Low-cost biometric recognition system based on NIR palm vein image

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Abstract: Palm vein recognition is motivated by the advantages of high security and liveness detection, but its popularity is prevented by the cost of palm vein capture devices. This study proposes a low-cost and practical palm vein recognition system. First, the authors’ system captures near-infrared (NIR) palm vein image with complementary metal–oxide–semiconductor camera in lieu of an NIR charge-coupled device camera. The goal is to reduce the cost of palm vein capture devices greatly. Second, this study adopts thenar area on the palm as the region of interest (ROI) for further palm vein recognition. The goal is to get the rich vessel and avoid the effect of palmprint. Finally, the discriminate palm vein features are extracted based on Haar-wavelet decomposition and partial least squares algorithm on the ROI image. The goal is to increase the recognition accuracy, though the resolution of the image is low. A database with 1500 palm vein images from 250 samples is setup with the capture device. Experiments in the self-built database and a public database show the effectiveness of the scheme.

1 Introduction
Palm vein recognition appeared in 1991 [1], and it attracted people's attention because of the high security, liveness detection, user acceptability, and convenience. First, palm vein recognition exhibits high security, as it uses the network of blood vessels underneath palm skin for identification. As palm vein is interior biological information of the body, vein patterns are much harder for intruders to copy compared with other biometric features. Palm vein is mostly invisible to the human eyes; they are commonly captured under near-infrared (NIR) light. Second, palm vein recognition ensures liveness in the presented biometric sample [2]. Without the blood flowing, the vascular image will disappear. Third, palm vein recognition systems have high user acceptability for the collection of an image is easy and non-intrusive [3, 4]. Since it acquires a palm vein pattern image without direct contact with the vein-pattern-extracting sensor, there is no contamination from the surface to the subject’s hand. Also, external conditions from the hand such as grease and dirt, wear and tear of the hands, and dry and wet hand surface do not affect the vein structure.

In the field of palm vein recognition, a number of research papers with different devices and technologies are highlighted [3–19]. While the high cost of exiting palm vein capture devices [4–14] usually prevent this biometric come to the product. In this paper, the authors’ goal is to propose a low-cost palm vein recognition so that palm vein biometrics are more popular.

The contributions of our work can be summarised as follows:
1. To alleviate the high cost of exiting palm vein capture devices, this research adopts a cheaper complementary metal–oxide–semiconductor (CMOS) sensor camera to decrease the main cost of palm vein image acquisition. On the basis of low-cost and low-resolution NIR palm vein images, this paper further presents a novel palm vein recognition system for personal identification.
2. In the system, our work extracts region of interest (ROI) from thenar area (thenar area: an area on the palm) while the other palm vein recognition literatures [15–19] extract the centre area of palm as ROI. The thenar area will not include three main lines of palmprint which form spurious palm vein information. This ROI extraction method is robust to four fingers (index finger, middle finger, ring finger, and little finger) open, closed, or with a ring. For the resolution of the capture device sensor is 352 × 288 px², our work proposes Haar-wavelet decomposition and partial least square (HDPLS) algorithm. This algorithm can effectively extract the main subspace feature of palm vein and neglect the non-significant noise from low-resolution palm vein image.
3. Finally, a database with 1500 palm vein images from 250 samples is setup with our capture device. Different from the other database, images in our database are of low resolution. Our system is tested by this database.

The rest of this paper is organised as follows: Section 2 describes the palm vein image recognition system design. Section 3 explains palm vein image ROI location algorithm in the thenar area. Section 4 explains the HDPLS feature extraction method. Section 5 reports our experiments and results in a self-built database and a public database. Section 6 gives the conclusions and future work.

2 Palm vein image recognition system design
In the field of the palm vein recognition, a number of research papers [4–13] with different devices and technologies are highlighted. Table 1 compares palm vein image devices and technologies in some literatures. Three main points: camera, light source, and image method are compared.

