Hybrid Approaches for Face Recognition Using Principal Component Analysis

Thesis Proposal

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A. Title

Hybrid Approaches for Face Recognition Using Principal Component Analysis

B. Statement of Purpose

Face recognition is the ability to recognize human faces with many variations of facial appearances such as facial expression, aging, facial hair and cosmetics. Face recognition is usually done by a computer analysis of two dimensional images that represent a three dimensional human face. The image often includes a human face together with a background. Thus, the face has to be extracted from the background under variety of light sources. This requires analysis of a number of human face characteristics that can be distinguished from other objects.

There are many face recognition issues such as recognizing identity, race and gender of human subjects. If we want to recognize the identity of a person, we need to analyze multiple face images of the person with different facial appearances. If we are to determine one's gender, we will need to focus on differences between male and female facial characteristics. This project will concentrate on identity recognition problem.

We would like to propose a face recognition system using Principal Component Analysis (PCA) for feature extraction and various neural networks for classification. Principal Component Analysis is used to extract a number of features from an original face image and this information can then be used to correctly identify the person. The details about PCA are explained in Methodology section.

PCA can be followed by an application of a neural network, which in turn can perform identity classification. There are many types of neural networks such as Mutilayer Perceptrons (MLP), Radial-Basis Function Networks (RBFN) and Hidden

Markov Models (HMM). All of them could have different structures of neurons, different learning methods and, finally, different firing rules.

Our proposed face recognition system will recognize a person, given his/her face image with various facial expressions. The images used for recognition will be taken from an image pool that contains images taken from different people. We will employ various kinds of neural networks to see which one will give the best results combined with PCA. If using PCA and neural networks alone cannot recognize a person correctly, an additional feature extraction technique, called Fast Fourier Transform (FFT), will be applied. Once the system is able to recognize a single person from the other people, it will be expanded to perform multiple persons' recognitions.

C. Literature Review And Current State-Of-The-Art:

Recent face recognition uses a general approach that consists of two components: feature extraction and Neural Network classification. First, the feature is extracted from the original image using feature extraction. Then the extracted features are classified by Neural Network. Figure 1 shows the general approach for recent face recognition.

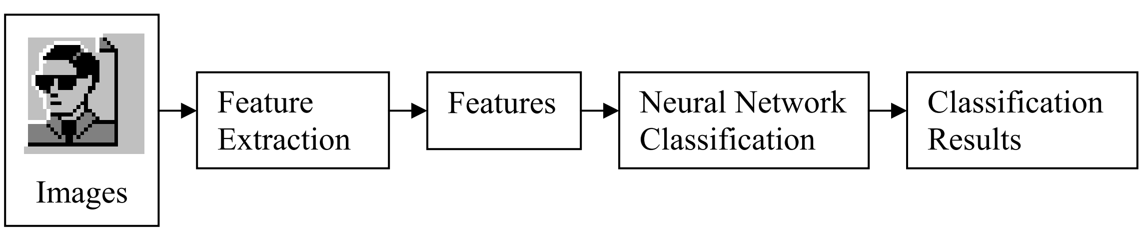

Figure 1. General Approach for Recent Face Recognition

There are, currently, many computer programs for facial feature extraction using Principal Component Analysis (PCA). Some researchers have compared PCA against other feature extraction algorithms such as Linear Discriminant Analysis (LDA) (Mao et al., 1994) and Self-Organizing Maps (Sim et al., 2000) in a variety of face classification problems. PCA could be combined with other algorithms with a goal of improving the quality of the classification (Su et al., 2003). The combination of PCA and LDA can be used to solve problems when there is only a few image training samples within a single class (Zhao et al., 1998). Besides LDA, PCA could be also combined with moment invariant method for local feature extraction (Phiasai et al., 2001). In addition to feature extraction, PCA might be used to reduce the dimensionality and redundancy of the image data (Lawrence et. al., 1996).

In order to proceed with a facial classification, various kinds of neural networks could be used. There are a number of different Neural Networks that have recently received attention from the research community. A very popular one is the Radial Basis Function Network (RBFN), and it is often used to classify features that are presented in frequency domain such as colors of the face image. One could also use a combination of PCA and LDA as the intermediate step between the frequency representation and the Neural Network (Su et. al., 2003). Another kind of Neural Network called Hidden Markov Model (HMM) could be also used for face classification, as the final step after a sequence of feature extraction algorithms (Phiasai et. al., 2001). Phiasai applied the HMM for classifying local features of facial expressions extracted by moment invariant method. Eickeler (1999) utilized HMM to classify faces originally stored in JPEG compressed images. The images underwent Discrete Cosine Transform (DCT) and the feature output was fed to the Neural Network. Besides RBFN and HMM, feed-forward networks with Backpropagation algorithm could be used for classifying faces in specific views (Huang et. al., 2000).

