Rotation Invariant Finger Vein Recognition*

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Abstract. Finger vein patterns have recently been recognized as an effective biometric identifier and many related work can achieve satisfied results. However, these methods usually suppose the database is non-rotated or slightly rotated, which are strict for preprocessing stages, especially for capture. As we all know, user-friendly capture tends to cause the rotation problem, which degrades the recognition performance due to the unregulated images or feature loss. In this paper, we propose a new finger vein recognition method to solve the common rotation problem of finger vein images. Two experiments are designed to evaluate the recognition performance in both verification mode and identification mode and to demonstrate the advantages and robustness of our method in different rotated databases compared with pattern binary based method like LBP. Experimental results show that the proposed method can not only achieve a lower EER (1.71%) than LBP (2.67%), but also can overcome the difficulties of rotation in rotated databases. The EERs of proposed method in three different rotated databases are 2.15%, 2.98% and 2.75% respectively, which shows that our method has better robustness in rotation than LBP.

Keywords: Finger Vein Recognition, Scale Invariant Feature Transform (SIFT), Rotation Invariance, Local Binary Pattern (LBP).

1 Introduction

Biometric recognition has been used in many areas such as border crossing, national ID cards and e-passports due to its efficiency and high security. Hand-based biometrics normally include fingerprint recognition, finger knuckle print recognition and palm recognition, in which fingerprint recognition is mature and has been widely researched [1]. However, the hand-based biometrics such as fingerprint, palm print and finger knuckle are easy to be forged and the surface conditions can influence the performance significantly [2]. To overcome the shortages of hand-based biometric systems, finger vein recognition is proposed and well studied these years [3]. The distinctive property of finger vein is non-contact [4] [5], which can overcome the difficulties mentioned before.

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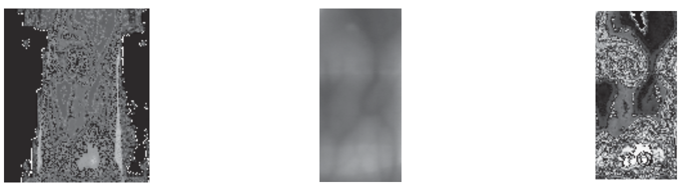
Feature extraction is important for finger vein recognition and many finger vein recognition methods utilize the features of blood vessel network [6]. However, the performance of recognition will degrade significantly, if the images have low quality and can not be segmented correctly. To solve this problem, binary pattern based methods such as LBP, LDP [7] and PBBM [8] have been proposed, and experiments show these methods have high accuracy of recognition. Although the binary pattern based methods can somewhat make up the deficiency of low quality and incorrect segmentation of finger vein images, the rotation problem of images remains unsolved. With slight rotation, the performance of binary pattern based methods will degrade severely due to unregulated images or feature loss. However the the rotated finger vein images are usually in user-friendly recognition system, and in a practical system the rotation problem is inevitable. To solve the problem, we proposed a new rotation invariant finger vein recognition method.

The rest of this paper is organized as follows: Section 2 describes the proposed method. In section 3, experiments and analysis will be presented and in the last section conclusions will be given.

2 Proposed Method

2.1 Preprocessing

The captured finger vein images usually have problems such as low contrast, non-uniform illumination and background noise, thus preprocessing is necessary for feature extraction and matching. In our method, segmentation and enhancement will be used in preprocessing stage. To exclude the influence of background noise, segmentation will be implemented. First with Sobel edge detection, we can get the edge outline of finger vein, and then inner rectangle will be used to intercept the finger vein image (Fig.1 (b)). Just as Fig.1shows, our preprocessing includes segmentation and enhancement. With suitable segmentation, the background is removed and with enhancement the contrast of venous regions and non-venous regions improve effectively. The finger-vein images are captured with infrared ray, and the background and the finger vein features can not distinguished without histogram equalization. By this preprocess, details of finger-vein can be shown clearly which is illustrated in Fig.1. It can effectively deal with the degradation. So we enhance the images with histogram equalization, which can overcome the difficulties caused by low contrast and non-uniform illumination. The enhanced finger vein image is shown in Fig.1 (c).



