Finger-Vein Recognition Based on Fusion of Pixel Level Feature and Super-Pixel Level Feature

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Abstract. Finger-vein is a promising biometric technique for the identity authentication. However, the finger displacement or the illumination variation in image capturing may cause bad recognition performance. To overcome these limitations, multi-biometric system, an effective method to improve the performance, is proposed. In this paper, a new multimodal biometric system based on pixel level feature and super-pixel level feature is proposed. First, the pixel level feature and the super-pixel level feature are extracted and matched by the Euclidean distance respectively. Then, pixel-super-pixel fusing score (PSPFS) is generated by the weighted fusion strategy. At last, the PSPFS is used to make the decision. Experimental results show that the proposed fusion method not only has better performance than the methods using single level feature, but also outperforms the fusion methods based on the fusion of two pixel level features.

Keywords: finger-vein recognition, pixel level feature, super-pixel level feature, score-level fusion.

1 Introduction

Biometrics, which makes use of biometric traits like faces [1], irises [2], gaits [3], fingerprints [4], and veins to identify individuals, has attracted more and more attention. Finger-vein recognition [5] is one of the new emerging biometrics and has been well studied recently. Compared with other biometric traits, finger-vein has higher degree of concealment and security in the identification. Furthermore, compared with other vein recognitions, such as, dorsal vein recognition [6], palm vein recognition [7], the size of imaging device in finger vein recognition is smaller and the credibility is higher. Currently, researchers have developed many kinds of algorithms to improve the recognition accuracy. In [8], local binary pattern (LBP) is proposed and applied to the finger-vein recognition [9]. In [10], the authors extract the finger-vein pattern from the image and take the pattern structure as feature to identify. In [11], the minutiae features, including bifurcation points and ending points, which can be used for geometric representation of the vein patterns shape, are extracted from these vein patterns.

However, for finger-vein recognition using single feature, when we capture the finger-vein image, the finger displacement variation may cause the large change within

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Z. Sun et al. (Eds.): CCBR 2013, LNCS 8232, pp. 274–281, 2013.

class, and the illumination variation result in lower image quality, the large change within class and the lower image quality may cause failure to recognition finally. In order to enhance the performance of finger-vein recognition, multi-biometric systems are employed, [12] exploits finger vein features in local moments, topological structure and statistics respectively, and a fusion scheme is adopted for decision making, obtaining a good performance rate. Wang and Liu extract the phase and direction texture features for combination in feature level fusion, finally a modified Hamming distance is used for matching in [13]. Although multi-biometric systems above can achieve high accuracy, the actual effects are all subjected to the characteristics of the pixels, which are sensitive to the pixel noise. Furthermore, because the complementarity of the pixel level features is inadequate, so the fusion effect is not perfect.

Due to the limitations mentioned above, super-pixel level feature has been proposed to overcome the existing problems. The SLIC method [14] clusters pixels into perceptually meaningful atomic regions firstly, which can be used to replace the rigid structure of the pixel grid, and then the features are computed at the small blob-based super-pixels. Super-pixel level features are the rough description of the finger-vein image and can overcome shortcoming of the pixel features as well as robust to the noise in pixel level. In addition, the super-pixel has its unique advantages, such as, high efficiency, homogeneity, and local image consistency, which can improve the recognition performance.

These advantages motivate us to fuse the pixel and the super-pixel level features together to make finger-vein more efficient for personal identification. In this paper, we propose a new finger-vein recognition method based on the fusion of pixel level and super-pixel level features. Extensive experiments show that the proposed method can significantly improve recognition performance as well as the universality.

The rest of this paper is organized as follows: Section 2, the proposed fusion method for finger-vein recognition is described. Section 3 presents the experimental result and analyses. Finally, Section 4 concludes the paper.

2 The Proposed Method

In this section, we describe the proposed fusion method in detail. We first describe the preprocessing of finger vein image. Then, different level features are extracted, including pixel level features and super-pixel level feature, and each matching score are computed. After these steps, the scores are fused by the weighted average strategy. Finally, the fused scores are used to make the final decision. Fig.1. shows the block diagram of our proposed method.

