A STUDY OF EIGEN VECTOR BASED FACE VERIFICATION IN STATIC IMAGES

A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Technology

In

Computer Science

By

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Department of Computer Science & Engineering

National Institute of Technology

Rourkela

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CERTIFICATE

This is to certify that the thesis entitled, "**A Study of Eigenvector Based Face Verification In Static Images"** submitted by Sri **N.Krishna** in partial fulfillment of the requirements for the award of Master of Technology Degree in Computer Science and Engineering at the National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

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ABSTRACT

As one of the most successful application of image analysis and understanding, face recognition has recently received significant attention, especially during the past few years. There are at least two reasons for this trend the first is the wide range of commercial and law enforcement applications and the second is the availability of feasible technologies after 30 years of research. The problem of machine recognition of human faces continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology. The strong need for user-friendly systems that can secure our assets and protect our privacy without losing our identity in a sea of numbers is obvious. Although very reliable methods of biometric personal identification exist, for example, fingerprint analysis and retinal or iris scans, these methods depend on the cooperation of the participants, whereas a personal identification system based on analysis of frontal or profile images of the face is often effective without the participant's cooperation or knowledge. The three categories of face recognition are face detection, face identification and face verification. Face Detection means extract the face from total image of the person. Face identification means the input to the system is an unknown face, and the system reports back the determined identity from a database of known individuals. Face verification means the system needs to confirm or reject the claimed identity of the input.

My thesis was face verification in static images. Here a static image means the images which are not in motion. The eigenvectors based face verification algorithm gave the results on face verification in static images based upon the eigenvectors and neural network backpropagation algorithm. Eigen vectors are used for give the geometrical information about the faces. First we take 10 images for each person in same angle with different expressions and apply principle component analysis. Here we consider image dimension as 48 x48 then we get 48 eigenvalues. Out of 48 eigenvalues we consider only 10 highest eigenvaues corresponding eigenvectors .These eigenvectors are given as input to the neural network for training. Here we used backpropagation algorithm for training the neural network. After completion of training we give an image which is in different angle for testing purpose. Here we check the verification rate (the rate at which legitimate users is granted access) and false acceptance rate (the rate at which imposters are granted

access).Here neural network take more time for training purpose. The proposed algorithm gives the results on face verification in static images based upon the eigenvectors and neural network modified backpropagation algorithm. In modified backpropagation algorithm momentum term is added for decrease the training time. Here for using the modified backpropagation algorithm verification rate also slightly increased and false acceptance rate also slightly decreased.

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Chapter 1

INTRODUCTION

Biometrics and ATM

Motivation

Face Recognition

Conclusion

1. INTRODUCTION

Biometrics can be defined as the use of physiological or behavioral characteristics to recognize or verify the claimed identity of an individual. Not surprisingly, biometrics developed in high security application areas, particularly military and other government applications, but had its (non-automated) roots in trading and later in criminology where, for fingerprint, it is most renowned. Paradoxically, on-line trading is one of the latest application areas to employ biometrics. Other growth application areas are immigration control, workstation/network access, and physical access security.

1.1 BIOMETRICS AND ATM

As cards and PINs (Personal Identification Numbers) were one of the first automated identity tokens (card) and identifiers (PIN), it is easy to see why the biometrics system vendors have suggested ATMs (Automated Teller Machines) as a potential application area for their products and, conversely, why ATM vendors and their customers saw biometrics as a possible replacement for PIN. Indeed, many ATM customers use biometrics as an alternative to card/PIN for internal physical access security. On the surface there are valid reasons [6] to replace PIN at the ATM.

- PIN does not prove the identity of the card holder – just that the user knows the PIN.
- PINs can be forgotten leading to user frustration and cost of card/PIN replacement.
- PINs are easily transferred or distributed
- PINs can be “stolen” by observation or fraud measure.
- People write down PINs as memory aid but risk fraud.
- 4 digit PINs only provide a variability of 1 in 10000.

Biometrics could provide a more secure, easier to use alternative. Ideally biometrics

- Proves the claimed identity of the card holder
- Cannot be forgotten
- Has very high variability
- Cannot be transferred or stolen.

What are the available biometric techniques? How do they work? How do you use them? Are they effective? Biometric techniques are split into the popular biometrics [6], which are detailed below and address the above questions, and some potentially interesting but unproven or impractical systems which are listed but cannot be described in detail at present. The popular biometrics are listed below in order of market size according to the International Biometric Group report of 2000.

- Finger print
- Face
- Iris
- Signature

In the above listed biometric techniques, we concentrate on the Face biometric.

1.2 MOTIVATION

As one of the most successful application of image analysis and understanding, face recognition has recently received significant attention, especially during the past few years. There are at least two reasons for this trend [12], the first is the wide range of commercial and law enforcement applications and the second is the availability of feasible technologies after 30 years of research. In addition, the problem of machine recognition of human faces continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology. The strong need for user-friendly systems that can secure our assets and protect our privacy without losing our identity in a sea of numbers is obvious. At present, one needs a PIN to get cash from an ATM, a password for a computer, a dozen others to access the internet, and so on. Although very reliable methods of biometric personal identification exist, for example, fingerprint analysis and retinal or iris scans, these methods depend on the cooperation of the participants, whereas a personal identification system based on analysis of frontal or profile images of the face is often effective without the participant’s cooperation or knowledge. This is our major motivation to do research on face recognition.

1.3 FACE RECOGNITION

A general statement of the problem of machine recognition of faces can be formulated as follows: given still or video images of a scene, identify or verify one or more persons in the scene using a stored database of faces. Available collateral information such as race, age, gender, facial expression, or speech may be used in narrowing the search (enhancing recognition). The solution to the problem involves segmentation of faces (face detection) from cluttered scenes, feature extraction from the face regions, for recognition, or verification .Generally for solving the face recognition the following solutions are listed below.

- Face Detection
- Face Identification
- Face Verification

1.3.1 Face Detection

Face Detection means extract the face from total image of the person. For using some DSP approaches (segmentation of faces from cluttered scenes) we can extract the face from total image of the person.

1.3.2 Face Identification

In identification problems, the input to the system is an unknown face, and the system reports back the determined identity from a database of known individuals. Face identification is a one-to-many matching process that compares a query face image against all the template images in a face database to determine the identity of the query face. The identification of the test image is done by locating the image in the database who has the highest similarity with the test image. The identification process is a "closed" test, which means the sensor takes an observation of an individual that is known to be in the database. The test subject's (normalized) features are compared to the other features in the system's database and a similarity score is found for each comparison. These similarity scores are then numerically ranked in a descending order. The percentage of times that the highest similarity score is the correct match for all individuals is referred to as the top match score

1.3.3 Face Verification

In face verification problem the system needs to confirm or reject the claimed identity of the input. In face verification problem we decided whether that face belongs to that person or not. Face Verification is a one-to-one match that compares a query face image against a template face image whose identity is being claimed. To evaluate the verification performance, the verification rate (the rate at which legitimate users is granted access) vs. false accepts rate (the rates at which imposters are granted access) is plotted, called ROC curve. A good verification system should balance these two rates based on operational needs.

Generally Face recognition problem involves in two ways.

- Face Recognition in Static images
- Face Recognition in Dynamic images like videos.

A static image means the image which is not in motion. A dynamic image means the image which is in motion. Finally we did research on Face Verification on static images. Here we explain introduction about face recognition.

Over the last ten years or so, face recognition has become a popular area of research in computer vision and one of the most successful applications of image analysis and understanding. Because of the nature of the problem, not only computer science researchers[12] are interested in it, but neuroscientists and psychologists also. It is the general opinion that advances in computer vision research will provide useful insights to neuroscientists and psychologists into how human brain works, and vice versa. Humans are very good at recognizing faces and complex patterns. Even a passage of time doesn't affect this capability and therefore it would help if computers become as robust as humans in face recognition. Face Recognition is a high dimensional pattern recognition problem. Even low-resolution face images generate huge dimensional feature spaces (22,500 dimensions in the case of a 150x150 pixels face image).

Generally in the procedure of machine face recognition two issues are central:

- What features can be used to represent a face under environment changes?
- How to classify a new face image, based on the chosen features, into one of the possibilities.

In first issue, many successful face feature extraction procedures have been presented and developed. In second issue, classifier plays an essential role in the face detection process Neural network based (NN) classifier [14] has been proven to have many advantages for classification such as incredible generalization and good learning ability. Among the most successful approaches used in face recognition we can mention neural network approach.

ANNs have been applied to an increasing number of real-world problems of considerable complexity. Their most important advantage is in solving problems that are too complex for conventional technologies like problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. In general, because of their abstraction from the biological brain, ANNs are well suited to problems that people are good at solving, but for which computers are not. These problems include pattern recognition and forecasting (which requires the recognition of trends in data). The invariance properties of moments of images have received considerable attention in recent years. The term invariant denotes an image feature remains unchanged if that image undergoes one or a combination of the changes such as: change of size (scale), change of position (translation), change of orientation (rotation), and reflection. This is main reason for using neural networks in my face verification thesis.

1.3.4 Face Verification Applications

- Human Computer interaction.
- Checking for the criminal records.

1.4 CONCLUSION

We explain brief introduction about the biometric techniques in this chapter. We also explain why researchers attract towards the biometric techniques. Here we give brief introduction about face recognition, face detection, and face verification.

Chapter 2

Overview of Face Verification

Key Design Issues

Previous Research on Face Recognition

Segmentation

Feature Extraction

Recognition

Previous Research on Face Verification in Static images.

Conclusion

2. OVERVIEW OF FACE VERIFICATION

As one of the most successful application of image analysis and understanding, face recognition has recently received significant attention, especially during the past few years. This is evidenced by the emergence of face recognition conferences such as International Conference on Automatic Face and Gesture Recognition (AFGR) since 1995 and Audio and Video-Based Authentication (AVBPA) since 1997 concentrated on systematic empirical evaluations of face recognition techniques (FRT). There are at least two reasons for this trend[12], the first is the wide range of commercial and law enforcement applications and the second is the availability of feasible technologies after 30 years of research. In addition, the problem of machine recognition of human faces continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology. The strong need for user-friendly systems that can secure our assets and protect our privacy without losing our identity in a sea of numbers is obvious. At present, one needs a PIN to get cash from an ATM, a password for a computer, a dozen others to access the internet, and so on. Although very reliable methods of biometric personal identification exist, for example, fingerprint analysis and retinal or iris scans, these methods rely on the cooperation of the participants, whereas a personal identification system based on analysis of frontal or profile images of the face is often effective without the participant's cooperation or knowledge. Commercial and law enforcement applications of FRT range from static, controlled-format photographs to uncontrolled video images, posing a wide range of technical challenges and requiring an equally wide range of techniques from image processing, analysis, understanding, and pattern recognition. One can broadly classify FRT systems into two groups depending on whether they make use of static images or of video. A general statement of the problem of machine recognition of faces can be formulated as follows: given still or video images of a scene, identify or verify one or more persons in the scene using a stored database of faces. Available collateral information such as race, age, gender, facial expression, or speech may be used in narrowing the search (enhancing recognition).). The solution to the problem involves segmentation of faces (face detection) from cluttered scenes, feature extraction from the face regions, for recognition, or verification. In identification problems, the input to the system is an unknown face, and the system reports back the determined identity from a database of known individuals, whereas in verification problems, the system needs to confirm or reject the claimed identity of the input.

