Face Recognition using Tensor Analysis

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ABSTRACT

Over the past fifteen years many methods have been developed to tackle the problem of recognizing human faces. Face recognition is currently one of the most researched areas in pattern recognition. Its popularity stems from the fact that its applications are used in a variety of real life situations ranging from human - computer interaction to authentication and surveillance. Although various machine learning techniques have been developed, their success is limited because of the restrictions imposed by data acquisition systems. This literature survey will evaluate some of the methods that have been tested and also discuss the advantages of tensor analysis over traditional methods.

INTRODUCTION

Human recognition processes consider a broad spectrum of stimuli obtained from many, if not all, of the senses. The human brain is a complex system that probably applies contextual knowledge to recognize faces. It is futile to even attempt developing a computer system using existing technologies that can closely resemble the remarkable ability of facial recognition in humans. However, the key advantage that such a computer system would have over a human classifier is due to the limitation of the human brain to accurately remember a large database of individuals. Over the past couple of decades, face recognition has emerged as one of the primary areas of research in pattern recognition. The fact that it has numerous potential applications in biometrics, surveillance, human-computer interaction, video based communication, and the emergence of technologies that enable the implementation of these algorithms in real-time are the main reasons for this trend. Over the past ten years, new conferences such as the International Conference on Audio and Video-Based Authentication (AVBPA) and International Conference on Automatic Face and Gesture Recognition (AFGR) and systematic empirical evaluations of face recognition techniques (FRT) have been started due to the growing interest in facial recognition among researchers in a variety of disciplines such as image processing, neural networks, computer graphics and psychology. FRT systems can be broadly classified into two groups depending on whether they make use of still images or video. In this study, I will focus only on FRT systems that make use of static images. The problem statement for facial recognition can be formulated as follows: Given an image of a person under varying conditions of illumination, pose or facial expression, verify/identify the person in the stored database of facial images.

BACKGROUND : PREVIOUS WORK

One of the first attempts at automatic face recognition was made by Kanade [1] in 1973. He used a robust feature detector to locate feature geometric points on the facial image. A feature vector was formed by calculating the geometrical parameters and a weighted Euclidian distance was defined on these features to measure the similarity between faces. This was a very simple algorithm that when tested on a database consisting of images obtained from 20 individuals performed at an accuracy of 45 ~ 75 %. Since Kanade's algorithm in 1973, different algorithms have been developed to tackle the problem of facial recognition. Some of the techniques involved feature extraction while others involved wavelet transform, principal component analysis, Gabor filters, etc. In this section we will look at some of the popular techniques that have been used over the years.

GEOMETRIC FEATURE BASED MATCHING

Brunelli and Poggio in 1992 extended Kanade's algorithm and used "Geometric Feature based Matching" for face recognition [2]. The basic idea behind their algorithm was to describe the overall configuration of the face by a vector of numerical data representing the relative position and size of the main facial features: eyes and eyebrows, nose and mouth. The classification was done using the nearest neighbor classifier on the vector corresponding to the given image with respect to the vectors corresponding to the images in the database. The results, although impressive at the time, were not conclusive since they only considered a database of 47 people with 4 images of each person.

EIGENFACES

Eigenfaces proposed by Turk *et al*. [3] are a set of orthonormal basis vectors computed from a collection of training face images. The provide a basis of low dimensional representation of the facial images and are optimal in the minimum least square error sense. If the training set of *N* facial images is represented by { z_1 z_2 ….. z_N}, Principal Component Analysis is applied to the set of training images to find the *N* eigenvectors of the covariance matrix $(1/N)\sum_{n=1}^{N}\left(z_n - \bar{z}\right)\left(z_n - \bar{z}^{T}\right)$, where $\bar{z} = (1/N)\sum_{n=1}^{N} z_n$ is the average of the ensemble. The eigenvectors corresponding to the largest *k* (pre-determined) eigenvalues form the basis of an eigenface space. Classification is based on the eigen-feature vectors. The simplest classifier is based on Euclidean distance even though nearest neighbor classifier can also be used. The fact that the algorithm is fast and easy to implement makes Eigenfaces a very appealing technique. However, the main constraint is that one the frontal view of the images can be used and they are sensitive to extreme changes in pose and expression [4].

SUPPORT VECTOR MACHCINES

In 2001, Guo *et al.* [5], incorporated Support Vector Machines (SVM's) with binary tree recognition for multi-class recognition. Given a set of points belonging to two classes, a traditional SVM finds a hyper-plane that separates the largest fraction of points of the same class on the same side while maximizing the distance from each class to the hyper-plane. However, in the case of Face Recognition, we have multiple classes, where each person belongs to a different class and therefore the authors had to extend SVM's so that they could be applied to the multi-class problem. They proposed a binary tree structure which is appropriate to extend the pairwise discrimination of the SVM's to a multi-class recognition scenario. In 2003, Li *et al.* [6], proposed a new algorithm for face recognition over multiple views. In order to accomplish this, they divide the “ view sphere” into different segments. On each segment a face detector is created and the pose of the detected face is explicitly predicted. The algorithm was tested for face recognition over multiple views but the results obtained were unsatisfactory. For images with frontal views, the accuracy of the SVM’s was found to be much higher compared to the Eigenface approach.

