LITERATURE SURVEY OF AUTOMATIC FACE RECOGNITION SYSTEM AND EIGENFACE BASED IMPLEMENTATION

A Thesis

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DECLARATION

I hereby declare that this thesis is based on the results found by ourselves. Materials of work found by other researcher are mentioned by reference. This thesis, neither in whole nor in part, has been previously submitted for any degree.

Signature of Supervisor	Signature of Author

ABSTRACT

There are three fundamental grounds for me to write this survey paper: the first is to provide an up-to-date review of the existing literature, and the second is to reveal some technical term that how a Computer can recognize a Face (mostly the Algorithms) and the final intention to let know the beginners research opportunity and various prospect of face recognition field

To provide a comprehensive survey, I started from the relevant psychophysical studies that how human being perform this work. Then move on to existing recognition techniques and present detailed descriptions of all techniques. In addition, I put some comparative studies between systems and tried to explain some pre-processing difficulty (illumination, pose variation, image quality etc.) and its explanation for face recognition system. Finally we tried to implement a AFR system based on Eigenface method where we have added a noise filtering .

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CHAPTER I

ANALYSIS OF HUMAN FACE

1.1 What is a Face?

Psychologically a face is a rich source of information about human behavior. Facial displays indicate emotion, regulate social behavior, reveal brain function and signal develop mental transitions in infants. Geometrically a face is 3D spaces sum of large no polygons that can be represent by pixel and facial features are related to face geometry.

Computationally Image data can be represented as vectors. For example, a $p \times q$ 2D image can be mapped to a vector $x \, \varepsilon \, R^{pq,}$ by lexicographic ordering of the pixel elements (such as by concatenating each row or column of the image).

Let $X = (x_1; x_2; : : : ; x_i; : : : ; x_N)$ represent the $n \times N$ data matrix, where each x_i is a face vector of dimension n, concatenated from a $p \times q$ face image, where $n = p \times q$. Here n represents the total number of pixels in the face.

1.2 How human being perform this task (FR)

The physiological study of face recognition divides into two slightly different topics. First there are projects that focus on the recognition of faces preciously unfamiliar to subjects. Second there is a large literature on process underlying recognition of familiar faces.

When viewing poor quality images (low resolutions) at recognizing familiar targets, and very poor at recognizing unfamiliar targets. How do we recognize familiar faces from a variety of viewpoints? This is a fundamental problem from both psychological and computational perspectives. The mechanism by which the brain recognizes a face has long fascinated neurobiologists, many of whom believe that the brain identifies faces as "special" and very different from other visual objects. The human brain combines motion and shape information to recognize faces and facial expressions. More recent studies have suggested that there may even be particular neurons tuned to the identity of one particular person. These neurons, according to that theory, lie in the "fusiform face area" FFA, known to be particularly active when a person encounters a face. An individual brain cell is capable of complex pattern recognition. Single neurons dedicated to the recognition of a particular person in different situations and appearances.

Now scientist’s mission to design computers that “see” faces the way humans do provides more evidence concerning a debate in cognitive psychology. Aleix Martinez, assistant professor of electrical engineering at Ohio State University developed a model of how the brain recognizes the faces of people we’ve seen before, and how we distinguish facial expressions. He has shown that his model of this brain function that we use our knowledge of motion and shape combine together to recognize faces and facial expressions. These two activities take place in different areas of the brain, and some scientists believe that the mental processes involved are completely separate as well; others believe that the two processes are closely linked.

1.3 In case of insect “Bees”

Honeybees may look pretty much all alike to us. But it seems we may not look all alike to them. A study has found that they can learn to recognize human faces in photos, and remember them for at least two days. The bees probably don’t understand what a human face is, to the bees the faces are spatial patterns. Bees are famous for their pattern-recognition abilities. new study shows that they can recognize human faces better than some humans can—with one-ten thousandth of the brain cells.

Fig.1.Bees recognizing Human face

The results also may help lead to better face-recognition software, developed through study of the insect brain. This is evidence that face recognition requires neither a specialized neuronal (brain) circuitry nor a fundamentally advanced nervous system stated by the researchers of Gutenberg University. Many researchers traditionally believed facial recognition required a large brain, and possibly a specialized area of that organ dedicated to processing face information. The bee finding casts doubt on that.

This raises the question of how bees recognize faces, and if so, whether they do it differently from the way we do it. Studies suggest small children recognize faces by picking out specific features that are easy to recognize, whereas adults see the interrelationships among facial features. Bees seem to show aspects of both strategies depending on the study, the human brain may not need to have a visual area specific for the recognition of faces. That may be helpful to researchers who are developing face-recognition technologies. Miniature brain can definitely recognize faces, and if in the future we can work out the mechanisms by which this is achieved, this might suggest ideas for improved face recognition technologies.

CHAPTER II

HOW A COMPUTER CAN PERFORM THIS TASK (AFR)

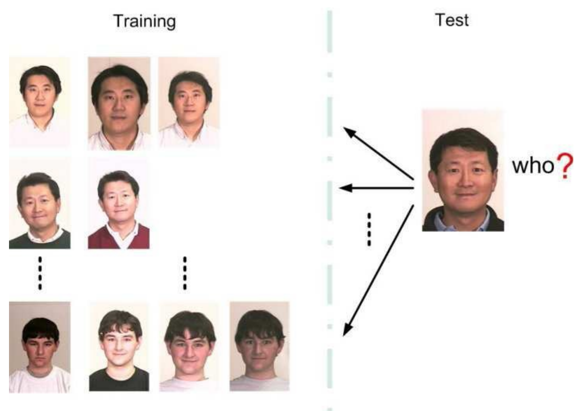


Fig.2.1. face query from the database

2.1 Face identification (”Who am I?”)

It’s 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 that 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 similarities 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”.

2.2 Introduction of AFR

Face recognition is a task humans perform remarkably easily and successfully. But the automatic face recognition seems to be a problem that is still far from solved. In spite of more than 30 years of extensive research, large number of papers published in journals and conferences dedicated to this area, we still can not claim that artificial systems can measure to human performance.

The automatic face recognition has been started science 1960. First automatic face recognition system was developed by Kanade. The performance of face recognition systems has improved significantly but still the problem is not accurately solved. Today's security issues make computer vision and pattern recognition researcher more concern on this facial recognition topic. The motivation to build of face recognition system is to use its advantage in daily life using low cost desktop and embedded computing systems.

Among the bioinformatics technologies face recognition has some additional advantages: it's Easy to use, Natural and Nonintrusive. This tends researcher to do further work. Facial features scored the highest compatibility in a Machine Readable Travel Documents (MRTD) system.

2.3 System overview

The ultimate goal of face Recognition system is image understanding - the ability not only to recover image structure but also to know what it represents.

A general statement of automatic face recognition 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. The solution to the problem involves segmentation of faces (face detection) from cluttered scenes, feature extraction from the face regions, recognition or verification. For identification, the input 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.

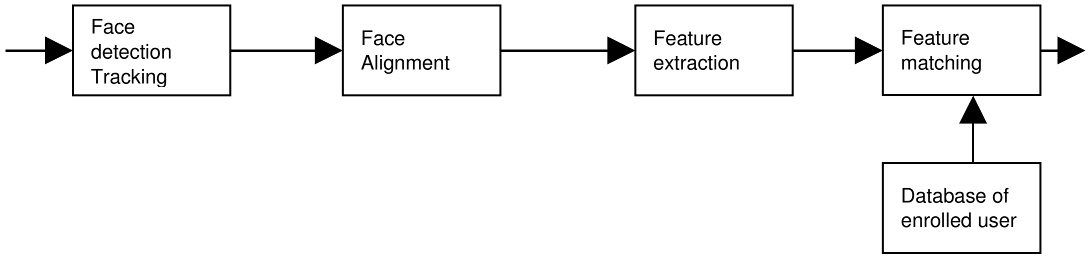


Fig.2.2. Process of face recognition.

A face recognition system can identify faces present in images and videos automatically .It can operate in either or both of two modes: (1) Face verification(authentication).(2) face identification (recognition).

Face verification involves a *one-to-one match* that compares a query face image against a template (model) face image whose identity is being claimed.

Face identification involves a *one-to-many match* that compares a query face image against all the template (model) images in the database to determine the identity of the query face.

2.3.1 Face Recognition Processing

A face recognition system can split into *four* modules. Face is a three-dimensional object and face recognition is a visual pattern recognition problem. For facial recognition purpose the following types of data can be used:

- 2D-Images.
- 3D- images (obtained from laser).

2.3.2 Processing steps before face recognition

1. Detection (Normalization): segment the face from the background.
2. Alignment (Localization): more accurate localization of the face and scale of each detected face.

The input face image is normalized Concerning geometrical properties, such as size and pose, (geometrical transforms or morphing) and Concerning photometrical properties such illumination and gray scale.

2.3.3 Analysis in Face Subspaces

Face recognition results depend highly on features that are extracted .The original image representation is highly redundant, and the dimensionality of this representation could be greatly reduced when only the face patterns are of interest. The face image is effectively represented as a feature vector. We can get Eigenfaces by:

- Principal Component Analysis (PCA).
- Karhunen-Loeve transforms (KLT).

Face detection can be considered as a task of distinguishing between the face and non face manifolds in the image space and face recognition between those of individuals in the face manifold. We detect face and non face manifold and within the detected PCA space we can distinguish individual faces.

2.4 Technical Challenges

The performance of many modern face recognition methods deteriorates with changes in lighting, pose, and other factors. The key technical challenges are:

i) Large Variability in Facial Appearance: The variations between the images of the same face due to illumination and viewing direction are almost always larger than the image variation due to change in face identity”. This variability makes it difficult to extract the basic information of the face objects from their respective images. Various imaging parameters, such as aperture, exposure time, lens aberrations, and sensor spectral response also increase variations.

ii) Highly Complex Nonlinear Manifolds: Challenges in face recognition from subspace viewpoint.

- Principal Component Analysis (PCA), Independent component analysis (ICA), linear discriminant analysis (LDA) techniques are unable to preserve the non convex variations of face manifolds necessary to differentiate among individuals

• Euclidean distance and Mahalanobis distance, which are normally used for template matching, do not perform well for Classifying between face and non face manifolds and between manifolds of individuals is a challenge this crucial fact limits the power of the linear methods to achieve highly accurate face detection and recognition

iii) High Dimensionality and Small Sample Size: The learned manifold or classifier is unable to characterize unseen images of the same individual faces.

