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REVIEW ARTICLE

Facial Recognition System: A Review

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Abstract— Biometric Recognition has always been the chief aspect for identification and verification, facial recognition among these is an increased use due to its authenticity and mass identification properties. Facial Recognition involves particular choice of features where feature selection involves concluding upon unique ones for better classification and simultaneously provides enhanced discriminatory power. PCA [Principal Component Analysis], works on orthogonal projection basis for recognition with Eigen faces of decreased face space, Independent Component Analysis [ICA] searches for linear transformation. PCA+LDA[Linear Discriminant Analysis] is applied continuously to a smaller and smaller set of samples, better separating classes while the number of classes become small deep down the tree. Application of kernel subspace representations to face recognition, gives us better discrimination. Lesser face space corrupts the software. Obstacles such as illumination and expressional variances along with pose and profile problems prevent 100% accuracy of the system. Most algorithms discussed, solve these problems to a certain extent. The working of the different algorithms followed by their advantages and disadvantages that lead to concluding combination or individual methods best suited.

Keywords— Eigen faces, kernel subspace, profile, accuracy, combinations, PCA, LDA

I. INTRODUCTION

Facial Recognition involves particular choice of features where feature selection involves concluding upon unique ones for better classification and simultaneously provides enhanced discriminatory power. Factors like pose, illumination and facial expression will still pose as a barrier for accurate facial recognition. Here consideration at component based recognition which involves individual vector considerations at every point. Changes in the head pose, mainly lead to changes in the position of the facial components which could be accounted for by the flexibility of the geometrical model.

II. PROCEDURES

A. Principal Component Analysis[PCA]

Principal Component analysis [PCA] requires additional discriminants and hence Independent Component Analysis [ICA] which involves three basic operations that help further bring down identification features or unique characteristics. [1] 1. Whitening: Transforms random vector to a unit covariance matrix 2. Rotation: This involves source separation 3. Normalization: This involves derivation of components in terms of orientation and order of projections. Independent Component Analysis [ICA] , with other discriminants such as Probabilistic Reasoning Models[PRM] and Enhanced FLD Models[EFM] show a comparable face recognition performance with seemingly more equivalence at further captured characteristics than at the ones that do not classify to be unique. Independent Component Analysis [ICA] with FLD undergoes a large amount of deterioration caused by additional FLD transformations which cancel to a large extent the interior values of Independent Component Analysis [ICA] at every random interval once or more than once [2]. Here, the trailing values are well subjected to noise due to cancellation of interior values by additional FLD transformations and thereby decreasing its capacity to analyse the characteristics and find a linear transformation that satisfies these independent variables

B. Linear Discriminant Analysis[LDA]

When considering the face sub-space y, the analysis converges upon only those features that are linearly dependant, leaving out other formed cluster features even around existing and detected features. In the prototyping stage, weights corresponding to the gallery set are compounded. In the testing stage weights corresponding to the probe set are calculated [2]. In LDA while considering two matrices, say C and (C +k I), they will have same eigenvectors but different Eigen values with the relationship:

Y(C + k I) = (Y + k) as long as (Y +k) is not equal to zero.

Calculation of within-class and between-class scatter matrices are also important. In the prototyping stage, weights corresponding to the gallery set are compounded. In the testing stage weights corresponding to the probe set are calculated [4]. Thus, a rank ordering of all the images in the gallery set is produced. Electronic modification of the images are to be done by creating occlusions, applying Gaussian blur, randomizing the pixel location and adding artificial back-ground. Training set includes two images of all, one with change in expression and the other with different lighting conditions. Non-face objects are omitted. Hence the PCA+LDA is applied continuously to a smaller and smaller set of samples, better separating classes while the number of classes become small deep down the tree.

