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Face Recognition using PCA and LDA Technique for Noisy Faces

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ABSTRACT
Face recognition is always a popular area of research. There are various techniques used in the face recognition system. Principal component analysis (PCA) and linear discriminate analysis (LDA) techniques are the two most well-known techniques for the face recognition. In this paper, the PCA and LDA technique based face recognition system are described. The performance of this technique is compare in term of PSNR and RMSE for noisy image. The Euclidean distance between feature templates and database futures are used for identifying the face image. There are basically three types of noises present, but in this paper I am going to compare the salt and pepper noise with the Gaussian noise in the detailed and analytical ways. After finding the features of the different noisy images I am going to compare both the PCA and LDA technique for the noisy pictures.

Keywords
Linear discriminate analysis (LDA), Principal component analysis (PCA).

1. INTRODUCTION

Face recognition is the most popular and most interesting area of the development. Since from the very beginning of identification, human has always taken "face" as the first priority for recognizing each and every being. Hence face recognition has become an active research area for the scientist. Now a day, so many techniques are developed for recognizing faces. But Linear discriminate analysis (LDA) has been widely adopted as the most promising face recognition technique.

The psychophysicists and neuroscientist have studied various issues such as about the uniqueness of the face, organization of the memory of face and how infants perceive different faces [1]. Hence, engineering scientist have designed and developed face recognition algorithms. In this paper, I am trying to continue the work done by engineering scientists in face recognition with the help of software and machines.

2. VARIOUS TECHNIQUES FOR FACE RECOGNITION

As the face recognition techniques are very widely adopted, many researchers have developed so many different approaches for recognizing any face [2]. As we all know in the human body so many body parts are unique such as fingerprints of each and every person are different, similarly in human faces so many thing such as shape of face, features, width of the nose and lips and chin etc. are different from each other and unique also. So on considering all these features into account various techniques for face recognition are proposed.

The four spatial techniques are explained. The following are the four different approaches in the face recognition.

2.1 PRINCIPAL COMPONENT ANALYSIS (PCA)

PCA is used to find a low dimensional representation of data. Some important details of PCA are highlighted as follows [3]. Let *X* = {*X*n_*Rd*| *n* = 1,..,*N* } be an ensemble of vectors. In imaging applications, they are formed by row concatenation of the image data, with *d* being the product of the width and the height of an image.

$$E(X) = \frac{1}{N}\sum_{n=1}^{N} X_n (1)$$

Let be the average vector in the ensemble. After subtracting the average from each element of X, We get a modified ensemble of vectors

$$\bar{X} = \{\bar{X}_n, n = 1, N\}\ with\ \bar{X} = X_n - E(X) \quad (2)$$

The auto-covariance matrix *M* for the ensemble *X* is defined by

$$M = COV(X) = E(X \otimes X) \qquad (3)$$

Where *M* is a *d*x*d* matrix, with elements

$$M(i,j) = \frac{1}{N}\sum_{n=1}^{N}\left(X_n(i)X_n(j)\right),\ 1 \le i\,, j \le d \quad (4)$$

It is well known from matrix theory that the matrix *M* is positively definite (or semi-definite) and has only real non-negative Eigen values [3]. The eigenvectors of the matrix M form an ortho-normal basis for Rd. This basis is called the K-L basis since the auto-covariance matrix for the K-L. Eigenvectors are diagonal, it follows that the coordinates of the vectors in the sample space X with respect to the K-L basis are un-correlated random variables. Let $\{\boldsymbol{Y_n}, n=1,..,d\}$ denote the eigenvectors and let K be the $\boldsymbol{d} \times \boldsymbol{d}$ matrix whose columns are the vectors $Y1$,.., Yd *[3]*. The adjoin matrix of the matrix K, which maps th standard coordinates into K-L coordinates, is called the K-L transform. In many applications, the eigenvectors in K are sorted according to the Eigen values in a descending order. The PCA of a vector y related to the ensemble X is obtained by projecting vector y onto the subspaces spanned by d' eigenvectors corresponding to the top d' Eigen values of the autocorrelation matrix M in descending order, where d' is smaller than d. This projection results in a vector containing d' coefficients$\boldsymbol{a_1}$, ..,$\boldsymbol{a_d}$'. The vector y is then represented by a linear combination of the eigenvectors with weights $\boldsymbol{a_1}$, .., $\boldsymbol{a_d}$.

