Finger Vein Recognition based on Histogram of Oriented Gradients (HOG)

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Abstract

In this paper, a Region of Interest (ROI) extraction method is proposed based on labeling vein images using morphological processing. Firstly, finger vein images are segmented to remove the unwanted background or the shape of the device. Secondly, the images are oriented to correct to solve the finger displacement's problem. Thirdly, ROI localization method is used to accurately extract the region of vein vessels. Finally, Histogram of Oriented Gradient (HOG) features are extracted to recognize that person is the genuine or imposter. Segmented finger vein and calculated orientation can support each other to produce higher accuracy in localizing ROIs. In addition, a simple feature differencing method is proposed to reduce the calculation time for matching.

Keywords: *finger vein, orientation correction, HOG features, ROI localization, segmentation, edge operator*

1. Introduction

Nowadays, personal verification based on biometric technology has been used in many kinds of applications such as door access control, ATM transactions and border crossing controls, etc. Biometric system is a pattern recognition system that recognition a person based on feature vectors derived from specific physical or behavioral characteristics such as fingerprint, palm print, iris, face, voice and gait. Compared with the traditional biometric characteristics, the advantages of finger vein patterns contain internal physiological characteristics which are difficult to forge, uniqueness, on-contact or weak contact, no interference by finger surface or surrounding environment [3].

It takes the snapshots of the vein in the source of infrared radiation at a specific wavelength. Hemoglobin in the blood takes oxygen in the lungs and carries oxygen to the tissues of the body through the arteries. After that hemoglobin release oxygen and carry deoxidized blood to the heart through the veins. The deoxidized hemoglobin absorbs the light at the wavelength of 760nm in near infrared region [1].

So, the near infrared light (NIR) lights (700-900nm) are often used in finger-vein image acquisition systems because they can penetrate a finger. However, in practice, obtaining reliable finger-vein images is quite difficult since they are often degraded seriously (blurred and low contrast) due to light scattering in the biological tissues [2].

Moreover, the current finger-vein ROI localization methods are all sensitive to finger position variation in practice. This badly effect on the accuracy of the finger vein recognition. In this paper, the orientation correction method is proposed to address the finger displacement' issue and the ROI localization method is described to accurately extract the ROI region.

2. Related Work

Recently, more and more literature has been studied to localize the ROI. In [4], Yang et al. proposed a method using a predefined window with a fixed height and an adjustable width in the finger vein imaging plane and Mahri et al. [5] proposed a finger edge based method for cropping ROI regions. Unfortunately, these methods are unreliable in localizing finger-vein ROI of the same person at different sessions in real application. In [12], the authors proposed a new texture descriptor called local line binary pattern (LLBP). The neighborhood shape in LLBP is a straight line. But it is depend on the line pattern value.

In [8], the authors proposed a ROI extraction method by cropping the region outside the internal tangents in finger vein candidate region, which will be used for detecting two phalangeal joints. But the distal inter-phalangeal joint, proximal inter-phalangeal joint and middle phalanx between the two joints, are all in the captured finger vein images.

In our proposed system, the image region is extracted by labeling the binary image and the orientation is corrected based on the value of the angle θ. HOG feature extraction method is used to handle the illumination changes.

The rest of the paper is organized as follows: the finger vein segmentation, orientation correction, and ROI localization method are proposed in section 3. The experimental results are shown in section 4. Finally, this paper is concluded in section 5.

3. Proposed System

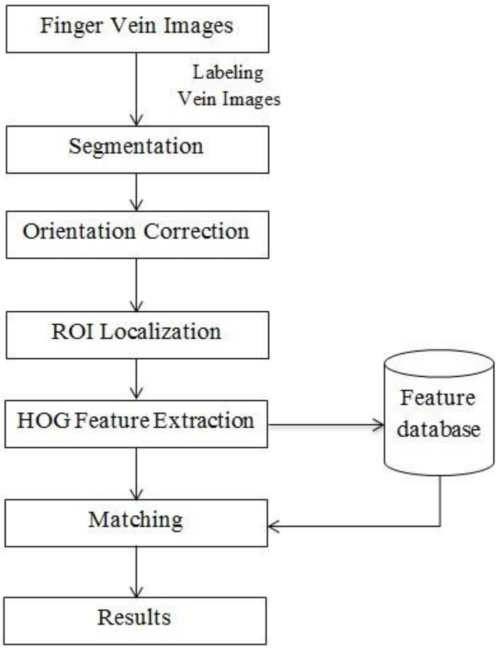


Figure 1. System Flow Diagram

3.1. Finger Region Segmentation

Finger region segmentation aims to segment the finger region from an acquired image with a complicated background. For finger region segmentation, there are basically three steps: (1) Cropping original vein images, (2) Edge detection with edge linking and (3) Labeling vein images.

