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Finger-vein Authentication Based on Wide Line Detector and Pattern Normalization

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***Abstract*—In the finger-vein authentication, there are two problems in practice. One is that the quality of the vein image will be reduced under bad environment conditions; the other is the irregular distortion of the image caused by the variance of the finger poses. Both problems raise the error ratios. In this paper, we introduced a wide line detector for feature extraction, which can obtain precise width information of the vein and increase the information of the extracted feature from low quality image. We also developed a new pattern normalization model based on a hypothesis that the finger's cross-sections are approximately ellipses and the vein that can be imaged is close to the finger surface. It can effectively reduce the distortion caused by the pose. In our experiment based on a database containing 50,700 images, our method shows advantages on dealing with the low quality data collected from the practical personal authentication system.**

Keywords-finger-vein; feature extraction; wide line detector; pattern normalization

I. INTRODUCTION

After year 2000, the finger-vein biometric is proposed to personal identification. Comparing with widely used fingerprint, the main advantage of the finger-vein is its high security since the vein patterns are inside the human body, which is difficult for people who want steal or fake the biometric patterns. In 2004, Miura Naoto and others proposed an authentication system using the finger-vein pattern expressed in binary image [1], and some other studies used similar frameworks [2-3]. Result shows that finger-vein based personal authentication can achieve a very low error rate under the database collected in the laboratory [2].

However, the finger-vein authentication still has some problems in practice. One is that the quality of original image of finger-vein will be reduced under some bad environment conditions, such as low temperature or outdoor illumination. One way to deal with the problem is to improve the imaging device [4]. Another way is to improve the feature extraction method to handle the low quality images [1-3]. Some methods can detect the position of the vein effectively but can't detect all the points of the vein, which will lose some useful information [1-2]. In 2007, L. Liu et al. proposed a wide line detector which can obtain all the points of the lines, and successfully used it for the palmprint identification [5]. In this paper, we introduce this method to extract the feature of the finger-vein.

Another problem to finger-vein authentication is the variance of the finger poses [1], which causes the distortion of the image and lower the accuracy of personal authentication. Some imaging devices restrict the pose of the finger, but it can also move in a relatively smaller room [2-4]. Using some simple normalization method and conventional matching method, we can avoid the effect of the shifting and rotation in some directions, but in other directions the problem still exists [1-3, 6]. In this paper, we proposed a new pattern normalization model based on a hypothesis that the finger's cross-sections are approximately ellipses and the vein that can be imaged are near the finger surface. The model can correct the distortion caused by the pose more effectively.

To evaluate the performance of the wide line detector and the pattern normalization model in personal authentication, we collected a database from a system in use containing 50,700 images of 10,140 different fingers, and designed an experiment to estimate the equal error rate (EER) and the receiver operating characteristic (ROC) curve of the proposed method.

II. FINGER-VEIN BASED PERSONAL AUTHENTICATION

A. A personal authentication system based on finger-vein pattern

We developed an improved image device to obtain the infrared image of the finger. The device has an advanced illumination control system and a grayscale 1/3–inch CMOS camera [4]. Fig.1 (b) shows a photo of the device.

Based on the imaging device, we developed and deployed an authentication system in our school. The system serves as a terminal checking attendance of

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exercise by students who take P.E lessons, with 10 outdoor terminals, 6,212 registered users in all and about 4,000 person-times using our system in average each day. The system worked well since deployed on March 2009. Fig.1 (a) shows the principle of the system.

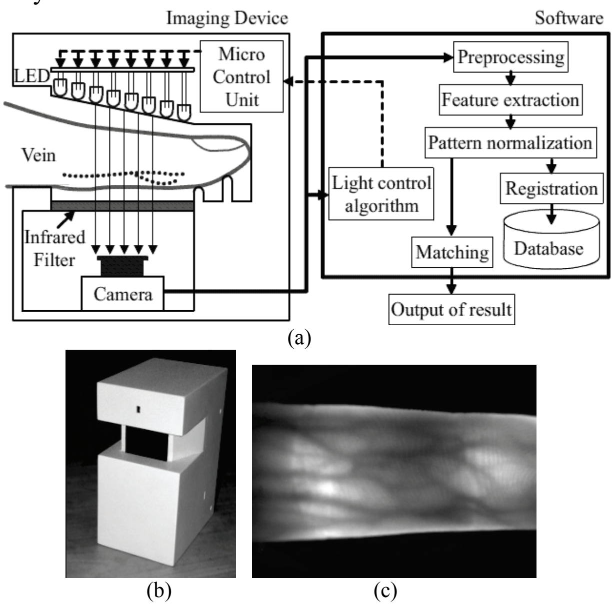


Figure 1. The finger-vein based personal authentication system: (a) system architecture, (b) finger-vein imaging device, (c) example of infrared image of finger-vein

B. Procedure for personal authentication

The procedure for finger-vein authentication is shown in Fig.1 (a). The details are described as follows.

