An Approach of Secure Face recognition using Linear discriminant analysis in Network

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Abstract— *Our aim is to apply Linear Discriminant Analysis (LDA) to face recognition which is based on a linear projection from the image space to a low dimensional space by maximizing the between class scatter and minimizing the within-class scatter. LDA allows objective evaluation of the significance of visual information in different features of the face for identifying the human face. The LDA also provides us with a small set of features that carry the most relevant information for classification purposes. LDA method overcomes the limitation of Principle Component Analysis method by applying the linear discriminant criterion. This criterion tries to maximize the ratio of determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples. Linear discriminant groups the images of the same class and separate images of different classes.*

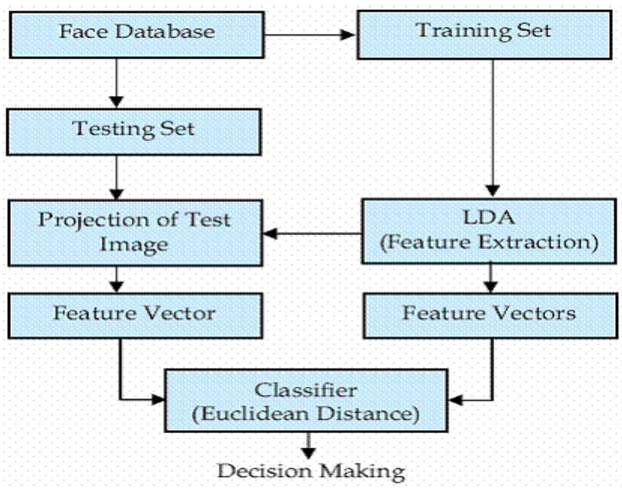
Keywords— Image Processing, Face recognition, Linear Discriminant Analysis.

I. INTRODUCTION

Linear discriminant analysis (LDA) is a generalization of Fisher's linear discriminant, a method used instatistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.

LDA is also closely related to principal component analysis (PCA) and factor analysis in that they both look for linear combinations of variables which best explain the data. LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities. Discriminant analysis is also different from factor analysis in that it is not an interdependence technique: a distinction between independent variables and dependent variables (also called criterion variables) must be made[1].

LDA is closely related to analysis of variance (ANOVA) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements. However, ANOVA uses categorical independent variables and a continuous dependent variable, whereas discriminate analysis has continuous independent variables and a categorical dependent variable (*i.e.* the class label). Logistic regression and probity are more similar to LDA than ANOVA is, as they also explain a categorical variable by the values of continuous independent variables. These other methods are preferable in applications where it is not reasonable to assume that the independent variables are normally distributed, which is a fundamental assumption of the LDA method.



LDA works when the measurements made on independent variables for each observation are continuous quantities. When dealing with categorical independent variables, the equivalent technique is discriminant correspondence analysis.

1.1 LDA for two classes

Consider a set of observations $\vec{x}$ (also called features, attributes, variables or measurements) for each sample of an object or event with known class *y*. This set of samples is called the training set[2]. The classification problem is then to find a good predictor for the class *y* of any sample of the same distribution (not necessarily from the training set) given only an observation $\vec{x}$.

LDA approaches the problem by assuming that the conditional probability density functions $p(\vec{x}|y=0)$ and $p(\vec{x}|y=1)$ are both normally distributed with mean and covariance parameters $(\vec{\mu}_0, \Sigma_0)$ and $(\vec{\mu}_1, \Sigma_1)$, respectively. Under this assumption, the Bayes optimal solution is to predict points as being from the second class if the log of the likelihood ratios is below some threshold T, so that;

$$(\vec{x}-\vec{\mu}_0)^T\Sigma_0^{-1}(\vec{x}-\vec{\mu}_0)+\ln|\Sigma_0|-(\vec{x}-\vec{\mu}_1)^T\Sigma_1^{-1}(\vec{x}-\vec{\mu}_1)-\ln|\Sigma_1| > T$$

Without any further assumptions, the resulting classifier is referred to as QDA (quadratic discriminant analysis).

