



FUSION OF LEFT AND RIGHT PALM PRINT IDENTIFICATION USING NOVEL FRAME WORK ALGORITHM

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ABSTRACT

Multi biometrics 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, palm print identification has received much attention because of its good performance. Combining the left and right palm print images to perform multi biometrics is easy to implement and can obtain better results. However, previous studies did not explore this issue in depth. Here, 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. As the proposed algorithm carefully takes the nature of the left and right palm print images into account, 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.

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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 Image processing is a physical process used to convert an image signal into a physical image. The image signal can be either digital or analog. The actual output itself can be an actual physical image or the characteristics of an image. The most common type of image processing is photography. In this process, an image is captured or scans using a camera to create a digital or analog image. In order to produce a physical picture, the image is processed using the appropriate technology based on the input source type. In digital photography, the image is stored as a computer file. This file is translated using photographic software to generate an actual image. The colors, shading, and nuances are all captured at the time the photograph is taken the software translates this information into an image. When creating images using analog photography, the image is burned into a film using a chemical reaction triggered by controlled exposure to light. The image is processed in a darkroom, using special chemicals to create the actual image. points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint [1]–[8]. Various palmprint methods, such as coding based methods [6]–[9] and principle curve methods [10], have been proposed in past decades. In addition 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. 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. 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. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analog image processing; it allows a much wider range of algorithms to be applied to the input data, and can avoid problems such as the build-up of noise and signal distortion during processing. [5] proposed a system which uses intermediate features of maximum overlap wavelet transform (IMOWT) as a pre-processing step. The coefficients derived from IMOWT are subjected to 2D histogram Grouping. This method is simple, fast and unsupervised.

Examples of fusion at feature level include the combination of and integration of multiple biometric traits. Matching score level fusion is classified into three types of score. First and second matching scores are obtained the left and right palm print. Third kind of score is calculated based on the crossing matching between the left and right palm print. For example, the left and right palmprint traits of the same subject can be viewed as

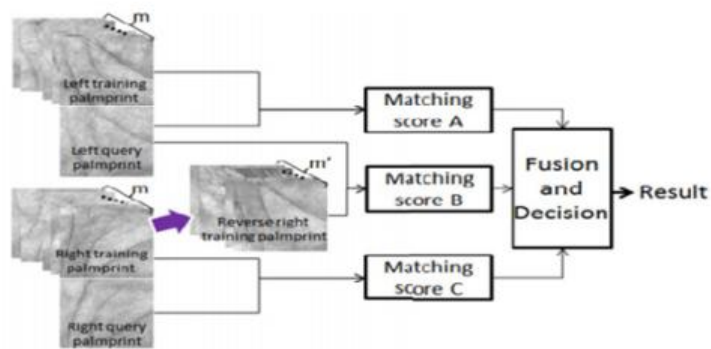


Fig.1.procedure of the proposed framework

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 performing 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 identification. 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 palm print and line based method's play an important role in palm print verification and identification. Line based methods use lines or edge detectors to extract the palm print lines and then use them to perform palm print verification and identification. In general, most palms have three principal lines: the heart line, headline, and lifeline, which are the longest and widest lines in the palm print image and have stable line



shapes and positions. Thus, the principal line based method is able to provide stable performance for palm print verification.

B. Coding Based Method

Coding based methods are the most influential palmprint identification methods [6]–[9]. Representative coding based methods include the competitive code method, ordinal code method, palmcode method and Binary Orientation Co-occurrence Vector (BOCV) method [34], and so on. The competitive code method [6] uses six Gabor filters with six different directions $\theta_j = j\pi/6$, $j \in \{0, 1, \dots, 5\}$, to extract orientation features from the palmprint as follows. Six directional Gabor templates are convoluted with the palmprint image respectively. The dominant direction is defined as the direction with the greatest response, the index j ($j = 0 \dots 5$) of which is indicated as the competitive code. In the matching stage of the competitive code method, the matching score between two palmprint images is calculated by using the angular distance, which can be defined as:

