Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.12785/amis/080653

Finger Vein Recognition based on Personalized Discriminative Bit Map

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Received: 23 Nov. 2013, Revised: 21 Feb. 2014, Accepted: 22 Feb. 2014
Published online: 1 Nov. 2014

Abstract: Finger vein recognition is a promising biometric recognition due to its some advantages. For a finger vein recognition system, feature extraction is a critical step for the final recognition. In our previous work, we proposed Personalized Best Bit Map(PBBM) which selected the stable bits from LBP. Although PBBM achieve a better performance, it still contains some useless bits for recognition. In this paper, we propose Personalized Discriminative Bit Map(PDBM) which select much more discriminative bits from PBBM. The bits of PDMB are more discriminative and more effective for the final recognition. In addition, compared with PBBM, the number of bits for matching is reduced, so PDBM can also reduce the computation complexity. Experimental results show that PDBM achieves not only better performance, but also consumes less time for matching.

Keywords: finger vein recognition; Personalized Best Bit Map; local binary pattern; Personalized Discriminative Bit Map

1 Introduction

In the recent years, biometric recognition has received attentions of lots of researchers because it is difficult to misplace, forge than traditional identification methods. Biometric recognition refers to the use of distinctive physiological and behavioral characteristics (e.g., fingerprints [1], face [2, 3], iris [4, 5], gait [6], signature [7]), called biometric identifiers or simply biometrics, for automatically recognizing a person [8, 9].

Finger vein recognition is a promising biometric recognition due to its some advantages [10]: (1) non-contact: finger vein patterns are not influenced by surface conditions, so this characteristic makes it more acceptable for the users (2) live-body identification: finger vein patterns can only be identified on a live body without fake finger attacks in fingerprint recognition; (3) high security: finger vein patterns are located inside the fingers that are difficult to forge and (4) small device size: most finger vein capturing devices are smaller in size as compared to palm vein based verification devices. Therefore, personalized identification with finger vein patterns has received lots of research interest [11–15], and [16–18] introduced several commercial products.

Finger vein recognition involves four main steps: image capture, pre-processing, feature extraction and matching. In the image capture step, an infrared LED light of 760C1,000 nm is able to pass through the skin of the finger while the hemoglobin in the vein can absorb the infrared light [19], and then the finger vein patterns are captured by an infrared LED and CCD camera. Image enhancement method [20–22] are proposed for pre-processing, which are used to improve the quality of images for better performance. Because the pre-processing procedure is not the core point of this paper, a detailed description of these approaches is not provided.

Feature extraction is the critical step in the finger vein recognition process. [23–30] extract the geometric shape, topological structure or other information of the segmented blood vessel network. Although the better performances are reported in their work, the performances of these features are depended on the vein pattern segmentation. [31, 32] proposed a new finger vein recognition method based on the binary pattern such as LLBP, LBP and LDP and achieve promising performance respectively. To degrade the noisy bit and obtain the stable bit from these binary patterns, [32] proposed

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PBBM which is rooted on LBP and achieve promising performance. However, for PBBM, only the stable bits of a subject are selected, the importance of discriminative bits between the different subjects is ignored. In other words, for a subject, not all the stable bits are useful for distinguishing this subject from other subjects, the common stable bits which different subjects shared are not only useless for recognition but also increase the complexity of the feature. So, selecting discriminative bits among subjects not only makes the feature more discriminative but also reduces the matching time consuming. Although [34] proposed PWM to assign weight for every stable bit, it still considered the different importance of the stable bits of a same subject, and ignoring the ability of stable bits for distinguishing different subjects.

In this paper, we propose a finger vein recognition method based on a personalized discriminative bit map (PDBM). We selected the personalized discriminative bits from the stable bits generated based on PBBM, which can degrade the useless bits for recognition. Extensive experiments show that PDBM can significantly improve recognition performance and have less time consuming.

The rest of this paper is organized as follows: Section 2 introduces the definition of the PDBM. Section 3 describes the framework of finger vein recognition based on PDBM. Section 4 reports the experimental results to verify the proposed method. Finally, Section 5 concludes this paper.

2 Personalized Discriminate Bit Map Based Finger Vein Recognition

[32] proposed a finger vein recognition method , which extracted binary pattern such as LBP based on the finger vein image without vein segmentation. Due to the low quality of finger vein image, the feature extracted by [32] may contain some noise. [33] proposed PBBM which was rooted on LBP, and select the stable bits(we called these bits as best bits) from the binary bits for the final matching, this method can degrade the noise to some degree and achieve better performance.