Step 1: Acquisition of an infrared image of the finger

Fig.1 (c) shows an example of the captured image. The image is gray scale, 512 x 384 pixels in size, with 8 bits per pixel. The finger tip's direction is right, but it is out of the region of image.

Step 2: Preprocessing of the image

Reduce the original image's size to 128 x 96 to make the processing faster.

Step 3: Extraction of finger-vein features

The finger-vein features are extracted by the wide line detector.

Step 4: Pattern normalization and template generation

The template of finger-vein pattern is generated by applying the pattern normalization model.

Step 5: Matching and output the result of verification

The correlations between an input pattern and the registered templates are calculated. If the input pattern is identified as a registered one, the required action such as outputting a success message is performed.

We use a similar conventional template-matching method as the method introduced in [1]. It can deal with the shifting of the template images.

III. FEATURE EXTRACTION USING WIDE LINE DETECTOR

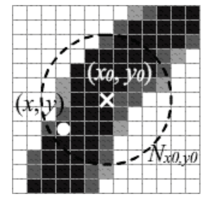


Figure 2. The circular neighborhood region

The method of feature extraction is described in this section. Through observation and experiment, we consider that the vein feature can be presented by lines with different width. We use the wide line detector described in [5] to extract all the points on the vein lines in the image.

Here, F is the finger-vein image and V is the feature image. Both F and V are 8 bit 128 x 96 bitmaps. We define the values of pixels in V as parts of the background as 0 and the values of pixels as parts of the vein region as 255.

For each point (x_0, y_0) in F, consider its circular neighborhood region with the radius r:

$$N_{(x_0,y_0)} = \left\{(x,y) \middle| \sqrt{(x-x_0)^2 + (y-y_0)^2} \le r\right\} \quad (1)$$

Fig.2 shows the neighborhood region $N_{(x0,y0)}$. Using the pixels in it, we can calculate the $\mathrm{V(x0,y0)}$ by (2)-(4):

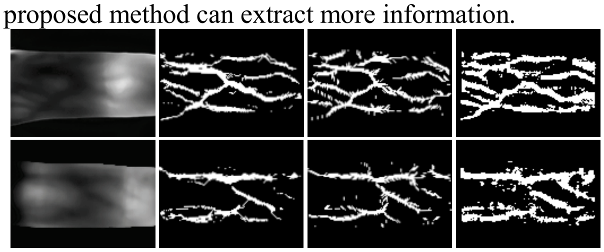
$$V(x_0,y_0) = \begin{cases} 0 & m(x_0,y_0) > g \\ 255 & otherwise \end{cases} \quad (2)$$

$$m(x_0,y_0) = \sum_{(x,y)\in N_{(x0,y0)}} s(x,y,x_0,y_0,t) \quad (3)$$

$$s(x,y,x_0,y_0,t) = \begin{cases} 0 & F(x,y) - F(x_0,y_0) > t \\ 1 & otherwise \end{cases} \quad (4)$$

Here t, g and the radius r are parameters. We set $r = 5$, t=1 and $g = 41$.

Fig.3 shows the extracted feature images of the proposed method and two other methods: line tracking [1] and curvature [2]. We can find that almost all points on the vein are extracted by proposed method while the other two methods lose a part of points, thus the proposed method can extract more information.



(a) Original. (b) Line tracking. (c) Curvature. (d) Proposed.

