Low Dimensional Representation of Dorsal Hand Vein Features Using Principle Component Analysis (PCA)

M.Heenaye-Mamode Khan, R.K. Subramanian, and N. A. Mamode Khan

***Abstract*—The quest of providing more secure identification system has led to a rise in developing biometric systems. Dorsal hand vein pattern is an emerging biometric which has attracted the attention of many researchers, of late. Different approaches have been used to extract the vein pattern and match them. In this work, Principle Component Analysis (PCA) which is a method that has been successfully applied on human faces and hand geometry is applied on the dorsal hand vein pattern. PCA has been used to obtain eigenveins which is a low dimensional representation of vein pattern features. Low cost CCD cameras were used to obtain the vein images. The extraction of the vein pattern was obtained by applying morphology. We have applied noise reduction filters to enhance the vein patterns. The system has been successfully tested on a database of 200 images using a threshold value of 0.9. The results obtained are encouraging.

***Keywords*—**Biometric, Dorsal vein pattern, PCA.

I. INTRODUCTION

PERSONAL verification is an important aspect of security access systems. Traditional personal verification methods such as passwords, personal identification numbers (PINS), magnetic swipe cards, keys and smart cards offer very limited security and are unreliable [1,13]. The recent increase of crime in high technology application has enhanced the attention of researches to adapt better security provisions. To ensure more reliable security, many biometric verification techniques have been developed and implemented. Compared to traditional methods, biometric features are harder for intruders to copy and forge [2]. Biometric involves the analysis of human biological, physical and behavioral characteristics. The most popular biometric features that are used are fingerprints, hand geometry, iris scans, faces, as well as handwritten signatures. A practical biometric security system should meet the specified recognition accuracy, speed and resource requirement, be harmless to users, be accepted by intended population and be sufficiently robust to various fraudulent methods and attacks to the system [11]. Biometric system using face recognition, iris and fingerprints are more developed compared to new emerging biometric like vein. However, each biometric has its strengths and weaknesses. Recently hand vein pattern biometric has attracted increasing interest from both research communities and industries. Anatomically, aside from surgical intervention, the shape of vascular patterns in the back of the hand is distinct from each other. Veins are found below the skin and cannot be seen with naked eyes. It is difficult for someone to tamper with the vein pattern. This feature makes it a more reliable biometric for personal identification [3]. Furthermore, the state of skin, temperature and humidity has little effect on the vein image, unlike fingerprint and facial feature acquirement [4]. The hand vein biometrics principle is non- invasive in nature where dorsal hand vein pattern are used to verify the identity of individuals [12].

The Principle Component Analysis (PCA) is a method proposed by Turk and Pentland [6] for automatic recognition of human faces to obtain eigenfaces. The system functions by projecting face images onto a feature space that spans the significant variations among known face images. These significant features are termed "eigenfaces" because they are principle components of the set of training face images. PCA was also applied on human hand[5] since the human hand contains a variety of features, for example, shape, texture and principal palm lines- that can be used for biometric systems. Features extracted by projecting palm images into the subspace obtained by the PCA transform are called eigenpalm features, whereas those extracted by projecting images of fingers and thumb are called eigenfinger and eigenthumb features [5]. We have extended the idea of using Principle Component Analysis (PCA) to the dorsal hand vein pattern and use it to obtain eigenveins which is a low dimensional representation of the vein features.

II. ACQUISITION OF VEIN IMAGES

A. Dorsal Hand Vein Biometric Procedure

Procedures have to be devised in order to obtain the essential features of the vein patterns. The figure below shows the steps that have been used to develop the dorsal vein biometric security system.

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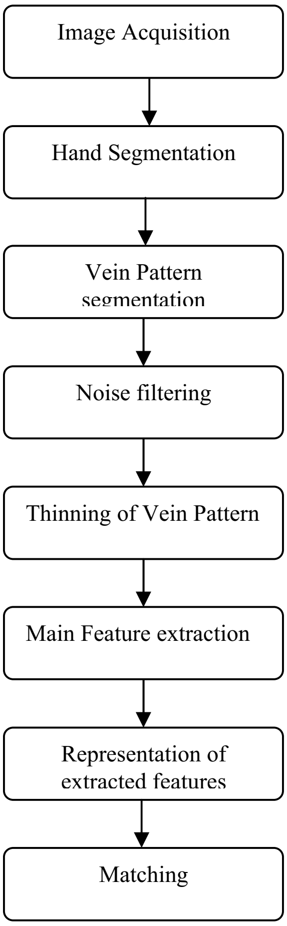

Figure 1: Biometric Procedure

Each of the procedures will be detailed in this paper.

