Visualizing Vein Patterns from Color Skin Images based on Image Mapping for Forensics Analysis

[1]Chaoying Tang, [1]Hengyi Zhang, [1]Adams Wai-Kin Kong and [2]Noah Craft
[1]*Forensics and Security Laboratory, School of Computer Engineering, Nanyang Technological University, Nanyang Avenue, Singapore, 639798*; [2]*Department of Medicine, Los Angeles Biomedical Research Institute Harbor-UCLA Medical Center1124 West Carson St. HH-207, Torrance, CA 90502*
tang0179@e.ntu.edu.sg, s090022@e.ntu.edu.sg, adamskong@ntu.edu.sg, ncraft@ucla.edu

Abstract

Traditionally, it was difficult to use vein patterns in evidence images for forensic identification, because they were nearly invisible in color images. We proposed a computational method based on skin optics to uncover vein patterns from color images. However, its performance is dependent on the accuracy of the skin optical model. In this paper, we propose an algorithm based on image mapping to visualize vein patterns. It extracts information from a pair of synchronized color and near infrared (NIR) images, and uses a neural network (NN) to map RGB values to NIR intensities. In addition, an NN weight adjustment scheme is proposed to improve the robustness of the algorithm. The proposed algorithm was examined on a database with 300 pairs of color and NIR images collected from the forearms of 150 subjects. The automatic matching results from the proposed algorithm were better than those from our previous method, and comparable to the results from matching NIR images with NIR images.

1. Introduction

Personal identification is a critical process in forensic investigation. Significant research effort has been expended to develop face, fingerprint, palmprint, DNA, and dental identification systems. These systems are regularly used by law enforcement agents around the world. However, they are not applicable in cases where only partial non-facial skin of criminals or victims is observable in photographic evidence or digital images. Sex offenses against children are among these cases. Pedophiles are usually careful not to show their faces in images for fear of identification. The problem of child pornography is increasing because of the proliferation of such material electronically and the lack of effective identification technology. The U.S. Customs Service estimated that 100,000 websites offer child pornography [1]. Development of effective methods to identify pedophiles based on images of partial skin is an essential measure to stop child sexual exploitation.

Tattoos and skin marks are possible features that can be used in these cases. However, tattoos are neither unique nor ubiquitous, and the skin exposed in evidence images may not have a sufficient number of identifiable skin marks for personal identification [2]. Traditionally, it was impossible to use vein patterns for forensic identification, because they were almost invisible to the naked eye in color images taken by consumer cameras. Recently, we overcame this limitation by developing a method to uncover vein patterns from color images [3][4]. This method is highly dependent on the accuracy of a skin optical model. Currently, it is very difficult to obtain a highly accurate skin optical model. In this paper, we propose an algorithm to visualize vein patterns. The algorithm extracts information from a pair of synchronized color and NIR images, and uses a neural network to map RGB values to NIR intensities. We also propose a new scheme adjusting the NN weights automatically to maximize the size of the vein patterns for enhancing the visualization performance.

The rest of this paper is organized as follows. Section 2 gives a brief review of current vein uncovering methods. Section 3 introduces the proposed algorithm with the adjustment scheme. Section 4 reports experimental results. Section 5 offers some concluding remarks.

2. Literature review

Claridge et al. proposed a method [5] using color images to diagnose pigmented skin lesions, which could reveal the distributions of melanin, hemoglobin, and the depth of dermis. They targeted medical applications, where the color images are collected in a controlled environment with white incident light. It was reported that their method could not work for images taken under uncontrolled illumination conditions [3]. Tsumura et al. proposed an Independent Component Analysis (ICA)-based method to analyze and synthesize the color and texture of human skin [6], which could possibly uncover veins. The original aim of this method was for computer graphics applications. It was also reported that Tsumura et al.'s method was effective neither in the skin with high concentration of melanin or fat, nor the hairy skin [3].

