# Face Recognition Project Proposal
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***Abstract*- I have designed a real time face recognition project that analyzes key features of a face and according to that it makes a match from a provided data set. This type of matching is a one to many matching. There are many approaches for carrying out facial recognition , here in this project I will be following the Principal Component Analysis approach for recognizing a face in an effective way. Though faces have a multi dimensional complex structure but the fact that faces are generally upright ease of the task as we can describe it as a collection of two dimensional views. The projection is basically done as feature space which is also known as "Face space", which intern can be described by the "eigen-faces". These eigen faces attributes provides an individual face with a scaled summation, these scaled attributes are compared with the known attributes of the faces already present in the database. In this approach I will be carrying out these project and analyze the performance and reliability of the recognition.**

## I. Introduction

IMAGES are normally a complex objects in which developing a computational model is difficult. Many parameters like intensity of light, angle of head, tilt of face, facial expression and aging make the problem of face recognition more complex. Still by comparing various images from the dataset a face recognition system tries to recognize a face with a fair accuracy. This is generally done by breaking the image into smaller components of characteristic images also known as "Eigen Faces", which are the main attributes of the training sets. The recognition is basically done by spanning a newly obtained image into a subspace of eigenfaces and after that the positions of the distinct weighted attributes of the face space are accessed and it is mapped with the existing known images positions. EigenFaces are normally a Eigenvectors which shows various dimensions of the attributes in the facespace. As images can be represented as a vector space and the single vectors can be seen as a eigenvector of the co vaiance matrix.

Face Reccognition ways can be broadly classified into two approaches which are as follows :-

(1) Geometric Approach (2) Photometric Approach

(1) Geometric Approach focuses on distinguishing features or landmarks in faces like the distance between eyes and nose, nose structure and various other features that are calculated by the angles obtained geometrically and the eucliedan distances between them.

In this approach the head rotation, lean and the tilt is deduced, once these parameters are calculated we can easily discard the effect of these transformations on the distance that is deduced.

(ii)*Photometric approach* deals with recovering or retrieving the structure/shape of an object or image from a wide variety of images present in the database that are captured under various lighting conditions. This approach deals with high speed photometric stereo and the object is scanned from different lighting condition. In this method the field structure of a distinct object are calculated in different illuminations.

Well known algorithms like principle component analysis using eigenfaces, can be used in face recognition.

Face recognition applications follow a two step procedure

1) Face Detection :- This includes detection of various structures of face which includes structure of nose eyes and lips, diameter of face, distance between eyes and nose, etc.

2) Face Recognition :- There is a big difference between face detection and recognition, where the former detects a face from an image but the later deduce information about the face to recognize it with an identity.

## II. Background and Research Conducted

The approaches for face recognition mainly focused on detecting distinct features like nose , eyes, diameter of face etc and the distances between these features. But soon it was shown by research that physical features and the distances are not alone sufficient factors for identifying a face with great reliability. Bledsoe in 1966 became the pioneer to attempt first half automated recognition of faces human to computer interaction system in which he categorized faces on the basis of constant points or marks that are entered manually on the photographs. In this research the parameters that were used were ratios among points such as nose tip, eye corners, end points of lip and chin point. However after this at 1971 significant work was done by researchers at Bell Labs where they saw image as a vector space and developed a vector consisting of twenty one standard features and used standard pattern classification system to identify faces. But the features were mostly subjective deductions like thickness of nose , area of lips which are made from human subjects , that became a pain to automate. Fischler and Elschlager in 1973 introduced a linear embedding algorithm which used a matching of local template with a global one to find a close match and thereby detect attributes of a face. This approach was further improved in 1989 by Yuille Cohen and Hallinan. They introduced a strategy called "deformable templates" which works on the