LDA instead makes the additional simplifying homoscedasticity assumption (*i.e.* that the class covariances are identical, so $\Sigma_0 = \Sigma_1 = \Sigma$) and that the covariances have full rank. In this case, several terms cancel:

$$\vec{x}^T\Sigma_0^{-1}\vec{x} = \vec{x}^T\Sigma_1^{-1}\vec{x}$$

$$\vec{x}^T{\Sigma_i}^{-1}\vec{\mu}_i = {\vec{\mu}_i}^T{\Sigma_i}^{-1}\vec{x}$$ because Σ_i is Hermitian

and the above decision criterion becomes a threshold on the dot product

$$\vec{w}\cdot\vec{x} > c$$

for some threshold constant *c*, where

$$\vec{w} = \Sigma^{-1}(\vec{\mu}_1 - \vec{\mu}_0)$$

$$c = \frac{1}{2}(T - {\vec{\mu}_0}^T\Sigma_0^{-1}\vec{\mu}_0 + {\vec{\mu}_1}^T\Sigma_1^{-1}\vec{\mu}_1)$$

This means that the criterion of an input $\vec{x}$ being in a class *y* is purely a function of this linear combination of the known observations[3].

It is often useful to see this conclusion in geometrical terms: the criterion of an input $\vec{x}$ being in a class *y* is purely a function of projection of multidimensional-space point $\vec{x}$ onto vector $\vec{w}$ (thus, we only consider its direction). In other words, the observation belongs to *y* if corresponding $\vec{x}$ is located on a certain side of a hyperplane perpendicular to $\vec{w}$. The location of the plane is defined by the threshold c.

The typical implementation of the LDA technique requires that all the samples are available in advance. However, there are situations where the entire data set is not available and the input data are observed as a stream. In this case, it is desirable for the LDA feature extraction to have the ability to update the computed LDA features by observing the new samples without running the algorithm on the whole data set.

For example, in many real-time applications such as mobile robotics or on-line face recognition, it is important to update the extracted LDA features as soon as new observations are available. A LDA feature extraction technique that can update the LDA features by simply observing new samples is an*incremental[4] LDA algorithm*, and this idea has been extensively studied over the last two decades. Catterjee and Roychowdhury proposed an incremental self-organized LDA algorithm for updating the LDA features. In other work, Demir and Ozmehmet proposed online local learning algorithms for updating LDA features incrementally using error-correcting and the Hebbian learning rules Later[5], Aliyari *et a*l. derived fast incremental algorithms to update the LDA features by observing the new samples.

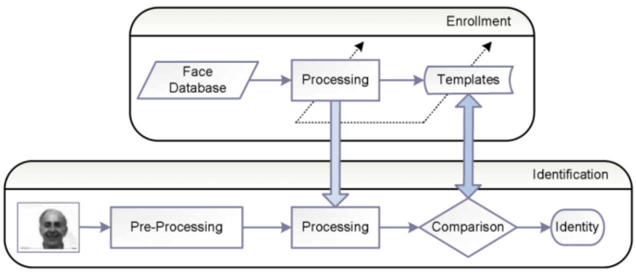


Figure 1.2 Face recognition Approach

II REVIEW OF LITERATURE

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 *SB* and the within-class scatter matrix *Sw* are defined. The goal is to maximize *SB* while minimizing *SW*, in other words, maximize the ratio det|*Sb*|/det|*Sw*| . This ratio is maximized when the column vectors of the projection matrix are the eigenvectors of (*Sw^-1 × Sb*). We were studied more than 25 research papers and articles for associated with our project. Here some few important work related to our research are-

2.1 Discriminant analysis for recognition of human face images

The discrimination power of various human facial features is studied and a new scheme for automatic face recognition (AFR) is proposed. The first part of the paper focuses on the linear discriminant analysis (LDA) of different aspects of human faces in the spatial as well as in the wavelet domain. This analysis allows objective evaluation of the significance of visual information in different parts (features) of the face for identifying the human subject. The LDA of faces also provides us with a small set of features that carry the most relevant information for classification purposes. The features are obtained through eigenvector analysis of scatter matrices with the objective of maximizing between-class variations and minimizing within-class variations. The result is an efficient projection-based feature-extraction and classification scheme for AFR. Each projection creates a decision axis with a certain level of discrimination power or reliability. Soft decisions made based on each of the projections are combined, and probabilistic or evidential approaches to multisource data

analysis are used to provide more reliable recognition results. For a medium-sized database of human faces, excellent classification accuracy is achieved with the use of very-low-dimensional feature vectors[6].