In this paper, the authors’ point is to reduce the cost of the palm vein image acquisition device, so that the recognition systems are more popular. The most costly part of the acquisition device is the camera. Most of the academic literatures [4–13] adopt costly NIR charge-coupled device (CCD) cameras that have high-resolution optics to capture the palm vein images. Wang used a JAI CV-M50IR 1/2" CCD NIR camera to capture palm vein image [5]. The literatures [3, 6–9] used the Chinese Academy of Sciences' Institute of Automation (CASIA) Multi-Spectral Palmprint Image Database [3]. It used NIR CCD camera for capturing palm vein

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image. All palm images were 8 bit grey-level Joint Photographic Experts Group (JPEG) files with pixel dimensions of 768 × 576 px². Wang et al. [10] also used CCD camera for capturing palm vein image. Yan et al. [6] used not only CASIA Multi-Spectral Palmprint Image Database, but also self-built database. All sample images in their databases were captured with a multi-spectral camera (AD-080GE) with a resolution of 1024 × 768 px in 940 nm active IR illumination. Zhou and Kumar [3] also used the PolyU (The Hong Kong Polytechnic University) multi-spectral palmprint database as their second database. Al-juboori used the PolyU multi-spectral palmprint database too [11]. The PolyU database adopted CCD camera. Lee [4] and Lee [12] also used a low-cost CCD camera – an adapted Sony XC711, costing about $1500. All above CCD cameras cost is far beyond CMOS camera. In this research, the cost of the CMOS camera was around $20. Antonio used a commercial ultrasound imaging machine to capture the three-dimensional (3D) palm vein pattern [14]. Compared to other low-cost recognition devices [20, 21], this commercial ultrasound imaging machine is too expensive to be practical for typical palm vein recognition applications. Fujitsu's palm vein verification product has high accuracy, but to the best of our knowledge, the features used are not disclosed in any published research articles.

Fig. 1 shows the inter-structure of the designed acquisition device. CMOS sensor has a low-cost, low-power consumption, and high conformability. We choose the CMOS camera which is sensitive to the NIR wavelength to get the high contrast palm vein image. The image quality of OV5116 CMOS sensor camera is similar to the image quality of a CCD sensor camera. The palm images are 8 bit grey-level JPEG files with a size of 764 × 568 px². The lowest illumination under NIR is 0 lux, so it is suitable for collection palm vein image without visible light. As the OV5116 is not as sensitive as the NIR CCD camera, we enhance the light power to let it closer to NIR CCD camera. The sensor's electronic noise can be reduced by enhancing the signal and noise compare rate.

In our system, an light-emitting diode (LED) array was chosen as the light source rather than a CCD light source, as the LED array is cheaper, and provides enough light intensity. The illumination part is set at 850 nm LED set.

All of the collection components are placed in the capture box to avoid visible light. There is internal reflective material inside the capture box. A black background plate is placed at the bottom of the box, and only a slot for the palm is provided for the user. The volunteer will place their hand flat on the bottom of the box. If the volunteer will not place their hand on the bottom of the box, they can hold on their hand flat above the bottom by themselves. The camera is placed in the centre of the LED set, and a light guide plate is positioned at the appropriate distance from the LED set to let the light homogeneous radiation.

### 3 Palm vein image ROI location

After conducting a low-pass filter of the palm vein image, an ROI is extracted from the palm vein image for further feature extraction and matching. The ROI can eliminate irrelevant data (such as background interference etc.). ROI greatly reduces the amount of computation for subsequent processing and reduces the influence of rotation and translation of the palm.

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**Table 1** Comparison of palm vein image devices and technologies

<table>
<thead>
<tr>
<th>Literature</th>
<th>Camera</th>
<th>Light source</th>
<th>Image method</th>
</tr>
</thead>
<tbody>
<tr>
<td>[4, 12]</td>
<td>CCD camera (Sony XC711) 850 nm LEDs</td>
<td>IR light sources</td>
<td>reflection</td>
</tr>
<tr>
<td>[6]</td>
<td>multi-spectral camera (AD-080GE) 700, 800, and 940 nm active IR illuminations</td>
<td>IR light</td>
<td>reflection</td>
</tr>
<tr>
<td>[7–9]</td>
<td>multi-spectral camera (AD-080GE) 940 nm active IR illumination</td>
<td>IR light</td>
<td>reflection</td>
</tr>
<tr>
<td>[10]</td>
<td>NIR CCD camera 850 nm LEDs</td>
<td>IR light source</td>
<td>reflection</td>
</tr>
<tr>
<td>[14]</td>
<td>3D ultrasound imaging machine</td>
<td>—</td>
<td>reflection</td>
</tr>
<tr>
<td>[19]</td>
<td>night-vision camera 850 nm LEDs</td>
<td>IR light source</td>
<td>reflection</td>
</tr>
</tbody>
</table>

**Fig. 2 Location of ROI in the literature**
3.1 ROI in related works

In current palm vein recognition approaches, many of the ROI orientation methods [15–19] locate the ROI in the centre of the palm, as shown in Fig. 2.