Figure 1 can simply describe the idea of PBBM .This figure gives an example of Binary Codes of six samples from a certain individual. Apparently, bit0, bit2, bit3, bit5, bit6 are very consistent, the values of bit1 are mostly 1s, the values of bit7 are mainly 0s, and bit4 has interlaced 1s and 0s values. As proposed in [33], in an ideal situation, if many samples are captured from the same individual, the values of each bit in same location of LBPCodes should be all identical without considering the interference factors such as displacement and rotation. If a bit has different value, it may be a noisy bit, which may have a negative effect on recognition performance, and the consistent bits through samples from same individual may be the stable feature which reflects the characteristics of the individual , these bits should be selected for the final recognition. Based on this idea, in figure 1,bit0, bit2, bit3, bit5, bit6 are stable, and the other bits may be the noise. In this example, we use bit0, bit2, bit3, bit5, bit6 as the best bits for the final recognition, which may result in better performance in recognition and time consumption than comparing all bits.

bit #	0	1	2	3	4	5	6	7
BinaryCode of Sample 1	0	1	1	1	0	0	1	0
BinaryCode of Sample 2	0	1	1	1	0	0	1	0
BinaryCode of Sample 3	0	0	1	1	1	0	1	0
BinaryCode of Sample 4	0	1	1	1	0	0	1	1
BinaryCode of Sample 5	0	1	1	1	0	0	1	1
BinaryCode of Sample 6	0	1	1	1	1	0	1	0

Figure 1 Examples of binary code.

Although PBBM can select the stable bits which are very useful for representing the subject, not all the stable bits are useful for distinguishing this subject from other subjects. Figure 2 shows the best bits of six individual. From Figure 2, we can see that the value of the bit0 and bit2 are all same for all the subjects, the two bits are less discriminative for the recognition. The value of bit5 of subject1 is different from other subjects, this bit can well distinguished subject1 from other subjects. So, for subject 1,only using the best bits such as bit5 which is more discriminative for matching can not only make the feature more discriminative but also can reduce the time consuming of matching. Because these best bits such as bit5 of subject1 is more discriminative, and these best bits are different from subject to subject, we call these best bits of a subject as Personalized Discriminative Bit Map(PDBM).

In this paper, a simple method is used for selecting PDBM. For subject *i*, we firstly obtain BBMi (PBBM of subject *i*), we compare each best bit of BBMi and BBM of other subjects. We use the Equation 1 to represent the discrimination of a best bit of subject *i*.

$$\begin{cases} label(j) = BBi \wedge BBj \\ DL = SUM(label) \\ R = DL/N \end{cases} \tag{1}$$

In Equation 1, BBi is a best bit of BBMi. BBj is a best bit of BBMj,whose location is the same as BBi. DL denote that how many subjects have the same value as BBi in the same location of BBi . N is the number of the subjects. We will give a threshold T, if the variable R in the equation(1) is lower than T, this best bit is a discriminative bit and used for the final matching. The

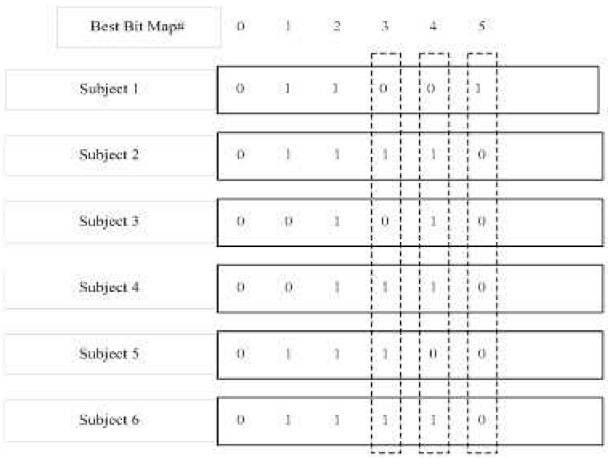

Figure 2 Examples of PDBM.

pseudo-code of generating PDBM of subjecti is summarized in GetPDBM Algorithm.

GetPDBM Algorithm

INPUT: BBM1 of Subject 1, BBM2 of Subject2,.., BBMN of SubjectN
//The number of the subject is N, the size of BBM is as same as the size of LBPCode. If the bit is the best bit ,the value of this bit is 0 or 1,or the value of this bit is 2.Only the best bit is used for the final matching.
OUTPUT: DBMi of Subject i.
Algorithm:
//row and column are the number of the row and column of the image respectively

```
for n=1 to row of the BMP
    for m=1tocolumn of the BMP do
      if(BBMi(n,m)≠ 2)
        for K=1:N
          lab(K)=BBMi(n,m)∧BBMK(n,m);
        end
      if(SUM(lab)≥ T)      // T is a threshold given by us
        PDBMi(n,m)=2;
      else
        PDBMi(n,m)=BBMi(n,m);
      end
      end
    end
end
```

In Figure 2, we set the threshold T as 0.2, for subject1,R are 1,2/3,1,1/3,1/3,1/6 for bit0,bit1,bit2,bit3,bit4 and bit5 respectively, bit5 is the discriminative bit for subject1 according to the Algorithm mentioned above.