Inspired by the human's ability to recognize faces as special objects and motivated by the increased interest in the commercial applications of automatic face recognition (AFR) as well as by the emergence of real-time processors, research on automatic recognition of faces has become very active. Studies on the analysis of human facial images have been conducted in various disciplines. These studies range from psychophysical analysis of human recognition of faces and related psycho visual tests1,2 to research on practical and engineering aspects of computer recognition and verification of human faces and facial expressions3 and race and gender classification.

The application of LDA to study the discriminatory power of various facial features in spatial and wavelet domain is presented. Also, an LDA-based feature extraction for face recognition is proposed and tested. A holistic projection-based approach to face feature extraction is taken in which eigen templates are the most discriminant vectors derived from LDA of face images in a rich enough database. The effectiveness of the proposed LDA-based features is compared with that of PCA-based eigen faces. For classification a variation of evidential reasoning is used, in which each projection becomes a source of discriminating information, with reliability proportional to its discrimination power. The weighted combination of similarity or dissimilarity scores suggested by all projection coefficients is the basis for membership values. Several results on face recognition and gender classification are presented, in which highly competitive recognition accuracies are achieved with a small number of features.The feature extraction can be applied to WT representation of images to provide a multiscale discriminant framework. In such cases the system becomes more complex at the expense of improving separability and performance. The proposed feature extraction combined with soft classification seems to be a promising alternative to other face-recognition systems.

2.2 Robust face recognition using sparse representation in LDA space

In this article[7], They address the problem of face recognition under uncontrolled conditions. The proposed solution is a numerical robust algorithm dealing with face images automatically registered and projected via the linear discriminant analysis (LDA) into a holistic low-dimensional feature space. At the heart of this discriminative system, there are suitable nonconvex parametric mappings based on which a fixed-point technique finds the sparse representation of test images allowing their classification. We theoretically argue that the success achieved in sparsity promoting is due to the sequence of values imposed on a characteristic parameter of the used mapping family. Experiments carried out on several databases (ORL, YaleB, BANCA, FRGC v2.0) show the robustness and the ability of the system for classification purpose. In particular, within the area of sparsity promotion, our recognition system shows very good performance with respect to those achieved by the stateof- the-art _1 norm-based sparse representation classifier (SRC), the recently proposed _2 norm-based collaborative representation classifier (CRC), the LASSO-based sparse decomposition technique, and the weighted sparse representation method (WSRC), which integrates sparsity and data locality structure.

They propose a new approach for face recognition in the framework of sparse recovery. We demonstrate its capability in producing well-separated classes in uncontrolled contexts and proving its applicability in real situations, giving good performance also when only few examples per subject are available in training. The reported results have been obtained on automatically localized faces, showing its ability in dealing with misalignments. As the solution has been conceived, it is robust to sparse and non-continuous noise and occlusions; however, to deal with more invasive corruptions, a part-based version of the method should be set up. Besides, we intend to integrate the system with other feature extractors (e.g., Gabor, HOG,...), aiming at enriching the system descriptive power and ultimately its robustness and applicability.

2.3 Face Recognition Using LDA-Based Algorithms

Low-dimensional feature representation with enhanced discriminatory power is of paramount importance to face recognition (FR) systems[8]. Most of traditional linear discriminant analysis (LDA)-based methods suffer from the disadvantage that their optimality criteria are not directly related to the classification ability of the obtained feature representation. Moreover, their classification accuracy is affected by the "small sample size" (SSS) problem which is often encountered in FR tasks. In this short paper, we propose a new algorithm that deals with both of the shortcomings in an efficient and cost effective manner. The proposed here method is compared, in terms of classification accuracy, to other commonly used FR methods on two face databases. Results indicate that the performance of the proposed method is overall superior to those of traditional FR approaches, such as the Eigenfaces, Fisherfaces, and D-LDA methods.

It is generally believed that, when it comes to solving problems of pattern classification, LDA-based algorithms outperform PCA-based ones, since the former optimizes the low-dimensional representation of the objects with focus on the most discriminant feature extraction while the latter achieves simply object reconstruction. However, the classification performance of traditional LDA is often degraded by the fact that their separability criteria are not directly related to their classification accuracy in the output space. A solution to the problem is to introduce weighting functions into LDA. Object classes that are closer together in the output space, and thus can potentially result in misclassification, should be more heavily weighted in the input space.

