Combining Left and Right Palmprint Images for Personal Identification

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Abstract-**Multibiometrics can provide higher identification accuracy than single biometrics, so it is more suitable for some real-world personal identification applications that need high-standard security. Among various biometrics technologies, palmprint identification has received much attention because of its good performance. Combining the left and right palmprint images to perform multibiometrics is easy to implement and can obtain better results. However, previous studies did not explore this issue in depth. In this paper, we proposed a novel framework to perform multibiometrics by comprehensively combining the left and right palmprint images. This framework integrated three kinds of scores generated from the left and right palmprint images to perform matching score-level fusion. The first two kinds of scores were, respectively, generated from the left and right palmprint images and can be obtained by any palmprint identification method, whereas the third kind of score was obtained using a specialized algorithm proposed in this paper. As the proposed algorithm carefully takes the nature of the left and right palmprint images into account, it can properly exploit the similarity of the left and right palmprints of the same subject. Moreover, the proposed weighted fusion scheme allowed perfect identification performance to be obtained in comparison with previous palmprint identification methods.**

Index Terms— Palmprint recognition, biometrics, multibiometrics.

I. INTRODUCTION

PALMPRINT identification is an important personal identification technology and it has attracted much attention. The palmprint contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint [1]–[8]. Various palmprint identification methods, such as coding based methods [5]–[9] and principle curve methods [10], have been proposed in past decades. In addition to these methods, subspace based methods can also perform well for palmprint identification. For example, Eigenpalm and Fisherpalm [11]–[14] are two well-known subspace based palmprint identification methods. In recent years, 2D appearance based methods such as 2D Principal Compo nent Analysis (2DPCA) [15], 2D Linear Discriminant Analysis (2DLDA) [16], and 2D Locality Pre-

serving Projection (2DLPP) [17] have also been used for palmprint recognition. Further, the Representation Based Classif-ication (RBC) method also shows good performance in palmprint identification [18]. Additionally, the Scale Invariant Feature Transform (SIFT) [19], [20], which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palmprint identification.

No single biometric technique can meet all requirements in circumstances [21]. To overcome the limitation of the unimodal biometric technique and to improve the performance of the biometric system, multimodal biometric methods are designed by using multiple biometrics or using multiple modals of the same biometric trait, which can be fused at four levels: image (sensor) level, feature level, matching score level and decision level [22]–[25]. For the image level fusion, Han et al. [26] proposed a multispectral palmprint recognition method in which the palmprint images were captured under Red, Green, Blue, and Infrared illuminations and a wavelet-based image fusion method is used for palmprint recognition. Examples of fusion at feature level include the combination of and integration of multiple biometric traits. For example, Kumar et al. [27] improved the performance of palmprint-based verification by integrating hand geometry features. In [28] and [29], the face and palmprint were integrated for personal identification. For the fusion at matching score level, various kinds of methodes are also proposed. For instance, Zhang et al. [30] designed a joint palmprint and palmvein fusion system for personal identification. Dai et al. [31] proposed a weighted sum rule to fuse the palmprint minutiae, density, orientation and principal lines for the high reso-lution palmprint verification and identification. Particularly, Morales et al. [20] proposed a combination of two kinds of matching scores obtained by multiple matchers, the SIFT and orthogonal line ordinal features (OLOF), for contactless palmprint identification. One typical example of the decision level fusion on palmprint is that Kumar et al. [32] fused three major palmprint representations at the decision level.

Conventional multimodal biometrics methods treat different traits independently. However, some special kinds of biometric traits have a similarity and these methods cannot exploit the similarity of different kinds of traits. For example, the left and right palmprint traits of the same subject can be viewed as

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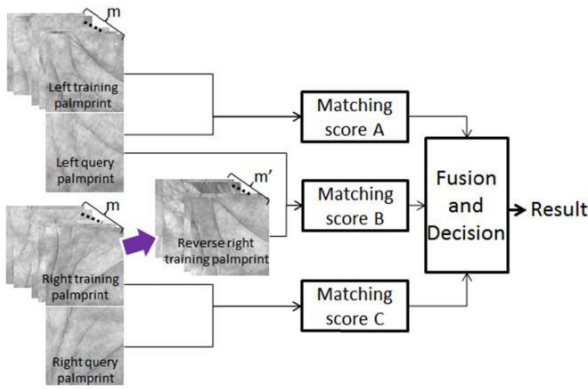**ISSN: 2278-0181**
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Fig. 1. Procedures of the proposed framework.