(a) The captured image (b) Segmentation (c) Enhancement with histogram equalization

Fig. 1. Preprocessing of finger vein images

2.2 Feature Extraction and Matching

After preprocessing, SIFT[9] will be used for feature extraction and matching. The reason that we choose this algorithm is the vantage in rotation-invariance. SIFT was first introduced by D.G Lowe to get better performance in object recognition. Due to its advantages of invariance to scale, rotation and affine transformation, SIFT is soon used in many application areas, especially in biometrics.

The principle of SIFT is to find extreme points in scale-space and filter them to get stable ones, and then local features of the images around these stable points are extracted, thus local descriptors are generated from these local features for matching. Four stages of SIFT algorithm can be described as follows: (1) Use a difference-of-Gaussian function to implement scale-space extrema detection; (2) Select stable keypoints from extreme points; (3) Assign orientations to each keypoint; (4) Generate local keypoint descriptors. With stable features are extracted from SIFT, influence of angles will be excluded and problems caused by rotation will be solved.

Feature points extracted from images are selected as matching pairs, and the number of matching pairs is used to measure the similarity of two finger vein images. Then the suitable threshold T (the number of matching pairs) is selected after testing the matching results of the whole database. For example, two finger vein images will be classified as the same class if the number of matching pairs is bigger than T , otherwise these two finger vein images will be classified as different classes. The matching result is shown in Fig.2.

Fig. 2. Matching result of two finger vein images

3 Experimental Results and Analysis

3.1 Database and Experiment Setting

We construct our database with 95 individuals (classes) and each class has 11 finger vein pictures with slightly rotation. All the captured finger vein images are stored by BMP format with resolution 320*240. All experiments are implemented by Visual C++ and MATLAB, and executed on a machine with 2.93GHz CPU and 4G memory. In this paper, two experiments are designed to evaluate the performance and robustness of proposed method: (a) Experiment 1 evaluates the performance of the proposed method with verification mode and identification mode respectively, and compare the results with LBP [7] based method; (b) Experiment 2 is conducted to show the advantages of our method in solving the rotation problem compared with LBP [7] based method.

3.2 Experiment 1

We perform experiments in verification mode and identification mode respectively. In verification mode, the class of each test sample is claimed and each test sample will be matched with templates of the claimed class by both SIFT and LBP. If the number of matching pairs is bigger than threshold, matching is successful. The successful matching is called intraclass matching or genuine matching. Otherwise, the unsuccessful matching is called interclass matching or imposter matching. In the experiments, we get $95 * C_{11}^2$ intraclass matching results (each class has C_{11}^2 matching results); also, we choose the first sample to perform interclass matching and get C_{95}^2 matching results. The performance of the proposed method and LBP is evaluated by EER (Equal Error Rate). The EERs of proposed method and LBP are 0.0171 and 0.0267 respectively, and the ROC curves are shown in Fig.3.

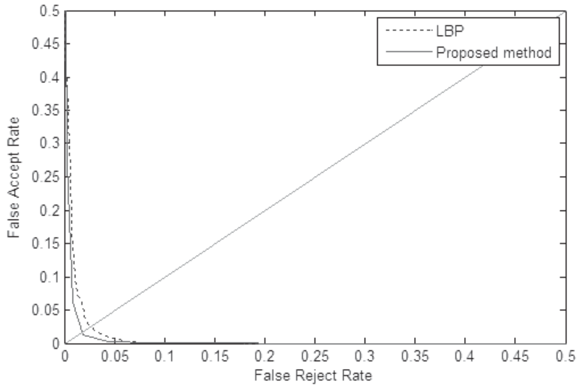


Fig. 3. ROC curves of different methods

In the identification mode, we conduct experiments in the close-set database (all the samples are in the enrollment database). We do not know the class of input finger vein and want to identify which class it belongs to. We choose the first sample in each class as template and use other ten samples in each class as test samples (probes). Therefore, we get 95 templates and 95*10 probes totally. Each probe will be matched with all the templates. For each probe, the matching result will be ranked based on the matching score. The CMC (cumulative match curves) is shown in Fig.4, and the rank-one recognition rate and lowest rank of perfect recognition is given in Table 1. From the experimental results we can see the proposed method is better than LBP based method.