3.1.1. Cropping Original Vein Images

Original finger vein images consist of noise and useless information such as the shape of the device. It may degrade the ROI segmentation accuracy. Therefore, firstly the captured images are cropped to remove the unwanted part and reduce the size based on the width and height of the image. The image is converted RGB to gray scale image and the minimum and maximum of the row and column is read to find the width and height value. The width value can be calculated the difference of the row maximum (xmax) and minimum (xmin) and like the height value can be calculated the difference of the column maximum (ymax) and minimum (ymin), respectively. After finding the value of the width and height, the image is cropped with these values by following equations:

$$Width = (xmax - xmin) + ceil\left(\frac{xmax}{8}\right) \quad (1)$$

$$Height = ymax - ymin \quad (2)$$

3.1.2. Edge detection with edge linking

In this step, the cropped images are detected to extract ROIs region. To detect the edges of the finger, the Sobel operator is applied to the finger vein region. The Sobel operator is a discrete differential operator. The operator utilizes 3x3 kernels: one estimates the gradient in the x-direction, while the other one estimates the gradient in the y-direction.

-1	-2	-1
0	0	0
1	2	1

G_x

-1	0	1
-2	0	2
-1	0	1

G_y

Figure 2. Sobel Operator uses 3x3 Kernel Masks

The image is convolved with both kernels to approximate the derivatives in horizontal and vertical change. The horizontal and vertical gradients Gx and Gy are computed using simple gradient operators such as a Sobel mask [2]. At each given point, magnitude of the gradient can be approximated with:

$$G = \sqrt{G_x^2 + G_y^2} \quad (3)$$

$$G_x(i,j) = \frac{1}{2}((G(i,j+1) - G(i,j)) + (G(i+1,j+1) - G(i+1,j))) \quad (4)$$

$$G_y(i,j) = \frac{1}{2}((G(i+1,j) - G(i,j)) + (G(i+1,j+1) - G(i,j+1))) \quad (5)$$

Where, G = the gradient magnitude of an image
G_x= horizontal gradient of an image
G_y= vertical gradient of an image

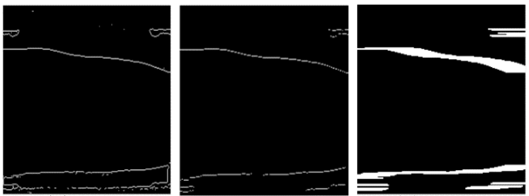
But, the Sobel edge detector cannot detect the missing part or disconnected lines of the edge and also inaccurate, sensitive to noise. In Lu Yang, Gongping Yang, Yilong Yin, and Rongyang Xia's paper [8], they assumed the missing parts of the edge cannot affect for their proposed method, but the disconnected edges in detection can directly affect the extraction ROI regions in our proposed method. Therefore, morphological processing is used to link the disconnected edges in our proposed system.

Morphology is a set of image processing operations that process images based on predefined structuring elements known also as kernels. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the kernel, a morphological operation is constructed to specific shapes regarding the input image. Two of the most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of the object in an image, while erosion does exactly the opposite. The amount of pixels added or removed, respectively depends on the size and shape of the structuring element used to process the image [13].

Firstly the detected edge lines are eroded by creating the structuring element array value [1 1] and then this lines are dilated with the shape of structuring element such as 'line' and 'rectangle'. In mathematical morphology, a structuring element (SE) is a shape, used to probe or interact with a given image, with the purpose of drawing conclusions on how this shape fits or misses the shapes in the image.

It is typically used in morphological operations, such as dilation, erosion, opening, and closing, as well as the hit-or-miss transform. After accurately detection the edges, the foreground region of the finger is extracted using labeling binary images.

By linking the disconnected edges using SE, the edge detection is more accurate than without edge linking technique in morphological processing.

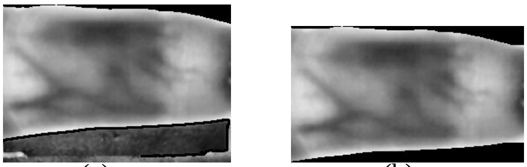


(a) (b) (c)

Figure 3. (a) Sobel edge image, (b) Effect of erosion using a structuring element SE= [1 1], (c) Effect of dilation using a 2×2 rectangle structuring element

3.1.3. Labeling vein images

Connected-component labeling is used in computer vision to detect connected regions in binary digital images, although color images and data with higher dimensionality can also be processed. It basically finds the connected components of a binary image. All the pixels in connected components are given a level. The searching of the connected components is done in the column-wise fashion, in other words, in top-to-bottom scan order. All pixels in the first connected component are labeled -1 and those in the second as 2 and so on. Among of the labeled components, label value 2 is marked for region extraction and the rest of the label is assigned the zero gray value.



