Palm Vein Recognition based on 2D-Discrete Wavelet Transform and Linear Discrimination Analysis

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Abstract

Palm Vein Recognition (PVR) is a promising new biometric that has been applied successfully as a method of access control by many organizations that has even further potential in the field of forensics. The palm vein pattern has highly discriminative features that are difficult to forge because of its subcutaneous position in the palm. Despite considerable progress and a few practical issues, providing accurate palm vein readings has remained an unsolved issue in the biometrics. In this paper, we propose an improved scheme of palm vein recognition method based on the Two Dimensional Discrete Wavelet Transform (DWT) and Linear Discrimination Analysis (LDA). The palm vein image is first subjected to 2D- DWT decomposition. Then the low frequency sub-bands approximate of the image is used as an input for LDA algorithm. LDA is a subspace projection method that aims to maximize between class covariance and minimize the within class covariance. It is used initially to reduce the features, and later followed by the matching procedure using cosine distance nearest neighbor. Based on our experiments, the method has produced an identification rate of 99.74% and 100% of verification rate and 0.0% of Equal Error Rate (EER) on 380 different palms from the hyperspectral PolyU database. The total images of 3800 were captured with the wavelength of 850nm and the performance of the proposed method was better compared to images extracted using the Gabor filter method.

Keywords: *Palm Vein, Feature Extraction, 2D-DWT, LDA.*

1   Introduction

In our modern society biometrics is a necessity. This can be observed in the new applications that rely on the accurate identification of the individuals for their

safety, such as high security government buildings, airports and online banking [1]. In these cases the traditional security methods that use passwords, personal identification numbers (PINs), magnetic cards, keys and smart cards are insufficient. Furthermore, the long heritage of biometrics in forensics applications can be assured by more reliable automatic systems [2]. Many biometrics systems have been developed over the years. However, most of them have their own limitations. For example, it is reported that 2% of the population can't use their fingerprint for recognition [3] beside it is hard to extract high quality fingerprints for manual workers. Face recognition is a popular biometric but still lacks the robustness against pose [4]   and illumination invariance [5]. Iris and Retina scanning system is uncomfortable to users. On the other hand, distinctiveness as well as the permanence of many of the behavioral characteristics proposed in the literature such as signature and gait are weak [6].

Among other biometrics the palm vein recognition offers a promising method. The hand print was the first biometric used for human identification in 1858. In addition to some palmprints in prehistoric caves claimed to be used as identity for cavemen [7]. In the contemporary age the palm vein is still a competitive biometric. It was first used in the 1990s and became popular since then [8, 9]. Palm vein is the vascular pattern inside the human palm. Palm veins are best visible under the Near Infra-Red light. Hence, it can be acquired by CCD camera sensitive to IR light. The palm vein images provide wide area for recognition. It introduces different types of features including minutiae points, ridges and texture features. Palm vein is proved to be highly discriminative by Fujitsu Labs [10]. They used 70,000 individuals and the system produced 0.00008% FAR and 0.01 % FRR. In addition the palm vein resides in the internal layers of palmar skin, hence it is hard to forge and normally has no hair cover. Also the contactless nature of the palm vein acquisition set up is appreciated by the users for health reasons.

Based on our review of current literature of palm vein research   , feature extraction methods in palm vein field can be divided into three categories minutiae based, texture features, line like features and subspace projections. Methods based on extracting minutiae points are implemented in [11]. These methods tend to lose some minutiae points in the pre-processing phase which affects the system accuracy. Texture based methods treat the palm vein image as texture image and uses methods as Gabor filter and Local Binary Pattern (LBP) to extract texture features. Adaptive Gabor filter is has been successfully used [8], they used large database to test the algorithm. It produced high recognition rate with short time for practical use. The algorithm extracts only local features and it requires global features to add more accuracy.In [12] Orientation of Local Binary pattern (OLBP) is extracted from palm vein, dorsal vein and fingers veins modalities and fused using support Victor Machine. The fused feature gave better results than each of the single modalities. In [13] a combination of 2d Gabor, local Binary pattern and histogram intersection is used to enhance feature

