Using Linear Kernel Entropy Component Analysis as a Feature Extraction Method in Face Recognition in video surveillance systems

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Abstract—*Kernel Entropy Component Analysis (KECA) is one of the latest improvements on Principal Component Analysis (PCA) and also Kernel Principal Component Analysis (KPCA). As KECA is actually an extend of KPCA, different types of KPCA can be used in this method. In this paper the performance of four different types of Kernel Entropy Component Analysis (Linear, Polynomial, Gaussian, and Sigmoid) on Surveillance Camera Face database and also Head Pose Image database is observed in order to prove that Linear Kernel Entropy Component Analysis is the most appropriate method in terms of video surveillance.*

Keywords: Face recognition, Kernel Principal Component Analysis (KPCA), video surveillance systems, Pattern recognition, Biometrics.

1 INTRODUCTION

The importance of face recognition in biometrics is still growing dramatically[1]. It is almost impossible to control all people all around the world using the current face recognition systems. Because of the wide use of video surveillance cameras[2] in today's world, the idea of using video surveillance cameras for the propos of identification and verification is rationale. For analyzing images in face recognition, Principal Component Analysis (PCA) [3][4]is known as a powerful method. This method extracts the valuable features from the images and reduces the dimension of the data to ease the mathematical calculations and enhance the reliability and accuracy of the method. PCA extracts the features linearly from the data. Kernel Principal Component Analysis (KPCA) was proposed after PCA to increase its performance. The main difference between KPCA [5]and PCA is that KPCA is a nonlinear method in which the data is first nonlinearly mapped and then

PCA is conducted on the mapped data. To improve KPCA, Kernel Entropy Component Analysis (KECA)[6] was proposed. In KECA, the way how to choose eigenvectors for the purpose of dimensionality reduction is totally different from that of KPCA although the results might be the same in some rare cases. In PCA, and KPCA, the eigenvectors having the top most eigenvalues are chosen. In KECA[7], the chosen eigenvectors should contribute to the entropy estimate of the input data. There are four ways to calculate the kernel function. Therefore, KECA, itself, could be implemented in four different types such as linear, polynomial, Gaussian, and Sigmoid. In these methods the way how to map the data before executing PCA on the data is done in a different way from that of the other ones. Head Pose Image database is another database on which KECA is performed. Because in video surveillance systems the pose of taken images is not totally controlled, Head Pose Image database is chosen to be examined in this paper as well. As Kernel Entropy Component Analysis (KECA) is believed to be more reliable than other 1-D PCA [8]methods and face recognition in video surveillance is very demanding and difficult compared to other kinds of face recognition, using KECA in video surveillance systems is proposed in this paper and comparative study on different kinds of KECA in video surveillance is observed to determine the most appropriate one in terms of video surveillance.

The remaining of this paper is organized as follows:
In Section 2, Kernel Entropy Component Analysis (KECA) is introduced briefly. In Section 3, Surveillance Camera Face database and Head Pose Image database are explained. In Section 4, experimental results on SCface database and Head Pose Image database are given and discussed. Finally, Section 5 concludes the paper.

2 KERNEL ENTROPY COMPONENT ANALYSIS (KECA)

Kernel Entropy Component Analysis was proposed to improve Kernel Principal Component Analysis. After mapping the input data using the specific function (linear, polynomial, Gaussian, or Sigmoid), the PCA is performed on the data. When choosing the appropriate eigenvectors to perform the projection, the chosen eigenvectors have to contribute to the entropy estimate of the input data in KECA. The mathematical explanation of calculating the entropy estimate is explained in this part:

Renyi quadratic entropy is introduced in Eq. (1) where probability density function of dataset is $p(\mathrm{x})$

$H(p) = -\log \int p^2(\mathrm{x})\mathrm{dx}$ (1)

Eq. (2) is used instead of Eq. (1) owing to the monotonic nature of logarithmic functions

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

$V(p)$is estimated in Eq. (3) and (4)

$\hat{p}(x) = \frac{1}{N}\sum_{x_t \in S} k_\sigma(x, x_t)$ (3)

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

$\hat{V}(p) = \frac{1}{N}\sum_{x_t \in S} \hat{p}(x_t) = \frac{1}{N}\sum_{x_t \in S} \frac{1}{N}\sum_{x_t \in S} k_\sigma(x_t, x_t) = \frac{1}{N^2} 1^T K 1$ (4)

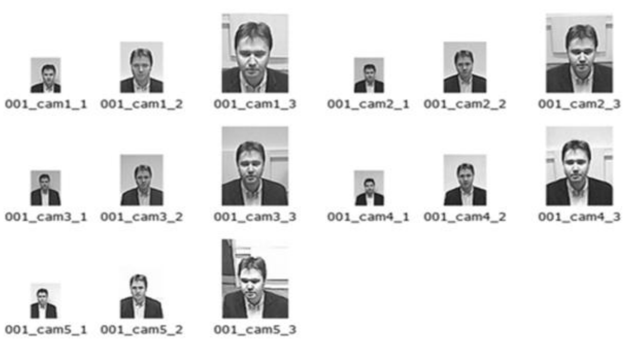
$K$is$k_\sigma(x, x_t)$ and 1 is $(N \times 1)$ vector containing all ones.