2.2 FEATURE BASE TECHNIQUE

The feature extraction model is biologically motivated, and the locations of the features often correspond to salient facial features such as the eyes, nose, etc. A feature-based approach to face recognition in which the features are derived from the intensity data without assuming any knowledge of the face structure is presented.

Topological graphs are used to represent relations between features, and a simple deterministic graph-matching scheme that exploits the basic structure is used to recognize familiar faces from a database. Each of the stages in the system can be fully implemented in parallel to achieve real-time recognition.

One standard solution to these problems is to employ pattern recognition processes as a front end in order to make explicit the relationships that are otherwise implicit in the input. These extrinsic relationships are then treated as features by the problem solving component. This process, called pattern classification, is illustrated in Fig. 1.

FEATURES

Pattern classification takes as input a pattern that may be a perspective view or may be partially occluded, and transforms the pattern through a process of normalization. It then extracts symbolic features that can be used by the decision procedure to classify the input.

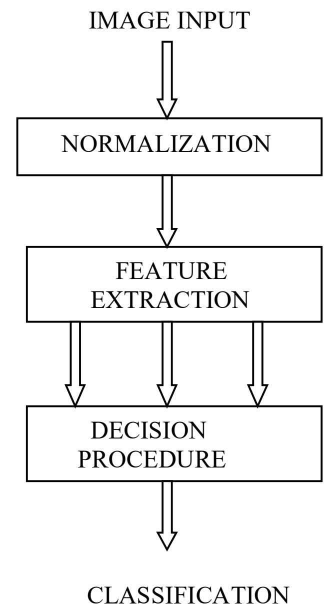

Figure 1: The Feature Extraction process

The features base face recognition techniques consist of three main stages.

1. We derive a description of intensity image in terms of features.
2. We construct a graph representation of face, with nodes in the graph representing feature information, and the links representing feature relations.
3. Final, stage involves the matching of the input graph with stored data.

Moreover, for recognizing relational structure, feature extraction can be like the tail wagging the dog. Not only is it a domain-specific black box, but there is typically no feedback from the decision procedure to the feature-extraction process. Feature extraction provides no general account of how to focus attention and it ignores cardinality and configuration information, so there must be a small number of relevant configurationally categories [4]. Most importantly, because features are extracted via arbitrary code, they are not systematically composed of simpler features that can be derived or learned from the input. The vocabulary of features is either fixed or determined by the task and the local features of the input. While top-down processing is important because it provides expectations in the form of a pragmatic (task-driven) context, it must be applied in a global-to-local fashion in order to provide a structural context as well.

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2.3 ELASTIC BUNCH GRAPH MATCHING --EBGM

Elastic Bunch Graph Matching make use of Gabor features, being the output of band pass filters, and this are closely related to derivatives and are therefore less sensitive to lighting change. Also, this approach uses features only at a key node of the image rather than the whole image; this can reduce the noise taken from the background of the face images. Together with other important advantages of it is that it is relatively insensitive to variations in face position, facial expression. The matching procedure uses the FBG as a face template for finding the precise fiducially point, which solve the problem for automatically localization [5].