In this paper, a new feature extraction method for face recognition tasks has been proposed. The method introduced here utilizes the well-known framework of linear discriminant analysis and it can be considered as a generalization of a number of techniques which are commonly in use. The new method utilizes a new variant of D-LDA to safely remove the null space of the between-class scatter matrix and applies a fractional step LDA scheme to enhance the discriminatory power of the obtained D-LDA feature space. The effectiveness of the proposed method has been demonstrated through experimentation using two popular face databases. The DF-LDA method presented here is a linear pattern recognition method. Compared with nonlinear models, a linear model is rather robust against noises and most likely will not overfit. Although it has been shown that distribution of face patterns is highly non convex and complex in most cases, linear methods are still able to provide cost effective solutions to the FR tasks through integration with other strategies, such as the principle of "divide and conquer," in which a large and nonlinear problem is divided into a few smaller and local linear subproblems. The development of mixtures of localized DF-LDA to be used in the problem of large size face recognition as well as the development of a nonlinear DF-LDA through the utilization of kernel machine techniques are research topics under current investigation.

2.4 LDA BASED FACE RECOGNITION BY USING HIDDEN MARKOV MODEL IN CURRENT TRENDS.

Hidden Markov model (HMM) is a promising method that works well for images with variations in lighting, facial expression, and orientation. Face recognition draws attention as a complex task due to noticeable changes produced on appearance by illumination, facial expression, size, orientation and other external factors. To process images using HMM, the temporal or space sequences are to be considered. In simple terms HMM can be defined as set of finite states with associated probability distributions. Only the outcome is visible to the external user not the states and hence the name Hidden Markov Model. The paper deals with various techniques and methodologies used for resolving the problem .We discuss about appearance based, feature based, model based and hybrid methods for face identification. Conventional techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) and feature based Elastic Bunch Graph Matching (EBGM) and 2D and 3D face models are well known for face detection and recognition. Face detection and recognition has emerged as an active area of research in fields such as security system, videoconferencing and identification. As security deserves prime concern in today's networked world, face recognition can be used as a preliminary step of personal identity verification, facial expression extraction, gender classification, advanced human and computer interaction. It is a form of biometric method utilizing unique physical or behavioral characteristics [9]. Face recognition is considered to be a complex task due to enormous changes produced on face by illumination, facial expression, size, orientation, accessories on face and aging effects. The difficulty level increases when two persons have similar faces. Usually, face recognition systems accomplish the task through face image based methods uses predefined standard face patterns where as feature based techniques concentrate on extracted features such as distance between eyes, skin colour, eye socket depth etc.

The report encloses various approaches and techniques to solve face identification problem. Appearance based methods namely Principal component analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) are gaining attention as efficient techniques for face recognition. Most of the conventional methods are feature based or appearance based and in many cases uses a combination of both (hybrid methods). Different decision making systems are utilized for implementing the recognition systems. Artificial neural networks play a remarkable role in resolving many of the related issues in face recognition because of the inherent properties of neural networks. The feed forward architecture of neural networks after proper training can function as powerful tool for face classification.

A major challenge faced by any face recognition system is its ability to identify images, which may be tampered or undetectable due to various reasons. Pre-processing and normalization of images becomes inevitable in the context of face identification. Varying lighting conditions or face expressions reduces the recognition rate resulting in poor performance of the system. In order to avoid these difficulties different image enhancement methods can be employed. The report gives a brief overview of some of the widely used methods. Model based approaches are equally significant as statistical methods in resolving the face identification problem. Accuracy and similarity to realistic face images are added features of model based systems. The use of face models and the transition from 2D to 3D face models have greatly improved the performance of face recognition systems. The introduction of 3D morph able models is a remarkable step in 3D face recognition over the last few decades.

2.5 FACE RECOGNITION BY LINEAR DISCRIMINANT ANALYSIS

Linear Discriminant Analysis (LDA) has been successfully applied to face recognition which is based on a linear projection from the image space to a low dimensional space by maximizing the between class scatter and minimizing the within-class scatter. LDA allows objective evaluation of the significance of visual information in different features of the face for identifying the human face. The LDA also provides us with a small set of features that carry the most relevant information for classification purposes. LDA method overcomes the limitation of Principle Component Analysis method by applying the linear discriminant criterion[10]. This criterion tries to maximize the ratio of determinant of the between-class scatter matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples. Linear discriminant groups the images of the same class and separate images of different classes. Here to identify an input test image, the projected test image is compared to each projected training, and the test image is identified as the closest training image[11]. The experiments in this paper we present to use LDA for face recognition. The experiments in this paper are performed with the ORL face database. The experimental results show that the correct recognition rate of this method is higher than that of previous techniques.