2.5 Technical Solutions

To construct a "good" feature space where face manifolds become simpler, a successful algorithm usually needed which combines both of the following strategies

(1) Normalize face images geometrically and photometrically, such as using morphing and histogram equalization.

(2) Extract features in the normalized images which are stable with respect to such variations, such as based on Gabor wavelets.

• **Geometric feature-based approach:** This technique can detect facial features such as eyes, nose, mouth, and chin. Properties of and relations (areas, distances, angles) between the features are used as descriptors for face recognition.

• **Statistical learning approach:** Learns from training data to extract good features and construct classification engines. During the learning, both prior knowledge about face and variations seen in the training data are taken into consideration

• **Appearance-based approach:** Approach generally operates directly on an image-based representation (array of pixel intensities). such as PCA and LDA based methods,

Above techniques are not accurate enough to describe subtleties of original manifolds in the original image space. This is due to their limitations in handling nonlinearity in face recognition.

Approach to handle the nonlinearity:

- Kernel techniques (kernel PCA and kernel LDA).
- Local features analysis (LFA).
- Gabor wavelet-based features.
- Local binary pattern (LBP).

CHAPTER III

COMLEXITY OF AFR

3.1 Some Major difficulty for AFR

In field settings, face images are subject to a wide range of variations. These include pose or view angle, illumination, occlusion, facial expression, time delay between image acquisition, and individual differences. The scalability of face recognition systems to such factors is not well understood. Most research has been limited to frontal views obtained under standardized illumination on the same day with absence of occlusion and with neutral facial expression or slight smile.

For faces to be a useful biometric, facial features used for face recognition should remain invariant to factors unrelated to person identity that modify face image appearance. While theory and some data suggest that many of these factors are difficult to handle, it is not clear where exactly the difficulties lie and what their causes may be.

The influence of facial expression on recognition is not well understood. Previous research has been limited primarily to neutral expressions and slight smiles. Because facial expression affects the apparent geometrical shape and position of the facial features, the influence on recognition may be greater for geometry based algorithms than for holistic algorithms.

Occlusion the performance of the face recognition algorithms under occlusion is in general poor. The face may be occluded by other objects in the scene or by sunglasses or other things. Occlusion may be unintentional or intentional. Under some conditions subjects may be motivated to thwart recognition efforts by covering portions of their face. Since in many situations, the goal is to recognize non- or even un-cooperating subjects,

Time delay Faces change over time. There are changes in hair style, makeup, muscle tension and appearance of the skin, presence or absence of facial hair, glasses, or facial jewelry, and over longer periods effects related to aging.

Pose Some unavoidable problems appear in the variety of practical applications, such as, the people are not always frontal to the camera, so the pose problem is a big obstacle for the face recognition system to be prevalence. In essence, the difference between the same people under the varied poses is larger than the difference between the distinct persons under the same pose. So it is difficult for the computer to do the face identification when the poses of the probe and gallery images are different. Pose variation still presents a challenge for face recognition. Frontal training images have better performance to novel poses than do non-frontal training images. For a frontal training pose, can achieve reasonable recognition rates of above 90%.

Illumination Pure illumination changes on the face are handled well by current face recognition algorithms. However, face recognition systems have difficulties in extreme illumination conditions in which significant parts of the face are invisible. Furthermore, it can become particularly difficult when illumination is coupled with pose variation.

Expression With the exception of extreme expressions such as scream, the algorithms are relatively robust to facial expression. Deformation of the mouth and occlusion of the eyes by eye narrowing and closing present a problem for the algorithms. Faces undergo large deformations under facial expressions. Humans can easily handle this variation, but the algorithms to have problems with the expression databases. Face recognition under extreme facial expression still remains an unsolved problem, and temporal information can provide significant additional information in face recognition under expression.

A neutral face is a relaxed face without contraction of facial muscles and without facial movements. Face recognition systems can achieve high recognition rate for good quality, frontal view, constant lighting and only subtle expression or expressionless face images. The performance of face recognition system significantly decreases when there is a dramatic expression on the face. Therefore, it is important to automatically find the best face of a subject from the images. Using the neutral face during enrollment and when authenticating, so that we can find the neutral face of the subject from the six universal expression like. Happiness, sadness, disgust, anger, fear, surprise.

Gender researchers found surprisingly consistent differences of face recognition rates related to gender. In two databases (AR and FERET) the recognition rate for female subjects is higher than for males across a range of perturbations. One hypothesis is that women invest more effort into modifying their facial appearance, by use of cosmetics, for instance, which leads to greater differentiation among women than men. Alternatively, algorithms may simply be more sensitive to structural differences between the faces of women and men. The finding that algorithms are more sensitive to women's faces suggests that there may be other individual differences related to algorithm performance.

Algorithms may, for instance, prove more accurate for some ethnic groups or ages than others. These experiments in total show that challenging problems remain in face recognition. Pose, occlusion, and time delay variation in particular present the most difficulties. While study has revealed many challenges for current face recognition research, the current study has several limitations.

One, we did not examine the effect of face image size on algorithm performance in the various conditions. Minimum size thresholds may well differ for various permutations, which would be important to determine.

Two, the influence of racial or ethnic differences on algorithm performance could not be examined due to the homogeneity of racial and ethnic backgrounds in the databases. While large databases with ethnic variation are available, they lack the parametric variation in lighting, shape, pose and other factors that were the focus of this investigation.

Three, faces change dramatically with development, but the influence of change with development on algorithm performance could not be examined.

Fourth, while we were able to examine the combined effects of some factors, databases are needed that support examination of all ecologically valid combinations, which may be non-additive. The results of the current study suggest that greater attention be paid to the multiple sources of variation that are likely to affect face recognition in natural environments

CHAPTER IV

DIFFERENT TECHNIQUE FOR FACE RECOGNITION

4.1 Different Approach

Face recognition can be done in both a still image and video which has its origin in still-image face recognition. Different approaches of face recognition for still images can be categorized into tree main groups such as:

1. Holistic approach.
2. Feature-based approach.
3. Hybrid approach.

4.1.1 Holistic Approach

In holistic approach, the whole face region is taken into account as input data into face detection system. Examples of holistic methods are Eigenfaces (most widely used method for face recognition), probabilistic Eigenfaces, fisherfaces, support vector machines, nearest feature lines (NFL) and independent-component analysis approaches. They are all based on principal component-analysis (PCA) techniques that can be used to simplify a dataset into lower dimension while retaining the characteristics of dataset.

4.1.2 Feature-based Approach

In feature-based approaches, local features on face such as nose, and then eyes are segmented and then used as input data for structural classifier. Pure geometry, dynamic link architecture, and hidden Markov model methods belong to this category.

4.1.3 Hybrid Approach

The idea of this method comes from how human vision system perceives both local feature and whole face. There are modular Eigenfaces, hybrid local feature, shape-normalized, component-based methods in hybrid approach.

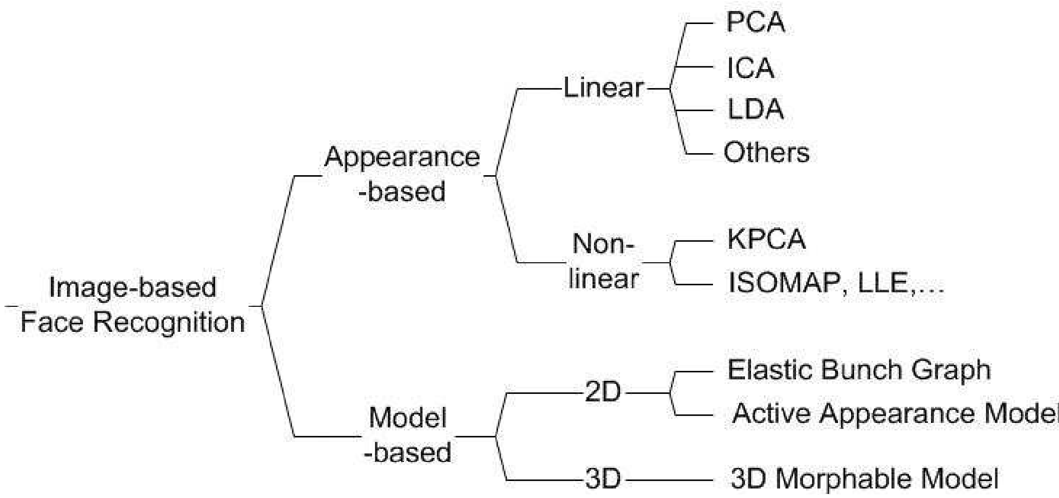


Fig.4.1. some Face recognition methods

4.2 Eigenfaces Method

Eigenfaces are a set of standardized face component based on statistical analysis of various face images. Mathematically speaking, Eigenfaces are a set of eigenvectors derived from the covariance matrix of a high dimensional vector that represents possible faces of humans. Any human face can be represented by linear combination of Eigenface images. For example, one person's face can be represented by some portion of Eigenface of one type and some other portion of Eigenface of another type, and so on. In Pentland's paper, motivated by principal component analysis (PCA), the author proposes this method, where principle components of a face are extracted, encoded, and compared with database.

A new face image is projected onto face space simply by multiplying the difference between the image and the average and the result is multiplied by each eigenvector. The result of this operation will be the weighted contribution of each Eigenface in representing the input face image, treating the Eigenfaces as a basis set for face images. The Euclidean distance taken from each face class determines the class that best matches the input image. Through Eigenfaces, the system can detect the presence of face as well. The face image projected onto face space does not change radically while any non-face image will look quite different; therefore, it is easy to distinguish between face images and non-face images. Using this basic idea, image is projected onto face space and then Euclidean distance is calculated between the mean-adjusted input image and the projection onto face space. The distance is used as “faceness” so the result of calculating the distance is a “face map”, where low values indicate that there is a face.

4.3 Principal Component Analysis (PCA)

Derived from Karhunen-Loeve’s transformation. Given an s-dimensional vector representation of each face in a training set of images, Principal Component Analysis (PCA) tends to find a t-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional ($t \ll s$). If the image elements are considered as random variables, the PCA basis vectors are defined as eigenvectors of the scatter matrix.