extraction. In [14] Gabor wavelet is used to extract texture features after image enhancement and skeletonization and in [15] researchers realized that the cross section of vein pattern resemble the Gaussian map hence they used the matched filter for extraction of vein texture and logical XOR operator for classification. The images used need enhancement to produce better results. However, the accuracy of the three later methods is not satisfactory. In [16] the fusion of texture features and minutiae features is explored, fusion at match score level provided better results than fusion at feature and decision levels. Line like feature are extracted using curvelet transform in [17] and [18], in these method accuracy came at the expense of storage.

Subspace methods project the palm vein image in a lower space for recognition. In this case only the discriminative features are fed into the classifier. The most common used subspace methods are Principal Component analysis (PCA), Independent Component Analysis (ICA) and Partial Least Square (PLS). PCA [19] and ICA [20] are able to fully represent the palm but their features are not useful for classification. .PLS suffers from the small sample size (SSS) problem. To solve this issue Discrete wavelet Transform (DWT) is used in [21] with high performance. However, the database used was small. "Lapacianpalm" which uses Locality Preserving Projection (LPP) to extract local features is introduced in [22]. Nevertheless, it handles the local features only and ignores the global features that are important for recognition. Hessian phase algorithm is developed in [23] it uses second-order derivative to calculate the local principal orientation of the image, it achieved high performance and uses small template size. Although it requires very clear palm images to easily extract the local features.

In this paper we propose using Linear Discrimination Analysis (LDA) for extracting the palm vein. LDA is first proposed by Fisher [24] in 1936. LDA algorithm could make not only the scatter between classes as large as possible, but the scatter within class as small as possible. So the features which are extracted by LDA are more reliable. LDA also has been successfully applied in palm print area [25] and palm dorsal vein [26]. And it is simple and fast. However, LDA suffers from the over fitting problem when used in large databases. We also met the challenge of the poor quality palm vein images used for recognition. To solve these issues we propose using Discrete Wavelet Transform (DWT) on the palm vein image before applying LDA algorithm. DWT is able to decompose the image into high frequency components and low frequency components. High frequency information is related to noise. Hence, in this paper we used the low frequency information to enhance the quality of the images and henceforth the overall performance of the scheme. In this paper we investigated Daubechies, Haar and Bior wavelets.

The rest of this paper is organized as follows: section 2 presents the preprocessing algorithm, section 3 introduce the 2D-DWT and how we used it, section 4 gives the background of the LDA algorithm used for feature extraction, section 5 reports the experimental results and Section 6 provides some conclusions.

2 Palm Vein Image preprocessing

The images used in this paper are taken from the PolyU hyper spectral palmprint database (PUHSPD) [27]. The database was collected at The Biometric Research Centre (UGC/CRC) at The Hong Kong Polytechnic University. The device used mainly contains liquid crystal tunable filter (LCTF), a charged coupled device (CCD) and two halogen lights. Fig.1 shows the imaging procedure and the direction and position of the hand during filming. The acquired images range between 420nm and 1100nm wave lengths with 10nm step length between spectra. This range includes the medical spectral window between 700nm and 900nm in which the light penetrate deeply inside the tissues of the human body [28]. Hence, depending on this fact we used palm vein images of the 850nm wave length. More precisely, it is found that light at 850nm reaches deep inside the palm area until 3.57mm. In addition, the palm veins absorb more light thus appear darker than the surrounding tissues providing a clear vein map. Furthermore, imaging at this wavelength avoid the interference with IR waves coming from the human body and the surrounding environment and is more tolerant to human's medical condition [28]. The images were taken from 380 different palms (left and right hands), in two sessions; the time span between each session was about one month and seven palm vein images were taken per session.