The literatures [3, 18] are accounted for contactless palm vein recognition. The location of ROI is based on two webs: the web between the index finger and middle finger together with the web between the ring finger and little finger, as shown in Fig. 2. The literature [4] locates the ROI depends on two key points and one distance. The first valley point is the valley point between the small finger and ring finger. The second valley point is the valley point between the middle finger and the index finger. The ROI lies within two key points at a distance, as shown in Fig. 2. The literature [7] defines the midpoint P1 of the two valley points on both sides of the index finger and the midpoint P2 of the valley points on both sides of the little finger as two reference points for the ROI extraction. These two key points make ROI larger, as shown in Fig. 2. The literature [12] locates the ROI similar with the literatures [3, 18], but the ROI of [12] is a rectangle. The reason for [12] extracts the ROI in the manner is that this ensures all the ROIs reference the same region in the palm vein image, as shown in Fig. 2. The literature [15] has three poles to help a user to fix his/her hand. It also uses two valley points to locate ROI. The first point is the valley point between the small finger and ring finger. The second point is the valley point between the middle finger and the index finger, as shown in Fig. 2. The literature [19] obtains ROI with four valleys of fingers, as shown in Fig. 2. They all include three main lines of palmprint which form spurious palm vein information.

While the centre area of the palm is suitable for palmprint recognition as the main information (principal lines and wrinkles) are there. However, through observation of palm vein images, we find that palm vein in the palm centre was not clear in a lot of samples, though it is feature rich for palmprint methodology.

3.2 Palm vein distribution in the palm

From the medical papers [22, 23], we know that palm is divided into three areas: thenar area, hypothenar area, and the centre of the palm area, as shown in Fig. 3.

The shallow vein distribution of vein in the palm is shown in Table 2.

The vessel in the centre of palm only about 0.1–0.5 mm, though mesh distribution, usually only 3–5 branches could be taken clearly. However, the vessel in the thenar area was wider than the other two areas. For these attributes, we adopt the thenar area as the ROI area. The thenar area will not include three main lines of palmprint which form spurious palm vein information.

3.3 ROI in our work

This paper located the thenar area on the palm as the area of ROI range. Without the use of a docking device to constrain the palm position when acquiring palm vein images, it is difficult to fix the ROI at the same position in different palm vein images.

Some stable feature points are detected, to position the thenar ROI in such images. Our method uses the following approach. It finds the maximum inscribed circle inside the contour to find four stable feature points in the palm: the maximum inscribed circle centre, three crossover points on a maximum inscribed circle with palm contour. Most of the maximum inscribed circle will fall on the side close to the wrist, and this paper calls it wrist side maximal inscribed circle (WSMIC). In the majority of cases, the WSMIC is often near the thenar area. The maximum WSMIC will have the crossover with the palm contour at the points of thumb palm contour, the valley of thumb and index finger, little finger palm contour line. In a minority of cases, the maximum inscribed circle will not be near the wrist. If that happens, it does not meet the conditions of WSMIC, and then this paper chooses the largest inscribed circle close to the wrist side. Thus, there are two stable feature points that we can use to locate the ROI. One is the centre point of WSMIC and the other is the tangency point of WSMIC with thumb palm contour. Since connection of these two points just passes the thenar area, we use it as the symmetry axis of ROI.

The detail positioning method is shown in Fig. 4. First, after the low filter, we extract palm contour, process WSMIC in it as shown in Fig. 4b. In Fig. 4b, point A and point O are the stable character points. They are slightly robust to palm rotation and translation. These two points will be used to position the ROI. Connect point A and point O to make the line AO. Now, we are going to draw ROI square of BCDE. Point O is the middle point of side DE. The side length of this square is \( (2 \times \sqrt{5} \times R) \). \( R \) is the radius length of circle WSMIC. Side DE is perpendicular to line AO. Draw line BE parallel to AO. The crossover point on circle WSMIC is B. B is another vertex of the square. In the same way, we find another vertex of C. Then take point B and point C as the two vertex points on the side of BC. Draw the square with the side length. Side BE is parallel with the segment A O.

