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Palm Vein Recognition: A Review

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Abstract . In this paper a review of palm vein recognition over the past years is presented. Palm vein is a recent biometrics modality; hence, many issues are yet to be resolved. These include feature extraction from palm vein images, the high dimensionality of the feature vectors, the databases used in the research, and the contactless nature of palm vein recognition setup. In this work details of the proposed schemes are given and the methods for feature extraction and feature reduction are discussed. In addition the accuracy levels obtained by previous research are mentioned and the potential reasons behind them are given.

***Index Terms*— Biometrics, Palm Vein Recognition, Feature Extraction, Feature reduction**

1.INTRODUCTION

Biometrics refers to the recognition of humans based on their physical traits such as fingerprint, face, iris and palm print, their behavior traits such as gait and signature, and their psychological characteristics like cognitive based biometrics and brain function biometrics [1].

In the modern society the identity theft of individuals constitutes a significant threat to the security of institutions and nations. Hence, biometrics have been proposed to replace or complement traditional methods such as passwords, magnetic cards, keys and smart cards. The later have failed to meet challenges posed by security venues that require a more accurate approach to the identification of individuals [2].

Biometric systems go through the following processes. Firstly, the processes of data collection from the users who will use the system. Secondly, the pre-processing to prepare the data/image for the following steps and to guarantee better recognition results. Thirdly, the feature extraction to select the most discriminating features from the original data with low dimension. Finally, the matching of the templates in the database. The matching procedure can be done into two modes. The first mode known as the verification mode involves matching the subject biometrics data with a template of their name to decide if the claimed identity by the user is true or false. The second mode is called identification where the individual biometrics data are compared with all the templates in the database to find their identity.

Many such biometrics systems that have been developed over the years remain subject to respective limitations. For example, it is found that 2% of the population cannot properly scan their fingerprints [3] and it is difficult to extract high quality fingerprints from manual workers. Also, facial recognition may be a popular biometric, but it faces many challenges such as noise, variations in pose and illumination [4] while iris and retina scanning are uncomfortable for users.

Moreover, the uniqueness as well as permanence of many behavioral characteristics proposed in the literature, such as signature and gait are weak [1]. Nevertheless, the palm has many advantages. It provides unique and stable features, wider area than fingerprint with the same characteristics. Reports of police departments show that 30% of latent prints in crime scenes are actually from palm print [5] . That led the FBI to include palm print in next generation identification (NGI) biometrics [6]. Furthermore, palm print is easy to integrate with other biometrics modalities and it is user friendly.

In this paper we give a comprehensive review of the previous research in the field of palm vein recognition. We focus on literature of palm vein recognition by giving the previous works proposed by researchers, discussion of each of the issues originated and the proposed solution to each of them by the scholars of the field. Finally, we present a conclusion of the paper. Figure 1 gives the hierarchy of palm based research.

2. THE PALM BASED BIOMETRICS

The Palm in biometrics is defined as the skin patterns of the inner surface of the human hand from the wrist to the root of the fingers. It provides many features including principal lines and wrinkles which appear in low resolution images (< 150 ppi), ridges and minutia points visible in high resolution images (> 400 ppi). The low resolution images are more suitable for civil applications such as access control and attendance systems. In the field of palm recognition, the low resolution images can be further classified to four types. The first type refers to the images captured under the white light usually called palm print. The second type is multispectral images. The third type is NIR presents rich palm vein features visible under infra-red light and it is known as palm vein images and the fourth is the 3D images. This paper focuses on the low resolution palm vein images.

