Personal Identification by Finger Vein Images Based on Tri-value Template Fuzzy Matching

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Abstract: To reduce the effect of fuzzy vein edges and tips of the infrared finger vein recognition, this paper presents a tri-value template fuzzy matching algorithm, which segments the vein feature image into three areas: subject area, fuzzy area and background area, and computes the average distance of non-background point to non-background area as the dissimilarity score between the two templates. The proposed matching method is robust against the fuzzy edges and tips. The experimental results show that the proposed method is feasible and practical by the recognition accuracy rate, 99.46 %, to 456 near-infrared finger vein images.

Key-Words: Personal identification; Infrared finger vein; Tri-value template; Fuzzy matching

1 Introduction

The identity authentication and privacy protection are becoming more and more important in the information society^[1]. The personal identification technology based on biological characteristic has shown many advantages because of the use of inherent physiology and behavior characteristics of human. More and more biometric features appear in the personal identification, such as face^[2], speech^[3], fingerprint^[4], palmline^[5] and iris^[6]. Compared to these available biometric features, the finger vein^[7] has four advantages:

Firstly, it does not need physical contact and will not make the people displeasure, much better than fingerprint and iris scanning.

Secondly, it has forceful universality and uniqueness. The adults' finger vein has less change with age. And different finger has different vein patterns.

Thirdly, it is very hard to capture the finger vein image for forgery in the normal actives because the vein is hypodermal, better than other biometric features on the surface, such as fingerprint and face. Fourthly, the temperature, humidity and cleanliness have little effect on the vein image.

The finger vein patterns can be adopted in general public use, such as for on-line identification and ATM(Automatic Teller Machines). In medicine field, the patterns can be used for patients' recognition and injecting vein.

As light within near-infrared band (wavelengths 720nm -- 1100nm) is absorbed intensively by the hemoglobin in the blood of vein and transmits other

tissues of finger easily, the finger vein patterns can be captured as the dark lines. Two examples of infrared finger vein images are shown in Fig. 1. Vein patterns have many trunks and branches, which can be used for line feature discrimination between different vein patterns.

From Fig. 1, the contrast of the origin infrared image is quite low and brightness is not uniform^[8]. The vein edges and tips in vein feature image are blurry and hard for matching. To solve this problem, we propose a tri-value template fuzzy matching method, which segments the vein feature image into three areas: subject area, fuzzy area and background area. Calculate the average distance of non-background point to non-background area as the dissimilarity score. This method has elastic matching capability by optimal distance norm to different non-background areas and does not need the knowledge of correspondence among points in the two matching templates.

This paper is organized as follows. Section 2 introduces the procedure of finger vein recognition with the tri-value template fuzzy matching. Section 3 presents the experiment and discussion, Section 4 draws the conclusions.



Figure 1 Infrared finger vein image examples

2 Personal Identification by Infrared Finger Vein Images

The flowchart of finger vein recognition is shown in Fig. 2 which is consisted of infrared finger vein image acquisition, preprocess, vein feature extraction and matching.



Figure 2 Flowchart of finger vein recognition

There are two types of infrared finger vein imaging techniques: Far-Infrared(FIR) and Near-Infrared (NIR) which both are contact-less acquisition method and require no injection of any agents into the finger blood vessels. The former, FIR imaging, bases on that the heated finger emits infrared radiation and veins have higher temperature than the surrounding tissues. Therefore, the thermal imaging camera can capture the FIR finger vein image which contains the heat distribution and can display the structure of finger vein patterns on finger. But the temperature distribution of finger is unstable and sensitive to the environment temperature. So FIR imaging is inadequate for real-time finger vein image acquisition. As mentioned above, the NIR imaging bases on that the external NIR light can be absorbed intensively by the vein and transmits other finger tissues easily. The finger vein patterns can be captured by the NIR camera as the dark lines. The external light source can be controlled and the absorbability is quite stable. So the NIR finger vein imaging is used in the real-time system of finger vein acquisition.

The origin image preprocess removes the noises and rotates the finger to horizon direction. Then cut the finger vein image by the normalized size to matching and register easily.

The extraction of finger vein feature is to enhance the line feature of vein or extract it and then register the feature in the database or used for matching.