The Eigenface algorithm uses PCA for dimensionality reduction to find the vectors which best account for the distribution of face images within the entire image space. These vectors define the subspace of face images and the subspace is called face space. All faces in the training set are projected onto the face space to find a set of weights that describes the contribution of each vector in the face space. To identify a test image, it requires the projection of the test image onto the face space to obtain the corresponding set of weights. By comparing the weights of the test image with the set of weights of the faces in the training set, the face in the test image can be identified. The key procedure in PCA is based on Karhumen-Loeve transformation. If the image elements are considered to be random variables, the image may be seen as a sample of a stochastic process. The PCA basis vectors are defined as the eigenvectors of the scatter matrix S_T,

$$S_T = \Sigma^{N}_{i=1} (x_i - \mu)(x_i - \mu)^T$$

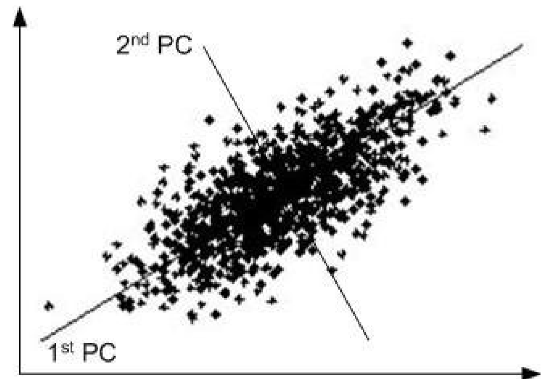


Fig.4.3.1. Principal Components (PC) of a two-dimensional set of points. The first principal component provides an optimal linear dimension reduction from 2D to 1D, in the sense of the mean square error.

4.4 Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is similar to PCA except that the distributions of the components are designed to be non-Gaussian. ICA minimizes both second-order and higher-order dependencies in the input data and attempts to find the basis along which the data (when projected onto them) are - statistically independent. Bartlett et al. provided two architectures of ICA for face recognition task:
Architecture I - statistically independent basis images,
Architecture II - factorial code representation.

4.5 Linear Discriminant Analysis (LDA)

Both PCA and ICA construct the face space without using the face class (category) information. The whole face training data is taken as a whole. In LDA the goal is to find an efficient or interesting way to represent the face vector space. But exploiting the class information can be helpful to the identification tasks,

Linear Discriminant Analysis (LDA) finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes the between-class scatter matrix S_B and the within-class scatter matrix S_W are defined. The goal is to maximize S_B while minimizing SW, in other words, maximize the ratio $\det|S_B|/\det|S_W|$. This ratio is maximized when the column vectors of the projection matrix are the eigenvectors of (S_W^-1 × S_B).

4.6 Evolutionary Pursuit (EP)

An Eigenspace-based adaptive approach that searches for the best set of projection axes in order to maximize a fitness function, measuring at the same time the classification accuracy and generalization ability of the system. Because the dimension of the solution space of this problem is too big, it is solved using a specific kind of genetic algorithm called Evolutionary Pursuit (EP).

4.7 Kernel Methods

The face manifold in subspace need not be linear. Kernel methods are a generalization of linear methods. Direct non-linear manifold schemes are explored to learn this non-linear manifold.

4.8 Trace Transform

The Trace transform, a generalization of the Radon transform, is a new tool for image processing which can be used for recognizing objects under transformations, e.g. rotation, translation and scaling. To produce the Trace transform one computes a functional along tracing lines of an image. Different Trace transforms can be produced from an image using different trace functional.

4.9 Support Vector Machine (SVM)

Given a set of points belonging to two classes, a Support Vector Machine (SVM) finds the hyper plane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyper plane. PCA is first used to extract features of face images and then discrimination functions between each pair of images are learned by SVMs.

4.10 Elastic Bunch Graph Matching (EBGM)

Elastic Bunch Graph Matching (EBGM). All human faces share a similar topological structure. Faces are represented as graphs, with nodes positioned at fiducial points. (Exes, nose...) and edges labeled with 2-D distance vectors. Each node contains a set of 40 complex Gabor wavelet coefficients at different scales and orientations (phase, amplitude). They are called "jets". Recognition is based on labeled graphs. A labeled graph is a set of nodes connected by edges, nodes are labeled with jets, and edges are labeled with distances.

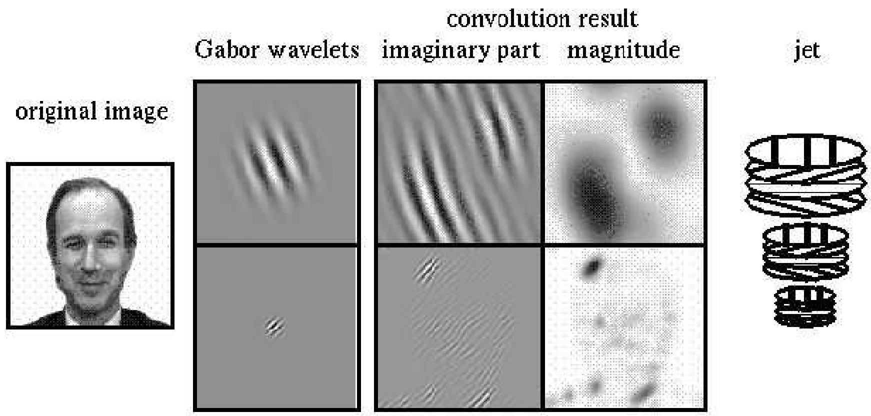


Fig.4.10.1. Jet

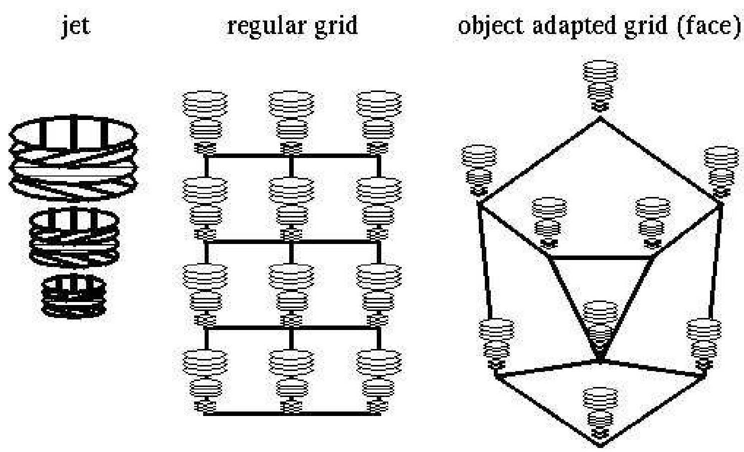


Fig.4.10.2. Labeled Graph

4.11 Active Appearance Model (AAM)

An Active Appearance Model (AAM) is an integrated statistical model which combines a model of shape variation with a model of the appearance variations in a shape-normalized frame. An AAM contains a statistical model if the shape and gray-level appearance of the object of interest which can generalize to almost any valid example. Matching to an image involves finding model parameters which minimize the difference between the image and a synthesized model example projected into the image.

The AAM is constructed based on a training set of labeled images, where landmark points are marked on each example face at key positions to outline the main features.

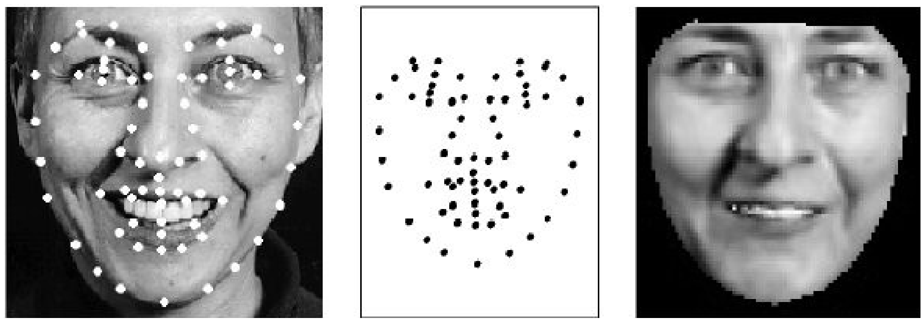


Fig.4.11.1. the training image is split into shape and shape-normalized texture.

4.12 3-D Morphable Model

Human face is a surface lying in the 3-D space intrinsically. Therefore the 3-D model should be better for representing faces, especially to handle facial variations, such as pose, illumination etc. Blantz et al. proposed a method based on a 3-D morphable face model that encodes shape and texture in terms of model parameters, and algorithm that recovers these parameters from a single image of a face.

4.13 3-D Face Recognition

The main novelty of this approach is the ability to compare surfaces independent of natural deformations resulting from facial expressions. First, the range image and the texture of the face are acquired. Next, the range image is preprocessed by removing certain parts such as hair, which can complicate the recognition process. Finally, a canonical form of the facial surface is computed. Such a representation is insensitive to head orientations and facial expressions, thus significantly simplifying the recognition procedure. The recognition itself is performed on the canonical surfaces.

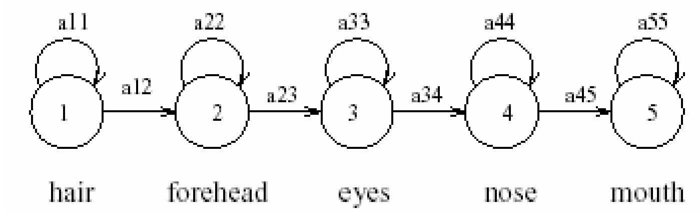
4.14 Bayesian Framework

A probabilistic similarity measure based on Bayesian belief that the image intensity differences are characteristic of typical variations in appearance of an individual. Two classes of facial image variations are defined: intrapersonal variations and extra personal variations. Similarity among faces is measures using Bayesian rule.

4.15 Hidden Markov Models (HMM)

Hidden Markov Models (HMM) are a set of statistical models used to characterize the statistical properties of a signal. HMM consists of two interrelated processes: (1) an underlying, unobservable Markov chain with a finite number of states, a state transition probability matrix and an initial state probability distribution and (2) a set of probability density functions associated with each state.

HMM approach for face recognition based on the extraction of 2-dimensional discrete cosine transformation (DCT) feature vectors. The author takes advantage of DCT compression property for feature extraction. An image is divided by blocks of a subimage associated with observation vector. In HHM, there are unobservable Markov chain with limited number of status in the model, the observation symbol probability matrix **B**, a state transition probability matrix **A**, initial state distribution **π,** and set of probability density functions (PDF). A HMM is defined as the triplets $\boldsymbol{\lambda} = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$. For frontal human face images, the important facial components appear in top to bottom order such as hair, forehead, eyes, nose, mouth, and chin. This still holds although the image rotates slightly in the image plane. Each of the facial regions is assigned to one state in 1-D continuous HMM. The transition probability *ai j* and structure of face model is illustrated in following Figure.



