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AN OPTIMAL IMAGE CROPPING APPROACH FOR FACE RECOGNITION IN VIDEO SURVEILLANCE SYSTEMS USING PCA-BASED METHODS

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ABSTRACT

Nowadays, face recognition systems are mostly cooperative meaning that they require the users to cooperate with the system during the verification process. However, this is not suitable if an identity needs to be searched ‘silently’ from the video surveillance cameras. Therefore, non-cooperative face recognition is desired to perform this task. Due to the resolution problems in common video surveillance footages, this paper presents a study on the effect of using different frontal face size which takes into account the difficulties to accurately detect a face from the video surveillance cameras. In this research, PCA-based methods namely, Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA) and Kernel Entropy Component Analysis (KECA) are used to determine the optimal frontal face size. The results reveal that using the ‘face-head' area with KPCA achieves the most superior result compared to ’face-only’ area. This research finding suggests that the face detection task can only focus on the face-head area instead of a precise face-only area.

Key words: Face recognition, Image Cropping, Kernel Entropy Component Analysis (KECA), Kernel Principal Component Analysis (KPCA), and Principal Component Analysis (PCA)

1. INTRODUCTION

The research of face recognition has been given a lot of attention in recent years. Among the various face recognition methods, Principal Component Analysis (PCA) [1] could be pointed as a powerful and highly used method. To improve PCA and make the accuracy of face recognition even higher, some methods such as Kernel Principal Component Analysis (KPCA) [2] and Kernel Entropy Component Analysis (KECA) [3] have been proposed which are proven to be much more appropriate than the PCA. One problem which face recognition researchers have been facing and dealing with is the way how to crop the face images before the implementation of face recognition to obtain more reliable results and to make sure that whatever information being worked on is totally related to the face area, not other areas like background [4]. Because using this extra information may cause the system to fail in real-world implementation, which is why cropping (ROI extraction) is of importance. Having a confident system, it is essential to crop images properly and analyze just the face related information. The mentioned reasons motivated us to implement a comparative study on original and two differently cropped sets of face images, namely ‘face-head’ and ‘face-only’, using Principal Component Analysis (PCA) [5], Kernel Principal Component Analysis (KPCA), and Kernel Entropy Component Analysis (KECA).

The remainder of this paper is organized as follows:

In Section 2 and Section 3, Kernel Principal Component Analysis (KPCA) and Kernel Entropy Component Analysis (KECA) are introduced respectively. Section 4, presents the optimal frontal face cropping method, and the recognition computation. Experimental results on Yale A, and Surveillance Camera Faces (SCface) database are given in Section 5. Finally, Section 6 concludes the paper.

2. KERNEL PRINCIPAL COMPONENT ANALYSIS (KPCA)

KPCA is an extension of PCA that nonlinearly extracts features. The principal components are computed in a high dimensional feature space *F*. This feature space is nonlinearly related to input dataset. The main idea of KPCA is that after mapping the input data X into a feature space F using a nonlinear mapping Φ, it performs the linear Principle Component Analysis (PCA) [6] in the mapped data [3].

Consider *F* is centred ($\sum_{i=1}^{M} \Phi(X_i) = 0$), where M is the number of input data. The covariance matrix of *F* is defined in Eq.(1)

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

To perform the calculation, the equation λ v = C v that is the eigenvalue equation should be solved for eigenvalues $\lambda \geq 0$ and eigenvectors $v \in$ 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 $\Phi(X_1)$, …, Φ (X_M), in where the coefficients $\alpha_i (i = 1, \ldots, M)$ are obtained such that

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

The equations can be given as follows

$$\lambda(\Phi(X_i).V) = (\Phi(X_i).Cv) \; for \; all \; i = 1, \ldots, M \tag{3}$$

Because of having *M* × *M* kernel matrix K by$K_{ij} = k(X_i, X_j) = (\Phi(X_i).\Phi(X_j))$, an eigenvalue problem occurs.

The solution to this problem is obtained from Eq. (4).

$$M\,\lambda\alpha = K\alpha \tag{4}$$

3. KERNEL ENTROPY COMPONENT ANALYSIS (KECA)

In Kernel Entropy Component Analysis (KECA) [4], transforming the data from the higher dimension to the lower dimension is conducted by projecting the data onto the kernel PCA axes that contribute to the *entropy estimated* for the input space data set. The used axes for projecting are not exactly the top eigenvalues and eigenvectors of the kernel matrix. In majority of PCA-based methods [5],[7] including KPCA, top eigenvalues and eigenvectors are chosen to be used in dimension reduction. In KECA, however, the data transformation from the higher dimension to the lower dimension is obtained by projecting the input data onto the Kernel PCA axes that contribute to the entropy estimated from the input space and these axes do not exactly correspond to the top eigenvalues and eigenvectors of the Kernel matrix [2].