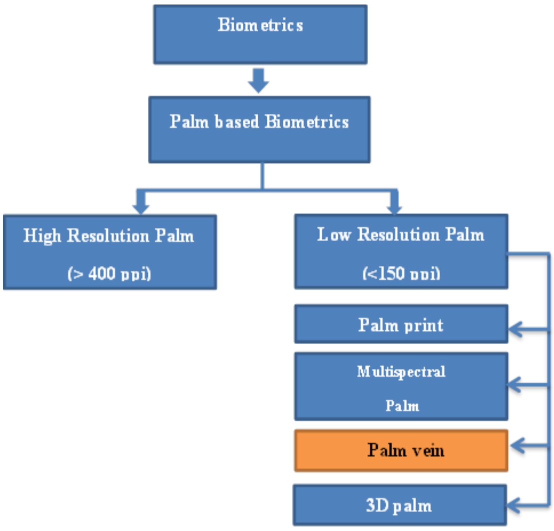

Fig. 1. Organization of the palm based research.

In addition, the human palm was used for centuries in fortune telling and palmistry. It is also associated with physical diseases like heart disease [7] and many mental diseases [8]. Table 1 gives a comparison between the different palm image.

Table 1. Comparison between different types of images in palm recognition.

Type of image	Advantages	Disadvantages	Application
High Resolution	Offers more features. Accurate.	Expensive devices. Complex algorithms. Slow algorithm Large storage space.	Law enforcement. Forensics.
Palm print	Cheap devices. Accurate. Fast.	Vulnerability to spoof attack. Illumination variant	Access control Attendance systems
Multispectral palm	Medium cost devices. Accurate. Fast. Illumination Invariant. Ability to detect spoof attack.	High dimensional data Data redundancy and correlation. Require information fusion.	Access control Attendance systems
3D Palm	Ability to detect spoof attack.	High Cost Devices. Complex Algorithms. Low accuracy Slow	Access control Attendance systems
Palm Vein	Accurate Fast Ability to detect spoof attack Moderate devices cost. Applied in real life in banks, schools and hospitals in USA and Japan.	Noisy images.	Access control Attendance systems

6. PALM VEIN RECOGNITION

This section will focus on the palm vein images. Firstly, a definition of the palm vein images is provided and the reasons behind choosing it. Secondly, the related works including the framework for the previously proposed methods will be presented including the issues of the field that governed the direction of the palm vein research and how they were solved by previous researchers and the limitations of each will be given.

6.1 DEFINITION OF THE PALM VEIN IMAGE

Palm vein is the vascular pattern inside the human palm. It is best visible under Near Infra-Red (NIR) light because the veins that contain deoxygenated blood absorb the NIR light, thus appearing darker than surroundings providing the vein map [9]. Hence, the palm vein images refer to the images taken under NIR light. More precisely in this study we used the 850nm and 880nm wavelengths from the electromagnetic spectrum. It is worth noting that the Infra-red light penetrates to the subcutis layer that contains the blood veins.

6.2 PREVIOUS WORKS

The previous literature in the field will be discussed in this section to provide the appropriate background to the issues of palm vein recognition. The description will follow the feature extraction classification. The methods of feature extraction can be categorized into lines based, minutiae points, subspace learning, Local point's descriptors and texture methods. In this section we will provide the detailed framework of each work in the previous literature.

Line Based Feature Extraction Methods

The palm vein images mainly contain lines and curves structure. Hence, it is normal to use line based feature extraction methods for palm vein recognition. There are many line based approaches proposed in literature. In [10] and [11] Curvelet transform is used to extract line features because it automatically takes edges as the basic representation. It also provides optimal sparse representation of objects along edges, which are sparser than DWT representation. To preserve the palm vein lines while reducing noise the authors in [10] used the Laplacian of Gaussian (LoG) filter. They used hamming distance to match the extracted coefficients. Nevertheless, the best accuracy (EER = 0.66%) is obtained when using 40% of the coefficients of scale 2 and 3 on PUMSPD. To add more accuracy they need to take more coefficients which will result in a larger feature vector size. They also need to integrate the information from scales 1, 2 and 3 to produce higher accuracy. The method in [11] used median filter and normalization to suppress noise and correct illumination respectively. Principal Component Analysis (PCA) was used for dimension reduction and Nearest Neighbor classifier with Euclidean distance for classification. Nevertheless, the method is tested under small database (1000 images for 100 hands) so the accuracy reported (99.60% for recognition rate) is unreliable and in both works the small template size came at the expense of the accuracy.

