

Finger Vein Recognition using PCA-based Methods

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Abstract—In this paper a novel algorithm is proposed to merit the accuracy of finger vein recognition. The performances of Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), and Kernel Entropy Component Analysis (KECA) in this algorithm are validated and compared with each other in order to determine which one is the most appropriate one in terms of finger vein recognition.

Keywords—Biometrics, finger vein recognition, Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), Kernel Entropy Component Analysis (KECA).

I. INTRODUCTION

THE importance of verification and identification has gained a lot of attention as the number of people who are not willing to be identified is getting larger and larger by passing the time[1]; illegal immigrants, criminals who are on the run can be two clear examples. Finger vein recognition is a recently proposed method in which finger vein patterns are analyzed. Based on the physical characteristics of the vein patterns, finger vein is unique and individual. As the database used in finger vein recognition is 'image', some face recognition algorithms[2] have already been experienced on finger vein database that were both successful and unsuccessful. Principal Component Analysis (PCA)[3] is a commonly used method for pattern extraction and face recognition. Based on previous research, Kernel Principal Component Analysis (KPCA)[4], and Kernel Entropy Component Analysis (KECA)[5] were proposed to enhance the performance of PCA. KPCA is an extension of PCA. PCA is a linear method which extracts the features and reduces the dimension. In case of KPCA, however, it is different. In KPCA the input data is first nonlinearly mapped to another feature space called F , and then a PCA will be performed on the mapped dataset. This nonlinear mapping of the input data is done by a function called Φ . Kernel Entropy Component Analysis is exactly the same as Kernel Principal Component Analysis except for one point that when it comes to choosing the eigenvectors to project onto the data, unlike KPCA (in which the top eigenvectors are chosen), in KECA[6] the chosen eigenvectors have to contribute to the entropy estimate of the input data.

In Section 2, Image acquisition is explained. In Section 3, finger vein recognition algorithm is introduced. In Section 4, Kernel Principal Component Analysis is explained briefly. In Section 5, Kernel Entropy Component Analysis (KECA) is explained. In section 6, experimental results on finger vein database are given. Finally, section 7 concludes the paper.

II. IMAGE ACQUISITION

Deoxygenated haemoglobin in the vein can absorb the light rays' based on this proven scientific; the absorption coefficient (AC) of the vein is higher than other parts of finger when you are capturing the image of finger vein. The following four low-cost prototype devices were used to capture the finger vein database: a computer to process the vein images, a microcomputer unit (MCU) to adjust and control the LED array, a suitable infrared LED and related control circuit (in this paper Osram SFH485 infrared light emitting diodes (IR LED) with wavelength 880nm at the top of the constructed capturing model has been used), a camera to capture finger vein images (Logitech V-UAV35 web-cam at the bottom of the design). The Logitech V-UAV35 web-cam blocks the infrared rays (IR), because it consists of an IR blocking filter. Hence, to make this camera sensitive to infrared rays, the negative film is employed instead of the blocking filter in order to capture the transmitted infrared rays. This negative film can operate to transmit 90% of radiation wavelength of 850nm as an IR pass filter. Figure 1 indicates the used devices to capture the database and the connections between them.



Fig. 1 used devices to capture finger vein images and the connections

III. FINGER VEIN RECOGNITION ALGORITHM

This section explains the used finger vein recognition algorithm in this work. The flow diagram of the finger vein is shown in Figure 2. Based on the diagram, this algorithm has five steps: first step is extracting the region of interest (ROI). The second step is enhancing the images by using contrast limited adaptive histogram equalization. Feature normalization of images is implemented in step three. Step four is employing the PCA, KPCA [7] and KECA to extract features, and reducing the dimension of the images. The last step is comparing test and train data using Euclidian distance.

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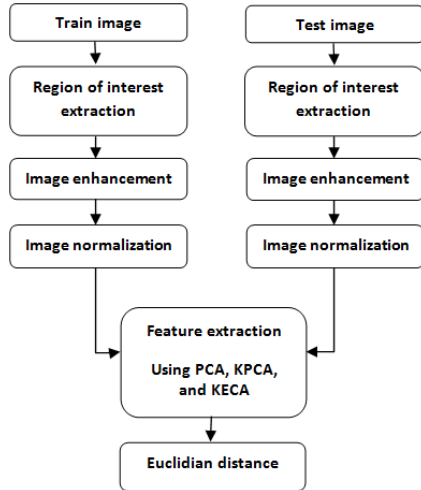


Fig. 2 Flow diagram of the proposed algorithm

A. Region of interest extraction

As it is shown in Figure 3, there is some unwanted black region around the finger images which should be omitted to increase the final accuracy and reliability.

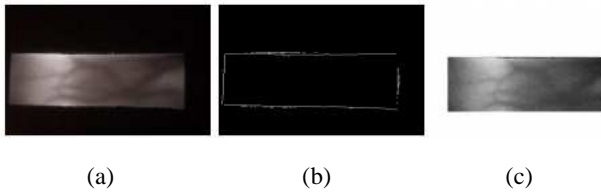


Fig. 3 (a) original image, (b) finger edges, (c) cropped image

Three major steps are used to crop images optimally: first one is detecting the edge. In order to perform the cropping part, two horizontal lines are determined as are shown in Figure 3(b). Two conditions should be satisfied to find the appropriate lines by edge detection algorithm: (1) the pairs of detected points should be located between 35% and 65% of the height of the captured image, and (2) among the detected pairs, the pair of the edge that are the widest will be chosen. Last step is to crop the images from 15% from right border and 5% percent from left border vertically

B. Image enhancement

Contrast limited adaptive histogram equalization (CLAHE) is a method to enhance the images, which results in increment in the accuracy and makes image clearer. Figure 4 shows an image before and after enhancing.