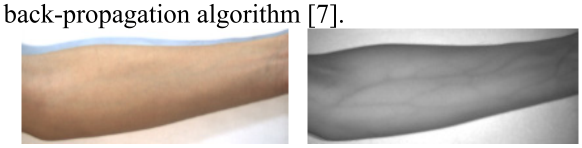
We proposed a computational method based on optics and skin biophysics to uncover vein patterns hidden in color images [3][4]. It mathematically reverses the process of skin color formation in an image, and derives corresponding biophysical parameters. Because the parameters of veins differ significantly from those of generic skin, the vein patterns can be seen from the spatial distributions of these parameters. The disadvantage of this method is its dependence on the accuracy of the skin optical model and the biophysical parameters used in the model.

3. The proposed vein visualizing algorithm

In this section, we present our vein visualizing algorithm. It is composed of two parts: a mapping model and an automatic neural network weight adjustment scheme.

3.1. An image mapping model

We used synchronized color and NIR images collected by a 2-CCD multi-spectral camera as training data to construct a mapping model. The camera simultaneously measures visible and NIR light spectrums through a single lens using two channels. The first channel has a Bayer mosaic color imager that only captures visible light, while the second channel has a monochrome imager for NIR light. The color and NIR images are perfectly registered and synchronized. We collected data from the forearms of ten Asian males, and selected the pair with the best image quality shown in Fig. 1 for model construction. Then we segmented the skin regions and cut the central parts with both vein and generic skin pixels as training data. We used the RGB values as inputs and the corresponding NIR intensity as target outputs to train a three-layered feed-forward neural network. The transfer functions in the hidden and output layers are respectively tan-sigmoid and linear functions. To avoid complex network structure and long training time, we put 5 neurons in the hidden layer. The network was trained with the Levenberg-Marquardt back-propagation algorithm [7].



(a) (b)

Figure 1. A pair of synchronized images of a male's left forearm obtained from the 2-CCD multi-spectral camera. (a) is the RGB image and (b) is its corresponding NIR image.

3.2. An automatic neural network weight adjustment scheme

The illumination condition can significantly influence the skin color in images. Therefore, the performance of the RGB-based mapping model deteriorates if the imaging condition in testing images is very different from that of the training image. To compensate it, we used an automatic intensity adjustment scheme [4]. In addition, veins look green in a color image because the ratio of G value to the sum of RGB values in vein pixels is higher than that in generic skin pixels. Therefore, the mapping approach is more sensitive to the G value. In this section, we propose a new scheme which automatically adjusts the NN input-layer weights to further improve the robustness of the algorithm.

Before presenting the new scheme, we give a brief review of our vein extraction algorithm [4]. Firstly, the contrasts of visualized images are normalized by the contrast-limited adaptive histogram equalization (CLAHE) method [8]. Then a Gabor filter bank is used to generate a filter response map and an orientation map. Structural information of veins is captured from these information maps for vein pattern enhancement. The enhanced vein images are binarized using Otsu's method and then skeletonized. Finally, the vein patterns are uniformly sampled and represented by a set of points for matching. Obviously, high quality images with longer veins and more efficient points will achieve more accurate matching results. Fig. 2 shows the procedure of vein extraction.

(a) (b) (c)

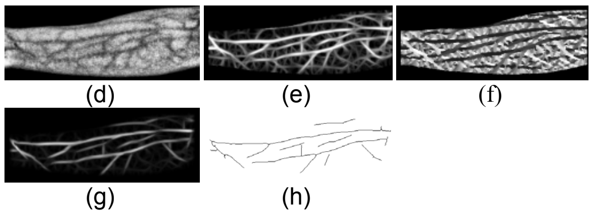


Figure 2. Our vein extraction procedure. (a) is a color skin image, (b) is its corresponding NIR image, (c) is the intensity image obtained by the proposed mapping model, (d) is the CLAHE result of (c), (e) and (f) are respectively the filter response and orientation maps of (d), (g) and (h) are respectively the enhanced and skeletonized images.