models which are parameterized and various features through which interation of image can be determined.
Now coming to recent approaches where there are significant developments. Zahid Riaz in 2005 used compressed face images for categorizing humans. Here he used Principle Component as a vector out of ninety two components as the size of the image he took was 112*92. This approach resulted in 87.39percent of accuracy. After this D.A Meedeniya used another approach where again the use of PCA comes to the picture. But here in a different way than the previous approach. This algorithm used eigen faces and eigen prices extracted from the images and a unitary matrix was formed using the financial measurement of the single price decomposition. This approach gave a performance of 93.7 percent. Janarthany Nagendrarajah in 2010 proposed a model where the expression of the face used in the training image and testing image diverge with each other and it results in a single image per class which is available in the system.Normally a frontal face is used as an input to the system which has a neutral expression and background is also same. This model also relies on the Principal Component Analysis , where it is applied on a collection of images and from their a collection of eigen faces and their scaled or weighted values are extracted. This values are used in the recognition and for the classification part the euclidean distance of the scaled vectors which are associated with each training image are used. He caried this research with 8 pictures and 6 different expressions with which he got a rate of recognition as 89%. Patrik Kamencay in 2021 used Scale Invariant Feature Transform(which detects features and describes local features in images) and segmentation algorithm for processing the face images. Karande Kailash in 2012 , used the pyramid representation of image processing in which he chose the laplacian pyramid technique in multiple orientations. It uses the differences in the blurred versions in each levels. As the smallest level is used for the reconstruction of an image with a high resolution. This approach is different from the previous approaches as he used both Principal Component Analysis(PCA) and Independent Component Analysis(ICA). Generally in PCA the basis functions that are derived from the eigen vectors are independent from each other i.e it cannot be predicted from other basis functions.Still there lies some higher order dependencies in them , so they are not properly seperated. In contast ICA provides a clear distinct separation in higher order relationships and hence information contained in higher order relations can be deduced easily. Now in this research two face datasets one with more variation in head tilt and facial expressions and the other with less face variations were taken and separate component were evaluated using PCA and ICA for retrieving a detailed recognized image. Shiji S.k in 2013 proposed a face image projection in an space of experience that takes into account various known faces with different variation. He used the eigen faces of a group of face , and the faces used might not have an accurate match with the percieved facial features but the approach of using eigen face using PCA became sucessful again and this technology was widely used in hotels, criminal identification and identity verification. Zhiyong Zeng in 2013 used a new process for recognizing and describing faces using shearlets transforms. Shearlets framework offers an efficient encoding of directionally dependent objects(anisotropic). So by using shearlet transform along with PCA the features from face were extracted which got the advantage of detecting faces that are directionally different with a high accurracy. Tomesh Verma in 2013 was first to use Linear Discriminant Analysis(LDA) along with PCA to obtain a image reduction method. This research as previous researches also used PCA for reducing dimensions of datasets and then using LDA the features were extracted for separating classes. Lastly in this approach testing was conducted using classification of nearest mean. This approach produced a very efficient recognition rate of 96.35%.

## III. FACE RECOGNITION METHODOLOGY

A) **Linear Discriminant Analysis(LDA)** is a technique by which data is classified and also dimensionality is reduced. It can effectively take care of the cases where frequencies within the class are uneven. This methods ensures maximum separation by increasing the ratio between variance of class to that of the variance of the within-class. When the object is transformed to a different space LDA does minimal change in location but it ensures maximum class separation so as to get a distinct decision range among classes.LDA has two different ways of transforming dataset and test vectors. *Class independent transformation* maximizes the ratio of the overall variance to the within class variance whereas *Class dependent transformation* maximizes the ratio between class variance to the within class variance. Linear Discrimination Analysis generally projects the features of a higher dimension space into a lower dimension space. Each class of images are grouped cohesively, if still there lies a distinct amount of separation between them, the cluster quality increases. LDA uses, two matrices, namely the within-class (Sw) and the between-class (Sb) matrices, and these matrices are used to measure the quality of the cluster.

$$S_b = \sum_{i=1}^{g} N_i (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})^T$$

$$S_w = \sum_{i=1}^{g} (N_i - 1) S_i = \sum_{i=1}^{g} \sum_{j=1}^{N_i} (x_{i,j} - \bar{x}_i)(x_{i,j} - \bar{x}_i)^T$$

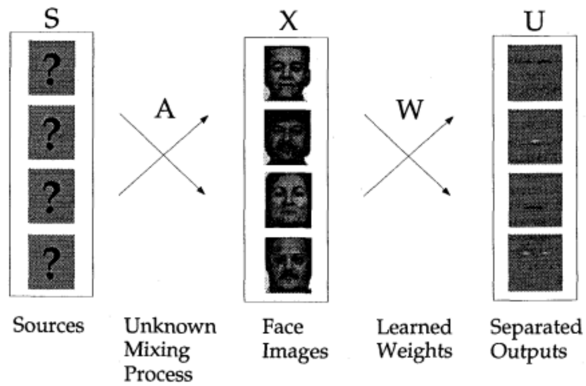
where $S_b$ is the mean distance between different classes which is also known as between class variance, $S_w$ is the within class variance which is the distance between the mean and the sample of each class.

$$P_{lda} = \arg\max_P \frac{|P^T S_b P|}{|P^T S_w P|}$$

Now P is the lower dimension project of the space which maximizes $S_b$ and minimizes $S_w$. This P is often known as Fisher's criterion.