Face recognition system is a computer application for automatically identify or verifying a person from a digital image or video frame from a video source. Facial recognition system typically used in security system. In this system automatically searching of faces from the face databases, typically resulting in a group of facial images ranked by computer evaluated similarity. Some facial recognition algorithm identifies faces by extracting landmarks, or features from an image of the subject face. For example, face recognition algorithm may analyze the relative position, size, shape of the eyes, nose cheekbones and jaw to recognize faces. Linear Discriminant analysis explicitly attempts to model the difference between the classes of data. LDA is a powerful face recognition technique that overcomes the limitation of Principle component analysis technique by applying the linear discriminant criterion. This criterion tries to maximize the ratio of the determinant of the between-class scatter matrix of the projected samples to the determinant of the within class scatter matrix of the projected samples. Linear discriminant group images of the same class and separates images of different classes of the images.

Linear Discriminant Analysis method has been successfully applied to face recognition which is based on a linear projection from the image space to a low dimensional space. But the major drawback of applying LDA is that it may encounter the small sample size problem. When the small sample size problem occurs, the within-class scatter matrix becomes singular. Since the within-class scatter of all the samples is zero in the null space of Sw, the projection vector that can satisfy the objective of an LDA process is the one that can maximize the between-class scatter. But face image data distribution in practice is highly complex because of illumination, facial expression and pose variation. The kernel technique is used to project the input data into an implicit space called feature space by nonlinear kernel mapping. Therefore kernel trick is used taking input space and after that LDA performed in this feature space, thus a non linear discriminant can be yielded in the input data.

2.6 PCA and LDA Based Face Recognition Using Feedforward Neural Network Classifier

Principal component analysis (PCA) and Linear Discriminant Analysis (LDA) techniques are among the most common feature extraction techniques used for the recognition of faces[12]. In this paper, two face recognition systems, one based on the PCA followed by a feed forward neural network (FFNN) called PCA-NN, and the other based on LDA followed by a FFNN called LDA-NN, are developed. The two systems consist of two phases which are the PCA or LDA preprocessing phase, and the neural network classification phase. The proposed systems show improvement on the recognition rates over the conventional LDA and PCA face recognition systems that use Euclidean Distance based classifier. Additionally, the recognition performance of LDANN is higher than the PCA-NN among the proposed systems.

The development in the multimedia applications has increased the interest and research in face recognition significantly and numerous algorithms have been proposed during the last decades.[13] Research in human strategies of face recognition, has shown that individual features and their immediate relationships comprise an insufficient representation to account for the performance of adult human face identification. Bledsoe was the first to attempt to use semi-automated face recognition with a hybrid human-computer system that classified faces on the basis of fiducially marks entered on photographs by hand. Fischler and Elschlager described a linear embedding algorithm that used local feature template matching and a global measure of fit to find and measure the facial features. Generally speaking, we can say that most of the previous work on automated face recognition has ignored the issue of just what aspects of the face stimulus are important for face recognition.

In this paper, two face recognition systems, the first system based on the PCA preprocessing followed by a FFNN based classifier (PCA-NN) and the second one based on the LDA preprocessing followed by another FFNN (LDA-NN) based classifier, are proposed. The feature projection vectors obtained through the PCA and LDA methods are used as the input vectors for the training and testing of both FFNN architectures. The proposed systems show improvement on the recognition rates over the conventional LDA and PCA face recognition systems that use Euclidean Distance based classifier. Additionally, the recognition performance of LDA-NN is higher than the PCA-NN among the proposed systems.