The mapping function is a feedforward neural network, which can be written as:

$$y = f^{o}(\mathbf{W}^{h} \cdot f^{h}(\mathbf{W}^{i} \cdot \mathbf{x} + \mathbf{b}^{i}) + \mathbf{b}^{h}), \quad (1)$$

where $\mathbf{x} = [R, G, B]^T$ is the input vector of color values and y is the output intensity value. and are respectively the transfer functions of the hidden and output layers, $\mathbf{W}^i$ and $\mathbf{W}^h$ are respectively the weight matrices of the input and hidden layers, and $\mathbf{b}^i$ and $\mathbf{b}^h$ are respectively the bias vectors of the input and hidden layers. $\mathbf{W}^i$ is a matrix with three columns corresponding to the input R, G, and B values:

$$\mathbf{W}^{i} = [\mathbf{w}^{i}_{R} \quad \mathbf{w}^{i}_{G} \quad \mathbf{w}^{i}_{B}]. \quad (2)$$

To reduce the sensitivity of the approach to the green channel, we introduce a parameter, a, to adjust the weights corresponding to the input G value:

$$\widetilde{\mathbf{W}}^{i} = [\mathbf{w}^{i}_{R} \quad \mathbf{w}^{i}_{G} \cdot a \quad \mathbf{w}^{i}_{B}]. \quad (3)$$

The average size of vein patterns in the skeletonized image is used as an objective function to determine the optimal adjustment ratio a^*:

$$a^{*} = \arg\max_{a \in \mathbf{A}} \left\{ \frac{1}{N} \sum_{i=1}^{N} S(v_i) \right\}, \quad (4)$$

where $\mathbf{A}$ is a set of different adjustment values, v_i is the i^{th} vein segment, which is determined as a 8-connected object in the skeletonized image, N is the total number of vein segments in the image, and S is a function calculating the size of the vein segments, which is defined as:

$$S(v_i) = \sqrt{(r_{\max} - r_{\min})^2 + (c_{\max} - c_{\min})^2}, \quad (5)$$

where $r_{\max}$ ($r_{\min}$) and $c_{\max}$ ($c_{\min}$) are respectively the maximum (minimum) row and column coordinates in the vein segment v_i.

Fig. 3 shows the effectiveness of the adjustment scheme. After adjusting the NN weights, the enhanced vein image and its skeletonized result contain longer and clearer vein patterns.

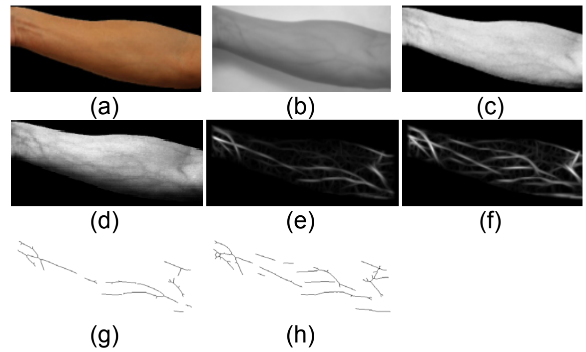


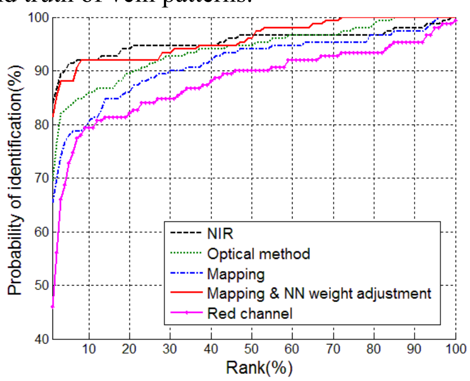
Figure 3. The NN weight adjustment result. (a) is a color skin image, (b) is its corresponding NIR image, (c) is the intensity image obtained by the mapping model only, (d) is the result with the NN weight adjustment. (e) and (f) are respectively the enhanced vein images extracted from (c) and (d), (g) and (h) are respectively the skeletonized images of (e) and (f).