Figure 3. Results of pattern extraction using different methods

IV. FINGER-VEIN PATTERN NORMALIZATION MODEL

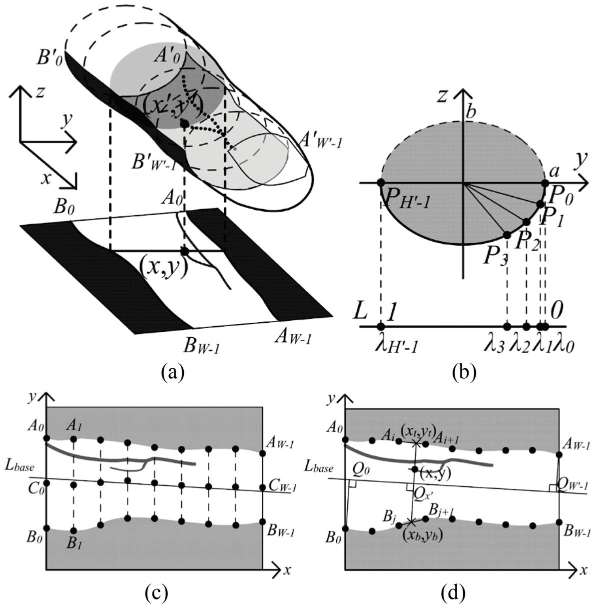


Figure 4. Finger-vein pattern normalization: (a) pattern normalization model, (b) ellipse cross-section, (c) base line of the finger, (d) transformation.

Fig.4 (a) shows a finger in 3-D room and its projection to a plane. The pattern normalization model is based on two assumptions: (a) the finger's cross-sections are approximately in the shape of ellipse; (b) the vein which can be imaged is close to the surface of the finger. With the two assumptions, we can transform the finger region $A_0A_{W-1}B_{W-1}B_0$ in the image to the region $A'_0A'_{W'-1}B'_{W'-1}B'_0$ in the finger surface, and develop the region $A'_0A'_{W'-1}B'_{W'-1}B'_0$ in the curved surface to a rectangular region in a plane.

Here, V is the vein feature image of the size $W \times H = 128 \times 96$. T is the normalized pattern of the size $W' \times H'$. We set W'=128, H'=80.

This algorithm consists four steps.

Step 4-1: Detection of the finger outline using active contour model

The finger outline contains two parts: the top outline $\{A_x = (x, y_x)|x = 0,1, \dots, W-1\}$ and the bottom outline $\{B_x\}$. Because the pattern normalization model requires precise outline information of the finger, we use the active contour model to detect the outlines. Using greedy algorithm can solve the active contour model in acceptable time [7].

Step 4-2: Calculation of the ellipse projective coefficients

Fig.4 (b) shows an ellipse section. The points $\{P_0, P_1, \dots, P_{H'-1}\}$ are on the ellipse, and all the lengths of the arc P_iP_{i+1} are equal. Here we set the ellipse's parameters $\mathrm{a} = 1$ and $\mathrm{b} = 0.8$. We use some numerical algorithms of elliptic integrals [8] to calculate the every coordinates of $P_i = (y_i, z_i)$, and normalize $\{y_i\}$ to the region $[0, 1]$ by defining a new sequence $\{\lambda_i = (1 - y_i)/2|i = 0,1, \dots, H' - 1\}$.

Step 4-3: Estimate the base line of the finger

Fig.4 (c) shows a finger-vein image. The top and bottom outlines of the finger are $\{A_x\}$ and $\{B_x\}$. Firstly, calculate all the midpoints $\{C_x\}$ of the line segments $\{\overline{A_xB_x}\}$. Then use the least square method to estimate a straight line L_{base} to fit $\{C_x\}$.

Step 4-4: The transformation of the normalization

Fig.4 (d) describes the transformation of the normalization. First of all, if the line L_{base} is up, make a line perpendicular to L_{base} over the point A_0 at the foot point Q_0, and make a line perpendicular to L_{base} over the point B_{W-1} at the foot point $Q_{W'-1}$ (if L_b is down, replace the A_0 by B_0 and B_{W-1} by A_{W-1}).

Consider a point $T(x', y')$ in the template, and its corresponding point in the finger-vein image is $V(x, y)$. The followed steps calculate the coordinate (x, y):

(a) Determine the point $Q_{x'}$ on the line segment $\overline{Q_0Q_{W'-1}}$ where $|\overline{Q_0Q_{x'}}| = \frac{x}{W'-1} |\overline{Q_0Q_{W'-1}}|$.