B) **Independent Component Analysis (ICA)**

This type of analysis is often used when there is a large amount of data and the information that is relevant is of small size. Distinct independent sources are separated from a mixed signal using ICA i.e the main focus of ICA is on independent components. ICA finds a linear transform of the input data that has statistically independent basis.ICA provides a great efficiency in face recognition because it successfully decorrelates higher order moments of the input along with the lower order moments and most of the information of an image are normally present in the higher order statistics .The underlying algorithm used for the separation of independent components is known as the "Cocktail party problem". With this algorithm a collection of independent images from a set of facial image is deduced and it is used to successfully recognize a face.



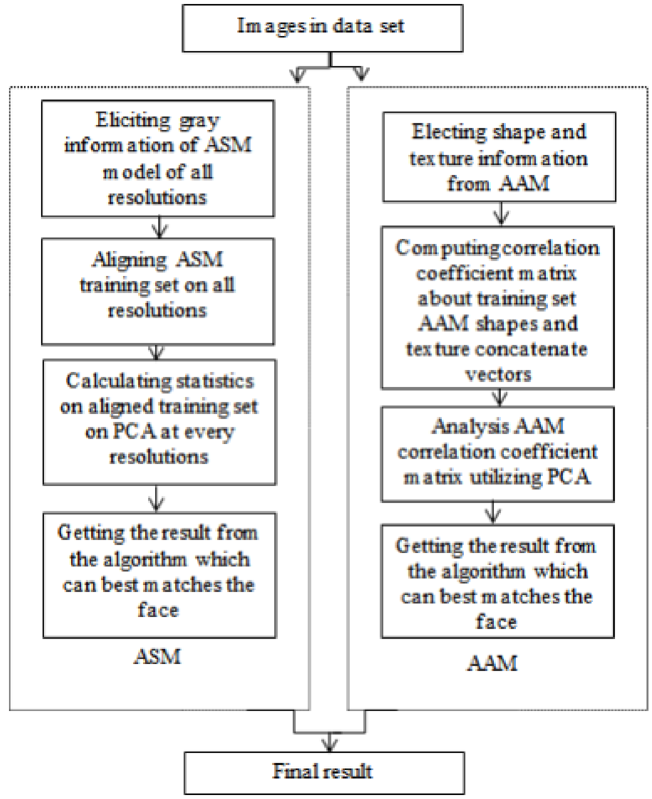

The above image is a basic synthesis model. X has images where the independent component images are derived from the linear combination of independent basis image in S. A is a unknown matrix used for mixing. Finally images are recovered from the learned weights matrix which produce a independent separated outputs.

C) **Active Shape Model (ASM)**

This is another technique used in Face recognition which is based on the fact that faces consist of many unique traits for example position of nose , eyes,etc. In this model sixty eight trait points are used to provide a detailed structure of the face. This trait points are considered as vectors each having a definite x and y coordinate. Now this trait point vectors are matched with the perceived image by doing proper scaling and rotation, to reduce the effective Euclidean distance mean among these trait points. Hence using this a mean shape of the percieved image is made. After this ASM tries to confirm the mean shape to that of a universal shape model which is given by a global face detector. It generally checks that the basic structure or shape points of the image is in the right places. The same process is carried out again and again to get a detailed fine resolution of an image.

D) **Active Appearance Model (AAM)**

This technique is a specialization of ASM model that gives high recognition rate of facial images. AAM is different from ASM in the form that it hints upon detailed texture of the image like intensity of light, color of face and hair,etc. Thereby it is very successful in generating a realistic image. In ASM the facial image is broken down into triangle shaped points where each corner represents a trait points of ASM. Now this trait points vectors are scaled and analyzed using PCA.




