fig. 12C). Some pseudo-vein patterns can be detected as large dark regions (Figs. 11B, 11D, 12A, 12D), or sometimes the vein is close to the dark region, and a longer vein is therefore segmented (Figs. 11C and 12C).

(A) (B)

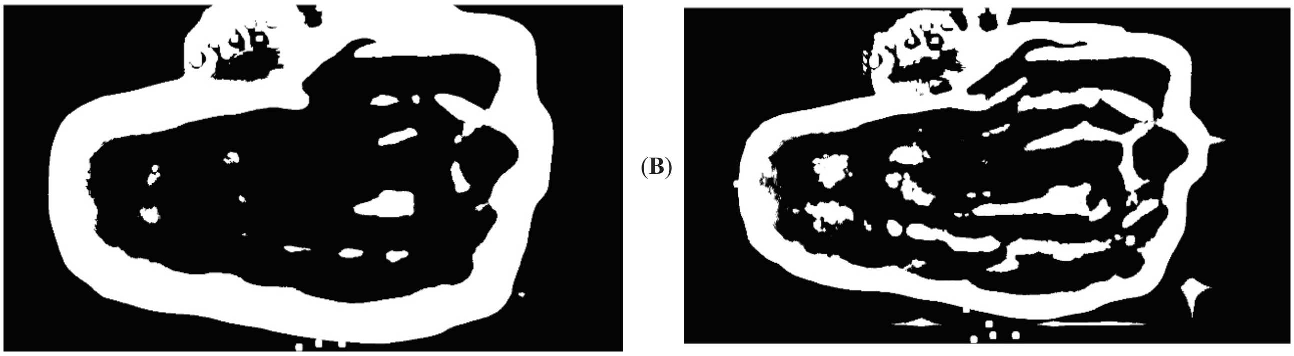

Fig. 10. Comparison of the result of the adaptive thresholding of Bradley, et al. (2011) [14] **and our modified technique.** (**A**) The original technique of Bradley, et al. (2011) has the kernel size of s=1/8th of image width and t=15%; (**B**) The modified technique has the kernel size of s=1/16th of image width and t=4%. The input image is Fig. 4D.

(A)
(B)
(C)
(D)

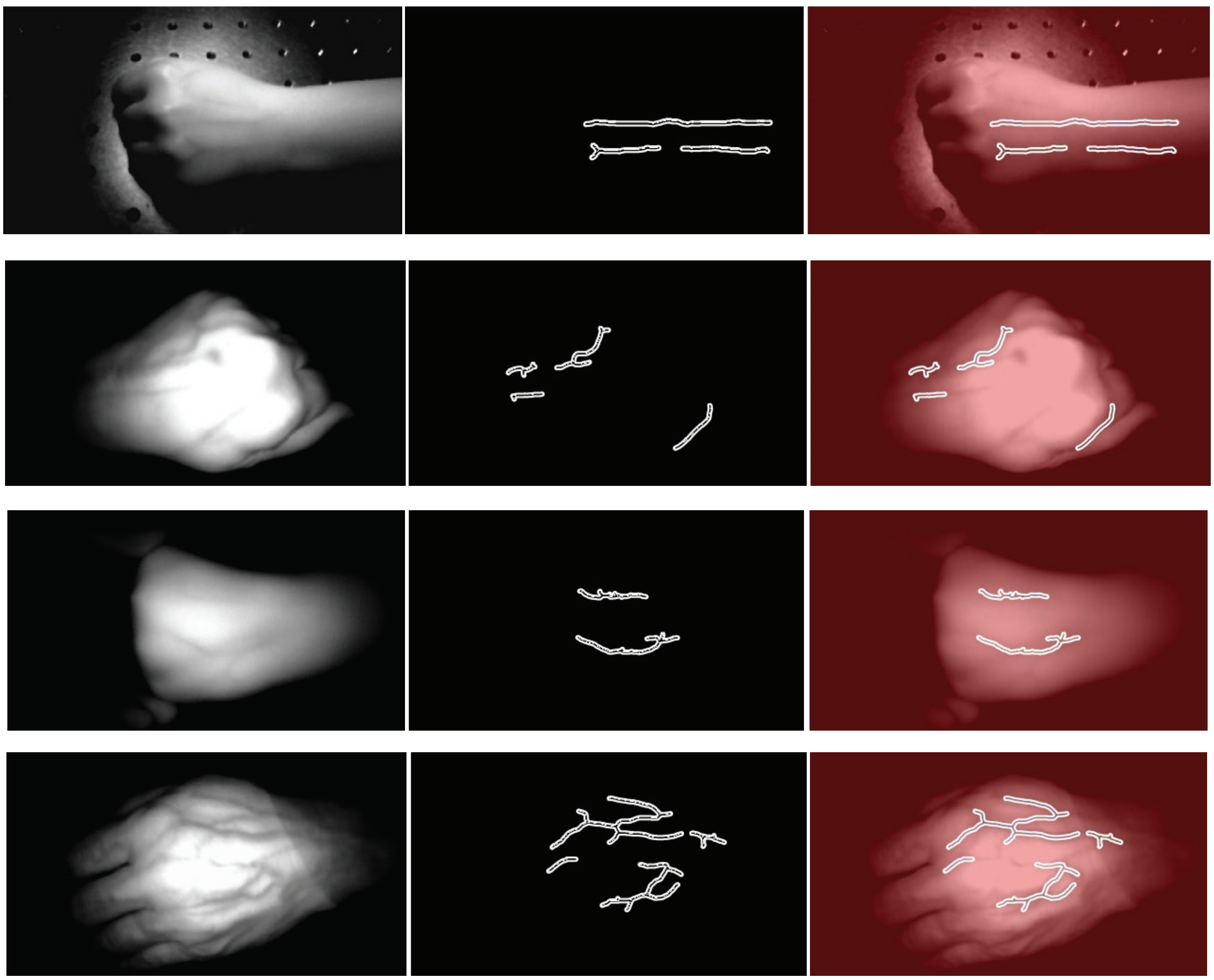

Fig. 11. Vein segmentation results of left-hand of females and males. (**A-D**) The images are the hands of females who are 23 and 56 years of age and males 9 and 66 years of age. The first column displays the original (grayscale) image, and the second contains the thinned and bounded vein patterns after removing the small objects. The last column shows the detected vein overlaid on the dorsal hand image from the first column.