$$SD = \frac{1}{3N} \sum_{i=1}^N \sum_{j=1}^N F(Dd(i, j), Dt(i, j)), \quad (1)$$

where Dd and Dt be two index code planes of two palm images and $F(\alpha, \beta) = \min(|\alpha - \beta|, 6 - |\alpha - \beta|)$. The N is the number of the pixels of the palmprint image. SD is in the range of 0 to 1. The smaller the SD is, the more similar the two samples are. The competitive code can be represented by three bit binary codes according to the rule of [6]. Then the Hamming distance can be used to measure the similarity between two competitive codes, which can be calculated by:

$$D(P, Q) = \frac{\sum_{Y=1}^N \sum_{X=1}^N \sum_{i=1}^3 P_i(X, Y) \otimes Q_i(X, Y)}{3N^2} \quad (2)$$

where $P_i(Q_i)$ is the i th bit binary code plane. “ \otimes ” is the logical “XOR” operation. The smaller the Hamming distance (angular distance) is, the more similar the two samples are. Therefore, the query palmprint is assigned to the class that produces the smallest angular distance. Differing from the competitive code method, the palmcode method uses only one optimized 2D Gabor filter with direction of $\pi/4$ to extract palmprint texture features. Then it uses a feature vector to represent image data that consists of a real part feature and an imaginary part feature. Finally it employs a normalized Hamming distance to calculate the matching score of two palmprint feature vectors. In ordinal code method [8], three integrated filters, each of which is composed of two perpendicular 2D Gaussian filters, three bit ordinal codes are obtained based on the sign of filtering results. Then the Hamming distance is used to calculate the matching score of two palmprint ordinal codes. In the fusion code method [9] multiple elliptical Gabor filters with four different directions are convoluted with palmprint images, and then the direction and phase information of the responses are encoded into a pair of binary codes, which are exploited to calculate the normalized Hamming distance for palmprint verification. In the BOCV method, the same six filters as the competitive code method are convoluted with the palmprint image, respectively. All six orientation features are encoded as six binary codes successively, which are joined to calculate the Hamming distance between the query palmprint and the gallery palmprint. The Sparse Multiscale Competitive Code (SMCC)



method [7] adopts a bank of Derivatives of Gaussians (DoG) filters with different scales and orientations to obtain the multiscale orientation features using the $l1 - norm$ sparse coding algorithm. The same coding rule as the competitive code method is adopted to integrate the feature with the dominant orientation into the SMCC code and finally the angular distance is calculated for the gallery SMCC code and the query SMCC code in the matching stage.

C. Subspace Based Methods

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

$$J_{PCA} = \arg \max_W |W^T S_t W|, \quad (3)$$

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 into 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.

D. SIFT Based Method

SIFT was originally proposed in [19] for object classification applications, which are introduced for contactless palmprint

identification in recent years [20], [38]. Because 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 accuracy 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 key points are selected based on the stability. Then one or more orientations are assigned to each key point location based on local image gradient directions. Finally, the local image gradients are evaluated at the selected scale in the region around each key point [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.

III. THE PROPOSED FRAMEWORK

In this paper, we propose a novel framework of combining the left with right palmprint at the matching score level. Fig.4. 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 performing 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 identification. Third, it conducts extensive experiments on both touch-based and contactless palmprint databases to verify the proposed framework. 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

ALGORITHM:

- Step 1: Start
- Step 2: Multi modal method.
- Step 3: Insert left training palm print.
- Step 4: Insert left query palm print.
- Step 5: Right training palm print.

Step 6: Right query palm print.

Step 7: Matching score for left training and query palm print.

Step 8: Cross matching score for left query and right training palm print.

Step 9: Matching score for right training and query palm print.

Step 10: Fusion of all the three matching score.

Step 11: final matching score.

