

Personal Authentication Using the Combination of Left and Right Palmprint Images

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ABSTRACT: This paper develops the accurate personal identification by combining the left and right palmprint images. The multibiometrics has received much attention in the palmprint identification. We, firstly propose a new approach for image level combination of RGB color to generate more reliable palmprint representation than the conventional gray level representation. This investigation is motivated to develop the similarity between the left and right palmprint images. Secondly this paper analysis the feature representation (SIFT and OLOF) and different database (Poly U and IITD). Then the left and right images to perform matching score-level fusion. The experimental results from this study suggests that the Scale Invariant Feature Transform (SIFT) and Orthogonal Line Ordinal Features, perform significantly better for the contactless palmprint images than other approach employed earlier on the more conventional palmprint imaging. The achieved error rates show a good performance of these features.

KEYWORDS: Multibiometric, Left and Right Palmprint images, SIFT and OLOF, Matlab basics

I. INTRODUCTION

Palmprint identification is an important personal identification technology. It contains not only principle curves and wrinkles but also rich texture and minuscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint. Palm is defined as the inner surface of our hand from our wrist to the root of the fingers. 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.

The authentication system consists of enrollment and verification stages. In enrollment, the training samples are collected and processed by pre-processing, feature extraction and modeling modules to generate the matching templates. In verification, a query sample is also processed by pre-processing and feature extraction method and then is matched with reference templates to decide whether it is sample or not. A setup system consisting of a palmprint 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 palmprint recognition to detect and describe local features in images.

II. 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 palmprint matching, right palmprint 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 palmprint databases to verify the proposed framework.

III. SYSTEM DESIGN

A palmprint recognition system generally consists of four parts: palmprint scanner, preprocessing, feature extraction and matcher. Palmprint scanner is to collect palmprint images. Preprocessing is to setup a coordinate system to align palmprint images and to segment a part of palmprint image for feature extraction. Feature extraction is to obtain effective features from the preprocessed palmprints. Finally, a matcher compares two palmprint features that 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 and performs matching score level fusion to integrate these three scores to obtain the identification result.

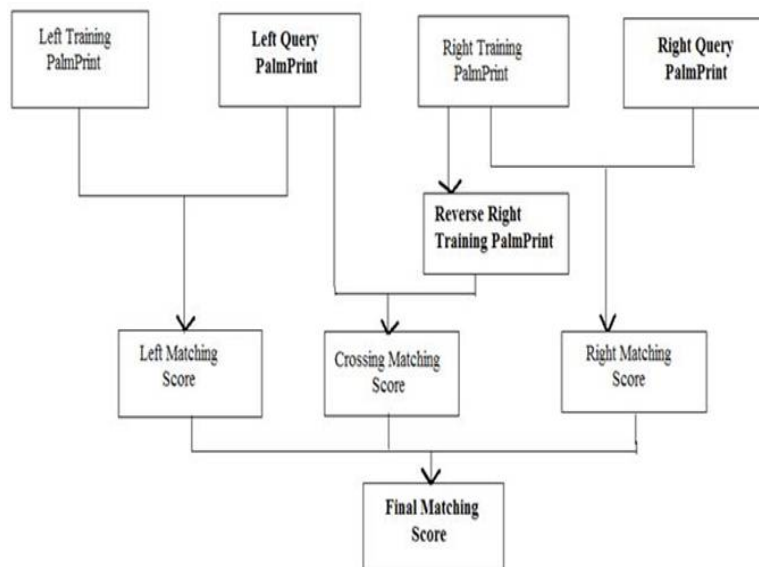


Fig. 1 Block diagram of proposed system

3.1 FEATURE EXTRACTION

The palmprint approaches based on global and local information of the palmprint. The Scale Invariant Feature Transform (SIFT) as approach based on local information and Orthogonal Line Ordinal Features (OLOF) as global appearance or texture approach.