Over the last ten years or so, face recognition has become a popular area of research in computer vision and one of the most successful applications of image analysis and understanding. Because of the nature of the problem, not only computer science researchers are interested in it, but neuroscientists and psychologists also. It is the general opinion that advances in computer vision research will provide useful insights to neuroscientists and psychologists into how human brain works, and vice versa.

A general statement of the face recognition problem [2] (in computer vision) can be formulated as follows :Given still images of a scene, identify or verify one person in the scene using a stored database of faces.

One of the most common causes of network security breaches is easily guessable or insecure passwords. Many users choose common names or words that are in any dictionary; others use the same passwords everywhere or write them down where they can be discovered. Wouldn’t it be great if you never had to remember another password? This is one of the claimed benefits of biometrics—technologies that let machines recognize you via one or more physical features. Devices are now available that can examine users’ fingerprints, facial features, and irises. Humans are very good at recognizing faces and complex patterns. Even a passage of time doesn't affect this capability and therefore it would help if computers become as robust as humans in face recognition. Face recognition system can help in many ways [14].

- Checking for criminal records. Post 9/11 has changed how the nation looks at security. Face Recognition system could be one solution to increase security.
- Enhancement of security by using surveillance cameras in conjunction with face recognition system.
- Finding lost children's by using the images received from the cameras fitted at some public places.
- Detection of a criminal at public place.

- Human Computer interaction.

The interest is motivated by applications such as access control systems, model-based video coding, criminal identification and authentication in secure system like computer or bank teller machine. Although many face recognition by human beings and machines, it is still difficult to design an automatic system for the task because in real world, illumination, complex background, visual angle and facial expression for face images are highly variable.

2.1 KEY DESIGN ISSUES

The following are key design issues in Face recognition system.

- Approximation
- Estimation
- Computation

Approximation means is the system capable of accurately approximating the desired relationship. Estimation means how much training data needed for your system. Computation means how should it best use that data to compute its predictions?

2.2 PREVIOUS RESEARCH ON FACE RECOGNITION

Over the past 20 years extensive research has been conducted by psychophysicists, neuroscientists and engineers on various aspects of face recognition by humans and machines. Psychophysicists and neuroscientists have been concerned with issues such as: Uniqueness of faces; whether face recognition is done holistically or by local feature analysis; analysis and use of facial expressions for recognition; how infants perceive faces; organization of memory for faces; inability to accurately recognize inverted faces; existence of a “grandmother” neuron for face recognition; role of the right hemisphere of the brain in face perception and inability to recognize faces due to conditions such as prosopagnosia. Some of the theories put forward to explain the observed experimental results are contradictory. Many of the hypotheses and theories put forward by researchers in these disciplines have been based on rather small sets of images. During the early and mid- 1970’s, typical pattern classification techniques, which use measured attributes between features in faces or face profiles, were used. During the 1980’s, work on face recognition remained largely dormant. Since the early 1990’s, research interest in FRT has grown very significantly. One can attribute this to several reasons: An increase in emphasis on civilian/commercial research projects; the reemergence of neural network classifiers with emphasis on real-time computation and adaptation; the availability of real time hardware; and the increasing need for surveillance-related applications due to drug trafficking, terrorist activities, etc. Over the last five years, increased activity has been seen in tackling problems such as segmentation and location of a face in a given image, and extraction of features such as eyes, mouth, etc. Also, numerous advances have been made in the design of statistical and neural network classifiers for face recognition. In addition to recognition using full face images, techniques that use only profiles constructed from a side view are also available. These methods typically use distances between the fiducial points in the profile (points such as the nose tip, etc.) as features. Modifications of Fourier descriptors have also been used for characterizing the profiles. Profile based methods are potentially useful for the mug shot problem, due to the availability of side views of the face.

One can broadly classify the challenges and techniques into two groups: static (no video) and dynamic (video) matching. Even among these groups, significant differences exist, depending on the specific application. The differences are in terms of image quality, amount of background clutter (posing challenges to segmentation algorithms), the availability of a well defined matching criterion, and the nature, type and amount of input from a human.

2.2.1 Is face recognition a dedicated process?

Evidence for the existence of a dedicated face processing system comes from three sources.

- Faces are more easily remembered by humans than other objects when presented in an upright orientation.
- Prosopagnosia patients are unable to recognize previously familiar faces, but usually have no other profoundagnosia. They recognize people by their voices, hair color, dress, etc. Although they can perceive eyes, nose, mouth, hair, etc., they are unable to put together these features for the purpose of identification. It should be noted that prosopagnosia patients recognize whether the given object is a face or not, but then have difficulty in identifying the face.

- It is argued that infants come into the world pre-wired to be attracted by faces.

2.2.2 Caricatures

Caricature formally defines [16] a "caricature as a symbol that exaggerates measurements relative to any measure which varies from one person to another." Thus the length of a nose is a measure that varies from person to person, and could be useful as a symbol in caricaturing someone, but not the number of ears. Caricatures do not contain as much information as photographs, but they manage to capture the important characteristics of a face; experiments comparing the usefulness of caricatures and line drawings decidedly favor the former.

2.2.3 Distinctiveness

Studies show that distinctive faces are better retained in recognition memory and are recognized better and faster than typical faces. However, if a decision has to be made as to whether an object is a face or not, it takes longer to recognize an typical face than a typical face.

2.2.4 Facial expression

Based on neurophysiologic studies, it seems that analysis of facial expressions [15] is accomplished in parallel to face recognition. Some prosopagnosic patients, who have difficulties in identifying familiar faces, nevertheless seem to recognize emotional expressions. Patients who suffer from "organic brain syndrome" suffer from poor expression analysis but perform face recognition quite well. Normal humans exhibit parallel capabilities for facial expression analysis and face recognition. Similarly, separation of face recognition and "focused visual processing" (look for someone with a thick mustache) tasks have been claimed.

2.2.5 Role of race/gender

Humans recognize people [19] from their own race better than people from another race. This may be due to the fact that humans may be coding an "average" face with "average" attributes, the characteristic of which may be different for different races, making the recognition of faces from a different race harder. Using the same data collected in some studies have been done to quantify the role of gender in face recognition. It has been found that in a Japanese population, a majority of the women's facial features are more heterogeneous than the men's features. It has also been found that white women's faces are slightly more variable than men's, but that the overall variation is small.

2.2.6 Image Quality

The relationship between image quality and recognition of a human face has been explored. The task required of observers is to identify one face from a gallery of 35 faces. The modulation transfer function area (MTFA) was used as a metric to predict an observers performance in a task requiring the extraction of detailed information from both static and dynamic displays. Performance for an observer is measured by two dependent variables- proportion of correct responses and response time. It was found that as the MTFA becomes moderately large, facial recognition performance reaches a ceiling which cannot be exceeded.

For engineers interested in designing algorithms and systems for face recognition, numerous studies in psychophysics and neurophysiological literature serve as useful guides. As an example, designers should include both global and local features for representing and recognizing faces. Among the features, some (hairline, eyes, mouth) are more significant or useful than others (nose). This observation is true for frontal images of faces, while for side views and profiles, the nose is an important feature. Studies on distinctiveness and caricatures can help add special features of the face that can be utilized for perceiving and recognizing faces. The role of spatial frequency analysis suggests multiresolution/multiscale algorithms for different problems related to face perception. Issues such as how humans recognize people from their own race better than people from another race, and how infants recognize faces, are very important in the design of systems for expert identification, witness face reconstruction, electronic mug shots books and lineups.

2.3 SEGMENTATION

One of the earliest papers that reported the presence or absence of a face in an image. Kelly introduced a top-down image analysis approach known as PLANNING for automatically extracting the head and body outlines from an image and subsequently the locations of eyes, nose, mouth. As an example, the head extraction algorithm works as follows: Smoothed versions of original images (obtained by local averaging) are first searched for edges that may form the outline of a head; extracted edge locations are then projected back to the original image, and a fine search is locally performed for edges that form the head outline. Several heuristics are used to connect the edges. Once the head outline is obtained, the expected locations for eyes, nose and mouth are searched for locating these features. Several heuristics are again employed in the search process.

The algorithm for extracting the body of a person, subtracts the image of the background without the person from the image that has the person. This difference image is reduced in size by averaging and then thresholded. After applying a connected component algorithm, the extremes of the regions obtained define the region in which the body is located. Govindaraju**.** consider a computational model for locating the face in a cluttered image. Their technique utilizes a deformable template which is slightly different than that of Yuille. Working on the edge image they base their template on the outline of the head. The template is composed of three segments that are obtained from the curvature discontinuities of the head outline. These three segments form the right side-line, the left side-line and the hairline of the head. Each one of these curves is assigned a four-tuple consisting of the length of the curve, the chord in vector form, the area enclosed between the curve and the chord, and the centroid of this area. To determine the presence of the head, all three of these segments should be present in particular orientations. The center of these three segments gives the location of the center of the face. The templates are allowed to translate, scale and rotate according to certain spring-based models. They construct a cost function to determine hypothesized candidates. They have experimented on about ten images, and though they claim to have never failed to miss a face, they do get false alarms.

Craw describes [16] a method for extracting the head area from the image. They use a hierarchical image scale and a template scale. Constraints are imposed on the location of the head in the image. Resolutions of 8 x 8, 16 x 16, 32 x 32, 64 x 64 and full scale 128 x 128 are used in their multi resolution scheme. At the lowest resolution a template is constructed of the head outline. Edge magnitude and direction are calculated from the gray level image using a Sobel mask. A line follower is used to connect the outline of the head. After the head outline has been located a search for lower level features such as eyes, eyebrows, and lips is conducted, guided by the location of the head outline, using a similar line following method. The algorithm for detecting the head outline, performed better than the one searching for the eyes.

Another method of finding the face in an image was defined by Burt. It utilized a coarse to fine approach with a template based match criteria to locate the head. Burt illustrates the usefulness of such techniques by describing a “smart transmission” system. This system could locate and track the human head and then send the information of the head location to an object based compression algorithm.

In Craw, Tock, and Bennet describe a system to recognize and measure facial features. Their work was motivated in part by automated indexing of police mug shots. They endeavor to locate 40 feature points from a grayscale image; these feature points were chosen according to Shepherd which was also used as a criterion of judgment. The system uses a hierarchical coarse-to fine search. The template drew upon the principle of polygonal random transformation in Grenander. The approximate location, scale and orientation of the head is obtained by iterative deformation of the whole template by random scaling, translation and rotation. A feasibility constraint is imposed so that these transformations do not lead to results that have no resemblance to the human head. Optimization is achieved by simulated annealing. After a rough idea of the location of the head is obtained, refinement is done by transforming individual vectors of the polygon. The authors claim successful segmentation of the head in all 50 images that were tested. In 43 of these images a complete outline of the head was distinguishable; in the remaining ones there was failure in finding the chin. The detailed template of the face included eyes, nose, mouth, etc, in all, 1462 possible feature points were searched for the authors claim to be able to identify 1292 of these feature points. The only missing feature was the eyebrow, as they did not have a feature expert for that. They attribute the 6% incorrect identification to be due to presence of beards and mustaches in their database, which caused mistakes in locating the chin and the mouth of the subject. It should be noted that due to its use of optimization and random transformation, the system is inherently computationally intensive.