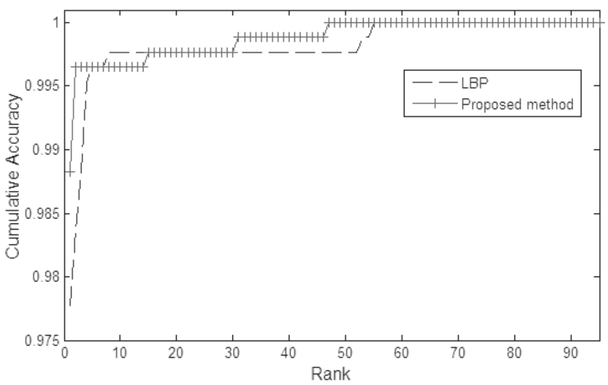


Fig. 4. Cumulative match curves by different methods

Table 1. Identification performance by different methods

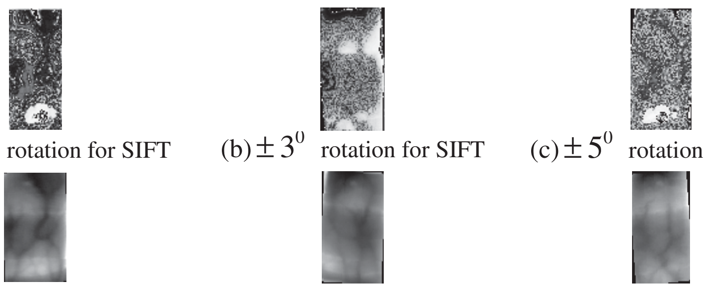
	rank-one recognition rate	lowest rank of perfect recognition
LBP[7]	0.9778	55
Proposed method	0.9883	47

3.3 Experiment 2

We conduct experiment to show the advantage of the proposed method in rotation and analyze the advantage in translation compared with LBP.

LBP is based on the computation on pixel level. LBP solves problem of translation by translating corresponding pixels to generate feature vectors and measuring similarities of these vectors. Although the problem in translation of images can be solved, the system is time-consuming. However, SIFT method extracts key points from scale-space and the extracted key points are independent of coordinate, which can overcome the problem in translation.

To verify the robustness in rotation invariance, we construct three simulated rotated databases based on the source database. We rotate all the samples in the source database with different rotated ranges to construct three rotated databases. The three rotation ranges are $\pm 1^0$, $\pm 3^0$ and $\pm 5^0$. For example, in the simulated $\pm 5^0$ database, the rotated degrees may range from -5^0 to $+5^0$.



(a) $\pm 1^0$ rotation for SIFT (b) $\pm 3^0$ rotation for SIFT (c) $\pm 5^0$ rotation for SIFT

(a) $\pm 1^0$ rotation for LBP (b) $\pm 3^0$ rotation for LBP (c) $\pm 5^0$ rotation for LBP

Fig. 5. Different preprocessing samples of two methods with different rotated degrees

We evaluate the performance of different methods in three rotated databases. Fig.5. shows different preprocessing samples with different rotated degrees. Table 2. shows the EERs of proposed method and LBP in different rotated databases. From Table.2, we can see the proposed method can overcome rotation problem better compared with LBP based method.

Table 2. EERs in different rotated databases with the proposed method and LBP

Degrees	LBP [7]	Proposed method
$\pm 1^0$	2.70%	2.15%
$\pm 3^0$	3.33%	2.98%
$\pm 5^0$	4.81%	2.75%

4 Conclusions

In this paper, a new finger vein recognition method is proposed to overcome the difficulties in rotation of images. Although SIFT has been used in finger-vein recognition, to the best of my knowledge, SIFT usually is only used in feature extraction. Our work mainly focus on the counter-rotation property of this algorithm. And also our experiments on the rotated databases verify the efficiency of proposed method. Experiments are conducted in different rotated databases to verify the efficiency and robustness in rotation invariance and it is suitable for a user-friendly system. Although the experimental results are satisfactory, the number of individuals is limited in constructed database. So, a large-scale real-world database will be applied in the proposed method in the future work.

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