Fig 1: PUHSPD Palm Vein recognition system setup [29]

The images provided in the database are cropped using the algorithm in [29]. The preprocessing algorithm is used to establish a coordinate system for the palm images and to crop the central part. The algorithm includes the following steps 1) Convolve the palm vein image by a low pass Gaussian filter then uses threshold to convert it into binary image 2) Trace the boundaries of the gaps $(F_j x_i, F_j y_i), j = 1, 2$ between the small and ring fingers and the middle and index

fingers respectively. 3) Compute the tangent between (x_1, y_1) and (x_2, y_2) where these points belong to any of $(F_1 x_i, F_1 y_i)$ and $(F_2 x_i, F_2 y_i)$. 4) Determine the Y-axis by connecting the two points (x_1, y_1) and (x_2, y_2) then take its perpendicular as the X-axis. 5) Find the origin of the system using the intersection of the two axes. 6) Crop a fixed size sub image around the origin. In this paper the size of region of interest is 128×128.

3   The Proposed Scheme of Palm Vein Feature Extraction Based On 2D- Wavelet Decomposition and Linear Discrimination Analysis

The proposed palm vein recognition scheme consist of the following steps of image collection ;image decomposition using 2D-DWT , image partitioning into training and testing sets, feature extraction and finally classification to produce the results. Fig. 2 gives the details of the proposed scheme.

