International Journal of Engineering, Mathematical and Physical Sciences
ISSN: 2517-9934
Vol:4, No:1, 2010

Feature Extraction of Dorsal Hand Vein Pattern using a fast modified PCA algorithm based on Cholesky decomposition and Lanczos technique

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Abstract—Dorsal hand vein pattern is an emerging biometric which is attracting the attention of researchers, of late. Research is being carried out on existing techniques in the hope of improving them or finding more efficient ones. In this work, Principle Component Analysis (PCA) , which is a successful method, originally applied on face biometric is being modified using Cholesky decomposition and Lanczos algorithm to extract the dorsal hand vein features. This modified technique decreases the number of computation and hence decreases the processing time. The eigenveins were successfully computed and projected onto the vein space. The system was tested on a database of 200 images and using a threshold value of 0.9 to obtain the False Acceptance Rate (FAR) and False Rejection Rate (FRR). This modified algorithm is desirable when developing biometric security system since it significantly decreases the matching time

Keywords—Dorsal hand vein pattern, PCA, Cholesky Decomposition, Lanczos algorithm.

I. Introduction

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], [2]. Biometric which involves the analysis of human biological, physical and behavioral characteristics has been developed to ensure more reliable security. The most popular biometric features that are used are fingerprints, hand geometry, iris scans, faces, as well as handwritten signatures. Recently dorsal hand vein pattern biometric is attracting the attention of researchers and is gaining momentum. 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. Its uniqueness, stability and immunity to forgery are attracting researchers. These 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 [5]. Vein pattern is also stable, that is, the shape of the vein remains unchanged even when human being grows.

Extensive researches are carried out on vein patterns and researchers are striving hard to find methods and techniques to develop dorsal hand vein security system. Any biometric system consists of four main steps namely the preprocessing, feature extraction, processing and matching phase. Feature extraction is a crucial step in biometric system and its capability directly influence the performance of the system. Principle Component Analysis (PCA) which is a famous technique for extracting features from images have been used in biometric security system. 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 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 [7].

We have extended the idea of using PCA to the dorsal hand vein pattern and used it to obtain eigenveins for matching [8]. Furthermore, we modified this PCA algorithm by decomposing the covariance matrix of the training set of the images using Cholesky decomposition [9]. This new PCA algorithm provides us with satisfactory results. The matching time is reduced by approximately 7s which is very encouraging in biometric security system. However, we note that the computation of eigenveins are quite costly and takes time since the matrices are high-dimensional. There is scope to further improve the PCA technique by integrating the Cholesky decomposition along with the Lanczos technique [10], [11] of calculating the eigenvalues of the covariance matrix. Thereafter, we use these eigenvalues to generate the set of eigenveins.

The paper is laid as follows: In section 2, we describe the pre-processing phases applied on the dorsal hand vein pattern and a Cartesian-based block matrix representation of the dorsal hand vein pattern. Section 3 explains the modified PCA algorithm based on the Cholesky decomposition and the Lanczos technique. In section 4, we perform the vein pattern matching. Experimental results are presented in section 5 and finally section 6 concludes the paper.

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II. A NOVEL REPRESENTATION OF DORSAL HAND VEIN FEATURES BASED ON A CARTESIAN BLOCK MATRIX

In this section, we present a novel representation of the dorsal hand vein pattern. This approach consists of a block matrix training set to represent the dorsal hand vein features. Firstly, it is important to obtain the vein pattern in the image captured. This procedure requires image acquisition, hand segmentation, vein pattern segmentation, noise filtering and thinning of the vein pattern. After these preprocessing techniques, we obtain an image consisting of a background represented in black and a thinned vein pattern in white.

A. Image Acquisition

Vein pattern is found beneath the skin and is invisible to the naked eye. Vein images can only be captured by using either near infrared or far infrared light. However, according to research better quality images can be obtained using near infrared light [12]. A thermal camera or alternative setup like using a charge coupled device (CCD) with alternative devices like infrared filter and frame grabber can be used to capture the dorsal hand vein pattern. Up to now, there is currently no public hand vein pattern database available to the research community [13]. In this work a database of 200 hand dorsal vein pattern was obtained by a group of researchers under the supervision of Prof.Ahmed Badawi from University of Tennessee Knoxville. The images were taken with a commercially available conventional charge couple device (CCD) monochrome camera. The hand was presented as a clenched fist with the thumb and all the other fingers hidden. In the setup the intensity of the IR source is attenuated by the use of diffusing paper, which also helps for obtaining an equally distributed illumination on the hand area. A frame grabber is used to capture the image for computer processing. Images were captured using a $320W \times 240H$ pixels video digitizer with a gray- scale resolution of 8- bits per pixel [5], [14], [15].

