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Self Geometric Relationship-based matching for Palmprint Identification using SIFT

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Abstract—SIFT-based identification techniques have been broadly criticised in biometrics due to its high false matching rate. To overcome this weakness, a new method for SIFT-based palmprint matching, called the Self Geometric Relationship-based matching (SGR-Matching) is presented. While existing matching techniques consider only the relationship between the SIFT-points of the query image on one hand and the points in the reference image on the other hand, SGR-Matching also takes into account the geometric relationship between the SIFT-points within the query image in comparison with the relationship of the corresponding matched points in the reference image. Assessed with the proposed SGR-Matching, the SIFT-based palmprint identification system has been shown to improve the performance significantly. Furthermore, experimental results have shown the superiority of the proposed technique over state-of-the-art techniques.

I. INTRODUCTION

Over the last decade, palmprint data have emerged as a powerful means for verifying and identifying individuals' identity. This has received increasing attention from researchers in the field of biometrics. Indeed, the palm of an individual contains all the distinctive features exhibited in fingerprints, such as singular points and ridges. Furthermore, it has some other unique and discriminative features (e.g., wrinkles and principle lines) that show stability and can be used for verifying individuals' identity [1]. The palmprint also has a large area pattern that allows the extraction of information-rich descriptors. Nowadays, palmprint-based recognition systems are attracting widespread attention from the research community when compared to other biometric systems. Texture, edges, and lines constitute the most observable traits in palmprint images [2]. This is the reason for which most of existing systems rely on edge and texture descriptors using different filters such as the Gabor filter in [2] [3], the ordinal filter in [4], and the wavelet filter in [5]. One of the first attempts in the literature [3] for palmprint-based recognition adopted a 2-D Gabor phase filter, applied in multiple directions, and followed by an orientation-based coding method. The scheme, called PalmCode, has been assessed on a low-resolution image dataset. The desirable property of PalmCode in identifying palmprint data with high accuracy and speed attracted other researchers who adopted a similar approach. Indeed, the competitive coding scheme was later developed in [6]. The competitive code relies on

the real part of a variant of 2-D Gabor filters, called the neurophysiology-based Gabor filters where the palm-line pattern was modelled as an upside-down Gaussian function. In [4], the 2-D Gaussian filter was adopted to obtain the weighted intensity of each line-like region in the palmprint. The idea is to compare each pair of filtered regions that are orthogonal to each in terms of the filters orientation. However, because code-based palmprint techniques are sensitive to small rotations and translations, the authors in [7] modified the Radon filter to generate a code-like matrix and proposed a new matching measure that takes into account small geometric changes by considering the neighbourhood of each pixel in the Radon-filtered image. The system has particularly been shown to enhance the performance of its previous competitors under such geometric distortions. The same authors addressed in [8] the problem of high dimensionality in the RLOC technique using the histogram of oriented lines where the magnitude and orientation of the Radon-filtered image were used to compute the histogram in a fashion that is similar to the conventional Histogram Of Gradient (HOG). Very recently, it has been found in [9] that the coding-based techniques offer more robustness when only two orientation angles are used in the filtering stage. This has significantly improved RLOC and the competitive coding technique. The aforementioned techniques mainly rely on global texture and edge features and are characterised by high identification accuracy and low computational complexity, which is a suitable property for real-time applications. However, such techniques suffer severely from changes in illumination and contrast as well as geometric transformations, such as rotation and shifting, which may well exist in touch-based and touch-less palmprint data. To overcome this issue, the local feature point descriptor based on the Scale Invariant Feature Transform approach (SIFT) [10] has been adopted in the literature. SIFT is one of the most powerful techniques to deal with rotated and shifted images. However, while SIFT offers excellent matching of genuine points in palmprint data which describe the same person, it also creates false matches that significantly affects the overall performance [11]. Attempts to remediate this problem have mainly addressed the matching stage in which a variety of similarity measures have been proposed. In this context, Jiansheng and Yiu-Sang proposed a technique