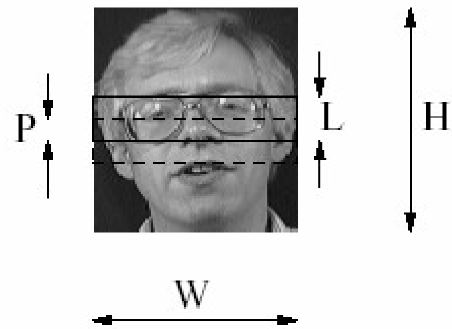


Fig.4.15.1. HMM for face recognition image. Fig.4.15.2.Block extraction form

4.16 Boosting & Ensemble Solutions

The idea behind Boosting is to sequentially employ a weak learner on a weighted version of a given training sample set to generalize a set of classifiers of its kind. Although any individual classifier may perform slightly better than random guessing, the formed ensemble can provide a very accurate (strong) classifier. Viola and Jones build the first real-time face detection system by using AdaBoost, which is considered a dramatic breakthrough in the face detection research. On the other hand, papers by Guo et al. are the first approaches on face recognition using the AdaBoost methods.

4.17 Nearest Feature Line Method

Its one of holistic matching methods to deal with problems in Eigenfaces approach. To create a feature point in feature space, it is assumed that there should be at least two prototype feature points available from the same class (image). A line passing the two prototype features forms a feature line (FL) that generalizes the two feature points. A feature line represents an approximate of two prototypes (images) that are captured under different conditions, such as different head gaze direction or different light illumination. An input image is then identified with a corresponding class, according to the distance between feature point of the given image and FL of the prototype images.

Facial image is represented as a point in the feature space, which is an eigen- space. The line **x**1 through **x**2 of same class denoted as **x**1 **x**2 is called feature line of that class. The query which is input image **x** is projected K onto an FL, and the FL distance **x** and **x**1**x**2 is defined as d(**x**, **x**1**x**2) = |**x** – **p**|, where | **.** | is some norm. The projection point can be found by setting up a vector line equation with parameter μ. Depending on the sign of μ **,** the position of **p** can be left of **x1**, right of **x2**, or between ***x1*** and **x*2*** on the line. The greater the value of the parameter is, the further the position of p from **x1** or **x2** becomes. The classification of the input image is done as follows: Let ***c x*** and ***c j x*** be two distinct prototype points in feature space.

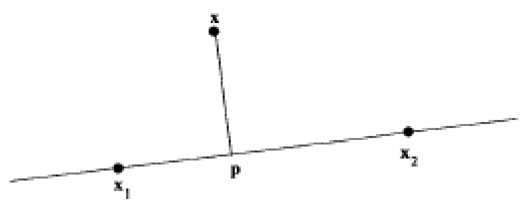


Fig.4.17.2.Generalizing two prototype feature points x1 and x2 [2].

The distance between image point **x** and each FL ***c c i j x x*** is calculated for each class c, where each pair *i ≠ j*. This will generate *N* number of distances, and these *N* distances are sorted in ascending order with each of them associated with class *c**. The first rank gives the NFL classification consisting of the best matched class *c*,* and the two best matched prototypes *i** and *j** of the class.

CHAPTER V

COMPARATIVE STUDY

5.1 Experimental Results

The success of face recognition depends on the solution of two problems:

1. Representation.
2. Matching.

Studies show that Eigenface algorithm, which is essentially a minimum distance classifier, works well when lighting variation is small. Its performance deteriorates significantly as lighting variation increases. The elastic matching algorithm, on the other hand, is insensitive to lighting, face position, and expression variations and therefore is more versatile. The performance of the Auto-Association and Classification nets is upper bounded by that of the Eigenface but is more difficult to implement in practice.

The Eigenface, Auto-Association and classification nets, and elastic matching algorithms were tested in face recognition experiments. Here, the results are presented and discussed, based on the mentioned data bases.

5.2 Data Bases

In this experiment researchers used four data bases to achieve a reasonably large size. The data bases were those of the MIT, the Olivetti Research Lab, the Weizmann Institute of Science, and Bern University.

The number of subjects in each data base ranges from 16 to 40, resulting in a total of 114. For each subject, there are10 to 30 pictures and they often contain significant variations in scale and viewing angle.

Since the Eigenface and neural-net techniques generally require the images to be of the same scale and viewing angle, the data bases were “trimmed” such that inside each trimmed data base, all images are frontal view and have roughly the same scale. The four trimmed data bases still have a total of 114 subjects but for each subject, there are now two to three pictures with variations in lighting, background, and expression. The four trimmed data bases were also combined to generate a single data base. Since the four data bases have different scales (even though within each data base the pictures have roughly the same scale), scale normalization was used such that in the combined data base, all images have roughly the same scale.

Table 5.2.1
The Original Data Bases and Their Variations.

Database	Subject	Variation	Total
MIT	16	27	432
Olivetti	40	10	400
Weizmann	28	30	840
Bern	30	10	300

Table 5.2.2
The "Trimmed" Data Bases and Their Variations.

Database	Subject	Variation	Total
MIT	16	3	48
Olivetti	40	2	80
Weizmann	28	3	84
Bern	30	2	60
Combined	114	2,3	272

The Eigenface, Auto-Association and classification nets, and elastic matching algorithms were run on each of the four individual data bases as well as on the combined data base. In this test first the researcher's intention to test these algorithms robustness over different data bases, later on they decided to test these algorithms efficacy on a relatively large data base in terms of the number of subjects.

In their experiments, the images were divided into training and test sets. To describe how the training samples were picked, we first need to describe how the data bases are organized.

The four individual data bases (MIT, Olivetti, Weizmann, and Bern) have the same organization, and the combined data base, being the combination of the four, also has that organization. Specifically, in each data base, every subject is photographed under a number of settings, say, settings 1, 2, 3…., k. Here, a setting amounts to a particular combination of lighting, background, etc. Setting 1 is usually taken as the “standard.” Figure shows the pictures of two subjects under three different settings from.

Fig.5.1. Examples of faces in the Weizmann data base.

The results of the face-recognition experiments are summarized in the following Tables.

Table 5.2.3
Classification Results for Four Individual Data Bases.

Database	Eigenface	Elastic Matching	Auto-Association and classification Networks
MIT	97%	97%	72%
Olivetti	80%	80%	20%
Weizmann	84%	100%	41%
Bern	87%	93%	43%

Table 5.2.4
Result for combined databases

Eigenface	Elastic Matching	Auto-Association and classification Networks
66%	93%	Not tested

From the tested data of above table we can evaluate the performance of these algorithms.

5.3 On the Four Individual Data Bases

The Eigenface did very well on the MIT data base (97% recognition) and the Bern data base (87%). Its performance on the two other individual data bases was somewhat less satisfactory.

5.3.1 Eigenface

In fact the Eigenface technique implements the minimum distance classifier, which is optimal if the lighting variation between the training and testing samples can be modeled as zero-mean AWGN. This might work if the mean is nonzero but small. When the lighting variation is not small, it could introduce a large bias in the distance calculation. In such cases, the distance between two face images is dominated by the difference in their lighting conditions rather than the differences between the two faces, thereby rendering the distance an unreliable measure for face recognition. Respective researcher proposed to take the derivative of the images to reduce biases caused by lighting change. When the lighting change is spatially varying, however—for example, half bright and half dark, as in the Weizmann database .the derivative will introduce its own biases at the boundary of the lighting change.

5.3.2 The elastic matching

The elastic matching did very well on all data bases (93–100% recognition) except on the Olivetti, where its performance was acceptable (80% recognition). The Olivetti data base contains some scale and rotation variations while their current elastic matching software could deal only with position, lighting, and expression variations. While competitive to the eigenface on all data bases, it did particularly well on the Weizmann data base (100% versus the eigenface's 84%). Two factors contributed to this good performance. First, the Gabor features, being the output of bandpass filters, are closely related to derivatives and are therefore less sensitive to lighting change. Second, the elastic matching uses features only at key points of an image rather than the entire image. Hence, biases at other points in the image do not contribute to the distance calculation.

5.3.3 Auto-Association and Classification Networks

The performance of the Auto-Association and classification nets was not satisfactory. There are several contributing factors. This technique can have good performance under the small lighting variations. All but the MIT database contain significant lighting variations. Again this technique also requires a lot of preprocessing; such as background elimination that the images only contain faces.

The other two techniques do not have such requirements. Indeed, the only preprocessing done was a sub sampling of the images to reduce the number of input nodes in the Auto-Association net (the original image size is too large for the net to be trained within a reasonable amount of computer time). Third, the Auto-Association and classification nets were nonlinear and contain many nodes and weights. It is possible that after a very long training period, the weights still did not converge to the optimal Eigenface solution. Last, from the analysis the performance of the Auto-Association and classification nets is upper bounded by that of the Eigenface.

5.4 On the Combined Data Base

The performance of the Eigenface deteriorated considerably, to 66% recognition. This is because there are significant lighting variations between the four data bases that make up the combined data base in addition to the lighting variations within each individual data base. As a result, the lighting change-related distance biases are much larger for the combined data base than those for the four individual data bases, this makes image distance a highly unreliable measure of face differences.

The elastic matching performed well, with 93% recognition. The main reason for this robust performance is that the elastic matching is relatively insensitive to the various lighting changes.

The Auto-Association and classification nets were not tested on the combined data base since they were unlikely to achieve dramatically better performance than that on the individual data bases but doing so would have required significantly more computation effort.

CHAPTER VI

EVALUATION OF FACE RECOGNITION SYSTEMS

The face recognition community has benefited from a series of U.S. Government funded technology development efforts and evaluation cycles, beginning with the FERET program in September 1993. The FRVT 2006 is the latest in a series of evaluations for face recognition that began in 1993.

The Face Recognition Vendor Test (FRVT) is a large-scale evaluation of automatic face recognition technology. The primary objective of FRVT is to provide performance measures for assessing the ability of automatic face recognition systems to meet real-world requirements. FRVT measures performance of the core capabilities of face recognition technology. It provides an assessment of the potential for face recognition technology to meet the requirements for operational applications. However, it does not address many application specific issues and, therefore, its not a “buyer’s guide” to face recognition.