B. Hand and Vein pattern segmentation

When a hand image is obtained, the hand background is first segmented from the image. For hand segmentation, morphological operations are applied on the hand image to estimate the background of the hand region. 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 background was subtracted from the original image. This allows us to obtain the region of interest. The contrast that varies all over the vein image has been adjusted. After this operation the hand is being segmented. In order to obtain the vein pattern, the image is then thresholded. Thresholding is the most common segmentation method which is computationally fast and inexpensive.

C. Enhancement and Thinning 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 [17] to suppress noises that exist in the vein pattern. This allowed us to obtain clearer vein pattern for feature extraction. As the size of veins grow as human beings grow, only the shape of the vein pattern is used as the sole feature to recognize each individual. A good representation of the pattern’s shape is via extracting its skeleton. A thinning algorithm was devised to obtain a thinned version of the vein pattern. Pruning eliminates the shadow in the images and retains the main vein patterns.

The resulting image is represented as a binary matrix of size 320×240 where the black color is coded as 0 and the white color is coded as 1. We provide an alternative matrix representation that converts these binary codes into a two-dimensional cartesian coordinate system where the black color takes value 0 for both the x and y co-ordinates and the white color is indexed by its i^{th} and j^{th} position in the binary matrix. We illustrate this concept through the following examples: Assume a 3×3 sub-matrix from the 320×240 binary image matrix.

$$\begin{pmatrix} 0 & 1 & 1 \\ 1 & 1 & 1 \\ 0 & 0 & 1 \end{pmatrix} \tag{1}$$

We convert this matrix in cartesian system as follows:

$$\begin{pmatrix} 0 & 0 & 1 & 2 & 1 & 3 \\ 2 & 1 & 2 & 2 & 2 & 3 \\ 0 & 0 & 0 & 0 & 3 & 3 \end{pmatrix} \tag{2}$$

Ultimately, the size of the two-dimensional cartesian coordinate based image matrix will be of size $320 \times 240 \times 2$. Assuming I images for training set X,i.e,

$$X = [X_1, X_2, \ldots, X_i, \ldots, X_I] \tag{3}$$

where

$$X_i = \begin{pmatrix} X_{i,1,1} & X_{i,1,2} & \ldots & X_{i,1,240\times2} \\ X_{i,2,1} & X_{i,2,2} & \ldots & X_{i,2,240\times2} \\ \vdots & \vdots & \vdots & \vdots \\ X_{i,320,1} & X_{i,320,2} & \ldots & X_{i,320,240\times2} \end{pmatrix} \tag{4}$$

where

$$X_{ijk} = (x_{ij}, y_{ik}) \tag{5}$$

where i is the index for the i^{th} image, j is the index corresponding x co-ordinate of the i^{th} image and k is the index corresponding to the y co-ordinate of the i^{th} image where $i = 1, \ldots, I$, $j = 1, \ldots, 320$ and $k = 1, \ldots, 240 \times 2$. Hence, the training block matrix X_i is of size $320 \times 2 \times I \times 240$. As it can be noted, the size of this matrix is large especially when I is large. To overcome this problem, we represent the dorsal hand vein features using the covariance matrix of the image points. This matrix will also measure the degree of correlation among the vein data.

$$C = \frac{1}{I} \sum_{i=1}^{I} \phi_i \phi_i^T \tag{6}$$

In our context, ϕ_i is a 320×240 matrix where the $(j,k)^{th}$ element of ϕ_i are given by

$$\phi_{ij} = x_{ij} - \psi_j \tag{7}$$

and

$$\phi_{ik} = y_{ij} - \psi_k \tag{8}$$

where

$$\psi_j = \frac{1}{I}\sum_{i=1}^{I} x_{ij} \tag{9}$$

and

$$\psi_k = \frac{1}{I}\sum_{i=1}^{I} y_{ik} \tag{10}$$

where x_{ij} and y_{ik} are the corresponding x and y coordinates from equation(5). Equation (6) can be re-formulated as

$$C = \frac{1}{I}AA^T \tag{11}$$

Following the PCA method of Turk and Pentland [6], we obtain

$$A^T A\nu_i = \mu_i\nu_i \tag{12}$$

Applying the above formulae provides satisfactory results. However, the computational time can further be reduced by modifying the matrices using Cholesky decomposition and Lanczos algorithm. This will eventually allow recognition of users faster.