this kind of special biometric traits owing to the similarity between them, which will be demonstrated later. However, there is almost no any attempt to explore the correlation between the left and right palmprint and there is no "special" fusion method for this kind of biometric identification. In this paper, we propose a novel framework of combining the left with right palmprint at the matching score level. Fig. 1 shows the procedure of the proposed framework. In the framework, three types of matching scores, which are respectively obtained by the left palmprint matching, right palmprint matching and crossing matching between the left query and right training palmprint, are fused to make the final decision. The framework not only combines the left and right palmprint images for identification, but also properly exploits the similarity between the left and right palmprint of the same subject. Extensive experiments show that the proposed framework can integrate most conventional palmprint identification methods for per-forming identification and can achieve higher accuracy than conventional methods.

This work has the following notable contributions. First, it for the first time shows that the left and right palmprint of the same subject are somewhat correlated, and it demonstrates the feasibility of exploiting the crossing matching score of the left and right palmprint for improving the accuracy of identity identification. Second, it proposes an elaborated framework to integrate the left palmprint, right palmprint, and crossing matching of the left and right palmprint for identity iden-tification. Third, it conducts extensive experiments on both touch-based and contactless palmprint databases to verify the proposed framework.

The remainder of the paper is organized as follows: Section II briefly presents previous palmprint identification methods. Section III describes the proposed framework. Section IV reports the experimental results and Section V offers the conclusion of the paper.

II. PREVIOUS WORK

Generally speaking, the principal lines and texture are two kinds of salient features of palmprint. The principal line based methods and coding based methods have been widely used in palmprint identification. In addition, sub-space based methods,

representation based methods and SIFT based methods can also be applied for palmprint identification.

A. Line Based Method

Lines are the basic feature of palmprint and line based methodes play an important role in palmprint verification and identification. Line based methods use lines or edge detectors to extract the palmprint lines and then use them to perform palmprint verification and identification. In general, most palms have three principal lines: the heartline, headline, and lifeline, which are the longest and widest lines in the palmprint image and have stable line shapes and positions. Thus, the principal line based method is able to provide stable performance for palmprint verification.

Palmprint principal lines can be extracted by using the Gobor filter, Sobel operation, or morphological operation. In this paper, the Modified Finite Radon Transform (MFRAT) method [10] is used to extract the principal lines of the palmprint. The pixel-to-area matching strategy is adopted for principal lines matching in Robust Line Orientation Code (RLOC) method [33], which defines a principal lines matching score as follows:

$$S(A, B) = (\sum_{i=1}^{m} \sum_{j=1}^{n} A(i, j) \, \& \, \bar{B}(i, j))/N_A ,\qquad (1)$$

where A and B are two palmprint principal lines images, "&" represents the logical "AND" operation, N_A is the number of pixel points of A, and $\bar{B}(i, j)$ can be defined as a set of five pixel points, $B(i-1, j)$, $B(i+1, j)$, $B(i, j)$, $B(i, j-1)$, and $B(i, j-1)$. The value of $A(i, j) \, \& \, \bar{B}(i, j)$ will be 1 if $A(i, j)$ and at least one of $B(i, j)$ are simultaneously principal lines points, otherwise, the value of $A(i, j) \, \& \, \bar{B}(i, j)$ is 0. $S(A, B)$ is between 0 and 1, and the larger the matching score is, the more similar A and B are. Thus, the query palmprint can be classified into the class that produces the maximum matching score.

B. Subspace Based Methods

Subspace based methods include the PCA, LDA, and ICA etc. The key idea behind PCA is to find an orthogonal subspace that preserves the maximum variance of the original data. The PCA method tries to find the best set of projection directions in the sample space that will maximize the total scatter across all samples by using the following objective function:

$$J_{PCA} = \arg \max_W |W^T S_t W|,\qquad (4)$$

where S_t is the total scatter matrix of the training samples, and W is the projection matrix whose columns are orthonormal vectors. PCA chooses the first few principal components and uses them to transform the samples in to a low-dimensional feature space.

