Multi-instance Finger Vein Recognition Using Local Hybrid Binary Gradient Contour

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***Abstract*—In a finger vein authentication system, the image of a finger acquired for recognition always suffers from noises due to imperfect acquisition device, signal distortion, and variability of individual physical appearance over time. To improve the system performance, we propose a multi-instances finger vein recognition using feature level fusion. Local Hybrid Binary Gradient Contour (LHBGC) is proposed as the finger texture descriptor and SVM is used for classification. Experiments are conducted using the Shandong finger vein database (SDUMLA-HMT) and also the University Sains Malaysia finger vein database (FV-USM). Experimental results show a significant increase in performance accuracy when more than one fingers are combined, with an EER as low as 0.0038%**

Keywords—finger vein; LHBGC; BGC; multi-instance

I. INTRODUCTION

Finger vein recognition is a personal identification system using vascular vein pattern inside the finger. Recently, finger vein recognition has become popular due to the uniqueness of the vein pattern such as stability and its ability to remain unchanged as people age [1]. Finger vein biometrics has some advantages over other biometrics like finger print, face, and palm print. As compared with hand biometric such as finger print, finger vein is less susceptible to forgery or theft and it is also unaffected by skin condition (sweat or dryness) due to the fact that the veins are reside inside the body. Besides, the process of vein image acquisition does not require contact between imaging device and the finger, thus ensuring no bad effect on sanitary and convenience for user. In addition, the size of the finger vein sensor is relatively small as compared to the other hand-based biometrics such as hand and palm vein sensors that are designed to capture the whole hand.

However, as reported in the previous research [1][2], a finger vein system always suffers from noisy data or low quality images that leads to a significant reduction of recognition accuracy. Some of the noises are caused by imperfect acquisition device, and some are caused by human physical appearance and conditions such as varying thickness of finger bones and muscles, and fluctuation in the amount of blood in vein caused by change in temperature, and also error in interaction between users and the acquisition device (such as differences in finger poses).

Multi-modal biometrics that fuses multiple evidences from the same individual are believed to be able to address the problems of noises in data. Moreover, this solution is also robust against spoof attacks since the attacker is required to spoof multiple biometric data at the same time. The use of multi-modal biometrics can also provide sufficient population coverage, and solve the problem of inter-class similarities (such as the faces from identical twin). Multi-modal biometrics consists of several integration scenarios including multi-sensors, multi-samples, multi-biometric traits, multi-instances, and multi-algorithms [3]. Among these scenarios, multi-instances and multi-samples appear to be the most inexpensive way to obtain multiple biometric evidences of a single biometrics without the need of multiple sensors and additional feature extraction algorithms. Furthermore, the multi-instance approach appears as a better alternative when a single biometric trait could not yield reasonable amount of discriminant information. When a biometric trait is not discriminative enough, there is of little use to generate multiple samples of the biometric trait as this will not increase the discriminative power of the biometric features. On the other hand, having multiple instances will help as it expands the richness/diversity of the feature set, In particular, multi-instance vein could compensate the insufficiency of unimodal finger print due to the changes of vein patterns due to the fluctuation of the blood flow in a finger caused by changes in temperature.

Yang et al. proposed a multi-instances biometrics using score level fusion to improve the recognition accuracy of the low quality finger vein images. LBP was proposed as the finger vein feature extractor, and the matching score was obtained after matching with the templates in database. Then the matching scores were fused using sum-rule and triangular-norms (t-norm) were adopted to integrate the scores. The best result they obtained was 0.83% EER with the use of three fingers fusion and Frank t-norm method. Ong et al [5], proposed a multi-instances finger vein based on the integration of the minutiae points from two fingers. Unified minutiae alignment and Genetic algorithm pruning approach was used to enhance the minutiae points and remove the redundant minutiae points, and *k*-modified Hausdorff distance was used as the distance measure. The best recognition rate of up to 99.7% had been achieved by the combination of the minutiae points from three fingers.

