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Robust Palm Vein Recognition Using LMKNCN Classification

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ABSTRACT
This paper presents a novel approach to improve the recognition percentage of palm-vascular-based authentication systems presented in the literature. The proposed method efficiently accommodates the rotational, translational changes and potential deformations by encoding the orientation preserving features. The proposed palm-vein approach is compared with other existing methods and obtained an improved performance in both verification and recognition scenarios. The experimental results obtained in this work based on PolyU and CASIA Vein databases conforms the superiority of the proposed method in both the recognition and verification.
***Index Terms*—**Biometrics, multispectral palm- print, palm-vein recognition, personal authentication, vascular biometrics.

I. INTRODUCTION

Biometrics is used for authentication and access control. It is also used to identify person's in-group that is under surveillance. Biometrics is the science of establishing the identity of an individual based on the physical or behavioral characteristics of the person. Biometric identifiers are classified as physiological versus behavioral characteristics. More conventional means of access controls are token-based identification systems, such as a driver's license or passport, and knowledge based authentication systems, such as a password or personal authentication number. Personal palms are very easy for imaging and by proper feature extraction techniques variety of information can be revealed [1]. Therefore, palmprint research has invited a lot of attention for access and forensic usage. However, the palmprint biometric is also disposed to sensor level spoof attacks like fingerprint, face, iris recognition methods [2].

The extrinsic features are more vulnerable for spoofing; these extrinsic features are easily accessible which leads to some privacy and security concerns. On the other hand, intrinsic biometrics (veins, DNA) requires more efforts to acquire without the knowledge of an individual. However, it is very important that high collectability of the biometric traits from the users must be taken using biometrics device. In this context, palm vein biometric system emerged as a promising alternative for personal authentication. Palm vein pattern biometric technology is a promising feature for use in forensic and access control applications. Palm vein biometric system is relatively new and is in the process of being continuously refined and developed. Palm vein authentication uses the unique patterns of palm veins to authenticate personals at a high level of accuracy [3], [4]. It has the advantage of the high efficiency but at the same time also ensures that the crucial identity information is unrevealed, therefore providing higher privacy and security for the user [5] - [10]. In personal palm different skin layers have different responses to the wavelength of the incident illumination.

The optical penetration depth for near-infrared imaging at 850 nm is estimated to be 3.57 mm and such illumination has shown to offer higher contrast for the veins while capturing an image. Therefore, the low-cost palm-vein imaging devices employing infrared illumination and a convention-imaging sensor can acquire subcutaneous vein patterns from the presented palms for secured personal authentication.

RELATED WORK

The palm-vein imaging typically requires infrared illumination which is one module of multispectral illumination for the multispectral palmprint imaging. Therefore, the multispectral palmprint images inherently acquire palm-vein details. However, as compared to the bispectral approaches, multispectral approaches commence a major amount of additional calculations which increases the cost. There are different methods that have been proposed in the literature for personal authentication using palm-vein images. The approaches can be broadly categorized in two categories on the basis of the nature of extracted features.

First approach is subspace learning in which the palm-vein images are projected into subspaces built from training data. Various subspaces have been explored in the literature for the palm-vein authentication: locality preserving projection (LPP), scale invariant feature transform (SIFT). These subspace learning generates sub- space coefficients (features) which are employed during the matching stage for the authentication. The other one is the line/curve matching using vessel extraction in which palm-vein images depict vascular structures and curve or line like features are extracted. The palm vein region of interest (ROI) extraction is done by spatial domain filtering. Several filters have been investigated for this purpose: Gaussian filters, Gabor filters, matched filters and SUSAN edge detector. The extracted line features are further encoded to form a template and employed during the authentication.

In addition, the prior efforts have been more focused on the multispectral palm images, rather than on single (near-infrared) spectrum palm-vein images [11] - [13]. This has motivated us to further explore the palm-vein authentication for real-world applications and ascertain the best possible performance from the near-infrared-based palm-vein authentication.

II. PROPOSED WORK

A review of prior work on palm-vein authentication presented in the previous section outlines the need for the comparative performance on the most promising palm-vein feature extraction and matching approaches [5]. In addition, the previous efforts have been more focused on constrained rather than contactless images. The contactless palm-vein authentication is more hygienic, can offer higher user acceptability, and preserves the vascular patterns from distortion and deserves further research efforts.

