Optimal Feature Extraction Dimension in Finger Vein Recognition Using Kernel Principal Component Analysis

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***Abstract*—**In this paper the issue of dimensionality reduction is investigated in finger vein recognition systems using kernel Principal Component Analysis (KPCA). One aspect of KPCA is to find the most appropriate kernel function on finger vein recognition as there are several kernel functions which can be used within PCA-based algorithms. In this paper, however, another side of PCA-based algorithms -particularly KPCA- is investigated. The aspect of dimension of feature vector in PCA-based algorithms is of importance especially when it comes to the real-world applications and usage of such algorithms. It means that a fixed dimension of feature vector has to be set to reduce the dimension of the input and output data and extract the features from them. Then a classifier is performed to classify the data and make the final decision. We analyze KPCA (Polynomial, Gaussian, and Laplacian) in details in this paper and investigate the optimal feature extraction dimension in finger vein recognition using KPCA.

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

I. Introduction

TRADITIONALLY, private information was considered as passwords and Personal Identification Numbers (PINs) among the society that was vulnerable to the risk of exposure and being forgotten or even stolen. Biometric systems, however, have been of importance and attracting scientists' attention more and more as it is believed that biometrics is a promising alternative to the traditionally used password or PIN based authentication techniques [1]. There are, nowadays, several different biometrics systems under research such as face recognition, finger print, palm print, voice recognition, iris recognition and so on [2]. Mainly, there are two difficulties in biometrics. The first one is that the main element by which the identity is verified or identified is accessible and forgeable, and the second one is that the rate of reliability of the mentioned systems in terms of having a satisfactory accuracy rate is not acceptable in many cases. For instance, finger and palm prints are usually frayed; iris images and voice signature are easily forged; face recognition could be considered difficult and unreliable when there are occlusions or face-lifts. Finger vein [3]-[5] recognition, however, is more secure and convenient and has none of the mentioned drawbacks because of the following three reasons: (1) human veins are mostly invisible and located inside the body; therefore it is difficult to be illegally copied or stolen. (2) It is more acceptable for the user as capturing finger-vein images is non-invasive and contactless. (3) The finger-vein data can only be captured from a live individual. It is thus a convincing proof that the subject whose finger-vein is successfully captured is alive.

Principal Component Analysis (PCA) [6], [7] is one of the common and powerful methods of pattern recognition and feature extraction which has been used a lot in biometrics. There have been several improvements [8]-[12] on PCA such as Kernel PCA (KPCA) [13]-[15]. In KPCA, the data is non-linearly mapped to kernel space using kernel functions and the PCA is performed on the mapped data. KPCA is known as a more superior method than PCA in terms of image classification. PCA, however, is considered as a much faster method than KPCA especially when analyzing a massive amount of data. There are several elements to investigate when using KPCA as a feature extractor method. First of all, finding the appropriate kernel function is essential as there could be considerable discrepancy between outputs when using different kernel functions. Each particular system for a specific purpose might have its own optimal kernel mapping. It means a particular KPCA algorithm may work optimally with different kernel functions when being applied on different types of data. Another element to be investigated in KPCA algorithm is the optimal value of the particular kernel function. Last but not least, the dimension of the feature vector is considered of importance as the higher the dimension of feature vector is the more time consuming the system will be. On the other hand, the lower the dimension feature vector is the more valuable information might be ignored, which may result in insufficiency. Therefore, there has to be a balance between the accuracy and speed in KPCA algorithms which can be controlled by the dimension of the feature vector. In this paper, this area is analyzed in details and the optimal feature dimension is investigated especially in finger vein recognition systems.

The remaining of this paper is organized as follows:

In Section II, Image acquisition is explained. In Section III, Kernel Principal Component Analysis is explained briefly. In Section IV, experimental results on finger vein database are given. Finally, Section V concludes the paper.