Table 1 shows the success face recognition rates in all these trials. Some researchers combine PCA with other algorithms to get better recognition rate. As visible from the table, only the Eickeler's paper reported the recognition time and the platform used, while the other papers do not.

Author	Algorithm	Average Rate of Success Face Recognition	Recognition Time
Mao	PCA + NN	85%	n.a.
	PCA + MD	77%	n.a.
	LDA + NN	89%	n.a.
	LDA + MD	84%	n.a.
Sim	PCA + CN	78%	n.a.
	SOM + CN	85%	n.a.
Su	FFT + PCA + LDA + RBFN	97%	n.a.
Zhao	PCA + LDA	92%	n.a.
Phiasai	PCA + MI	95%	n.a.
Lawrence	PCA + CN	83%	n.a.
Eickeler	HMM + DCT	100%	1.5s (PII/400 Mhz)
Huang	PCA + BP	99%	n.a.

Key:

BP - Backpropagation
CN – Convolutional Network
DCT – Discrete Cosine Transform
FFT – Fast Fourier Transform
HMM – Hidden Markov Model
LDA – Linear Discriminant Analysis
MD – Minimum Distance Classification
MI – Moment Invariant
NN – Nearest Neighbor Classification
PCA – Principal Component Analysis
RBFN – Radial Basis Function Network
SOM – Self-Organizing Map

Table 1. Success Face Recognition Rates for Various Algorithms

D. Methodology

Our proposed face recognition system has two major components: feature extraction and classification. Figure 2 represents the model:

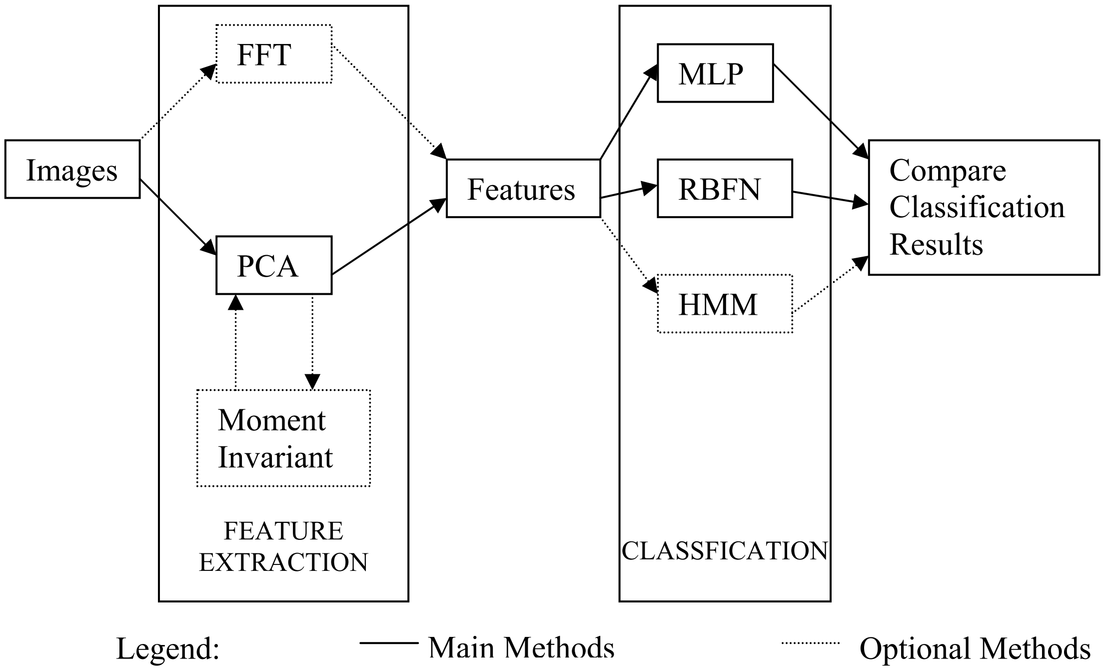

Figure 2. Our Proposed Face Recognition System

In the feature extraction phase, Principal Component Analysis technique will be applied. The final result of the PCA will be an image that contains face features. This image is known as an eigenface. The name is based on the fact that this image is an eigenvector of the original image covariance matrix. An example of an eigenface is given in the Figure 3.

Figure 3. Eigenfaces (bottom) for corresponding persons (top)

PCA involves some mathematical procedures that transforms a number of correlated variables into smaller number of uncorrelated variables which are called principal components. The first principal component represents most of the variance of the data, while the other principal components represent the remaining variance.