2.7 A Direct LDAAlgorithm for High-Dimensional Data – with Application to Face Recognition

Linear Discriminant Analysis (LDA) has been successfully used as a dimensionality reduction technique to many classification problems, such as speech recognition, face recognition, and multimedia information retreival. The objective is to find a projection A that maximizes the ratio of between-class scatter Sb against within-class scatter Sw (Fisher's criterion):

$$\arg\max_{A} \frac{|AS_bA^T|}{|AS_wA^T|}$$

However, for a task with very high dimensional data such as images, the traditional LDA algorithm encounters several difficulties. Consider face recognition for example. A low-definition face image of size 64 by 64 implies a feature space of 64 × 64 = 4096 dimensions, and therefore scatter matrices of size 4096 × 4096 = 16M. First, it is computationally challenging to handle big matrices (such as computing eigenvalues). Second, those matrices are almost always singular, as the number of training images needs to be at least 16M for them to be non-degenerate. Due to these difficulties, it is commonly believed that a direct LDA solution for such high-dimensional data is infeasible. Thus, ironically, before LDA can be used to reduce dimensionality, another procedure has to be first applied for dimensionality reduction. In face recognition, many techniques have been proposed. Among them, the most notable is a two-stage PCA+LDA approach [4,1]:

$$A = A_{\mathrm{LDA}} A_{\mathrm{PCA}}$$

Principal Component Analysis (PCA) is used to project images from the original image space into a face-subspace, where dimensionality is reduced and Sw is no longer degenerate, so that LDA can proceed without trouble. A potential problem is that the PCA criterion may not be compatible with the LDA criterion, thus the PCA step may discard dimensions that contain important discriminative information.

Chen et al. have recently proved that the null space of Sw contains the most discriminative information [2]. But, their approach fell short of making use of any information outside of that null space. In addition, heuristics are needed to extract a small number of features for image representation, so as to avoid computational problems associated with large scatter matrices. In this paper, we present a direct, exact LDA algorithm for high dimensional data set. It accepts high dimensional data (such as raw images) as input, and optimizes Fisher's criterion directly, without any feature extraction or dimensionality reduction steps.

In this paper, we proposed a direct LDA algorithm for high-dimensional data classification, with application to face recognition in particular. Since the number of samples is typically smaller than the dimensionality of the samples, both Sb and Sw are singular. By modifying the simultaneous diagonalization procedure, we are able to discard the null space of Sb – which carries no discriminative information – and to keep the null space of Sw, which is very important for classification. In addition, computational techniques are introduced to handle large scatter matrices efficiently. The result is a unified LDA algorithm that gives an exact solution to Fisher's criterion whether or not Sw is singular.

III PROBLEM IDENTIFICATION

3.1 Problem Identification

After reviewing more than 25 papers result shows that different types of algorithm available for analyze and recognize the face and facial expression also. Face recognition performance has improved significantly since the first automatic face recognition system developed by Kanade. Face detection, facial feature extraction, and recognition can now be performed in "real time" for images captured under favorable, constrained situations. Although progress in face recognition has been encouraging, the task has also turned out to be a difficult endeavor, especially for unconstrained tasks where viewpoint, illumination, expression, occlusion, accessories, and so on vary considerably. However, there are two directions to look at towards possible solutions: One is to construct a "good" feature space in which the face manifolds become less complex i.e., less nonlinear and non convex than those in other spaces. This includes two levels of processing: (1) normalize face images geometrically and photo metrically, such as using morphing and histogram equalization; and (2) extract features in the normalized images which are stable with respect to the said variations, such as based on Gabor wavelets. The second strategy is to construct classification engines able to solve less, although still, nonlinear problems in the feature space, and to generalize better.

3.2 Solution of the Problem

The discrimination power of various human facial features is studied and a new scheme for automatic face recognition (AFR) is proposed. Linear discriminant analysis (LDA) of different aspects of human faces in the spatial as well as in the wavelet domain. This analysis allows objective evaluation of the significance of visual information in different parts (features) of the face for identifying the human subject[19]. The LDA of faces also provides us with a small set of features that carry the most relevant information for classification purposes. The features are obtained through eigenvector analysis of scatter matrices with the objective of maximizing between-class variations and minimizing within-class variations. Each projection creates a decision axis with a certain level of discrimination power or reliability. Soft decisions made based on each of the projections are combined, and probabilistic or evidential approaches to multisource data analysis are used to provide more reliable recognition results. For a medium-sized database of human faces, excellent classification accuracy is achieved with the use of very-low-dimensional feature vectors.

Moreover, the method used is general and is applicable to many other image-recognition tasks.