KECA based on the Renyi [8] quadratic entropy which is defined in Eq.(5).

$$H(p) = -\log \int p^2(\mathrm{x})\mathrm{dx} \tag{5}$$

Here p(x) is the probability density function which generates the data set.

The Eq.(6) can be considered because of the monotonic nature of logarithmic function.

$$V(p) = \int p^2(\mathrm{x})\mathrm{dx} \tag{6}$$

Then, the estimation of *V(p)* is computed using the Parzen window density estimation which is given below in Eq.(7):

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

Where, $k_\sigma(x, x_t)$ is the kernel centered at $x_t$with width parameter, σ. Therefore,

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

Where, 1 is an (N $\times$ 1) vector containing all ones and K is $k_\sigma(x, x_t)$

The Renyi entropy [4][5] estimation might be obtained in terms of eigenvectors and eigenvalues of the kernel matrix, which may be decomposed as ***K=EDE^T***, where ***E*** is the matrix with the corresponding eigenvectors as columns and ***D*** is the diagonal matrix containing the eigenvalues

Rewriting the Eq.(8), we have

$$\hat{V}(p) = \frac{1}{N^2}\sum_{i=1}^{N}\left(\sqrt{\lambda_\iota}\alpha_i^T 1\right)^2 \tag{9}$$

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 (in our experiment), between the entries,X_i, of the input vector X. The required computation is prohibitive when $d > 2$ [2].

$$\left(\Phi_d(X).\Phi_d(y)\right) = \sum_{i_1,\dots,i_{d=1}}^{N} x i_1.\dots.x i_d.y i_1.\dots.y i_d = \left(\sum_{i=1}^{N} x_i.y_i\right)^d = (x.y)^d \qquad (10)$$

4. OPTIMAL FRONTAL FACE IMAGE CROPPING

Face recognition is dependent on the face detection. Most of current face recognition systems require the face to be detected accurately in order to achieve better recognition rates. However, this is really difficult in video surveillance system due to camera resolution. As such, we propose an optimal approach of cropping the frontal face image by considering the possibilities and difficulties in face detection. Notice that, high accuracy of face detection is required if high accuracy face recognition is desired. This is different if face detection is used for some other purposes, for instance, to count face in an area. Figures 1 to 3 illustrate three different size of frontal face images used to confirm the optimal size. Figure 1 shows the original, Figure 2 shows the 'face-head' area while Figure 3 indicates the 'face-only' area.

Fig. 1. *Original images of one subject from YALE (A) (Original)*

Fig. 2. *'Face-head' images of one subject) from YALE (A*

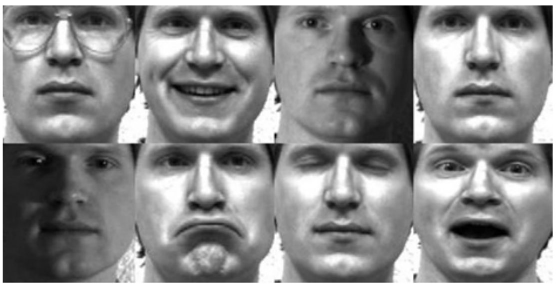

Fig. 3. *'Face-only' images of one subject from YALE (A) - excluding hair and ears*

5. EXPERIMENTAL RESULTS ON YALE (A) FRONTAL IMAGES

5.1. Experimental setup – 1

In this section, the implementations to determine how to crop images to get the highest accuracy in PCA-based methods for face recognition in surveillance are introduced. The experiments are conducted using three different cropping size of YALE (A) [9] database as shown in Figures 1,2 and 3. The Yale (A) face database contains 165 gray scale images in GIF format of 15 individuals. There are 11 images for each subject with different facial expression or configuration: such as centre-light, wearing glasses, happy, left-light, wearing no glasses, normal, right-light, sad, sleepy, surprised and winking. In this experiment, original faces shown in Figure 1, cropped faces without any loss of information regarding the whole head including hair, ears and etc ('face-head') shown in Figure 2, and another type of image which includes only specific information on face ('face-only') shown in Figure 3 were used.

