2015 IEEE International Conference on Computational Intelligence & Communication Technology

# Experimental Analysis: Hybrid Scheme for face recognition using KPCA & SVD

Himani Vyas,
Department of computer Science,Lachoo Memorial college Of Science & Technology,Jodhpur
hhimani.vyas@gmail.com

Rajeev Mathur,
Department of computer Science ,Lachoo Memorial college Of Science & Technology,Jodhpur
rajeev.mathur69@gmail.com

***Abstract*- For the various classification tasks of several visual phenomena non-linear subspaces derived from the kernel methods are preferable than the linear subspaces. In these methods some methods KPCA, KDA, KSVD and KQR are based on kernel approach. According to the studies and researches incremental computation algorithms do not available also the practical implementation and execution of these methods on large database or online video processing is not at great extent. Here,we are experimentally discussing the hybrid scheme regarding KPCA + SVD algorithm , that we have suggested earlier. We have defined the steps of required algorithms involved in it and also the results from the experiments explore the efficacy of the suggested method.**

***Keywords—Biometrics; Face Recognition; Linear and nonlinear subspace analysis; Kernel Principal Component Analysis ;Singular Value Decomposition; Independent Component Analysis.***

## I. INTRODUCTION

For the various security reasons the biometric based surveillance in the Contemporary society has predominant importance**. As** the nonlinear variations cannot be described by the linear subspace analysis though it has predominant role in the field of face recognition . On the other side the feature space based on kernel methods reflects the nonlinear information of different faces. The features used by the classifier has specific and important role in the success of the face recognition methodology. Many Researchers has been used the Linear subspace analysis methods that extract only features from the input space. These methods are as Principal Component Analysis, Fisher Linear Discriminant analysis and do not consider the nonlinear information. Whereas some methods produce non linear subspace through the kernel approach and they are more superior then their linear subspace counterparts. Some methods are Kernel SVD, Kernal PCA, Kernal DA, and Kernel QR. Some approaches like KVSD, KPCA, KQR, and KD are kernel methods and are highly nonlinear due to their kernel trick they are found more superior. Examples in Face recognition approaches include [10], [12], and [8]. Here, the face recognition paradigm for the matching set of images has been focused [1], [10], and [11]. The faces are taken usually under distinct styles of poses, illumination conditions. Here our focus on the large dataset of images .The image set is large due to video recordings or long time observations. Therefore an incremental updating of the face representation or classifier is required. Here it is found that due to incremental SVD computation algorithm [3], linear subspace methods possessed good results [11], [5]. Also there is limitation or a performance barrier due to linear approach in the methods, while nonlinear subspace derived from the kernel methods (e.g. KPCA [8], KQR [10]) posses' superior accuracy. But these methods are not practically usable for large image sets or online video processing as here they do not consider the incremental computation procedures. Here an incremental KPCA + SVD algorithm is suggested for nonlinear subspace. An incremental SVD is elaborated by the researchers for kernel subspace [3]. From this the explicit mapping can be avoided for the input data to the kernel induced feature space. A distinct representation of sparse is symbolize by applying RSCT (Reduced set construction) of non linear subspace. The suggested algorithm is than applied on the face. An incremental SVD is elaborated by the researchers for kernel subspace [3]. From this the explicit mapping can be averted for the input video database to explore the importance of face recognition techniques.

## II. PREVIOUS WORK

O. Yamaguchi, K. Fukui, and K. Maeda have been given a technique of Mutual subspace for face recognition where the inputs are the sequence of temporal images [11]. The faces are distinguished

978-1-4799-6023-1/15 $31.00 © 2015 IEEE
DOI 10.1109/CICT.2015.27

IEEE computer society

by distances between the subspaces. Also a linear subspace is estimated from a sequence to represent the face. The Kernel Mutual Subspace was given by H. Sakami , N. Mukawa, and T. Nakamura to expand the MSM to use non linear data by applying KPCA[7][8]. M. Brand has suggested that linear subspace methods have reduced good results at high speeds due to the availability of incremental SVD computation algorithms [3]. The use of open source CV library is explained by G. Bradski, A. Kaehler, and V. Pisarevsk in his research work for face identification[2].