4. Experimental results

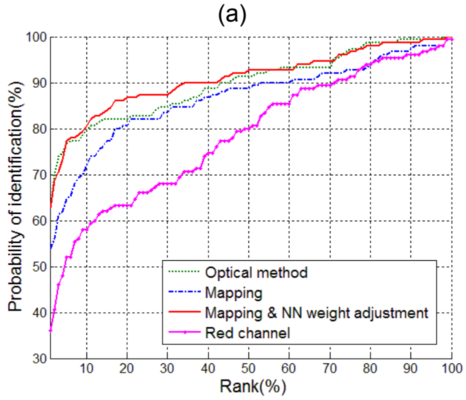
We used our vein extraction and matching algorithms [4] to verify the visualized vein patterns. For the case where only partial image of a forearm is available in the database, we can perform manual matching. Our database contains 300 color images and 300 NIR images from 150 different forearms. The images were collected on two separate occasions, at an interval of around two weeks. In our database, each subject in each session has one color image and one NIR image. The color images were collected by Nikon D70s and Canon 500D cameras, while the NIR images were collected by a JAI camera. Note that the color and NIR images were not captured simultaneously by the 2-CCD multi-spectral camera. In addition, the camera models and imaging conditions were different from those of the training image.

The proposed vein visualizing algorithm was applied to the color images. Vein patterns were extracted from the resultant images. Cumulative match curves generated from the matching results were used as a performance indicator. Two sets of experiments were performed. The first set was to match vein patterns from the same type of images (i.e. color vs. color and NIR vs. NIR) taken on different occasions. The second set was to match vein patterns from different types of images (color vs. NIR) taken on different occasions. The optical method [4] and vein patterns from the red channel were employed for comparison. The red channel was included in the experiments because it is close to the NIR channel. For the optical method, vein patterns were extracted from the distribution maps of the depth of dermis. Fig. 4

shows the cumulative match curves. Table 1 lists the rank-one and rank-10% identification accuracy. The term “rank-10% identification accuracy” refers to the percentage of input vein patterns whose corresponding vein patterns can be found in the database within the top 10% of the vein patterns given by the algorithm. The rank-10% identification accuracy of the proposed algorithm is 92%, which is enough for forensic analysis. The experimental results demonstrate that: (1) vein patterns can be visualized using information extracted from corresponding color values and NIR intensities, (2) the proposed NN weight adjustment is effective, (3) the final identification accuracy of the proposed algorithm is higher than the optical method, and (4) the result of the proposed algorithm from the same-type-image matching is comparable to the result from the NIR images, which are usually considered as ground truth of vein patterns.



(a)



(b)

Figure 4. Cumulative match curves. (a) from the same type of images (color vs. color and NIR vs. NIR), (b) from different types of images (color vs. NIR).

Table 1. Matching results (a) from same image type and (b) from color images to NIR images

(a)

	rank-one	rank-10%
NIR images	84%	92%
Red channel	46%	79.3%
Optical method	69.4%	86%
Mapping	65.3%	80.7%
Mapping & weight adjustment	81.4%	92%

(b)

	rank-one	rank-10%
Red channel	36%	58%
Optical method	62.7%	80%
Mapping	54%	72%
Mapping & weight adjustment	62.7%	80.6%

5. Conclusion

In this paper, we proposed an algorithm which extracts information from synchronized color and NIR images to visualize vein patterns from color images. An automatic NN weight adjustment scheme was also proposed to improve the performance. The matching experiments on a database with 600 images from 150 forearms indicate that the identification accuracy of the proposed algorithm was higher than our previous optical method, and comparable to that of NIR images.

Acknowledgements

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