The Face Recognition Grand Challenge (FRGC) was a face recognition technology development effort that supported the development of the face recognition algorithms from high-resolution still and 3D imagery. The goal of the FRGC was a decrease in the error rate of face recognition algorithms by an order of magnitude. The FRVT 2006 documented a decrease in the error rate by at least an order of magnitude over what was observed in the FRVT 2002. This decrease in error rate was achieved by still and by 3D face recognition algorithms. In FRVT 2002 ten participants were evaluated under the direct supervision of the organizers supported by U.S. Government.

For the first time in a biometric evaluation, the FRVT 2006 integrated human face recognition performance into an evaluation and directly compared human and machine face recognition performance. This inclusion allowed a direct comparison between humans and state-of-the-art computer algorithms. The study focused on recognition across changes in lighting. The experiment matched faces taken under controlled illumination against faces taken under uncontrolled illumination. The results show that, at low false alarm rates for humans, seven automatic face recognition algorithms were comparable to or better than humans at recognizing faces taken under different lighting conditions.

Furthermore, three of the seven algorithms were comparable to or better than humans for the full range of false alarm rates measured.

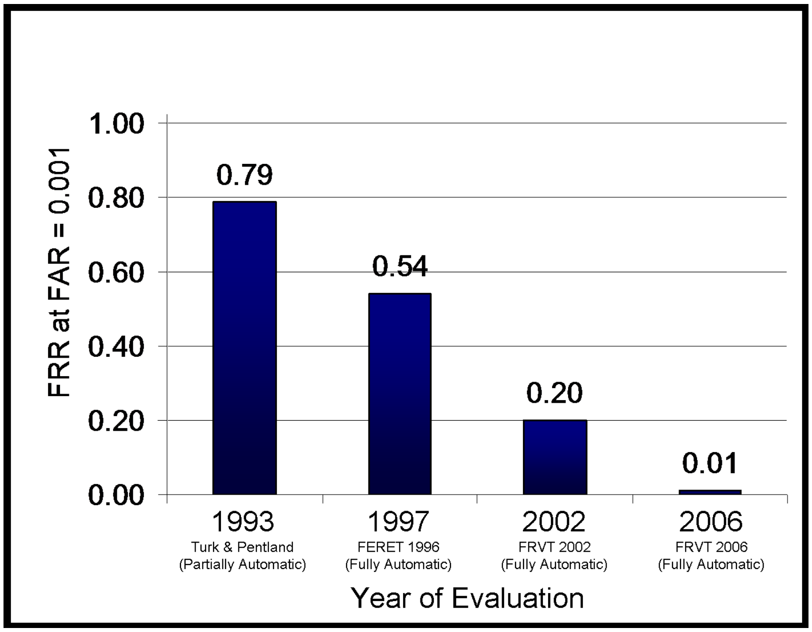


Fig.6.1. the reduction in error rate for state-of-the-art face recognition algorithms as documented through the FERET, the FRVT 2002, and the FRVT 2006 evaluations.

CHAPTER VII

APPLICATIONS

Google upped its stalker factor by adding face recognition abilities to its image search. While currently unofficial and unannounced, users can search for images that only contain faces by appending a query string onto the end of a search URL. For example, a general image search for "Ars Technica" produces a variety of image results, but when appending "&imgtype=face" to the end of the URL, all new results contain photos of people

Table 6.1

Various application of automatic face recognition.

Category	Exemplar application scenarios
Face ID	Driver licenses, entitlement programs, immigration, national ID, passports , voter registration, welfare registration
Access control	Border-crossing control, facility access, vehicle access, smart kiosk and ATM, computer access, computer program access, computer network access, online program access, online transactions access, long distance learning access, online examinations access, online database access
Security	Terrorist alert, secure flight boarding systems, stadium audience scanning, computer security, computer application security, database security, file encryption, intranet security, Internet security, medical records, secure trading terminals
Surveillance	Advanced video surveillance, nuclear plant surveillance, park surveillance, neighborhood watch, power grid surveillance, CCTV control, portal control
Smart cards	Stored value security, user authentication
Law enforcement	Crime stopping and suspect alert, shoplifter recognition, suspect tracking and investigation, suspect background check, identifying cheats and casino undesirables, post-event analysis, welfare fraud, criminal face retrieval and recognition
Face databases	Face indexing and retrieval, automatic face labeling, face classification
Multimedia management	Face-based search, face-based video segmentation and summarization, event detection
Human computer interaction (HCI)	Interactive gaming, proactive computing
Others	Antique photo verification, very low bit-rate image & video transmission, etc.

CHAPTER VIII

FOR PROSPECTIVE RESEARCHERS

Automatic recognition is a vast and modern research area of computer vision and Artificial intelligence, reaching from recognition of faces, facial expressions analysis, facial geometry, building successful face model, automatically detecting, locating and tracking faces, as well as extraction of face orientation and facial features.

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.

This Research Front on Face Recognition from the field of Computer Science was selected for mapping from the list of Top Topics for June 2008. The map is a diagrammatic representation of the 33 core papers comprising the front in Computer Science. Each circle represents a highly cited paper. The lines between circles represent the strongest co-citation links for each paper that is, indicating that the papers are frequently cited together. Papers close to each other on the map are generally more highly co-cited. The most recent paper(s) are indicated in dark.

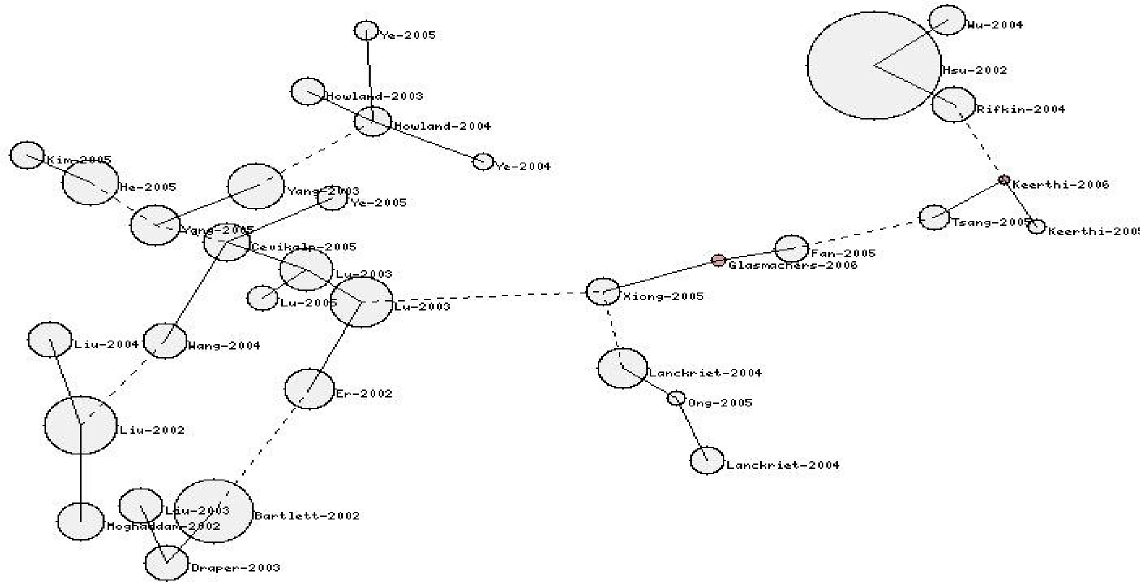


Fig.7.1.Face Recognition Core Paper

Table 7.1

Internet Resources for Research and Databases

Research pointers	
Home page	www.face-rec.org
Face recognition homepage	www.cs.rug.nl/~peterkr/FACE/frhp.html
Face detection homepage	home.t-online.de/home/Robert.Frischholz/face.htm
Facial analysis homepage	mambo.ucsc.edu/psl/fanl.html
Facial animiation homepage	mambo.ucsc.edu/psl/fan.html
Face databases	
FERET database	http://www.itl.nist.gov/iad/humanid/feret/
XM2TVS database	http://www.ee.surrey.ac.uk/Research/VSSP/xm2vtsdb/
UT Dallas database	http://www.utdallas.edu/dept/bbs/FACULTY PAGES/otoole/database.htm
Notre Dame database	http://www.nd.edu/~cvrl/HID-data.html
MIT face databases	ftp://whitechapel.media.mit.edu/pub/images/
Shimon Edelman's face database	ftp://ftp.wisdom.weizmann.ac.il/pub/FaceBase/
CMU face detection database	www.ius.cs.cmu.edu/IUS/dylan usr0/har/faces/test/
CMU PIE database	www.ri.cmu.edu/projects/project 418.html
Stirling face database	pics.psych.stir.ac.uk
M2VTS multimodal database	www.tele.ucl.ac.be/M2VTS/
Yale face database	cvc.yale.edu/projects/yalefaces/yalefaces.html
Yale face database	B cvc.yale.edu/projects/yalefacesB/yalefacesB.html
Harvard face database	hrl.harvard.edu/pub/faces
Weizmann face database	www.wisdom.weizmann.ac.il/~yael/
UMIST face database	images.ee.umist.ac.uk/danny/database.html
Purdue University face database	rvl1.ecn.purdue.edu/~aleix/aleix face DB.html
Olivetti face database	www.cam-orl.co.uk/facedatabase.html
Oulu physics-based face database	www.ee.oulu.fi/research/imag/color/pbfd.html

Table 7.2

Available Commercial Face Recognition Systems

Commercial products	Websites
FaceIt from Visionics	http://www.FaceIt.com
Viisage Technology	http://www.viisage.com
FaceVACS from Plettac	http://www.plettac-electronics.com
FaceKey Corp.	http://www.facekey.com
Cognitec Systems	http://www.cognitec-systems.de
Keyware Technologies	http://www.keywareusa.com/
Passfaces from ID-arts	http://www.id-arts.com/
ImageWare Sofware	http://www.iwsinc.com/
Eyematic Interfaces Inc.	http://www.eyematic.com/
BioID sensor fusion	http://www.bioid.com
Visionsphere Technologies	http://www.visionspheretech.com/menu.htm
Biometric Systems, Inc.	http://www.biometrica.com/
FaceSnap Recoder	http://www.facesnap.de/htdocs/english/index2.html
SpotIt for face composite	http://spotit.itc.it/SpotIt.html

Automatic recognition of people is a challenging problem. Whether there is any hope for face recognition is a burning question now. In a general context, the automatic face recognition in complex scenarios may remain unsolved for the next years. Almost in any face recognition application; a face detection stage is needed. Although face detection poses also a very challenging problem. At present Face recognition systems have problems recognizing differences in lighting, pose, facial expressions, and picture quality. So by applying some sort of robust processing technique can increase the success rate.