Flow Chart to explain how ASM and AAM experiments are carried out.

E) **PRINCIPAL COMPONENT ANALYSIS(PCA)**

PCA is a technique in which information of faces are extracted and a product is constructed based on computations of this information. An image which we generally see as a single object is composed of numerous data points. These data points are generally multi dimensional and this makes it more difficult for computation. So the first goal is to simplify the image object by reducing dimensions which are not of significant use. Before taking a dive into PCA we will gradually describe about the terms and keywords that are needed to fully understand the concept.

**Variance(var(x))** is used for calculating the distribution/spreading of the datasets from the mean value.

**Covariance(cov(x,y))** describes the extent to which elements of data from two different sets move in the same direction. Covariance is often used to determine how two data sets are interrelated with each other.

$$var(x) = \frac{\sum(x_i - \bar{x})^2}{N}$$

$$cov(x,y) = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{N}$$

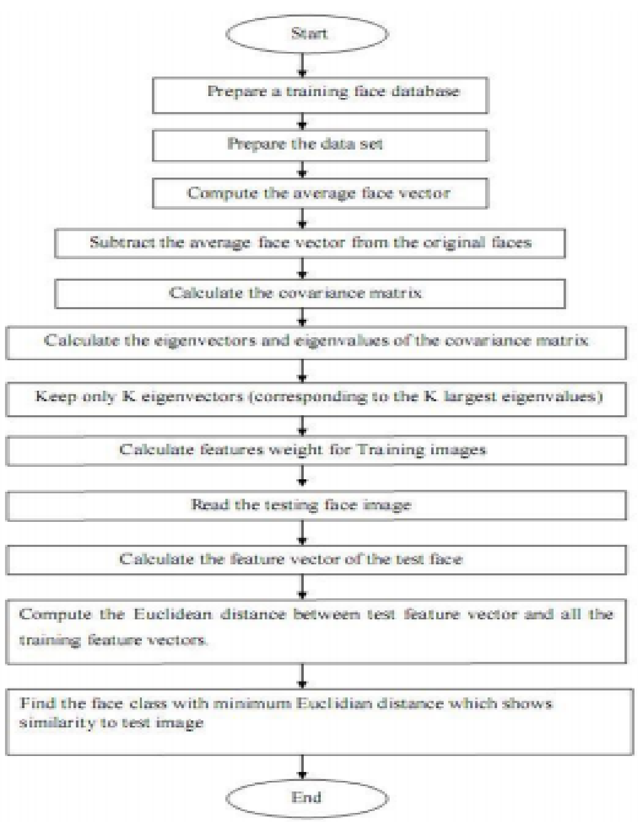
x bar and y bar are mean value of x and y. "i" represent dimension.

For any pattern recognition task the first and foremost task is to find patterns among various datasets. The more the data is spread across each dimension the more clear pattern can be visible. Also another criteria is to find dimensions which are linearly independent of each other. Thus dimensions having zero covariance are selected as they are independent from each other, these dimensions can be easily represented as linear combination of basis. PCA does the above work by finding dimensions that are linearly independent to each other and then ordering them with respect to these variance. PCA calculates the covariance matrix where the diagonal represents the variation in the specific dimensions and the non diagonal entries represents the covariance between two dimension. In this way it finds linearly independent dimensions along with the variance in each dimensions. Now for PCA to work the covariance matrix should have large value in diagonal(which represents higher spread) and zero value in non diagonals which represents linear independence. So here comes the requirement of transforming a normal covariance matrix to a diagonal matrix which is known as matrix diagonalization.

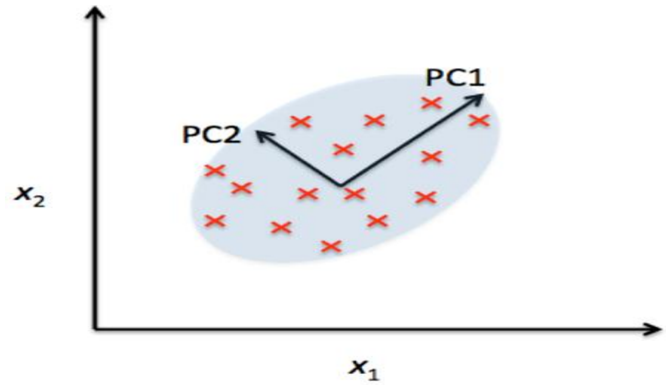
$$C_x = \frac{1}{n-1}(X-\bar{X})(X-\bar{X})^T$$