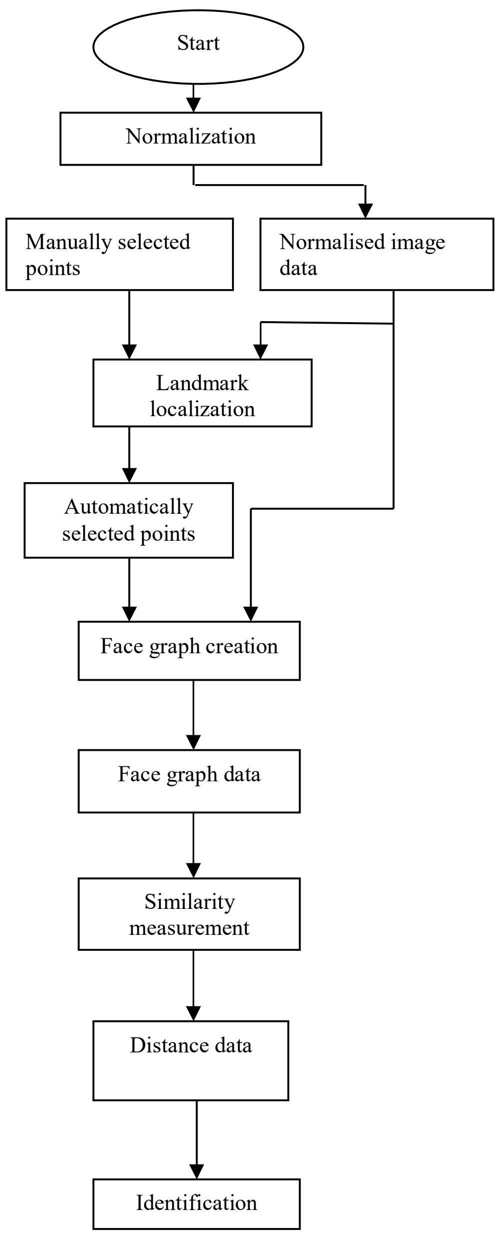

Figure 2: A sample line graph using colour which contrast well both on screen and on a black-and-white hardcopy

The stored data can be easily expanded to a database for storage. When a new face images is added, no additional afford is needed to modify templates, as it already stored in the database. This advantage had overcome the Eigen faces because the Eigen faces need to be recalculated as shown in Fig. 2 above.

The, EBGM algorithm is a feature-based approach to the face identification problem. Figure 2above shows a flow diagram of the algorithm's implementation. In the context of EBGM, the facial features that are used are called fiducially points. For the training step, the exact coordinates of these points are assumed to be known (usually hand-annotated by humans). Images are represented internally by the algorithm using spectral information of the regions around these features, which is obtained after convolving those portions of the image with a set of Gabor wavelets of varying size, orientation and phase. The results of the convolution for specific position (called the Gabor Jet) are then collected for all fiducially points on a given image and aggregated (together with the feature coordinates) in that image's Face Graph[6]. Having applied this process to all images in the training set, all the resulting Face Graphs are concatenated in a stack-like structure called the Face Bunch Graph (FBG). This is the system's model of all individuals it can identify. For the testing step, on the other hand, minimal information about the features is available (at best we have the eye pupil coordinates). Rather, the algorithm constructs the test image's Face Graph by estimating the positions of fiducially points in an iterative manner, using the information stored in the FBG and previously estimated feature positions. This automatic feature localization capability is one of the major advantages of the EBGM algorithm.

2.4 INDEPENDENT COMPONENT ANALYSIS –ICA

Independent Component Analysis (ICA) is a technique for extracting statistically independent variables from a mixture of them. The technique is quite new and has originated from the world of signal processing. A classical example demonstrating the original problem is the cocktail-party problem where two people being in the same room speak simultaneously. Two microphones are placed at different locations recording the mixed conversations. It would be very useful if one could estimate the two original speech signals from the two mixed recordings. Surprisingly it turns out that it is enough to assume that the two speech signals are statistically independent. This is not an unrealistic assumption, but it does not need to be exactly true in practice. ICA can be used to estimate the contribution coefficients from the two signals, which allows us to separate the two original signals from each other.