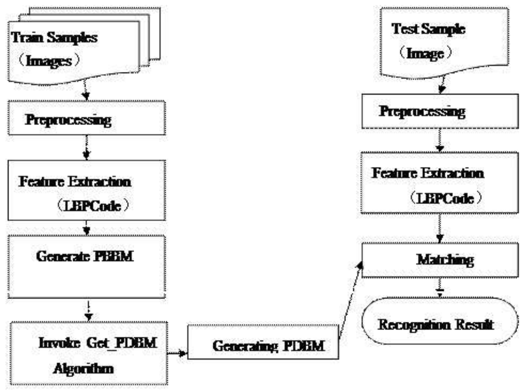

Figure 3 Framework of the proposed method.

After obtaining PDBM of a subject, we calculate the matching score between an image and PDBM of a subject to decide if this image belong to this subject.The matching score is estimated as follows:

$$Matching\ Score = 1 - \frac{\|PDBM \otimes LBPCode\|}{Length\ of\ PDBM} \quad (2)$$

In Equation 2,$\otimes$ is a Boolean exclusive-OR operator between two binary patterns; the length of PDBM is the numbers of the Best Bit of a certain individual. Note that not every bit of LBPCode, but only the bits which have the same location as in the PDBM are operated on by the Boolean exclusive-OR operator.

3 The Proposed Method

Based on the mentioned PDBM, we propose a finger vein recognition method which mainly involves two stages: a training stage and a recognition stage. The training stage aims to generate the PDBM for each subject, which includes preprocessing, feature extraction, PBBM generation and finally generating the PDBM using certain number of training samples. In the recognition stage, we first preprocess the test sample, and then extract the corresponding binary code, and next compute the similarity between this test sample and the PDBM template of a certain subject in the enrolled database, finally obtain a recognition result with a given threshold. The framework of the proposed method is demonstrated in Figure 3.

3.1 Preprocessing

For obtaining efficient features, image preprocessing is necessary. We use the preprocessing method proposed in [33]. The preprocessing mainly includes image gray processing, ROI extraction, size normalization and gray normalization.

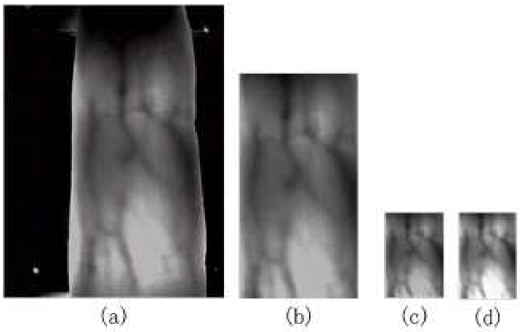

Figure 4 Examples of preprocessing. (a) Original image. (b) ROI extraction. (c) Size normalization. (d) Gray normalization.

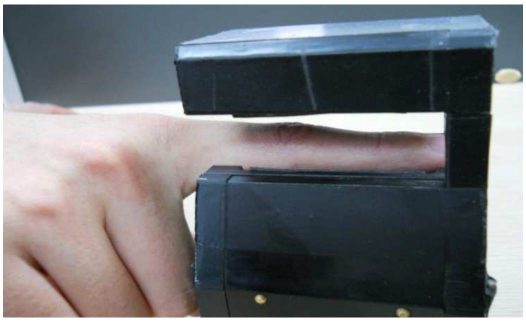

Figure 5 Performance of different methods in the verification mode.

Image gray processing: the original image (an example is shown in Figure 4(a)) captured by the device in this paper is a 24-bit color image with a size of 320 $\times$ 240. In order to reduce the computational complexity, we transform the original image to an 8-bit gray image based on the gray-scale equation Y = R $\times$0.299 + G $\times$ 0.588 + B $\times$ 0.114, where R, G, and B denote the value of red, green, and blue primaries.

ROI extraction: As the background of finger vein region might include noise, we employ an edge-detection method to segment the finger vein region from the gray-scale image. A Sobel operator with a 3$\times$3 mask $\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$ is used for detecting the edges of fingers. The width of the finger region can be obtained based on the maximum and minimum abscissa values of the finger profile, and the height of the finger region is similarly detected. A rectangle region can be captured based on the width and height. This rectangle region is called ROI (as shown in Figure 4(b)).