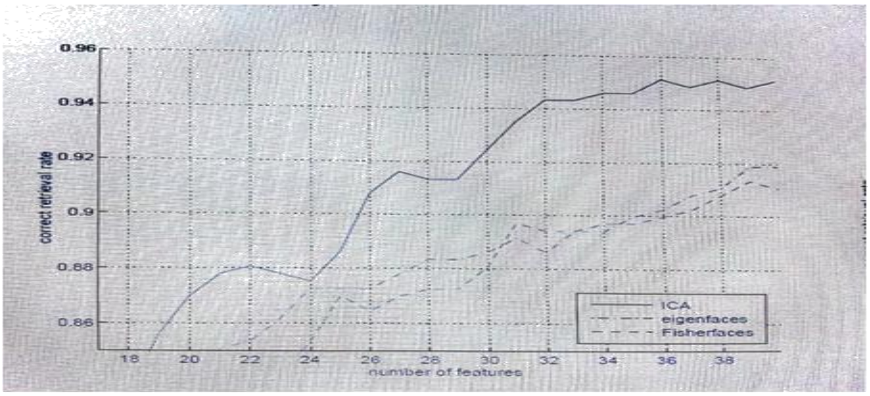

Fig. 1 Comparisons with Fisherfaces and Eigenfaces show much improved performance

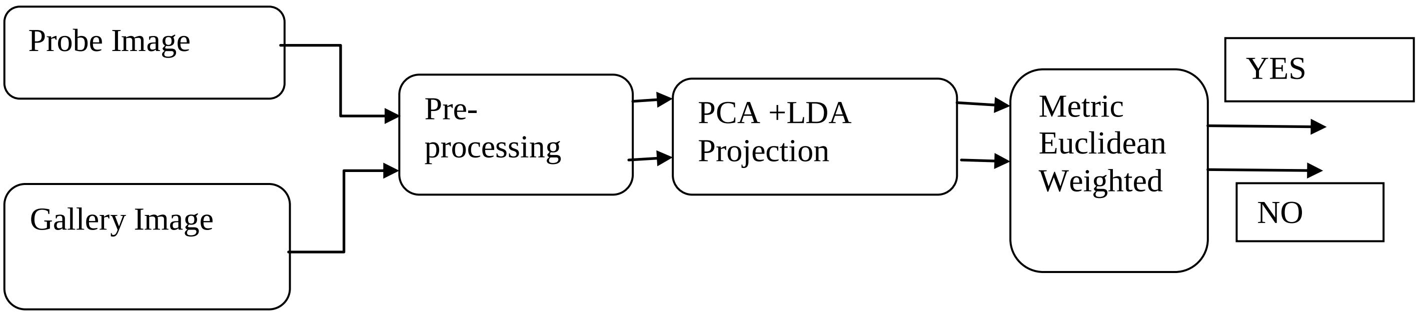

Fig. 2 The generalized LDA face recognition system

C. Kernel Methods

Applying kernel subspace representations to face recognition, gives us KPCA[3] . Intra-personal space: Constructed by collecting all the difference images between any two image pairs belonging to the same individual, to capture all intra-personal variations. Proposal of a probabilistic analysis of the kernel principal components, which integrates a probabilistic PCA (PPCA)[4] into the KPCA. Similar to the

FDA, an extra-personal space (EPS) can be constructed to mimic the between-class difference. The MAP (maximum a posteriori probability) could be used to receive a converged estimate of an unobserved quantity on the basis of empirically analysed data. It is closely related to Fishers method of maximum likelihood (ML), but employs an augmented optimization objective which incorporates a prior distribution over the quantity one wants to estimate. For kernel applications, a subset of the FERET database with 200 subjects alone were considered, one with controlled lighting, neutral expression ,other with same lighting but different facial expression and the last with a different lighting condition but with a mostly neutral expression. The sets were randomly divided into two, one to try on and come up with the theory and the other to test the theory on and wait for results.

D. 3-D Morphing

Factors like pose, illumination and facial expression will still pose as a barrier for accurate facial recognition. Here consideration at component based recognition which involves individual vector considerations at every point. Changes in the head pose, mainly lead to changes in the position of the facial components which could be accounted for by the exhibit of the geometrical model. Here the 3D morphing finds its use. Based on only three images of a person's face, the morph able model allows the formation of a 3D face model using an analysis by synthesis method[5]. A 3D model is created from a set of 2D images. Goes through four-teen independent component classifiers of which nine are used. Thus the normalized outputs of the SVM classifiers are taken and the identity associated with the face classifier with the highest normalized output is taken to be the identity of the face. In 3D morphing, once received all the images, generation of arbitrary synthetic face images takes place under varying pose and illumination. On getting an initial database correspondences between the head models were established in a fully automatic way using techniques derived from optical computation[5][6]. Based on these correspondences, a new 3D face model can be generated by morphing between the existing models in the database. Further a histogram-equalized inner face region was added to improve recognition[7] shift Lin-ear SVM Max Output final decision.

