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Intelligent Techniques for Matching Palm Vein Images

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Abstract

The palm vein is one of the most reliable physiological characteristics that can be used to distinguish between individuals. Palm vein technology works by identifying the vein patterns in an individual's palm. The key techniques of palm vein recognition can systematically described in five parts extracting region of interest (ROI), preprocessing to image, extracting palm vein pattern, extracting features and features matching. In this paper we propose an image analysis method to extract (ROI) from palm vein image. After extracting ROI we design a sequence of preprocessing steps to remove the translation and rotation of palm vein images using Homomorphic filter and Canny filter to detect the edges on images. Then we present a comparison between three algorithms of feature extraction principal component analysis (PCA) , Scale invariant feature transform (SIFT) and Local Binary Patterns (LBPs)algorithms with k-Nearest Neighbors (K-NN) classifier for matching using CASIA Multi-Spectral Palmprint Image Database V1.0 (CASIA database) .

Key Words: *Biometric, palm vein pattern, region of interest (ROI) extraction, feature extraction, matching.*

1. Introduction

Recently, many researchers investigated the finger, hand, and palm vein recognition for automated personal identification. By using modern technology a person can control their personal information easily at any time and any place, but also there are some risks that other people can take control of this information. Because of these risks researchers tried to use biometric authentication technologies [1]. Biometrics is automated methods of recognizing a person based on a physiological or behavioral characteristic. An example of behavioral characteristic are face recognition, fingerprints, hand geometry, signature verification, iris, retinal, finger/hand/palm vein recognition, ear recognition, and voice recognition.

Academic and industry tried to develop a device that can catch the vascular patterns under the skin .Fujitsu has developed a palm vein pattern authentication technology that uses vascular patterns as personal identification data [2] .Vein recognition technology is secure because the authentication data exists inside the body and so it is very difficult to forge [3]. It is highly accurate. This technology has many applications like in banking, hospitals, government to offices, in passport issuing, libraries, personal computer, etc. Business growth will be achieved with these solutions by reducing the size of the palm vein sensor and shortening the authentication time [3]. The contactless palm vein authentication technology consists of image sensing and software technology [4]. Palm vein recognition system consists of four key steps: Infrared palm images capture Detection of Region of Interest (ROI) and pre-processing and Palm vein pattern extraction, feature extraction and feature matching [5].

This paper presents an approach to extract region of interest (ROI) and enhancement the palm vein image. The second step enhancement the image by removed illumination and using edge detector to perfectly find the edges of the palm vein. The removed illumination served very efficiently by using Homomorphic filtering. Homomorphic filtering is most commonly used for correcting non-uniform illumination in images. After extract palm vein pattern we use these patterns to extract the features to use its outputs in matching step. We use three different algorithms to extract features from pattern principal component analysis (PCA), Scale invariant feature transform (SIFT) and Local Binary Patterns (LBPs) algorithms. In vein pattern matching a one-to-one match is done use the k-NN classifier with the Euclidian distance as the similarity measure. We make a comparison between these three algorithms and the results show that the best result in recognition is the SIFT algorithm with Correct Recognition Rate (CRR) is 96.13% and the speediest algorithm is also SIFT with 0.045 second.

The rest of the paper is organized as follows. In Section 2, we introduced the related work and explanation of the general architecture of the palm vein system. Section 3 introduces the details of detection of Region of Interest (ROI). The preprocessing algorithm introduces in section 4. Section 5 introduces the details of extraction of palm vein pattern using preprocessing steps. The explanation of PCA, SIFT and LBP algorithms is introduces in section 6. The explanation of matching algorithm K-NN is introduces in section 7. Section 8 discusses the result of algorithms and the comparison of them. Finally, conclusion and discussion are presented in Section 9.

2. Palm Vein Model and Related work

Extraction of region of interest (ROI) is extract from the original images a specific portion to work with. The ROI extraction has many important advantages .First; it serves as a pre-processing to remove the translation and rotation of palm vein images introduced in the data collection process. Second, ROI extraction extracts the most informative area in the images. It reduces a lot of data amount without losing much useful information. This will speed up the following feature extraction and matching processes. In the image-based biometric systems, a number of pre-processing tasks are required prior to enhance the image quality, such as: contrast, brightness, edge information, and noise removal, sharpen image, etc. [6]

Zhou and Kumar [7] preprocessed the palm-vein images acquired from the completely contactless imaging by normalize it. First segmenting the ROI, the acquired palm images are first binarized so that they 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. After segmentation, the ROI images are scaled to generate a fixed size region. Finally, histogram equalization is employed to obtain the normalized and enhanced palm-vein image. The enhancement has been quite successful in improving the details and contrast of the ROI images. Most of researchers employed this method to find the ROI [8].