LDA tries to find an optimal projection matrix W and transforms the original space to a lower-dimensional feature space. In the low dimensional space, LDA not only maximizes the Euclidean distance of samples from different classes but also minimizes the distance of samples from the same classes. As a result, the goal of LDA is to maximize the ratio of the between-class distance against within-class distance which is defined as:

$$J_{LDA} = \arg\max_{W} \frac{|W^T S_b W|}{|W^T S_w W|}, \tag{5}$$

where S_b is the between-class scatter matrix, and S_w is the within-class scatter matrix. In the subspace palmprint identification method, the query palmprint image is usually classified into the class which produces the minimum Euclidean distance with the query sample in the low-dimensional feature space.

C. Representation Based Method

The representation based method uses training samples to represent the test sample, and selects a candidate class with the maximum contribution to the test sample. The Collaborative Representation based Classification (CRC) method, Sparse Representation-Based Classification (SRC) method and Two-Phase Test Sample Sparse Representation (TPTSSR) method are two representative representation based methods [35], [36]. Almost all representation based methods can be easily applied to perform palmprint identification. The CRC method uses all training samples to represent the test sample. Assuming that there are C classes and n training samples $x_1 x_2 \ldots x_n$, CRC expresses the test sample as:

$$y = a_1 x_1 + a_2 x_2 + \ldots + a_n x_n, \tag{6}$$

where y is the test sample, and a_i $(i = 1, 2, \ldots n)$ is the Weight coefficient. It can be rewritten as $y = XA$, where $A = [a_1 a_2 \cdots a_n]$, $X = [x_1 x_2 \cdots x_n]$. $x_1 x_2 \cdots x_n$ and y are all column vectors. If X is nonsingular, A can be obtained by using $A = X^{-1} y$. If X is singular, A can be obtained by using $A = (X^T X + \delta I)^{-1} X^T y$, where δ is a small positive constant and I is the identity matrix. The contribution of the i th training sample to representing the test sample is $a_i x_i$. So the sum of the contribution from the j th class is $s_j = a_{j1} x_{j1} + a_{j2} x_{j2} + \cdots + a_{jn} x_{jn}$, jk $(k = 1, 2 \ldots)$ is the sequence number of the kth training sample from the j th class. The deviation of s_j from y can be calculated using

$$e_j = \|y - (a_{j1} x_{j1} + a_{j2} x_{j2} + \cdots + a_{jn} x_{jn})\|^2,$$
$$j \in C. \tag{7}$$

The TPTSSR method was proposed in 2011 and it has performed well in face recognition and palmprint identification [37]. The method first determines M nearest neighbor training samples for the test sample. Then it uses the determined M neighbor training samples to represent the test sample, and selects the class with the greatest contribution to representing the query sample as the class to which the query sample belongs.

III. THE PROPOSED FRAMEWORK

A. Similarity Between the Left and Right Palmprints

In this subsection the illustration of the correlation between the left and right palmprints is presented. Fig. 2 shows palmprint images of four subjects. Fig. 2 (a)-(d) show four left palmprint images of these four subjects. Fig. 2 (e)-(h) show four right palmprint images of the same four subjects. Images in Fig. 2 (i)-(l) are the four reverse palmprint images of those shown in Fig. 2 (e)-(h). It can be seen that the left palmprint image and the reverse right palmprint image of the same subject are somewhat similar.