Then draw a line OO’ parallel to the y-axis. \( O’ \) is the crossover point of the line OO’ with the palm outline. The intersection angle between lines AO and OO’ is \( a \). Rotated the image with the included angle \( -a \) to OO’ and the centre point is O, as shown in Fig. 4c. Square BCDE is the ROI we want, as shown in Fig. 4d. This ROI extraction method is robust to four fingers (index finger, middle finger, ring finger, and little finger) open, closed, or have a ring.

4 Palm vein feature extraction based on HDPLS

There are two main problems in palm vein recognition. First, skin scattering and optical blurring [24] obscuring the thin vessels in some people’s images. To solve this problem, an algorithm has to be designed that extracts the main features of palm vein and neglects the non-significant ones. Second, changes in the hand position between one image and the next causing image translation make classification difficult. Thus, the algorithm should extract the information which is good for classifying.

There are mainly four types of algorithms currently used in palm vein recognition: (i) geometry-based method [3, 25–27], (ii) statistics-based method [8–12, 28], (iii) local invariant-based method [6, 29, 30], and (iv) subspace method [4, 5]. Geometry-based methods typically use vascular structure information such as the point feature or line feature to describe the palm vein. However, when skin scattering and optical blurring happens, some of the vessels or part of the vessels cannot be imaged. Thus, the recognition rate is not good. The statistics-based methods would be affected by the texture information not rich enough in some people’s palm. Local invariant-based methods such as scale invariant feature transform (SIFT) faces the main problem of low speed. Subspace methods take the palm vein image as the whole object. Although all these methods and respective papers illustrate a high level of accuracy, the practical feasibility of these systems has not been shown. This paper adopts the subspace method. PLS [31] regression method is a type of subspace method and a classical multivariate statistical learning method. It realises principal component extraction and dimensionality reduction, which can solve the first problem faced by palm vein recognition. PLS realises the largest category relevance at the same time, which solves the second problem faced by palm vein recognition. However, PLS faces an initial small sample size (SSS) problem. When the instances number is smaller than the dimensions of the input data, the within-class scatter matrix is singular, which is also named the SSS problem [32]. Wavelet decomposition [33–35] not only can settle this problem, but also can significantly reduce the computational complexity. So this paper improves PLS to HDPLS. The flowchart of HDPLS is shown in Fig. 5.

HDPLS applies Haar-wavelet decomposition in the ROI. The implementation of wavelet decomposition is carried out by applying a 1D transform to the rows of the original image data and the columns of the row transformed data. After the one-level decomposition, the ROI is decomposed into four subbands, as shown in Fig. 6b. The LL band is a coarser approximation to the original image. It contains powerful information for palm vein recognition. The bands HL and LH record the change of the image along vertical and horizontal directions. While the band HH shows
the high-frequency component of the image. It contains the detail information of palm vein and noises. So we can ignore the high-frequency part in the image and extract the features in the low-resolution image to reduce the computational complexity. This also improves the robustness of our algorithm to the noise and image translation. In the two-level wavelet decomposition, further decomposition can be conducted on the LL subband. After three-level wavelet transform, an image is decomposed into subbands of different frequency components. They are shown in Fig. 6. Since the resolution of ROI image is 128 × 128, the subbands 1, 2, 3 and 4 are of size 16 × 16, the subbands 5, 6, 7 are of size 32 × 32 and the subbands 8, 9, 10 are of size 64 × 64. After K-level wavelet decomposition, the resolution rates in different sub-images are reduced, so the data involved in computation is only $2^{-2K}$ of the original image. The K of decomposition is determined by the experiment.

HDPLS aims to model the relationship between independent variable $X$ and dependent variable $Y$ whose values are known for $B$ observations.

The external relationship of independent variable $X$ and dependent variable $Y$ can be expressed as

$$X = TP^T + E$$

$$Y = UQT + F$$

The internal relationship of independent variable $X$ and dependent variable $Y$ can be expressed as

$$Y = XB$$

$T$ and $U$ are the principal components of $X$ and $Y$; $P$ and $Q$ are the line expresses of $X$ and $Y$; $E$ and $F$ are residual; $B$ describes the internal space relationship of $X$ and $Y$.