SCALE INVARIANT FEATURE TRANSFORM (SIFT)

This approach is based on application of SIFT algorithm to 2D Gabor filter enhanced palmprint images. The features extracted are invariant to image scaling, rotation, and partially invariant to change in illumination and projective distortion. The SIFT algorithm is based on the study of information around several keypoints in palmprint images. The keypoints selection and characterization is done following three steps.

Scale-space extrema detection: The $I(x, y)$ Gabor enhanced input image is transformed to:

$$L(x, y, \sigma) = N(x, y, \sigma) * I(x, y)$$

where * corresponds to convolution operator and $N(x, y, \sigma)$ is a Gaussian function with bandwidth σ .

Keypoint localization: The keypoints $c_i = \{x_i, y_i\}$ are obtained evaluating the maxima and minima of the difference-of-Gaussian function:

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$

The number of keypoints selected depends on the palmprint image. Therefore if we consider each color components as independent image the number and location of keypoint depends on the employed color component. Keypoint descriptor: each keypoint c_i is defined by a descriptor vector d_i containing the orientations and gradients magnitudes around the keypoints coordinates. The verifier evaluates the number of matches between test and training images based on Euclidean distance of the keypoint descriptors vectors.

ORTHOGONAL LINE ORDINAL FEATURES (OLOF)

The OLOF method was originally introduced and was investigated for the palmprint feature extraction. The comparison of OLOF method with several other competing methods in this reference suggests the superiority of OLOF with such competitive feature extraction methods. The OLOF presented significantly improved results but on conventional databases that are acquired from constrained imaging. The orthogonal filters are obtained using two Gaussian filters as follows

$$OF(\theta) = f(x, y, \theta) - f\left(x, y, \theta + \frac{\pi}{2}\right)$$

Each palm image is filtered using three ordinal filters, $OF(0)$, $OF(\pi/6)$ and $OF(\pi/3)$. In order to ensure the robustness against brightness, the discrete filters $OF(\theta)$, are turned to have zero average. The palmprint features are obtained filtering the palm image by the three ordinal filters, binarising the results with a threshold equal to zero, and resizing the binary image $n \times n = 50 \times 50$ pixels. An example of the feature matrix obtained using the three ordinal matrixes can

be seen in Fig. 2.

The matching distance between the palmprint image feature matrix $Q = \{Q^{\theta=0}, Q^{\theta=\pi/6}, Q^{\theta=\pi/3}\}$ and the palmprint image feature matrix $P = \{P^{\theta=0}, P^{\theta=\pi/6}, P^{\theta=\pi/3}\}$ is computed by the normalised Hamming distance, which can be described as follows

$$D = (D^{\theta=0} + D^{\theta=\pi/6} + D^{\theta=\pi/3})/3$$

being

$$D^\theta = 1 - \frac{\sum_{i=1}^n \sum_{j=1}^n P^\theta(i, j) \otimes Q^\theta(i, j)}{n^2}$$

where the Boolean operator \otimes is the conventional XOR operator. The numeric value of D ranges between 0 and 1 and the best matching is observed when the value of D is 1. Because of the inherent intra-class variations in the contactless imaging and imperfections in preprocessing, the vertical and the horizontally translation ordinal feature map is used to ascertain the best possible matching score.