When the scenario departs from the easy scenario, then face recognition approaches experience severe problems. Among the special challenges as for example: pose variation, illumination conditions, scale variability, images taken years apart, glasses, moustaches, beards, low quality image acquisition, partially occluded faces etc.

However, much more effort should be put in knowing the HVS and its influence on face recognition. Although there has been a lot of work trying to understand the HVS, not enough cooperative research has been conducted between the computer vision, signal processing and psychophysics and neurosciences communities.

CHAPTER IX

EIGENFACE APROCH FOR FACE RECOGNITION

Eigenfaces is a known term that represents the significant features or principal components of human faces. Each feature or component is represented as an eigenvector. These eigenvectors do not correspond to the physical entities at the face (e.g., eye, nose, mouth, etc.). In the process of recognizing human faces, each face is projected into a set of Eigenface features. The eigenvectors corresponding to these features are weighted. Usually, the sum of these weights is a good representation of a given face. Recognition approaches that use Eigenfaces for recognition ignore the third dimensional information and base their models on two-dimensional information only. The foundation of using Eigenfaces in face recognition is based on the fact that each image can be represented as a matrix. A matrix has a set of eigenvectors that represent the principal components of the matrix. Eigenfaces are the eigenvectors of the covariance matrix of all faces. Similar faces can be described in a space with lower dimensionality. Most of the research on Eigenfaces is concerned with one pose and on rotating the image about the image centre. A collection of different pictures of different angles or emotions of a same person is needed to estimate the actual face. The more sample picture of a person is given; the better accuracy will be found to recognize that person.

CHAPTER X

HOW DOES IT WORKS

The task of facial recognition is discriminating input signals (image data) into several classes (persons). The input signals are highly noisy (e.g. the noise is caused by differing lighting conditions, pose etc.), yet the input images are not completely random and in spite of their differences there are patterns which occur in any input signal. Such patterns, which can be observed in all signals could be – in the domain of facial recognition– the presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called eigenfaces in the facial recognition domain (or principal components generally). They can be extracted out of original image data by means of a mathematical tool called Principal Component Analysis (PCA).

PCA one can transform each original image of the training set into a corresponding eigenface. An important feature of PCA is that one can reconstruct reconstruct any original image from the training set by combining the eigenfaces. Remember that eigenfaces are nothing less than characteristic features of the faces. Therefore one could say that the original face image can be reconstructed from eigenfaces if one adds up all the eigenfaces (features) in the right proportion. Each eigenface represents only certain features of the face, which may or may not be present in the original image. If the feature is present in the original image to a higher degree, the share of the corresponding eigenface in the"sum" of the eigenfaces should be greater. If, contrary, the particular feature is not (or almost not) present in the original image, then the corresponding eigenface should contribute a smaller (or not at all) part to the sum of eigenfaces.

So, in order to reconstruct the original image from the eigenfaces, one has to build a kind of weighted sum of all eigenfaces. That is, the reconstructed original image is equal to a sum of all eigenfaces, with each eigenface having a certain weight. This weight specifies, to what degree the specific feature (eigenface) is present in the original image.

If one uses all the eigenfaces extracted from original images, one can reconstruct the original images from the eigenfaces exactly. But one can also use only a part of the eigenfaces. Then the reconstructed image is an approximation of the original image. However, one can ensure that losses due to omitting some of the eigenfaces can be minimized. This happens by choosing only the most important features (eigenfaces). Omission of eigenfaces is necessary due to scarcity of computational resources. How does this relate to facial recognition? The clue is that it is possible not only to extract the face from eigenfaces given a set of weights, but also to go the opposite way. This opposite way would be to extract the weights from eigenfaces and the face to be recognized. These weights tell nothing less, as the amount by which the face in question differs from"typical" faces represented by the eigenfaces. Therefore, using this weights one can determine two important things:

1. Determine, if the image in question is a face at all. In the case the weights of the image differ too much from the weights of face images (i.e. images, from which we know for sure that they are faces), the image probably is not a face.
2. Similar faces (images) possess similar features (eigenfaces) to similar degrees (weights). If one extracts weights from all the images available, the images could be grouped to clusters. That is, all images having similar weights are likely to be similar faces.

CHAPTER XI

OVERVIEW OF THE ALGORITHM

The algorithm for face recognition using eigenfaces is basically described in figure 1. First, the original images of the training set are transformed into a set of eigenfaces E. After that the weights are calculated for each image of the training set and stored in the set W. Upon observing an unknown image X, the weights are calculated for that particular image and stored in the vector WX. Then, WX is compared with the weights of images, of which one knows for certain that they are faces (the weights of the training set W). One way to do it would be to regard each weight vector as a point in space and calculate an average distance D between the weight vectors from WX and the weight vector of the unknown image WX (the Euclidean distance described in appendix A would be a measure for that). If this average distance exceeds some threshold value Θ, then the weight vector of the unknown image WX lies too "far apart" from the weights of the faces. In this case, the unknown X is considered to not a face. Otherwise (if X is actually a face), its weight vector WX is stored for later classification. The optimal threshold value Θ has to be determined empirically.

CHAPTER XII

EIGENVECTORS AND EIGENVALUES

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. This relationship can be described by the equation $M \times u = \lambda \times u$, where u is an eigenvector of the matrix M and λ is the corresponding eigenvalue.

Eigenvectors possess following properties:

• They can be determined only for square matrices

• There are n eigenvectors (and corresponding eigenvalues) in a $n \times n$ matrix.

• All eigenvectors are perpendicular.

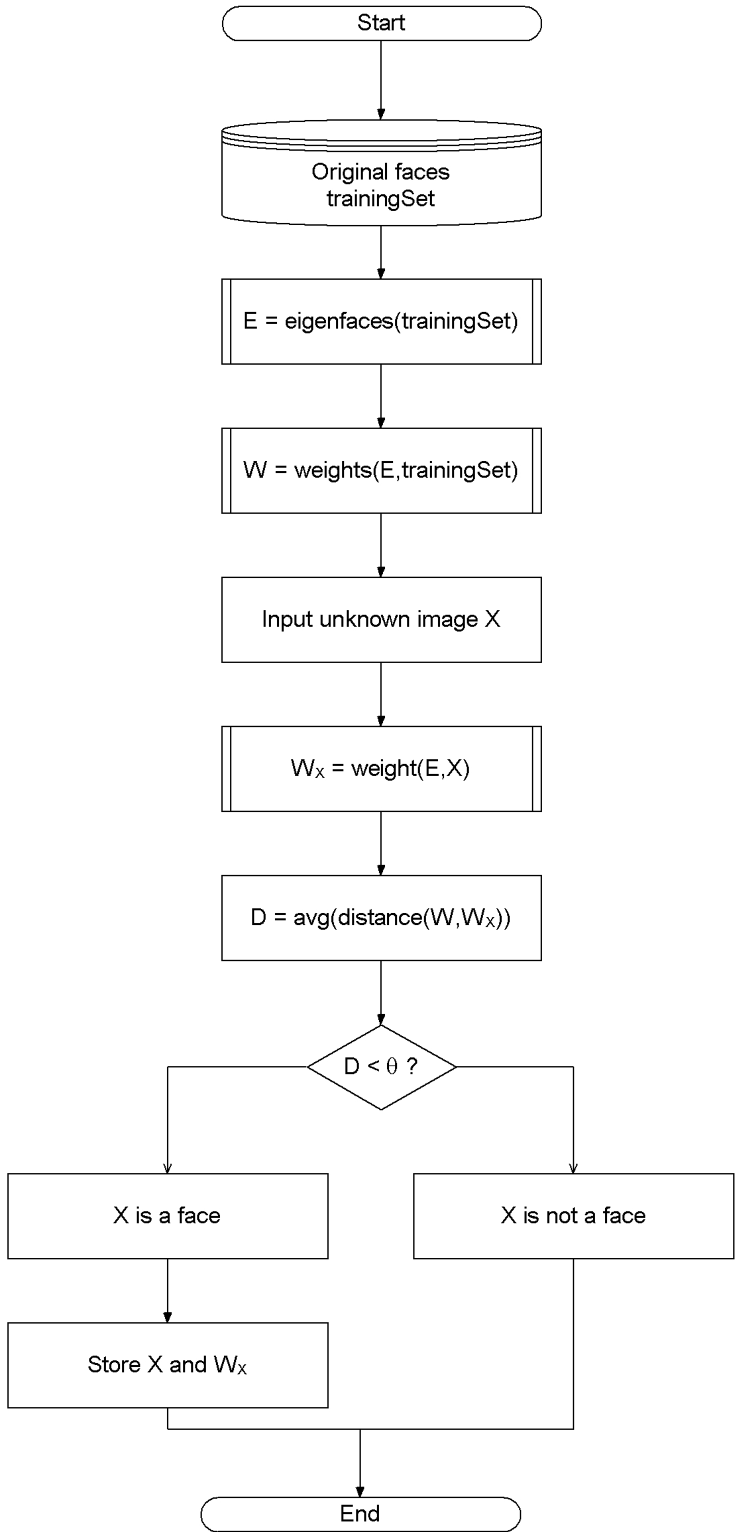

Start
Original faces
trainingSet
E = eigenfaces(trainingSet)
W = weights(E,trainingSet)
Input unknown image X
W_X = weight(E,X)
D = avg(distance(W,W_X))
D < θ ?
X is a face
X is not a face
Store X and W_X
End

Figure 12.1. Functioning principle of the eigenface-based face recognition algorithm

CHAPTER XIII

MATHAMETICAL CALCULATION

13.1 Eigenface Calculation

Step 1: Prepare the data

In this step, the faces constituting the training set (Γ_i) should be prepared for processing.