In our solution, we denote the sample composed by palm vein image sets as independent variable $X$; the sample category information as dependent variable $Y$.

Step 1: Extract the first principal component from two groups: $T_1$ and $U_1$.

$T_1$ is the linear combination of $X$

$$T_1 = \omega_{11}X_1 + \omega_{12}X_2 + \cdots + \omega_{1p}X_p = \omega_1^TX$$

$U_1$ is the linear combination of $Y$

$$U_1 = \nu_{11}Y_1 + \nu_{12}Y_2 + \cdots + \nu_{1q}Y_q = \nu_1^TY$$

$T_1$ and $U_1$ should carry the variation information of their matrixes as far as possible, at the same time, the relevance extents of $T_1$ and $U_1$ must reach the most. That means (6) must be met

$$\text{MAX}(\text{cov}(T_1, U_1)) = \sqrt{\text{var}(T_1)\text{var}(U_1)r(T_1, U_1)}$$
regression of $X$ on principal components of HDPLS: $Y$

Do the linear regression of principal component of HDPLS. Do the linear regression of is (10)

$$\omega_{1T}X\beta_{1} + \cdots + \omega_{mT}X_{m} + Y_{m}$$

This is the model of palm vein feature extraction. The feature vector set $\beta_{1}, \beta_{2}, \cdots, \beta_{m}$ is a set of the coordinate coefficient. We project the ROI into the feature vector, a set of coordinates can be obtained. This coordinate denotes the place where the image is in the subspace. The coordinate is the basis of classification.

### 5 Experiments and results

The experiments conducted below were run on an Intel(R) Core(TM) i5-5200U central processing unit 2.2 GHz personal computer with 4 GB random access memory using MATLAB 2015. This methodology uses data from two databases. The first is a self-built database, where the goal is to test the effectiveness of our system. The other database is a public database, Chinese Academy of Sciences' Institute of Automation (CASIA) Multi-Spectral Palmprint Image Database, where the goal is to test our feature extraction algorithm. Actually, there are three more public databases for palm vein images. We compare them and our database in Fig. 7.

PolyU Multi-spectral Palmprint Database just provides the ROI in the centre of the palm. We need to extract ROI in the thenar area; obviously, this database is not suitable for our experiment. VERA Palmvein Database [36] only provides the first 50 users now. PUT database [37] is a database that comprises of 50 users. For this reason, we choose CASIA as a public database in this paper. In the self-built palm vein database experiment, this paper first selects the best parameter to the proposed feature extraction algorithm, and then this paper compares it with the other typical palm vein recognition algorithms. In the CASIC database, we experiment our feature extraction algorithm too and compare it with the other typical palm vein recognition method which adopted the same database.

#### 5.1 Introduction of self-built palm vein database

Our research team conducted a data collection which contains 1500 images from left hands of 250 different volunteers participated in both visits. The age distribution is from 18 to 60 years old. Each individual provided six images. In the first stage, three images of each palm vein are acquired, and these data are used for training. Two weeks later, three more images of each palm vein are taken, and these data are used for testing. The volunteers put their left hand into the slot of the capture device, facing upwards with at
least 1.5 cm of the wrist in the image. The palm images were 8-bit grey-level JPEG files with pixel dimensions of 764 × 568 px.

There are four hands in Figs. 6a–d separately. Each hand has two images. They are slightly different between images from the same hand. Scale variation occurs in the two images of Fig. 8a.

There are slight tilts forward or backward between images, just like two hands in Fig. 8b. Tilts to the left or right occur just like in Fig. 8c. In Fig. 8d, two images have difference in finger gesture.