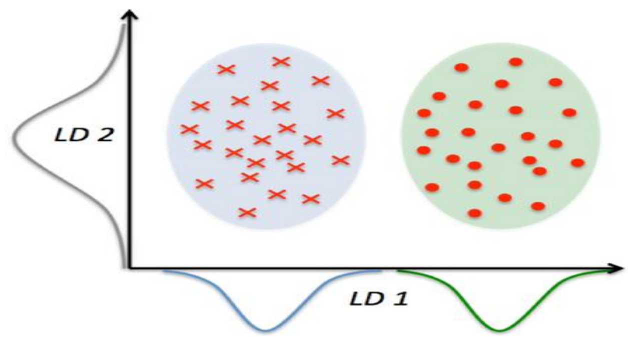
$X^T$ is the transpose of the matrix. $C_x$ is the covariance matrix. This diagonalization of the matrix is done with the help of eigen vectors and the value present in it are known as eigen values. From this matrix the columns are sorted in decreasing order with respect to the eigen values. Now as per the requirement first K dimensions are extracted from these sorted pairs which forms the basis vectors.

FlowChart of PCA




As previously discussed about LDA which is a supervised compared to PCA which is unsupervised. Though both are linear transformation technique but LDA tends to find subspace maximizing the class separability but PCA calculates the direction of maximum variance. Below are two images that shows the difference between PCA and LDA.



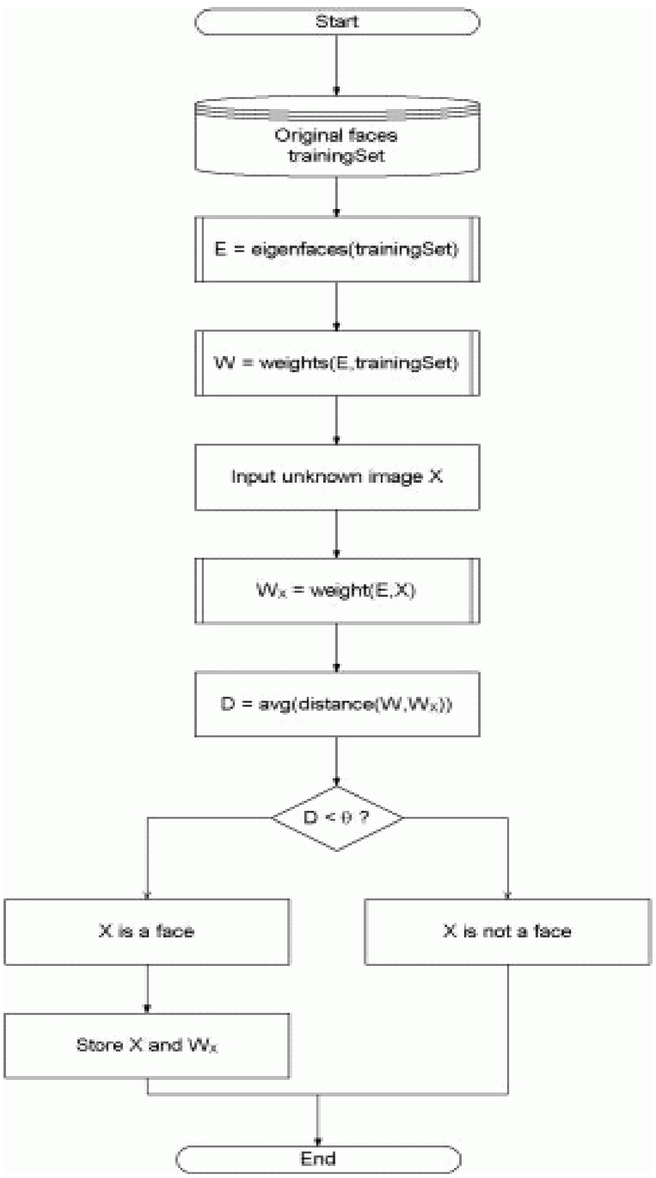

When the number of samples in a given class are relatively small then PCA's recognition rate and its performance is higher than the other technique that are mentioned.