To explain PCA mathematically, suppose we have a random vector x, where $x = (x_1, \ldots, x_n)^T$. The mean of the population is denoted by $\mu_x = E\{x\}$, where E is the statistical expectation operator. The covariance matrix of the same data set is $C_x = E\{(x - \mu_x)(x - \mu_x)^T$. The eigenvectors e_i and the eigenvalues λ_i are the solutions of the equation $C_x e_i = \lambda_i e_i$, where $i = 1, \ldots, n$. These values can be found by finding the solutions of the equation $| C_x - \lambda I | = 0$, where I is the identity matrix having the same order than C_x and $|.|$ denotes the determinant of the matrix. The principal components p_i can be calculated by the equation $p_i = e_i^T x$.

There are many different methods for PCA implementation. Some of the methods are: eigenvalue decomposition and Neural Network implementation with Oja's rule. The PCA method that our system will use is based on the Oja's rule. In the Oja's rule the strengths of the synaptic connections are updated by positive reinforcement, with the growth of the connections is bounded. Thus, the connection growth will become stable, and the final result will represent the corresponding eigenface. We choose Oja's rule Neural Network as our PCA method because it will generate the first principal component (Oja, 1982) without involving too many expensive matrix calculations.

If PCA method is not successful, additional feature extraction techniques such as FFT and Moment Invariant Method will be used. FFT can be used to extract the frequency information from the face, while Moment Invariant Method can be used to extract the local features of the faces such as nose, eyes, ears and mouth. Both of the mentioned techniques can be combined with PCA to improve the recognition rate.

In the classification phase, the extracted features will be used as a training set to a number of different Neural Networks. After the training is done, the neural networks will be used to classify features of a specific person. The Neural Networks to be tested include Multilayered Perceptron and Radial Basis Function Networks. If these two networks are not successful, then an additional neural network based on Hidden Markov Models will be used.

Multilayered Perceptron (MLP) contain several layers of neurons: one input layer, one or more hidden layers and one output layer. During the training, the connection strengths between the layers are adjusted by backpropagation algorithm.

Radial-Basis Function Network (RBFN) contains one input layer and one output layer with a single hidden layer. The radial basis functions are used within the hidden layer. The training is done by adjusting the center parameters in the radial basis functions that will be used to calculate the connection strengths between the hidden layer and output layer.

Hidden Markov Model (HMM) is a triplet that includes vector of the initial state probabilities, state transition matrix and confusion matrix. Each probability in the state transition matrix and confusion matrix is time independent. Training is done by finding the probability of the observed sequences and finding the most likely sequences of hidden states that generate the particular observed sequences.

Our proposed face recognition system will be implemented in Sun One Studio 4, Community Edition with Java 2 Platform, Standard Edition (J2SE™ Platform).

For FFT feature extraction, we may use FFTW scientific package that is available on FFTW website (FFTW.org, 2003). The package consists of Java wrappers developed by Daniel Darabos, and the C library for Complex Fast Fourier Transform.

Some of the matrix manipulation methods necessary for the Neural Networks implementations can be found in JMAT Java package that is available on SourceForge.Net website (SourceForge.Net, 2004).

The face images database used in our recognition system will be the ‘Olivetti Research Laboratory (ORL) Database’ available at AT&T Laboratories Cambridge website (AT&T, 2002). This database is used extensively in the literature and contains images taken from 40 different persons. Each person is represented by 10 images that are taken at different times, various lighting condition, facial expressions (open/closed eyes, smiling/non-smiling) and facial details (glasses/no-glasses). All images are taken against a dark background and the persons are in up-right, frontal position. Each image has the size of 92 x 112 pixels with 8-bit levels of gray. Some of the faces from the database are given in Figure 4.

Figure 4. Face Images Database that will be used for our recognition system

In order to import images in our java application, the face images will be transformed from the original PGM format into the java-supported JPG format.

The proposed face recognition system will be considered successful if the success recognition rate and recognition time are comparable with the ones in the literature review. The success recognition rate will be measured by counting number of times that a person is correctly classified using our system, and the recognition time will be measured based on Pentium 4 2.26Ghz computer. We will use the face images in ORL database as our training inputs and testing inputs.

E. Contributions

The goal of our proposed face recognition system is to find the combination of feature extraction and classification algorithms that achieves the highest recognition accuracy and the fastest performance, based on the benchmark data set "ORL database" implemented on Pentium 4 2.26 Ghz computer.

The feature extraction algorithms to be considered are: Fast Fourier Transform, Principal Component Analysis and Moment Invariant, while the classification algorithms to be considered are: Multi-Layered Perceptron, Radial Basis Function Network and Hidden Markov Model.

Since we are exploring all combinations of these algorithms, we will be able to rank their performance according to both face recognition success rate and recognition time. The main contribution of this study is to establish a unified frame for ranking alternate combinations of existing algorithms according to both face recognition success rate and recognition time, since it is not usually reported in the literature.

After we find the best combination of feature extraction and classification algorithm, we will perform comparison of our proposed system performance with the ones presented in the literature review.

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