3.1   Discrete Wavelet Transform

The 2D-DWT is a multiresolution transform that gives time and frequency information. Wavelet decomposition depends on a single wave called the mother wavelet, it can be also considered as band pass filter. High pass filter produces the detailed components of the image, while the low pass filter produce the coarse approximate of the image [30, 31]. The palm vein image is decomposed using the 2D-DWT. We compared the performance of three different types of mother wavelet viz., Daubechies ,Haar and Bior wavelets. The decomposition results in four sub images the approximate (cA) and the three details sub images horizontal (cH), vertical (cV) and diagonal (cD). The high frequency details correspond to noise usually. For this reason this paper uses the approximate image since it contains the important information for recognition with less noise. Hence, given an image I, after applying k level decomposition we get $I = \{cA_k, cH_k, cV_k, cD_k\}$ and we apply the next decomposition using the approximate image cA_k. Fig. 3 below shows level-2 decomposition of sample palm vein image using Daubechies-1(db1) wavelet.
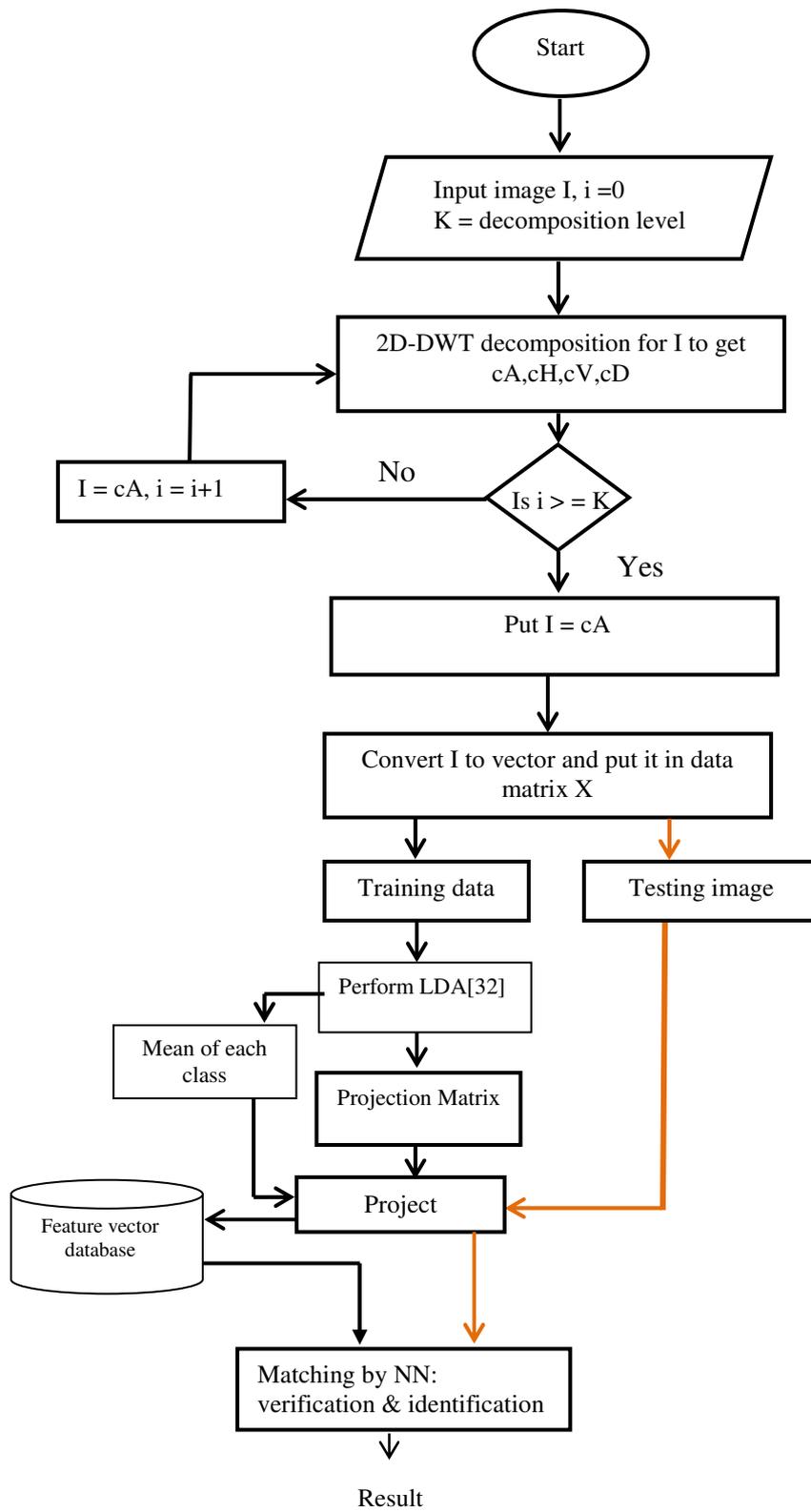
Fig 2: The Proposed Scheme of Palm Vein Recognition

Then the matrix cA_k is transformed into vector and used in the next step of feature extraction. We notice also that the resolution of the palm vein image is decreased by half at each decomposition level. We used two levels decomposition, so the original image resolution was 128×128 and it has been reduced to 64×64.

| Original | cA1 | cH1 | cA2 | cH2 |
| | cV1 | cD1 | cV2 | cD2 |

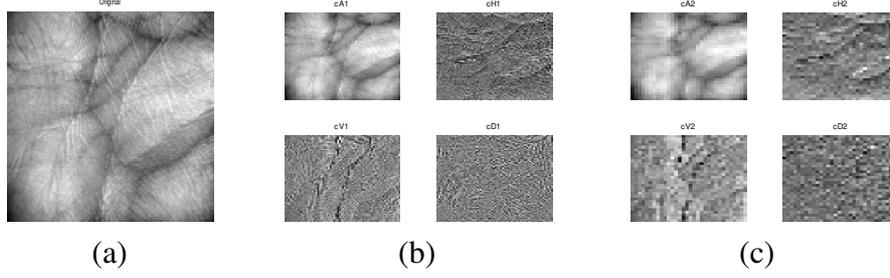(a)   (b)   (c)

Fig 3: D - Wavelet decomposition (a) the original image (b) level -1 decomposition (c) level-2 decomposition

3.2 Linear Discrimination Analysis

Feature reduction is achieved using Linear Discriminative Analysis (LDA). LDA is a popular feature reduction method as it provides well separated classes that are reliable for classification.