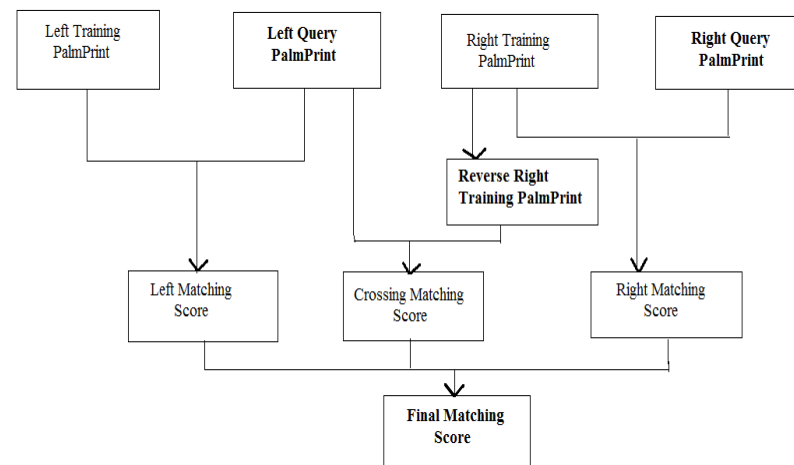


Fig.4. Fusion at the matching score level of the proposed method

a&d.Image Acquisition: In the process, the first step in the process is image acquisition→that is, to acquire a digital image. It highly requires an imaging sensor and the capability to digitize the signal produced by the sensor.

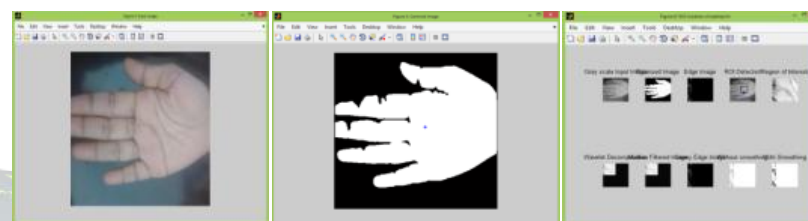


b&e. Image Preprocessing : The key function of preprocessing is to improve the image in ways that increase the chances for success of the other processes. Image Enhancement: More suitable than original image for a specific application.

c. Image Segmentation: The region of interest is calculated for the left palm, by using gray scale images, obtaining zeros or one from the region then it is processed by using edge detectors to provide clear information about the image in the palm, then smoothing of image takes place to take accurate region of interest.

f. Image Capturing : Roi Of Right Palm Similarly as the left palm image the right palm is processed and ROI of image obtained

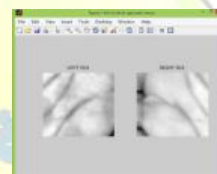
g. Image Recognition By Roi Method It proposes an elaborated framework to integrate the left palm print, right palm print, and crossing matching of the left and right palm print for identity identification by using left and right ROI.



d

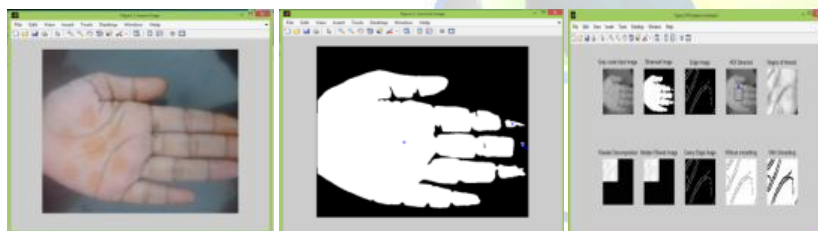
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g

a&d) image acquisition of right and left palm. b&e) image preprocessing. f) image capturing. g) image recognition



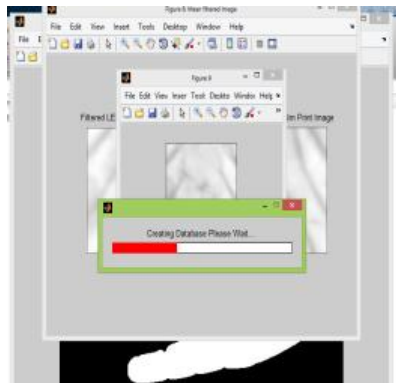
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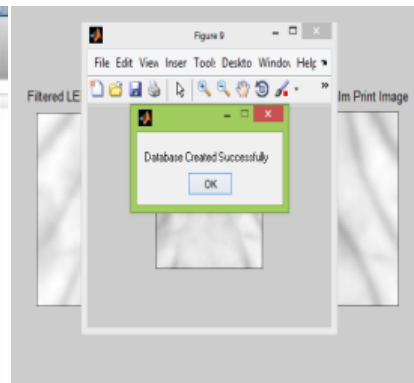
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IV. EXPERIMENTAL RESULTS