In [12] a line based method was implemented. The method used a series of steps for preprocessing to remove the noise, segment and thinning the palm vein images. They used local average direction as features by firstly finding the direction for each pixel and then dividing the direction matrix into blocks and taking the mean of each block as feature. Using PUMSPD, the highest identification rate (99.95%) was obtained by city block distance with fine thinning and the lowest EER for verification experiments is 0.24%. However, the method is complicated and the reported EER is high because the preprocessing steps including segmentation and thinning reduced the information of the original image and subsequently lowered the verification accuracy.

Two line based schemes were introduced in [13], namely, Local Radon Transform based approach and Hessian Matrix based feature extraction approach. Firstly, the contrast of the images is enhanced by estimating the background intensity and subtracting it from the original image, then applying histogram equalizer to normalize the images. For the first approach they used Local Radon Transform (LRT) for feature extraction and hamming distance neighborhood matching. For the second approach they used the Hessian Matrix which extracts the local dominant curvature of the palm vein image by calculating the magnitude of the Eigen values of the second order derivative of the image. The LRT can handle variations in translation and rotation because it encodes the orientations in six directions. However, Hessian approach doesn't make use of all of the information in the training samples and it introduces redundancy to the feature vector. It also cannot extract features well if the palm vein images are not clear which is the case mostly. The approach generates small size template but enhancement is needed in the accuracy level. The Radon Transform is complex because it encoded the features in different orientations and used neighborhood matching which required dividing the image into blocks and matching the corresponding blocks. In addition, the radon transform usually introduced artefacts to the image and reduce resolution which result in loss of some information valuable to the recognition [14].

Minutiae Points Feature Extraction Methods

Minutiae based methods, also called geometric approaches, extract local features such as the locations and local statistics of the principal veins, minutiae points, and ridge bifurcations. In [15] the authors used feature level fusion of minutiae point and SIFT descriptors for both palm vein and signature modalities. They used the Linear Vector Quantization (LVQ) networks for classification. They also extracted features from signature and fused it with palm vein at feature level. The palm vein feature produced lower accuracy (GAR = 95.68%) than the fused feature but higher than signature. Nevertheless, the accuracy of the method is generally low and the database used is small (185 pam vein images from 37 persons).

In [16] minutiae points are extracted for person recognition. The database used contains 180 images and the accuracy level is low (EER = 1.82%). The reason is that they depend on methods used in fingerprint technology for extracting and matching the features. These methods cannot be applied to the palm vein because the structure of the palm vein is different from a fingerprint. The palm veins are more sparse and irregular compared to fingerprint.

Subspace Learning Feature Extraction Methods

Thirdly, subspace based approaches like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Local Projection Pattern (LPP) have been proposed for palm vein recognition. The authors in [17] used PCA for feature extraction and Euclidean distance for matching to identify users. The accuracy of the system is low (CRR = 85%) and the database used is only 100 images from 20 persons which is too small for a credible decision. The reason is that PCA extracted only global features and ignored the local/details features that are important for recognition. In [18] the authors used the modified two-directional two-dimensional linear discriminant analysis $(2D)^2$ (LDA) for feature extraction and minimum distance for matching. They also used median filter to reduce noise and subtracted the background intensity to correct illumination. The $(2D)^2$ (LDA) used small size feature vector and it also exploited the variance in both rows and columns directions and it produced high accuracy. However, the method needed ten images for training to produce this recognition accuracy.

In [19] the authors used PCA features and Euclidean distance matching for multispectral palm print recognition. They tested the performance of the uni-modal bands gray, red, green, blue and infrared images from the PolyU multispectral database. The infrared images produced the highest accuracy rate (EER = 0.056 % and CRR = 99.3%) proving the superiority of infrared images. In [20] the researchers proposed an approach based on Locality Preserving Projections (LPP) that extracts local line features. The method applies image level fusion for palm print and palm vein images that preserve lines of both modalities. The palm vein image produced better accuracy than the palm print however its error rate is higher than the fused image and the overall accuracy is low (EER = 2.7%). The justification of the low accuracy can lay in the difficulties in building a reliable neighborhood pattern structure in the "Laplacian" palm vein process, and also to the fact that LPP does not compute local textural features; hence, it is less robust when challenged by small variations in the database [13].