(a) (b)

Figure 4. Sobel edge detection results. (a) Vein image extraction without edge linking, (b) vein image extraction with edge linking using structuring element

3.2. Orientation Correction

To solve the finger placement's issue, the extracted region images are need to determine that images are skew or not because this distortion can affect to accurately extract feature extraction and matching. Therefore, for skew correction we need to calculate the skew angle value θ using Linear Regression Line also called least-square method [8]. First of all, line function of the finger is synthesized by all midpoints is shown in equation (6), and then the skew angle value is computed by using equation (7). If the angle value is equal to zero, these images are normal, otherwise the image is de-skewed depend on the skew angle value.

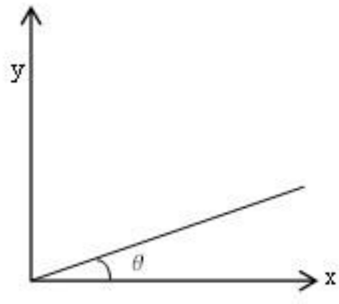


Figure 5. Skew angle (θ) detection

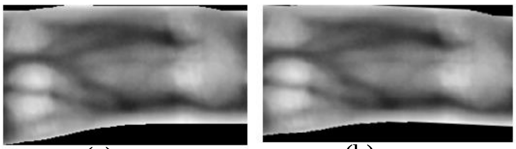
$$\boldsymbol{y = kx + b} \quad \textbf{(6)}$$

$$\boldsymbol{k} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad \textbf{(7)}$$

Where, xi=1, 2… n, i=1, 2….n. skew angle value is computed by using k parameter, which is used to correct the skew image in equation (8).

$$\theta = arctan(k) \times \frac{180}{\pi} \quad \textbf{(8)}$$

The finger skew image is corrected by using angle value θ, and the corrected image is shown in Figure 6.



(a) (b)

Figure 6. Corrected Images

3.3. ROI Localization

In the proposed method, to extract a ROI as large as possible, the width of the segmentation ROI is same with the cropped image's size, but the height of the ROI is defined as the value of y1 and y2 as shown in red point in blue line figure (Figure 7). In this way, the ROI is localized using the height of the finger based on y1 and y2.

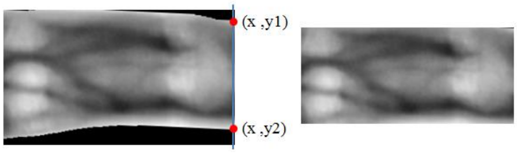


Figure 7. ROI Localized and Segmentation Result

3.4. HOG Feature Extraction

In this step, features are extracted to recognize the person using Histogram of Oriented Gradients (HOG) method. The features are returned in a 1-by-N vector, where N is the HOG feature length and used for identifying the person is valid or not. Scanning on the input image is based on detection window. The window is divided into cells, for each cell accumulating a histogram of gradient orientations over the pixels of the cell. For better invariance to illumination, histogram normalization can be done by accumulating a measure of the local histogram energy over blocks and using the results to normalize all cells in the block. The normalized histograms (HOG features) are collected over the detection window. The collected features are fed to matching step for classification the person is valid or invalid.

3.5. Matching

In this proposed method, we used differencing method to match the vein images. The feature value of incoming test image is subtracted from the feature value of training images. If the subtracted value of incoming test image is minimum than other images, that image is decided 'Valid', otherwise is 'Invalid'. The decision results are shown in experimental results.

$$difference\ value = \sum features_{train} - \sum features_{test} \qquad \textbf{(9)}$$

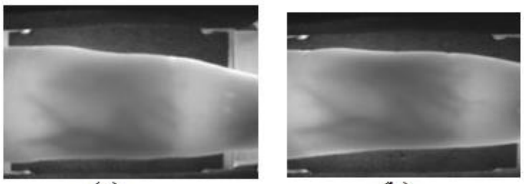
$$result = minimum(difference\ value) \qquad \textbf{(10)}$$

4. Experimental Results

In this section, the proposed method is applied to recognize the vein images are truly imposter or genuine based on Homologous Multi-modal Traits Database (SDUMLA-HMT) from Shandong University [9], using MATLAB (R2014a) on a computer with an Intel Core i7 and 8GB of RAM.

SDUMLA-HMT consists of finger vein images captured from 106 volunteers. The device used to capture finger vein images is designed by Joint Lab for Intelligent Computing and Intelligent Systems of Wuhan University. In the capturing process, each subject was asked to provide images of his/her index finger, middle finger and ring finger of both hands, and the collection for each of the 6 fingers is repeated for 6 times to obtain 6 finger vein images. Therefore, finger vein database is composed of 3,816 images. Every image is stored in "bmp" format with 320×240 pixels in size, and thus, the finger vein database takes up around 0.85G Bytes in total.