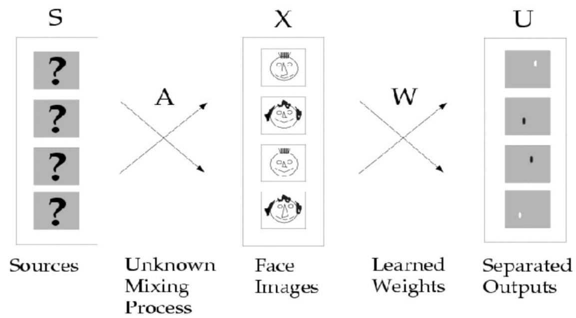

Figure 3: Example of an ICA technique module

For finding a set of independent component images, the face images X are considered to be a linear combination of statistically independent basis images S, where A is an unknown mixing matrix. The basis images are recovered by a matrix of learned filters W, which produces statistically independent outputs U (Figure 3).

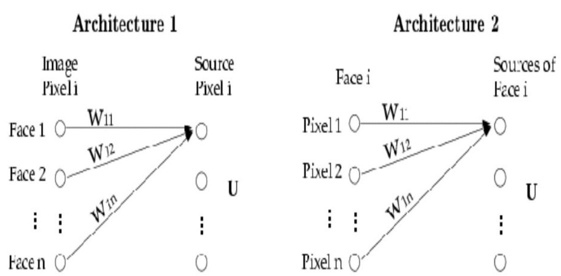

Figure 4: Source separation on ICA (a) face image (b) face pixels

Two approaches for recognizing faces across changes in pose were explored using ICA. The first architecture provided a set of statistically independent basis images for the faces that can be viewed as a set of independent facial features (Figure 4a). This corresponds very much to the classical cocktail-party problem performing a blind separation of a mixture of auditory signals [7]. These ICA basis images were spatially local, unlike the PCA basis vectors. The representation consisted of the coefficients for the linear combination of basis images that comprised each face image. The second architecture produced independent coefficients (Figure 4b). This provided a factorial face code, in which the probability of any combination of features can be obtained from the product of their individual probabilities. Classification was performed using nearest neighbour, with similarity measured as the cosine of the angle between representation vectors. Both ICA representations showed better recognition scores than PCA when recognizing faces across sessions, changes in expression, and changes in pose.

2.5 LINEAR DISCREMINATE ANALYSIS (LDA)

The Fisher face method, One of the appearance-based FR methods, those utilizing linear/fisher discriminate analysis (LDA) techniques have shown promising results as it is demonstrated in (Belhumeur et al., 1997; Zhao et al., 1999; Chen et al., 2000; Yu and Yang, 2001; Liu and Wechsler., 2002; Lu et al., 2003a, b; Ye and Li., 2004), applies linear discriminate analysis (LDA) to find a set of basis images that maximizes the ratio of between-class scatter to that of within-class scatter. In face recognition application, one problem for LDA is that the within-class scatter matrix is almost always singular since the number of image pixels in image is usually much larger than the number of images which can increase detection error rate if there is a significant variation in pose or lighting condition within same face images.

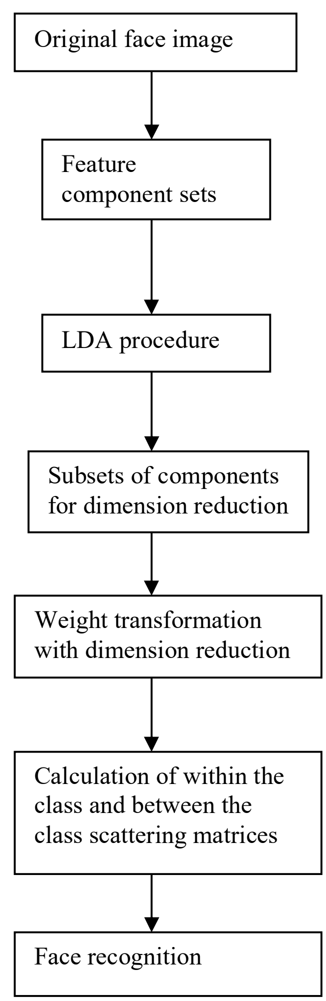

Figure 5: flow chart of LDA

In order to overcome the complication of a singular matrix, many algorithms have been proposed [4-10]. Since, the fisher faces approach takes advantage of within-class information; minimizing variation within each class, yet maximizing class separation, the problem with variations in the same images such as different lighting conditions can be overcome.

