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Accurate Personal Authentication by Combining Left and Right Palm Print Images

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ABSTRACT:

This paper develops the accurate personal identification by combining the left and right palm print Images. Recognition of persons by means of biometric characteristics is an important technology in the society, because biometric identifiers can't be shared and they intrinsically represent the individual's bodily identity. But in single biometric technology there is more number of chances for fraudulent activities. When we use the multi biometric, it can provide higher accuracy than any other technologies. Among those palm print identification has received much attention because of its good performance. Combining the left and right palm print images to perform multi biometric is easy to implement and can obtain better results. In this paper, we proposed a novel framework to perform multi biometrics by comprehensively combining the left and right palm print images. This framework integrated three kinds of scores generated from the left and right palm print images to perform matching score-level fusion. The first two kinds of scores were, respectively, generated from the left and right palm print images and can be obtained by any palm print identification method, whereas the third kind of score was obtained using a specialized algorithm proposed in this paper.

Index Terms—Palmprint recognition, biometrics, multi biometrics.

1. INTRODUCTION

Important personal identification technique is palm print identification. It the palm print identification has capacity to achieve a high accuracy, since technique contains not only principle curves, wrinkles, rich texture and minuscule points, and also due to availability of rich information in palm print. Various palm print identification methods, such as coding based methods and principle curve method have been proposed in past years. Along with those methods one more method called subspace based methods in this method also Palm is defined as the inner surface of human hand from human wrist to the root of their fingers. Many other techniques are deployed for palm printing in that Representation Based Classification (RBC) method also shows good performance in this regard and also Scale Invariant Feature Transform (SIFT) which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palm print identification. A print is an impression made in or on a surface by pressure. A palm print is defined as the skin pattern of a palm, composed of the physical characteristics of skin pattern such as lines, points and texture. Palm print is rich in principal lines, wrinkles, ridges, singular points and minutiae points. Palm print has a much larger area than finger tip. As the security system has very much important in several fields, it is very important to authenticate the users for any access. As many studies have been proposed but these researches did not explore the security issue in depth, so in this paper we established a framework in order to perform multi biometrics by combining left and right palm print images. The authentication system consists of enrolment and verification stages. In enrolment stage, will consider the training samples and processed by pre-processing, feature extraction and modeling modules to produce the matching templates. Where as in verification, a query sample is also processed by preprocessing and feature extraction method and then is matched with reference templates to decide whether it is sample which we considered or not. A setup system consisting of a palm print based authentication system can work with multipurpose camera in an uncontrolled circumstances like mounted on a laptop, mobile device. Unlike earlier biometric systems, it does not require equipment and have attained higher accuracy value equivalent to fingerprint. We used SIFT and OLOF method, is an algorithm in palm print recognition to detect and describe local features in images.

Old multi biometrics methods treat different pattern independently. However, some special kinds of biometric traits have a similarity and these methods cannot exploit the similarity of different kinds of pattern. For example, the left and right palm print traits of the same subject can be viewed as 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 palm print and there is no “special” fusion method for this kind of biometric identification. This specialized algorithm carefully takes the nature of the left and right palm print images into consideration, it can properly examine the similarities between the left and right palm prints of the same object/human.

The framework which we implemented here will integrate three kinds of scores; these scores are generated from the left and right palm print images to do matching score level fusion. First two kind of scores can be obtained from any other conventional methods easily but the third kind of score has to obtain using specialized algorithm, which takes the nature of the left and right palm print images into consideration, it can properly exploit the similarity of the left and right palm prints of the same subject. Moreover, the proposed weighted fusion scheme allowed perfect identification performance to be obtained in comparison with previous palm print identification methods. . Moreover, the proposed specialized fusion scheme allowed perfect identification performance to be obtained in comparison with old conventional palm print identification methods.

2. RELATED WORK

The proposed technique combines the left with right palmprint at the matching score level. The framework, contains three types of matching scores, which are respectively obtained by the left palm print matching, right palm print matching and crossing matching between the left query and right training palmprint, are fused to make the final decision. It 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 can integrate most conventional palmprint identification methods for performing identification and can achieve higher accuracy than conventional methods.

This work has the following notable contributions, First, 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, the proposed system integrating the left palmprint, right palmprint, and crossing matching of the left and right palmprint for identity identification. Third, it conducts testing on both touch-based and contactless palm print databases to verify the proposed framework.