IV PROPOSED METHODOLOGY

Face Recognition is a term that includes several sub-problems. The most evident face features were used in the beginning of face recognition. It was a sensible approach to mimic human face recognition ability[20,21]. There was an effort to try to measure the importance of certain intuitive features (mouth, eyes, and cheeks) and geometric measures (between-eye distance, width-length ratio). Nowadays is still an relevant issue, mostly because discarding certain facial features or parts of a face can lead to a better performance. In other words, it's crucial to decide which facial features contribute to a good recognition and which ones are no better than added noise. However, the introduction of abstract mathematical tools like Eigen faces created another approach to face recognition. It was possible to compute the similarities between faces obviating those human-relevant features. This new point of view enabled a new abstraction level, leaving the anthropocentric approach behind. There are still some human-relevant features that are being taken into account. For example, skin colourr is an important feature for face detection. The location of certain features like mouth or eyes is also used to perform normalization prior to the feature extraction step. To sum up, a designer can apply to the algorithms the knowledge that psychology, neurology or simple observation provide. On the other hand, it's essential to perform abstractions and attack the problem from a pure mathematical or computational point of view.

4.1 A Simple face recognition system

The input of a face recognition system is always an image or video stream[22]. The output is an identification or verification of the subject or subjects that appear in the image or video.

Some approaches define a face recognition system as a three step process - see Figure 4.1. From this point of view, the Face Detection and Feature Extraction phases could run simultaneously. Face detection is defined as the process of extracting faces from scenes. So, the system positively identifies a certain image region as a face. This procedure has many applications like face tracking, pose estimation or compression.

Figure 4.1 Simple Face Recognition

The next step -feature extraction- involves obtaining relevant facial features from the data. These features could be certain face regions, variations, angles or measures, which can be human relevant (e.g. eyes spacing) or not. This phase has other applications like facial feature tracking or emotion recognition. Finally, the system does recognize the face. In an identification task, the system would report an identity from a database. This phase involves a comparison method, a classification algorithm and an accuracy measure. This phase uses methods common to many other areas which also do some classification process -sound engineering, data mining et al.

These phases can be merged, or new ones could be added. Therefore, we could find many different engineering approaches to a face recognition problem. Face detection and recognition could be performed in tandem, or proceed to an expression analysis before normalizing the face.

4.2 Face detection

Nowadays some applications of Face Recognition don't require face detection[23]. In some cases, face images stored in the data bases are already normalized. There is a standard image input format, so there is no need for a detection step. An example of this could be a criminal data base. There, the law enforcement agency stores faces of people with a criminal report. If there is new subject and the police has his or her passport photograph, face detection is not necessary. However, the conventional input image of computer vision systems is not that suitable. They can contain many items or faces. In these cases face detection is mandatory. It's also unavoidable if we want to develop an automated face tracking system.

Face detection must deal with several well known challenges. They are usually present in images captured in uncontrolled environments, such as surveillance video systems. These challenges can be attributed to some factors:

- **Pose variation**: The ideal scenario for face detection would be one in which only frontal images were involved. But, as stated, this is very unlikely in general uncontrolled conditions.
- **Feature occlusion**: The presence of elements like beards, glasses or hats introduces high variability. Faces can also be partially covered by objects or other faces.
- **Facial expression**: Facial features also vary greatly because of different facial gestures.
- **Imaging conditions:** Different cameras and ambiental conditions can affect the quality of an image, affecting the appearance of a face.

4.3 Face detection problem structure

Face Detection is a concept that includes many sub-problems[24]. Some systems detect and locate faces at the same time, others first perform a detection routine and then, if positive, they try to locate the face. Then, some tracking algorithms may be needed - see Figure 4.2.

4.3 Linear Discriminant Analysis (LDA)

The purpose of Discriminant Analysis is to classify objects (people, customers, things, etc.) into one of two or more groups based on a set of features that describe the objects (e.g. gender, age, income, weight, preference score, etc.).

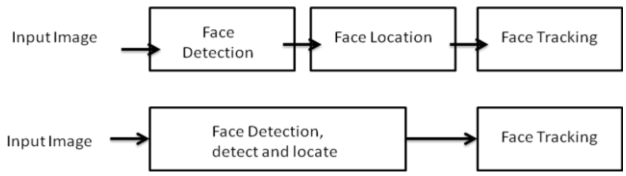


Figure 4.2 Face Detection Process

In general, we assign an object to one of a number of predetermined groups based on observations made on the object. Note that the groups are known or predetermined and do not have order (i.e. nominal scale). The classification problem gives several objects with a set features measured from those objects. What we are looking for is two things:

1. Which *set of features* can best determine group membership of the object?

2. What is the classification *rule* or *model* to best separate those groups?

The first purpose is feature selection and the second purpose is classification. However, we do cover the second purpose to get the rule of classification and predict new object based on the rule.