The key contributions from this paper can be summarized as follows. First, this paper investigates two new approaches which extract palm-vein features and achieves most promising performance. The subspace learning approach using kernel principal component analysis (KPCA) investigated in this paper extracts the vessel structures by analyzing the eigenvalues ofthe normalized palm-vein images. This approach offers a computationally efficient and most compact (minimum template size) alternative for generating palm-vein templates than the existing methods. The Local mean based k-nearest centroid neighbor approach achieves the best performance as compared to the prior palm-vein authentication approaches presented in the literature. We present a systematic analysis of the proposed approaches in contactless and constrained palm-vein imaging environment and ascertain the robustness of our methods.

It is well known that minimum number of training samples are desirable in a civilian biometrics system to ensure better user acceptability. Therefore, we rigorously evaluate the performance for the palm-vein authentication with the variation in the size of enrollment or training samples and ascertain the performance. The palm-vein literature has been highly focused on the verification problem and there are little or negligible efforts to ascertain the performance for the recognition problem. Therefore, this paper has also presented recognition performance from various (also proposed ones) approaches on the two different databases (please refer to Section IV) to comparatively ascertain the performance from various approaches.

The rest of the paper is organized as follows: Section II presents the details on the preprocessing steps that normalize the palm-vein images acquired from the completely contactless imaging. Section III describes our proposed feature extraction and matching approach for the automated palm-vein authentication. The experimental results are presented in Section IV and Section V provides discussion on the observations from our experimental results, including simulation results for the palm-vein authentication. Finally, the key conclusions from this paper are summarized in Section VI.

PREPROCESSING

The palm-vein images in contactless imaging present a lot of translational and rotational variations. Therefore, more stringent preprocessing steps are required to extract a stable and aligned ROI. The preprocessing steps essentially recover a fixed-size ROI from the acquired images which have been normalized to minimize the rotational, translational, and scale changes.

A. Image Segmentation and Normalization

The key objective while segmenting the ROI is to automatically normalize the region in such a way that the image variations, caused by the interaction of the user with the imaging device, can beminimized. In order to make the authentication process more effective and efficient, it is necessary to construct a coordinate system that is invariant/robust (or nearly) to such variations. It is judicious to associate the coordinate system with the palm itself since we are seeking the invariance corresponding to it. Therefore to build up the coordinate system, key points must be localized and these key points are easily identified in touch-based imaging but should be automatically generated for contactless imaging.

The acquired palm images are first binarized, so that we are able to separate the palm region from the background region. This is followed by the estimation of the distance from center position of the binarized palm to the boundary of palm .The potential scale changes in the contactless environment can be quite large, and in order to account for this variation, it is wise to adaptively select the location and size of the ROI according to certain image-specific measures from the palm. This method is more computationally efficient since no additional sampling/computations are required. After segmentation, the ROI images are scaled to generate a fixed size region and the whole process is illustrated in Fig. 2.

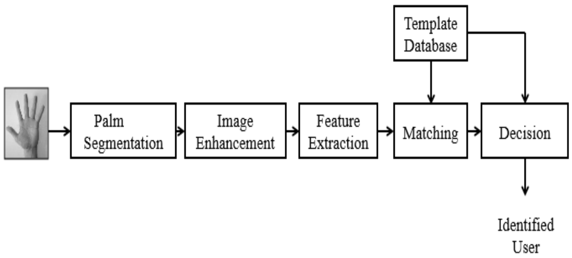


Fig. 1. Block diagram for personal authentication using palm-vein images.