Fig. 3 (a)-(d) depict the principal lines images of the left palmprint shown in Fig. 2 (a)-(d). Fig. 3 (e)-(h) are the reverse right palmprint principal lines images corresponding to Fig. 2 (i)-(l). Fig. 3 (i)-(l) show the principle lines matching images of Fig. 3 (a)-(d) and Fig. 3 (e)-(h), respectively. Fig. 3 (m)-(p) are matching images between the left and reverse right palmprint principal lines images from different subjects. The four matching images of Fig.3(m)-(p)
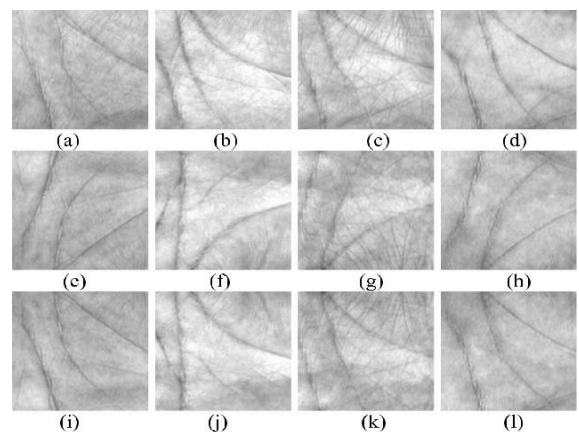

Fig. 2. Palmprint images of four subjects. (a)-(d) are four left palmprint images; (e)-(h) are four right palmprint corresponding to (a)-(d); (i)-(l) are the reverse right palmprint images of (e)-(h).
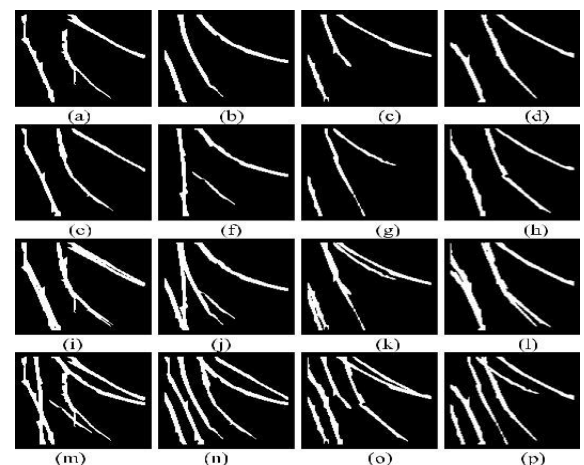

Fig. 3. Principal lines images. (a)-(d) are four left palmprint principal lines images, (e)-(h) are four reverse right palmprint principal lines image, (i)-(l) are principal lines matching images of the same people, and (m)-(p) are principal lines matching images from different people.

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are: (a) and (f) principal lines matching image, (b) and (e) principal lines matching image, (c) and (h) principal lines matching image, and (d) and (g) principal lines matching image, respectively.

Fig. 3 (i)-(l) clearly show that principal lines of the left and reverse right palmprint from the same subject have very similar shape and position. However, principal lines of the left and right palmprint from different individuals have very different shape and position, as shown in Fig. 3 (m)-(p). This domenstrates that the principal lines of the left palmprint and reverse right palmprint can also be used for palmprint verification/identification.

B. Procedure of the Proposed Framework

This subsection describes the main steps of the proposed framework. The framework first works for the left palmprint images and uses a palmprint identification method to calculate the scores of the test sample with respect to each class. Then it applies the palmprint identification method to the right palmprint images to calculate the score of the test sample with respect to each class. After the crossing matching score of the left palmprint image for testing with respect to the reverse right palmprint images of each class is obtained, the proposed framework performs matching score level fusion to integrate these three scores to obtain the identification result. The method is presented in detail below.

We suppose that there are C subjects, each of which has m available left palmprint images and m available right palmprint images for training. Let X_i and Y_i denote the i th left palmprint image and i th right palmprint image of the kth subject respectively, where $i = 1, \ldots, m$ and $k = 1, \ldots, C$. Let Z_1 and Z_2 stand for a left palmprint image and the corresponding right palmprint image of the subject to be identified. Z_1 and Z_2 are the so-called test samples.

Step 1: Generate the reverse images Y^k of the right palmprint images Y^k and Y^k will be used as training samples. Y^k is obtained by: $Y_k(\,,) = Y_k(L_Y - l + 1$, $l = 1 \ldots L_Y, c = 1 \ldots CY$), where L_Y and C_Y are the row number and column number of Y_i respectively.