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II. Image Acquisition

In this section, we briefly explain how the finger vein images were captured and what devices were used building the scanner. Based on the proven scientific fact that the light rays can be absorbed by deoxygenated hemoglobin in the vein, absorption coefficient (AC) of the vein is higher than other parts of finger. Having said that, we designed a scanner consisting of four low cost prototype devices such as infrared LEDs (830 nm wavelength) and the control circuit to drive the LEDs properly, a camera to capture the images, an infrared pass filter and a computer to process the images. To make the camera sensitive to the IR light, there have been some modifications to it; The IR blocking filter was removed and replaced with an IR pass filter which blocks visible wavelengths of light and passes the IR light. Fig. 1 shows an example of the obtained original and cropped images.

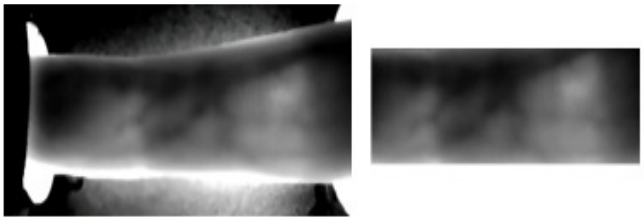

Fig. 1 (a) Original image, (b) Cropped image

III. Kernel Principal Component Analysis (KPCA)

Unlike PCA, KPCA extracts the features of the data nonlinearly. It obtains the principal components in F which is a high dimensional feature space that is related to the feature spaces nonlinearly. The main idea of KPCA is to map the input data to the feature space F first using a nonlinear mapping Φ. when input data have nonlinearly been mapped, the Principle Component Analysis (PCA) will be performed on the mapped data [3]. Assuming that F is centered, $\sum_{i=1}^{M}\Phi(X_i)=0$ where M is the number of input data. The covariance matrix of F can be defined as

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

To do this, this equation $\lambda v = C v$which is the eigenvalue equation should be solved for eigenvalues $\lambda \geq 0$ and eigenvactors $v \in F$.

As Cv = (1/M) $\sum_{i=1}^{M}(\Phi(X_i).v)\Phi(X_i)$, solutions for v with $\lambda \neq 0$ lie within the span of $\Phi(X_1), \ldots, \Phi(X_M)$, these coefficients $\alpha_i (i=1,\ldots,M)$ are obtained such that

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

The equations can be considered as follows

$$\lambda(\Phi(X_i).V)=(\Phi(X_i).Cv)\ for\ all\ i=1,\ldots,M \quad (3)$$

Having$M\times M$ matrix K by $K_{ij}=k(X_i,X_j)=(\Phi(X_i).\Phi(X_j))$, causes an eigenvalue problem. The Solution to this is

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

By selecting the kernels properly, various mappings can be achieved. One of these mappings can be achieved by taking the d-order correlations, which is known as ARG, between the entries,X_i, of the input vector X. The required computation is prohibitive when $d>2$.

$$(\Phi_d(X).\Phi_d(y))=\sum_{i_1,\ldots,i_{d=1}}^{N} x_{i_1}\ldots.x_{i_d}\,.y_{i_1}\ldots.y_{i_d}=(\Sigma_{i=1}^{N}x_i.y_i)^d=(x.y)^d. \quad (5)$$

There are several kernel functions, three well-known of which are Polynomial, Gaussian, and Laplacian. Note that using KPCA in image classification can be confusing as each image consists of a fixed amount of pixels with their corresponding value. When applying KPCA on images, each image is considered as one particular data point in the whole data space. What practically is done, is that all images are converted into 1-D vectors (it is because KPCA is an extension of 1-DPCA). After that all data is transferred into kernel space which is as high as the number of input data. Then, the Eigen-decomposition step is taken to extract kernel feature axes (kernel feature dimensions). When the kernel feature vectors are extracted and rearranged in descending order, the dimension of kernel feature vector space onto which data is projected is of importance. This stage is investigated in details in this research.

IV. Experiment Results on Finger Vein Database

In this section, the performances of three different kernel Principal Component Analysis (KPCA) (Polynomial, Gaussian, and Laplacian) are validated. This database contains 500 images which were collected from 50 individuals. 10 samples were taken from each subject. Six different implementations have been conducted on the database using each of three kernel mappings. 4, 5, 6, 7, 8, and 9 samples were used to train each time and 1, 2, 3, 4, 5, and 6 images were used to test respectively. The results then have been gathered and shown in Figs. 2-4.