2.4 FEATURE EXTRACTION

Recently, the use of the Karhunen-Loeve (KL) expansion [22] for the representation and recognition of faces has generated renewed interest. The KL expansion has been studied for image compression for more than 30 years its use in pattern recognition applications has also been documented for quite some time .One of the reasons why KL methods, although optimal, did not find favor with image compression researchers is their computational complexity. As a result, fast transforms such as the discrete sine and cosine transform have been used]. In Sirovich and Kirby revisit the problem of KL representation of images (cropped faces). Once the eigenvectors (referred to as “eigenpictures”) are obtained, any image in the ensemble can be approximately reconstructed using a weighted combination of eigenpictures. By using an increasing number of eigenpictures, one gets an improved approximation to the given image. The authors also give examples of approximating an arbitrary image (not included in the calculation of eigenvectors) by the eigenpictures. The emphasis in this paper is on the representation of human faces. The weights that characterize the expansion of the given image in terms of eigenpictures serve the role of features.

In a subsequent extension of their work, Kirby and Sirovich [22] include the inherent symmetry of faces in the eigenpicture representation of faces, by using an extended ensemble of images consisting of original faces and their mirror images. Since the computations of eigenvalues and eigenvectors can be split into even and odd pictures, there is no overall increase in computational complexity compared to the case in which only the original set of pictures in used. Although the eigen representation for the extended ensemble does not produce dramatic reduction in the error in reconstruction when compared to the unextended ensemble, still the method that accounts for symmetry in the patterns is preferable.

Generally the KL is combined with two other operations to improve the performance of the extraction technique for the classification of front-view faces. The application of the KL expansion directly to a facial image without standardization does not achieve robustness against variations in image acquisition. uses standardization of the position and size of the face. The center points are the regions corresponding to the eyes and mouth. Each target image is translated, scaled and rotated through affine transformation so that the reference points of the eyes and mouth are in a specific spatial arrangement with a constant. distance. An empirically defined standard window encloses the transformed image. The KL expansion applied to the standardized face images is known as the Karhunen-Loeve transform of intensity pattern in affine-transformed target (KL-IPAT) image. The KL-IPAT was extracted from 269 images with 100 eigenfaces. The second step is to apply the Fourier Transform to the standardized image and use the resulting Fourier spectrum instead of the spatial data from the standardized image. The KL expansion applied to the Fourier spectrum is called the Karhunen-Loeve transform of Fourier spectrum in the affine-transformed target (KL-FSAT) image. The robustness of the KL-IPAT and KL-FSAT was checked against geometrical variations using the standard features for 269 face images.

Generally the image features are divided into four groups [23]: visual features, statistical pixel features, transform coefficient features, and algebraic features, with emphasis on the algebraic features, which represent the intrinsic attributes of an image. The singular value decomposition (SVD) of a matrix is used to extract the features from the pattern. SVD can be viewed as a deterministic counterpart of the KL transform. The singular values (SV's) of an image are very stable and represent the algebraic attributes of the image, being intrinsic but not necessarily visible. This proves their stability and invariance to proportional variance of image intensity in the optimal discriminant vector space, to transposition, rotation, translation, and reflection which are important properties of the SV feature vector. The Foley-Sammon transform is used to obtain the optimal set of discriminant vectors spanning the Sammon discriminant plane. For a small set of 45 images of nine persons two of the vectors seem to be adequate for recognition; more discriminant vectors will be needed for recognition with more images. The SVD operation is applied to each image matrix for extracting SV features and the SV vector.

Yuille, Cohen, and Hallinen describe extract facial features using deformable templates. These templates are allowed to translate, rotate and deform to fit the best representation of their shape present in the image. Preprocessing is done to the initial intensity image to get representations of peaks and valleys from the intensity image. Morphological filters are used to determine these representations. Their template for the eye has eleven parameters consisting of the upper and lower arcs of the eye; the circle for the iris; the center points; and the angle of inclination of the eye. This template is fit to the image in an energy minimization sense. Energy functions of valley potential, edge potential, image potential, peak potential, and internal potential are determined. Coefficients are selected for each potential and an update rule is employed to determine the best parameter set. In their experiments they found that the starting location of the template is critical for determining the exact location of the eye. When the template was started above the eyebrow, the algorithm failed to distinguish between the eye and the eyebrow. Another drawback to this approach is its computational complexity. Generally speaking, template based approaches to feature extraction are a more logical approach to take. The problem lies in the description of these templates. Whenever analytical approximations are made to the image, the system has to be tolerant to certain discrepancies between the template and the actual image. This tolerance tends to average out the differences that make individual faces unique.

2.5 RECOGNITION

One of the earliest works in computer recognition of faces is reported by Bledsoe. In this system, a human operator located the feature points on the face and entered their positions into the computer. Given a set of feature point distances of an unknown person, nearest neighbor or other classification rules were used for identifying the label of the test image. Since feature extraction is manually done, this system could accommodate wide variations in head rotation, tilt, image quality, and contrast.

A landmark work on face recognition is reported in the doctoral dissertation of M. D**.** Kelly. Kelly's work is similar in framework to that of Bledsoe, but is significantly different in that it does not involve any human intervention. Although we cite this work in connection with face recognition, Kelly's dissertation has made several important contributions to goal directed (also known as top-down) and multiresolution image analysis. Kelly uses the body and close up head images for recognition. The body measurements include heights, widths of the head, neck, shoulders, and hips. Measurements from the face include width of the head and distances between eyes, top of head to eyes, between eyes and nose and the distance from eyes to mouth. The nearest neighbor rule was used for identifying the class label of the test image; the leave one-out strategy was used. The dataset consisted of a total of 72 images, comprised of 24 sets of three images of ten persons. Each set had three images per person; image of the body, image of the background corresponding to the body image and a close-up of the head.

Kaya report a basic study using information theoretic arguments in classifying human faces. They reason from the fact that to represent N different faces a total of log2 N bits are required (upper bound on the entropy). They contend that since illumination and background are the same for all face images and the images taken are photographs of front views of human faces, with mouth closed, no beards, and no eyeglasses, therefore the dimensionality of the parameter space can be reduced from the above upper bound. Sixty two photographs were taken with a special apparatus to ensure correct orientation and lighting conditions. An experiment was conducted using 10 – 40 human subjects to identify prominent geometric features from three different faces. The authors identify nine of these parameters to run statistical experiments on. these parameters form a parameter vector composed of internal biocular breadth, external biocular breadth, nose breadth, mouth breadth, bizygomatic breadth, bigonial breadth, distance between lower lip and chin, distance between upper lip and nose and height of lips. They construct a classifier based on the parameter vector and its estimate, i.e., if X is the parameter vector then the estimate Y is given as Y = X+D where D is the distortion vector. The distortion vector D has two components Dm**,** the distortion due to data acquisition and sampling error and D_i due to inherent variations in facial features. The authors discuss two cases, one in which D, is negligible and the other where D is comparable to D_i. For each parameter a threshold is determined from its statistical behavior. Classification is done using the absolute norm between a stored parameter set and the input image parameter values. It should be noted that the parameter values are determined manually.

2.6 PERVIOUS RESEARCH ON FACE RECOGNITION IN STATIC IMAGES

One method of characterizing the face is the use of geometrical parameterization [20], i.e., distances and angles between points such as eye comers, mouth extremities, nostrils, and chin top .The data set used by Kanade consists of 17 male and three female faces without glasses, mustaches, or beards. Two pictures were taken of each individual, with the second picture being taken one month later in a different setting. The face-feature points are located in two stages. The coarse-grain stage simplified the succeeding differential operation and feature-finding algorithms. Once the eyes, nose and mouth are approximately located, more accurate information is extracted by confining the processing to four smaller regions, scanning at higher resolution, and using the “best beam intensity” for the region. The four regions are the left and right eye, nose, and mouth. The beam intensity is based on the local area histogram obtained in the coarse-grain stage. A set of 16 facial parameters which are ratios of distances, areas, and angles to compensate for the varying size of the pictures is extracted. To eliminate scale and dimension differences the components of the resulting vector are normalized. The entire data set of 40 images is processed and one picture of each individual is used in the training set. The remaining 20 pictures are used as a test set. A simple distance measure is used to check for similarity between an image of the test set and the image in the reference set. Matching accuracies range from 45% to 75% correct, depending on the parameters used. Better results are obtained when several of the ineffective parameters are not used.

2.6.1 Statistical Approach

Turk and Pentland [7] used eigenpictures (also known as “eigenfaces”) for face detection and identification. Given the eigenfaces, every face in the database can be represented as a vector of weights; the weights are obtained by projecting the image into eigenface components by a simple inner product operation. When a new test image whose identification is required is given, the new image is also represented by its vector of weights. The identification of the test image is done by locating the image in the database whose weights are the closest (in Euclidean distance) to the weights of the test image. By using the observation that the projection of a face image and a nonface image are quite different, a method for detecting the presence of a face in a given image is obtained. Turk and Pentland illustrate their method using a large database of 2500 face images of 16 subjects, digitized at all combinations of three head orientations, three head sizes and three lighting conditions. Several experiments were conducted to test the robustness of the approach to variations in lighting, size, head orientation, and the differences between the training and test conditions. The authors reported 96% correct classification over lighting variations, 85% over orientation variations and 64% over size variations. It can be seen that the approach is fairly robust to changes in lighting conditions, but degrades quickly as the scale changes.

One of the applications the authors consider is interactive search through the database. When the system is asked to present face images of certain types of people (e.g., white females of age 30 years or younger), images that satisfy this query are presented in groups of 21**.** When the user chooses one of these images, the system presents faces from the database that look similar to the chosen face in the order of decreasing similarity. In a test involving 200 selected images, about 95% recognition accuracy was obtained-i.e. for 180 images the most similar face was of the same person. To evaluate the recognition accuracy as a function of race, images of white, black and Asian adult males were tested. For white and black males accuracies of 90% and 95% were reported, respectively, while only 80% accuracy was obtained for Asian males. The use of eigenfaces for personnel verification is also illustrated.

In mug shots applications, usually a frontal and a side view of a person are available. In some other applications, more than two views may be available. One can take two approaches to handling images from multiple views. The first approach will pool all the images and construct a set of eigenfaces that represent all the images from all the views. The other approach is to use separate eigenspaces for different views, so that the collection of images taken from each view will have its own eigenspace. The second approach, known as the view-based eigenspace, seems to perform better. For mug shots applications, since two or at most three views are needed, the view-based approach produces two or three sets of eigenspaces.

The concept of eigenfaces can be extended to eigenfeatures [20], such as eigeneyes, eigenmouth, etc. Just as eigenfaces were used to detect the presence of a face, eigenfeatures are used for the detection of features such as eyes, mouth etc. Detection rates of 94%, 80%, and 56% are reported for the eyes, nose and mouth, respectively, on the large dataset with 7562 images.

Using a limited set of images (45 persons, two views per person, corresponding to different facial expressions such as neutral versus smiling), recognition experiments as a function of number of eigenvectors for eigenfaces only and for the combined representation were performed. The eigenfeatures performed as well as eigenfaces; for lower order spaces, the eigenfeatures fared better; when the combined set was used, marginal improvement was obtained.