5.2. Experimental setup – 2

In this part, the experiments have been extensively conducted to validate the results observed in 5.1. Figure 4 shows how the experiments are conducted and in Figure 5 the detailed information about the implementations are indicated.

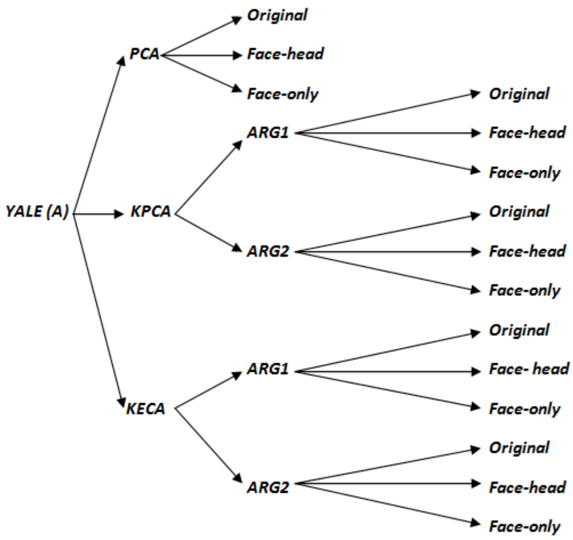

Fig. 4. *The diagram of the experiments conducted on YALE (A) database*

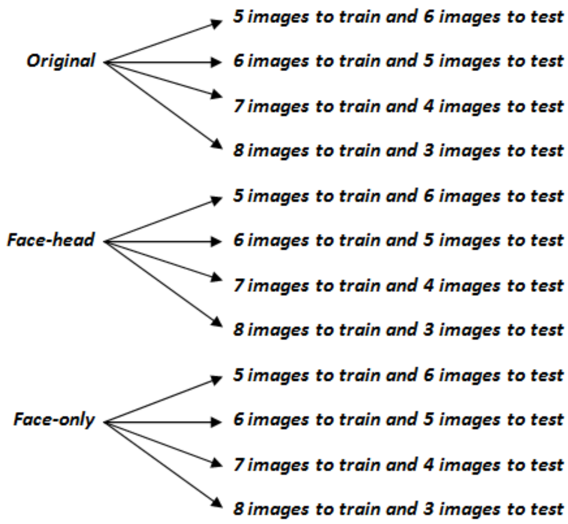

Fig. 5. *Detailed information about the number of YALE (A) images used for each experiment*

In the second experiment, the results obtained on different kinds of cropping are compared with each other using classification error rate as a criterion. The averaged error rate is calculated [10] as follows

$$E_{ave}=\frac{(\sum_{i=1}^{r} t_{mis}^{i})}{(rt)} \tag{11}$$

Where t is the number of total test sample of each run, t_{mis}^{i} is the number of misclassification in the ith run, and r is the number of runs.

From Figure 4 and Figure 5, t can be noted that 60 different experiments have been conducted on the three frontal face image sizes. The results are shown in Figures 6, 7, and 8.

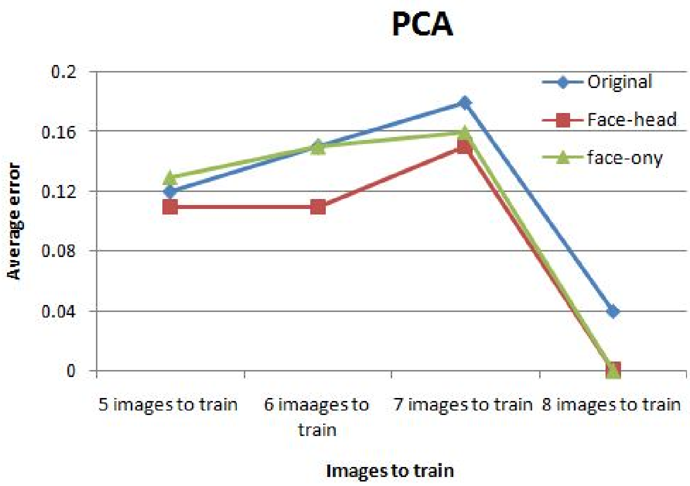

Fig. 6. *Comparison of average error rate on the three frontal face sizes of YALE (A) database using PCA*