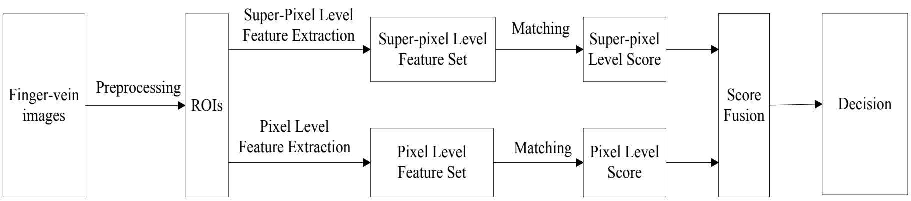

Fig. 1. The block diagram of the proposed finger vein recognition method

2.1 Preprocessing

Usually, the captured finger-vein images have many problems such as low contrast, non-uniformed illumination and background clutter, thus preprocessing is necessary for feature extraction and matching. The preprocessing we used mainly includes image gray processing, ROI extraction, size and gray normalization.

Image gray processing: we transform the original 24-bit color image with a size of 320×240 (as shown in Figure 2(a)) to an 8-bit gray image to reduce the computational complexity based on the gray-scale equation.

ROI extraction: the width and height of the finger region can be obtained based on the maximum and minimum abscissa values of the finger profile. A rectangle region can be captured based on the width and height (as shown in Figure 2(b)).

Size and gray normalization: we use the bilinear interpolation for size normalization, and the size of the normalized ROI is set to be 96 × 64. In order to extract efficient features, gray normalization is used to obtain a uniform gray distribution (as shown in Figure 2(c)).

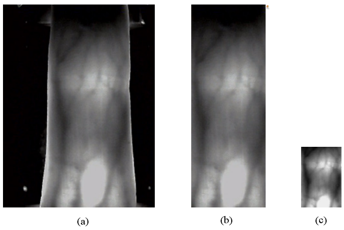

Fig. 2. Example of processing

2.2 Feature Extraction and Matching

A. Pixel Level Features Extraction

In order to prove that the super-pixel level feature is general, we respectively fuse it with three kinds of pixel-level features, including LBP feature representing the whole image information, pattern structure (PS) feature denoting the vein pattern and minutiae (M) feature with the minutiae information.

LBP Feature

The LBP operator is an ordered set of binary values determined by comparing a pixel value and values of its neighboring pixels. We use LBP operator [14] to extract a finger vein binary codes. And then transform the binary codes into decimal number as LBP feature. Lastly we adopt the Euclidean distance to measure dissimilarities between two LBP features.

PS Feature

The PS feature can be defined as a topology structure of the binary finger vein pattern image, as shown in Fig. 3.

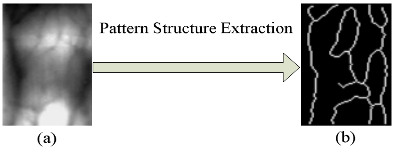

Fig. 3. Extracted PS feature

We adopt the following matching method to measure the similarity of two PS features, as shown in Equation (1-2).

$$D(L,K) = \frac{2}{N_L+N_k} \times \sum_{i=1}^{M}\sum_{j=1}^{N}[L(i,j) \cap K(i,j)] \quad (1)$$

$$PS_{Score} = max_{0<s<p1,0<t<p2} D_n(s,t) \quad (2)$$

where, $\cap$ is a Boolean exclusive-AND operator, $M \times N$ is the size of the image.N_L and N_k denote the number of points in finger-vein image L and K respectively.