2.6.2 Neural Network Approach

The use of neural networks (NN) in face recognition [2] has addressed several problems: gender classification, face recognition, and classification of facial expressions. One of the earliest demonstrations of NN for face recall applications is reported in Kohonen’s associative map. Using a small set of face images, accurate recall was reported even when the input image is very noisy or when portions of the images are missing.

A single layer adaptive NN (one for each person in the database) for face recognition, expression analysis and face verification is reported. Named Wilkie, Aleksander, and Stonham’s recognition device (WISARD), the system needs typically 200-400 presentations for training each classifier, the training patterns included translation and variation in facial expressions. Sixteen classifiers were used for the dataset constructed using 16 persons. Classification is achieved by determining the classifier that gives the highest response for the given input image. Extensions to face verification and expression analysis are presented. The sample size is small to make any conclusions on the viability of this approach for large datasets involving a large number of persons.

Golomb, Lawrence, and Sejnowski present a cascade of two neural networks for gender classification. The first stage is an image compression NN whose hidden nodes serve as inputs to the second NN that performs gender classification. Both networks are fully connected, three-layer networks with two biases and are trained by a standard back-propagation algorithm. The images used for testing and training were acquired such that facial hair, jewelry and makeup were not present. They were then preprocessed so that the eyes are level and the eyes and mouth are positioned similarly. A 30 x 30 cropped block of pixels was extracted for training and testing. The dataset consisted of 45 males and 45 females; 80 were used for training, with 10 serving as testing examples. The compression network indirectly serves as a feature extractor; in that the activities of 40 hidden nodes (in a 900 x 40 x 900 network) serve as features for the second network,that performs gender classification. The hope is that due to the nonlinearities in the network, the feature extraction step may be more efficient than the linear KL methods. The gender classification network is a 40 x n x 1 network, where the number n of hidden nodes has been 2,5,10, 20, or 40. Experiments with 80 training images and 10 testing images have shown the feasibility of this approach. This method has also been extended to classifying facial expressions into eight types.

Using a vector of 16 numerical attributes such as eyebrow thickness, widths of nose and mouth, six chin radii, etc., Brunelli and Poggio also develop a NN approach for gender classification. They train two HyperBF networks one for each gender. The input images are normalized with respect to scale and rotation by using the positions of the eyes which are detected automatically. The 16D feature vector is also automatically extracted. The outputs of the two HyperBF networks are compared, the gender label for the test image being decided by the network with greater output. In the actual classification experiments only a subset of the 16D feature vector is used. The database consists of 21 males and 21 females. The leave-one-out strategy was employed for classification. When the feature vector from the training set was used as the test vector, 92.5% correct recognition accuracy was reported; for faces not in the training set, the accuracy further dropped to 87.5%.

2.7 CONCLUSION

Here we explain detailed literature review about Face recognition and Face verification. Here we also explain previous research on Face detection .

Chapter 3

PCA and NEURAL network

Historical Background

Benefits of Neural Network

Models Of neuron

Types of Activation Function

Network Architectures

Training

Backpropagation Algorithm

Applications of Neural networks

Principle Component analysis

Conclusion

3. PCA AND NEURAL NETWORKS

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. Neural networks resemble the human brain in the following two ways.

- A neural network acquires knowledge through learning.
- A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

Neural networks are also referred in literature as neurocomputers, connectionist networks, parallel distributed processors etc**.**

3.1 HISTORICAL BACKGROUND

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys the first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much.

3.2 BENEFITS OF NEURAL NETWORK

Neural network derives its computing power through, first, its massively parallel distributed structure and, second, its ability to learn and therefore generalize. Generalization refers to the neural network producing reasonable outputs for inputs not encountered during training (learning).These two information processing capabilities make it possible for neural networks to solve the complex (large-scale) problems that are currently intractable .The use of neural networks offers the following useful properties and capabilities.

3.2.1 Nonlinearity

An artificial neuron can be linear or nonlinear. A neural network, made up of an interconnection of nonlinear neurons is itself nonlinear. Nonlinearity is a highly important, particularly, if the underlying physical mechanism responsible for generation of the input signal is inherently nonlinear.

3.2.2 Input-Output mapping

A popular paradigm of learning is called learning with a teacher or supervised learning involves modification of the synaptic weights of a neural network by applying a set of labeled training samples. Each example consists of a unique input signal and a corresponding desired response .The network is presented with an example picked at random from the set, and the synaptic weights of the network are modified to minimize the difference between the desired response and the actual response of the network produced by input signal in accordance with an appropriate statistical criterion.

3.2.3 Adaptivity

Neural networks have a built in capability to adapt their synaptic weights to changes in the surrounding environment. In particular a neural network trained to operate in specific environment can be easily retrained to deal with minor changes in the operating environmental conditions. Moreover, when it is operating in a nonstationary environment (i.e where statistics change with time), a neural network can be designed to change its synaptic weights in real time .the natural architecture of a neural network for pattern classification,signal processing, and control applications coupled with the adaptive capability of the network ,make it useful tool in adaptive pattern classification, and adaptive signal processing.

3.2.4 Self Organization:

An ANN can create its own organization or representation of the information it receives during learning time.

3.2.5 Fault Tolerance

A neural network implemented in hardware form has the potential to be inherently fault tolerant, or capable of robust computation in the sense that its performance degrades gracefully under adverse operate conditions. For example if a neuron or its connecting links are damaged, recall of a stored pattern is impaired in quality.

3.3 MODELS OF NEURON

A neuron is an information processing unit that is fundamental to the operation of a neural network **.**An artificial neuron is a device with many inputs and many outputs. Each input is multiplied by a corresponding weight, analogous to a synaptic strength, and all the weighted inputs are then summed to determine the activation level of the neuron. These weighted inputs are then added together to produce 'net' output and if they exceed a pre-set threshold value, the neuron fires. The '**NET**' output produced is further processed by an activation function (**f**) to produce the neuron's output signal. A neuron is an information processing unit that is fundamental to the operation of a neural network. The following fig 3.1 represents basic model of neuron.

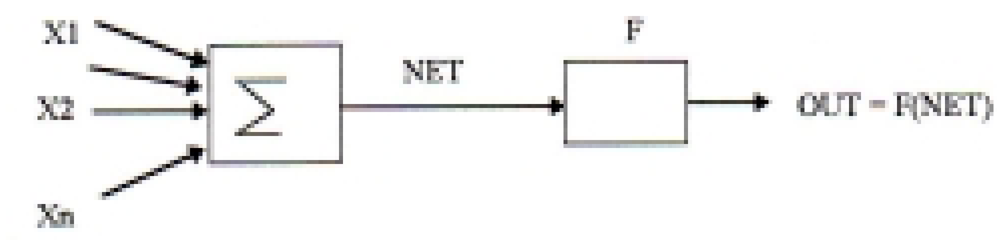

Fig 3.1: Basic model of neuron

The neuron contains three basic elements.

- A set of synapses or connecting links, each of which is characterized by a weight or strength of its own.
- An adder for summing the input signals weighted by the respective synapses of the neuron.
- An activation function for limiting the amplitude of the output of a neuron. The activation function is also referred to as a squashing function in that it squashes the permissible amplitude range of the output signal to some finite value.

3.4 TYPES OF ACTIVATION FUNCTION

The activation function is used for limiting the amplitude of the output of a neuron. Activation functions for the hidden units are needed to introduce nonlinearity into the network. This activation function is also called squashing function. This activation function squashes the permissible amplitude range of the output signal to some finite value. There are three types of activation functions. The activation function denoted by $\varphi(\upsilon)$,defines the output of a neuron in terms of the induced local field υ

- Binary Function
- Sigmoid Function
- Hyperbolic Tangent Function

3.4.1 Binary Function

The $\sum$ unit multiplies each input by a weight and sums the weighted inputs. If this sum is greater than a predetermined threshold, the output is one; otherwise it is zero. This activation function is called Binary Function.

$$\varphi(\upsilon) = 1 \text{ if } \upsilon > 0$$

$$= 0 \text{ if } \upsilon < 0$$

3.4.2 Sigmoid Function

The sigmoid function ,whose graph is s shaped is by far the most common form of activation function used in the construction of artificial neural networks. The block '**f**' accepts the **NET** output and produces the signal labeled **OUT**. If the **'f'** processing block compresses the range of **NET**, so that **OUT** never exceeds some limits regardless of the value of **NET**, **'f'** is called a squashing function. The squashing function is often chosen to be the logistic function or "sigmoid". This function is expressed in mathematically

$$\mathbf{OUT = 1/(1+e^{-NET})}$$

The non-linear gain is calculated by finding the ratio of the change in **OUT** to a small change in **NET.** It varies from a low value at large negative excitations, to a high value at zero excitation, and it drops back as excitation becomes very large and positive.

3.4.3 Hyperbolic Tangent Function

Another commonly used activation function is the hyperbolic tangent. Used as an artificial neural network activation function it is expressed mathematically

$$\mathbf{OUT = Tanh(x)}$$

Like the logistic function, the hyperbolic tangent function is S shaped, but symmetrical about the origin, resulting in **OUT** having the value 0 when **NET** is 0. Unlike the logistic function, the hyperbolic tangent function has a bipolar value for **OUT**, a characteristic that has been shown to be beneficial in certain networks.

3.5 NETWORK ARCHITECTURES

The manner in which the neurons of a neural network are structured is intimately linked with the learning with the algorithm used to train the network. There are three fundamentally classes of network architectures.

- Single layer feed forward Networks
- Multi layer feed forward Networks
- Recurrent networks**.**

3.5.1 Single layer feed forward Networks:

In a layered neural network the neurons are organized in the form of layers. In the simplest form of a layered network, input layer of source nodes that projects onto an output layer of neurons (computation nodes), but not vice versa. In other words this network is strictly a feed forward networks. Here single layer referring to the output layer of computation nodes.

3.5.2 Multilayer feed forward networks:

The second class of a feed forward neural network distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons or hidden units. The source nodes in the input layer of the network supply respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e. the first hidden layer).The output signals of the second layer are used as inputs to the third layer, and so on for the rest of the network. Typically the neurons in each layer of the network have as their inputs the output signals of preceding layer only. The set of output signals of the neurons in the output layer of the network constitutes the overall response of the network to the activation pattern supplied by the source nodes in the input layer .A feed forward network with m source nodes, h_1 neurons in the first hidden layer,h_2 neurons in the second hidden layer, and q neurons in the output layer is referred to as an m-h_1-h_2-q network. The following fig 3.2 shows the multilayer networks.

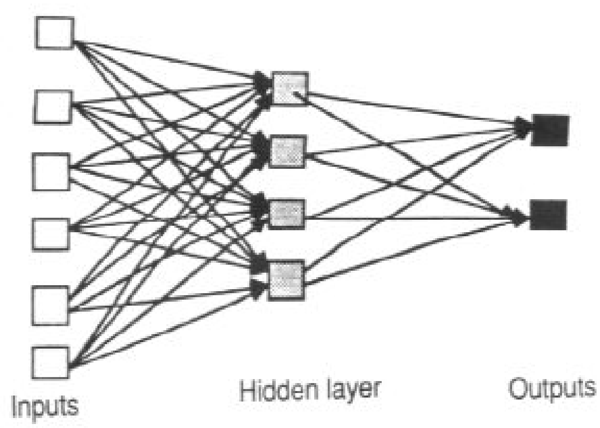

Fig 3.2 Multilayer network

3.5.3 Recurrent networks:

A recurrent network distinguishes itself from a feed forward neural network in that it has at least one feedback loop. A recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all other neurons.