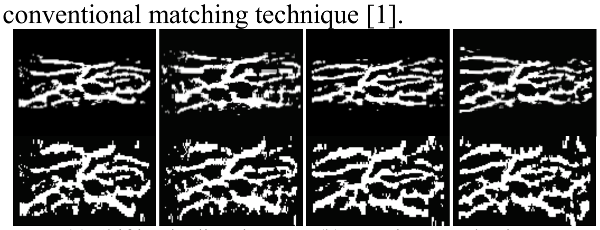
(b) Make a line perpendicular to L_{base} over the point Q_x, which crosses the line segment $\overline{A_iA_{i+1}}$ at the point (x_t, y_t), and crosses the line segment $\overline{B_jB_{j+1}}$ at the point (x_b, y_b).

(c) Calculate the coordinate (x, y) by:

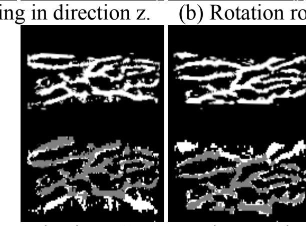
$$\begin{cases} x = x_b + \lambda_{y'}(x_t - x_b), \\ y = y_b + \lambda_{y'}(y_t - y_b). \end{cases} \tag{5}$$

(d) Do the transformation $V(x, y) \to T(x', y')$. We use the nearest sampling method in the realization.

Fig.5 (a) and (b) show the normalization can reduce the distortion caused by the finger's displacement in the direction *z* shown in Fig.4 (a) and the rotation round the axis *y*. And Fig.5 (c) shows that it can transform the irregular distortion caused by the finger's rotation round the axis *y* to the regular shifting in the template image, which can be solved by the conventional matching technique [1].



(a) Shifting in direction z. (b) Rotation round axis y.



(c) Rotation round axis x. Gray area denotes the area which can match with the other template.

Figure 5. Examples of pattern normalization results

V. EXPERIMENTAL RESULTS

A. Database for the experiment

From the archiving data of finger-vein based personal authentication system introduced in section 2, we eliminate some not active users from the all 6,212 users because they have too few records. Finally we get a test database [9]. It contains 50,700 infrared finger-vein images of 10,140 different fingers (5 images per finger) of 5,208 people (1-4 fingers per person).

All the images in the test database are collected when the real users used the system. Each finger's 5 images are collected in different places and with the probability that several months apart between two samples.

B. Performance for personal authentication t

To examine the performance of proposed method for personal authentication, we did an experiment using the method described in [10] to evaluate the false accepted rate (FAR) and false rejected rate (FRR). We also evaluate the EER, which is the rate of trials in which the FAR equaled the FRR, and the ROC curve, which shows the relationship between FAR and FRR. Except the proposed method, we introduce the line tracing method [1] and the curvature method [2] for comparison.

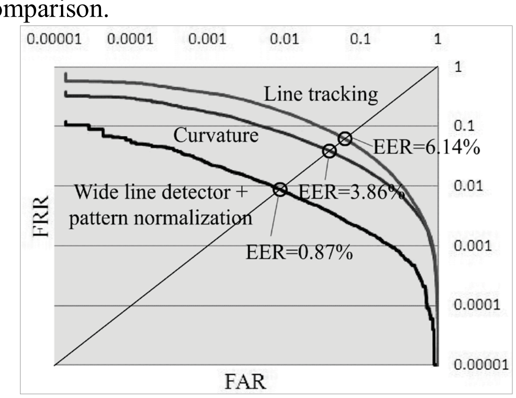


Figure 6. The ROC Curves

The ROC curves of finger-vein authentication algorithms are shown in Fig.6, and Table 1 shows the EER of the algorithms. Firstly, the results base on this database are worse than the results base on the database collected in laboratory [1-2]. Secondly, we find all the algorithms using the pattern normalization have lower error rates than the version without normalization. Thirdly, the wide line detector method shows its advantage than the other two feature extraction methods. Finally, wide line detector combining with pattern normalization gets best result, and the EER is 0.87%.

TABLE I. EER OF THE ALGORITHM

	Line tracking	**Curvature**	**Wide line detector**
Without normalization	**6.14%**	**3.86%**	2.86%
With normalization	5.00%	2.80%	**0.87%**

VI. CONCLUSION

In this paper, we introduced a wide line detector to extract vein patterns. It can obtain all the points on the lines of vein in the image and increase the information of the feature. We also proposed a new pattern normalization method, which can reduce the irregular distortions caused by variance of finger pose. The experimental result based on a database including 50,700 images shows that the proposed method is effective for practical personal authentication.

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