III. THE PROPOSED FRAMEWORK

A. Similarity Between the Left and Right Palm prints

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In this subsection the illustration of the correlation between the left and right palm prints is presented. Fig. 1 shows palm print images of four subjects. Fig. 1 (a)-(d) show four left palm print images of these four subjects. Fig. 1 (e)-(h) shows four right palm print images of the same four subjects. Images in Fig. 1 (i)-(l) are the four reverse palm print images of those shown in Fig. 1 (e)-(h). It can be seen that the left palm print image and the reverse right palm print image of the same subject are somewhat similar. Fig. 2 (a)-(d) depicts the principal lines images of the left palm print shown in Fig. 1 (a)-(d). Fig. 2 (e)-(h) are the reverse right palm print principal lines images corresponding to Fig. 1 (i)-(l). Fig. 2 (i)-(l) show the principle lines matching images of Fig. 2 (a)-(d) and Fig. 2 (e)-(h), respectively. Fig. 2 (m)-(p) are matching images between the left and reverse right palm print principal lines images from different subjects. The four matching images of Fig. 2 (m)-(p) 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. 2 (i)-(l) clearly show that principal lines of the left and reverse right palm print from the same subject have very similar shape and position. However, principal lines of the left and right palm print from different individuals have very different shape and position, as shown in Fig. 2 (m)-(p). This demonstrates that the principal lines of the left palm print and reverse right palm print can also be used for palm print

Verification/identification.

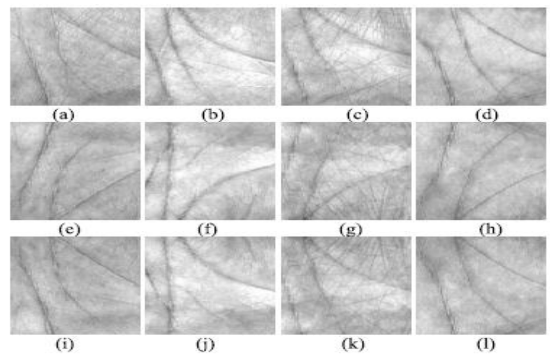

Fig. 1. Palm print images of four subjects. (a)-(d) are four left palm print images; (e)-(h) are four right palm print corresponding to (a)-(d); (i)-(l) are the reverse right palm print images of (e)-(h).

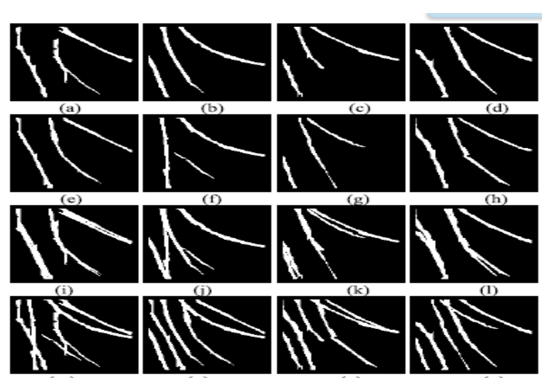

Fig. 2. Principal lines images. (a)-(d) are four left palm print principal lines images, (e)-(h) are four reverse right palm print principal lines image, (i)-(l) are principal lines matching images of the same people,

and (m)-(p) are principal lines matching images from different people.

B. Procedure of the Proposed Framework

This subsection describes the main steps of the proposed framework. The framework first works for the left palm print images and uses a palm print 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 palm print image for testing with respect to the reverse right palm print 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 palm print images and m available right palm print images for training. Let X_i^K and Y_i^K denote the i th left palm print image and i th right palm print image of the kth subject respectively, where $i = 1, \ldots, m$ and $k = 1, \ldots, C$. Let $Z1$ and $Z2$ stand for a left palm print image and the corresponding right palm print image of the subject to be identified. $Z1$ and $Z2$ are the so-called test samples.

Step 1: Generate the reverse images Y_i^K of the right palm print images Y_i^K Both Y_i^K and Y_i^K will be used as training samples. Y_i^K is obtained by:

$$\tilde{Y}_i^k(\dot{l}, c) = Y_i^k(L_Y - l + 1, c),\ (l = \dot{1} \ldots \dot{L}_Y,\ c = 1 \ldots \dot{C}_Y),$$

where LY and CY are the row number and column number of Y_i^K respectively.

Step 2: Use $Z1$, X_i^K s and a palm print identification method, such as the method introduced in Section II, to calculate the score of $Z1$ with respect to each class. The score of $Z1$ with respect to the i th class is denoted by si .