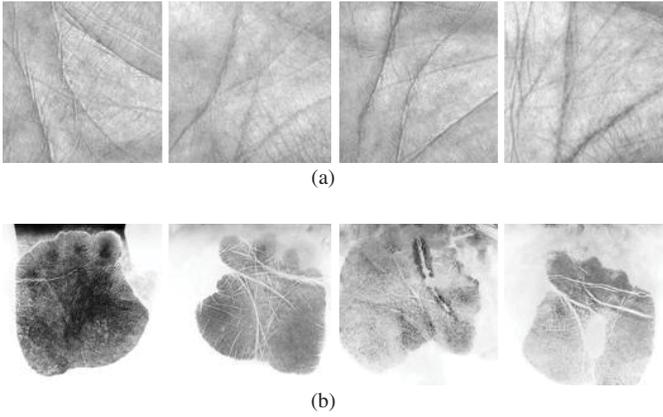


Fig. 1. Samples palmprint images used in experiments. (a) Extracted ROIs from PolyU palmprints. (b) HUPALMLAB palmprints.

based on time series technology [12]. Firstly, they used SIFT to extract the unique features of a palm image and then matching the extracted features using pointwise matching method. Secondly, extending time series technology for using with 2-Dimensions data and utilising it for representing and matching palmprint images [12]. Nibouche and Jiang [13] employed an SVD-based method to process the similarity and proximity matrices from which the matched points, extracted through the Harris-Laplace detector, are deduced. While the aforementioned attempts improved the matching accuracy of the conventional SIFT, they still fail to compete with coding-based techniques, especially on touch-based palmprint datasets that are acquired under a relatively good alignment conditions. In this paper, an improved SVD-based palmprint matching method is proposed. The objective is to reduce the number of mismatched SIFT points while maintaining high accuracy of genuine points matching. Unlike existing work which considers only the relationship between SIFT points in the query image on one hand and the reference image on the other hand, the main contribution in this paper is based on an algorithm that also measures the geometric relationship of SVD-matched points in each of the query and template images separately. The proposed algorithm is denoted in this paper by SGR-Matching. The rest of the paper is structured as follows. Section II describes the proposed matching approach. Section III provides experimental Results. The last section draws the conclusion of this study.

II. PROPOSED SIFT-SGR MATCHING SYSTEM

A. SIFT-based Feature extraction

In this paper, palmprint images are assumed to be cropped to contain the region of interest (ROI) as exemplified in Fig. 1(a). More details on the pre-processing step can be found in [12]. The Palmprint identification system relies on local features, extracted with the well-known Scale Invariant Feature Transform (SIFT), to perform the matching. Basically, the number of matched points between two images determines the degree of similarity. SIFT is viewed as one of the most

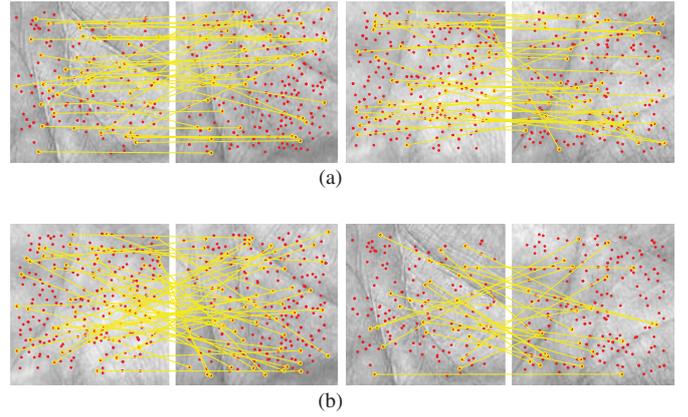


Fig. 2. Correct and false matching points with the SVD-based palmprint matching method [13]. (a) Matching across different sessions of the same individual. (b) Matching across different sessions of different individuals.

powerful tools to detect and describe local features (i.e. points of interest) when the image undergoes illumination changes and geometric transformations [10]. Furthermore, SIFT uses a rotation and scale invariant descriptor for each detected point using local normalised histograms.