The matching is between the input finger vein feature and the one in the database and the recognition provides the matching result: pass or refuse.

2.1 Infrared finger vein image acquisition

In the experiment, the schematic diagram for nearinfrared finger vein image acquisition is described in Fig. 3. An eight near-infrared LEDs array is used as the light source, which wavelength is 850nm, and its intensity of light can be manually adjusted. The infrared light transmits the dorsal side of the finger, the infrared filter and be captured by a CMOS camera. The light source and camera can be controlled by a PC.



Figure 3 The schematic of infrared finger vein image acquisition

2.2 Preprocess and normalization

In the Fig. 1, the origin infrared finger vein image is blurry with speckle noises and the direction of finger is declining. These should be adjusted. Preprocess and normalization include low-pass filter, finger outline detection, finger body extraction, finger rotation and size normalization which flowchart is shown in Fig. 4.

Gaussian low-pass filter is used to remove speckling noises in the origin image. Sobel edge detection extracts the finger's outline, which describes the shape of the finger and can be used to extract the finger body. The areas outside finger body are zero padded. Use least-squares line-fit of the finger outline to estimate the slope angle of the finger. Then the finger image is rotated to horizon by the slope angle. The finger image is cut out from the tip to the root by a normalized size.



Figure 4 Flowchart of finger vein preprocess

2.3 Vein feature extraction

In our study, the repeated line tracking^[9] is used to extract the vein feature. This scheme is based on that the vertical section profile of a vein looks like a valley, which is shown in Fig.5(a) and Fig.5(b), and this can be tracked and detected, which is shown in Fig.5(c):



Figure 5 Character of vein profile and the line tracking process. (a) The profile on vein. (b) The gray distribution of the profile. (c) A line tracking on a vein.

Fig.5(c) shows an example of the spatial relationship between the current tracking point(xc,yc) and the cross-sectional profile. Pixel p is a neighbor of the current tracking point in the upper-right direction. The profile s-p-t of the current point(xc,yc) looks like a valley. Therefore, the current tracking point is on a dark line. The direction of this dark line can be detected by checking the depth of the valley with varying detect angle θ i. This can find the deepest valley at a θ i. After that, the current tracking point moves to the pixel closest to this direction, pixel p. If the valley is not detectable in any direction angle θ i, the current tracking point is not on a dark line and a fresh tracking operation starts at another position.

This vein line feature extraction procedure consists of tracking a dark line, iteratively tracking the lines and obtaining vein patterns by the number of times of tracking and it is illustrated as following steps:

Step 1: Determinate the start point for line tracking and the moving-direction attribute.

The line-tracking operation starts at a random pixel which is called the current tracking point as mentioned above. The moving-direction maybe left-right, up-down or all-direction by random probability 50%, 25%, 25% respectively.

Step 2: Detection of the direction of the dark line and movement of the tracking point.

Calculate the vertical cross-profile valley depth of the points set on the moving-direction near the start point. Then detect the dark line direction and move the current tracking point to this position, which is shown in the Fig.5(c). If there is no point in the bottom of valley, go to Step 4.

Step 3: Updating the number of times points in the locus space have been tracked.

At the beginning of first tracking, a tracking information registration image which is called locus space, is built and initialized to 0. The number of times that each pixel has become the current tracking point is recorded in the locus space image.

Step 4: Repeated execution of step 1 to step 3 for N times. Repeat the line track at 3000 random start points.

Step 5: Acquisition of the finger-vein pattern from the locus space.

Step 6: Labeling of the locus space.

The positions with high values in the locus space have high probabilities of being the positions of veins. Therefore, the paths of finger vein are obtained as chains of high-value positions in the locus space. The current tracking point may track noise region by chance. But vein regions have much more probability to be tracked many times than noise regions. Thus, noise regions in locus space have lower tracking record times than vein regions.

The locus spaces of finger vein examples are shown in the Fig. 6(a). But the contrast of locus space is also low, and there are be many random flocky lines on vein edges and tips if segmented directly, which is shown in Fig. 6(b) and it is hard to matching. The locus space must be enhanced before segmentation. To reduce the effect of flocky tracking, image resizing is used to smooth the vein edges and center enhance filter to strengthen the vein midlines. The locus space is zoomed out to one-second of origin size, which can remove flocky noises, and then zoom in to origin size using bilinear interpolation. A center enhance filter is used to enhance the locus space. The resized locus space and enhance vein feature image are shown in the Fig. 6(c), (d) and (e). The filter is a center enhance mask and shown in Table 1.