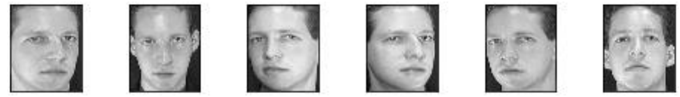
## IV. Eigen Faces

Not all aspects of face features are important for face recognition. This was ignored in many previous approaches. This approach was first to use relevant information and face features for calculating an image and these features weights were adjusted to reconstruct the image. We can say that by using this important information of the facial image is encoded efficiently and then it is compared with a pool of image encodings that are present in the database. This important information of an image are extracted by taking into account the variation of features from the pool of images which are independent of other variables and then comparing these variations with an individual image. These important features are sometimes referred as Principal Components of the face distribution. Also mathematically it can be said as eigen vectors of the covariance matrix. In this kind of representation images are often treated as a point in a high dimensional space. As written earlier eigen vectors represents variation of characteristics of the face images. Every image makes a contribution for creating a eigen vector and these vectors are represented as an Eigen Face. Eigen Faces deviates from the original images because some facial features from the original image are either absent or scaled to get that eigen face. Each and every faces can be represented as a linear combination of

eigen faces. Individual faces can be represented by numerous eigen faces but only those with maximum eigen values which has largest variance and zero covariance are taken into account. Hence the K eigen faces that are chosen among others spans a subspace which is also known as "Face Space".
For recognizing a face firstly K images are chosen from the training set which provides maximum eigen values. With the help of these images the face space is defined. After this the distribution for each and every faces are calculated in K dimensional space and there projection forms the "Face space". These are the data that are derived using the training datasets. Now when a new face arrives its K dimensional eigen faces and the scaled weights can be calculated using projections from the training datasets. After that the face space of the image is compared to that of the training datasets face space so as to ensure that the face has human face general characteristics. In previous steps if it is found as a human face then the weight patterns are classified , which tells that the face is known or unknown.

Flowchart of EigenFace algorithm

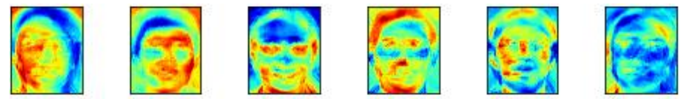


Traning sets data (i)

Normalized Faces(iii)

Mean Face(ii)



Eigen Faces (iv)

## V. Detailed Algorithm of Recognition

Here I will be providing a step by step process for Face Recognition. It is a two step process where first step is for
(i)Training the model using the datasets.
(ii) Detection of a face.

Dataset Training Part

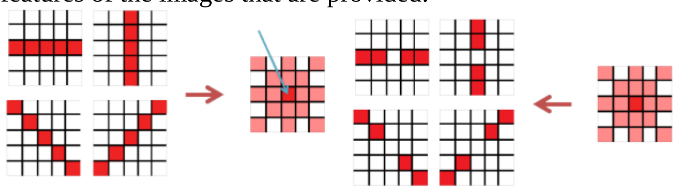
a) The image is needed to be represented in a vector form from which the covariance can be calculated. This process is known as flattening of image.

| | | |
|---|---|---|
| 1 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | 9 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | 4 | 7 | 2 | 5 | 8 | 3 | 6 | 9 |

b)Mean faces is needed to be computed which is nothing but the sum of the flattened image to number of image ratio.

c) Normalization of the training set is done after this , which is nothing but subtracting each image with the mean. This step is necessary because mean is often considered to have elements that are common in all images. Now as the trained model is needed to be versatile which must have the capability to identify any face with high accuracy so the mean is subtracted from each and every image to feed the distinct feature of each image to the model. By this the model gets the average common features of all faces and also it contains the distinct features of the images that are provided.

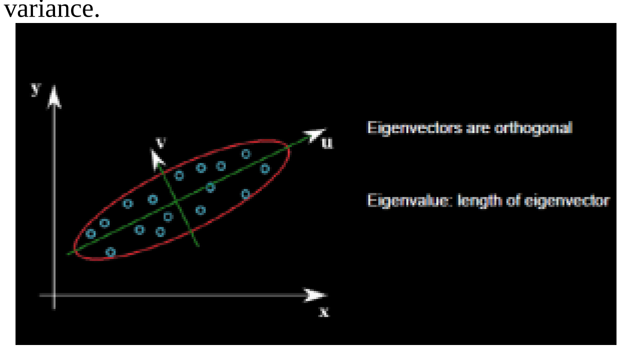


d) The next step is to calculate the covariance which as discussed earlier gives a detail representation of variance(the spread of the function from its mean) in its diagonal and also the covariance(extent to which a function moves in the same direction). This step is necessary because dimensions having zero covariance are selected as they are independent from each other, these dimensions can be easily represented as linear combination of basis.