B. SGR-Matching

The traditional approach for SIFT-points matching relies on the Euclidean distance as suggested by Lowe in [10]. If the distance between two point descriptors is below a certain threshold, the points are said to be matched. However, as reported in the literature [11], the Lowe's SIFT-based method suffers from high false matching rates. Fig. 2 illustrates the correct and false matching between two palmprint images in the case of the same and different palms. To overcome this limitation, we propose a two-stage SIFT-point matching method as follows. Stage 1: In this stage, we adopt the SVD-based matching process, proposed in [13], to obtain one-to-one matched points. That is, each point in the query image is matched with at most one point in the reference image. This will serve our requirement in stage 2 of the proposed method. The SVD-based matching algorithm first enforces the principle of proximity. This aims to select the closest point among similar ones so that each point in the query image is associated with the most similar point in the reference image. Denote by I and J two images containing m and n keypoints p_I^i ($i = 1, 2, \dots, m$) and p_J^j ($j = 1, 2, \dots, n$), respectively. Let $S_{ij} = \text{Dist}(I_{p_I^i}, J_{p_J^j})$ be the Euclidean distances measured between two SIFT-descriptors from a point p_I^i in I and another point p_J^j in J . Here, S_{ij} represents the similarity matrix. The proximity matrix G can be built between the two images I and J using the Gaussian kernel as follows:

$$g_{ij} = \exp\left(\frac{-S_{ij}^2}{2\sigma^2}\right) \quad (1)$$

Where σ denotes the standard deviation of Gaussian kernel (Normally $\sigma = 4$). In the Second step, the obtained proximity

matrix \mathbf{G} is further factorized using SVD as

$$\mathbf{G} = \mathbf{U}\Sigma\mathbf{V}^T \quad (2)$$

The finale step consists of replacing the diagonal elements of the obtained matrix Σ with ones giving another diagonal matrix Ω . It results

$$\mathbf{E} = \mathbf{U}\Omega\mathbf{V}^T \quad (3)$$

The SVD-factorized proximity matrix \mathbf{E} is used along with the similarity matrix \mathbf{S} . The SVD-based matching algorithm [13] only considers those points that meet the maximum in \mathbf{E} (row-wise and column-wise) and the minimum in \mathbf{S} (row-wise and column-wise), respectively.

However, although the SVD-based matching method reduces the false matches that involve one-to-many correspondences, it still suffers from false matches that exist in related or unrelated palms at different locations. Fig. 2 shows samples of the matching results obtained from incorporating SIFT-features with the SVD-based matching algorithm.

It can be seen that the amount of the false matching is considerable. It also reveals that one cannot rely only on the similarity and proximity matrices to exclude all the incorrectly matched points. From a different perspective, one can clearly see that the main problem in such a matching process resides in the incorrect geometric distribution of the matched points in each of the query and the reference palms. This is the key observation on which our contribution is based. It is worth mentioning that the point-to-point matching process yields the same number of matched points from each of the query palm and the reference one. This serves our requirement for improving the SVD-based matching algorithm proposed in [13]. In fact, the output of the SVD-based matching algorithm is further enhanced by incorporating a geometry-based exclusion method using SGR-Matching. Stage 2: First, given \mathbf{K} matched points from the query image \mathbf{I} and the reference image \mathbf{J} , denote by $D_I^{i,q}$ the Euclidean distances between the i^{th} point in \mathbf{I} , p_I^i ($i = 1, 2, \dots, \mathbf{K}$), and all the remaining points p_I^q ($q \geq i$). Similarly, $D_J^{i,q}$ represent the Euclidean distances between the i^{th} point in \mathbf{J} , p_J^i ($i = 1, 2, \dots, \mathbf{k}$), and all the remaining points p_J^q . Likewise, if we take the horizontal axis as a reference point, $\theta_I^{i,q}$ are the angles determined by the i^{th} point in \mathbf{I} , p_I^i ($i = 1, 2, \dots, \mathbf{K}$), and all the remaining points p_I^q ($q \geq i$). Similarly, $\theta_J^{i,q}$ represent the angles described by the i^{th} point in \mathbf{J} , p_J^i ($i = 1, 2, \dots, \mathbf{k}$) and all the remaining points p_J^q . Denote by $MS_{I,J}$ the matching score between \mathbf{I} and \mathbf{J} . The following algorithm is proposed.