Li et al. [9] adopted a 5x5 median filter to remove the speckling noise in the ROI image. Ladoux et.al [10] extracted the region of interest (ROI) and applied 5x5 box filter on the ROI in order to reduce the noise. After then, they corrected the brightness, which is not uniform, by applied a Gaussian low-pass 51x51 filter on the ROI in order to obtain the brightness image which is considered as low frequencies. Then, the brightness is subtracted of the original ROI. At this step, the contrast was still too bad. Therefore they applied a normalization method.

In [6] a small area (128*128 pixels) of the palm image capture is located as the region of interest (ROI). After that, noise reduction and contrast enhancement are carried out to produce a better quality of image through the following steps: a. Binarization that transforms the grayscale pattern into a black and white image. b. Skeletonization that reduces the width of lines to one pixel c.Isolated Pixel Removal that eliminates the unwanted isolated points.

S.Manikanda prabu et al [11], presented a new approach for the personal identification using palm vein images attempted to improve the performance of palm vein based verification system with the help of energy feature based on wavelet transform. Palm vein recognition involves a training stage and a recognition stage. In training stage, energy features of the training samples are calculated and stored in a template database. In the recognition stage, energy feature of the input vein is computed and then by using Euclidean distance, this energy is compared with the stored template to obtain the recognition result. The size of the original palm vein image was 251 x 362 pixels and 256 gray levels. The central 128 x 128 part of the image was cropped to represent the region of interest, using db6 wavelet transform the image were decomposed to the third level. The experiments are conducted in two modes. One is covering aspects of preprocessing in connection with approximation of level3 and the second one dealing with extraction of energy features from decomposed image. The Euclidean distance is used to measure the similarity between energy features. The equal error rate is 0.73%.

Dhanashree Vaidya et al [12] proposed a very simple entropy based method for the recognition based on palm print and palm vein. A JAI AD-080-GE camera is used to capture NIR hand vein images. The camera contains two 1/3” progressive scan CCD with 1024x768 active pixels, one of the two CCD’s is used to capture visible light images (400 to 700 nm), while the other captures light in the NIR band of the spectrum (700 to 1000nm). Image is filtered using Gaussian filter in order to remove any noise which may cause problems while thresholding the image. This filtered image is converted to binary image using a global threshold T. The “erosion” and “dilation” operations of morphology are used to reduce noise effect. Using entropy based features for palm print and palm vein. The recognition accuracy was up to 99%.

AliMohsin Al-juboori et al [13] proposed a multiple features extraction based on global and locate features and merging with locality preserving projections (LPP). The global features extracted using wavelet transform coefficients combine with locality preserving projections and create feature vector called wavelet locality preserving projections (WLPP) and the local binary pattern variance (LBPV) represents the locale features for the palm vein image combined with locality preserving projections and create feature vector called local binary pattern variance-locality preserving projections (LBPV-LPP). Based on the proposed palm vein features representation methods, a palm vein authentication system is constructed. The nearest neighbor method is proposed to match the test palm vein images. First of all, the palm vein image is enhanced using matching filter and then the features are extracted (WLPP and LBPV-LPP). After similarity measure for each feature, fusion technique is applied to fuse all the matching scores to obtain a final decision. The experimental result shows that the EER to the proposed method is 0.1378%.

M. Senthil Kumar and R. Gayathri [14] investigated two new approaches which extract palm-vein features and achieve most promising performance. The first approach using kernel principal component analysis (KPCA) investigated in this paper extracts the vessel structures by analyzing the eigen values of the 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 second approach is 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. 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.

Palm vein technology works by identifying the vein patterns in an individual's palm. When a user's hand is held over a scanner, a near-infrared light maps the location of the veins. The red blood cells present in the veins absorb the rays and show up on the map as black lines, whereas the remaining hand structure shows up as white. This vein pattern is then verified against a preregistered pattern to authenticate the individual. As veins are internal in the body and have a wealth of differentiating features, attempts to forge an identity are extremely difficult, thereby enabling a high level of security [15]. Figure 1 shows the general processes of the identification model using Palm veins biometrics.

After image capture, a small area of a palm image is located as the region of interest (ROI) to extract the features and to compare different palms. Using the features within ROI for recognition can improve the computation efficiency significantly [16]. In the image-based biometric systems there is a number of processing tasks used to produce a better quality of image that will be used on the later stage as an input image and assuring that relevant information can be detected. Normally, the captured palm vein pattern is grayscale and subject to noise. Noise Reduction and Contrast Enhancement are crucial to ensure the quality of the subsequent steps of feature extraction [16]. Also, the vein pattern extracted from infrared-ray images is represented as dark lines. To extract these lines many researcher used edge detection and morphological operators [4].