5.2 Best parameter selection to the proposed algorithm

To select the best parameter to the proposed algorithm, HDPLS computes the recognition performances of one-level, two-level, and three-level decompositions with different component numbers. The image size is 64 × 64 px after one-level wavelet decomposition. The image is represented by a 4096D vector. So \( X \) is a 1500 × 4096D vector. The image size is 32 × 32 px after two-level wavelet decomposition. The image is represented by a 1024D vector. So \( X \) is a 1500 × 1024D vector. The image size is 16 × 16 px after three-level wavelet decomposition. The image is represented by a 256D vector. So \( X \) is a 1500 × 256D vector. The principal component numbers are chosen from 20 to 300. Considering the time consumption, we do not extend components number. To three-level decomposition, just 256 px in the image, 260–300 principal components cannot be implemented. After the feature extraction stage, the feature matching stage is followed. As the data category is 250, a total of 1, 124, 250(250 × 249 × 6 × 6/2 + 250 × 6 × 5/2) comparisons are performed. Inter-class matching times are 1, 120, 500 (250 × 249 × 6 × 6/2). Intra-class matching times are 3750 (250 × 6 × 5/2).

The most common evaluation metrics for palm vein recognition includes false acceptance rate (FAR), false recognition rate (FRR), and equal error rate (EER) [38]. FAR represents the number of impostors that is classified as genuine, divided by the total of impostor comparisons. FRR is the number of genuine that are classified as an impostor, divided by the total of genuine comparisons. EER is the error when \( \text{FAR}(i) = \text{FRR}(i) \). The recognition performance of different wavelet levels decomposition with different component numbers is shown in Fig. 9.

As illustrated in Fig. 9, one-level wavelet decomposition demonstrates the best performance with EER than two level and three level. For more palm vein information, details are concealed by two-level decomposition and three-level decomposition. Table 3 shows the time consumption and EER of 240–300 principal components.

For the feature, matching time plays an important role in the time consumption of a real recognition system. Principal components 260–300 cost too much system time. We will compute it in 5.3 system speed.

Therefore, one-level decomposition with principal components number 240 is optimal for our system. The EER is 0.4058%. In Fig. 10, we show the detailed performance of the proposed parameter.

Fig. 10a shows a curve of intra-class and inter-class matching distributions. The curve implies the intra-class distance and inter-class distance is separated clearly. FAR is 0.5895% and FRR is 0.1333%. So we can see the beautiful figure in Fig. 10b. The experiment also evaluated the EER of the proposed method by making trade-offs between the FRR and FAR. From Fig. 10c, we can see the receiver operating characteristic curve (ROC) where the EER is 0.4058%.

From all the evaluation metrics we illustrated above, our system has been demonstrated to obtain effective recognition performance.
in person set of 250 with low-resolution images in palm vein recognition.

5.3 System speed

Identification includes four part times: palm vein image acquisition, ROI extraction, feature extraction, and matching with the other images feature in the database. The execution time for each step is listed in Table 4.

For the match time may be 1–1500, this paper takes the average feature matching time as the average feature matching time during identification. That is \( (0.0017 \times 1500 + 0.0017) / 2 = 1.2759 \) s. So the execution time is about 2.004 s (1 s + 0.3 s + 0.4282 s + 1.2759 s). Since the speed of matching is acceptable, it can easily be applied to the real identification system. While using the same method, we can compute when the principal components number is 260. The execution time is about 4.0266 s (1 s + 0.3 s + 0.4362 s + 1.1214 s). It is not a practicable time for a real system.

5.4 Comparisons to other algorithms in self-built database

To illustrate the effectiveness of the proposed method, we conducted detailed comparisons with some typical algorithms. To run the algorithms of these conventional methods, we wrote codes based on the corresponding publications. Table 5 illustrates the EER, extraction time, and matching time of these two methods are faster than our method. From the recognition accuracy, our method is better than them. From Table 5, we can conclude that our method has superior performance in EER, but the system speed is not fast.

5.5 Experiment on the CASIA database

To evaluate HDPLS method, 600 right-palm images in the CASIA Multi-Spectral Palmprint Image Database, which were captured from 100 different people using a self-designed multiple spectral imaging devices operating at a wavelength of 850 nm, were utilised in our experiments. All palm images were 8 bit grey-level JPEG files with pixel dimensions of 768 x 576. For each individual, all samples were captured in two sessions and the time interval between the two sessions was more than 1 month. In each session, three samples were captured with a certain degree of hand posture variation between them to increase the diversity of intra-class samples in an effort to simulate an actual application.