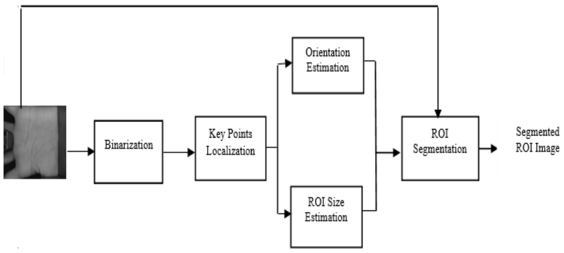
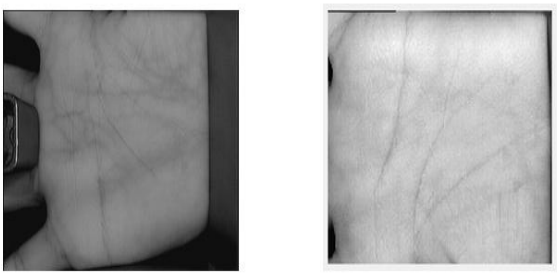
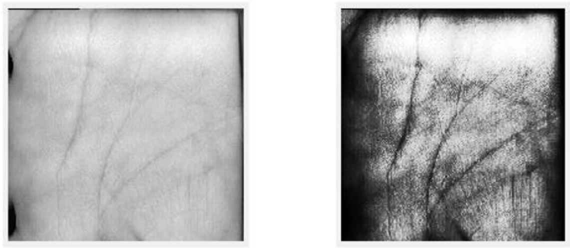


Fig. 2. Key steps in segmenting ROI images from contactless palm-vein images.



(a) (b)

Fig. 3. Illustration of segmentation of palm-vein ROI from an (a) acquired sample image with the illustration of key points, (b) the ROI image of (a)



(a) (b)

Fig. 4. Illustration of image enhancement: (a) original ROI images, (b) correspondingly enhanced ROI images of (a).

B. Image Enhancement

The palm-vein images employed in our work were acquired under near-infrared illumination (NIR); the images generally appear darker with low contrast. Therefore, image enhancement is essential to clearly illustrate the vein and texture patterns. We first estimate the background intensity profiles by dividing the image into slightly overlapping 32X32 blocks and the average gray-level pixels in each block are computed. As can be observed from Fig. 4, the enhancement has been quite successful in improving the details and contrast of the ROI images.

III. FEATURE EXTRACTION AND CLASSIFICATION

The normalized and enhanced palm-vein images depict curved vascular network/patterns, and these vessels can be approximated by small line segments which are rather curved. Therefore, in this paper, we propose a new approach to extract such line-like palm-vein features which can effectively account for more frequent rotational, translational variations, and also to some image distortions in the acquired image.

A. Kernel Principal Component Analysis feature extraction

In Principal Component Analysis, first of all, all eigenvalues and eigenvectors are calculated and sorted. Then the top most eigenvectors are chosen to project the input data into them. By projecting the input data into the chosen eigenvectors, the dimension of the input data is practically reduced.

First, the mean center of the images is calculated, m' is the mean image.

$$m' = \frac{1}{M'}\sum_{i=1}^{M'} x \quad (1)$$

Mean cantered image is represented in Eq. (2)

$$m_i = x - m' \quad (2)$$

Then, covariance matrix is achieved by,

$$C = MM^T \tag{3}$$

M represents the composed matrix of the column vectors mi.

Solving λn =Cn eigenvectors and eigenvalues are achieved; assuming λ is eigenvector and v is eigenvalue.

$$MM^T(Mn) = \lambda'(Mn) \tag{4}$$

It means that the first M- 1 eigenvectors (λ) and eigenvalues (n) could be obtained by calculating (MMT).

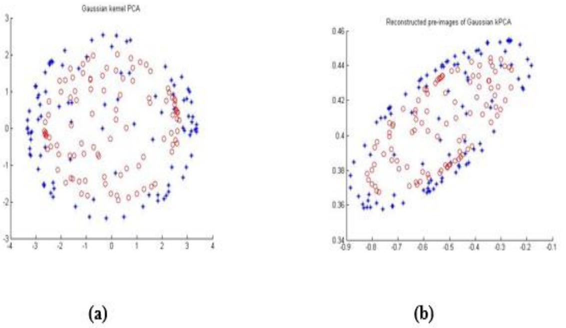


Fig.5. Illustration of KPCA feature extraction: (a) KPCA extraction using Gaussian mapping, (b) reconstructed image of (a)

When M eigenvectors and eigenvalues are achieved, the images will be projected onto L<<M dimensions using the following equation

$$\Omega' = [n_1 n_2 ..... n_L]^T \tag{5}$$

Where, (Ω') represents the projected value. To determine which face provides the best description of an input image, the Euclidean distance is obtained using equation (6).

$$\in'_k = \| \Omega' - \Omega'_k \| \tag{6}$$

And at last step, the minimum assigns the unknown data into k class. KPCA is exactly the same as PCA except for the fact that in KPCA, the input data is first non-linearly mapped and then PCA will be performed on the mapped data. The mapping is called Φ.