(A)

(B)

(C)

(D)

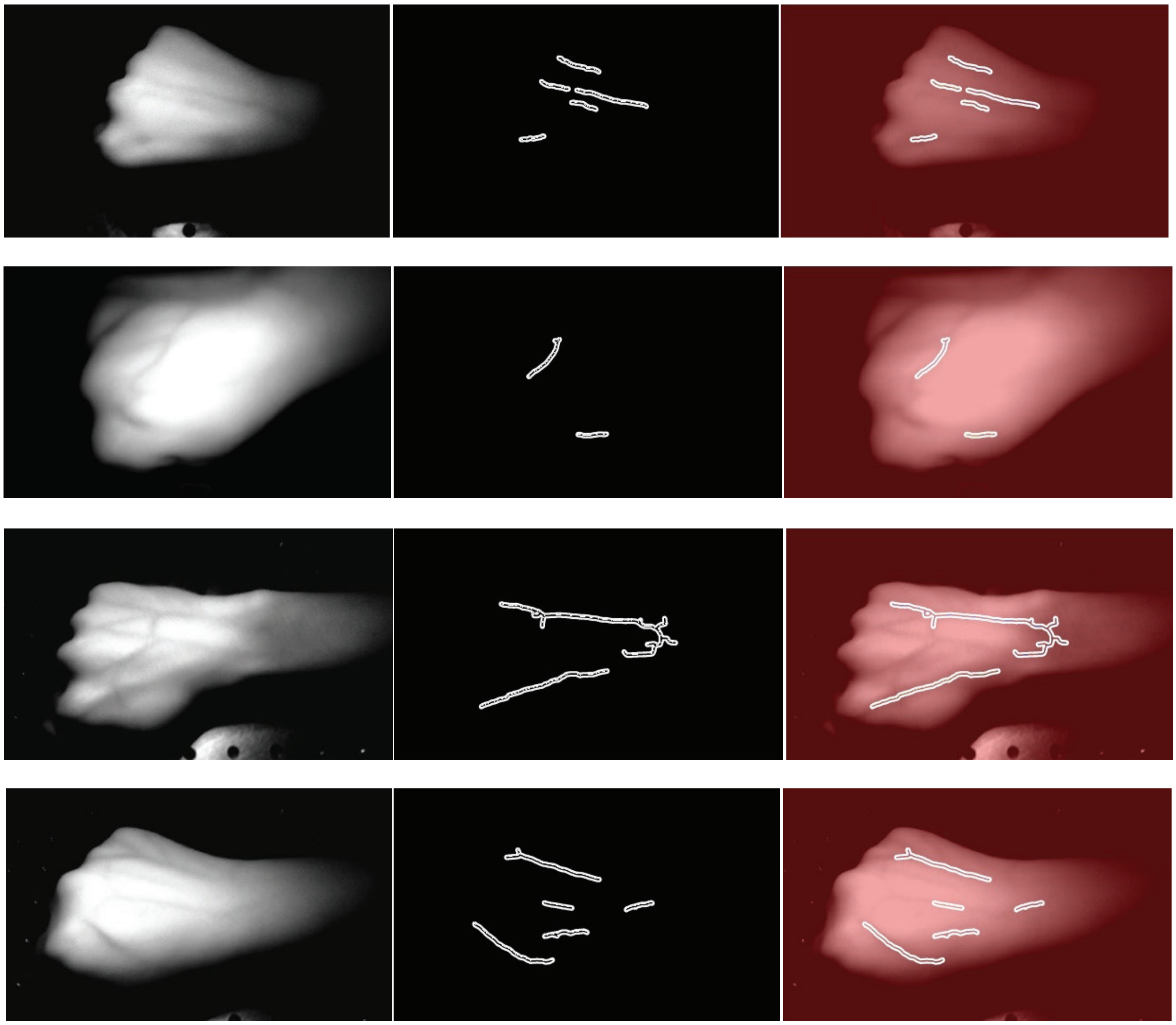

Fig. 12. Vein segmentation results of right-hand of females and males. (A-D) The images are the hands of females 23 and 40 years of age and males 22 and 35 years of age. The order of images is similar to Fig. 11.

Conclusions

This work has optimised the vein detection method and projection in 10 steps categorised under low- and high-level processes. The low-level process filters out the noise, enhances the contrast, and enlarges the dark regions to improve the image quality. A modified fast adaptive thresholding algorithm segmented the objects in the high-level process; a clear and refined vein pattern was extracted and projected back onto the original image. This method allows for the visualisation of precise, high-resolution vein patterns with a faster, simpler algorithm. This method can potentially assist and increase the success rate of venepuncture by visualising and locating vein patterns.

COMPETING INTERESTS

The authors declare that there is no conflict of interest regarding the publication of this article.

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