3.6 TRAINING

A network is trained so that application of a set of inputs produces the desired set of outputs. Each such input set is referred to as a vector. Training is accomplished by sequentially applying input vectors, while adjusting network weights according to a predetermined procedure. During training, the network weights gradually converge to values such that each input vector produces the desired output vector. Training algorithms are categorized into two types.

- Supervised training
- Unsupervised training

3.6.1 Supervised Training:

Supervised learning which incorporates an external teacher, so that each output unit knows what its desired response to input signals ought to be. In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually changed. The set of data which enables the training is called the "training set." During the training of a network the same set of data is processed many times as the connection weights are ever refined.

3.6.2 Unsupervised Training:

Unsupervised learning uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. In unsupervised training, the network is provided with inputs but not with desired outputs. The system itself must then decide what features it will use to group the input data.

3.7 BACK PROPAGATION ALGORITHM

For many years, there was no theoretically sound algorithm for training multilayer artificial neural networks. The invention of the backpropagation algorithm has played a large part in the resurgence of interest in artificial neural networks. Backpropagation is a systematic method for training multilayer artificial neural networks (Perceptrons).Each input is multiplied by corresponding weights, analogous to a synaptic strength, and all the weighted inputs are then summed to determine the activation level of the neuron. These summed (NET) signals are further processed by an activation function (F) to produce the neuron’s output signal (OUT). In backpropagation, the function used for the activation is the logistic function or Sigmoid. This function is expressed mathematically as:

$$F(x) = \frac{1}{1+e^{-x}} \quad \text{thus } OUT = \frac{1}{1+e^{-NET}}$$

The Sigmoid compresses the range of NET so that OUT lies between zero and one. Since the back-propagation uses the derivative of the squashing function, it has to be everywhere differentiable. The Sigmoid has this property and the additional advantage of providing a form of automatic gain control (i.e. if the value of NET is large, the gain is small and if it is small the gain is large).

3.7.1 Backpropagation Training Algorithm

The objective of training the network is to adjust the weights so that the application of a set of inputs (input vectors) produces the desired outputs (output vectors). Training a backpropagation network involves each input vector being paired with a target vector representing the desired output; together they are called a training pair. The following Fig 3.3 shows the architecture of the multilayer backpropagation neural network.

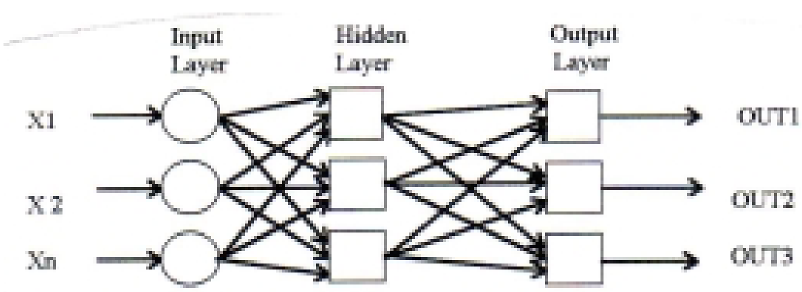

Fig3.3: Multilayer back propagation neural network

Before starting the training process, all of the weights are initialised to small random numbers. Training the backpropagation network requires the following steps:

1. Select a training pair (next pair) from the training data set and apply the input vector to the network input.
2. Calculate the output of the network, i.e. to each neuron NET=$\sum X_i W_i$ must be

calculated and then the activation function must be applied on the result F (NET).

3. Calculate the error between the network output and the desired output (TARGET – OUT).
4. Adjust the weights of the network in a way that minimises the ERROR .
5. Repeat step 1 through 4 for each vector in the training set until no training pair produces an ERROR larger than a pre-decided acceptance level

3.8 APPLICATIONS OF NEURAL NETWORKS

Neural networks have broad applicability to real world business problems. Since neural networks are best at identifying patterns or trends in data, they are well suited for prediction or forecasting needs including. Neural networks are very useful for following applications

- Facial recognition
- Written word recognition;
- Three-dimensional object recognition
- Undersea mine detection
- Recognition of speakers in communications;
- Sales forecasting
- Recovery of telecommunications from faulty software

3.9 PRINCIPLE COMPONENT ANALYSIS

PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. PCA is also called as eigen space based algorithm. The fundamental idea behind principal component analysis (PCA) with eigenvectors [4] has its basis in linear algebra. Put simply, if there are a series of multi-dimensional vectors representing objects which have similarities, it is possible to use a transformation matrix and eigenvectors to orient a space which requires fewer dimensions to accurately describe these multidimensional vectors. For instance, if in three dimensional space, there was a cloud of particles that lied in a two dimensional plane skewed from the axes, it would be possible to orient a new space with a new origin and new unit vectors such that the cloud which previously required a three dimensional representation could now easily be represented in only two dimensions. To a computer, a face, like any other image, is a matrix of several hundred pixels by several hundred pixels. Dealing with many faces , in the form of pictures, can be very time consuming and difficult. If, however, one applies principal component analysis, the task becomes much more manageable. If the picture's pixel matrix is turned into a vector, then that picture will have a location vector in a hundred thousand dimensional space. If the same is done with other pictures, their location vectors will wind up in the same area of this huge multi-dimensional space. We call this small subsection of the multi-dimensional space the "face space." Then using eigenvectors to create a new basis for the representing the images, one can now represent images as coordinates in a much smaller dimensional space. Images of the same person, will, of course, be located nearer to one another in this space, as they are similar to one another. At this level, the task of recognition becomes merely a matter of determining the location of the vector form of a new picture in a lower dimensional space relative to pictures of recognized faces.

Extract relevant information in a face image [Principal Components] and encode that information in a suitable data structure. For recognition take the sample image and encode it in the same way and compare it with the set of encoded images. In mathematical terms we want to find Eigen vectors and Eigen values of a covariance matrix of images[1]. Where one image is just a single point in high dimensional space [n * n], where n * n are the dimensions of an image. There can be many Eigen vectors for a covariance matrix but very few of them are the principle ones. Though each Eigen vector can be used for finding different amount of variations among the face image. But we are only interested in principal eigen vectors because these can account for substantial variations among a bunch of images. They can show the most significant relationship between the data dimensions. Eigenvectors with highest Eigen values are the principle component of the Image set. We may lose some information if we ignore the components of lesser significance. But if the eigenvalues are small then we won't lose much. Using those set of Eigen vectors we can construct eigenfaces. In order to apply the ideas of principal component analysis to face recognition,. Our first task was to find an average face. This was easily done by taking the arithmetic mean of the face vector. The following points are the steps for the Algorithm.

3.9.1 Steps Of PrincipleComponent analysis

Step 1: Get some data.

Here We take bunch of sample images for each person in different expressions. Find the mean image of each person.

Step 2: Subtract the mean

For PCA to work properly, you have to subtract the mean from each of the data dimensions. The mean subtracted is the average across each dimension. This produces a data set whose mean is zero. So we found mean image for each person and that mean image is subtracted from that person training images for get the zero mean.

Step 3: Calculate the covariance matrix

Standard deviation and variance only operate on 1 dimension, so that you could only calculate the standard deviation for each dimension of the data set independently of the other dimensions. However, it is useful to have a similar measure to find out how much the dimensions vary from the mean with respect to each other. Covariance is such a measure. Covariance is always measured between 2 dimensions. If you calculate the covariance between one dimension and itself, you get the variance. Here I found the covariance matrix for each persons training set using the covariance formula.

Step 4: Calculate the eigenvalues of the covariance matrix

Since the covariance matrix is square, we can calculate the eigenvalues for this matrix. Eigen values are calculated for NxN square matrix only. For finding the eigen values of any square matrix it must require one equation called characteristic equation. Eigen values are useful for giving more information for about that matrix.

Step 5: Calculate the eigenvectors of the covariance matrix

An eigenvector of a matrix is a vector such that, if multiplied with the matrix, the result is always an integer multiple of that vector. This integer value is the corresponding eigenvalue of the eigenvector.

Eigenvectors possess following properties:

- They can be determined only for square matrices
- There are n eigenvectors (and corresponding eigenvalues) in a n × n matrix.
- All eigenvectors are perpendicular, i.e. at right angle with each other.

Step 6: Choosing components and forming a feature vector

Here is where the notion of data compression and reduced dimensionality comes into it. In fact, it turns out that the eigenvector with the *highest* eigenvalue is the principle component of the data set. In general, once eigenvectors are found from the covariance matrix, the next step is to order them by eigenvalue, highest to lowest. This gives you the components in order of significance. Here the highest eigenvalues are called principle components because it gives more information about matrix .This highest eigenvalues are very less compared to lowest eigen values. Here ignoring the some eigen values loose some information about that matrix but if the eigenvalues are small you don't lose much .If you leave out some components, the final data set will have less dimensions than the original. To be precise, if you originally have n dimensions in your data, and so you calculate n eigenvectors and eigenvalues, and then you choose only the first p eigenvectors, then the final data set has only p dimensions. So feature vector contain the eigenvectors which is correspond to the highest eigenvalues.

3.10 CONCLUSION

We explain some neural network concepts which is useful for our research. Here we also explain principle component analysis which is very useful in face verification algorithm.

Chapter 4

Face Verification Algorithms

Face Verification Algorithm

Role of PCA in Face Verification

Proposed Algorithm

Simulation results

Conclusion

4. FACE VERIFICATION ALGORITHMS

Face Recognition is a high dimensional pattern recognition problem. Even low-resolution face images generate huge dimensional feature spaces (10000) dimensions in the case of a 100x100pixels face image). The interest is motivated by applications such as access control systems, model-based video coding, criminal identification and authentication in secure system like computer or bank teller machine. Although many face recognition by human beings and machines, it is still difficult to design an automatic system for the task because in real world, illumination, complex background, visual angle and facial expression for face images are highly variable .Several methods have been proposed for face detection, including graph matching , neural networks, and also geometric feature based They differ mostly in the kind of projection method been used and in the similarity matching criterion employed.

Generally in the procedure of machine face recognition two issues are mainly important.

- What features can be used to represent a face under environment changes?
- How to classify a new face image, based on the chosen features, into one of the Possibilities?

In first issue, many successful face feature extraction procedures have been presented and developed. In second issue, classifier plays an essential role in the face detection process Neural network based (NN) classifier [2] has been proven to have many advantages for classification such as incredible generalization and good learning ability. Among the most successful approaches used in face recognition we can mention neural network approach. ANNs have been applied to an increasing number of real-world problems of considerable complexity. Their most important advantage is in solving problems that are too complex for conventional technologies the problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. In general, because of their abstraction from the biological brain, ANNs are well suited to problems that people are good at solving, but for which computers are not. These problems include pattern recognition and forecasting (which requires the recognition of trends in data).

The invariance properties of moments of images have received considerable attention in recent years. The term invariant denotes an image feature remains unchanged if that image undergoes one or a combination of the changes such as: change of size (scale), change of position (translation), change of orientation (rotation), and reflection.