B. Acquisition of Images

Veins are found beneath the skin and thus, it is very difficult to obtain the vein pattern in visible light. To capture the vein images, a CCD camera with near infrared has been used. The vein pattern is best defined when a fist is made. The figure below shows one of the sample of vein images, which is of size 240x320.

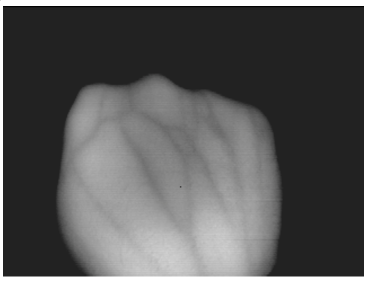

Figure 2: original hand dorsal vein pattern

III. SEGMENTATION OF THE HAND AND VEIN PATTERN

First, we extracted the hand, which is the region of interest, from the background. Then the vein patterns are extracted. The steps involved in our techniques are described below:

Morphological opening was used to estimate the background (Figure 4). The two morphological operations are dilation and erosion, where dilation is an operation that "grows" objects and erosion "thins" objects in a binary image. Erosion followed by dilation was used and this creates an important morphological transformation called opening. The opening of an image X by structuring element B is denoted by XoB and is defined as [7] :

$$X \circ B = (X \oplus B) \oplus B$$

The background was subtracted from the original image. This allows us to obtain the region of interest. (Figure 4).The contrast that varies all over the vein image has been adjusted. (Figure 5)

The vein pattern is then thresholded using different threshold values. Thresholding is the most common segmentation method which is computationally fast and inexpensive (Figure 6).

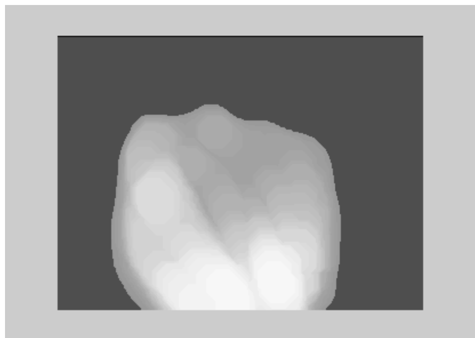

Figure 3: Estimation of the background

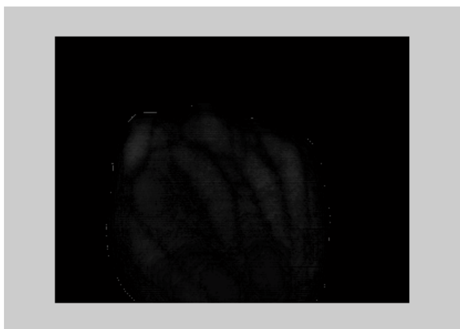

Figure 4: Subtraction of the background

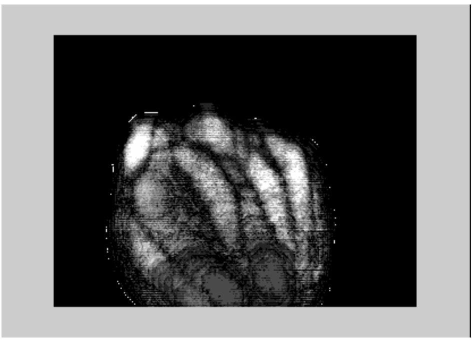

Figure 5: Contrast Adjustment

Figure 6: Threshold of the vein pattern

After carrying out the different processes, the vein pattern is extracted. However, there are noises that need to be removed to get clearer images.

IV. NOISE REDUCTION AND EXRACTION OF THE VEIN PATTERN

The clearness of the vein pattern varies from image to image. Thus, we had to enhance the quality of the image to obtain the vein structures. We used Match filter, Wiener filter and smoothing filter as proposed by S.Zhao, Y.Wang and Y.Wang [8] to suppress noises that exist in the vein pattern. This allowed us to obtain clearer vein pattern for feature extraction. However, it was found that Wang and Leedham [3] applied a 5x5 Median filter and a 2- D Gaussian low pass filter to suppress the effect of high frequency noise. Unfortunately, the method could not be applied in all cases. This is because, the images acquired by Wang and Leedham [3] were taken from a thermal camera compared to a low cost CCD camera.