Other than finger vein, Uhl and Wild [6] proposed hybrid finger recognition of multi-instances fingerprint and eigenfinger features using weighted score level fusion method. Minutiae points of the fingerprint were extracted using NIST's MINDTCT, and NIST's Bozorth's was used as the minutiae features matcher. Eigenfinger was a set of eigenvectors obtained from the covariance matrix of the probability distribution over high-dimensional space, and Manhattan distance was used as the eigenfinger matcher. They achieved EERs of 0.11% and 1.20% for separate matching of multi-instances fingerprint and eigenfinger scores using weighted sum rules, respectively. The lowest error rate 0.08% EER was achieved by using product rules fusion of minutiae and eigenfinger scores.

Rattani et al [7] proposed feature level fusion on multi-modal and multi-unit features. Multi-modal was achieved by fusion of face and iris while multi-units was accomplished by fusion of the right and left irises. In each sources, SIFT features was computed and each SIFT features were concatenated into a super feature vector for classification. The proposed method achieved EER around 0.05%.

Guru [8] proposed a multi-instances finger knuckle prints fused at feature level. Zernick moment was first extracted from the finger knuckles and the feature sets were fused by concatenation rule after feature reduction using principal component analysis (PCA). In their experiment, the best recognition rate obtained was 99.091% when using 80% of the data for training. Another multi-instances on iris recognition system was proposed by Mehrotra et al. [9], with fusion at the score level. The method was able to achieve an improvement of up to 4% by using Relevance Vector Machine (RVM) as the score level fusion strategy.

It is evident that biometric data can be fused at either sensor level, feature level, score level, or decision level. A biometric system that performs fusion at the early stage is believed to be more effective because it contains more information than those that perform integration at the later stage. Hence, in this work we propose a feature level fusion strategy for the integration of multi-instances of finger vein using texture-based feature extraction method. Texture-based finger vein feature extraction method such as LBP has been proposed in [4] and [2] where the methods were able to achieve high recognition accuracy. As compared to the other finger vein feature extraction methods such as vein lines and minutiae extraction, the texture-based methods have advantages of fast computational time, robust against irregular shading and saturation factors that might cause error in vein lines and minutiae extraction [2]. In this work, Local Hybrid Binary Gradient Contour (LHBGC) is adopted as the texture descriptor for the finger vein image. Binary Gradient Contour (BGC) is a variation of LBP. However, unlike LBP which performs thresholding of the center pixel with it neighbourhoods, BGC performs pairwise comparison of the adjacent pixel intensity value and traces along the periphery of 3x3 neighbourhoods. From the result reported by [10], the method has better texture discrimination capability than LBP. The proposed LHBGC is a locally computed histogram of the texture and magnitude codes of BGC.

The remainder of the paper is organized as follows. Section 2 presents the proposed solution. Section 3 presents the experimental setup and Section 4 concludes the work.