In this database the total number of images for each person is 10.None of the 10 samples are identical to each other. They vary in position, rotation, scale and expression. The change in orientation has been accomplished by rotating the person in the same plane, and also each person has changed his face expression in each of 10 samples. The change in scale has been achieved by changing the distance between the person and the video camera. Each image was digitized and presented by 640*480 pixel array .One sample of these images is shown in figure. We also use a database of 10 images of 9 individuals. A total of 90 images are used to train and another 90 are used to test, where each person has 10 testing images.

Face recognition is broadly classified into three categories. This is broad area for doing thesis.

1. Face detection
2. Face identification
3. Face verification.

Face detection [16] means detect the face from each person image. Using some DSP Algorithms extract the face from each person image. Face identification means identify the faces of different persons using training database. So here neural network and DSP approaches are very useful. In neural network approach take each person images with different expressions. In training phase using the neural network training algorithms train these images. In testing phase give each person testing images and recognize the person. Face verification means take one person images in same angle with different expressions and train these images using the neural network training algorithm. In testing phase recognize same person faces with different angles and different expressions. This is called face verification. We mainly concentrate on the face verification only.

4.1 FACE VERIFICATION ALGORITHM

Here first we collected the database of our friend’s faces with different expressions using digital camera .These all images are same angles with different expressions. Different expressions means happy, sorrow, angry etc. These all are color images. First we convert these color images into gray scale images using matlab command. These all images are in different dimensions. So we convert all these images into one common dimension. Here we perform resize operation on all images and convert these images into 48x48 dimensions. In this algorithm we take 10 images for training and 10 images for testing from nine individuals. .So our database contains total 90 images for training and another 90 for testing. The training images are in same angle with different expressions. Our testing images are different angle with different expressions.

4.1.1 Eigenvectors Based Face Verification Procedure

Collect each person’s 10 training images in same angle with different expressions and 10 testing images in different angle with different expressions. Here we explain only one person. This procedure repeat for all remaining person’s in our database.

Procedure

- First we take one person‘s ten color images in same angle with different expressions and convert all these images into gray scale images.
- These all images are in different dimensions. So convert all these images dimensions into one common dimension.
- Apply principle component analysis to all these images .
- Here finally we got the eigenvectors .These eigenvectors are belong to highest ten eigen values of that covariance matrix.
- So these eigenvectors(feature vectors) are given as input to the neural network for training purpose.
- For training a neural network error correction back propagation algorithm is used.
- Here target vectors are given as 1….9 depend on the number of person in our database. Suppose ramesh is first person in our database we give 1 as target vector. Here input size is 48x10.So we give ten 1’s to the target vector for the first person. After complete the training we give one test image and check the verification rate for that person. In testing

phase we use nearest neighbor classifier for decided whether test image is belong to that training person or not. In this way we test all ten testing images and verify that testing images belong to that person or not.

- This procedure is repeated for all nine person's in our database.

4.2 ROLE OF PRINCIPLE COMPONENT ANALYSIS IN FACE VERIFICATION

Our approach to the face verification problem [2] is combining the principle component analysis and neural network. We describe the application on Vertically oriented frontal views of human face. Principle component analysis is applied to find aspects of the face which are important for face verification. Its purpose is creating that spanning base of pictures. Using this base we can represent the face with several coefficients instead of having to use the whole picture. We use the highest ten coefficients .Neural networks are used to recognize the face through learning correct coefficients calculated by eigenface algorithm. The network is being trained on the from the database first, and then it is ready to verify that face image belong to that person or not. We use principle component analysis to reduce the input series (ten input units) of the neural network[2][4], so that application time can be decreased **.**

4.2.1 Principle component Analysis Algorithm

- Let the training set of face images be $\Gamma_1, \Gamma_2, \ldots.. \Gamma_{M.}$
- The average face of the set is described by ψ using following formula.

$$\psi = 1/M \sum_{n=1}^{M} \Gamma_n$$

- Each face differs from the average by the vector

$$\Phi_i = \Gamma_i - \psi$$

- This set of very large vectors is then subjected to the principle component analysis, which seeks a set of M orthonormal vectors u_n and their associated eigen values λ_k which best describe the distribution of the data. The vectors u_k and λ_k are eigen vectors and eigen values respectively of the covariance matrix.

$$C = 1/M \sum_{n=1}^{M} \Phi_n^T \Phi_n$$

- where the matrix $A= [\Phi_1 \ldots\ldots \Phi_m]$
- Here we got 48x48 matrix. After finding the covariance matrix we find eigenvalues for this matrix. For 48x48 matrix 48 eigenvalues are there. Out of 48 eigenvalues we just consider highest 10 eigen values.
- Finally we found the eigen vectors for these highest 10 eigen values.
- These eigen vectors are input to the neural network training [2] algorithm.

4.2.2 Training Algorithm

The following steps are same for after finding the feature vectors of nine persons using above procedure. These multilayer neural networks contain one input layer, one hidden layer and one output layer. The input layer contains 10 input neurons and hidden layer contain 10 neurons. Finally the output layer also contains 10 output neurons. Here ten 48x1 eigenvectors are input to the neural network. The size of the input is 48X10.Here first taken weights are all zeros and bias is all 1's.The following steps of backpropagation algorithm is same for training all nine persons

Steps

1. Apply the input vector $X_p = (x_{p1,} x_{p2} \ldots\ldots x_{pn})$ to the input units.
2. Calculate the net input values to the hidden layer units using following formula.

$$net_{pj}^h = \Sigma w_{ji}^h x_{pi} + \theta_j^h$$

3. Calculate the outputs from the hidden layer unit using following formula.

$$i_{pj} = f_j^h(net_{pj}^h)$$

4. Move to the output layer. Calculate the net input values to each unit

$$net_{pk}^o = \Sigma w_{kj}^o i_{pj} + \theta_k^o$$

5. Calculate the outputs.

$$O_{pk} = f_k^o(net_{pk}^o)$$

6. Calculate the error terms for the output units.

$$\delta_{pk}^o = (y_{pk} - o_{pk}) \, f_k^{o'} (net_{pk}^o)$$

7. Calculate the error terms for the hidden units

$$\delta_{pj}{}^{h} = f_j^{h'}(net_{pj}{}^{h}) \Sigma \ \delta_{pk}{}^{o} w_{kj}{}^{o}$$

Notice that the error terms on the hidden units are calculated before the connection weights to the output layer units have been updated.

8. Update weights on the output layer.

$$w_{kj}{}^{o}(t+1) = w_{kj}{}^{o}(t)+\eta \cdot \delta_{pk}{}^{o}.p_j$$

9. Update weights on the hidden layer

$$w_{ji}(t+1) = w_{ji}{}^{h}(t)+ \eta \ \delta_{pj}{}^{h}.x_i$$

Be sure to calculate the error term

$$E_p = 1/2 \ \Sigma \ \delta_{pk}{}^{2}.$$

Since this quantity is measure of how well the network is learning. When the error is acceptably small for each of the training vector pairs, training can be discontinued. The above procedure is continuing for all nine persons images until we reach the minimum error.

4.2.3 Testing Phase

Here we used nearest neighbor classifier algorithm for testing the image. We built one multilayer network for each person to training. After completion of training we apply different test image means different angle with different expression and test whether that test image is belongs to that person or not. In this way we test all nine persons test images. This is the total procedure for the eigenvectors based face verification algorithm. Nearest neighbor classifier means if your output values just near to any of the person target value, we classified that test image belongs to that person.

4.3 PROPOSED ALGORITHM

The existing algorithm eigenvectors based face verification used backpropagation algorithm for training the network .The disadvantage of the backpropagation algorithm is slow convergence rate and it take more time for training. In this algorithm learning parameter also fixed in entire iterations. So in our proposed algorithm we concentrate to avoid these disadvantages. In our previous algorithm we reduced the space complexity using principle component analysis. Based upon the space and time only we decided whether your algorithm is good or not. The previous algorithm reduced the space complexity based on principle component analysis but not reduce the time complexity because here we used backpropagation algorithm for training. In backpropagation algorithm the learning parameter was constant in total iterations until mean square error was reached. Here one more term was added for reduced the training time and increase convergence speed. The term is momentum. Here we consider momentum constant also. In our previous algorithm momentum term was not there. This is used in backpropagation algorithm for increase convergence speed. So finally adding the momentum constant we reduced the training time .Here slightly changes in results are come compared to previous one. Here we explained modified backpropagation algorithm. Only except these change remaining everything was same what we explained previously. This means we trained the network using modified backpropagation algorithm. This definitely reduced the training time compared to previous eigenvectors based face verification algorithm and slightly increase the performance also.

4.3.1 Modified Algorithm

- Let the training set of face images be $\Gamma_1, \Gamma_2, \ldots.. \Gamma_M$.
- The average face of the set is described by ψ using following formula.

$$\psi = 1/M \sum_{n=1}^{M} \Gamma_n$$

- Each face differs from the average by the vector

$$\Phi_i = \Gamma_i - \psi$$

- This set of very large vectors is then subjected to the principle component analysis, which seeks a set of M orthonormal vectors u_n and their associated eigen values λ_k which best describe the distribution of the data. The vectors u_k and λk are eigenvectors and eigen values respectively of the covariance matrix.

$$C = 1/M \sum_{n=1}^{M} \Phi_n^T \Phi_n$$

- where the matrix A= $[\Phi_1 \ldots\ldots \Phi_m]$
- Here we got 48x48 matrix. After finding the covariance matrix we find eigen values for this matrix. For 48x48 matrix 48 eigen values are there. Out of 48 eigen values we just consider highest 10 eigenvalues.
- Finally we found the eigen vectors for these highest 10 eigen values.
- These eigenvectors are input to the neural network training algorithm.

- Here for training modified backpropagation algorithm is used.

4.3.2 Modified BackPropagation Algorithm

The following steps are explained modified backpropagation algorithm. Here input vector or feature vectors are eigenvectors for eigen vectors based face verification.

STEPS:

1. Apply the input vector $X_p = (x_{p1,} x_{p2} \ldots\ldots x_{pn})$ to the input units.
2. Calculate the net input values to the hidden layer units using following formula.

$$net_{pj}^{h} = \Sigma\, w_{ji}^{h} x_{pi} + \theta_j^{h}$$

3. Calculate the outputs from the hidden layer unit using following formula.

$$i_{pj} = f_j^{h}(net_{pj}^{h})$$

4. Move to the output layer. Calculate the net input values to each unit

$$net_{pk}^{o} = \Sigma\, w_{kj}^{o}\, i_{pj} + \theta_k^{o}$$

5. Calculate the outputs.

$$O_{pk} = f_k^{o}(net_{pk}^{o})$$

6. Calculate the error terms for the output units.

$$\delta_{pk}^{o} = (y_{pk} - o_{pk})\, f_k^{o'}\, (net_{pk}^{o})$$

7. Calculate the error terms for the hidden units

$$\delta_{pj}^{h} = f_j^{h'}\, (net_{pj}^{h})\, \Sigma\, \delta_{pk}^{o}\, w_{kj}^{o}$$

Notice that the error terms on the hidden units are calculated before the connection weights to the output layer units have been updated.

8. Update weights on the output layer.

$$w_{kj}^{o}(t+1) = \alpha w_{kj}^{o}(t) + \eta\cdot \delta_{pk}^{o}.p_j$$

where α is the momentum constant. It always positive and in between 0-1.