Eq. (5) can be achieved by rewriting the Eq. (4)

$\hat{V}(p) = \frac{1}{N^2}\sum_{i=1}^{N}\left(\sqrt{\lambda_i}\alpha_i^T 1\right)^2$ (5)

4 SURVEILLANCE CAMERA FACE DATABASE & HEAD POSE IMAGE DATABASE

Face recognition in video surveillance camera systems is much more demanding in comparison to other types of face recognition because of some differences such as uncontrolled illumination, uncontrolled conditions, different distances, different qualities of images, and different resolutions. The Surveillance Camera Face database includes 4160 static images taken from 130 subjects.The images were taken from three different distances and five different cameras with different qualities and resolutions were used. In addition to the mentioned problems, a little difference in pose makes the database even more demanding. In Figure 1 original and cropped images of one subject of SCface database are shown



(a)

(b)

Fig. 1: A subset of (a) Original and (b) cropped images of one subject from SCface database

Head Pose Image database[9] is also used in this paper due to the fact that in this database as there are 2790 images from only 15 individuals in this database. The tilt and pan vary from -90 to +90 degrees. Two series of 93 images with different poses were taken from each subject. The reason why there are two series of each person is to be able to use one set of images to test and another one to test. One subset of cropped images of one subject from Head Pose Image database is indicated in Figure 2.

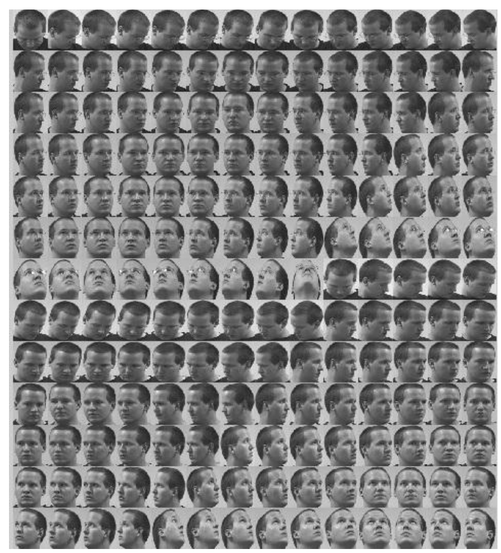


Fig 2: A subset of cropped images of one subject from Head Pose Image database

5 RESULTS AND DISCUSSION ON SCFACE & HEAD POSE DATABASES

In this part, the experiments on the mentioned databases and also the results are given and discussed. First thing is to crop the images and extract the face area of images. We need to make the size of images small to make the system fast if the system is meant to be practical. The optimized size of image in this case is 10×10. Hence, the next step is to normalize the images. Then, different types of Kernel Entropy

Component Analysis are conducted on the data and the features of the images are extracted. Finally, Euclidian distance is calculated to classify the data and calculate the accuracy. The flow of the method is shown in Figure 3.

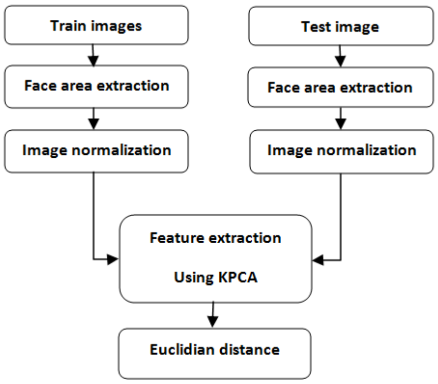
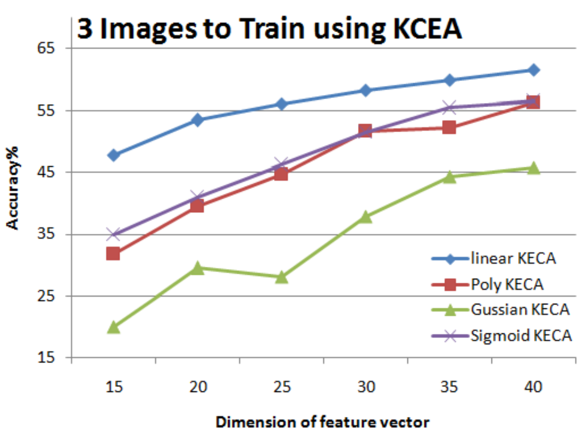
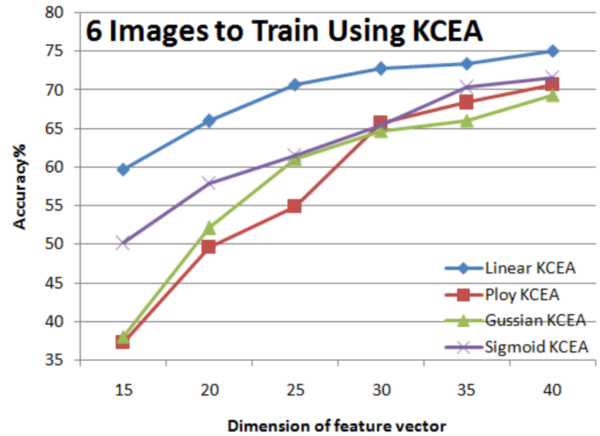