-0.7980	-0.8930	-0.8933	-0.8933	-0.8933	-0.8930	-0.7980
-0.8930	-0.9995	-0.9980	-0.9871	-0.9980	-0.9995	-0.8930
-0.8933	-0.9980	-0.3088	4.1076	-0.3088	-0.9980	-0.8933
-0.8933	-0.9871	4.1076	36.7403	4.1076	-0.9871	-0.8933
-0.8933	-0.9980	-0.3088	4.1076	-0.3088	-0.9980	-0.8933
-0.8930	-0.9995	-0.9980	-0.9871	-0.9980	-0.9995	-0.8930
-0.7980	-0.8930	-0.8933	-0.8933	-0.8933	-0.8930	-0.7980

Table 1 Center Enhancement filter



Figure 6 Locus space resizing and enhancement (a) Locus space. (b) Binary image of (a) by direct segmentation. (c) Locus space zoomed out to one-second of (a). (d) Locus space zoomed in to origin size. (e) Center enhanced locus space

2.4 Matching and recognition

Template matching is appropriate to vein patterns which have sparse structure points composing trunks and branches. Though there are some other matching methods, such as structural matching and neural networks, but they usually need quite accurate segmentation or many training samples. In the enhanced locus space, the edges and tips of vein are still fuzzy and have some random noises which effect the matching of structural matching and neural networks. To solve the problem, this paper presents tri-value template fuzzy matching, which segments the vein feature image into three areas: subject area which includes the stable vein trunks, fuzzy area which includes dubious vein edges and tips, and the background area. The proposed method calculates the average distance of non-background point to non-background area as the dissimilarity score between the two tri-value templates.

2.4.1 Tri-value template definition

Tri-value template is defined like binary image. There are three possible values 1, 0.5 and 0 in the template image. Every point has one of the three values, 1 means stable subject, 0.5 means fuzzy object between the subject and background and 0 means the background. A tri-value template example is shown in the Fig. 7.



Figure 7 The tri-value template example

2.4.2 Tri-value template acquisition

Set the enhanced vein feature image as I_F . The trivalue template M is the segmentation of I_F by two thresholds T1 and T2 in formula (1):

$$\begin{cases} M(i, j) = 1 & I_F(i, j) \ge T1 \\ M(i, j) = 0.5 & T2 < I_F(i, j) < T1 \\ M(i, j) = 0 & I_F(i, j) \le T2 \end{cases}$$
(1)

Where, M(i,j) is the point value at (i,j) in the template and $I_F(i,j)$ is the one at same position. High threshold T1 is used to confirm the subject area and low threshold for background area.

2.4.3 Distance map of tri-value template

It is efficient to compute the distance map for distance calculation between templates. Generally, the distance map is calculated by the distance transform(DT). For the binary image, DT is a process that assigns a value at each location within the object that is the shortest distance between that location and the complement of the object. In the trivalue template, the object includes subject and fuzzy area. Both of them must be considered in the distance map.

Similar to the binary image, the distance between point 'a' and subject point 'b' is defined as Euler distance:

$$d_{b=1}(a,b) = \sqrt{(i_a - i_b)^2 + (j_a - j_b)^2}$$
(2)

Where, i_a , i_b , j_a and j_b are the row and column coordinates of point 'a' and 'b', respectively.

Since the importance account of fuzzy area is less than the subject area. The distance between point 'a' and fuzzy subject point 'c' should be further than Euler distance. It is defined as:

$$d_{c=0.5}(a,c) = k * \sqrt{(i_a - i_c)^2 + (j_a - j_c)^2}$$
(3)
Where, k > 1.

The distance between point 'a' and the subject area 'S' is defined as:

$$d(a,S) = \min(d_{\forall b \in S}(a,b)) \tag{4}$$

The distance map of subject area ' D_s ' is defined by the formula (5):

$$D_{\mathcal{S}}(i,j) = d(M(i,j),S)$$
⁽⁵⁾

Similarly, the distance map of fuzzy area ' D_F ' is defined by the formula (6):

$$D_F(i,j) = d(M(i,j),F)$$
(6)

Where, 'F' is the fuzzy area in the tri-value template.