The KMS method exceeds the MSM even when it has lower dimension subspaces . It was applied in face image sequences, indicating that non-linear subspaces derived using KPCA are more capable in capturing the complex structure of face images under distinct styles of pose, illuminations. However, this method is again not feasible for large image set .It is due to the batch computation trick of KPCA for all images. The feature space can be neglected that is produced by the explicit mapping to the kernel of the input data. Reduced set construction techniques are suggested by B. Scholkopf and A. Smola , applied at every iteration to produce sparse representations of the on-linear subspaces so that constant processing speed and memory usage can be achieved[9][5].

L. Wolf and A. Shashua have introduced conceptual Kernal Principal Angels for pattern classification that involve matching vector sets[10]. This algorithm perform a QR decomposition of the vector sets mapped to the feature space that is obtained by the kernel approach and thus get a principal angels between the subspaces. An iterative algorithm for KPCA called the Kernel Hebbian Algorithm (KHA), was suggested by K. I. Kim, M. O. Franz, and B. Scholkopfc. In their research work [6].

GHA(Generalized Hebbian Algorithm)is an online algorithm for PCA . The KHA showed comparable results to KPCA and enabled the processing of large databases by iteratively subjecting each image to the GHA neural network over multiple passes. Here an incremental and iterative computational algorithm is required for KSVD so that it is unnecessary to consider all available images more than once.

## III. THE SVD AND FACE RECOGNITION

Initially a matrix of data $a = [x_1 \ldots\ldots\ldots. x_n] \in R^{m \times n}$ from our image set, with $x_i \in R^m$ being the i-th input image. In generalised form , it is assumed that m is less than n. It is given that when SVD is applied on a then , a== UΣV T, The rank-r of a is computed by

$$a^r = U^r \Sigma^r (V^r)^T, \qquad (1)$$

with $r < n$, $U^r = U(:, 1 : r)$, $V^r = V(:,1 : r)$ and $\Sigma^r = \Sigma(1 : r, 1 : r) = \mathrm{diag}(\sigma 1, \ldots, \sigma r)$ with $\sigma_1$ , $\sigma_r > 0$ by using a Matlab notation.

Here span(Ur) is used in representation of the faces that generate image set a . Ur is an ortho - normal basis for an r-dimensional subspace that minimizes

$$a - a^r , \qquad (2)$$

where $ar = U^r (U^r)^T a$ is the rank-r approximation of a and k·kF indicates the Fresenius norm. Face image sets are classified by calculating the distances between subspaces.

The Ur is the principal component of a where the vectors in are centred prior to perform the SVD. The resulting subspace basis $U^r$ are the principal components of a. The SVD is a application to perform PCA, In some applications requires raw SVD instead of PCA. This make a vastly different subspace .Here ,as this work is concerned , the class specific subspace is suggested and it is mentioned that t for our purpose here the class-specific subspaces are derived without data centring.

## IV. THE PROPOSED ALGORITHM

The following code is used to apply PCA And then SVD to our code:

Steps:

- Read an input image.
- Extract its features and register it into database
- Read Query Image
- Extraction of the features by Kernel PCA first & then apply SVD for the resultant for Query Image.

- For i=1 to n (Dataset Images)
- Extract the Features by Kernel PCA first & then apply SVD from Dataset[I]
- Compare Feature Dataset[I] = Feature Query Image
- Store the difference that is Distance.

- Display most 16 relevant Images matching with Query Image with their Distance.

## V. EXPERIMENTAL RESULTS

To assess the proposed method, experiments were performed using the ORL (Olivetti Research Laboratory) database. The images were taken at different times for some subjects. Also there are variations in the faces expressions like smiling or none smiling or faces of closed eyes etc.