MATCHING INEXACT GRAPHS

In 2001 Cesar *et al.* [7] approached facial feature recognition as a problem of matching inexact graphs where the graphs were built from regions and relationships between regions in an image. The image where recognition has to be performed is represented as a graph G_D based on an over-segmentation performed using the watershed algorithm. Each region in the segmented image corresponds to a node in the graph. There exists a model graph G_M where each node corresponds to a facial feature and the algorithm focuses on using the inexact graph matching technique to map G_D to G_M since the number of nodes in each graph are different. Recognition is then performed by searching for a homomorphism between G_D and G_M that satisfies both structural and similarity constraints. The authors do not talk about extending their results from the inexact graph matching technique to face recognition. However, their results suggest that it is an interesting idea to pursue, even though traditional face recognition techniques that rely on facial feature recognition have not been successful due to the lack of algorithms that can accurately extract facial features from images.

DEPTH AND TEXTURE MAPS

Texture coding provides information about facial regions with little geometric structure like hair, forehead and eyebrows whereas a depth map provides us with information about regions with little texture such as chin, jaw line and cheeks. Considering this fact, BenAbdelkader *et al.* proposed that the accuracy of FRT systems can be improved by considering not only the texture map but also the depth map [8]. While the results of their 3-D face recognition system are excellent, it may not always be feasible to use a structured light based 3D camera that can simultaneously capture the 3D shape and texture of the face in all applications.

MULTIRESOLUTION ANALYSIS

Ekenel and Sankur [9] proposed multiresolution facial recognition in 2005. They employ multiresolution analysis to decompose the image into its subbands prior to the subspace operations such as principal or independent component analysis. Some of the earlier techniques like Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Multidimensional Scaling (MDS) suffer from a performance drop whenever facial appearance is subject to occlusion and variations in illumination, expression, pose, accessories and aging. They applied a multiresolution technique to mitigate the loss of performance due to changes in facial appearance. A 2-D discrete wavelet transform was used to extract those components that are less sensitive to intrinsic deformations and then either PCA/ICA is performed on the vectors obtained from subband decomposition. Their algorithm obtains a significant performance gain especially against changes in facial expression. Even though multiresolution analysis addresses the issues of face recognition under varying illumination and facial expressions, it still fails to remove the constraint that the photographs need to be taken from a frontal view.

GABOR FEATURE CLASSIFIER

Liu *et al.* [10] describe a novel Gabor Feature Classifier (GFC) method for face recognition. The kernels of Gabor wavelets are similar to the 2D receptive field profiles of the mammalian cortical simple cells and exhibit desirable characteristics of spatial locality and orientation selectivity. The biological relevance and computational properties of Gabor wavelets for image analysis have been well documented [11],[12]. As a result, the Gabor transformed face images yield features that display scale, locality, and differentiation properties that are suitable for facial recognition. The Gabor feature vector is obtained from the Gabor Wavelet transformation of the face images. The GFC method employs an enhanced Fisher's Discriminant model on the Gabor feature vector. The results of the GFC method have been found to be quite robust to variations in illumination and facial expressions.

TENSOR ANALYSIS

Vasilescu *et al.* [13] tried to solve the problem of facial recognition using Tensor Analysis. They identified the analysis of an ensemble of facial images resulting from the confluence of multiple factors related to scene structure, illumination, and viewpoint as a problem in multilinear algebra in which the image ensemble is represented as a higher-dimensional tensor. Using the "N-mode SVD" algorithm, a multilinear extension of conventional matrix singular value decomposition (SVD), this image data tensor is decomposed to separate and parsimoniously represent the constituent factors. The authors also propose a recognition method based on multilinear analysis which is analogous to the conventional one for linear PCA. The recognition algorithm performs TensorFaces decomposition of the Tensor containing vectorized training images and constructs the basis tensor *B.* The classifier uses the projection vector B^{-T} in order to find the image with least error.

CONCLUSIONS

During my survey, I have studied various approaches that have been applied to recognize faces over the past ten years. The qualitative comparison of the all the techniques is shown in Table 1.

	Resistance to			**Computational**	**Classification**
	Illumination	**View**	**Expression**	**Efficiency**	**Quality**
Technique					
Geometric Features	good	poor	good	good	very poor
Eigenfaces	average	poor	average	good	average
SVM	average	average	average	good	very good
Depth and Texture Maps	good	good	good	average	very good
Multiresolution Analysis	good	good	very good	average	very good
Gabor Feature Classifier	good	good	good	average	very good
Tensor Analysis	very good	very good	very good	average	very good

Table 1

Based on preliminary examination, Tensor Analysis seems to give extremely good results for facial recognition under varying conditions of illumination, expression and pose. During the course of the project, I aim to make a complete study of the various Face Recognition Techniques and also extend the concept of TensorFaces and investigate the dimensionality reduction in conjunction with TensorFaces.

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