Feature extraction plays an important role in palm vein recognition because the performance of feature matching is greatly influenced by its output [4]. Feature matching is achieved by check whether the input image exist in the database to give the permission to that person being authenticated. When one place his/her palm the sensor sense the veins and if they are matched with the registered ones the system allows the person to use it [2].

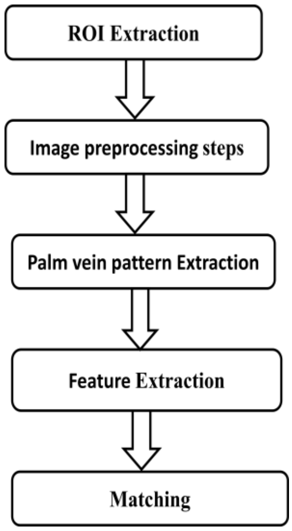

Figure 1.The processes of the identification model using Palm veins biometrics.

3. Detection of Region of Interest (ROI) Step Algorithm

In the first step we have to find the ROI from the image. Figure 2 show the results of the following steps to extract ROI.

1. Convert image to binary
2. Estimates the area of the palm in binary image then apply a *201*201* square mask that could perfectly cover the whole region of palm.
3. After then apply the dilatation filter again to get one point that is the middle point of the hand.
4. Then apply the erosion filter on the same square mask, this time to get exact square placed at same point where the region of interest is placed in actual image
5. Then find *xmin, ymin, length, and width* of this square to crop ROI from original image

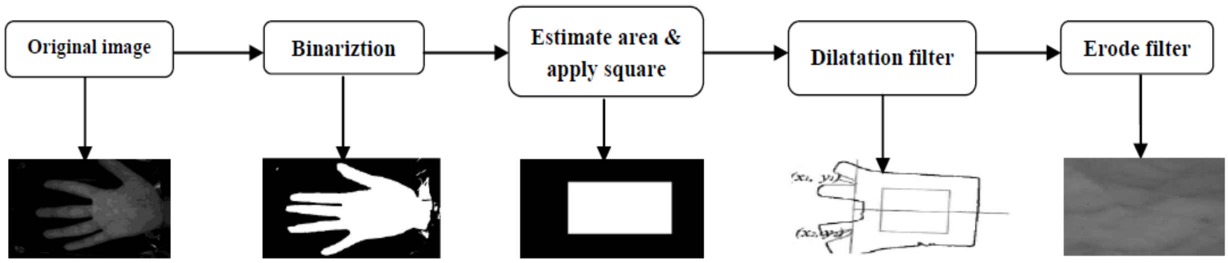

Figure 2.The steps to detect ROI

4. Preprocessing Step Algorithms

Homomorphic filtering is a generalized technique for image enhancement and/or correction. It simultaneously normalizes the brightness across an image and increases contrast. The Homomorphic filtering can be summarized in steps show following:

1- An image $I\ (x,\ y)$ can be expressed as the product of illumination and reflectance components:

$$I(x,y) = L(x,y)\,R(x,y) \qquad (1)$$

2- Because the Fourier transform of the product of two functions is not separable, we define

$$Z(x,y) = ln\,I\,(x,y) = ln\,L(x,y) + ln\,R(x,y) \qquad (2)$$

Or

$$Z\,(u,v) = I\,(u,v) + R\,(u,v) \qquad (3)$$

3- Doing the Fourier transform, as

$$\begin{aligned} S\,(u,v) &= H\,(u,v)\,Z\,(u,v) \\ &= H\,(u,v)\,I\,(u,v) + H\,(u,v)\,R\,(u,v) \end{aligned} \qquad (4)$$

4- Taking inverse Fourier transform of $S\ (u,\ v)$ brings the result back into natural log domain

$$\begin{aligned} S(x,y) &= F^{-1}\{S\,(u,v)\} \\ &= F^{-1}\{\,H\,(u,v)\,I\,(u,v)\,\} + F^{-1}\{\,H\,(u,v)\,R\,(u,v)\}\,. \end{aligned} \qquad (5)$$

5- So the output image can be expressed by the function [17].

$$g(x,y) = e^{s(x,y)} \qquad (6)$$

The overall model in block diagram will look as follow: in Figure 3.