M Feature

The minutiae consist of cross points and extreme points. For a 3×3 block shown in Fig.4, if the value of p_0 is 1, and N_{trans} is greater or equal to 6, which demotes the alternate switching frequency from 0 to 1, the point p_0 is seen as the cross point, and if the N_{trans} is equal to 2, the point p_0 is regarded as the extreme point. A modified Hausdorff distance (MHD) [11] is adopted to get the M-Score between two point sets.

p_8	p_2	p_3
p_7	p_0	p_4
p_6	p_6	p_5

Fig. 4. Example of a 3×3 block

B. Super-pixel (SP) Feature Extraction

We introduce the effective algorithm SLIC proposed by [13], to produce super-pixels, which clusters pixels in the combined five-dimensional color and image plane space to efficiently generate compact, nearly uniform super-pixels. SLIC method produces super-pixels at a lower computational cost while achieving a good segmentation quality, as shown in Fig. 5.

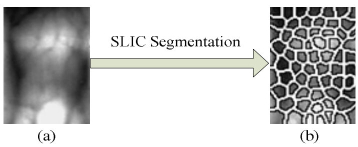

Fig. 5. Image segmented using SLIC into super-pixels of (approximate) size 65

SP feature is extracted from the super-pixel image, as shown in Fig. 4(b). In this paper, we extract three super-pixel level features to constitute a three dimensional feature vector, which are histogram feature, gradient feature and entropy feature. The extractions of these features are as follows:

Histogram feature: we extract the histograms of each super-pixel block firstly, then, a histogram feature vector is generated by these histograms, which will be the first dimension of the SP feature.

Gradient feature: in the first place, the gradient values of each super-pixel block are extracted, next a gradient feature vector is generated by these values, that is the second dimension of the SP feature.

Entropy feature: we first extract the entropies of each super-pixel block, next an entropy feature vector is generated, which is the third dimension of the SP feature.

2.3 Score-Level Fusion

A number of matching scores had been produced in Section 2.2. Since the scores are heterogeneous, score normalization is needed to transform these scores into a common domain [0,1] to combining them. The different features extracted from the same pattern have different effects on recognition, so the scores are fused by the weighted average strategy based on the equation *(3)* and the EER is minimized to obtain the optimum weights W_i. The equation *(3)* is defined as follow.

$$Matching\ Score = \sum_{i=1}^{2} Score(Feature_i) \times W_i \tag{3}$$

3 Experimental Results and Analysis

3.1 Database

The experiments were conducted using the self-built finger vein database which was collected from 34 individuals. Each individual is asked to provide 30 images for each of the index and middle fingers on the both hands. So our database includes 4,080 (34 × 4 × 30) finger vein images.

3.2 The Experiment Settings

In this work, two experiments are designed to evaluate the proposed method: (a) Experiment 1 is performed to evaluate the performance of the fusion of super-pixel level features with LBP feature, PS feature and M feature respectively. (b) Experiment 2 compares the fusion of pixel level features and the fusion of super-pixel level and pixel level features.

We perform the experiments in verification and identification mode respectively. In verification mode, we get 59,160 ($136 \times C_{30}^{2}$) intra-class matching results and 82,620

(68×3×135× 3) interclass matching results. The EER (equal error rate) is used to evaluate the verification performance .Closed-set identification experiments were also conducted. We use the first 10 finger vein images of each class as test samples and randomly select one image from the remaining 20 samples as templates. So, there are 136 templates and 1,360 (130 × 10) probes in total. We use the recognition rate to evaluate the identification performance.

3.3 Experiment 1

Firstly, we compare the fusion method of the SP feature and the LBP feature with the single SP feature and the single LBP feature separately. The ROC curves are shown in Fig. 6(a).The rank one recognition rate and the lowest rank of perfect recognition (i.e., the lowest rank when the recognition rate reaches 100%) are listed in Table 1(n.1).From the ROC and the Table1 we can see that the fusion method performs better than the single LBP-based method and the SP-based method.