Given the data matrix $A = \{a_1, a_2, ..., a_n\} \in \mathrm{R}^{m\times n}$, in our case A represents the labelled training set of the palms images. We are looking for the projection matrix E that maximizes the following Fisher criteria[32]:

$$F(E) = \arg \max_{E} \frac{E^T S_B E}{E^T S_W E}$$

(1)

Where S_B is the between class scatter matrix and S_W is the within class scatter matrix.

Then, we divided A into classes where,

$A = \{C_1, C_2, ..., C_N\}$

Each $a_j \in C_i$, $i = 1, 2, ..., N$ and $j = 1, 2, ..., n$.

$$S_B = \sum_{i=1}^{N} n_i (m_i - m)(m_i - m)^T \tag{2}$$

$$S_w = \sum_{i=1}^{N} \sum_{j=1}^{n_i} \frac{n_i}{n} (a_j - m)(a_j - m)^T \tag{3}$$

First, we computed the between class scatter matrix and the within class scatter matrix using the Following equations:

m_i is the class mean defined as: $m_i = \dfrac{1}{n_i} \sum_{j=1}^{n_i} a_j$

m is the global mean defined as: $m = \dfrac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{n_i} a_j$

n_i is number of elements in class C_i

To find the desired Projection matrix, we solved the following Eigen value problem:

$$S_B E = S_W E \lambda, \quad \lambda \neq 0 \tag{4}$$

Where λ is the diagonal matrix of the Eigen values.

If S_w is non – singular, "(4)" can be written as:

$$S_W^{-1} S_B E = E \lambda, \quad \lambda \neq 0 \tag{5}$$

Since at most there are $N-1$ nonzero Eigen values, then, the dimension of the projection space will also be at most $N-1$. The Eigen vectors corresponding to the highest

$(r \leq N-1)$ is composed of the projection matrix E, where,

$$E = [e_1, e_2, ..., e_r] \tag{6}$$

E was used to project the image into LDA space to find the LDA features as follows:

$$f_i = \mathrm{E}^T(a_i - m) \tag{7}$$

Where $f_i \in \mathrm{R}^r$ represent the r dimensional feature vector of the centered palm data vector $a_i \in \mathrm{R}^m$. Fig 2 shows the image of the palm vein after projection into fisher space in (c). We used 20 classes to construct this image, (b) is the global mean image used and (a) is sample image from the class. Fig 4 below shows the image of the palm vein after projection into fisher space in (c), we used 20 classes to construct this image, (b) is the global mean image used and (a) is sample image from the class.

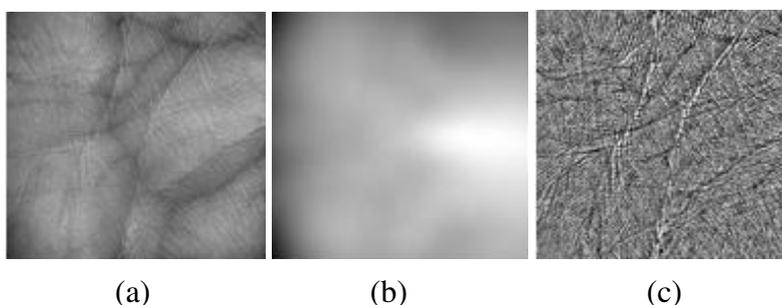(a)   (b)   (c)

Fig 4: Images from feature extraction stage (a) sample palm vein image from class no 1 (b) the global mean for the palm vein images (c) The LDA palm vein for image (a) that is used in classification.