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 and the result is viewed as:



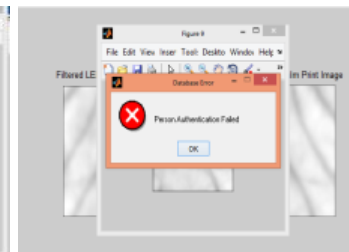
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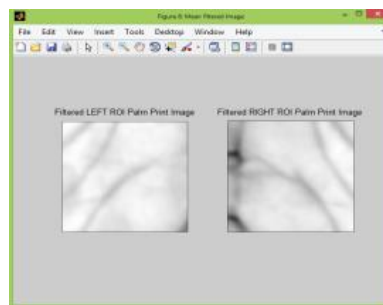
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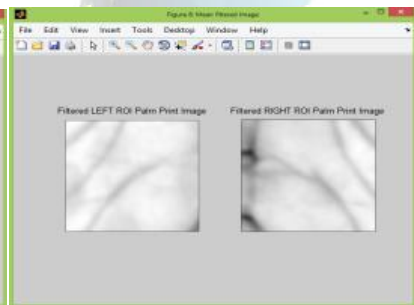
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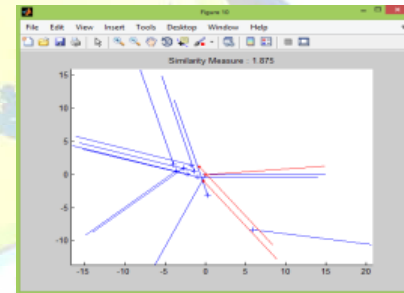
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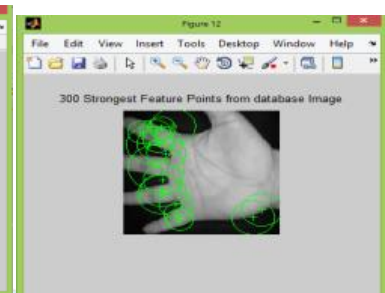
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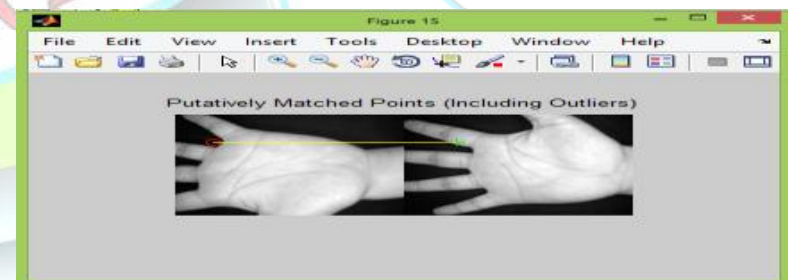
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i



a)creating database .b)database created c)filtered ROI of left and right palm print. d)matching score of palm print. e)authenticated. f)authenticated failed f)similarity graph .g)feature points i)matched point

V. CONCLUSIONS

It shows that the left and right palm print 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 project. The line based method Lines or edge detectors are used to extract the palm print lines.in line method the principle lines may be same it is not that much reliable. The code based method Includes competitive code method and palm code method. In code method angular distance is calculated but it take More processing time.

In Scale Invariant Fourier Transform(SIFT) method ,involve determination of finer location and scale at each candidate location and key points are selected based on the stability, but performs poorly with low quality images. To overcome the disadvantages in these method the region of interest method is used. The Region of Interest method carefully takes the nature of the left and right palm print images into account. To Designs an algorithm to evaluate a similarity between them. It is used to integrate the three kinds of scores generated from the left and right palm print images so provide good output. 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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