Step 2: Use Z_1, X^k_i s and a palmprint identification method, such as the method introduced in Section II, to calculate the score of Z_1 with respect to each class. The score of Z_1 with respect to the i th class is denoted by s_i.

where Y is a palmprint image. X^k are a set of palmprint images

Step 3: Use Z_2, Y^k_i s and the palmprint identification method used in Step 2 to calculate the score of Z_2 with respect to each
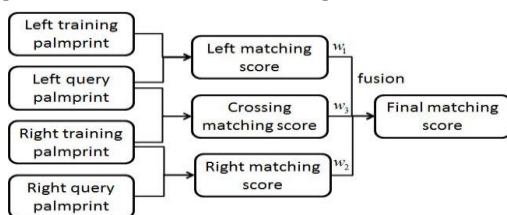

Fig. 4. Fusion at the matching score level of the proposed framework.

C. Matching Score Level Fusion

In the proposed framework, the final decision making is based on three kinds of information: the left palmprint, the palmprint. As we know, fusion in multimodal biometric systems can be performed at four levels. In the image (sensor) level fusion, different sensors are usually required to capture the image of the same biometric. Fusion at decision level is too rigid since only abstract identity labels decided by different matchers are available, which contain very limited information about the data to be fused. Fusion at feature level involves the use of the feature set by concatenating several feature vectors to form a large 1D vector. The integration of features at the earlier stage can convey much richer information than other a better identification accuracy than fusion at other levels. However, fusion at the feature level is quite difficult to implement because of the incompatibility between multiple kinds of data. Moreover, concatenating different feature vectors also lead to a high computational cost. The advantages of the scorelevel fusion have been concluded in [21], [22], and [39] and the weight-sum scorelevel fusion strategy is effective for component classifier combination to improve the performance of biometric identification. The strength of individual matchers

Fig. 4 shows the basic fusion procedure of the proposed method at the matching score level. The final matching score is generated from three kinds of matching scores. The first and second matching scores are obtained from the left and right palmprint, respectively. The third kind of score is calculated based on the crossing matching between the left and right palmprint. w_i ($i = 1, 2, 3$), which denotes the weight assigned to the i th matcher, can be adjusted and viewed as the impor-tance of the corresponding matchers
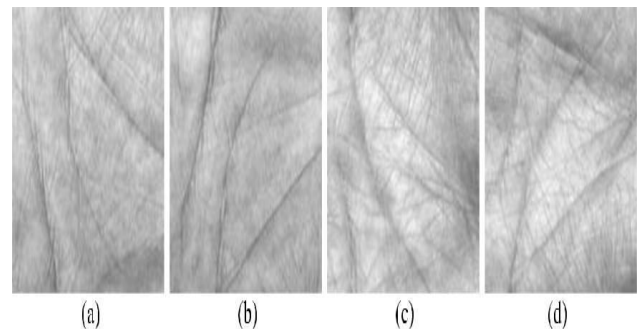

Fig. 5.(a)-(d) are two pairs of the left and right palmprint images of two subjects from PolyU database.

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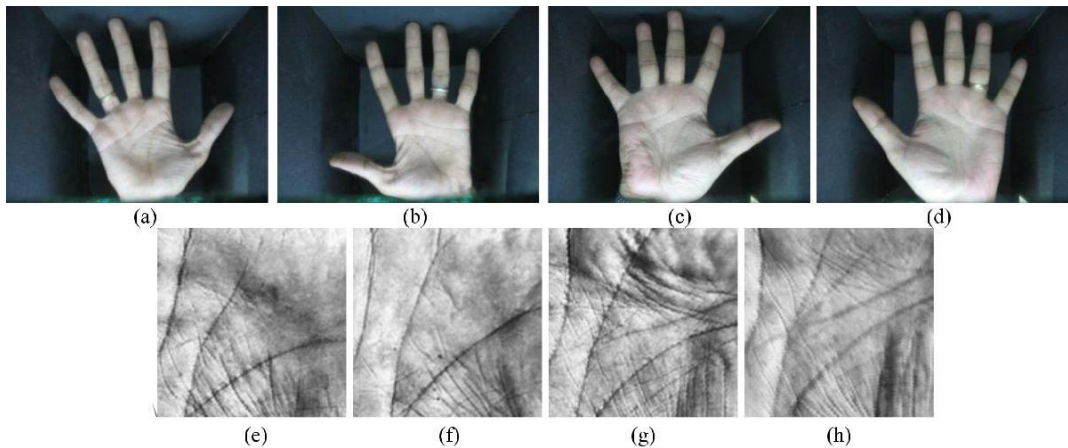**RTICCT - 2017 Conference Proceedings**