Step 3: Use $Z2$, Y_i^K s and the palm print identification method used in Step 2 to calculate the score of $Z2$ with respect to each class. The score of $Z2$ with respect to the i th class is denoted by ti.

Step 4: $Y\tilde{}j^k(j = 1, \ldots, m\_, m\_ \leq m)$, which have the property of $Sim\_score(\tilde{}Yj^k, X^k) \geq$ *match threshold*, are selected from $Y\tilde{}^k$ as additional training samples, where *match threshold* is a threshold. $Sim\_score(\tilde{}Y^k_j, X^k)$ is defined as:

$$Sim\_score(Y, X^k) = \sum_{t=1}^{\dot{}} (S(\hat{Y}_t, X^k))/T, \quad \text{----}(1)$$

and

$$S(\hat{Y}_t, X^k) = \max(Score(\hat{Y}_t, \hat{X}_i^k{}_t)), \quad i = \{1 \ldots m\}, \quad \text{---}(2)$$

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where Y is a palmprint image. X^k are a set of palmprint images from the kth subject and $Xk\ i$ is one image from Xk. $\hat{X}^k_i$ and $\hat{Y}$ are the principal line images of $\hat{X}^k_i$ and Y, respectively. T is the number of principal lines of the palmprint and t represent the tth principal line. *Score*(Y, X) is calculated as formula (1) and the *Score*(Y, X) is set to 0 when it is smaller than *sim_threshold*, which is empirically set to 0.15.

Step 5: Treat $\tilde{Y}^k_j$ s obtained in Step 4 as the training samples of $Z1$. Use the palmprint identification method used in Step 2 to calculate the score of $Z1$ with respect to each class.

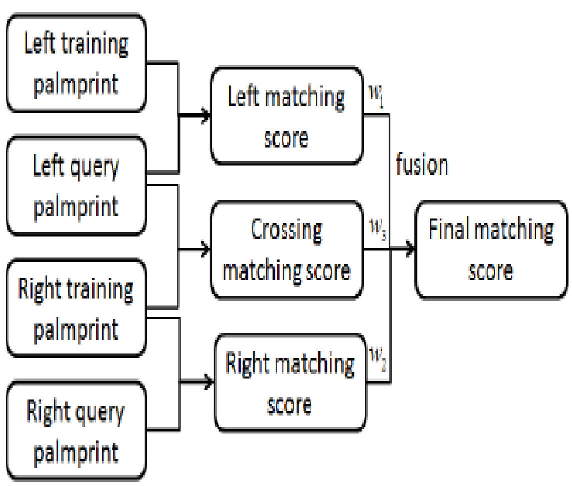

Fig. 3. Fusion at the matching scores level of the proposed framework.

The score of the test sample with respect to $\tilde{Y}^k_j$ s of the i th class is denoted as gi .

Step 6: The weighted fusion scheme $fi = w1si + w2ti + w3gi$, where $0 \leq w1, w2 \leq 1$ and $w3 = 1 - w1 - w2$, is used to calculate the score of $Z1$ with respect to the i th class.

If $q = \text{argmin}\ I\ fi$, then the test sample is recognized as the qth subject.

C. Matching Score Level Fusion

In the proposed framework, the final decision making is based on three kinds of information: the left palmprint, the right palm print and the correlation between the left and right 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 fusion strategies. So feature level fusion is supposed to provide 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 score level fusion have been concluded in

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[21], [22], and [39] and the weight-sum score level fusion strategy is effective for component classifier combination to improve the performance of biometric identification. The strength of individual matchers can be highlighted by assigning a weight to each matching score. Consequently, the weight-sum matching score level fusion is preferable due to the ease in combining three kinds of matching scores of the proposed method.

Fig. 3 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. *wi (i* = 1, 2, 3*)*, which denotes the weight assigned to the *i* th matcher, can be adjusted and viewed as the importance of the corresponding matchers.

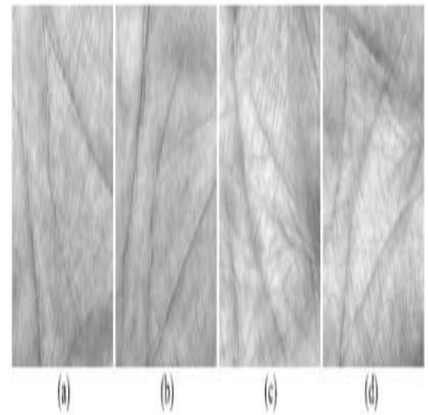

Fig. 5. (a)-(d) are two pairs of the left and right palmprint images of two subjects from PolyU database.