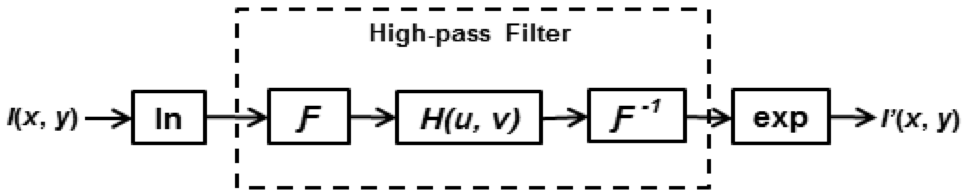

Figure 3.The homomorphic filtering.

5. Extraction of Palm Vein Pattern

By using canny edge detector filter can find the edges .The Canny Edge Detector is one of the most commonly used image processing tools, detecting edges in a very robust manner. There are three basic objectives of canny edge detector. The first objective is low error rate: All edges should be found with minimum of spurious responses. The second one is Edge points should be well localized: The distance between one detected point and the true edge point should be the minimum. And the last one is Single edge point response: Only one point should be detected for each true edge point [18].

The canny edge detector algorithm runs in 5 separate steps:

1. Smoothing: Blurring of the image to remove noise.
2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.
3. Marking non-maximum suppression: Only local maxima should be marked as edges.
4. Double thresholding: Potential edges are determined by thresholding.
5. Tracking edge by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

6. Feature Extractions Algorithms

After extract palm vein pattern we use these patterns to extract the features to use its outputs in matching step. We use three different algorithms to extract features from pattern principal component analysis (PCA), Scale invariant feature transform (SIFT) and Local Binary Patterns (LBPs) algorithms. In this section we explain these three algorithms in shortly.

6.1 Principal Component Analysis (PCA) Algorithm

Principal component analysis (PCA) is among the most popular algorithm in machine learning, statistics, and data analysis more generally. PCA is the basis of many techniques in data mining and information retrieval, including the latent semantic analysis of large databases of text and HTML documents described in [19].This algorithm using for extracting features from palm vein images. PCA is applied to generate vector of features that represent the highest detailed variant information. A matching process is then applied to find the best match from the data base to recognize and authenticate the person. It is one of the most widely implemented tools for dimensionality reduction or data exploration used in a variety of scientific and engineering disciplines. It transforms a number of possibly correlated variables into a smaller number of new variables, known as principal components. Since a digital image can be regarded as a two – or more – dimensional function of pixel values and represented as a 2D (grayscale image) or 3D (color image) data array, PCA can be performed on such an m x n matrix[20].

<u>The algorithm:</u>

1- Assume data matrix is *B* of size *m x n.* Compute mean μ_i for each dimension.

2- Subtract the mean from each column to get *A*.

3- Compute covariance matrix C of size n x n which $C = A^T A$.

4 Compute the eigenvalues and eigenvectors *(E, V)* of the covariance matrix *C*.

5- Project the data step by step onto the principle components $\vec{v_1}, \vec{v_2}, \ldots\ldots,$ *etc.*

6- Select *n* eigenvectors that correspond to the largest *n* eigenvalues to be the new basis.

6.2 Scale Invariant Feature Transform (SIFT) Algorithm

Scale Invariant Feature Transform (SIFT) algorithm is a kind of algorithm that extracting local features and then looking for extreme points in the scale space, extracting the invariant like location, scale, rotation and so on[21]. The SIFT algorithm has four main steps: (1) Scale Space Extreme Detection to make sure the position and scale of the feature points,

(2) Key point Localization, (3) Orientation Assignment and (4) Description Generation. The invariant features extracted from images can be used to perform reliable matching between different views of an object or scene. The features have been shown to be invariant to image rotation and scale and robust across a substantial range of affine distortion, addition of noise, and change in illumination [22].

Calculation of SIFT image features is performed through the four consecutive steps which are briefly described in the following:

- Scale-space local extrema detection - the features locations are determined as the local extrema of Difference of Gaussians *(DoG)* functions with different values of σ, the *DoG* function is convolved of image in scale space separated by a constant factor k as in the following equation.

$$D(x,y,\sigma) = (G(x,y,k\sigma) - G(x,y,\sigma) \times I(x,y) \quad (7)$$

where, *G* is the Gaussian function and *I* is the image. Now the Gaussian images are subtracted to produce a *DoG*, after that the Gaussian image subsample by factor 2 and produce *DoG* for sampled image. A pixel compared of 3×3 neighborhood to detect the local maxima and minima of *D(x, y, σ)* [23].

