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Authentication using hand gesture

JENIFER A[1], GEETHA S[2]
[1] *Assistant Professor, Computer Science and Engineering, Sri Sairam College of Engineering, Anekal, Bangalore, Karnataka*
[2] *Assistant Professor, Electronics and Communication Engineering, Sri Sairam College of Engineering, Anekal, Bangalore, Karnataka*
Corresponding Author Orcid ID : https://orcid.org/0000-0002-4644-039X

ABSTRACT
In some real-world personal identification applications requiring high security standards, multibiometrics can provide higher identification accuracy than single biometrics. Due to its good performance, palmprint identification has received a lot of attention among other biometrics technologies. Combining left and right palmprints for multibiometrics is easy to implement and can produce better results. However, previous studies did not explore this issue in depth. An innovative framework for performing multibiometrics by combining left and right palmprint images is presented in this paper. This framework integrated three kinds of scores generated from the left and right palmprint images to perform matching score-level fusion. These first two scores were generated from left and right palmprint images, respectively, and can be obtained using any palmprint identification method. However, the third score was obtained using a specialized algorithm. Due to the careful consideration of the left and right palmprint images, the proposed algorithm can effectively exploit the similarity between the left and right palmprints. Moreover, the proposed weighted fusion scheme allowed perfect identification performance to be obtained in comparison with previous palmprint identification methods.
Keywords— Palmprint recognition, biometrics, multi-biometrics.

1. 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.Various palmprint identification methods, such as coding based methods and principle curve methods, perform well for palmprint identification. For example, Eigenpalm and Fisherpalm are two well-known sub space based palmprint identification methods. In recent years, 2D appearance-based methods such as 2D Principal Component Analysis (2DPCA) [15], 2D Linear Discriminant Analysis (2DLDA), and 2D Locality Preserving Projection (2DLPP) have also been used for palmprint recognition. Further, the Representation Based Classif-ication (RBC) method also shows good performance in palmprint identification. Additionally, the Scale Invariant Feature Transform (SIFT), 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. 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. For the image level fusion, Han et al 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. improved the performance of palmprint-based verification by integrating hand geometry features. In, the face and palmprint were integrated for personal identification. For the fusion at matching score level, various kinds of methods are also proposed. For instance, Zhang et al. designed a joint palmprint

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and palm vein fusion system for personal identification. Dai et al. proposed a weighted sum rule to fuse the palmprint minutiae, density, orientation and principal lines for the high resolution palmprint verification and identification. Particularly, Morales et al. 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. fused three major palmprint representations at the decision level.

2. Experimental Methods or Methodology

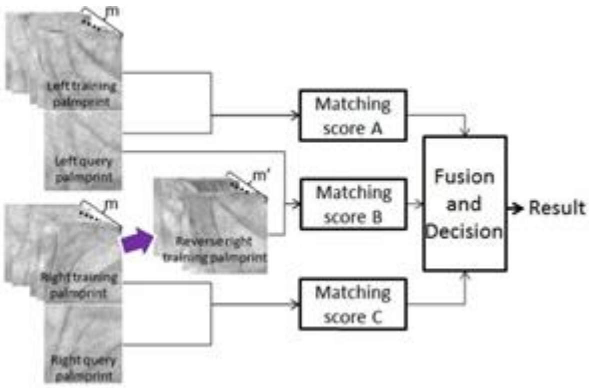

Fig 1. Procedures of the proposed framework

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.

3. Results and Discussion

3.1 *Line Based Method*

Lines are the basic feature of palmprint and line based methods 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:

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

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where *A* and *B* are two palmprint principal lines images, “&” represents the logicaloperation, N_A is the “AND” number represents a neighbor of pixel points of *A*,*B i j* area and (,) can be defined as a set of *B i* *j* five of *B(i, j)*. For example, (,) pixel points, *B(i* − 1*, j), B(i* + 1*, j), B(i, j), B(i, j* − 1*)*, and

B i *j* will be 1 if *A ij* 1*)*. The value of *A(i, j)* & *B(i, j* (,) (,) are simultaneously principal + *B i* *j* lines and at least one of is 0. (,) *B i j S* *A B* points, otherwise, the value of *A(i,* *j)* & (,) (,) 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.