1. For $i = 1, \dots, k$ do
 - 1.1 Initialize $R_{I,J}^i = 0$. For $q = i, \dots, k$ do
 - Calculate $D_I^{i,q}$, $D_J^{i,q}$, $\theta_I^{i,q}$, and $\theta_J^{i,q}$
 - If $|D_I^{i,q} - D_J^{i,q}| < T$ and $|\theta_I^{i,q} - \theta_J^{i,q}| < \tau$ then $R_{I,J}^i = R_{I,J}^i + 1$

where T is a small integer representing the tolerance threshold given in pixels and τ is the angle tolerance threshold. The final matching score $MS_{I,J}$ is given by

$$MS_{I,J} = \max_i(R_{I,J}^i) \quad (4)$$

The rationale behind the proposed algorithm is that the Euclidean distance between two correctly matched points in the query image should be identical to the one between their corresponding points in the reference image regardless of the geometric changes that might affect one of the images (query or reference). Therefore, the matching score $MS_{I,J}$ should be maximal if two palms represent the same individual because the correct matches will be dominant in this case. On the other hand, it is unlikely that two incorrectly matched points, either for the same or a different palm, satisfy the geometric requirement on the difference in distance (compared against a threshold T). The reason for reducing the number of calculated distances $D_I^{i,q}$ and $D_J^{i,q}$ in the inner loop is twofold. First, in the case of the same palm, the function $R_{I,J}^i$ may increase against i and attain its maximum value $R_{I,J}^{i^*}$ where i^* is the first correctly matched point. This obviously leads to $MS_{I,J} = R_{I,J}^{i^*}$ because the incorrectly matched points cannot generate more distances that satisfy the geometric requirement than correctly matched points. On the other hand, if a different palm is used in the matching, $R_{I,J}^i$ may decrease against i because the matched points normally do not meet the geometric requirement while the number of points, involved in calculating the distances, decreases in the loop. For the sake of demonstration, Fig. 3 and 4 illustrate the matching process with both the SVD-based matching method and the proposed one in the case of the same and different individual, respectively.

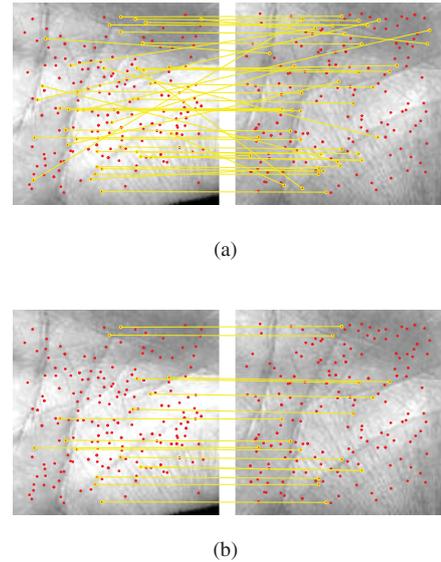


Fig. 3. Matched keypoints obtained on palmprint images of the same individual. (a) using SVD-algorithm [13], and (b) using SIFT-SRG

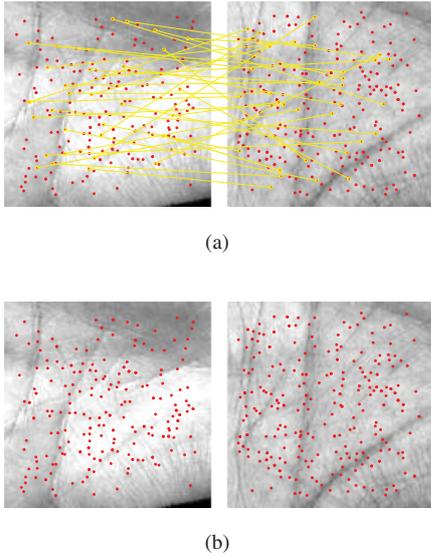


Fig. 4. Matched keypoints obtained on palmprint images of different individuals. (a) using SVD-algorithm [13], and (b) using SIFT-SRG (no matched points)

III. EXPERIMENTAL RESULTS

The proposed SIFT-SGR matching system has been implemented and evaluated on two different databases. It is worth mentioning that the competing palmprint identification systems, listed below, have been implemented in this work for the sake of comparison and analysis. The parameter settings of our system correspond to $T = 5$ pixels and $\tau = 30$ degrees.