This proposes hybrid scheme for face recognition based on kernel PCA and SVD with image sets.

In the "fig.1.", is registration process where the face of the new employee is registered? The following figures indicate GUI of proposed system.

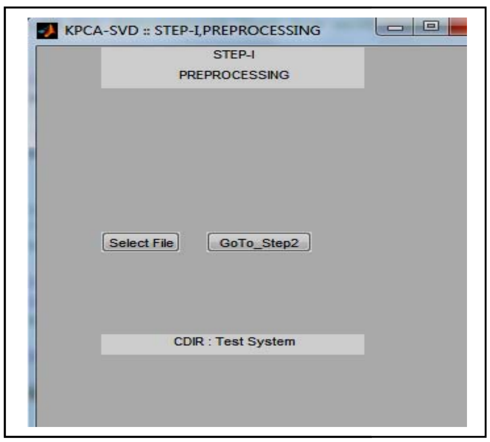


Fig. 1. GUI of Proposed System: Step 1: Preprocessing

The "fig.2." depicts browsing to select the real image.

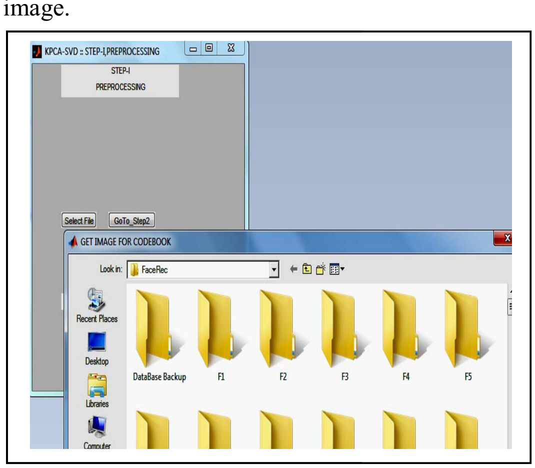


Fig. 2. GUI of Proposed System: Selection of real image

In the next step, once the image is uploaded the massage will be displayed.


Fig. 3. GUI of Proposed System: image uploading massage

To select the query image we work on the "fig.4." The following figure selects the query image.

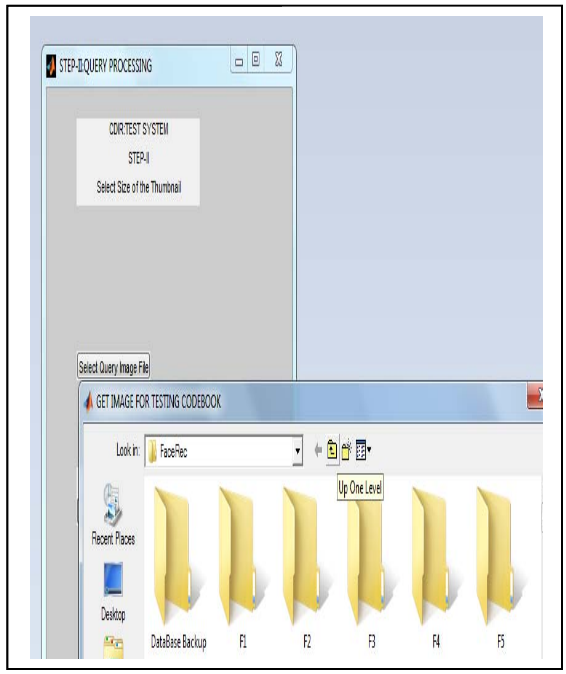


Fig. 4. GUI of Proposed System: Selection of query image

After selection of query image, the following GUI shown in "fig.5." is displayed that shows the time taken to recognize the similar face


Fig. 5. GUI for Time taken in matching Image

Now the resulting image has minimum Euclidian distance that is the exact near match. It is shown in “fig. 6.” Below.