Local Points Descriptors Based Feature Extraction Methods

Schemes based on local points descriptors like Scale Invariant Feature Transform (SIFT) were proposed in many references. In [21] the authors proposed a new approach based on RootSIFT features, the pre-processing steps include difference of Gaussian to reduce noise and histogram equalizer to provide uniform illumination. For matching they used an approach based on LBP histogram. The approach provided 1.329% EER for CASIA database and 3.112% EER for self- built database. It is worth noting that the mentioned EER is high. The reason could lay in the complicated steps of the method in each step especially the preprocessing by difference of Gaussian which reduced the image data immensely in both low and high frequencies as mentioned by the authors. In [22] the authors collected 1440 palm vein images from 24 individuals in a constrain environment and extracted the discriminating features using SIFT method and Euclidean distance based matching algorithm. To reduce noise a box filter and Gaussian low pass filter were used. The EER of the method is 0.14% using single image as training set. However, the database used is very small and it is constrained which means there is small movement of the hand.

In [23] the authors proposed three different schemes based on SIFT, Speeded-Up Robust Features (SURF) and Affine-SIFT(ASIFT) and the matching was performed by Euclidean distance. These algorithms are expected to provide translation, rotation and scale invariance. However, they didn't test the algorithms under these conditions. The first two methods produced small size features vectors but the accuracy is low (EER is 2.2 % for SIFT and 0.4 % for SURF) for database PolyU multispectral database and for self-built database consisting of 1200 images from 100 subjects (EER is 4 % for SIFT and 4 % for SURF). ASIFT on the other hand is highly accurate but it is complicated and it produced large feature vector which make it impractical for real time solutions as mentioned by the authors.

In [24] the authors first extracted the principal veins by methods used in [16] then extracted SIFT key points as features from the principal image. The database is small containing only 300 images from 50 subjects. The accuracy level is low (CRR = 97.86%) especially for small database. The low accuracy for SIFT features can be attributed to the fact that it extracted only local information and ignored the global features which made it lose some information that is important for recognition.

Texture Based Feature Extraction methods

Fifthly, the line patterns of the palm veins have obvious and stable directions. Hence, it can be considered as a textured image. This motivated the researchers to extract texture features as local ridges and valleys from the palm vein images. Many works have been proposed in literature to enhance palm vein recognition based on texture features. The most used methods are wavelet transform and Gabor filter.

Wavelet transform is used in many works for palm vein recognition For example, the authors in [25] proposed a scheme based on wavelet transform and Partial least square. They used Euclidean distance for matching. The database used contained 300 images from 50 people. The authors used wavelet decomposition to solve the small sample size (SSS) problem of Partial Least Square (PLS). They obtained high recognition rate (RR = 99.86%) when using "Haar" function by level 3 decomposition. However, the database used is small (300 images) and they used only the approximate image and discarded the details images which are important to classification especially in large database environment.

In [26] researchers used a wavelet transform based approach to verify humans. They used averaging filter and Gaussian low pass filter to remove noise and correct the brightness respectively. The features were taken as the energy of the approximate image and Euclidean distance was used for matching. One image was used for enrolment. However, the error rate was high (0.73% as EER) without any details about the database used in the experiments. The low accuracy can be attributed to the use of approximate image only ignoring the detail images. In [27] a comparison between wavelet and Curvelet transform features was made. They used median filter to remove noise and normalization to correct illumination. Using a database of 480 palm vein images and minimum distance classifier (MDC) the Curvelet transform obtained higher accuracy than wavelet transform. This can be explained by the fact that Curvelet can represent edges and other singularity better. However, the overall accuracy was low (2.3% as EER for wavelet transform).