A. Results on PolyU Palmprint Database

This database consists of 7,680 *low-resolution* palmprint images that represent 384 different classes. Each class contains 20 versions of full palm print images that collected over two different sessions separated by a minimum of two-months period of time. In our experiment, ten full palmprint images were considered in each session. The ROI is extracted from each full palmprint during the pre-processing stage. A total of 1500 of different palmprint images (250 classes where each contains 6 palms) from the first session are used as reference palms, while 1500 (representing the same 250 people) from the second session are used as query palms. Note that this setting is more challenging than the one which has been widely adopted (i.e. using mixed sessions in both training and testing) because the images in the second session have been subjected to illumination and small geometric changes to simulate the real world. For comparison, six state-of-the-art palmprint-based recognition systems have also been applied on the same set of images. Here, we consider the identification performance which is measured by the rate of correctly identified images (in SIFT-based methods, the closest image is the one that corresponds to the highest number of matched points). Also, the verification performance is measured by the Receiver operating characteristic (ROC curve) and the corresponding

Equal Error Rate (EER). ROC curves are illustrated by Fig. 5 accordingly. It can be seen that the proposed method sig-

TABLE I
IDENTIFICATION AND VERIFICATION RESULTS ON THE POLYU DATABASE.

Techniques	EER %	IDENT %
Palm Code [3]	1.64	97.33
Competitive Code [6]	4.26	94.00
RLOC [7]	24.95	71.86
FAST-RLOC [9]	2.33	94.53
HOL [8]	4.45	92.33
SIFT-SVD [13]	26.10	53.00
SIFT-SGR Matching	1.22	97.93

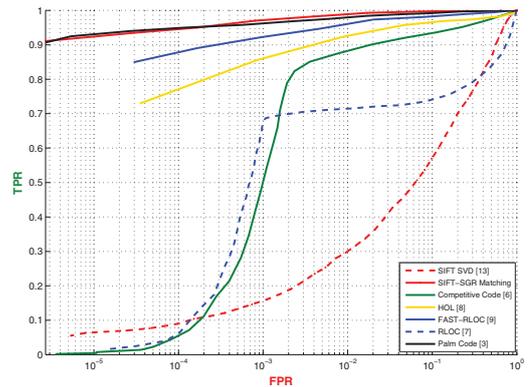


Fig. 5. ROC curve using PolyU database

nificantly outperforms other competing systems. Our results are in perfect agreement with [9] in the sense that the two-angle based RLOC enhances the performance of [7]. Note that SIFT-SVD [13] delivers the worst performance in the first experiment due to illumination changes in the query palms that seem to create false feature points.

B. Results on HUPALMLAB Palmprint Database

The HUPALMLAB database contains 1280 different palm impressions. These *high-resolution* palm impressions were collected from 80-individuals over two different sessions. For each individual, 8-impressions were collected per-session. Fig. 1(b) presents some samples of HUPALMLAB database. Table II depicts EER and the identification rate achieved using our SIFT-SGR matching method in comparison with other competitors. Likewise, ROC curves are illustrated by Fig. 6. As can be seen, the SIFT-SGR matching system delivers the best performance in terms of identification and verification.

Observe that, although this dataset provides high resolution images, it is still more challenging than the PolyU database as it includes geometric changes from which global feature-based techniques (such as Palm Code, and Competitive Code) suffer severely. Overall, it is worth mentioning that RLOC and HOL perform worse than their earlier competitors, namely the competitive code and Palm code. This is in perfect agreement with the results reported in [8]. This can be justified by the fact that the Gabor filter, used to encode the palm in different

TABLE II
IDENTIFICATION AND VERIFICATION RESULTS ON THE HUPALMLAB
DATABASE.