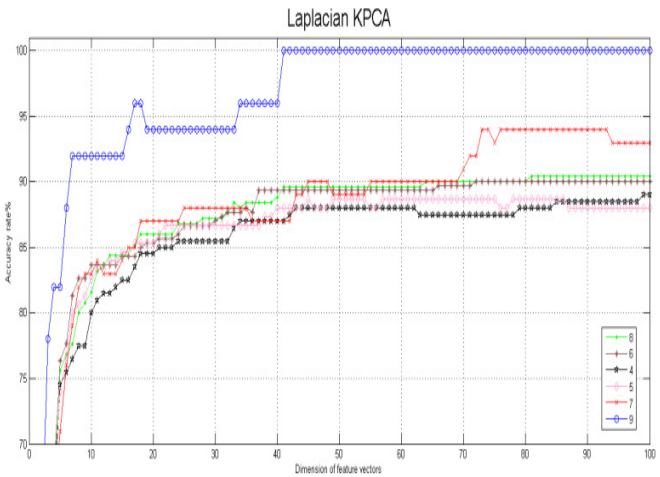

Fig. 2 Laplacian KPCA using 4, 5, 6. 7. 8. And 9 to train

Fig. 2 indicates the comparison of all results obtained from Laplacian KPCA. As expected, the more the number of train samples gets, the higher overall accuracy goes. It is observed that the trend of all graphs is upward and the accuracy rates goes up as the dimension of feature vector increases. However, the up-ward trend is faster from dimension of 5 to the dimension of 50. It means the most valuable information are carried by these feature vectors as the accuracy fluctuates after the point of 50 in feature dimension. This is almost the same in all implementations using different numbers of training and testing. Note that, in KPCA when the number of training samples changes, the dimension of kernel feature space changes as well because they are dependent on each other. For example in our experiments, there are 50 individuals and in each experiment 4, 5, 6, 7, 8, and 9 samples are used to train. Therefore, the dimension of kernel space and correspondently the highest dimension of feature vector equals to 200, 250, 300, 350, 400, and 450 respectively. We only show the feature vector dimension up to 100 as after this point the results remain almost the same without any considerable fluctuation.

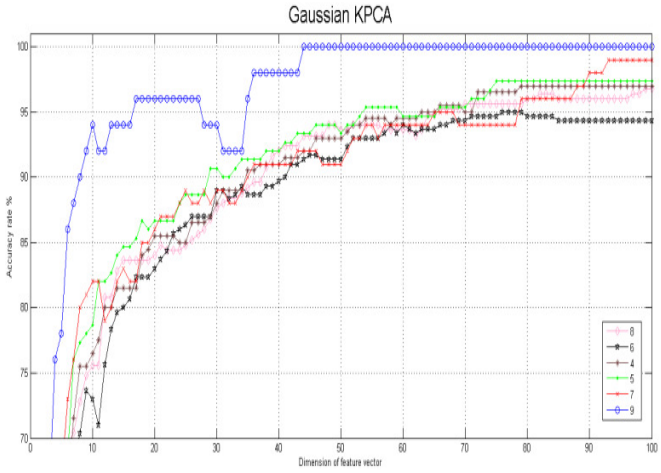

Fig. 3 Gaussian KPCA using 4, 5, 6. 7. 8. And 9 to train

The Laplacian KPCA achieves its highest accuracy between the dimensions of 20 and 50 as after this dimension the accuracy almost remains the same. It means that using Laplacian KPCA in terms of finger vein recognition for a total number of 50 individuals achieves its optimal results in the dimensions of 20 to 50, which is %5 to %15 of the dimension of kernel feature space. From another point of view, %85 to %95 reduction of the dimension results in the most optimal performance for Laplacian KPCA in finger vein recognition. Fig. 3 shows the results of performing Gaussian KPCA on finger vein data. The overall trend is close to that of Laplacian KPCA. However, Gaussian KPCA starts fluctuating after the dimension of 80. Also Gaussian KPCA obtains higher accuracy than Laplacian KPCA in overall although they get almost the same accuracies when 9 samples to train and 1 to test. Except for the experiment where 9 samples were used to train, almost all of the different types of Gaussian KPCA have the same trend and reach to their highest accuracies between the dimensions of 70 to 90, which is %20 to %30 of the dimension of the kernel feature space.