III. Modified PCA integrating Cholesky decomposition and Lanczos algorithm (MPCACL)

Cholesky decomposition is a form of triangular decomposition that is applied to positive definite symmetric or positive definite Hermitian matrices. A symmetric or Hermitian matrix A is said to be positive definite if $x^T Ax > 0$ for any non-zero x. Positive definite matrix is one that has all eigenvalues greater than zero. At first, we use the matrix $A^T A$ to calculate the eigenveins. The matrix $A^T A$ is a symmetric positive definite matrix. We note that the matrix involve many flop counts and in terms of computation, it is quite time consuming and expensive. We propose instead to simplify this matrix $A^T A$ by the Cholesky decomposition since it is well symmetric positive definite. The Cholesky decomposition yields two lower triangular matrices. We use one of these two matrices to calculate the eigenveins by multiplying its diagonal elements. It is to be noted that through simulations, we have seen that there is no loss of information regarding the matching of the eigenveins. Consider the formula below,

$$A^T A\nu_i = \mu_i\nu_i \tag{13}$$

Instead of calculating the eigenvalues of $A^T A$, Cholesky decomposed triangular matrix was used to calculate the eigenvalues, i.e, $A^T A$ can be written LL^T where L is the lower triangular matrix and LL^T is the decomposition of $A^T A$. The eigenvalues are obtained using the following formula:

$$L\nu_i = \mu_i\nu_i \tag{14}$$

where ν_i is the eigenvein corresponding to the eigenvalue μ_i. Instead of using the conventional method, that is, solving characteristic polynomial to obtain eigenvalues, we propose to calculate the eigenvalues using the Lanczos algorithm. Below, we provide the steps to calculate the vector of eigenvalues using the Lanczos algorithm.

1) Let μ_i be a random vector of norm 1
2) $\mu_0 \leftarrow 0$
3) $\beta_1 \leftarrow 1$
4) for $j = 1, 2, 3, \ldots,$ until convergence
5) $\omega_j \leftarrow L\mu_j - \beta_j\mu_{j-1}$
6) $\alpha_j \leftarrow \omega_j^T\mu_j$
7) $\omega_j \leftarrow \omega_j - \alpha_j\mu_j$
8) $\beta_{j+1} \leftarrow \|\omega_j\|$
9) $\mu_{j+1} \leftarrow \frac{\omega_j}{\beta_{j+1}}$

For each eigenvector, a family of eigenvein has to be generated. However, many eigenveins are being generated. In order to determine how many eigenveins are required, the following formula is being used:

$$\frac{\sum_{i=1}^{2N'}\mu_i}{\sum_{j=1}^{320}\mu_j} > 0.9 \tag{15}$$

$$\frac{\sum_{i=1}^{2N'}\mu_i}{\sum_{j=1}^{320}\mu_j} > 0.95 \tag{16}$$

We have already obtained $2N'$ 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 weight is small, this implies there is no huge 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:

$$\varphi_k = \frac{1}{320 \times 240}\sum_{i=1}^{320}\sum_{j=1}^{240}(L\nu_k)^T(X_{ij}^T - \phi_j^T) \tag{17}$$

Each element in the training set has a weight to determine their contribution they have to the vein space [8], [9].

IV. Vein 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 analyzed.

V. Experimental results

Principle component analysis has been modified based on Lanczos algorithm to obtain the eigenvein features. Different threshold values are 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. Table 1 shows the experimental results obtained. By choosing the threshold to be 0.95, the system achieves 1 percent of false acceptance rate and 2 percent of false rejection rate. However when choosing the threshold to be 0.9, the system achieves 0 percent false acceptance rate and 0 percent false rejection rate. The threshold 0.9 is the ideal threshold value since it caters for some variations in the image captured. The results obtained are encouraging but however it was tested on a small database where the images were taken in a controlled manner. Our main concern is to reduce the processing time of our hand dorsal vein recognition system. From Table 2, we note the matching time consumed by MPCACL is considerably lesser than PCA as illustrated by the difference. In fact, when using PCA, the average time taken for 1 image is around 13.5s whereas MPCACL takes around 5.2s for one image.

TABLE I
FALSE ACCEPTANCE RATE AND FALSE REJECTION RATE

Threshold value	False acceptance rate	False rejection rate
0.1	98	99
0.2	82	79
0.3	69	65
0.4	47	44
0.5	32	32
0.6	21	19
0.7	11	10
0.8	4	3
0.9	0	0
0.95	1	2

TABLE II
COMPARISON OF TIME USING PCA AND MPCACL

Number of Images	PCA (sec)	MPCACL (sec)	Diff
100	1400	650	-750
80	1130	310	-820
60	843	350	-493
40	560	265	- 295
20	278	118	-160
10	135	52	-83

VI. Conclusion

The PCA technique previously applied on face and hand geometry has successfully worked on the vein images producing satisfactory results. Cholesky decomposition and Lanczos algorithm are integrated with PCA (MPCACL) to reduce the processing time of the vein patterns matching. The experimental results are satisfactory and further methods are being investigated to develop cheaper hand dorsal vein security system.

Acknowledgment

We express our deepest thanks to Prof. Ahmed M. Badawi, from University of Tennessee, Knoxville, for providing us with a dataset of 200 images of hand dorsal vein pattern.

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