- Keypoint localization - the detected local extrema are good candidates for keypoints. Key point candidates are localized and refined by eliminating the key points where they rejected the low contrast points [24].
- Orientation assignment - once the SIFT-feature location is determined, a main orientation is assigned to each feature based on local image gradients. For each pixel of the region around the feature location the gradient magnitude and orientation are computed respectively as:

$$m(x, y) = \sqrt{(L(x+1,y,\sigma) - L(x-1,y,\sigma))^2 + (L(x,y+1,\sigma) - L(x,y-1,\sigma))^2} \quad (8)$$

$$\Theta(x, y) = \arctan(((L(x,y+1,\sigma) - L(x,y-1,\sigma))/ (L(x+1,y,\sigma) - L(x-1,y,\sigma))) \quad (9)$$

- In description generation stage is to compute the local image descriptor for each key point based on image gradient magnitude and orientation at each image sample point in a region centered at key point these samples building 3D histogram of gradient location and orientation; with 4×4 array location grid and 8 orientation bins in each sample. That is 128-element dimension of key point descriptor.

Figure 4 illustrates the computation of the key point descriptor. First the image gradient magnitudes and orientations are sampled around the key point location, using the scale of the key point to select the level of Gaussian blur for the image. In order to achieve orientation invariance, the coordinates of the descriptor, then the gradient orientations are rotated relative to the key point orientation. Figure 4 illustrated with small arrows at each sample location on the left side.

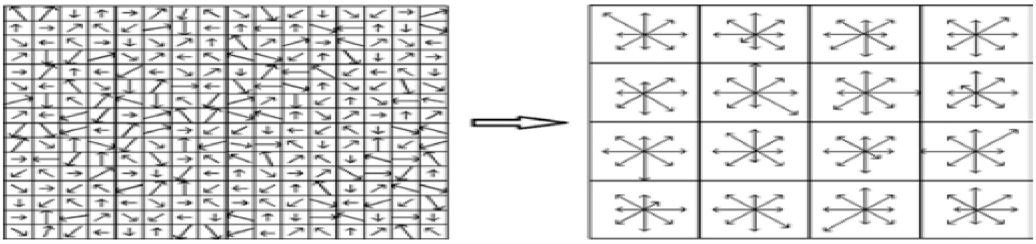

Figure 4.The SIFT descriptor generation.

The key point descriptor is shown on the right side of Figure 4. It allows for significant shift in gradient positions by creating orientation histograms over 4x4 sample regions. The figure shows 8 directions for each orientation histogram, with the length of each arrow corresponding to the magnitude of that histogram entry. A gradient sample on the left can shift up to 4 sample positions while still contributing to the same histogram on the right. So, 4×4 array location grid and 8 orientation bins in each sample. That is 128-element dimension of key point descriptor [23].

6.3 local Binary Pattern (LBP) Operator

Palm veins are line structures with changing width, whose gray-level values differ from the background. The LBP operator is based on gray-level differences in local neighborhoods. Therefore it has the potential to extract discriminative features from palm vein images. The size of the operator must be adapted to the size of the information to be extracted. In the case of a neighborhood containing a vein region, the vein will either cross the local neighborhood or end inside. Thus, the resulting patterns of interest will not present many discriminative bitwise transitions indicating gray-level changes. It is therefore logical to consider “uniform” patterns. The direction of veins presents a discriminative feature; therefore it is not necessary to consider rotation-invariant patterns. In order to preserve local spatial information, the LBP operator is applied on partitions of an image and not to the whole image.the size of neighborhoods *(P,R)* and the number of sub-images are the prime parameters to be determined to best extract discriminative vein information[25].The notation *(P, R)* will be used as indication of neighborhood configurations. P represents the number of pixels in the neighborhood and R represents the radius of the neighborhood. . The neighborhood can be either in a circular or square order See Fig. 5 for an example of a circular neighborhood for the same neighbor set of pixels but with different values of the radius.

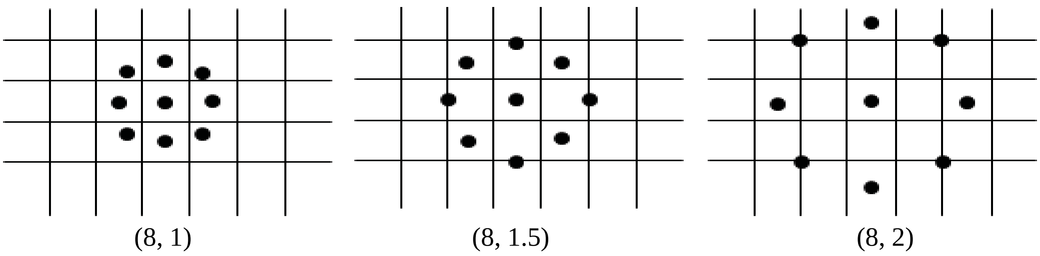

Figure 5.Three different neighborhoods in IBP operator.