Nevertheless, in the practice of palm print [25] and palm vein the within class scatter matrix S_w is non-singular. Because its rank is at most less than the difference between the number of images (n) and the number of classes (N). In addition, usually the number of images in the training set is much less than the number of pixels in each image. This may result in using a projected matrix with zero within class scatter matrix. One of the solutions to this issue is to project the data matrix into a lower dimension space before applying the LDA projection matrix. This can be achieved using Principal Component Analysis (PCA) as mentioned in [33] .Therefore,

$$\mathrm{E} = \mathrm{E}_{LDA}\, E_{PCA} \tag{8}$$

Where,

$$E_{PCA} = \arg \max_{E} \left| E^T S_T E \right| \tag{9}$$

and,

$$E_{LDA} = \arg \max_{E} \frac{\left| E^T E_{PCA}^T S_B E E_{PCA} \right|}{E^T E_{PCA}^T S_W E E_{PCA}} \tag{10}$$

To calculate S_T in "(9)" for a matrix of n sample images $\{a_1, a_2, ..., a_n\} \in \mathrm{R}^{m \times n}$, we divided this matrix into N classes $\{C_1, C_2, ..., C_N\}$ where each image $a_j \in C_i$. The total scatter matrix is defined by:

$$S_T = \sum_{i=1}^{n} (a_i - m)(a_i - m)^T \tag{11}$$

Based on "(11)", the projection scatter matrix E_{PCA} is defined to satisfy the condition in "(9)" where,

$$E_{PCA} = \arg \max_{E} \left| E^T S_T E \right| = [\mathrm{e}_1, e_2, ..., e_r] \in \mathrm{R}^{m \times r} \tag{12}$$

that formed the set of vectors in S_T corresponding to the highest r Eigen values. Now, we can extract the PCA reduced image vectors using E_{PCA}:

$$f_i = E_{PCA}^T a_i \ , \ i = 1, 2, ..., n \tag{13}$$

4   Experimental Results of the Proposed Scheme for Palm Vein Recognition

The proposed palm vein recognition system works in two modes, verification and identification. In the identification mode the comparison is one – to – one. i.e. the similarity distance between the stored template and the live image is calculated to be used in decision making. If the distance is less than a predefined threshold then the person is deemed as a genuine user, otherwise he/she is an imposter. However, in the identification mode the comparison is one –to-many. In this case we are looking at all the stored templates in the database for the user with the highest similarity score compared with the presented image. In some cases the system

also search for the top k ranks to which the tested sample belongs, where $k = 1, 2, 3, ..., n$ (n is the number of users). This is useful for law enforcement to identify groups of the suspects. To match the LDA features we need a distance measure to calculate the difference between the live test sample and the stored template. The stored template is taken as the mean of the feature vector of the training set [34] for each class. We investigated the cosine distances measure:

Cosine distance: $d_{\cos}(f, \overline{f}) = 1 - \dfrac{f - \overline{f_i}}{\|f\| \|\overline{f}\|}$

Where, f is the feature vector of the palm vein and $\overline{f_i}$ is the stored template of the enrolled user u_i, $i = 1, 2, 3, ..., n$.

The performance of the proposed method is measured for the two modes of operation, identification and verification. For identification the Rank One Recognition (ROR) rule is used.

$$ROR = \frac{\# of\ genuine\ accep\tan ce}{\# of\ total\ identification\ attempts}$$

For verification experiments the proposed scheme will be evaluated using the verification rate and Equal Error Rate (EER). Verification Rate is defined as:

$$VR = \frac{\#of\ genuine\ accepance}{\#of\ genuine\ attempts}$$

Equal Error Rate (EER) is the rate of False Acceptance Rate (FAR) equals False Rejection Rate (FRR).

$$FAR = FRR$$

where;

$$FAR(\%) = \frac{\#of\ false\ accepances}{\#of\ total\ imposter\ attempts}$$

$$FRR(\%) = \frac{\#of\ false\ rejections}{\#of\ total\ genuine\ attempts}$$

For experiments large number of images taken from the $850nm$ wavelength of the PolyU database was used. The database contains 14 images for each palm. However, due to some missing images only 10 images per palm were used. These images were collected from190 different subjects using the left and right hands.