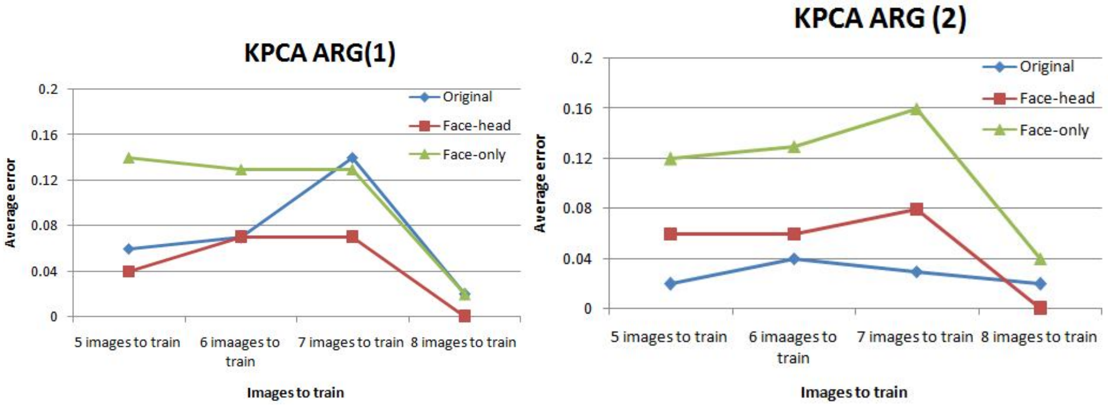

Fig. 7. *Comparison of average error rate on the three frontal face sizes of YALE (A) using KPCA; (a) ARG (1), and (b) ARG (2)*

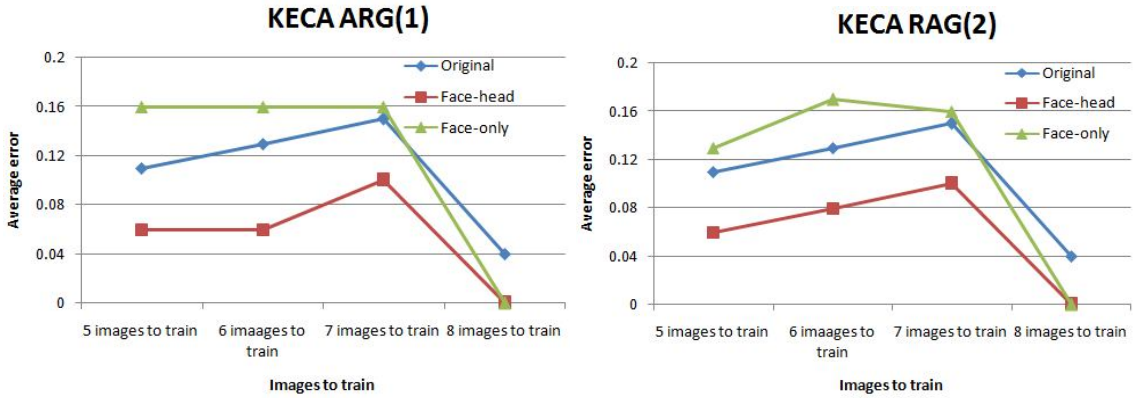

Fig. 8. *Comparison of average error rate on the three frontal face sizes of YALE (A) using KECA; (a) ARG (1), and (b) ARG (2)*

5.3. Experimental setup – 3

Knowing the best face size to implement PCA-based methods from previous sections, the experiments of the mentioned methods on SCface database is explained and discussed in this part. SCface database consists of 4160 images taken in uncontrolled environment form 130 individuals. Five cameras used to take the photos from the individuals were totally different in terms of quality, type and resolution. The illumination was uncontrolled and finally the distances were different; three different distances have been used in this database. The mentioned reasons make this database even more demanding compared to other databases. A subset of original and cropped images of SCface is shown in Figure 9.

Fig. 9. *Cropped images of one subject from SCface database*

After cropping all images, the experiments are conducted by first considering only images from one camera as the training images. Subsequently, the training images are then increased to images from two, three and four cameras as shown in Figure 10 (a), (b), (c), and (d). It is clearly observed from the results that by using the 'face-head' size images, the accuracy can be achieved more than 96% while by using the original images the accuracy is not even more than 75%.