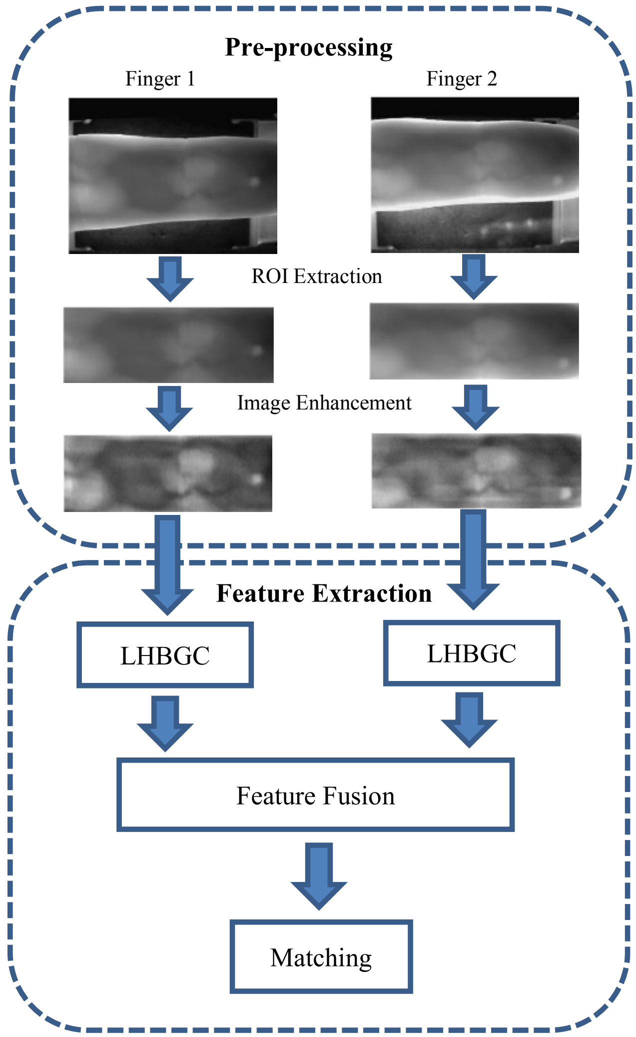

Figure 1. Block diagram of proposed method

II. PROPOSED METHOD

A. Pre-processing

The pre-processing stage includes ROI extraction, image segmentation, and image enhancement. During the ROI extraction process, the finger region is first segmented with the method proposed by [2]. Then the finger region is cropped to separate the region from the background for further process. Finally, the adaptive histogram equalizer is used to enhance the local contrast of the vein image so that the vein line looks more visible.

B. Feature Extraction

Local Hybrid Binary Gradient Contour (LHBGC) is adopted to extract the finger vein features without the extraction of the vein lines. The implementation is simple and is robust against irregular shadings and saturation factors. LHBGC is the variant of BGC operator proposed by [10]. BGC operator is a texture descriptor that performs pairwise comparison of adjacent pixel intensity value and traces along the periphery of 3x3 neighbourhoods. Figure 2a shows the computation of the original BGC operator.

LHBGC consists of both magnitude and texture components, as compared to the original BGC with texture feature only. In particular, the texture component preserves much information of local difference, while the magnitude components serve as an additional discriminant information. The magnitude component can be easily extracted along the way together with the texture component. Figure 2 shows an example of the extraction of the texture and magnitude components.

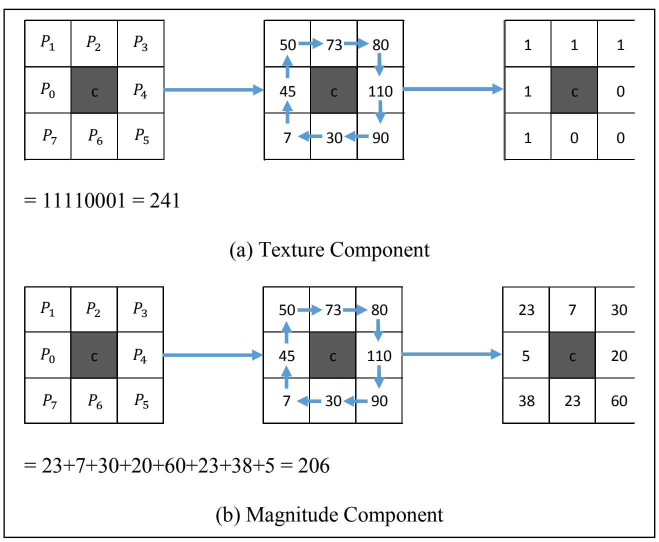

Figure 2. Hybrid Binary Gradient Contour (HBGC).

In Figure 2, $[P_0, P_1, .., P_7]$ is the adjacent pixels along the periphery of 3x3 neighbourhoods. The hybrid BGC operator is shown in equation (1), the distance from the comparison between a pair of the pixel can be denoted as d_i as shown in equation (2).

$$f\mathrm{BGC(x)} = \sum_{i=0}^{7}(d_i)2^i - 1 \tag{1}$$

$$d_i = P_i - P_{(i+1)\mathrm{mod}\ 8}, i = 0,1,..,7 \tag{2}$$

From equation (3), d_i can be decomposed into two components t_i and m_i, which represent the texture and magnitude components, respectively. The function t_i is defined in equation (4), while m_i is the absolute value of d_i. Furthermore, to obtain the texture and magnitude values, $[t_0, t_1, .., t_7]$ is converted into decimal value and the magnitude values are obtained by the summation of $[m_0, m_1, .., m_7]$.