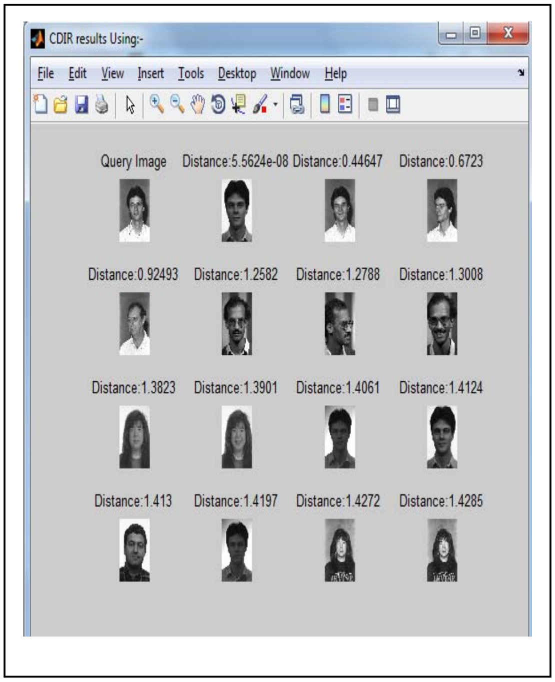


Fig. 6. GUI of Proposed System: Euclidian distance

The next figure shows the match with the most relevant image.

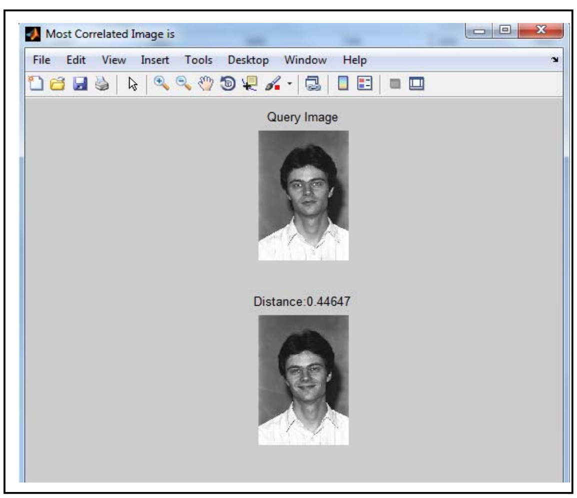


Fig. 7. GUI of Proposed System: Matching Image

Some more results have been given using different query Images to analyse the result:”Fig 8” shows the different result sets of matching images.

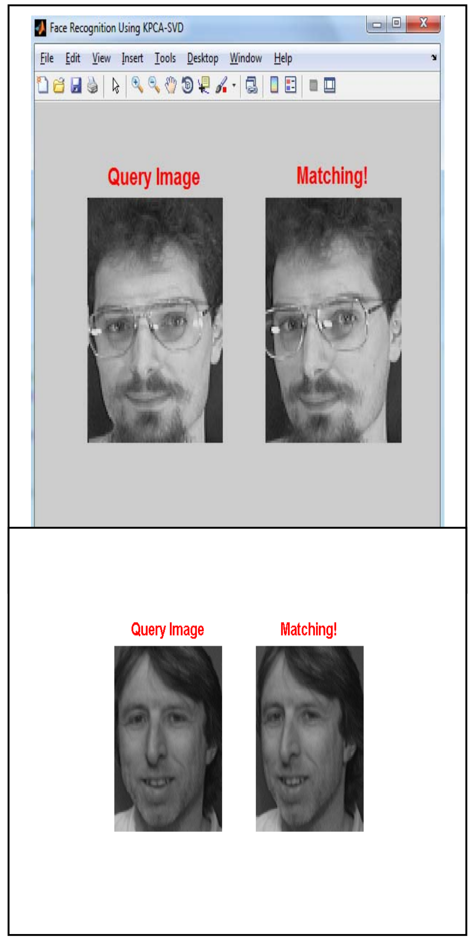


Fig. 8. GUI of Proposed System: Query Results

## VI. DISCUSSIONS

The ORL Database is taken for the purpose of testing. It contains 400 images corresponding to 40 different views. The variations include changes in expression, facial details and a very little difference in pose. Few example images are shown in figure. First 5 samples are used for training and remaining images were used for testing. It is clear from the “table 1” that the proposed approach has performed tremendously better than conventional counterpart algorithm in terms of running time costs and accuracy.