III. ADVANTAGES AND DISADVANTAGES

A. PCA and ICA

1) Advantages:

- Identifies independent source components from observables
- More powerful data representation
- No further discriminant analysis

2) Disadvantages:

Lesser face space corrupts the software: A reduced face space means lesser number of features that can be considered and which makes recognition of one from the crowd more unique. This would be more advantageous but less of face space attracts more trailing Eigen values that at-tract noise and hence corrupt.

B. LDA

1) Advantages:

LDA+PCA can better analyse the images with changed expressions or even different lighting, unlike only with PCA.

2) Disadvantages:

Now that all eigenvectors available in the beginning are normalized, the less subspace in some cases may not be enough to contribute for the next cycle of PCA.

C. Kernel Methods

1) Advantages:

- Drastic improvements in recognition considering illumination and expressional variances in the same individual.
- Similar computing factor, complexity and time

2) *Disadvantages:*
Reduction in face space to a limit less than required could lead to increase in number of false recognition rejects.

D. 3-D Morphing

1) *Advantages:*
- More robust against pose changes.
- Require only three face im-ages of each person. Recognition is at around 90% for faces rotated up to approximately half-pro le in depth.

2) *Disadvantages:*
Required increase in the size of the database

IV. INFERENCE

PCA and ICA Identifies independent source components from observables. (80%) Expression change: PCA: 68% ICA (53%), LDA levels Illumination (72%) while Kernel levels Illumination (65%). 3D Morphing disables Expression Change (73%) Pose Changes (76%) Profile variations (84%)

TABLE I
COMPARISON OF ALGORITHMS

Algorithms Parameters	PCA &ICA	LDA	KERNEL	3D MORPHING
Face space'm'	Optimal	High	low	Optimal
Discriminants	Not required	Required	Required	Not required
Use of Additional classifiers	Only Bayes[1]	Corrupts result	Corrupts result	Corrupts result
Implementation	Easy	Easy	Moderate	Complicated
Duration of Ananlyis	Very high since followed by additional processes	Comparatively lower	Low	Very low
Problems solved+(Extent)	Identifies independent source components from observables.(80%)[1] Expression change: PCA:68% ICA:53%	Illumination (72%)	Illumination (65%) Expression Change (73%)	Pose Changes (76%) Profile variations (84%)
Database sample requirement for testing	Optimal (in 500-1000)	High(In over 5000)	Less (200 or less)	Can work with less but better results with increased database samples.

TABLE III
EXACT PERCENTAGES WITH AND WITHOUT KERNEL METHODS[4]

	PKPCA/IPS	PPCA/IPS	KFDA	FDA	KPCA	PCA	KICA	ICA
Expression	79%	78%	73%	72%	64%	68%	61%	53%
Illumination	84%	82%	65%	75%	52%	73%	61%	57%

V. OBSERVATION

Lesser face space corrupts the software: A reduced face space means lesser number of features that can be considered and which makes recognition of one from the crowd more unique. This would be more advantageous but less of face space attracts more trailing Eigen values that attract noise and hence corrupt.
Drastic improvements in recognition considering illumination and expressional variances in the same individual possible on integrating different processes that solve different recognition problems. While the LDA solves illumination problems to a greater ex-tent than kernel methods, kernel methods solve both illumination and expression change problems at a level much higher than optimal and is hence more advantageous. 3 D morphing alone solves the pose and pro- le problems to a great extent.

VI. CONCLUSION

Facial Recognition involves particular choice of features where feature selection involves concluding upon unique ones for better classification and simultaneously provide enhanced discriminatory power. With excessive trailing Eigen values tending to capture noise as their values are too small, affecting the process, cuts down on its accuracy and too less does not meet the need of the required amount of information that shall be sufficient for the analysis. PCA + LDA is applied continuously to a smaller and smaller set of samples, better separating classes while the number of classes become small deep down the tree. Proposal of a probabilistic analysis of the kernel principal components, which integrates a probabilistic PCA (PPCA)[4] into the KPCA. Similar to the FDA, an extra-personal space (EPS) can be constructed to mimic the between-class difference. Factors like pose, illumination and facial expression will still pose as a barrier for accurate recognition, however normalized outputs of the SVM classifiers are taken and the identity associated with the face classifier with the highest normalized output is taken to be the identity of the face.

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