LBP operator can also be extended to other definitions and patterns. One of the most important and successful extensions to the basic LBP operator is called uniform LBP (ULBP). An LBP is called uniform if the binary pattern contains at most two different conversions from 0 to 1 or 1 to 0 when the binary string is viewed as a circular bit string. For example, 11000011, 00111110 and 10000011 are uniform patterns. A large number of statistics have been extracted from images and the results indicated that most of patterns in images are uniform patterns. Ojala reported that with (8, 1) neighborhood, uniform patterns account for a little less than 90% of all patterns and with (16, 2) neighborhood, uniform patterns account for around 70% of all patterns . The LBP is used to label an image and the histogram of the labeled image can be defined as follows:

$$H_i = \sum_{x,y} I(f(x,y) = i), i = 0,1, \dots . n-1 \quad (10)$$

where *'n'* is the number of different labels produced by the LBP operator, *f(x, y)* is the labeled image and *I (A)* is a decision function with value 1 if the event A is true and 0 otherwise. To form the LBP histogram, the image has to be divided into 9 sub-regions. Then, the LBP histogram for each subregion has to be computed. Finally, the nine sub-region histograms have to be combined to form the feature histogram of the image. The LBP histogram of one sub-region contains the local feature of that sub-region and combining the LBP histograms for all sub-regions represent the global characteristics for the whole image [26].

7. Matching Algorithm

The K-Nearest Neighbor or K-NN algorithm has been used in many applications in areas such as data mining, statistical pattern recognition, image processing. Successful applications include recognition of handwriting and satellite image. The K nearest neighbor (kNN) classifier is an extension of the simple nearest neighbor (NN) classifier system. The nearest neighbor classifier works based on a simple nonparametric decision. Each query image *I*q is examined based on the distance of its features from the features of other images in the training database. The nearest neighbor is the image which has the minimum distance from the query image in the feature space. The distance between two features can be measured based on one of the distance functions such as, city block distance d1, and Euclidean distance d2 or cosine distance *dcos*[27].

$$d_1(x,y) = \sum_{i=1}^{N} |x_i - y_i| \quad (11)$$

$$d_2(x,y) = \sqrt{\sum_{i=1}^{N} |x_i - y_i|} \quad (12)$$

$$d_{cos}(x,y) = 1 - \frac{\vec{x}.\vec{y}}{|x|.|y|} \quad (13)$$

K nearest neighbor algorithm uses K closest samples to the query image. Each of these samples belongs to a known class *Ci*. The query image *Iq* is categorized to the class *CM* which has the majority of occurrences among the *K* samples. The performance of the kNN classifiers highly related to value of the *k*, the number of the samples and their topological distribution over the feature space.

8. Results and Discussion

8. 1 Database Dataset

All the experiments reported in this paper for the palmvein identification CASIA Multi-Spectral Palmprint Image Database V1.0 (CASIA database) [28]. This CASIA database has been acquired using a contactless imaging device and have images from 100 users. Six images were acquired from each user and these images were acquired in two different data acquisition sessions (three images in each session) with a minimum interval of one month. Since our work is focused on palmvein identification and the vascular details are typically observed in the NIR illumination, only the images that were acquired under 850 nm wavelength illuminations from CASIA database were utilized in the following experiments.

8.2 Experimental Results

Palm vein recognition involves a training stage and a recognition stage. In training stage, features of the training samples are calculated and stored in a template database. In the recognition stage, features of the input vein is computed and then by using K-NN (Euclidean distance) matching classifier, these features is compared with the stored template to obtain the recognition result. We do our experiment by divided the database to 5 Cases as table 1 shows. The algorithm implemented by using Matlab R2012a program.

Table 1.The DB divided for Experimental

Case 1		**Case 2**		**Case 3**	
Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
1 image to each person(100 images)	5 image to each person (500 images)	2 image to each person (200 images)	4 image to each person(400 images)	3 image to each person (300 images)	3 image to each person (300 images)
Case 4		**Case 5**			
Training	**Testing**	**Training**	**Testing**		
4 image to each person(400 images)	2 image to each person (200 images)	5 image to each person (500 images)	1 image to each person (100 images)		

By applying the PCA, SIFT and LBPs algorithms with K-NN (Euclidean distance) the result is 100% for all training cases and Testing result of each case showed in table 2 and figure 6.