Size normalization: The size of the ROI is different from image to image due to personal factors such as different finger size and changing location. Therefore it is necessary to normalize the ROI region to the same size before feature extraction. We use the bilinear interpolation for size normalization in this paper, and the size of the normalized ROI is set to be 96 $\times$ 64 (as show in Figure 4(c)).

Gray normalization: In order to extract efficient features, gray normalization is used to obtain a uniform gray distribution (as shown in Figure 4(d)). In this paper, we use:

$$p(i,j) = \frac{p'(i,j) - G_1}{G_2 - G_1} \tag{3}$$

where p'(i,j) is the gray value of pixel (i, j) of original image, G_1 is the minimum gray value of original image, and G_2 is the maximum gray value of original image.

3.2 Template training

After pre-processing, we use the method as proposed in [32] to extract LBPcode for the training samples of each subject, and then train PBBM for each subject using the method proposed in [33],and based on PBBM of each subject, we obtain the PDBM template of each subject.

4 Experimental Results and Analysis

4.1 The Experimental Database

The experiments were conducted using our finger vein image database. Our finger vein image database consists of 4,080 images acquired from 34 volunteers (20 males and 14 females) who are students, professors and staff at our school. To acquire these natural finger vein images. The finger vein images were acquired in two separate sessions with an interval of 20 days. The age of the volunteers was between 19 and 48 years. Each volunteer provides four fingers, which are left index, left middle, right index and right middle fingers, each of which contributes 30 images. In the first session, 20 images of each subject are captured, and the 10 images of each subject in the second session. We treat a finger as a subject. The capture device was manufactured by the Joint Lab for Intelligent Computing and Intelligent System of Wuhan University, China. The capture device mainly consists of a near-infrared light source, lens, light filter, and image capture equipment. Vein patterns can be viewed through an image sensor which is sensitive to near-infrared light (wavelengths between 700 and 1,000 nanometers), because near-infrared light passes through human body tissues and is blocked by pigments such as hemoglobin or melanin. A groove in the shell of the device is used to guide the finger orientation, and the capture device is shown in Figure 5.

Several finger vein images in our database are shown in Figure 6. The first two images in each row are from the first session, and the last two in each row are from the second session. They are captured by rotating the finger

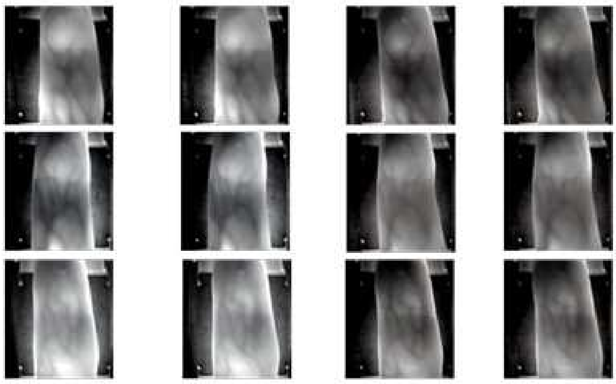

Figure 6 Performance of different methods in the verification mode.

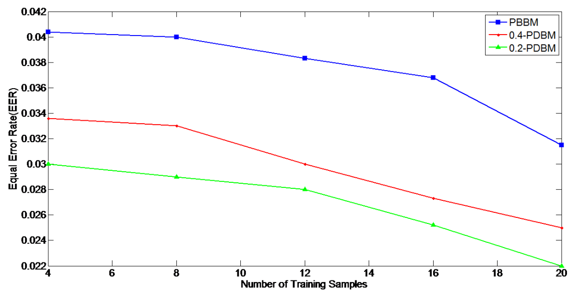

Figure 7 Performance of different methods in the verification mode.

different angles. The low spatial resolution of the image is 320×240, after ROI extraction and Size Normalization; the size of the region used for feature extraction is reduced to 96×64.

4.2 The Experimental Settings

All the experiments are implemented in MATLAB, and conducted on a PC with 2.4G CPU and 4G memory. In order to verify the proposed method comprehensively, we design three experiments: (a) in Experiment 1, we compare the performances of the PDBM and PBBM [33] in verification mode. (b) Experiment 2 reports the recognition result of the PDBM and PBBM [33] in identification mode. (d) Experiment 3 discusses the computation time of the PDBM and PBBM [33]. We use EER (Equal Error Rate) in verification mode and recognition rate in identification mode as the performance measure respectively. In the identification mode, we want to identify input finger vein which class it belongs to. We construct the PDBM template for every class, there are 136 class template in total. A test image was matched with all the class template according to Equation 2. If Matching Score(f,Tj) = max (Matching Score(f,Ti)(i = 1, 2, ... , 136)), then this test image goes to the jth class. We can compare the prediction label and its truth label to judge if this test image is classified correctly. For N test images, we assume u test images are classified correctly, and then the recognition rate can be calculated as $\frac{u}{N}$.