The Gabor filter is used extensively in the field of palm vein recognition. To enhance palm vein recognition authors in [28] proposed a new approach based on Gabor wavelet. They used Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement and Gaussian low pass filter to remove the lines of the palm print. Before feature extraction they apply segmentation and thinning to the palm vein images. They used Eigen vectors to select the relevant features and correlation coefficient for classification. The method provided better performance than minutiae features, Principal Component Analysis (PCA) and Local Projection Pattern (LPP) because it collects information in different scales and orientations, hence can better represent the palm vein. However, the database used is small (178 images) and the overall accuracy is low (Correct Recognition Rate = 98.88%). The reason can lie in the preprocessing steps because the segmentation and thinning caused the images to lose some information and this reduces the amount of the discriminating features.

In [29] a novel approach named Enhanced Local Gabor Binary Patterns Histogram Sequence (ELGBPHS) was proposed. The approach first uses Gabor filter in different scales and orientations, then Local Binary Pattern (LBP) is applied to capture local features like edges. Finally, the image is divided into sub images and a histogram taken. For matching they apply histogram intersection. The method provided FRR of 1.7% and a FAR of 0% on CASIA multispectral database. However, they didn't provide the EER which important to assess the quality of biometric system. Also they used CASIA database which is small database (contains 600 images). In [30] the authors presented a Gabor filter based palm vein recognition scheme. They corrected the illumination by subtracting the background intensity profile. Hamming distance was used for classification. To choose the optimal combination of parameters for Gabor filter they used an adaptive method to estimate the values of orientation, center of frequency and standard deviation parameters. The method scored correct recognition rate of 99.38% when tested on a database containing 4140 images. To add more accuracy to the method they need to add coarse features and to control the movement of the hand.

The authors in [31] used the Gabor filter in four orientations to extract the palm vein features. The features were chosen to be the coefficients of the real part of Gabor filter. They encoded the features and used hamming distance for matching. The accuracy of the method is low (EER = 0.28% and CRR = 98.73%) and the database is small (800 images). The reason for the low accuracy is not selecting the optimum value of the parameters of Gabor filter. The authors in [32] used Gabor filter by 8 scales and 8 orientations. The center of frequency varies depending on the value of the standard deviation (σ) and the scale. The method produced 64 filtered images as feature vector. To reduce this huge size they used FDA. Using nearest neighbor matching by

Euclidean distance on PolyU Multispectral database they obtained 0.2335% as Equal Error Rate (EER).

In [33] the authors explored the Score level fusion of Gabor filter and Curvelet transform features. Gabor filter features by 6 orientations were encoded in 3 bits format and only 10% of the Curvelet coefficients are used for recognition. Matching score were obtained by hamming distance. Using PolyU multispectral database the fused features produced 0.1023% as EER, better accuracy than the wavelet (2.3%) and Curvelet (1.7%) features confirming the results in [27]. The authors in [34] used Gabor filter by four orientations to extract features from palm vein and dorsal veins. For image enhancement they used Median filter, Wiener filter and CLAHE. They used the real and imaginary parts of Gabor filter, then converted it to binary code and used hamming distance for matching. Using a database of 700 palm vein images (from 70 persons) the palm vein system attained 1.39% as EER. The high EER in the three later methods can be returned to the values of Gabor filter parameters. Since Gabor filter is sensitive to parameter values, using non optimum values affect its performance significantly.

In [35] a method based on matched filters was proposed. The matched filters were used for feature extraction because the cross section of palm vein is Gaussian. Nevertheless, the matched filters produced a lot of noise. To reduce noise and clarify the edges in the collected images the multiscale products were used. Then matching was performed by logical “exclusive or” operation. However, the images were still noisy which reduced the accuracy level (98.8% for recognition rate and 5.5%. for FAR) especially for small database (144 images from 24 persons).