$$d_i = t_i * m_i \ and \begin{cases} t_i \\ m_i = |d_i| \end{cases} \tag{3}$$

$$t_i = \begin{cases} 1, d_i \geq 0 \\ -1, d_i < 0 \end{cases} \tag{4}$$

After the extraction of texture and magnitude components, these values are divided equally into a set of cells with c be the number of columns and r be the number of rows. Then, the histogram is computed in each cell, and the magnitude values become the weight representation of the distribution of the texture values. The histograms count occurrences of the texture magnitude in local part of the image. Finally, the histogram is converted into vector format and concatenated with the other cells histogram vector. After the feature sets from each instance of the finger is obtained, the feature sets are fused together by concatenation into a super-vector based serial feature fusion. Figure 3 shows the pseudo-code of the local histogram approach. Figure 4 shows the overall process of LHBGC.

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Both of the texture code and magnitude components obtained is divided
into cells,
Let c be number of columns, r be number of rows, and let B be number
of histogram bins.

Cell_width = width_of_texture_code/ c;
Cell_height = height_of_texture_code/ r;
Forcell=1 to (c*r)
    For i =1 toB
    bin = (255/B)*i
        foreachtexture_value in the cell
            if the texture_value <bin
                H(i)= H(i)+magnitude_value;
            Endif
        Endforeach
    endfor
H = normalization (H);
Feature_vector((cell-1)*B+1 tocell*B)=H;
Endfor
```

Figure 3. Local histogram pseudocode.

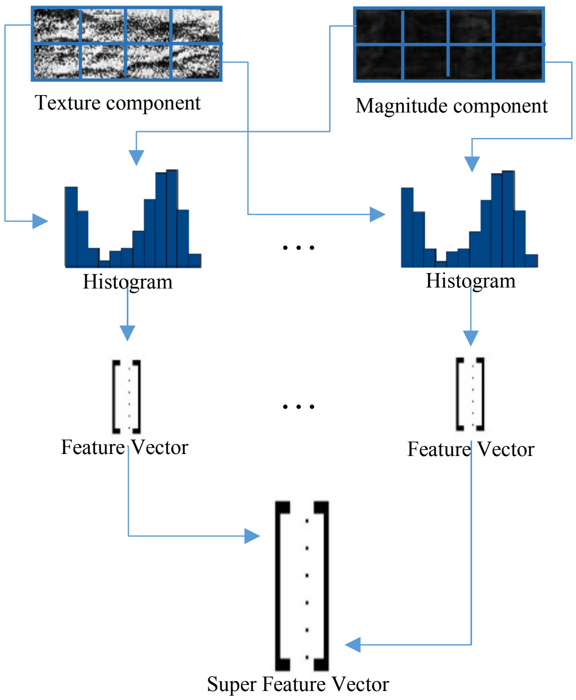

Figure 4. LHBGC

III. EXPERIMENTAL SETUP

A. Database setup

Our experiment is conducted by using two sets of publicly available database provided by Shandong University and University Sains Malaysia (USM), respectively. The Shandong Finger vein database is also known as SDUMLA-HMT (FV-SDU). The finger vein database consists of a total of 3816 finger vein images from 106 subjects. Six samples from each of the index, middle, and ring fingers of both hands are captured and resized to 320x240 pixels and stored in bmp format. The other database provided by USM (FV-USM) consists of two sessions of finger vein images. In each session, a total of 2952 finger vein images are collected from 123 subjects, with six samples from each index and middle of both hands. The images are stored in png format with image size of 640 x 480 pixel. Moreover, they also provide the extracted finger ROI images with image size of 100 x 300 pixels using their proposed algorithm [11]. SDU-RI, SDU-RM, SDU-RR indicate the right index finger, right middle finger, right ring finger of FV-SDU database, respectively. In FV-USM, the acronyms USM-RI and USM-RM indicate the right index finger and right middle finger, respectively. Due to the fact that the FV-USM database only provides the index and middle finger, the left index finger from the FV-USM database is assumed to be the ring finger in the FV-USM database. Hence, USM-RR indicates the right index finger in the FV-USM database.