In the LDA process firstly the image to be tested is taken from the input. Then according to the feature consideration all the features are extracted. All the features after extraction are being arranged in a set. Now LDA procedure is applied so that the dimensions can be reduced and made according to the requirements. Then weight is calculated of the different sub sets. Now the scattering matrices are calculated which are known as within the class and between the class scattering matrices [7] .The following is the procedure to calculate the scattering matrices:

Let the between-class scatter matrix $S_b$be defined as-

$$S_b=\sum_{i=1}^{g} N_1 (\bar{X_i}-\bar{X})(\bar{X_i}-\bar{X})^T \qquad (5)$$

And the within-class scatter matrix $S_w$be defined as

$$S_W=\sum_{i=1}^{g}(N_i-1)S_i=\sum_{i=1}^{g}\sum_{j=1}^{N_i}(\bar{X_i}-\bar{X})(\bar{X_i}-\bar{X})^T \quad (6)$$

Where *j ix,* is the *n*-dimensional pattern *j* from class *i*p ,*i N* is the number of training patterns from class *i*p , and*g* is the total number of classes or groups.

4. NOISY IMAGES

The noise, in the image can be defined as the degradation in an image signal due to some external disturbance at the time of capturing the image or at the time of sending the image through any medium. This external disturbance is random in nature. This disturbance or noise are classified into groups and given names. The following are the classification of noise in the images:

1. Poisson noise
2. Gaussian noise and
3. salt and pepper noise

In this paper I am going to explain the Poisson and Gaussian noise in details and then on applying the PCA and LDA technique to check the accuracy of both the technique and see which better.

4.1 PCA NOISE

The full name of PCA is **Principal component analysis (PCA).**The Poisson noise which occurs due to the image during the time of the quantity observable present in the image during the time of taking the image. On the technical basis the Poisson noise is the noise which is caused due to statistical quantum fluctuations. When Poisson noise is present in the image then the image appears to be lighter in some parts of the image depending upon the level of noise. The Poisson noise is also known as short noise, which has a root-mean square value proportional to the square root of image intensity and noise at different pixels are independent of one another.

4.2 GAUSSIAN NOISE

Gaussian noise is a statistical noise which is generated due to the interference of the movement of electricity in lines. Although there are many methods to reduce and even eliminate the Gaussian noise such as spatial filter etc. , but it must be kept in mind that when reducing noise, we also reduce the fine scales image details because they also has high frequency.

Hence, I am going to try to note the accuracy between the Poisson and Gaussian noise images.

4.3 SALT AND PEPPER NOISE

Another name of the salt and pepper noise is impulsive noise. The salt and pepper nose is the noise which is caused due to the sudden disturbance in the image signal. The appearance of this typical noise is, as the randomly occurrence of white and black pixels into the image. The random white pixel over the image is called as the salt noise and the random black pixels over the image are known as pepper noise. On combining these two when both (white and black) pixels occurs over the image then it is known as salt and pepper noise.

In this paper the method of the identification of the noise for the images having Gaussian noise and salt and pepper noise has been shown. The comparison of the PCA and LDA technique for the noise environment is done .According to the analysis the result will be drawn.

5. PROPOSED METHOD

The approach to face recognition involves the following operations

1. Acquire an initial set of N face images (training images).

2. Calculate the Eigen face from the training set keeping only the M images that correspond to the highest Eigen values. These M images define the "face space". As new faces are encountered, the "Eigen faces" can be updated or recalculated accordingly.

3. Calculate the corresponding distribution in M dimensional weight space for each known individual by projecting their face images onto the “face space”.