Table 2.The testing result of different algorithms

Case No.	PCA	LBP	SIFT
1st case	93%	94%	95%
2nd case	94%	96%	96%
3rd case	94%	97%	96%
4th case	97%	96%	98%
5th case	97%	97%	98%

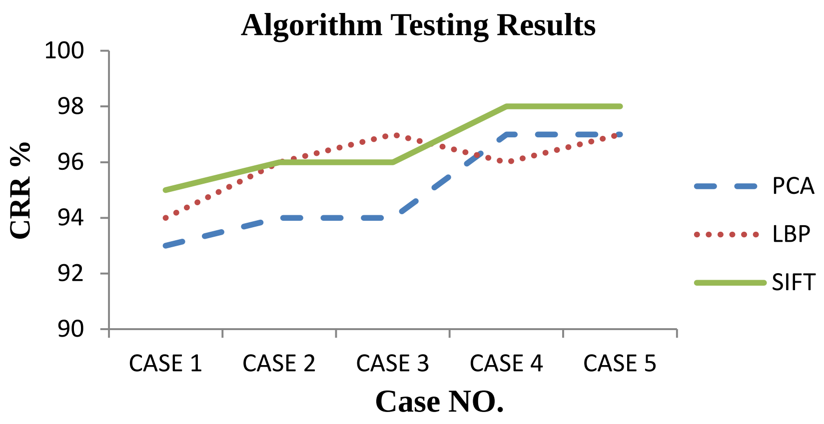

Fig.6 Different algorithms algorithm result

The result of compare the three algorithms show in table 3.

Table 3 CRR for different algorithms

Algorithm	Correct Recognition Rate (CRR %)	Time (s)
PCA	94.30%	0.058 s
LBP	95.60%	0.089 s
SIFT	96.13%	0.045 s

9. Conclusion

Palm vein verification is a promising technique for the authentication of an individual. This biometric modality is also difficult to copy that makes it a good candidate for many applications. In this paper we make a comparison of three algorithms used in extract features from palm vein pattern PCA – SIFT- LBP and using KNN classifier in matching and the experimental results show that the best result in recognition is the SIFT algorithm with Correct Recognition Rate (CRR) is 96.13 and the speediest algorithm is also SIFT with 0.045 second. Finally we can deduce that SIFT algorithm is more accurate and does not need more preprocessing steps to identify people.

References

[1]. S. Prabhakar, S. Pankanti, and A. K. Jain, "Biometric Recognition: Security and Privacy Concerns", IEEE Security and Privacy, Vol.1, No. 2, pp. 33-42, 2003.

[2]. Shigeru Sasaki, and Akira Wakabayashi, "Business Expansion of Palm Vein Pattern Authentication Technology", Fujitsu Sci.Tech.J, Vol.41, No.3, pp: 341-347, 2005.

[3]. "Palm Vein Pattern Authentication Technology", Fujitsu white paper, 2005.

[4]. Hao luo, Fa-Xin Yu, Jeng-Shyang Pan,Shu-Chuan Chu and Pei-Wei Tsai, "A Survey of Vein Recognition Techniques" ,information technology Journal,Vol.9,No.6,pp.1142-1149,2010.

[5]. Bhudev Sharma, "Palm Vein Technology", Sardar Vallabhbhai National Institute of Technology, December-2010.

[6]. Debnath Bhattacharyya , Poulami Das, Tai-hoon Kim and Samir Kumar Bandyopadhyay, “Vascular Pattern Analysis towards Pervasive Palm Vein Authentication”, Journal of Universal Computer Science, Vol. 15, No. 5, pp.1081-1089, 2009.

[7]. Yingbo Zhou and Ajay Kumar, “Human Identification Using Palm-Vein Images”, IEEE transactions on information forensics and security, Vol. 6, No. 4, pp.1259-1247, December 2011.

[8]. Y.B. Zhang, Q.Li,J.You and P.Bhattacharya , “Palm vein extraction and matching for personal authentication”, in Lecture Notes in Computer Science, Springer, pp: 154–164 , 2007.

[9]. Qiang Li, Yan'an Zeng , Xiaojun Peng and Kuntao Yang, “Curvelet-based palm vein biometric recognition” ,CHINESE OPTICS LETTERS,Vol.8,No. 6, pp.577-579,June 2010.

[10]. Pierre-Olivier Ladoux, Christophe Rosenberger and Bernadette Dorizzi ,“Palm Vein Verification System based on SIFT matching” ,Third International Conference on Advances in Biometrics, pp. 1290-1298, June 2009.

[11]. S.Manikanda prabu and S.N.Sivanandam, “A Novel Biometric system for Person Recognition Using Palm vein Images”, International Journal on Computer Science and Engineering (IJCSE), Vol. 5, No. 08, pp.692-697, Aug 2013.