Fig. 6. (a)-(d) are two pairs of the left and right hand images of two subjects from IITD database. (e)-(h) are the corresponding ROI images extracted from (a) and (d).

Differing from the conventional matching score level fusion, the proposed method introduces the crossing matching score to the fusion strategy. When $w3 = 0$, the proposed method is equivalent to the conventional score level fusion. Therefore, the performance of the proposed method will at least be as good as or even better than conventional methods by suitably tuning the weight coefficients.

IV. EXPERIMENTAL RESULTS

More than 7,000 different images from both the contact-based and the contactless palmprint databases are employed to evaluate the effectiveness of the proposed method. Typical state-of-the-art palmprint identification methods, such as the RLOC method, the competitive code method, the ordinal code method, the BOCV method, and the SMCC method [7], are adopted to evaluate the performance of the proposed framework. Moreover, several recent developed contactless based methodes, such as the SIFT methods [19] and the OLOF+SIFT method [20], are also used to test the proposed framework. For the sake of completeness, we compare the performance of our method with that of the conventional fusion based methods.

A. Palmprint Databases

The PolyU palmprint database (version 2) [40] contains 7,752 palmprint images captured from a total of 386 palms of 193 individuals. The samples of each individual were collected in two sessions, where the average interval between the first and second sessions was around two months. In each session, each individual was asked to provide about 10 images of each palm. We notice that some individual provide few images. For example, only one image of the 150th indi-vidual was captured in the second session. To facilitate the evaluation of the performance of our framework, we set up a subset from the whole database by choosing 3,740 images of 187 individual, where each individual provide 10 right palm-print images and 10 left

palmprint images, to carry out the following experiments. Fig. 5 shows some palmprint samples on the PolyU database.

The public IITD palmprint database [41] is a contactless palmprint database. Images in IITD database were captured in the indoor environment, which acquired contactless hand im-ages with severe variations in pose, projection, rotation and translation. The main problem of contactless databases lies in the significant intra-class variations resulting from the absence of any contact or guiding surface to restrict such variations [20]. The IITD database consists of 3,290 hand images from 235 subjects. Seven hand images were captured from each of the left and right hand for each individual in every session. In addition to the original hand images, the Region Of Interest (ROI) of palmprint images are also available in the database. Fig. 6 shows some typical hand images and the corresponding ROI palmprint images in the IITD palmprint database. Compared to the palmprint images in the PolyU database, the images in the IITD database are more close to the real-applications.

B. Matching Results Between the Left and Right Palmprint

To obtain the correlation between the left and right palm-print in both the PolyU and the IITD databases, each left palmprint is matched with every right palmprint of each subject and the principal line matching score is calculated for the left palmprint and this subject. A match is counted as a genuine matching if the left palmprint is from the class; if otherwise, the match is counted as an imposter matching.

C. SIFT Based Method

SIFT was originally proposed in [19] for object classi-fication applications, which are introduced for contactless palmprint identification in recent years [20], [38]. Because

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the contactless palmprint images have severe variations in poses, scales, rotations and translations, which make conventional palmprint feature extraction methods on contactless imaging schemes questionable and therefore, the identification accu-racy of conventional palmprint recognition methods is usually not satisfactory for contactless palmprint identification. The features extracted by SIFT are invariant to image scaling, rotation and partially invariant to the change of projection and illumination. Therefore, the SIFT based method is insensitive to the scaling, rotation, projective and illumination factors, and thus is advisable for the contactless palmprint identification.