The authors in [36] introduced two new schemes based on Local Binary Projection (LBP) and Local Derivative Pattern (LDP) features. The palm vein images were enhanced by histogram equalization before LBP method. Using histogram intersection for matching LDP gave 0.0009% as EER and 97% for identification rate, better than LBP (0.004 as EER and 93% as identification rate). Possible reason is that LDP collects higher derivative directional information while LBP focus only on first order derivative. It is notable that the accuracy for both features is low in the identification experiment because in the identification case the test images were matched by all records in the database, which introduces more challenge to the recognition process and require highly discriminating features. They used the CASIA Multispectral database which is a small contactless database (1200 images from 100 persons).

In [37] the authors proposed a scheme based on match score fusion of palm print and palm vein. The palm vein images were enhanced by erosion and dilation operation to remove the palm print lines. The matched filters were used for feature extraction and a distance based on AND & OR logical operators was used for matching. The palm vein provided 0.39% as EER. The database used contained 6000 images from 500 palms. A possible reason for the low accuracy is that the matched filters introduced noise to the palm vein images which caused intra class variations in the database and consequently raised the false reject rate.

A new scheme based on local and global features by Local Binary Projection (LBP) and wavelet transform respectively was proposed in [38]. They used linear dimension reduction by Isometric Projection method for each feature vector and then fused the reduced feature vector at match score level by sum rule. Using Manhattan Distance the approach produced 0.17488% as EER on PUMSPD. The same authors of [38] proposed another method based on local and global features by Local Binary Projection (LBP) and wavelet transform in [39]. In this work they used another linear dimension reduction technique named locality preserving projections (LPP) method for each feature vector and then fused the reduced feature vector at match score level by weighted sum rule. Using Euclidean distance the approach produced 0.1378% as EER on PUMSPD. However, in both work they used linear method for dimension reduction which is not suitable for nonlinear data such as palm vein features extracted by wavelet and LBP. Another defect in the method is that it uses only the approximate image of the wavelet decomposition and ignores the detailed images which are important for recognition.

In [40] the author proposed an approach based on directional empirical mode decomposition (DEMD) feature extraction. They tested two variations of DEMD ensemble DEMD and multichannel DEMD. The feature matrix produced by these methods have high dimension hence they used two dimension reduction techniques namely, Two Dimensional Linear Discriminating Analysis (2D-LDA) and Two Dimensional Two Directional LDA ($(2D)^2$LDA). Then the matching was performed based on Euclidean distance nearest neighbor classifier. Using a self-built database that contained 4800 palm vein images the method scored 99.73% recognition rate and 0.63% EER. The high EER can be attributed to the use of linear dimension reduction technique with nonlinearly distributed data such as palm vein feature vector. They also adopted a dynamic method to choose the dimension of the feature vector which add more complication to the method and contribute to reducing the accuracy level. summarizes the previously mentioned related literature.

8. Conclusion

This paper was dedicated to review the latest literature in the field of palm vein recognition specifically. According to the final observations and based on rigorous analysis of the previous studies it was decided to use NIR palm vein images. The palm vein images were chosen among other options including palm print, multispectral palm, 3D palm and palm vein images.

Based on the presented previous works it was found that the methods used for feature extraction and reduction for palm vein recognition did not provide the optimal solution to the problem in hand. These previous methods suffer from five problems. Firstly, some of them were tested under small database and hence the acquired accuracy is unreliable. Secondly, the accuracy level is not acceptable. Thirdly, they didn’t use dimension reduction techniques or they used unsuitable methods that didn’t improve the accuracy significantly. Fourthly, some of the methods are complicated and use fusion for the features. Fifthly, the feature extraction methods extract either local or global method and there was no single (not hybrid) algorithm that extracted both important kinds of data. In conclusion we found that the feature extraction algorithm used in the field of palm vein recognition needed more enhancements to produce higher accuracy. The solution is to propose a feature extraction method that extracts both local and global features without the need for fusion at any level because the fusion complicates the system and is impractical for real time applications. Also the proposed method must provide decomposition in different scale and orientation to deal with variation of poses in the database. In addition the feature should be from low and high frequencies to capture different frequency information and hence add more discrimination ability and subsequently obtain high recognition accuracy. Finally, it is more optimal to use nonlinear dimension reduction methods than linear dimension reduction methods for palm vein feature vector.

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