[12]. Dhanashree Vaidya, Sheetal Pawar, Dr. Madhuri A. Joshi, Dr. A. M. Sapkal and Dr. S. Kar,“ Feature-level Fusion of Palm Print and Palm Vein for Person Authentication Based on Entropy Technique”, International Journal of Electronics & Communication Technology (IJECT), Vol. 5, pp.53-57, Jan - March 2014.

[13]. AliMohsin Al-juboori,Wei Bu, Xiangqian Wu and Qiushi Zhao,“ Palm Vein Verification Using Multiple Features and Locality Preserving Projections”, Hindawi Publishing Corporatione Scientific World Journal, Vol. 2014, pp.1-11, February 2014.

[14]. M.Senthil Kumar, R. Gayathri, “Robust Palm Vein Recognition Using LMKNCN Classification”, Journal of Engineering Research and Applications, Vol.4, pp.221-226, January 2014.

[15]. Ishani Sarkar, Farkhod Alisherov, Tai-hoon Kim, and Debnath Bhattacharyya, “Palm Vein Authentication System: A Review”, International Journal of Control and Automation, Vol. 3, No. 1, pp.27-34, March, 2010.

[16]. Hassan Soliman, Abdelnasser Saber Mohamed and Ahmed Atwan,” Feature Level Fusion of Palm Veins and Signature Biometrics”, International Journal of Video & Image Processing and Network Security IJVIPNS-IJENS Vol: 12 No: 01, pp.28-39, 2012.

[17]. Wenli Liu, Peng He, Hui Li, Hongbo Yu, “Improvement on the Algorithm of Homomorphic Filtering” International Conference on Electrical and Computer Engineering Advances in Biomedical Engineering, Vol.11, pp.120-124,2012.

[18]. F.Mai, Y.Hung, H. Zhong and W. Sze, “A hierarchical approach for fast and robust ellipse extraction. Pattern Recognition”, The Scientific World Journal, Vol 41, No.8, pp.2512–2524, August 2008

[19]. Nathan Halko, Per-Gunnar Martinsson, Yoel Shkolnisky and Mark Tygert,“ An algorithm for the principal component analysis of large data sets” ,Siam journal on scientific computing ,vol. 33, No. 5 , pp.1-12, October 2011.

[20]. Aleš Hladnik, “Image Compression and Face Recognition: Two Image Processing Applications of Principal Component Analysis”, International Circular of Graphic Education and Research, No. 6, 2013.

[21]. Pengrui Qiu, Ying Liang and Hui Rong, “Image Mosaics Algorithm Based on SIFT Feature Point Matching and Transformation Parameters Automatically Recognizing”, the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE), pp: 1560-1563, 2013.

[22]. YU MENG and Dr. Bernard Tiddeman, “Implementing the Scale Invariant Feature Transform (SIFT) Method”, Department of Computer Science University of St. Andrews, 2008.

[23]. P M Panchal, S R Panchaland S K Shah, “A Comparison of SIFT and SURF”, International Journal of Innovative Research in Computer and Communication Engineering, Vol. 1, Issue 2,pp. 323-327, April 2013.

[24]. Alhwarin, F., Wang, C., Ristic-Durrant, D.and Graser, “Improved SIFT-features matching for object recognition”, Visions of Computer Science – BCS International Academic Conf., Imperial College, pp179-190, September 2008.

[25]. Leila Mirmohamadsadeghi and Andrzej Drygajlo, “Palm Vein Recognition with Local Binary Patterns and Local Derivative Patterns” International Joint Conference on Biometrics, pp. 1-6, 2011

[26]. Abdallah A. Mohamed, Roman V. Yampolskiy, “An Improved LBP Algorithm for Avatar Face Recognition” , Information, Communication and Automation Technologies (ICAT) , pp. 1-5, 2011

[27]. Muhammad Naufal Mansor, Sazali Yaacob, Hariharan Muthusamy, Shafriza Nisha Basah, Shahrul Hi-fi Syam bin Ahmad Jamil, Mohd Lutfi Mohd Khidir,Muhammad Nazri Rejab,Ku Mohd Yusri Ku Ibrahim, Addzrull Hi-fi Syam bin Ahmad Jamil, Jamaluddin Ahmad and Ahmad Kadri Junoh,“ PCA- Based Feature Extraction and k-NN algorithm for Early Jaundice Detection”, International Journal of Soft Computing And Software Engineering (JSCSE),Vol.1,No.1,pp25-29, 2011.

[28]. CASIA MS Palmprint V1 Database [Online].Available: http://www. cbsr.ia.ac.cn/MS_Palmprint.