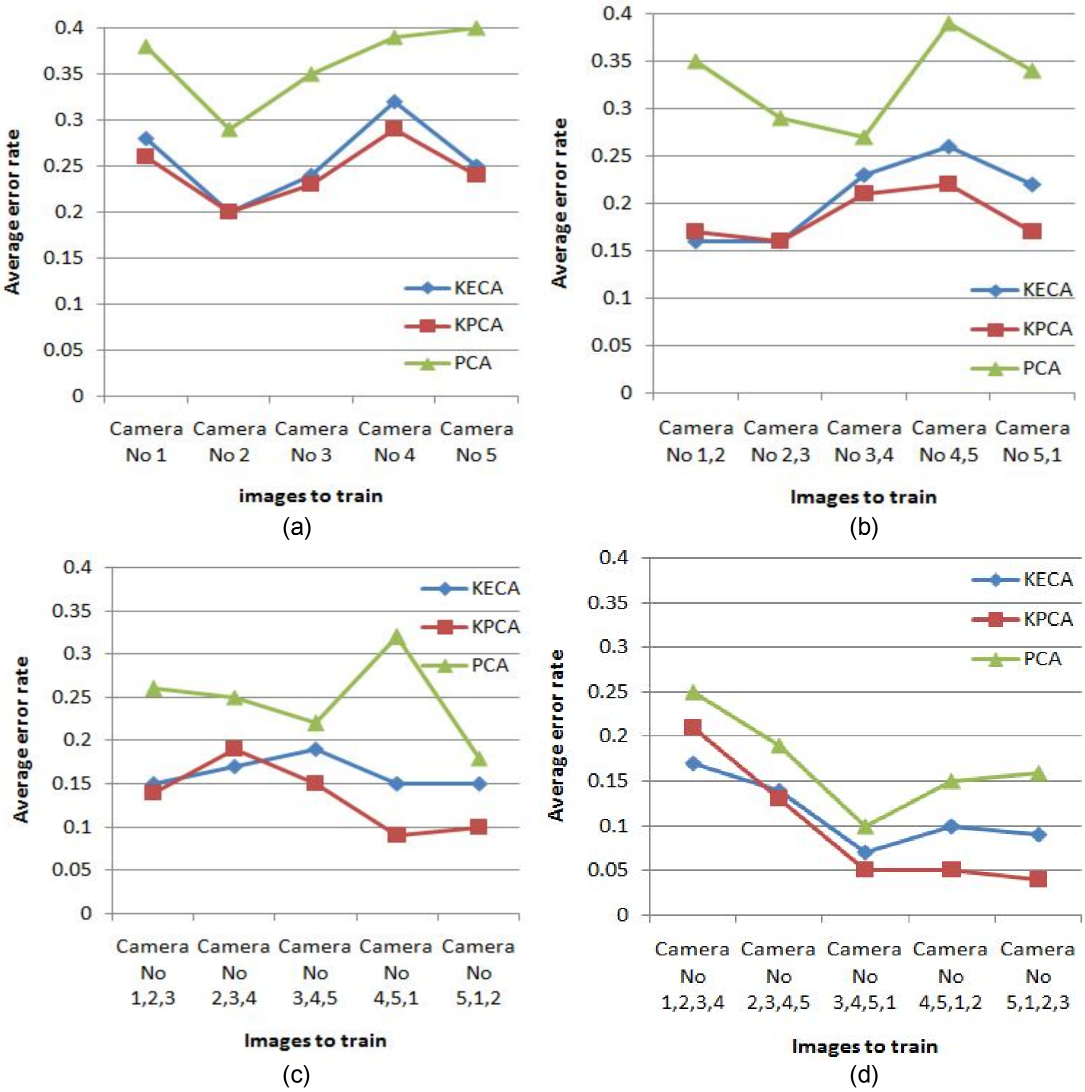

Fig. 10. *Comparison of average error rate on the three frontal face sizes of SCface database using PCA, KPCA, and KECA*

It can be observed from Figure 10: (a), (b), (c), and (d), that by increasing the number of cameras to train the accuracy increases as well. In part (d), the highest accuracy is given which is more than 96% using KPCA. By looking more carefully at the graphs, it can also be understood that KPCA is able to get higher accuracy in comparison to the other methods in video surveillance.

6. CONCLUSION

The performance of Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA) and Kernel Entropy Component Analysis (KECA) on different sizes of frontal face cropping using YALE (A) database has been validated in this paper. It is observed from Figure 6, 7, and 8 that the average error rate of face-head' images is the least compared to the original and 'face-only' images. Hence, it is proven that the face and head (face-head) images are more appropriate than the other two in the case of PCA-based methods for face recognition. Moreover, KPCA is found to be the most appropriate method among the other PCA-based methods. Furthermore, in terms of video surveillance database, the experimental results indicate that less error (the accuracy is more than 96%) is produced when images from cameras 1, 2, 3 and 5are used to train.

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