As shown in Figure 8(a), images included in Homologous Multi-modal Traits Database (SDUMLA-HMT) [9] have dark backgrounds. After cropping images, the contours of the image region can extract accurately ROIs. And these ROI images can be de-skewed depend on the skew angle value.



(a) (b)

Figure 8. (a) Original Image (b) Cropped Image

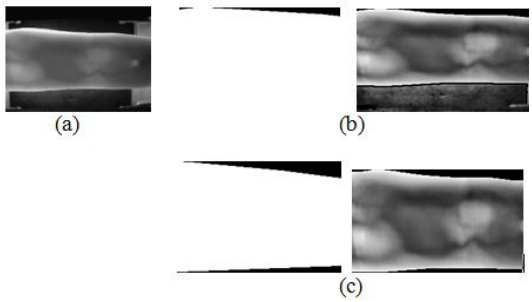
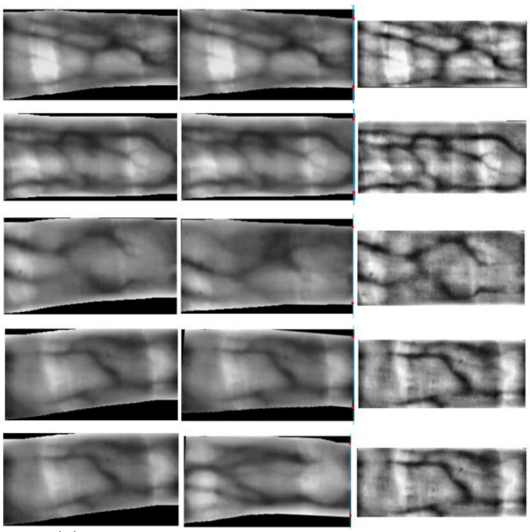


Figure 9. Some finger vein images from SDUMLA-HMT and their corresponding segmented images. (a) Original finger vein image, (b) ROI extraction using simple Sobel mask, (c) ROI extraction using proposed method



(a) (b) (c)

Figure 10. Skew correction and ROI localization results by proposed method: (a) Region Extraction based on Labeling Images, (b) Skew correction Images, (c) ROI Localization based on y1 and y2 value

By comparing the segmentation results with edge linking using morphological processing and without edge linking, the proposed idea's effectiveness percentage can be measured. The output image without false background is as a correct segmentation as shown in Figure 9(c). Otherwise, the output with false background (e.g. Figure 9(b) is identified as a false segmentation). The segmentation accuracy is improved by using skew correction method and can be computed as follows:

$$Accuracy = \frac{Number\ of\ Correct\ Segmented\ Image}{Tested\ Segment\ Images}$$

As shown in TABLE I, the accuracy of the proposed method is known from the segmentation results. We randomly pick 200 images (4×50 person) from the database to compute the accuracy of the following two methods. The average accuracies of 200 images are calculated the number of correct segmented images by dividing tested segmented images and the results are shown in TABLE 1. In matching process, extracted features from train finger vein images are stored in feature database and the incoming test features are matched using differencing method. For 50 person, total testing images are 100 images (2×50 person). In order to evaluate the performance after the matching, the equal error rate(EER) or recognition rate (RR) , which is the value where the false accept rate (FAR) is equal to the false reject rate (FRR) is adopted to evaluated the matching accuracies. To calculate EER, four finger vein images from one individual are selected as the training set, while the other two images are used as test set. So, the training database is composed of 2,544 images, while the testing database is composed of 1,272 images.

In this paper, training set consists of 200 images and test set consists of 100 images for 50 people. The number of genuine matches is 43 people, and the number of imposter matches is 7 people. Our proposed feature differencing method for matching is simple and fast with a reasonably high accuracy and 86 % success rate for only 50 people.

Table 1. Comparison of Segmentation Accuracy Using Two ROI Methods

Methods	The Average Accuracies
ROI segmentation without morphological processing	0.74 (74%)
Proposed Method	0.91 (91%)

Table 2. Comparison of average processing time

Methods	Average Processing Time (s)			Feature dimensionality
	Feature Extraction Time	Matching Time	Total Processing Time	
Without Skew Correction	0.250	0.055	0.305	4860
With Skew Correction	0.221	0.063	0.284	4860

5. Conclusion

In this paper, finger vein ROI extraction method based on labeled binary image is proposed. Edge linking using erosion and dilation by creating structuring element is used to link the disconnected locus points and to eliminate the wrong points located in the false background. To extract the ROI accurately as possible, edge detection is extended using morphological processing such as erosion and dilation with appropriate structuring element value.

In experiment, the results showed our proposed method is better accuracy than the ROI extraction without morphological processing. Moreover, we investigated a method to solve the finger displacement's issue using Linear Regression Line method. For further work, how will the result of the image enhancement using Gabor filter be analyzed and a new statistical feature extraction method will be proposed using statistical correlation value of HOG orientation matrix in our next experiments.

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