So the distance map of tri-value template ' D_M ' can be defined as:

$$D_M(i, j) = \min(D_S(i, j), D_F(i, j))$$
 (7)

The flowchart of distance transform to tri-value template is shown in the Fig. 8.



Figure 8 Flowchart of tri-value template DT (a) The tri-value template by the enhanced locus space in Fig. 6(e). (b) The region of interesting (ROI) of (a) since veins in the finger tip are too thin and concentrated to extract for CMOS camera and vein patterns are similar in this area. (c) The subject area of (b). (d) Distance map of

(c). (e) Fuzzy area of (b). (f) Distance map of (e). (f) The distance map of (b)

2.4.4 Tri-value template matching

Set the input tri-value template as M_i and the registered tri-value template in database as M_r . The corresponding distance maps are D_i and D_r . The average distance of non-background point to non-background area as the dissimilarity score between M_i and M_r is calculated by formula (8):

$$C(M_{i},M_{r}) = \frac{1}{2*(N_{i}+N_{r})}*$$

$$\sum (M_{i}(i,j)*D_{r}(i,j)+M_{r}(i,j)*D_{i}(i,j))$$
(8)

Where N_i and N_r are the numbers of the nonbackground points in M_i and M_r . The lower the score is, the similar the two templates.

3 Experimental Results

In the experiment, 456 infrared finger vein images are captured from 76 fingers, and each finger is captured 6 images. The age and sex distribution are shown in the table 2, respectively:

1 dole 2. Age and sex distribution in the experiment							
Age	16	-20	21-25	26-30	30-	50	Total
Num.	2	1	50	30	2	2	76
Sex			Male	Femal	e		Total
Num. 60		16			76		

Table 2: Age and sex distribution in the experiment

3.1 Experiment environment and parameters The experiment hardware and software environment are described in table 3:

Table 3:	Computer	^c configuration
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Ha	ardware	Software		
CPU	Celeron 2.66G	Soft	Visual C++ 6.0	
Memory	DDR 768M	Lib.	OpenCV 1.0	

The still resolution of infrared camera is 320*240. In Fig. 1, the size of infrared finger vein image example is 198*132. The finger edges are reserved for template matching because the shape of finger outline also has distinct line character. The size of tri-value template ROI is 132*88. The two thresholds in formula (1) are initialized by: T1 = 192 and T2 = 128. And the value of k is 1.21 in formula (3). Sliding window matching is used for matching registration. The size of sliding window is 100*60. The minimum score of the sliding match records is regarded as the dissimilarity of the two tri-value templates.

3.2 Matching results

In our study, arbitrary two images of the 456 images are tested by the tri-value template fuzzy matching.

3.2.1 Matching results by proposed method

Firstly, the tri-value template matching between two images from one finger is calculated by the proposed matching method using formula (8). The result is signed as C_{s} . Fig. 9 draws its histogram.



Figure 9 Histogram of matching between two tri-value templates of one finger

Values of C_s are centered at 1.5. In Fig.9 the height of the black bar denotes the accumulated numbers of identical finger and the width of the black bar means the range of dissimilarity score. The bins are 30 equally spaced between the minimum and maximum score values in the matching result.

Then, the tri-value templates between two images of different fingers are calculated. The result is signed as C_D . Fig. 10 draws its histogram.



Figure 10 Histogram of matching between two tri-value templates of different fingers

Values of C_D are centered at 3.9. In Fig.10 the bins are 420 equally spaced between the minimum and maximum values in the matching result.

3.2.2 Matching result discussion

Fig. 11 shows the histogram of the arbitrary two fingers matching result by the tri-value template fuzzy matching.