If we want to know whether a soap product is good or bad based on several measurements on the product such as weight, volume, people's preferential score, smell, color contrast etc. The object here is soap. The class category or the group (good and bad) is what we are looking for (it is also called dependent variable). Each measurement on the product is called features that describe the object (it is also called independent variable).

Thus, in discriminant analysis, the dependent variable (Y) is the group and the independent variables (X) are the object features that might describe the group. The dependent variable is always category (nominal scale) variable while the independent variables can be any measurement scale (i.e. nominal, ordinal, interval or ratio). If we can assume that the groups are linearly separable, we can use linear discriminant model (LDA). Linearly separable suggests that the groups can be separated by a linear combination of features that describe the objects. If only two features, the separators between objects group will become lines. If the features are three, the separator is a plane and the number of features (i.e. independent variables) is more than 3, the separators become a hyperplane.

4.4 LDA Formula

Using classification criterion to minimize *total error of classification* (TEC), we tend to make the proportion of object that it misclassifies as small as possible. TEC is the performance rule

in the 'long run' on a random sample of objects. Thus, TEC should be thought as the probability that the rule under consideration will misclassify an object. The classification rule is to a *ssign an object to the group with highest conditional probability* . This is called Bayes Rule[25]. This rule also minimizes the TEC. If there are groups, the Bayes' rule is to assign the object to group where

P(i|x) > p(j|x), for ¥ j≠ I ……………………………………….equation 4.1

We want to know the probability P(i|x) that an object is belong to group i , given a set of

measurement x. In practice however, the quantity of P(i|x)is difficult to obtain. What we can get is P(x|i) . This is the probability of getting a particular set of measurement x given that the object comes from group . For example, after we know that the soap is good or bad then we can measure the object (weight, smell, color etc.). What we want to know is to determine the group of the soap (good or bad) based on the measurement only. Fortunately, there is a relationship between the two conditional probabilities that well known as Bayes Theorem:

P(i/x)= P(x|i),P(i) / ∑ P(x|j), P(j) ……………………………….equation 4.2

Prior probability P(i) is probability about the group known without making any measurement. In practice we can assume the prior probability is equal for all groups or based on the number of sample in each group. In practice, however, to use the Bayes rule directly is unpractical because to obtain P(x|i) need so much data to get the relative frequencies of each groups for each measurement. It is more practical to assume the distribution and get the probability theoretically.

Appearance-based methods are widely used in object recognition systems. Within this paradigm, PCA and LDA have been demonstrated to be useful for many applications such as face recognition. Although one might think that LDA should always outperform PCA (since it deals directly with class discrimination), empirical evidence suggests otherwise.

V EXPECTED RESULT

The method introduced here utilizes the well-known framework of linear discriminant analysis (LDA) and it can be considered as a generalization of a number of techniques which are commonly in use. Low-dimensional feature representation with enhanced discriminatory power is of paramount importance to face recognition (FR) systems. Most of traditional linear discriminant analysis (LDA) based methods suffer from the disadvantage that their optimality criteria are not directly related to the classification ability of the obtained feature representation. So our System will overcome these deficiencies.

VI CONCLUSION AND SCOPE OF FURTHER WORK

6.1 Conclusion

Linear discriminant analysis (LDA) is a popular face recognition method. However, conventional LDA faces difficulty in addressing the non-Gaussian aspects of sample distributions due to its parametric nature of scatter matrices. LDA is a new feature extraction method for face recognition tasks has been proposed. The method introduced here utilizes the well-known framework of linear discriminant analysis and it can be considered as a generalization of a number of techniques which are commonly in use. The new method utilizes a new variant of D-LDA to safely remove the null space of the between-class scatter matrix and applies a fractional step LDA scheme to enhance the discriminatory power of the obtained D-LDA feature space. The effectiveness of the proposed method has been demonstrated through experimentation using two popular face databases.

6.2 Scope of Further Work

Every research has a scope to be work, Here the given research is for face recognition we can do it via video streaming. The new LDA method will be use for the our next research in future.

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