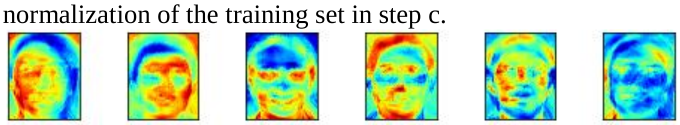
$$\begin{bmatrix} V_a & C_{a,b} & C_{a,c} & C_{a,d} & C_{a,e} \\ C_{a,b} & V_b & C_{b,c} & C_{b,d} & C_{b,e} \\ C_{a,c} & C_{b,c} & V_c & C_{c,d} & C_{c,e} \\ C_{a,d} & C_{b,d} & C_{c,d} & V_d & C_{d,e} \\ C_{a,e} & C_{b,e} & C_{c,e} & C_{d,e} & V_e \end{bmatrix}$$

$V_a$ represents the variance within dimension a
$C_{a,b}$ represent the co variance between dimension a & b.

e) Eigen vectors are calculated after the above steps which describes the direction of the data and linearly independent data are calculated with ease using eigen vectors. Sometime it is also known as vector of co-variance. From here we have to sort the vectors with respect to eigen values which represents variance.




f) Eigen faces Calculation is done in this step. This is done by multiplying the eigen vectors with the data obtained from normalization of the training set in step c.



g) The next step is to identify the most relevant eigenfaces among many faces. For this step some heuristics algorithms are used and the eigen faces are chosen according to that. Normally heuristically a threshold value is chosen and eigen faces above that threshold value is taken into consideration. The reduction in dimension often depends over the number of eigen faces that are chosen.

h) The last step is to calculate the weight of the image. Here each of the chosen eigen faces are multiplied with the normalized training sets. In this process each image is converted into a linear combination of eigen faces.

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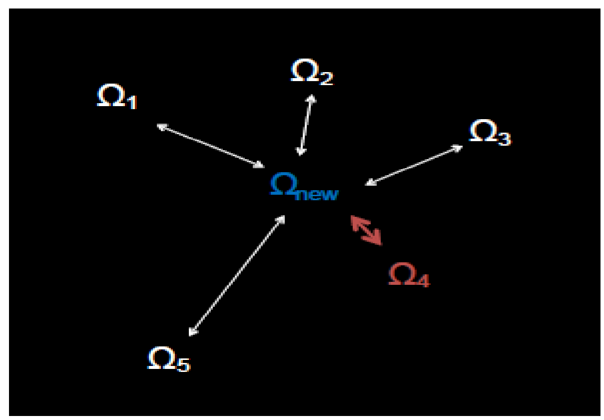
<u>Detection of a face</u>

All the steps that are carried out in dataset training model are also carried out in detecting a face , the only difference is that they use the testing pictures instead of the training picture.
Now when the weights of the testing data is calculated it is then verified to ensure that it is a face or not. This process is done by accessing the distances between the new image and that of trained images. The mean distance of the above calculated distances are used to check that if it is greater than a threshold value which provides a criteria for recognizing if its a face or not. Again this threshold is calculated using heuristics.




Ω represents distances.

## VI. Conclusion

Earlier Face Recognition techniques were not so powerful because of limited use of face features and the matching techniques were not so much efficient. The eigen face approach was a huge success because it has the capability of recognizing face using minimal image features. Still there are many shortcomings of the eigen face approach but because it is fast and simple .Many recognition system does not need a perfect match of the perceived image ,just it has to check whether the image matches a existing image in the database. So in face identification kind of recognition eigen face approach tend to work very well as a close match of the perceived image and the images present in the database is done. This same thing happens in the security systems where the face images that can gain access to the system are stored previously and when a face tries to access the system, it gets verified or matched with the database image using the key points of the image to that of the key points of the normalized image face derived from the training sets image in the database.

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