Figure 11 Histogram of matching between two tri-value templates of arbitrary finger images

Black bars(C_{S}) mean the same finger matching result and the height refers to the left vertical coordinates. The gray $bars(C_D)$ mean the different finger matching result and the height refers to the right vertical coordinate. Since the overlapping between C_S and C_D is very little, the infrared finger vein identification is possible. Assume the recognition threshold is C_T. The error rate of identification accuracy includes false acceptance rate (FAR) and false rejection rate (FRR), which is defined as:

$$\begin{cases} FAR = \frac{N_{C_D < C_T}}{N_2} \\ FRR = \frac{N_{C_S \ge C_T}}{N_1} \end{cases}$$
(9)

Where N_1 is the number of matching between identical fingers and N₂ is that between different fingers, N₁ = 1140 and N₂ = 102600. The $N_{C_D < C_T}$ is the number of $C_{\rm D}$ value less than $C_{\rm T}$ and the $N_{C_s \ge C_T}$ is the number of C_S value more or equal than C_{T} . In our study, the error rate (EER) is defined as FAR+FRR. To evaluate the optimal threshold for minimum error rate, C_T is defined as a variable which increases 0.01 from 0 to 7. The FAR and FRR are calculated by C_T and the error rate curves are plotted in the Fig. 12. The Min. EER is determined by searching a value of C_T so that (FAR + FRR) is minimized.

The C_T which make FAR = FRR may not exist since FAR and FRR are discontiguous variable. The error rate is shown in Table 4.



Table 4: The error rate of proposed method					
Threshold C _T	2.21	2.73	2.84		
FAR	0	0.11%	1.28%		
FRR	2.36%	0.43%	0		
EER	2.36%	0.54%	1.28%		

From the Fig.12 and table 4, it can be seen that the Min. EER is 0.54% when threshold $C_T = 2.73$, on which FAR = 0.11% and FRR = 0.43%. In our study, the recognition accuracy rate is used to evaluate the performance of the proposed matching method. It is defined as 1 - EER. The corresponding recognition accuracy rate is 99.46%.

3.2.3 Distance norm parameter discussion

In our study, Euclidean distance is used in the distance norm for subject area. Fig. 13 shows the discussion of distance norm for fuzzy area. As mentioned in formula (3), k > 1. Fig. 13(a) is a 3*3 matrix which means the location of point p1, p2, ..., p9. Assume that p2 is a subject point, p5 is a fuzzy point, and the other points are background points. So their distance maps are Fig. 13(b) and Fig. 13(c), respectively. It is familiar that the fuzzy points are around subject points in Fig. 7. The distance value in p4 maybe $\sqrt{2}$ or k in Fig. 13(b) and Fig. 13(c). The point p5 is nearer to p4 than p2. So $k < \sqrt{2}$. The range of k is $(1\sqrt{2})$. To evaluate the optimal distance norm for fuzzy area, k is defined as a variable which increases 0.01 from 1 to $\sqrt{2}$. Then EER is calculated to k. The k-EER curve is plotted in the Fig 14.

p1	p4	p7	1	$\sqrt{2}$	√5	$\sqrt{2}k$	k	$\sqrt{2}k$
p2	p5	p8	0	1	2	k	0	k
P3	p6	p9	1	$\sqrt{2}$	√5	$\sqrt{2}k$	k	$\sqrt{2}k$
	(a)			(b)			(c)	

Figure 13 Distance norm discussion

(a) A a 3*3 position matrix. (b) The distance map with p2 = 1. (c) The distance map with p5 = 0.5.



Figure 14 k-EER curve

From the k-EER curve, the minimum EER is 0.54% when k = 1.21.

3.3 Matching method discussion

Other three matching method are tested on the experiment data: the normalized gray correlation coefficient(Correlation Coefficient)^[10], the modified Hausdorff distance (MHD)^[11] and the miss-point statistic match(Miss-match)^[9] method.

The direct gray correlation coefficient is defined as formula (10):

$$r = \frac{\sum_{i=j}^{\infty} (M_{1}(i,j) - \overline{M_{1}})(M_{2}(i,j) - \overline{M_{2}})}{\sqrt{(\sum_{i=j}^{\infty} (M_{1}(i,j) - \overline{M_{1}})^{2})(\sum_{i=j}^{\infty} (M_{2}(i,j) - \overline{M_{2}})^{2})}}$$
(10)

Where, M_1 is the average value of the template

 M_1 and $\overline{M_2}$ is the average value of the template M_2 . The Modified Hausdorff Distance(MDH) is defined as:

$$H_{MHD}(M_1, M_2) = \frac{N_1 h(M_1, M_2) + N_2 h(M_2, M_1)}{N_1 + N_2} \quad (11)$$

Where, $h(M_1,M_2)$ is the direct Hausdorff distance from M_1 to M_2 and $h(M_2,M_1)$ is the direct Hausdorff distance from M_2 to M_1 .