In order to evaluate the performance of the multi-instances finger vein method, two experiments are conducted. The first experiment is to find a suitable parameter setting for the FV-SDU and FV-USM databases by using single-instance finger. The second experiment is a comparison of the single-instance and multi-instances performances. Support Vector Machine (SVM) is used to determine the performance of both the single and multi-instances methods. In the database each individual has six samples finger image, where four samples are selected for SVM training while the other two samples are for testing. To ensure a fair evaluation, a leave-*p*-out cross validation [12] is applied to obtain the mean EER.

B. Experiment Results

1) Experiment 1

The first experiment is conducted to find a suitable parameter setting of SDU-RI and USM-RI because different databases have different image acquisition environment. The default parameter for histogram bin is set to 15 for each database. The parameters for column, c, is set to 12, 14, 16, while the row, r, is set to 1, 2, 3 for the tests. Table I shows the summary of the test results. We observe that both of the databases achieve the best performance when c is set to 14. FV-SDU and FV-USM reach the best performance when r is set to 1 and 3, respectively.

TABLE I. RESULT OF USING DIFFERENT PARAMETER SETTING

Database	***r***	**EER (%)**		
		c		
		12	**14**	**16**
SDU-RI	**1**	0.2897	**0.2802**	0.3129
	2	0.5392	0.5253	0.5680
	3	1.1158	1.0953	1.1120
USM-RI	**1**	0.5224	0.4923	0.4175
	2	0.1800	0.1675	0.1721
	3	0.1568	**0.1546**	0.1613

2) Experiment 2

In the second experiment, we compare single-instance and multi-instances of the original BGC method and the proposed method. The best parameters for FV-SDU and FV-USM obtained from experiment 1 are used as the parameters for this experiment. The speed for running each test is also reported. The experiment was performed on a PC with processor Intel(R) Core(TM) i5-2450M CPU @ 2.50GHz. From Table II, we can conclude that the proposed method outperforms BGC. However the proposed method computational time is slightly higher than BGC. Another observation from the experiment is that the more instances being included in recognition, the better the recognition rate is. The best performance using the proposed method from FV-SDU database is 0.0359%, and FV-USM database is

0.0038% by a combination of three fingers. The best performance using the BGC method from the FV-SDU database is 1.3886%, and FV-USM database is 1.4439% by a combination of three fingers. However, computation time increases slightly as more finger instances are being included in the test.

TABLE II. RESULT OF COMPARISON PROPOSED METHOD AND BGC

Method	Database	EER (%)	Computation Time (ms)
Proposed method	SDU-RI	0.2802	0.0353
	SDU-RI + SDU-RM	0.0923	0.0713
	SDU-RI + SDU-RM + SDU-RR	0.0359	0.1086
	USM-RI	0.1546	0.0385
	USM-RI + USM-RM	0.0454	0.0827
	USM-RI + USM-RM + USM-RR	0.0038	0.1265