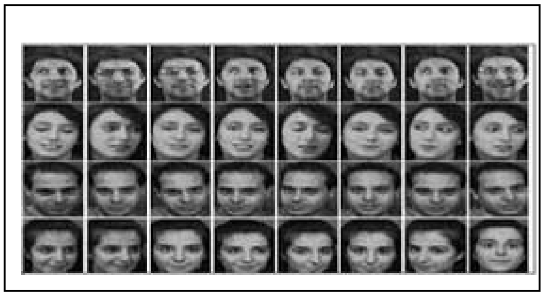

Fig.9. Sample Faces from ORL Dataset.

Here a comparison is performed of proposed algorithm with the existing methods PCA, FLD and their combinations. The comparison is shown in the "Table 1".

Table 1: Comparison with existing scheme

| Methods | Accuracy | Dimension | Time |
|---|---|---|---|
| PCA | 92 | 151 | 25.77 |
| PCA+SVD | 94 | 187 | 17.89 |
| FLD | 83.50 | 149 | 36.98 |
| FLD+SVD | 86.25 | 187 | 29.33 |
| **KPCA+SVD (Proposed)** | **96** | **187** | **17.03** |

## VII. CONCLUSION

Hybrid approach for face recognition based on KPCA and SVD proves better than the existing methods of SVD & KPCA. It is also an efficient algorithm as we take KPCA first and then apply SVD. Accuracy is improved due to hybrid model. We can get better results if the above approach is added with ICA.

## REFERENCES


[1] Dr Rajeev Mathur and Himani Vyas "Hybrid scheme for face recognition using KPCA and SVD", Vision & Quest, ISSN: 0975-8410, July- Dec 2014 issue .

[2] A. Kaehler, G. Bradski, V. Pisarevsky, "Learning Based Computer Vision With Intel's Open Source Computer Vision Library ", Intel technology Journal , 9(2):119-130,2005

[3] M.Brand," Incremental Singular Value Decomposition of Uncertain Data with Missing Value", In ECCV, 2002.

[4]N.Cristianini and J.Shawe Taylor,"Kernel Methods For Pattern Analysis", Cambridge University Press, 2004.

[5] K. Fukui and O. Yamaguchi. "Face recognition using multi-viewpoint patterns for robot vision". In 10th International Symposium of Robotics Research, 2003.

[6] K. I. Kim, M. O. Franz, and B. Scholkopf. , "Iterative kernel principal component analysis for image modelling". IEEE PAMI, 27(9):1351–1366, 2005.

[7] J. Meltzer, M.-H. Yang, R. Gupta, and S. Sotto. "Multiple view feature descriptors from image sequences via kernel principal component analysis", ECCV, 2004.

[8] H. Sakano, N. Mukawa, and T. Nakamura. "Kernel mutual subspace method and its application for object recognition". Electronics and Communications in Japan, 2/88, 2005.

[9] B. Scholkopf and A. Smola. "Learning with kernels". The MIT press, 2002.

[10] L. Wolf and A. Shashua.," Learning over sets using kernel principal angles". JMLR, 4:913–931, 2003.

[11] O. Yamaguchi, K. Fukui, and K. Maeda." Face recognition using temporal image sequence". IEEE AFGR, pages 318– 323, 1998.

[12] M.-H. Yang, N. Ahuja, and D. Kriegman. "Face recognition using kernel eigenfaces". IEEE ICIP, 2000.