The SIFT based method firstly searches over all scales and image locations by using a difference-of-Gaussian function to identify potential interest points. Then an elaborated model is used to determine finer location and scale at each candidate location and keypoints are selected based on the stability. Then one or more orientations are assigned to each keypoint location based on local image gradient directions. Finally, the local image gradients are evaluated at the selected scale in the region around each keypoint [19]. In the identification stage, the Euclidean distance can be employed to determine the identity of the query image. A smaller Euclidean distance means a higher similarity between the query image and the training image.

It seems that the crossing matching score can also be calcu-lated based on the similarity between the right query and left training palmprint. We also conduct experiments to fuse both crossing matching scores to perform palmprint identification. However, as the use of the two crossing matching scores does not lead to more accuracy improve-ment, we exploit only one of them in the proposed method.

D.. *Computational Complexity*

In the proposed method, since the processing of the reverse right training palmprint can be performed before palmprint identification, the main computational cost of the proposed method largely relies on the individual palmprint identification method. Compared to the conventional fusion strategy that only fuses two individual matchers, the proposed method consists of three individual matches. As a result, the proposed method needs to perform one more identification than the conventional strategy. Thus, the identification time of the proposed method may be about 1.5 times of that of conventional fusion strategy.

To evaluate the computational cost of the proposed method, algorithms adopted in the proposed method are implemented by using MATLAB 7.10.0 on a PC with dou-ble-core Intel(R) i5-3470 (3.2GHz), RAM 8.00GB, and Windows 7.0 operating system. The time taken for the pro-cessing the reverse right training palmprint for each class is about 4.24s and 2.91s on both databases. Some representa-tive average identification time of the proposed method and conventional fusion strategy.
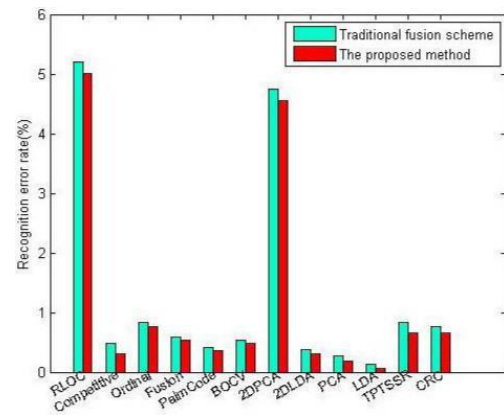

Fig. 8. The comparative results between the proposed method and the conventional fusion method on the PolyU database.

It is impossible to exhaustively verify all possible weight coefficients to find the optimal coefficients. Due to the limit of space, only a set of representative weight coeffi-cients that minimize the final identification error rate of our framework and conventional fusion methods are re-ported. Empirically, the score that has the lower identifi-cation error rate usually has a larger weight coefficient. In addition, the optimal weight coefficients vary with the methods, since each method adopted in the proposed framework utilizes different palmprint feature extraction algorithm.

The first m left and m right palmprint are selected as the training samples to calculate the left matching score s_i and the right matching score t_i, respectively. The rest of the left and right palmprints are used as test samples. m reverse right palmprints are also selected as the train-ing samples to calculate the crossing matching score g_i based on the rule of the proposed framework. Table I-VI list the identification error rate of the proposed frame-work using different palmprint identification methods.

The experimental results of the PolyU database show that the identification error rate of the proposed method is about 0.06% to 0.2% lower than that of conventional fusion methods. The comparison between the best identification results of the proposed method and conventional fusion scheme are depicted as Fig. 8, which shows that the frame-work using different methods outperform the conventional fusion schemes.

V. CONCLUSION

This study shows that the left and right palmprint images of the same subject are somewhat similar. The use of this kind of similarity for the performance improvement of palm-print identification has been explored in this paper. The proposed method carefully takes the nature of the left and right palm-print images into account, and designs an algorithm to evalu-ate the similarity between them. Moreover, by employing this similarity, the proposed weighted fusion scheme uses a meth-od to integrate the three kinds of scores generated from the left and right palmprint images. Extensive experiments demon-strate that the proposed framework obtains very high accuracy and the use of the similarity score between the leftand right palmprint leads to important improvement in the accuracy.

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This work also seems to be helpful in motivating people to explore potential relation between the traits of other bi-modal biometrics issues

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