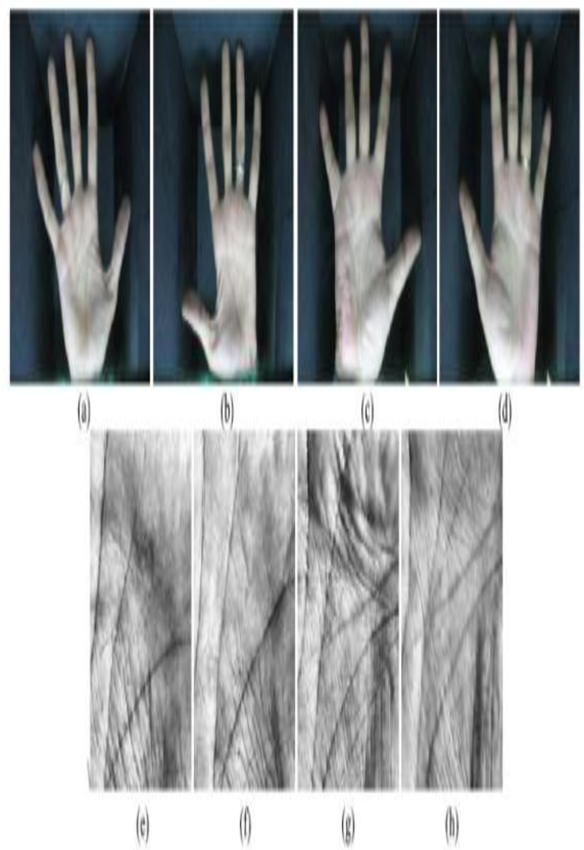

Fig. 4. (a)-(d) are two pairs of the left and right hand images of two subjects from IITD database. (e)-(h) are the corresponding ROI images extracted from (a) and (d).

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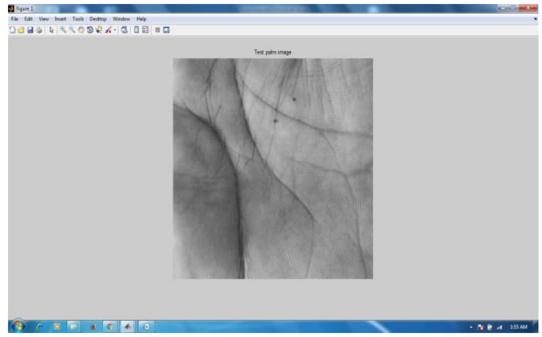
Differing from the conventional matching score level fusion, the proposed method introduces the crossing matching score to the fusion strategy. When $w3 = 0$, the proposed method is equivalent to the conventional score level fusion. Therefore, the performance of the proposed method will at least be as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

5. RESULTS

In the proposed method, since the processing of the reverse right training palm print can be performed before palm print identification, the main computational cost of the proposed method largely relies on the individual palm print identification method. Compared to the conventional fusion strategy those 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 reduced, compared to conventional fusion strategy.

The output screenshots of the proposed system as follows.

Input palm image



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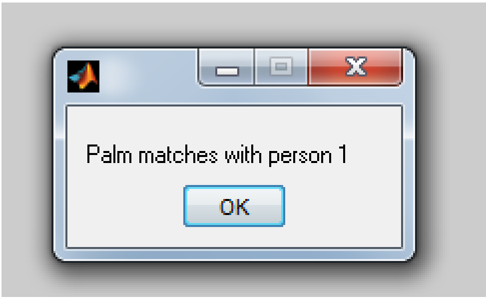
Output compare database



6. CONCLUSION

In this paper we demonstrated that the left and right palm print images of the same subject are almost similar. For the performance improvement of palm print identification by using the similar patterns has been proposed 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 evaluate the similarity between them as we used canny edge detection and Gabor feature extraction techniques. Since, by utilizing this similarity, the proposed weighted fusion scheme uses a method to integrate the three kinds of scores generated from the left and right palm print images. Effective experimental results shows that the proposed framework obtains very high accuracy as we used many pre-processing techniques and the use of the similarity score between the left and right palm print leads to important improvement in the accuracy. This work also seems to be helpful in motivating people to explore potential relation between the traits of other bimodal biometrics issues.

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