9. Update weights on the hidden layer

$$w_{ji}(t+1) = \alpha w_{ji}^{h}(t) + \eta\, \delta_{pj}^{h}.x_i$$

where α is the momentum constant.

Be sure to calculate the error term

$$E_p = 1/2\, \Sigma\, \delta_{pk}^{2}.$$

Since this quantity is measure of how well the network is learning. When the error is acceptably small for each of the training vector pairs, training can be discontinued. The above steps are useful for training the neural network using modified backpropagation algorithm. This steps are same for each and every person in our database.

4.3.3 Testing Phase

Here also we used nearest neighbor classifier algorithm for testing the image. We built one multilayer network for each person to training. After completion of training we apply different test image means different angle with different expression and test whether that test image is belongs to that person or not. In this way we test all nine persons test images. This is the total procedure for the eigenvectors based face verification algorithm. Nearest neighbor classifier means if your output values just near to any of the person target value, we classified that test image belongs to that person.

This proposed algorithm definitely decreases the training time of the neural network. It also decreases the false acceptance rate compared to previous algorithm. Another advantage is it increases the verification rate also.

4.4 SIMULATION RESULTS

Here we keep only database for one person. After that we show the training graph for that person using backpropagation algorithm and modified backpropagation algorithm. Finally we give the results of verification rate and false acceptance rate using existed and proposal algorithm.