Fig. 3: Flowchart of the used method

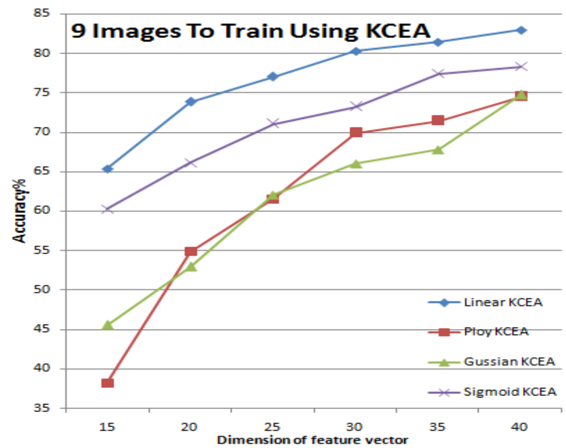
Four different experiments have been conducted on SCface database. 3, 6, 9, and 12 images were used to train in each experiment as there are five cameras in this database; each camera were used to take three images from each subject. In other words, in the first implementation just 1camera was used to train and the remaining 4 cameras were used to test. In the second one, 2 cameras were used to train and 3 to test.Finally, 3 and 4 cameras were used to train and 2 and 1 cameras to test in the third and fourth steps respectively. The results of implementing KECA on SCface database are shown in Figure 4 (a), (b), (c), and (d).



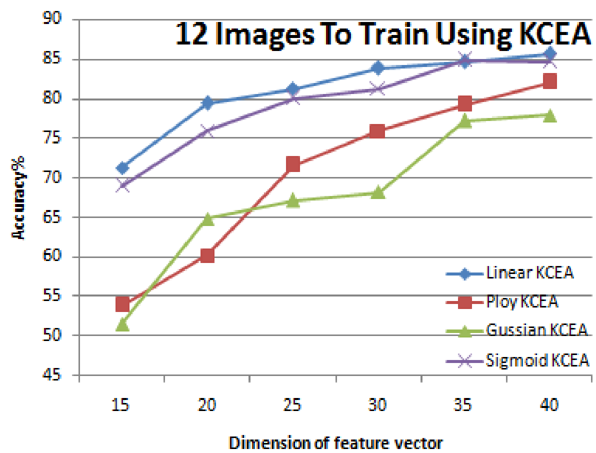
(a)



(b)



(c)



(d)

Fig 4: Results on SCface database using (a) 3, (b) 6, (c) 9, and (d) 12 images to train

As it is clear from the figures Linear Kernel Entropy Component Analysis gets the highest accuracy in almost all implementations and the highest accuracy using KECA is near 85% when using the images of 4 cameras to train and the images of one camera to test.

The results on Head Pose database is indicated in Figure 5. It is observed from the results that Linear KECA results in highest accuracy in all points.

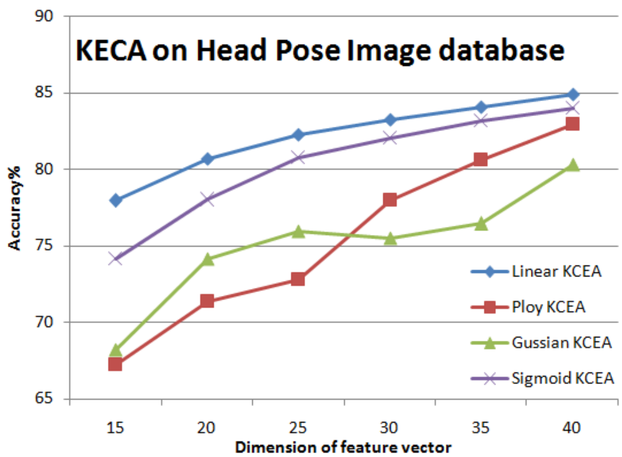


Figure 5: Results on Head Pose Image database using 93 images to train and 93 to test for each subject

6 CONCLUSION

The performance of different types of Kernel Entropy Component Analysis on two surveillance-related database is evaluated and compared with each other in this paper. The comparative results proves that Linea Kernel Entropy Component Analysis is the most appropriate one in comparison to other types of Kernel Entropy Component Analysis such as polynomial, Gaussian, and Sigmoid in terms of video surveillance component analysis.

7 REFERENCES

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