As the size of veins grow as human beings grow, only the shape of the vein patstern is used as the sole feature to recognize each individual. A good representation of the pattern's shape is via extracting its skeleton [3]. In fact, the thinning algorithm devised by Zhang and Suen [9] was applied on the vein pattern. After the pruning process, the vein pattern is enhanced. Pruning eliminates the shadow in the images and retains the main vein patterns. The following figure shows one of the vein images which was thinned and pruned.

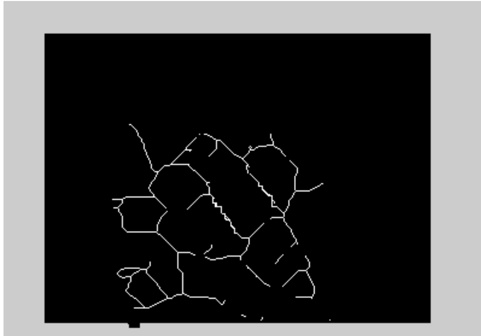

Figure 7: Thinned and pruned vein pattern

After obtaining the vein pattern, the coordinates were extracted from the pattern. Each coordinate represent the pixel values of the image.

V. REPRESENTATION OF THE KEY FEATURES OF THE VEIN PATTERN

The technique applied which is PCA (Principle Component Analysis) was originally used on human faces [10] and on hand geometry [5]. The same method is used on the vein pattern for obtaining a low dimensional representation of dorsal hand vein features. This technique is expected to reduce the matching time since it does not distinguish veins by comparing the properties and relations between pixel values

Turk and Pentland [10] decomposes face images into a small set of characteristic feature images called "eigenfaces" which are nothing more but principle components of the set of training images [6]. This method was used in face recognition system. In fact, Turk and Pentland[10] were motivated by a technique developed by Sirovich and Kirby. The latter demonstrated that any particular face can be economically represented in terms of a best coordinate system and the system was termed "eigenpictures". Eigenpictures are eigenfunctions of the averaged covariance of the ensemble of faces. In other words, they showed that in principle, a collection of face images can be approximately represented by a small set of standard pictures with a small weight for each of the standard pictures [6].

Dagher, Kobersy and Nader [5] developed a human hand recognition using PCA. The human hand contains a wide variety of features, for example, shape, texture and principle palm lines that can be used by biometric systems. Features extracted by projecting palm images into the subspace obtained by the PCA transform are called eigenpalm features, whereas those extracted by projecting images of fingers and thumb are called eigenfinger and eigenthumb features. The authors used two techniques based on principal component analysis and independent component analysis. Eigenpalm, eigenfingers and the eigenthumb features are obtained using a fast incremental principal non- Gaussian direction analysis algorithm called IPCA- ICA.

In our case, PCA was applied on the vein pattern to obtain "eigenvein" features. These features were then projected onto a vein space.

A. eigenveins using principle comnponent analysis

We have applied PCA on the vein pattern to obtain eigenvein features as described below:

i) A set of vein images were acquired.
ii) Coordinates that represent the feature points were extracted.
iii) The coordinates were converted into a training set.
iv) Perform the computation of the eigenvalues.
v) Generate a space of eigenveins. Only M eigenveins corresponding to M largest eigenvalues were retained. These eigenveins spanned the vein space which constituted of the training set.
vi) Compute the weight of each eigenvein to determine its contribution in the vein space.

Steps (i) - (vi) were applied on each of the vein images obtained.

B. procedures for identifying images

To ascertain whether the test image is in the database or not, we obtain the eigenvein of the test image following the procedure described above and the procedure described below:

i) Perform all the operations described above for the test image.
ii) The test image was projected on each of the eigenveins. This was done by finding the set of M weights corresponding to the test image.
iii) The distance between the test image and the vein space is compared to an arbitrary distance threshold to check whether the test image was sufficiently close to the vein space.
iv) If it is sufficiently close to the vein space, the distance of the M weights of the test image to the M weights of each vein in the training set is calculated. This is done to check whether the test image correspond to any known identity. The test image is then assigned with the identity of the image which has the smallest distance.

VI. DETAILED PROCEDURE OF EIGENVEIN APPROACH

The procedure shown in this section describes how eigenvein is obtained. This procedure is based on the eigenface approach developed by Turk and Pentland [10]. First, coordinates obtained from the pattern have to be represented in a matrix for processing. This representation, known as training set, is important to generate eigenvalues. Then we have to calculate the mean in order to reduce the variation in the images. This mean is subtracted from the original images found in the training set to obtain a new set of images. The covariance matrix is deduced to measure the degree of similarity between the data. A weight is then calculated to deduce the contribution of each eigenvein, to project it onto the vein space.