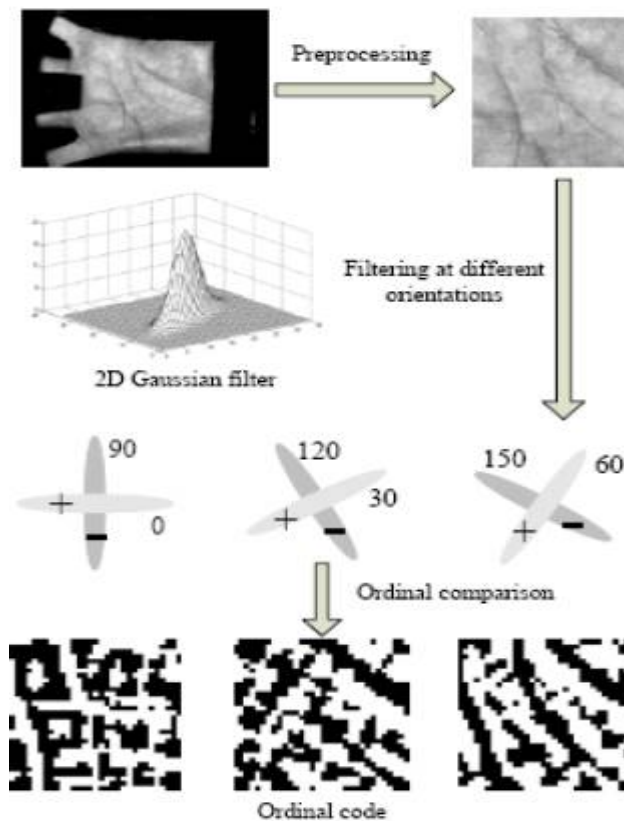


Fig. 2: Orthogonal line ordinal features for palm print recognition

as the final matching score. If the final matching score is greater than a threshold, the training templates and the questioned images are authenticated as belonging to the same person.

Matching score fusion

Combining scores obtained from different feature extraction approaches is a popular method of improving the performance for the multibiometrics identification. The OLOF and MSIFT scores were first normalized based on min-max approach. The combined matching scores were generated using the weighted sum approach as follows

$$s_{\text{fusion}} = w s_{\text{MSIFT}} + (1 - w) s_{\text{OLOF}}$$

where S_{MSIFT} and S_{OLOF} are the scores obtained with MSIFT and OLOF features, w is the weighting factor and S_{fusion} is the combined score which will be used to verify the input identity.

The distance between genuine and forgeries for OLOF approach Δ_{OLOF} is obtained in the same way. The weighting factor is obtained as

$$w = \Delta_{MSIFT} / (\Delta_{OLOF} + \Delta_{MSIFT})$$

IV. EXPERIMENTAL RESULTS

We used the two databases as described in Table 1 to perform rigorous experiments to comparatively ascertain the performances on different scenarios. The experimental results are evaluated using DET curves, equal error rates (EER), false acceptance and rejection rates (FAR and FRR, respectively). The FAR and FRR are estimated from a decision threshold estimated a priori. A common method of estimating this decision threshold is to employ the point where the probability density function of the genuine and imposter scores intersect. Both types of scores are obtained from the training samples of all the users. In this scenario, the threshold is obtained with information of the future imposters. The palmprint database images were acquired in single session, therefore we used all the images for the performance evaluation.

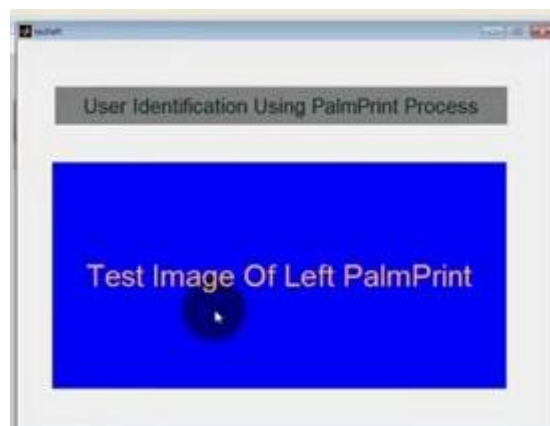
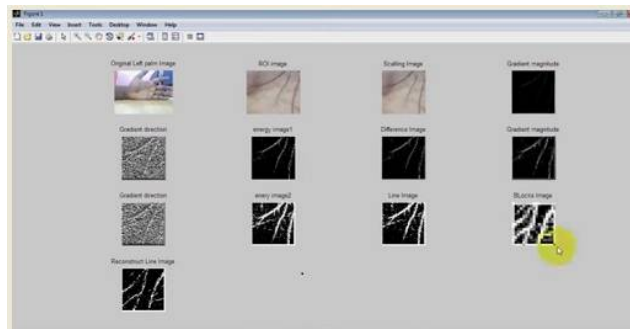