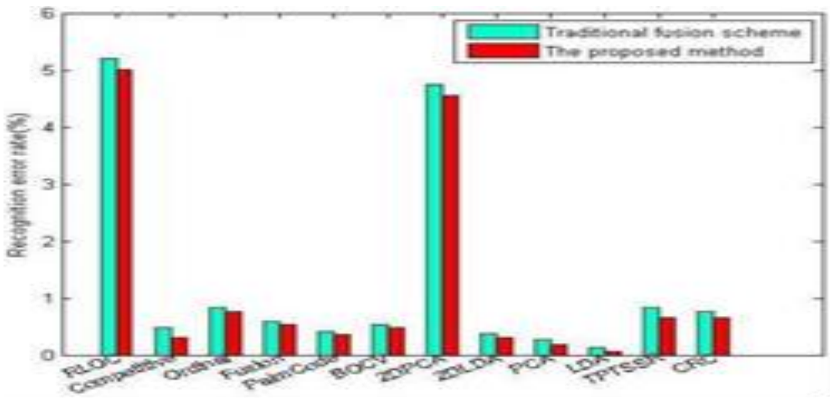
3.2 *Subspace Based Methods*

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:

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

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



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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:

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

where S_b is the between-class scatter matrix, and S_w is the within-class scatter matrix. In the subspace palmprint identifi-cation 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.

3.3 *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:

3.4 Compressive strength

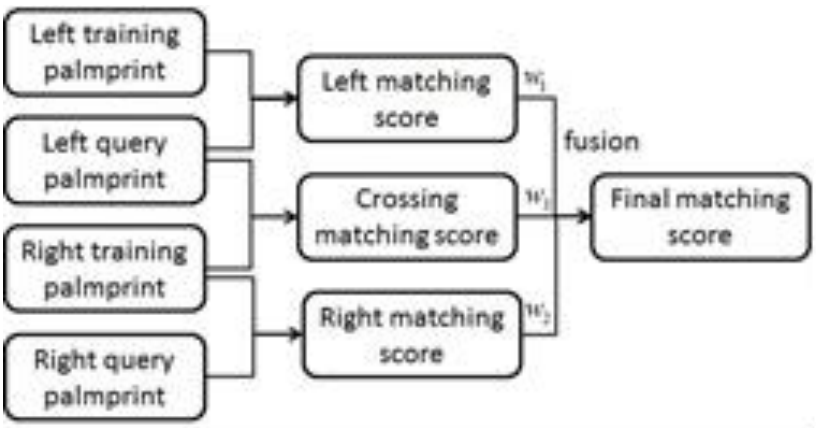
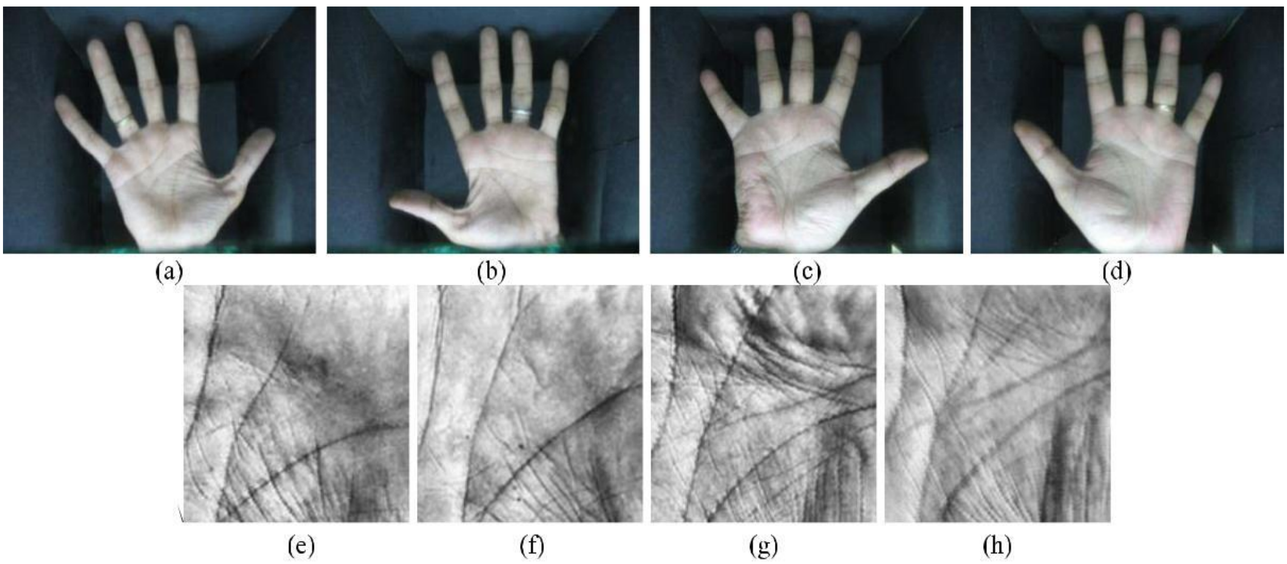


Fig. 6. GGBS Compressive strength



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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 palmprint images into account, and designs an algorithm to evaluate the similarity between them. Moreover, by employing this similarity, the proposed weighted fusion scheme uses a method to integrate the three kinds of scores generated from the left and right palmprint images. Extensive experiments demonstrate that the proposed framework obtains very high accuracy and the use of the similarity score between the left and right palmprint 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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