First of all a set of n images is obtained. This can be represented as the following set A. $A=[I_1, I_2, I_3, ..., I_n]$. Each image has a set of coordinates which represent the pictures.

Each coordinate is represented by (x,y) pair denoting the position in the image. The matrix is as follows:

$$veinmat = \begin{bmatrix} image1 & image2 & image3 & image4 \\ (x_1, y_1) & (x_1, y_1) & \cdots & (x_1, y_1) \\ (x_2, y_2) & (x_2, y_2) & & (x_2, y_2) \\ \vdots & \vdots & & \vdots \\ (x_n, y_n) & (x_n, y_n) & & (x_n, y_n) \end{bmatrix}$$

For using the PCA technique, we have to convert the set of coordinates into a training set, which is represented as follows:

$$T = \begin{bmatrix} image1 & image2 & image3 & image4 \\ \begin{pmatrix} x_1 \\ y_1 \end{pmatrix} & \begin{pmatrix} x_1 \\ y_1 \end{pmatrix} & \cdots & \begin{pmatrix} x_1 \\ y_1 \end{pmatrix} \\ \begin{pmatrix} x_2 \\ y_2 \end{pmatrix} & \begin{pmatrix} x_2 \\ y_2 \end{pmatrix} & & \begin{pmatrix} x_2 \\ y_2 \end{pmatrix} \\ \vdots & \vdots & & \vdots \\ \begin{pmatrix} x_n \\ y_n \end{pmatrix} & \begin{pmatrix} x_n \\ y_n \end{pmatrix} & & \begin{pmatrix} x_n \\ y_n \end{pmatrix} \end{bmatrix}$$

To reduce the variation in the element of the training set and to make it standardize, the average $\psi = \frac{1}{M}\sum_{n=1}^{M} T_n$ is calculated and subtracted from the images of training set as follows: $\phi_i = T_i - \psi$ resulting to the following new training set:

$\{\phi_1, \phi_2, \phi_3, \ldots\ldots\ldots\ldots, \phi_M\}$

Eigenfaces are the set of principal components of the training set. To obtain the eigenface description of the training set, the training images are subjected to PCA, which seeks a set of vectors which significantly describes the variations of the data. Mathematically, the principal components of the training set are the eigenvectors of the covariance matrix of the training set [6].

In our case, we must calculate a matrix that will measure the degree of correlation among the vein data and this is done by using covariance.

$$C = \frac{1}{M}\sum_{n=1}^{M} \phi_n \phi_n^T \qquad (1)$$

Which can also be formulated as follows:

$$C = \frac{1}{M} AA^T \qquad (2)$$

The formula used deduces the similarity between the objects. However, too much eigenvectors and eigenvalues were generated A simpler technique [10] was applied to reduce the dimension of the matrix. The formula used is shown below:

$$A^T A v_i = \mu_i V_i \qquad (3)$$

The matrix $A^T A$ was constructed and respective eigenvalues and eigenvectors were calculated. However, with the eigenvalues obtained many eigenvectors can be generated. The question that arises is to know how much eigenveins is to be used. Turk and Pentland proposed the following formula:

$$\frac{\sum_{i=1}^{M'} \mu_i}{\sum_{j=1}^{M} \mu_j} > 0.9 \qquad (4)$$

However, in our case, we have accounted for more than 95% of the variation in the training set. The following formula was used:

$$\frac{\sum_{i=1}^{M'} \mu_i}{\sum_{j=1}^{M} \mu_j} > 0.95 \qquad (5)$$

This improves error reduction in the matching process.

We have already obtained M' eigenveins. For each element in the training set, the weight is calculated. This weight will demonstrate the contribution of each eigenvein to respective training element. If the weight is bigger, then the eigenvein has shown the real vein. If the value is less, there is no big contribution with the real vein for that particular eigenvalue. The following operation shows how each element in the training set is projected onto the vein space:

$$\begin{aligned} \omega_k &= (Av_k)^T (T_i - \psi) \\ 1 \le k &\le M', 1 \le i \le M \end{aligned} \qquad (6)$$

Each element in the training set has a weight to determine their contribution they have to the vein space.