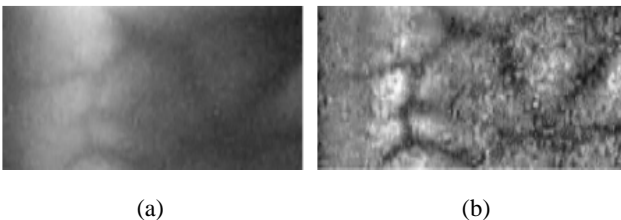


Fig. 4 (a) original image, (b) image after enhancing

C. Image normalization

Images are normalized to smaller size to achieve the highest accuracy before implementing KECA. The experimental results show that although making the size of images smaller causes the system to be faster, it results in lower accuracy. To obtain the optimal size which contributes to highest accuracy, images are normalized into 10×10 pixels which is the most optimal size based on the experiments.

IV. KERNEL PRINCIPAL COMPONENT ANALYSIS (KPCA)

The main idea of KPCA is to map the input data X to a features space called F nonlinearly. Once the input data has been mapped by Φ , PCA will be performed in F . After centering F , $\sum_{i=1}^M \Phi(X_i) = 0$ in where M is the number of input data. The covariance matrix of F is defined in Eq. (1)

$$C = \frac{1}{M} \sum_{i=1}^M \Phi(X_i) \cdot \Phi(X_i)^T \quad (1)$$

For this porous, the eigenvalue equation ($\lambda v = C v$) should be solved when eigenvectors $v \in F$ and eigenvalues $\lambda \geq 0$.

where $Cv = (1/M) \sum_{i=1}^M (\Phi(X_i) \cdot v) \Phi(X_i)$, the solutions for v when $\lambda \neq 0$ are in $\Phi(X_1), \dots, \Phi(X_M)$, these coefficients $\alpha_i (i = 1, \dots, M)$ are obtained in a way that

$$V = \sum_{i=1}^M \alpha_i \Phi(X_i) \quad (2)$$

The mentioned equations could be considered as Eq. (3)

$$\lambda(\Phi(X_i) \cdot V) = (\Phi(X_i) \cdot Cv) \quad \text{for all } i = 1, \dots, M \quad (3)$$

Because the kernel matrix K is $M \times M$, $K_{ij} = k(X_i, X_j) = (\Phi(X_i) \cdot \Phi(X_j))$, an eigenvalue problem occurs. The solution to the problem equation is defined in Eq. (4)

$$M \lambda \alpha = K \alpha \quad (4)$$

V. KERNEL ENTROPY COMPONENT ANALYSIS (KECA)

In KECA the eigenvectors used for the purpose of reducing the dimension by transforming the data from higher dimension to lower dimension are obtained in such way that contributes to the entropy estimate of the input data. Despite of the fact that the eigenvectors might not be always different from those of PCA and KPCA, chosen eigenvectors are not necessarily the same as the top eigenvectors. Renyi entropy is defined in Eq. (5)

$$H(p) = -\log \int p^2(x) dx \quad (5)$$

Where $p(x)$ is the probability density functions.

Instead of Eq. (5), The Eq. (6) should be consider, because the monotonic nature of logarithmic functions

$$V(p) = \int p^2(x) dx \quad (6)$$

Eq. (7) defines The estimation of $V(p)$

$$\hat{p}(x) = \frac{1}{N} \sum_{x_t \in S} k_\sigma(x, x_t) \quad (7)$$

$k_\sigma(x, x_t)$ is refer to the kernel centred

$$\hat{V}(p) = \frac{1}{N} \sum_{x_t \in S} \hat{p}(x_t) = \frac{1}{N} \sum_{x_t \in S} \frac{1}{N} \sum_{x_t \in S} k_\sigma(x_t, x_t) = \frac{1}{N^2} \mathbf{1}^T K \mathbf{1} \quad (8)$$

K is $k_\sigma(x, x_t)$ and $\mathbf{1}$ is $(N \times 1)$ vector containing all ones.

VI. EXPERIMENTAL RESULTS ON FINGER VEIN DATABASE

In this section, the performances of Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), and Kernel Entropy Component Analysis (KECA) are validated. This database contains 2040 images which were taken from 204 individuals. 10 images were taken from each subject. Consists of 2040 images from 204 subjects; 10 images were taken from each subject. Five different implementations have been conducted on the database. 3, 4, 5, 6, and 7 images were used to train each time and 7, 6, 5, 4, and 3 images were used to test respectively. As it is clear from Table I, the more images are used to train, the more accuracy is gained. The highlighted point about the results is that the proposed algorithm which uses Kernel Principal Component Analysis as a feature extractor achieves the highest accuracy in all different experiments. It also results in 100% accuracy when 7 images are used to train.

TABLE I
THE OBTAINED ACCURACIES USING PCA, KPCA, KECA

| | Accuracy of implementing PCA | Accuracy of implementing KPCA | Accuracy of implementing KECA |
|----------------------------------------|------------------------------------|-------------------------------------|-------------------------------------|
| 3 images to train and 7 images to test | 91.18% | 97.69% | 92.93% |
| 4 images to train and 6 images to test | 93.71% | 98.45% | 95.34% |
| 5 images to train and 5 images to test | 95.59% | 99.31% | 97.06% |
| 6 images to train and 4 images to test | 96.45% | 99.87% | 98.28% |
| 7 images to train and 3 images to test | 97.55% | 100% | 98.69% |

VII. CONCLUSION

In this paper we have proposed a simple algorithm to merit the finger vein recognition. Performances of Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), and Kernel Entropy Component Analysis (KECA) are evaluated. Based on the results, KPCA matches the proposed algorithm best. Not only is KPCA the most appropriate one in comparison to the other methods, but also it is efficient enough to be used in finger vein recognition.

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