In our experiment, we perform all matching strategies. Fig. 11 shows a curve of intra-class and inter-class matching distributions. The curve implies the intra-class distance and inter-class distance is separated clearly. FAR is 0.0415% and FRR is 0. So we can see the beautiful figure in Fig. 11b. The experiment also evaluated the

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Performance EER, %</th>
<th>Feature extraction, s</th>
<th>Feature matching, s</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA + LPP [5]</td>
<td>0.7376</td>
<td>0.3171</td>
<td>1.2211 x 10^{-6}</td>
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<tr>
<td>SIFT [30]</td>
<td>27.8405</td>
<td>1.1214</td>
<td>0.0018</td>
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<tr>
<td>grey-scale surface matching [39]</td>
<td>3.9351</td>
<td>0</td>
<td>0.0796</td>
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<tr>
<td>mutual foreground local binary pattern (LBP) [7]</td>
<td>43.900</td>
<td>5.3444 x 10^{-4}</td>
<td>4.7000 x 10^{-4}</td>
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<tr>
<td>modified (2D)2LDA [4]</td>
<td>4.4002</td>
<td>0.007</td>
<td>1.3747 x 10^{-4}</td>
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<tr>
<td>proposed</td>
<td>0.4058</td>
<td>0.4282</td>
<td>0.0017</td>
</tr>
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</table>

![Performance curves of the proposed algorithm in the CASIA database](image-url)

(a) Intra-class and inter-class matching curves, (b) FAR and FRR distribution curves, (c) ROC curve
Table 6 Summary of EER derived from several state-of-the-art methods using the CASIA database

<table>
<thead>
<tr>
<th>References</th>
<th>Year</th>
<th>Methodology</th>
<th>EER, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhou and Kumar [18]</td>
<td>2010</td>
<td>Hessian phase</td>
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<td></td>
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<td>scores combined of above four methods</td>
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<tr>
<td>Zhou and Kumar [3]</td>
<td>2011</td>
<td>Neighborhood matching radon transform (NMRT)</td>
<td>0.51</td>
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<tr>
<td>Kang and Wu [7]</td>
<td>2014</td>
<td>improved LBP method on mutual foreground fusion with sub-block histogram matching</td>
<td>0.287</td>
</tr>
<tr>
<td>Kang et al. [29]</td>
<td>2014</td>
<td>RootSIFT feature extraction on preprocessing image, and matching after LBP-based mismatching removal</td>
<td>0.996</td>
</tr>
<tr>
<td>Yan et al. [6]</td>
<td>2015</td>
<td>multi-sampling and feature-level fusion</td>
<td>0.16</td>
</tr>
<tr>
<td>Ma et al. [9]</td>
<td>2017</td>
<td>adaptive gabor filter</td>
<td>0.12</td>
</tr>
<tr>
<td>this paper</td>
<td>2018</td>
<td>HDPLS</td>
<td>0.0292</td>
</tr>
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</table>

EER of the proposed method by making trade-offs between the FRR and FAR. From Fig. 11c, we can see the ROC curve where the EER is 0.0292%. From all the parameters we illustrated in Fig. 11, our algorithm has shown the effective recognition performance in the public database.

To further illustrate the effectiveness of our method, an EER comparison with several state-of-the-art methods for palm vein recognition using the CASIA database is given in Table 6. These results are their published qualitative result. Table 6 shows that our proposed method has superior performance.

6 Conclusion

In this paper, we have proposed a biometric recognition system based on NIR palm vein image with low-cost CMOS camera. This project aims to reduce the high cost of the palm vein capture device. We extract the vein area as ROI. It is a novel area for ROI. This area avoids most influence by three main lines of palmprint. In the stage of feature extraction, we performed HDPLS algorithm. Euclidean distance is used in the step of matching. Experiments in the self-built database show the high recognition accuracy of EER 0.4058% using the proposed method. The whole recognition can be performed in 2.004 s in our prototype system. The speed of the system is rapid enough for real-time palm vein recognition. Meanwhile, to compare our algorithm with the other recently published methods for palm vein recognition using the CASIA Multi-Spectral Palmprint Image Database, an experiment on CASIA is done. Our proposed algorithm has the super EER of 0.0292%.

In the further work, we will focus on how to keep down the volume of the capture equipment. As part of our future work, we explore fast and efficient algorithms that can potentially decrease the time required for the proposed system.

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8 References