VII. PATTERN MATCHING

When a person wants to get access to the system, the picture of the vein is captured. The coordinates are obtained and represented as the training set. The weight of the new image is calculated and projected on the vein space. If it is vein image, then it is accepted. The vein space contains all the vein images. Thus, we have to check whether the input image exist in that space. The Euclidean distance between the projected image and those stored is being calculated. First of all, our system checks whether the test image is a vein by testing it with an arbitrary value. Then the Euclidean distance is computed to check whether the test image exist in the database. The results were recorded and tested.In the next step, we will use different techniques for matching and we will compare they differ in the matching phase.

VIII. EXPERIMENTAL RESULTS

Principle Component Analysis was applied to the vein features. Different threshold values were used for vein pattern matching to deduce the false acceptance rate and the false rejection rate. False Acceptance Rate refers to the total number of unauthorized persons getting access to the system over the total number of people attempting to use the system. False Rejection Rate refers to the total number of authorized persons not getting access to the system over the total number of people attempting to get access to the system. The table below shows the result obtained:

Threshold Value	**Acceptance Rate (%)**
0.10	98%
0.20	82%
0.30	69%
0.40	47%
0.50	32%
0.60	21%
0.70	11%
0.80	4%
0.90	0%
0.95	1%

Table 1: Table showing false acceptance rate for a sample of 200

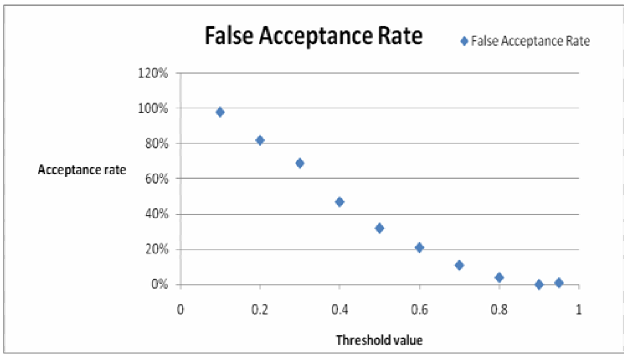

Figure 8: Scatter plot for false Rejection rate

Threshold Value	**Rejection Rate (%)**
0.10	99%
0.20	79%
0.30	65%
0.40	44%
0.50	32%
0.60	19%
0.70	10%
0.80	3%
0.90	0%
0.95	2%

Table 2: Table showing false rejection rate for a sample of 200

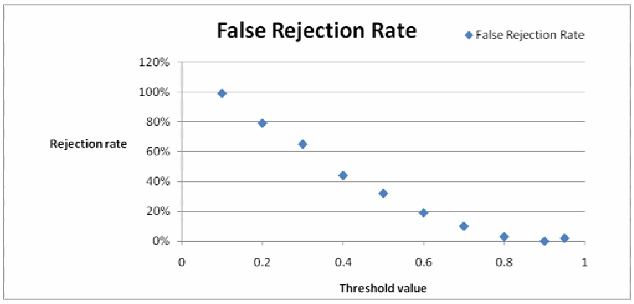

Figure 9: Scatter plot for false Rejection rate

By choosing the threshold to be 0.95, the system achieves 0% of false acceptance rate and 0.01 % of false rejection rate. However when choosing the threshold to be 0.9, the system achieves 0% false acceptance rate and 0% false rejection rate. The results obtained are encouraging but however it was tested on a small database where the images were taken in a controlled manner. The ROC curve below illustrates the results.

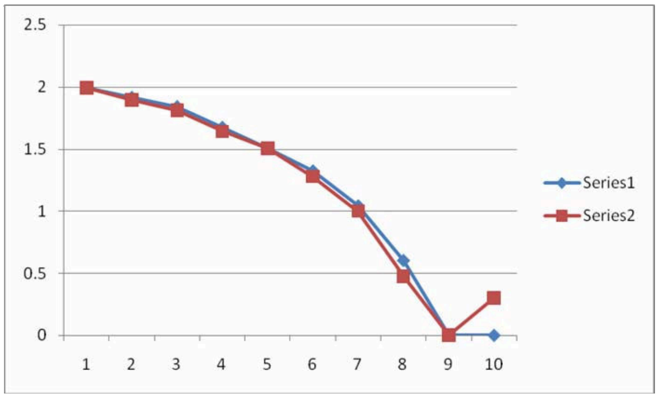

Figure 10: ROC curve for FAR and FRR

IX. Conclusion

The PCA technique previously applied on face and hand geometry has successfully worked on the vein images producing satisfactory results. We are also attempting to identify some classification of the dorsal vein patterns so that matching could be speeded up.

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