4. Calculate a set of weights projecting the input image to the M “Eigen faces”.

5. Determine whether the image is a face or not by checking the closeness of the image to the “face space”.

6. If it is close enough, classify, the weight pattern as either a known person or as an unknown based on the Euclidean distance measured.

7. If it is close enough then cite the recognition successful and provide relevant information about the recognized face from the database which contains information about the faces.

8. Repeat the above classification with noisy images.

6. EXPERIMENTAL SETUP

The experimental results are shown below which are done in MATLAB on the basis of the method explained above. The performance of the PCA and LDA technique over the Gaussian noise is shown below in which the text image is recognized in among the 60 file stored as the form of data.

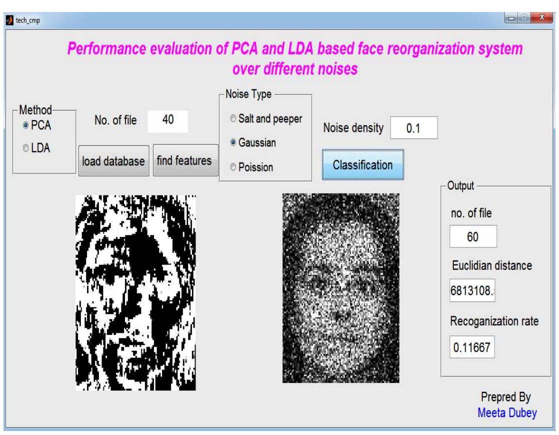

Figure 6. Output of PCA having Gaussian noise

Similarly, the MATLAB output based over the LDA technique of the face recognition with the Gaussian noise. In this shown figure there are total no. of images, the LDA technique is following:

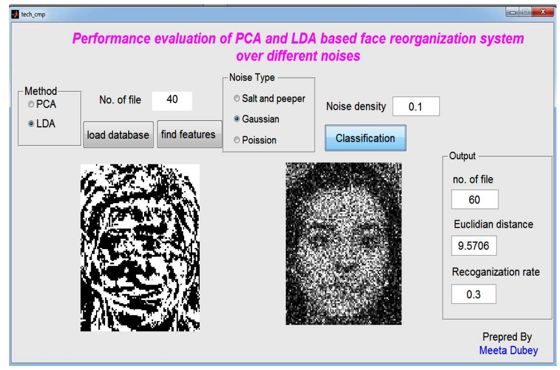

Figure 7. Output of LDA using Gaussian noise

The image recognition for the salt and pepper noise is the noise having the random white and black pixels. The pixels are clearly in the following output:

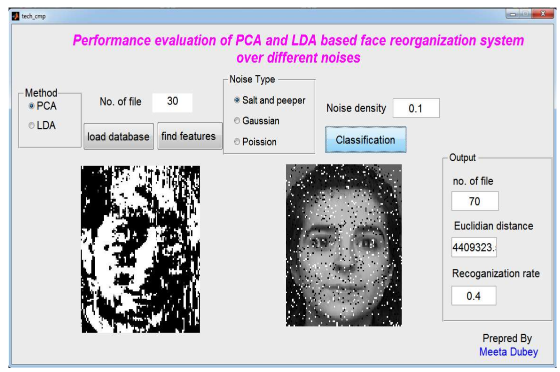

Figure 8. Output of salt and pepper noise for PCA

The above output shows the Euclidean distance and the recognition rate for the test image being recognised among the 70 number of images in the data stored.

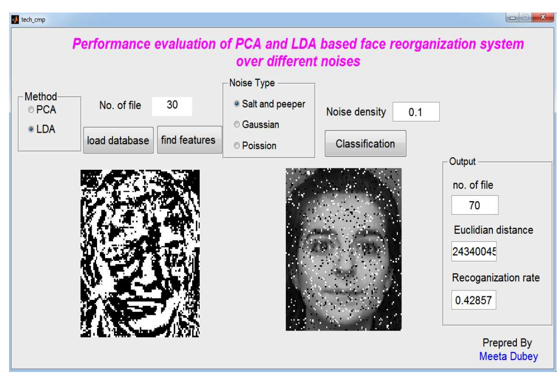

Figure 9. Output of salt and pepper noise for LDA

The above output is the similar output which we get for the LDA technique for the face recognition system.