BGC [10]	SDU-RI	5.7783	0.0249
	SDU-RI + SDU-RM	2.1841	0.05
	SDU-RI + SDU-RM + SDU-RR	1.3886	0.0811
	USM-RI	7.478	0.0282
	USM-RI + USM-RM	3.0538	0.0547
	USM-RI + USM-RM + USM-RR	1.4439	0.0834

3) Experiment 3

In this experiment, the proposed method is compared with the other multi-instance finger vein methods mentioned in the literature. The method proposed by Ong et al. [5] and Yang et al. [4] is re-implemented. Ong et al. method extracts the minutiae points with the integration of minutiae pruning using Genetic algorithm, and fusion of minutiae points is performed at feature level. Meanwhile, Yang et al. method uses LBP as the feature extractor. The fingers are fused at score level by using sum rule. Table III shows the comparative performance.

The results show that the proposed method is better than the other methods in both databases, and also for fusion of two instances and three instances schemes. The reason for the good performance is because our proposed method utilizes hybrid information of texture and magnitude features extracted from BGC, while the method proposed by [4] only utilizes texture feature extracted from LBP. Besides, the proposed method is fused at feature level which is believed to have richer information than fusion at score level. As compared with the method proposed by [5], our proposed method uses texture information from the whole finger, and does not depend on extraction of the vein lines, so there is no possibility of missed extraction of minutiae points. The ROC for the comparison results of Table III is illustrated in Figures 5 and 6.

TABLE III. RESULT OF COMPARISON PROPOSED METHOD AND OTHER EXISTING MULTI-INSTANCE FINGER VEIN METHODS

Ref.	Method	Database	EER (%)
[5]	Minutiae Points + Feature level fusion	SDU-RI + SDU-RM	5.6186
		SDU-RI + SDU-RM + SDU-RR	3.6844
		USM-RI + USM-RM	1.1198
		USM-RI + USM-RM + USM-RR	0.4129
[4]	LBP + Score level fusion	SDU-RI + SDU-RM	4.2426
		SDU-RI + SDU-RM + SDU-RR	2.1564
		USM-RI + USM-RM	0.6931
		USM-RI + USM-RM + USM-RR	0.1965
*	Proposed method	SDU-RI + SDU-RM	0.0923
		SDU-RI + SDU-RM + SDU-RR	0.0359
		USM-RI + USM-RM	0.0454
		USM-RI + USM-RM + USM-RR	0.0038

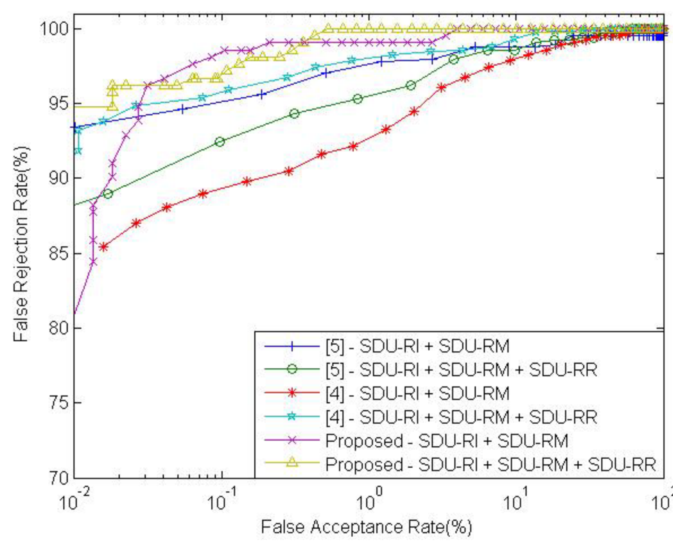

Figure 5. ROC comparison of proposed method and other method by using FV-SDU database

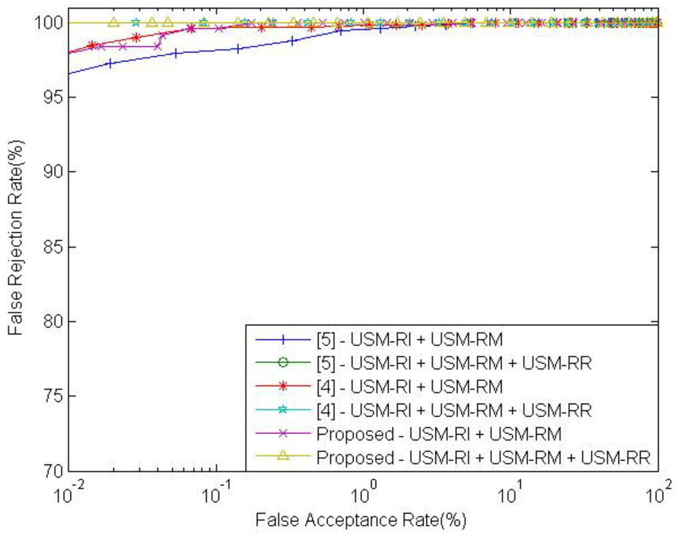

Figure 6. ROC comparison of proposed method and other method by using FV-USM database

IV. CONCLUSIONS

In this work, a multi-instance finger vein recognition system is proposed to increase the performance of the system over the problem of noises in finger image. The proposed method employs an enhanced version of BGC texture descriptor which is called LHBGC and fusion is performed at features level. The features is classified using SVM and is evaluated using the FV-SDU and FV-USM databases. The best result are EER of 0.0359% and 0.0038% using the FV-SDU and FV-USM databases, respectively by fusion of three instances.

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