The miss-point statistic match method defines the mis-match ratio as:

$$R_{miss-match} = \frac{N_m}{N} \times 100\%$$
(12)

Where N_m is the sum of overlapped points which one belongs to vein area and the other one belongs to ambiguous area in the two templates. N is the sum number of non-zero points in two templates.

The matching result of four match methods is shown in the Table 5:

Table 5 The matching result of four match methods

	Recognition accuracy rate
The proposed method	99.46%
Correlation Coefficient	75.70%
MHD	99.15%
Miss-match	98.46%

The gray images of finger after preprocess also keep the low contrast and unclear edges. Calculating the correlation coefficient directly of gray images is not suitable for matching. Although the MHD method has some fuzzy matching capability, there are many ambiguous edges and tips around the vein which lead to the primary similar error effect in matching. MDH is not the optimized method for our experiment. The miss-point statistic matching ignores the effect of ambiguous area and leads to some additional error rate correspondingly.

Tri-value template fuzzy matching utilizes a priori knowledge that different class regions have different amounts of importance. In measuring the distance between two point sets, we increase the distance norm on the fuzzy area properly. Thus the effect of ambiguous edges around veins is weakened and depressed. Table 5 shows the proposed method has the best recognition accuracy rate among these methods.

3.4 Effect of feature extraction scheme and matching ROI

The performance of vein line feature extraction scheme is very important for the matching. In our study, other two schemes of the vein feature extraction are tested on the experiment data. One is matched filter^[12] and the other is local threshold^[13].

The matched filter concludes four direction enhance filters, in which the horizon filter is defined as Table 6, and the other 3 filters are this filter rotated by multiples of 45° , 90° and 135° :

Tabl	e o mai	in muer r	nask on	norizonta	al difectio)II
26	8	-18	32	-18	8	26
26	8	-18	32	-18	8	26
26	8	-18	32	-18	8	26
26	8	-18	32	-18	8	26
26	8	-18	32	-18	8	26
26	8	-18	32	-18	8	26
26	8	-18	32	-18	8	26

Table 6 Match filter mask on horizontal direction

The local threshold scheme uses OSTU threshold on the local 7*7 blocks. Fig. 15 shows the feature and binary images by mentioned two vein line feature extraction methods.



Figure 15 Results of match filter and local threshold (a) The feature image processed by matching filter. (b) The binary image of (a). (c) The feature image processed by local threshold. (d) The binary image of (c).

From Fig. 15, these two vein feature extraction methods are not robust to the infrared finger vein images. Table 7 shows the recognition accuracy rate by 3 matching methods:

 Table 7 Recognition accuracy rate using other two vein feature extraction schemes

	Match filter	Local threshold
Proposed method	95.68%	95.96%
MHD	94.85%	95.30%
Miss-match	90.73 %	92.52%

These two vein feature extraction methods are not robust to the infrared finger vein images and reduce the recognition accuracy rate.

It is important to choose the appropriate ROI to the template. As mentioned above, the veins in the tip part of finger are too slight and dense to extract robustly. If make the entire finger image as ROI, which size is 198*132, and choose sliding window size 120*90. Table 8 shows the matching result by repeated line tracking:

Table 8 Recognition accuracy rate using entire finger as ROI in matching

	0
Matching method	Accuracy rate
Proposed method	86.77%
MHD	84.44%
Miss-match	80.38%

From Table 5, 7 and 8, it can be seen that the proposed matching method has the best recognition accuracy rate error rate in the same conditions.

4 Conclusions

In this paper, we propose a tri-value template fuzzy matching for finger vein recognition. Experiment results show that the recognition accuracy rate of proposed method is 99.46% and it is feasible for

vein fuzzy matching. Further works include searching for faster distance transform algorithms on tri-value template and designing better infrared image capture system.

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