B. Local Mean based k-nearest Centroid Neighbor classification

KNN is well-known as a very simple, effective, and fast method to classify data. In this method, Euclidian distance is used as a criterion for classifying. To enhance the performance of KNN, a variety of methods have been proposed the latest one of which is called LMKNCN. The following part of this section consists of the mathematical explanation of LMKNCN.

The number of training samples in Ti, assuming that x is equal to query pattern, and k is equivalent to the size of neighborhood,

First of all, for each class, the distances are calculated ci to x as shown in Eq. (7)

$$u(x, y) = \sqrt{(x-y)^T(x-y)} \tag{7}$$

The first nearest centroid neighbor to x for each class ci is achieved. Then, K nearest centroid neighbors of x are calculated except for the first ones.

$$S'_{i(x)} = A_i - B_i^{NCN}(x) \tag{8}$$

$$S'_i(x) = \{y_{il}^{NCN} \in B^m\}_{l=1}^{K_i(x)} \tag{9}$$

In this step, sum of the previous j-1 nearest centroid will be obtained. Centroids which are in the set s' are achieved for all samples, and for all classes as indicated in Eq. (10)

$$y_{il}^f = 1/j(y_{il} + sum_i^{NCN}(x)) \tag{10}$$

Next, the distances between the X (query pattern) and centroids are calculated

$$u_{il}^f(x, y_{il}^c) = \sqrt{(x - y_{il}^f)^T(x - y_{il}^f)} \tag{11}$$

Then, jth nearest centroid neighbors to each class should be calculated

$$y^{NCN} = x_{mim\_index}^{NCN} \tag{12}$$

y^{NCN} Are added to $B_i^{NCN}(x)$ (13)

$$A_{ik}^{NCN}(v) = B_i^{NCN}(x) \tag{14}$$

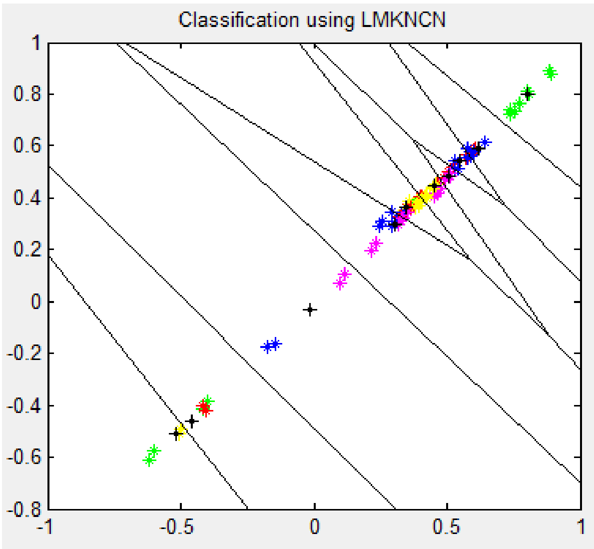


Fig. 6. Classification of test sample with the trained samples using LMKNCN

In this step, local centroid means vector are obtained for the set in all classes indicated as,

$$h_{ik}^{NCN} = 1/k \sum_{j=1}^{k} y^{NCN} \tag{15}$$

In the last part, X is assigned to the f based on nearest local centroid mean vector

$$f = \arg\min_{fi} u(x, h_{ik}^{NCN}) \tag{16}$$

IV. EXPERIMENT AND RESULTS

We thoroughly evaluated all these methods together with our proposed ones, so that we can get more insights into the problem of palm-vein authentication.