Step 2: Subtract the mean

The average matrix, ψ, has to be calculated, then subtracted from the original faces (Γ_i) and the result stored in the variable ϕ_i:

$$\Psi = \frac{1}{M} \sum_{n-1}^{M} \Gamma_n$$

$$\Phi_i = \Gamma_i - \Psi$$

Step 3: Calculate the covariance matrix

In the next step the covariance matrix C is calculated according to

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

Step 4: Calculate the eigenvectors and eigenvalues of the covariance matrix

In this step, the eigenvectors (eigenfaces) u_i and the corresponding eigenvalues λ_i should be calculated. The eigenvectors (eigenfaces) must be normalized so that they are unit vectors, i.e. of length 1. The description of the exact algorithm for determination of eigenvectors and eigenvalues is omitted here, as it belongs to the standard arsenal of most math programming libraries.

Step 5: Select the principal components

From M eigenvectors (eigenfaces) u_i, only M′ should be chosen, which have the highest eigenvalues. The higher the eigenvalue, the more characteristic features of a face does the particular eigenvector describe. Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of characteristic features of the faces. After M′ eigenfaces u_i are determined, the ‘training” phase of the algorithm is finished.

CHAPTER XIV

IMPROVEMENT OF THE ALGORITHM

The covariance matrix C in step 3 has a dimensionality of $N_2 \times N_2$, so one would have N_2 eigenfaces and eigenvalues. For a 256 × 256 image that means that one must compute a 65, 536 × 65, 536 matrix and calculate 65, 536 eigenfaces. Computationally, this is not very efficient as most of those eigenfaces are not useful for our task.

So, the step 3 and 4 is replaced by the following steps:

$$C = \frac{1}{M} \sum_{n-1}^{M} \Phi_n \Phi_n^T = AA^T$$

$$L = A^T A \quad L_{n,m} = \Phi_m^T \Phi_n$$

$$u_l = \sum_{k-1}^{M} v_{lk} \Phi_k \quad l = 1, \ldots, M$$

Where L is a M × M matrix, v are M eigenvectors of L and u are eigenfaces. Note that the covariance matrix C is calculated using the formula C = AA^T. The advantage of this method is that one has to evaluate only M numbers and not N^2. Usually, M << N^2 as only a few principal components (eigenfaces) will be relevant. The amount of calculations to be performed is reduced from the number of prixels ($N^2 \times N^2$) to the number of images in the training set (M).

In step 5, the associated eigenvalues allow one to rank the eigenfaces according to their usefulness. Usually, we will use only a subset of M eigenfaces, the M′ eigenfaces with the largest eigenvalues.

CHAPTER XV

CLASSIFYING THE FACES

The process of classification of a new (unknown) face Γ_{new} to one of the classes (known faces) proceeds in two steps.

First, the new image is transformed into its eigenface components. The resulting weights form the weight vector $\Omega^T_{new.}$

$$\omega_k = u_k^T(\Gamma_{\text{new}} - \Psi) \quad k = 1 \ldots M'$$
$$\Omega^T_{\text{new}} = [\ \omega_1 \quad \omega_2 \quad \ldots \quad \omega_{M'}\ ]$$

The Euclidean distance between two weight vectors d (Ωi, Ωj) provides a measure of similarity between the corresponding images i and j. If the Euclidean distance between Γ_{new} and other faces exceeds - on average - some threshold value Θ, one can assume that Γ_{new} is no face at all. d (Ωi, Ωj) also allows one to construct "clusters" of faces such that similar faces are assigned to one cluster.

Then computation of the distance between the face and its reconstruction is done,

$\xi^2 = ||rrm - rs||^2$

After this we have to distinguish between face and non-face images, by applying these conditions on our calculated result. The conditions are:

1. If $\xi \geq \Theta$, then the image is not a face.
2. If $\xi < \Theta$ and $\varepsilon_i \geq \Theta$, then it's a new face.
3. If $\xi < \Theta$ and min {εi} < Θ, then it's a known face.

CHAPTER XVI

CONCLUSION

The approach is definitely robust, simple, and easy and fast to implement compared to other algorithms. It provides a practical solution to the recognition problem. We are currently investigating the system to deal with a range of aspects like defining a small number of face classes of each person corresponding to their characteristics. We are going to implement a GUI for our software.

An intelligent system should have an ability to learn or have ability to adapt over time. When an image is sufficiently close to the face space but not a known face, the system marked it as an unknown face. Computer stores the unknown face’s pattern vector of the corresponding image. Further these types of vector are cluster in the space, the presence of new but unknown face is postulated.

Further more if the image is noisy one, then the performance is not very accurate, it degrades gradually. We should give focus on this problem also, how to deal with a noisy image or how can we remove noise from the image.

CHAPTER XVII

INTRODUCTION

Images are often corrupted by impulse noise due to errors generated from sensors or communicational channels. It is important to eliminate noise from images before face recognition, edge detection, and image segmentation procedures. To remove the noise from images, there are some filtering methods like max and min filters, median filters, harmonic mean filter, low pass, high pass, band pass filters etc. Among them the well-known median filter has been recognized as an effective way of removing impulse noise. The success of median filters is based on two main properties: edge preservation and efficient noise attenuation. Edge preservation is essential in image processing due to the nature of visual perception. Despite its effectiveness in smoothing noise, median filters tend to remove fine details when applied to an image.

To eliminate the drawbacks of median filter, the adaptive median filter, has been proposed. This filter is a modified and complex than median filter and is capable of performance superior than others. It has variable window sizes for removing impulses while preserving sharpness at the same time. In this way, the integrity of edge and detail information becomes better.

CHAPTER XVIII

ADAPTIVE MEDIAN FILTER

The adaptive median filter is designed to eliminate the problems faced with the standard median filter. The basic difference between the two filters is that, in the adaptive median filter, the size of the window surrounding each pixel is variable. This variation depends on the median of the pixels in the present window. If the median value is an impulse, then the size of the window is expanded. Otherwise, further processing is done on the part of the image within the current window specifications. 'Processing' the image basically entails the following: The center pixel of the window is evaluated to verify whether it is an impulse or not. If it is an impulse, then the new value of that pixel in the filtered image will be the median value of the pixels in that window. If, however, the center pixel is not an impulse, then the value of the center pixel is retained in the filtered image. Thus, unless the pixel being considered is an impulse, the gray-scale value of the pixel in the filtered image is the same as that of the input image. Thus, the adaptive median filter solves the dual purpose of removing the impulse noise from the image and reducing distortion in the image.

The median filter performs well as the spatial density of the impulse noise is not large. It can perform well if the probability of se is less than 0.2. The adaptive median filter can handle impulse noise with probabilities even larger than these. An additional benefit of adaptive median filter is that it seeks to preserve detail while smoothing non-impulse noise, that traditional median filter does not do.

CHAPTER XIX

THE ALGORITHM

As in all the other filters, the adaptive median filter also works in a rectangular window area $S_{xy.}$ The adaptive median filter change (increases) the size of S_{xy} during filter operation, depending on certain condition as listed below. The output of the filter is a single value which replaces the current pixel value at (x, y), the particular point on which the window S_{xy} is centered at a given time.

Z_{min} = Minimum gray level value in $S_{xy.}$

Z_{max} = Maximum gray level value in S_{xy}

Z_{med} = Median of gray levels in S_{xy}
Z_{xy} = gray level at coordinates (x, y)

S_{max} = Maximum allowed size of S_{xy}

The adaptive median filter works in two levels denoted Level A and Level B as follows:

Level A: A1= Z_{med} - Z_{min}
A2= Z_{med} - Z_{max}

If A1 > 0 AND A2 < 0, Go to level B
Else increase the window size

If window size <= S_{max} repeat level A
Else output Z_{xy}.

Level B: B1 = Z_{xy} – Z_{min}
B2 = Z_{xy} – Z_{min}
If B1 > 0 AND B2 < 0 output Z_{xy}
Else output Z_{med}.

CHAPTER XX

HOW IT WORKS

The algorithm has three main purposes:

(a) To remove impulse noise.
(b) To provide smoothing of other noise that may not be impulsive.
(c) To reduce excessive distortions such as too much thinning or thickening of object boundaries.

The steps are follows:

Step 1 Initialization

Start with the smallest windows size S = 3. Let the maximum window size be S_{max} (again, an odd number).

Step 2 Computation of order statistic

Let Z_{min} = S (0) ([Sk,l]) be the output of the 0-th order statistic filter. Z_{max} = S(N)([wk,l]) is the output of the N-th order statistic filter and Z_{med} =S((N+1)/2) ([wk,l]) is the output of the median filter.

Step 3 Evaluation of the terminating condition

If the condition $Z_{min} < Z_{med} < Z_{max}$ is satisfied then the processing ends with the computation of the output value which is defined as follows: If $Z_{min} < Z_{xy} < Z_{max}$ then the pixel is not corrupted by noise and the output value is the value of the original pixel, i.e. $Z_{xy} = Z_{xy}$. If $Z_{min} < Z_{xy} < Z_{max}$ is not satisfied then the output value is the median of the window, i.e. yuv = Z_{med}. If the condition is not satisfied then the computation continues.

Step 4 Increasing of the window size

If the condition $Z_{min} < Z_{med} <$ Zmax is not satisfies, it can be interpreted as follows. If many pixels have the same value then it is impossible to determine (with the current window size) whether the pixels are corrupted with high intensity noise or whether it is the constant area with all pixels of the same color. This is the reason why the window size has to be increased.

If the window W is smaller than Smax, increase the size of the window, i.e. S = S + 2, and repeat the computation from step 2. If the size of the window W reaches the maximum value S_{max}, the processing ends and the output value is defined as $Z_{xy} = Z_{med}$.

The values Z_{min} and Z_{max} are considered statistically by the algorithm to be "impulselike" noise components, even if these are not the lowest or highest possible pixel values in the image.

With these observations, we see that the purpose of level A is to determine if the median filter output, Z_{med}, is an impulse or not. If the condition $Z_{min}<Z_{med}<Z_{max}$ holds, then Zmed cannot be an impulse. In this case, we go to level B and test to see if the point of the center of the window, Z_{xy}, is itself an impulse. If the condition B1 > 0 AND B2 < 0 is true, then $Z_{min}<Z_{xy}<Z_{max,}$ and Z_{xy} cannot be an impulse. In this case, the algorithm outputs the unchanged pixel value, Z_{xy}. If the condition B1 > 0 AND B2 < 0 is false, then either $Z_{min}=Z_{xy}$ or $Z_{max=,}$ and Z_{xy}. In either case the value of the pixel is an extreme value and the algorithm outputs the median value Z_{med}, which we know from level A is not a noise impulse. The last step is what the median filter does. The problem is that the standard median filter replaces every point in the image by the median of the corresponding neighborhood. This causes unnecessary loss of detail.