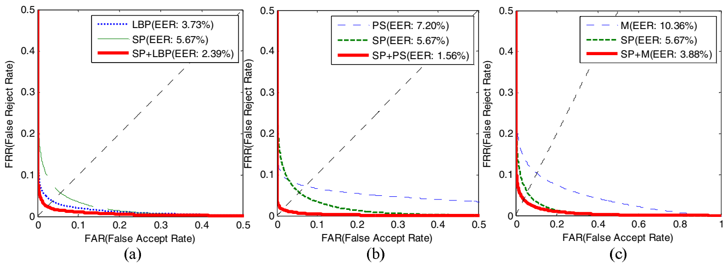

Fig. 6. The ROC curves in the verification mode

Table 1. Identification performance by different methods

n.1	Recognition Rate	n.2	Recognition Rate	n.3	Recognition Rate
LBP	96.91%	PS	92.21%	M	87.72%
SP	89.78%	SP	89.78%	SP	89.78%
Fusion	98.01%	Fusion	95.66%	Fusion	95.29%

Secondly, we compare the fusion method of the SP feature and the PS feature with the single SP feature and the single LBP feature separately. Their ROC curves are shown in Fig. 6 (b). And the rank one recognition rate and the lowest rank of perfect recognition are listed in Table 1(n.2). From the experimental results we can see that the performance of the fusion method is much better than that of the single PS-based method and the SP-based method.

Thirdly, we compare the fusion method of the SP level feature and the M feature with the single minutiae feature and the single SP feature. The ROC curves are shown in Fig. 6 (c). The rank one recognition rate and the lowest rank of perfect recognition are listed in Table 1(n.3). From the experimental results we can see that the fusion method is much better than that of the single M-based method and the SP-based method.

3.4 Experiment 2

In this experiment, we evaluate the performance of the fusions of two random pixel level features, and compare the proposed fusion method and the fusion in pixel level. Fig.6 shows the comparison between pixel level fusion method and single pixel level feature base on the EER conditions. The verification performance by different methods is listed in Table 2. From Fig.7 and Table 2, we can see that among these methods, the first two fusion methods give higher performance result in recognition, however, the third is lower than the single feature and it is apparent that the fusion method based on the pixel feature and the super-pixel level features, not only has good performance than methods based single feature, but also outperforms the pixel-pixel fusion methods.

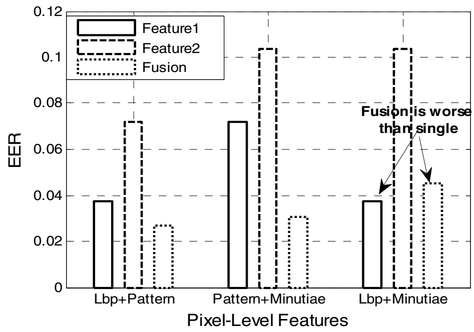

Fig. 7. Comparison of EER between fusion methods and the single-feature methods

Table 2. EER of different fusion methods

LBP(0.0373)+		PS(0.0720)+		M(0.1036)+	
LBP+M	0.0453	PS+M	0.0354	M+LBP	0.0453
LBP+PS	0.0270	PS+ LBP	0.0270	M+PS	0.0354
LBP+SP	0.0239	PS+SP	0.0156	M+SP	0.0348

4 Conclusions and Future Work

In this paper, we propose a novel finger-vein recognition method based on the score-level fusion of pixel and super-pixel level feature. The experimental results show the superior performance of our method in comparison with the methods based single feature as well as the fusions in pixel level. The advantages of our method can be summarized as follows: (1) Pixel level feature can describe the details of the finger-vein image. (2) Super-pixel level feature can descript the rough feature of the image and it is highly robust to the pixel noise. (3) The features in two level have great complementary, so their fusion can improve the recognition performance greatly.

In the future, the research is planned to focus on two aspects: one is the exploration of the super-pixel segmentation algorithm that is most suitable for the finger-vein; the other is the choice of the effective and complementary super-pixel level features of finger-vein image.

Acknowledgments. This work is supported by National Natural Science Foundation of China under Grant No.61173069 and 61070097, Program for New Century Excellent Talents in University of Ministry of Education of China and Shandong Natural Science Funds for Distinguished Young Scholar. The authors would like to thank the anonymous reviewers for their helpful suggestions.

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