A. Database

In this work, we first employed the CASIA Multi-Spectral Palmprint Image Database V1.0 (CASIA database) which has been acquired from the contactless palm imaging of 100 subjects. All the images have been acquired in two data acquisition sessions with a minimum interval of one month, and at each time three samples were acquired from each user. The second database employed in this work is the PolyU Multispectral Palmprint Database (PolyU database), and all the images were acquired with a constrained device with finger-pegs, and is composed of images from 250 individuals with 12 images from each individual. These images were captured in two sessions (six images in each session) with an average interval of nine days. We employed these two databases, in our study so as to comparatively evaluate the performance from various methods and determine the robustness of our methods on different imaging setups. Since the focus of our work is on palm-vein authentication, and the palm-vein images are largely observed in NIR, only the images that were acquired under 850-nm wavelength illumination from the CASIA database and near-infrared images from the PolyU database were used in the following experiments.

B. Authentication Experiments

The extensive experiments conducted to evaluate the performance of KPCA based feature extraction method and LMKNCN classifications on palm vein database is introduced in this section. In this experiment, considering 5 images of a single subject, 4 images are used to train and the remaining imageis used to test. The accuracy is evaluated in each experiment and the following figures indicate the results.

Table I. Tabular Column showing the values of matching score for palm-vein images

No of Images	Matching Score
1	21.0703
2	6.65633
3	11.9287
4	5.15419
5	100
6	5.55519
7	100
8	100
9	0.231813
10	68.1643
11	10.2866
12	0
13	77.2004
14	100
15	100
16	22.9022
17	72.937
18	2.04576
19	-45.8949
20	-55.7383
21	6.49062
22	100
23	100
24	100
25	0.982657
26	-1.83527
27	1.03842
28	1.11496
29	0.602667
30	64.1386
31	100
32	100
33	6.12831
34	7.95865
35	6.42991
36	11.1219
37	8.46819
38	78.1311
39	100
40	99.7779

C. Verification Experiments

The selection of appropriate partition size for KPCA feature extraction is critical in achieving higher performance; if the selected size is too small, the partition may represent a lot of noise and thus not representative to the true dominant feature in the particular area. In other words, partitions which are too small in size tend to have higher genuine matches; however, it also leads to higher imposter/noisy matches which deteriorates the performance. On the contrary, partitions which are too large in size will suppress the representative local features and instead emphasize on the global ones, which is contrary to the motivation for our matching approach and is thus expected to deteriorate the performance. Fig.7 shows the genuine and imposter distribution using proposed approach on the CASIA and PolyU databases, respectively, and illustrates relatively clear separation between the genuine scores and imposter scores

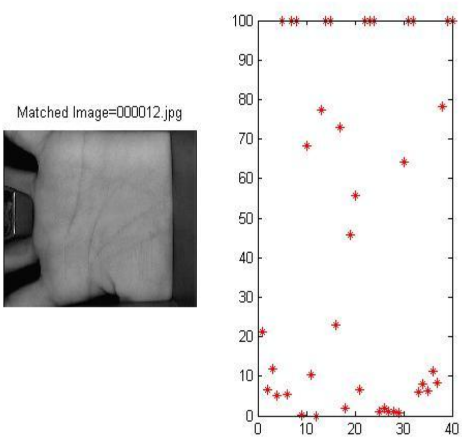


Fig.7. Verification and Result for matched Image

V. DISCUSSION

The experimental results presented in Section IV consistently suggests that palm-vein authentication using KPCA and LMKNCN achieves significantly improved performance over the earlier proposed approaches on both contactless and constrained palm-vein images.

VI. CONCLUSION

This paper investigated a novel approach for personal authentication using palm-vein images. We propose a novel feature extraction and matching approach that can effectively accommodate the potential image deformations, translational, and rotational variations by matching to the neighborhood of the corresponding regions and generating more reliable matching scores. The performances of Kernel Principal Component Analysis as a feature extraction method when the classifier is LMKNCN on palm vein database are compared and discussed in this paper. The experimental results reveal that the proposed method is most appropriate one among the other methods in terms of palm vein recognition. The performance gain achieved from the additional training samples is quite significant while the sample size is still small, but the redundant information accumulates rapidly as the training sample size increases. The efficiency of the palm vein authentication system can be improved by introducing fusion technique with appropriate selection of different algorithms. Multimodal biometrics can also be used to improve the efficiency of the proposed method. A combination of palm-vein and surface finger-vein is worth exploring for a large contactless database and is suggested for the further/future work.

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