Hence, the total images used in this paper were 3800 images from 380 distinct palms.

The performance graphs were used to measure the accuracy of the features for the different possible threshold values. Because using single threshold value will result in an imbalanced FAR and FRR values. In verification, the Receiver Operating Characteristic (ROC) curve was used to depict the behavior of the algorithm, it plots the values of False Acceptance Rate (FAR) against False Rejection Rate (FRR). In identification experiments the rank one recognition values were presented using the Cumulative Match Curve (CMC) that plots the recognition rate against the different ranks. In our case, four images were used for training and the following images as the testing images. The hardware platform used in this paper is a PC with processor intel (R) Core (TM) i5-4440 , 3.10 GHZ CPU, 4 GB memory and the software used was Matlab 2012a.

In the feature extraction stage the 2D-DWT followed by LDA was used. Many types of wavelet were investigated. Based on our experiments, level -1 and level -2 decomposition yields better results than level three and above. This can be justified by the loss of information in the decomposition pyramid since only the approximate image is used to obtain the next level. This in turn will lead to low image quality as appeared in Figure3-(c) which affect the classification process. Hence, the decomposition level should be examined carefully by the experiment. The wavelets investigated in this paper are Haar, Daubechies-1(db1), db2,db3, db4 and db5, Daubechies and Haar wavelet are asymmetric and orthogonal. We also used the biorthogonal wavelet Bior1.3, Bior1.5, Bior2.2. These wavelets are symmetric and not orthogonal. The rank one recognition rate, verification rate, the equal error rate and the time for each of the wavelets combined with LDA method features and NN classifier with cosine distance are presented in table 1 and 2 below. The time value used is the total time of feature extraction and matching procedures.

Table 1: Classification results for level –1 decomposition of different wavelet and LDA feature

Level 1	ROR	VR	EER	Time
Db1	99.74%	100.00%	0.00%	0.8348
Db2	99.74%	100.00%	0.00%	0.868
Db3	99.74%	100.00%	0.00%	0.8602
Db4	99.74%	100.00%	0.00%	0.9046
Db5	99.61%	100.00%	0.00%	0.9898
Haar = db1	99.74%	100.00%	0.00%	0.8404
Bior1.3	99.61%	100.00%	0.00%	0.8578
Bior 1.5	99.61%	100.00%	0.00%	0.9038
Bior 2.2	99.61%	100.00%	0.00%	0.863

Table 2: Classification results for level –2 decomposition of different wavelet and LDA feature

Level 2	ROR	VR	EER	Time
Db1	99.47%	100.00%	0.00%	0.3912
Db2	99.47%	99.87%	0.13%	0.4226
Db3	99.61%	100.00%	0.00%	0.4158
Db4	99.47%	99.87%	0.13%	0.4444
Db5	99.34%	100.00%	0.00%	0.4514
Haar = db1	99.47%	100.00%	0.00%	0.3982
Bior1.3	99.47%	100.00%	0.00%	0.323
Bior 1.5	99.61%	99.87%	0.13%	0.4626
Bior 2.2	99.47%	100.00%	0.00%	0.3822