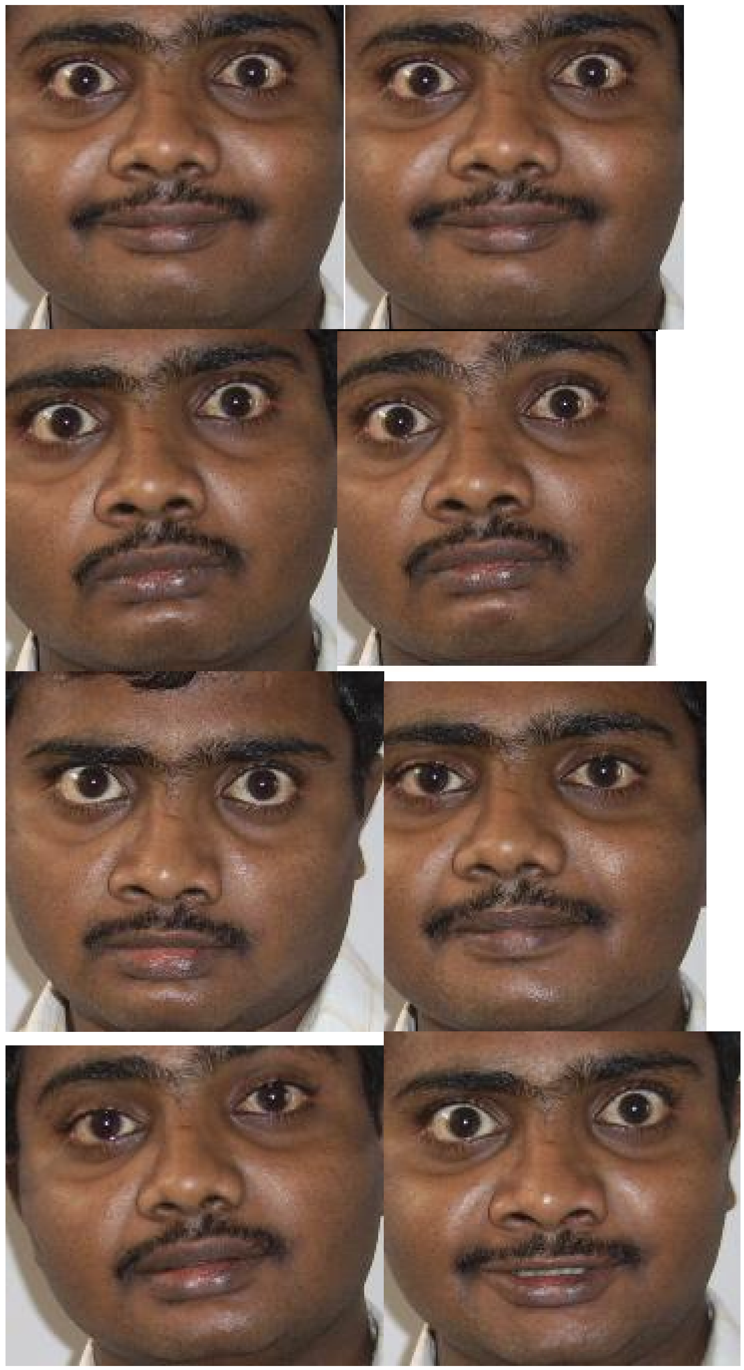

Fig 4.1 Single Person training database

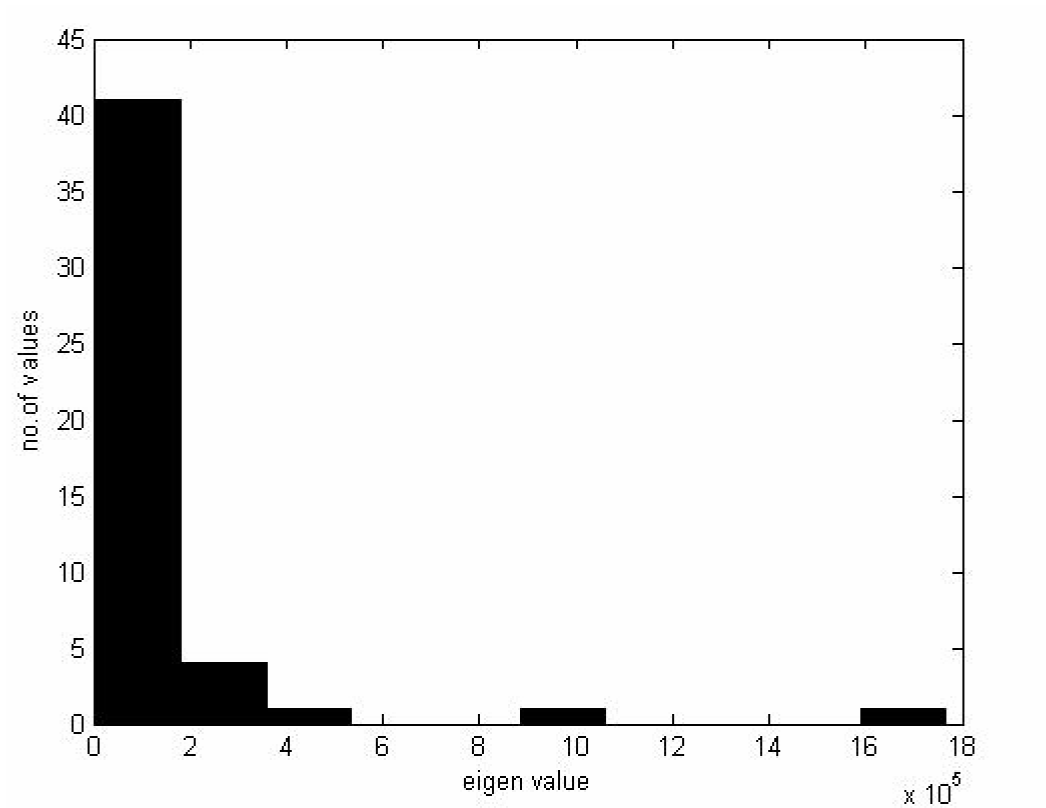

Fig 4.2 Graph between eigenvalues and number of eigen values

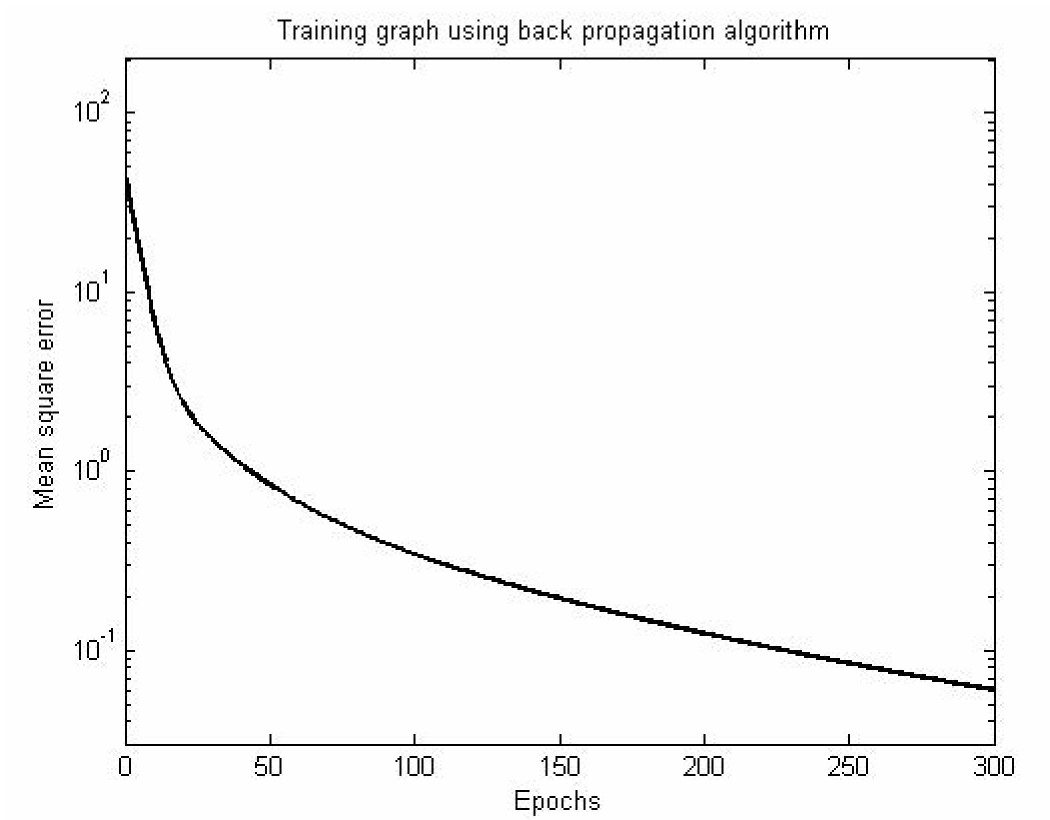

Fig 4.3 Training graph using Backpropagation algorithm

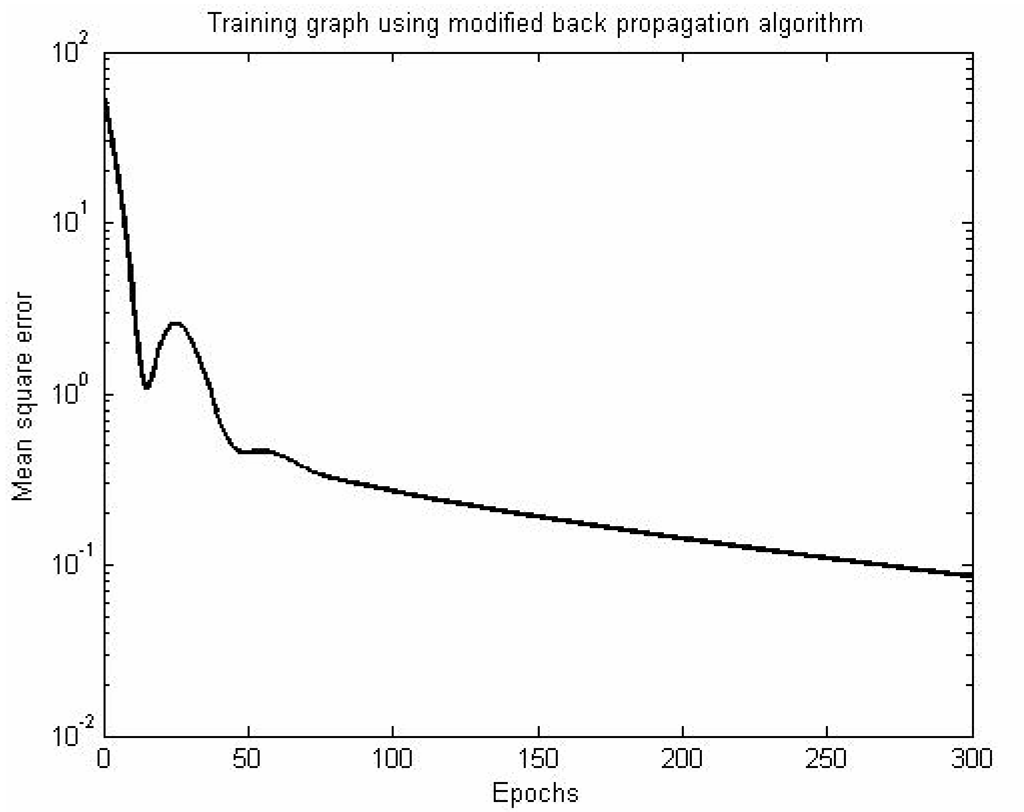

Fig 4.4 Training graph for modified backpropagation algorithm

sno	Name	Existing alg verification rate	Modified alg verification rate
1	Ramesh	0.9	0.9
2	Kamal	0.8	0.8
3	Murthy	0.6	0.7
4	Rambabu	0.8	0.9
5	Rajesh	0.8	0.9

Table 4.1 Table for different persons verification rates in existing & modified alg

sno	Name	Existing alg avg false acceptance rate	Modified alg avg false acceptance rate
1	Ramesh	0.86	0.74
2	Kamal	0.72	0.38
3	Murthy	0.54	0.54
4	Rambabu	0.86	0.72
5	Rajesh	0.72	0.72

Table 4.2 Table for different persons Avg false acceptance rate in existing & modified alg

Here we find the values of the different persons verification rate and average false acceptance rate based on existing and modified algorithms

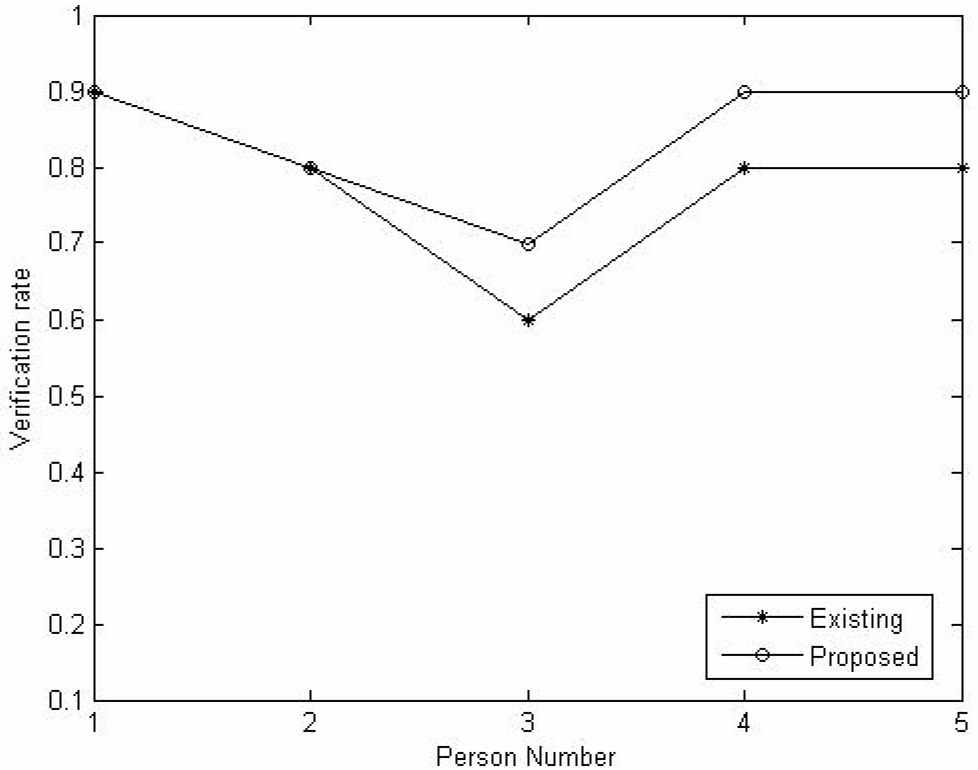

Fig 4.5 Graph between person no & verification rates in existing &modified algorithms

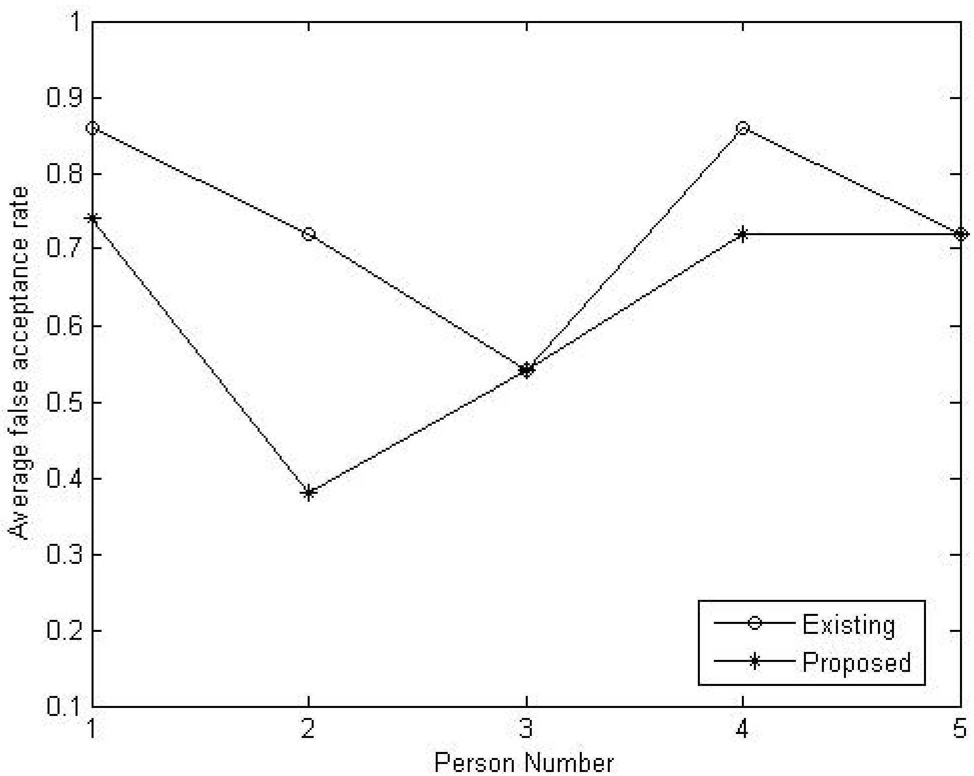

Fig 4.6 Graph between person no & AVG False acceptance rates in existing &modified alg

4.5 CONCLUSION

In this chapter we explain face verification and different algorithms on face verification. Face verification is very useful in Human computer interaction and identify the criminals at airports. Verification rate means the rate at which legitimate users is granted access. This means suppose we test the ramesh image using the ramesh training network. At that time how many times ramesh network recognizes whenever we give the ramesh face as a test image. Suppose we give ten ramesh testing faces,out of 10 ramesh network recognize 8 ramesh test faces. So the verification rate is 8/10 means 0.8.Finally the false reject rate is nothing but

False reject rate = 1-verification rate.

So here 0.2 is the false reject rate. False reject rate means how many times ramesh network not recognized ramesh photo is called False reject rate. False accept rate means how many times ramesh network recognized as ramesh whenever we give other than ramesh faces. This is nothing but False accept rate. Finally after observing the simulation results we knows verification rate is slightly increased by using modified backpropagation algorithm compared to Backpropagation algorithm. At the same time False acceptance rate and training time also slightly decreased. The reason is for adding the momentum term in our modified algorithm, it gives faster convergence compared to previous one. This means network training is good compared to previous one. So our modified algorithm gives good results means slightly increase verification rate and decrease training time and false acceptance rate also.

Chapter 5

Conclusion and Future work

Conclusion

Future work

5. CONCLUSION& FUTURE WORK

5.1 CONCLUSION

Generally in face verification problem the system needs to confirm or reject the claimed identity of the input. This face verification is very useful for identify the criminals at airports and human computer interaction also. The existing algorithm gave the results on face verification in static images based upon the eigenvectors and neural network backpropagation algorithm. Here using 10 eigenvectors we can check the verification rate (the rate at which legitimate users is granted access) and false acceptance rate (the rate at which imposters are granted access).These 10 eigenvectors are represent highest 10 eigenvalues of the covariance matrix. This algorithm gave 60-70% verification rates for many of persons in our database. But here the neural network took more time for training purpose. Here backpropagation algorithm was used for the training. It took more time for better convergence. So in the proposed algorithm we concentrated only this particular disadvantage. The proposed algorithm give the results on face verification in static images based upon the eigenvectors and neural network modified backpropagation algorithm. In modified backpropagation algorithm we just added momentum term. Momentum is always positive value and in between 0-1.These adding momentum term reduces the training time for get faster convergence compared to previous one. It will also slightly increase verification rate and decrease the false acceptance rate also.

5.2 FUTURE WORK

The three categories of face recognition are face detection, face identification and face verification. . Face Detection means extract the face from total image of the person. Face identification means the input to the system is an unknown face, and the system reports back the determined identity from a database of known individuals. Face verification means the system needs to confirm or reject the claimed identity of the input. My thesis was face verification in static images.

Here we explain first way of extend your research. Generally we collect the different persons face images as database. Here we have a scope to extend the research by collecting different persons total images as database and extract the faces from that images using different face detection algorithms. This is one way of scope to extend the research..

Here we explain second way of extend the research Generally in our thesis we create one network for each person and train the network .After completion of training we test that network using different testing images and find verification rate and false acceptance rate. It means we train one person at a time using the network Instead of training a one person at a time, we train multiple persons at a time using same network .After completion training we give test image to that network and identify the testing image of the person. This is nothing but face identification. We have a chance extend the thesis in this way also.

One more way of extend the research is by using unsupervised training. Here in our thesis we used supervised training technique. Supervised learning which incorporates an external teacher, so that each output unit knows what its desired response to input signals ought to be. In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. This means we already know the outputs before the training. So here we have scope to extend the research by using unsupervised training. In unsupervised training, the network is provided with inputs but not with desired outputs. The system itself must then decide what features it will use to group the input data.

The fourth way of extend the research is by using the RBF networks for training. RBF means radial basis function. In our thesis we used backpropagation algorithm for training. RBF have many advantages compared to backpropagation algorithm. It will increase the performance also.

These are the ways anybody has extended our research in future.

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