7. EXPERIMENTAL RESULT

Now the analysis of the above all the output for the different- different number of samples rate. The graph has been drawn between the training samples and the accuracy. The graph is very important for the analysis of both the face recognition techniques.

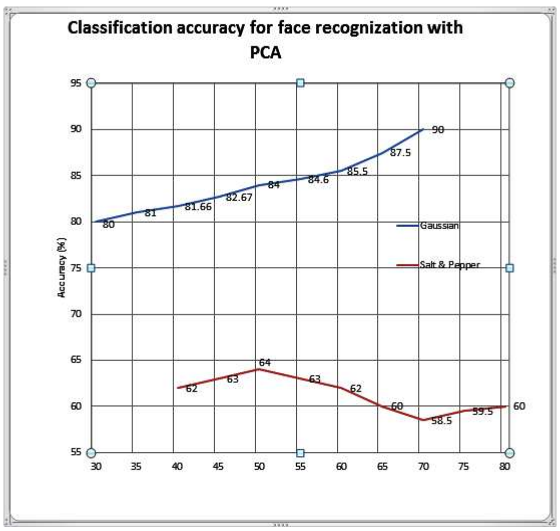

Figure 10: Classification accuracy for face reorganization with PCA

From the graph it is clear that for the PCA base feature , as the training samples increases the Eigen distance is decreases in the case of Gaussian and salt & pepper noise whereas it is opposite in the Poisson noise.

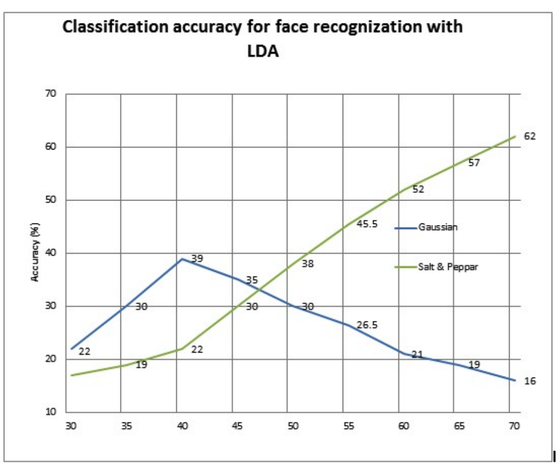

Figure 11: Classification accuracy for face reorganization with LDA

From the graph it is clear that for the LDA base feature , as the training samples increases the Eigen distance is increases in the case of Gaussian and Poisson noise whereas it is opposite in the salt & pepper noise.

8. CONCLUSION

The behaviour of the PCA and LDA technique varies with the type of noise. From all the above results we can conclude that performance of PCA is better than LDA in Gaussian noise, whereas performance of LDA is higher in comparison of PAC in presence of salt & pepper noise.

REFERENCES

[1] Review of Face Detection using PCA and ANN Techniques Sachin Shende & Rahila Patel.

[2] SUPPORT VECTOR MACHINES, PCAAND LDA IN FACE RECOGNITION.

[3] BDPCA Plus LDA: A Novel Fast Feature Extraction

[4] Technique for Face Recognition Wangmeng Zuo, David Zhang, Senior Member, IEEE, Jian Yang, and Kuanquan Wang.

[5] Template Based Face Recognition using Real Images Upneet Kaur Department of Computer Science and Engineering CEC, Landran, Punjab, India

[6] A Survey of Face Recognition Techniques RabiaJafri and Hamid R. Arabia.

[7] Comparison of Different Algorithms of Face Recognition, Ajeet Singh*, BK Singh and Manish Verma.