Figure 3 Left palmprint image

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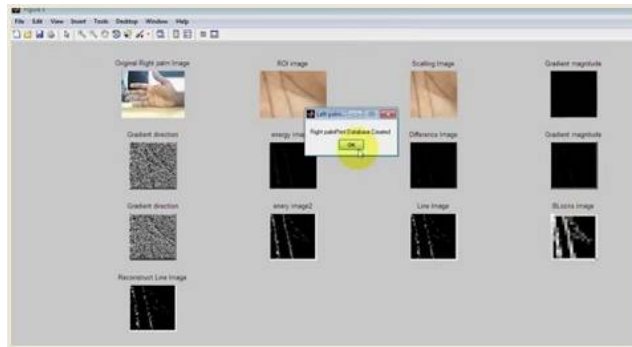


Figure 4 Right palmprint image

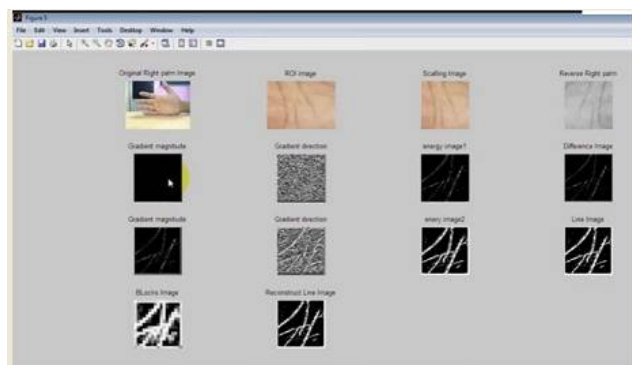




Figure 5 Reverse right palmprint image

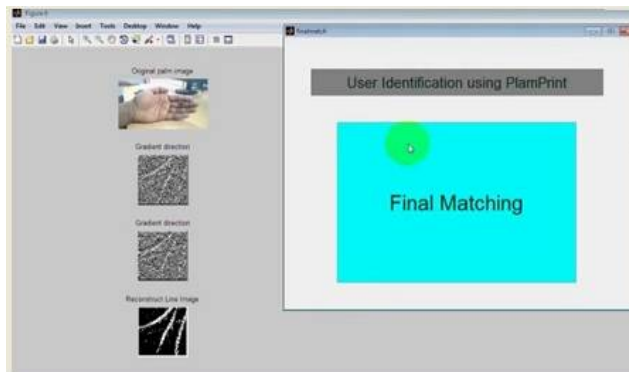


Figure 6 Describes the matching between two palm images.

Matcher	EER(%)	A priori threshold	
		FAR(%)	FRR(%)
MSIFT _R	0.33	0.47	0.28
MSIFT _L	0.27	0.53	0.14
OLOF _R	1.31	1.51	1.12
OLOF _L	0.61	0.65	0.59
Fusion _R	0.21	0.36	0.16
Fusion _L	0.20	0.29	0.12

Table 1 Average performance (EER) from IITD database.

V. CONCLUSION

In this paper, we analyzed the correlation between two state-of-the-art palmprint verification algorithms: SIFT and OLOF. Based on the observations, a feature extraction and cross matching level fusion scheme by exploiting the consistency between the two codes was proposed. The experimental results on the public database showed that by keeping the consistent orientation features, the palmprint verification accuracy could be

improved significantly compared with either the original SIFT or OLOF algorithm. Compared to other extraction approaches, this is efficient and have higher matching scores rate. This can be the future work subsequent to our experiments.

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