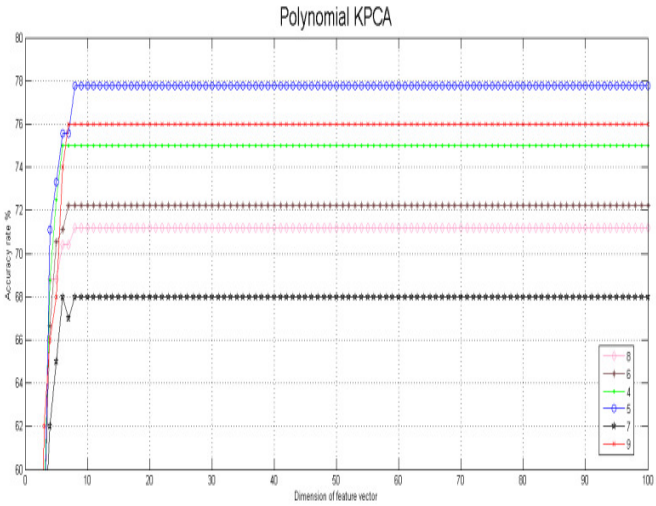

Fig. 4 Polynomial KPCA using 4, 5, 6. 7. 8. And 9 to train

Results using Polynomial KPCA are shown in Fig. 4. The trend of Polynomial KPCA is totally different from those of Laplacian KPCA and Gaussian KPCA as Polynomial KPCA rocket up from its lowest accuracy to its highest accuracy before the dimension of 10 and remains the same without any change. Unlike Laplacian and Gaussian KPCA, Polynomial KPCA reaches its optimal accuracy between the dimensions of 5 to ten and after that remains steady, meaning that dimensionality reduction around %97 is optimal in terms of Polynomial KPCA in finger vein recognition. Although Polynomial KPCA can be considered faster than Laplacian and Gaussian KPCA, it is not as strong as them from accuracy point of view.

TABLE I
MAXIMUM ACCURACIES BY LAPLACIAN, GAUSSIAN, AND POLYNOMIAL KPCA

	Laplacian KPCA	Gaussian KPCA	Polynomial KPCA
4 to train & 6 to test	%87.5	%95	%68
5 to train & 5 to test	%88.67	%96	%71.2
6 to train & 4 to test	%90	%97	%72.22
7 to train & 3 to test	%90.4	%97.33	%75
8 to train & 2 to test	%94	%99	%76
9 to train & 1 to test	%100	%100	%77.78

The maximum accuracies obtained by Laplacian, Gaussian, and Polynomial KPCA are gathered in Table I for the sake of better comparison. It is observed that the overall accuracy rate of Gaussian KPCA is higher than those of Laplacian and Polynomial. Among Laplacian and Gaussian KPCA, although both of them achieve the accuracy of %100 when using 9 samples to train, the Gaussian KPCA seems to be stronger than Laplacian as the lowest accuracy it gets is %95. Polynomial KPCA, however, is not comparable with the other ones as its accuracies are not promising.

V. Conclusion

In this paper, we performed three different types of KPCA (Laplacian, Gaussian, and Polynomial) on finger vein database. The goal of this work is to analyze the mentioned KPCA algorithms in order to determine the optimal dimension of kernel feature vectors in finger vein recognition. Extensive experiments revealed that in terms of Laplacian KPCA, the optimal dimensionality reduction is between %85 and %95. In Gaussian KPCA, it is between %79 and %80. Finally, in Polynomial KPCA, the optimal reduction percentage is around %97. It is also observed that Gaussian KPCA achieves the highest accuracies while it could be considered the slowest algorithm because its optimal reduction percentage is lower than the others and also, Polynomial KPCA is the fastest one while it gets the lowest accuracies.

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