Continuing with the explanation, suppose level A doe find an impulse. The algorithm increases the size of the window and repeats level A. This looping continues until the algorithm either finds a median value that is not an impulse or the maximum window size is reached. If the maximum window size is reached, the algorithm returns the value of Z_{xy}. But it should note that, there is no guarantee that this value is not an impulse. The smaller the noise probabilities are or the larger the window size, the less likely it is that a premature exit condition will occur. As the density of the impulse increases, it stands to reason that we would need a larger window to clean up the noise spikes.

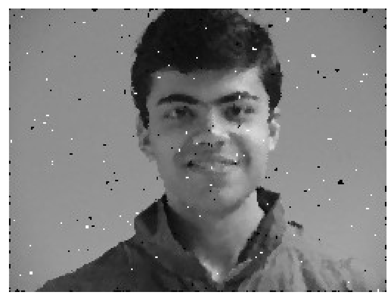
Every times the algorithm outputs a value, the window S_{xy} is moved to the next location in the image. The algorithm then is reinitialized and applied to the pixels in the new location.

CHAPTER XXI

EXPERIMENTAL RESULTS AND ANALYSIS

The adaptive median filter is designed to remove impulsive noise from images. Therefore, our algorithm's performance was first tested with basic salt and pepper noise with a noise density of 0.35.

(a)



(b)

Fig21.1:
(a) The image with 'salt and pepper' noise of 0.35 noise density.
(b) Output of the standard median filter.

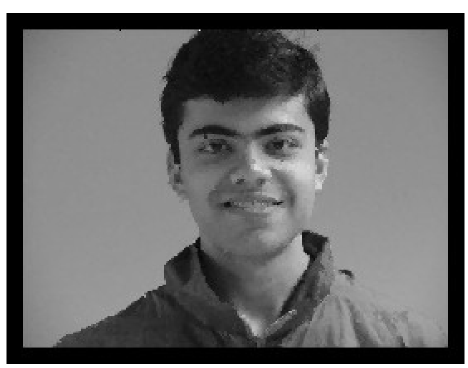
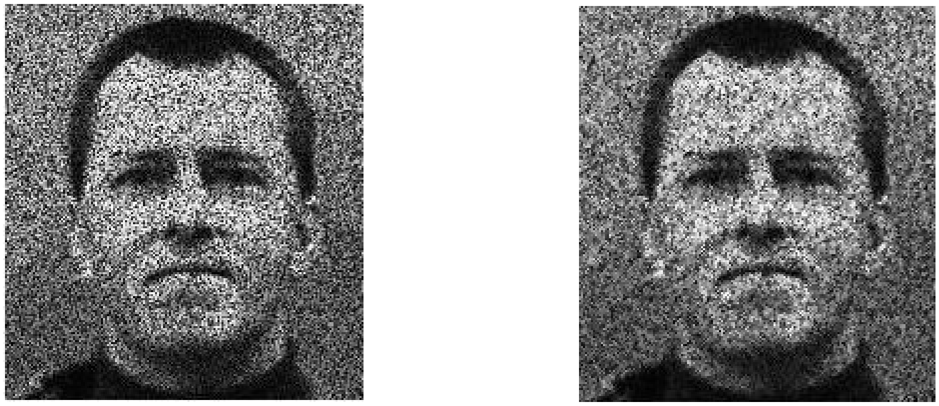


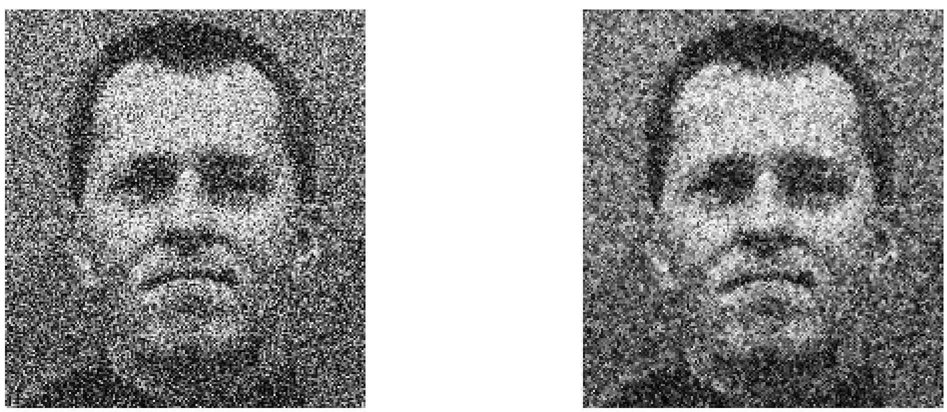
Fig 21.2: Output of the adaptive median filter shows the improvement in performance with respect to the standard median filter.



(a) (b)

Fig 21.3:

(c) The image with ‘speckle’ noise of 0.6 variance.
(d) Output of Adaptive Median Filter



(a) (b)

Fig 21.4:

(c) Image with ‘Gaussian’ noise with 0 mean and 0.02 variance
(d) Output of Adaptive Median Filter

CHAPTER XXII

CONCLUSION

Still Few faces are there which really tough to distinguished for instance twin siblings. Building a system that can distinguish between the two look-alikes can be a challenge. Moreover we want a Computer that can recognize someone, even though there is only one picture of that person on file, and it was taken at a different angle, in different lighting, or they were wearing sunglasses as like human being. May be in near future you can imagine your desktop PC saying, ‘you seem upset, what can I do to help?

REFERENCE

[1] Handbook of Face Recognition by Stan Z. Li Anil K. Jain.

[2] Turk, M. A., Pentland, A. P., Eigenfaces for recognition, 1991, Cognitive Neurosci., V. 3, no.1, pp.71-86.

[3] M. Turk, "A Random Walk Through Eigenface", IEICE Trans. INF. & SYST., Vol. E84-D, No. 12, Dec. 2001.

[4] Zhao, W., Chellappa, R., Phillips, P. J., Rosenfeld, A., 2003, Face recognition: A literature survey, ACM Computing Surverys (CSUR), V. 35, Issue 4, pp. 399-458.

[5] M. Yang, D. J. Kriegman, and N. Ahuja, "Detecting Face in Images: A Survey", IEEE Trans. on PAMI, Vol. 24, No. 1, pp. 34-58, Jan. 2002.

[6] Survey paper: Face Detection and Face Recognition By Hyun Hoi James Kim

[7] Face Recognition: a Summary of 1995 – 1997 by Thomas Fromherz

[8] Nefian, A.V. et al., 1998, Hidden markov models for face recognition, In Proceedings, International Conference on Acoustics, Speech and Signal Proceeding, 2721 -2724

[9] Face recognition: eigenface, elastic matching and neural nets Jun Zhang; Yong Yan; Lades, M. Proceedings of the IEEE Volume 85, Issue 9, Sep 1997 Page(s):1423 – 1435

[10] Thomas Fromherz, Peter Stucki, Martin Bichsel "A Survey of Face Recognition", MML Technical Report, No 97.01, Dept. of Computer Science, University of .Zurich.

[11] Y.-L. Tian and R. Bolle. Automatic detecting neutral face for face authentication. In Proceedings of AAAI-03 Spring Symposium on Intelligent Multimedia Knowledge Management, CA, 2003.

[12] Y.-L. Tian, T. Kanade, and J. Cohn. Recognizing action units for facial expression analysis. IEEE Trans. on Pattern Analysis and Machine Intell., 23(2):1–19, 2001.

[13] Comprehensive Database for Facial Expression Analysis BY Takeo Kanade Jeffrey F. Cohn, Yingli Tian

[14] 5. V. Blanz and T. Vetter. A morphable model for the synthesis of 3d faces. In Computer Graphics Proceedings, Annual Conference Series (SIGGRAPH), 1999.

[15] Xiujuan Chai , Shiguang Shan, Wen Gao. Pose Normalization for Robust Face Recognition Based on Statistical Affine Transformation ICICS-PCM 2003 15-18 December 2003 Singapore.

[16] Labeled graphs and Dynamic link matching for Face Recognition and Scene Analysis by Laurenz Wiskott.(PhD thesis)

[17] L. Torres, Is there any hope for face recognition?, Proc. of the 5th International Workshop on Image Analysis for Multimedia Interactive Services, WIAMIS 2004, 21-23 April 2004, Lisboa, Portugal

[18] FRVT 2006 and ICE 2006 Large-Scale Results

[19] The FERET Evaluation Methodology for Face-recognition Algorithms, by P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, IEEE trans. Pattern Analysis and Machine Intelligence. (625KB)

[20] Jorge Orts, “ECE533 – Image Processing Project”, Face Recognition Techniques, The University of Wisconsin.

[21] Wlodzimierz M. Baranski, Andrzej Wytyczak-Partyka, Tomasz Walkowiak, “Computational complexity reduction in PCA-based face recognition”, Institute of Computer Engineering, Control and Robotics, Wroclaw University of Technology, Poland.

[22] Lindsay I Smith, “A tutorial on Principal Components Analysis”, February 26, 2002.

[23] Gregory Shakhnarovich and Baback Moghaddam, “Face Recognition in Subspaces”, Mitsubishi Electric Research Laboratories, May 2004. Published in: Handbook of Face Recognition, Eds. Stan Z. Li & Anil K. Jain, Springer-Verlag, 2004

[24]http://openbio.sourceforge.net/resources/eigenfaces/eigenfaceshtml/facesOptions.html

[25] Adaptive median filters: new algorithms and results Hwang, H.; Haddad, R.A.; Image Processing, IEEE Transactions on, Volume: 4 Issue: 4, April 1995: Page(s): 499 -502

[26] Selective removal of impulse noise based on homogeneity level information Gouchol Pok; Jyh-Charn Liu; Nair, A.S.; Image Processing, IEEE Transactions on , Volume: 12 Issue: 1, Jan. 2003: Page(s): 85 -92

[27] S.-Q. Yuan and Y.-H. Tan, “Erratum to” impulse noise removal by a global-local noise detector and adaptive median filter”: [signal processing 86 (8) (2006) 2123-2128],” Signal Processing, vol. 87, no. 5, p.1171, 2007.