We notice that the Daubechies and Haar wavelets yield superior performance than Bior wavelets. This is due to the asymmetric and orthogonal properties of these wavelets which are important to perfect image decomposition and reconstruction [35]. The time is less than one second for all types of wavelets and it is less for level -2 decomposition due to down sampling process. Based on the above tables we will focus on Haar, db3 and Bior2.2 wavelets. Also we can see in figure 5 the average of False Accept Rate (FAR) and False Reject Rate (FRR) for these three wavelets in level one and two decomposition. We notice in Fig 5 that in level one FAR is higher than FRR producing a low EER. However, in level two we find the two errors are closed to each other which result in high EER as seen in table 1 and 2 above.
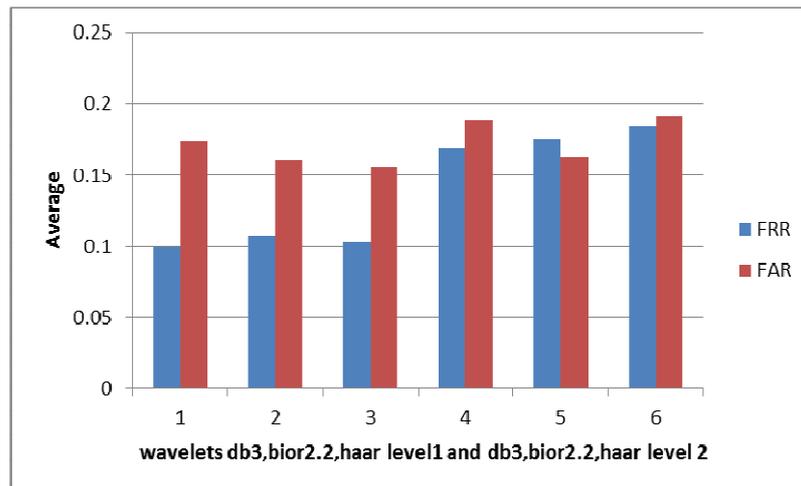

Fig 5: The average FRR and FRR for db3+LDA,bior2.2+LDA and Haar +LDA level 1 and 2 respectively

Based on the experiments in the former two sections we will apply the nearest neighbour classifier with cosine distance for verification and identification experiments. Four images will be used for training and the remaining six images for testing. The proposed method will be compared with the subspace method PCA and the texture extraction method Gabor filter. In addition to LDA method to show the improvement by Wavelet transform. The verification rate, rank one recognition, EER and time results of using the LDA, Gabor filter and PCA features are presented in Table 3. The time recorded is the total of feature extraction and matching. We notice from Table 4 that the proposed algorithm gave the highest performance in terms of accuracy and speed compared with Principal component analysis and 2D-Gabor filter. The latter is used widely in palm vein recognition [8] [14]. Possible reason for that was the fact that Gabor filter is a complex method because it decomposes the image in different scales and orientations. In this paper we used 6 scales and 8 orientations. Hence, it was computationally expensive. PCA on the other hand aims at maximizing the within class scatter matrix only to find the maximum variance direction in the dataset while ignoring the between class variance. LDA is effective in class separation. However, it extracts only global features and both PCA and LDA have no mechanism to deal with the noise in the images like DWT. Hence, DWT is expected to produces more discriminative feature than the subspace learning methods of PCA and LDA. The computation time of the method is 0.8348 second which is suitable for real time applications.

Table 3: Results of the proposed method, PCA, LDA and Gabor filter algorithms

Algorithm	ROR	VR	EER	Time(s)
2D-Gabor filter	99.60%	99.87%	0.13%	6.3262
PCA	96.45%	98.82%	1.18%	0.2118
LDA	97.63%	99.30%	0.70%	0.3366
Wavelet(db1)+ LDA	99.74%	100.00%	0.00%	0.8348

5 Conclusion and Future Work

In this paper, we have proposed using 2D-Discrte Wavelet Transform for palm vein recognition to improve the linear discriminant analysis as a feature extraction method. We explored level one and level two decompositions, and the results show that the level one yields better output. From the experiments, we found that the wavelets that significantly improved the performance were Haar, db3 and Bior2.2 with Nearest neighbor classifier using cosine distance for classification. The conducted experiments on 3800 images from the PolyU public database reveal that the proposed method provides high identification rates of 99.74% and verification rate of 100% with 0% EER when using db3 and haar at level one combined with LDA algorithm for dimension reduction. In the future, we plan to

investigate the detailed information of the wavelet transform in the higher decomposition levels for palm vein recognition.

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