Technique	EER %	IDENT %
Palm Code [3]	9.78	86.41
Competitive Code [6]	17.84	70.31
RLOC [7]	10.16	81.41
FAST-RLOC [9]	15.71	66.25
HOL [8]	17.51	53.75
SIFT-SVD [13]	16.18	87.81
SIFT-SGR Matching	5.39	90.63

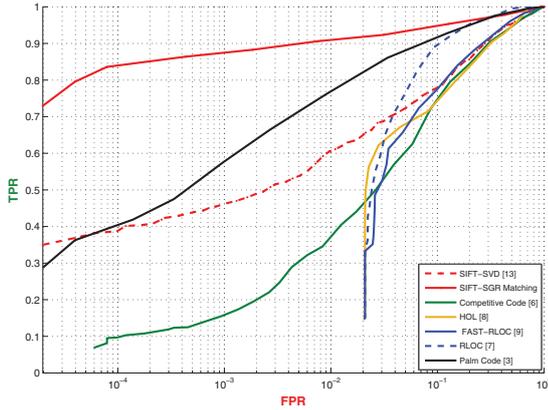


Fig. 6. ROC curve using HUPALMLAB database

orientations, is more robust than the radon transform used in [7] [8] [9] especially when the training and test images are taken in different sessions.

IV. CONCLUSION

In this paper, a new matching method for SIFT-based palm identification and verification, called the Self Geometric Relationship-based matching (SGR-Matching) has been proposed. The idea relies on the process of excluding the false matching keypoints based on the geometrical relationship between the matched points from the query palmprint image on one hand and the acquired palm on the other hand. Experimental palmprint identification and verification results with a number of implemented palm-based recognition systems, including the propose one (SGR-Matching), show the superiority of the proposed system over the-state-of-the art techniques.

REFERENCES

- [1] D.D. Zhang, *Palmprint authentication*, Springer Science & Business Media, 2004.
- [2] A. Kong, D. Zhang, and M. Kamel, "Palmprint identification using feature-level fusion," *Pattern Recognition*, vol. 39, no. 3, pp. 478–487, Mrch 2006.
- [3] D. Zhang, W.K. Kong, J. You, and M. Wong, "Online palmprint identification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 9, pp. 1041–1050, Sep 2003.
- [4] S. Zhenan, T. Tieniu, W. Yunhong, and Li. S. Z, "Ordinal palmprint representation for personal identification [representation read representation]," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, June 2005, vol. 1, pp. 279–284.

- [5] W. Xiang-Qian, W. Kuan-Quan, and D. Zhang, "Wavelet based palm print recognition," in *Machine Learning and Cybernetics, 2002. Proceedings. 2002 International Conference on*. IEEE, 2002, vol. 3, pp. 1253–1257.
- [6] A.W.-K. Kong and D. Zhang, "Competitive coding scheme for palmprint verification," in *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*, 2004, vol. 1, pp. 520–523.
- [7] W. Jia, D.-S. Huang, and D. Zhang, "Palmprint verification based on robust line orientation code," *Pattern Recognition*, vol. 41, no. 5, pp. 1504–1513, May. 2008.
- [8] W. Jia, R.-X. Hu, Y.-K. Lei, Y. Zhao, and J. Gui, "Histogram of oriented lines for palmprint recognition," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 44, no. 3, pp. 385–395, March 2014.
- [9] Q. Zheng, A. Kumar, and G. Pan, "Suspecting less and doing better: New insights on palmprint identification for faster and more accurate matching," *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 3, pp. 633–641, 2016.
- [10] D.G. Lowe, "Distinctive image features from scale-invariant keypoints," *International journal of computer vision*, vol. 60, no. 2, pp. 91–110, 2004.
- [11] M. Aythami, M.A. Ferrer, and A. Kumar, "Towards contactless palmprint authentication," *IET computer vision*, vol. 5, no. 6, pp. 407–416, 2011.
- [12] C. Jiansheng and M. Yiu-Sang, "Using sift features in palmprint authentication," in *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, 2008, pp. 1–4.
- [13] O. Nibouche and J. Jiang, "Palmprint matching using feature points and svd factorisation," *Digital Signal Processing*, vol. 23, no. 4, pp. 1154 – 1162, 2013.