Experiment 1

In the experiments, we use 4,8,12,16,20 samples of each class in the database to generate the PDBM respectively and the remain ten as testing samples.For each test image, we match this test image and all 136 subjects. Consequently, there are 1360 $\times(136 \times 10)$ intra-class matching and 183600 $\times(136 \times 135 \times 10)$ interclass matches in total. To obtain PDBM, the threshold T is set as 0.2 and 0.4 respectively in the propose algorithm, the corresponding PDBM is called as 0.2-PDBM and 0.4-PDBM respectively. In this experiment, we evaluate the performance by the equal error rate (EER), which is suited for measuring the overall performance of biometrics systems. The performance of different methods is shown in Figure 7.

From Figure 7, we can see that EER is reduced with the number of training samples increasing. This is because that the number of the training samples is larger, the template can reflect more characteristics of the subject and more useful bits can be selected for the final matching. In addition, the performance of PDBM is better than PBBM, the reason is that PDBM select more discriminative bits from the best bits, which is more effective for the final matching. The performance of 0.2-PDBM is better than 0.4-PDBM. Because the threshold is smaller, the selected bit is more discriminative and the corresponding PDBM is more effective.

Experiment 2

The experiments of identification are also reported. We generate PDBM and the test samples by using the same method as Experiment 1. For each test sample, we calculate the similarity between this sample and the PDBM template of 136 subjects, this sample is classified into the class whose PDBM is the most similar with this sample. We calculate the recognition rate by comparing the consistence of the predict label and ground truth of each test sample. The performance of different method is shown in Figure 8.

From Figure 8, we can see that Recognition rate is increased with the number of training samples increasing. This is because that more effective template can be obtained by more training samples. In addition, the performance of PDBM is better than PBBM, the reason is that the bits for matching of PDBM are more

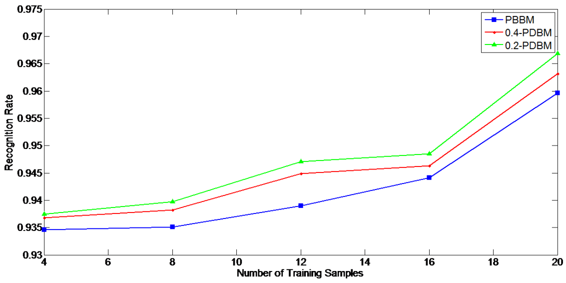

Figure 8 Performance of different methods in the identification mode.

discriminative.The performance of 0.2-PDBM is better than 0.4-PDBM. Because the threshold is smaller, more discriminative bits can be selected to make PDBM more effective for the final matching.

Experiment 3

In this experiment, to demonstrate the efficiency of PDBM, we compare matching time consuming of different methods. The PDBM template is trained by using 12 training samples for each individual. The time consuming are shown in Table 1.

Table 1: Comparison for linear kernel

Method	Matching Time Consuming
PBBM	17ms
0.4-PDBM	10ms
0.2-PDBM	8ms

From Table 1, we can see that the time consuming of PDBM is less than PBBM, 0.2-PDBM is less than 0.4-PDBM. This is because that PDBM select more discriminative bits from the best bits, the number of bits of PDBM for matching is much smaller than PBBM. Because the threshold is smaller, 0.2-PDBM select less bit but discriminative than 0.4-PDBM, 0.2-PDBM have less time consuming than 0.4-PDBM.

5 Conclusions

This paper presents a finger vein recognition method based on PDBM. PDBM can be seen as an improvement of PBBM, compared with PBBM,the advantages of PDBM can be summarized as follows: (1) PDBM can effectively select more discriminative best bits which are more effective for the final matching.(2)The number of discriminative bits in PDBM is reduced, so the computation complexity is reduced. In this paper, we only use the threshold for selecting the discriminative bits, designing more powerful method for selecting more discriminative bits will be the focus of our future work.

Acknowledgement

The work is supported by National Science Foundation of China under Grant No. 61070097, 61173069, Program for New Century Excellent Talents in University of Ministry of Education of China NCET-11-0315, Shandong Natural Science Funds for Distinguished Young Scholar JQ201316, Program of Shandong Province Higher Educational Science and Technology No.J13LN23.The authors would particularly like to thank the anonymous reviewers for their helpful suggestions.

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