

Face Detection Using Gabor Filters with ANN and Eigen Face Scheme

Ms. Kavita Bramhankar¹, Mr. Nitin Mishra²

¹Student of IT department NRIIST, Bhopal Madhya Pradesh, India

²Asst. Professor, IT department NRIIST, Bhopal Madhya Pradesh, India

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ABSTRACT : This paper proposes an implementation of classification based face detection method using Gabor filter features along with Eigen face recognition scheme. The procedure involves usage of Eigen faces for the recognition of faces. The feature vector based on Gabor filters is used as the input of the classifier which is a feed forward neural network. The image will be convolved with Gabor filters by multiplying the image by Gabor filters in frequency domain. The objective of the work is to implement a classifier based on neural network for face detection and Eigen face scheme for face recognition.

Keywords: Gabor filters, Feed forward neural network, Face detection, face recognition, ANN.

I. INTRODUCTION

Human Automated face recognition has become a major field of interest. Face recognition algorithms are used in a wide range of applications viz., security control, crime investigation, and entrance control in buildings, access control at automatic teller machines, passport verification, identifying the faces in a given databases, advanced human and computer interaction, gender classification. Most methods are based on neural network approaches, feature extraction, skin color and others are based on template matching [1]. In this paper we design an ANN algorithm in order to achieve image classification. Eigen face approach treats face recognition as a 2d recognition problem, taking advantage of the fact that faces are normally upright and thus may be described as a small set of 2d characteristics views.

II. FACE DETECTION

Face detection is a concept that includes many sub-problems. 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. Several methods have been proposed to detect a face in a single image of intensity or color images. face detection can be viewed as two-class recognition problem in which an image region is classified as being “face” or “Non face”. Face detection also provides challenges to the underlying pattern classification and learning techniques. The class of face and non face image are characterized by multimodal distribution function and decision boundaries are likely to be nonlinear in the image space [2].

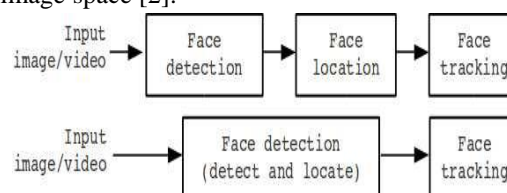


Figure 1: Face detection process.

In general detectors can make two types of errors: false negatives in which faces are missed results in low detection rates and false positives in which an image is declared to be face. Current work uses ANN for classification using Gabor filters with Eigen faces and system is implemented in software resulting in a good performance. Before recognition step MLP algorithm is used to classify face and non face patterns.

a. TRAIN THE NETWORK

The MLP neural network has three layers input, hidden and output layer. Input units are fully connected to the I hidden layer units which are in turn connected to the J output layers units. we are designing the feed forward neural network with 100 neurons in the hidden layer and one neuron in the output layer. All the data from face and non face folders will be gathered in a large cell array. Each column will represent the features of an image. Rows are as follows

Row 1: File name

Row 2: Desired output of the network corresponds to the feature vector.

Row 3: Prepared vector for the training phase.

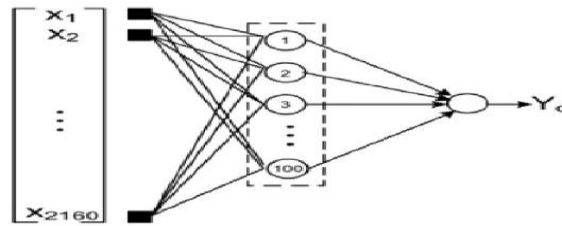


Figure 2: Architecture of a proposed system.

Multi-Layer Perceptions (MLP) with a feed forward Learning algorithms was chosen for the proposed system because of its simplicity and its capability in supervised Pattern matching [5].

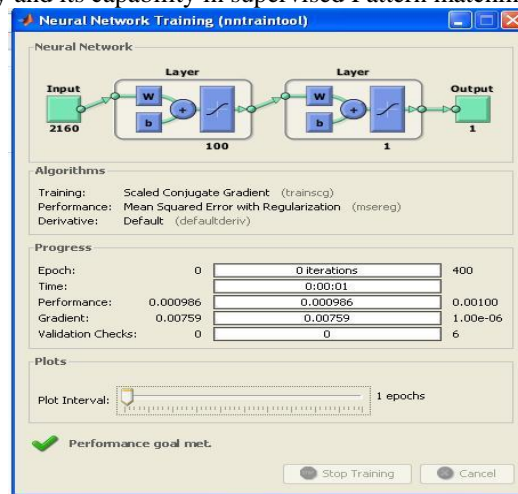


Figure 3: Neural Network Training

b. 2D GABOR WAVELET REPRESENTATION OF FACES

We will adjust the histogram of the image for better contrast. Then the image will be convolved with Gabor filters in frequency domain To save time they have been saved in frequency domain before features is a cell array contains the result of the convolution of the image with each of the forty Gabor filters. We only need the magnitude of the result It means the input vector would have a large amount of computation. So we have reduced the matrix size to one third of its original size by deleting some rows and columns.

An image can be represented by the Gabor wavelet transform allowing the description of both the spatial frequency structure and spatial relations [2]. Convolve the image with complex Gabor filters with 5 spatial frequency ($\nu = 0, \dots, 4$) and 8 orientation ($\mu = 0, \dots, 7$) captures the whole frequency spectrum, both amplitude and phase. An image is represented by the Gabor wavelet transform. Gabor's are local spatial band pass filters. Each image is processed through a Gabor filter. Convolve the image with Gabor filters captures the frequency spectrum, amplitude and phase [2].



Figure 4: Extracted feature points

Match the features of input image and images store in databases. Too less or redundant features can lead to a loss of accuracy of the recognition system.

III. EIGEN FACE SCHEME FOR FACE RECOGNITION

The eigenface approach used in this scheme has advantages over other face recognition methods in its speed, simplicity, learning capability and robustness to small changes in the face image.



Figure 5: Recognition Process in Eigen faces Approach

The following steps summarize the recognition process [3].

1. Initialization: Acquire the training set of face images and calculate the eigenfaces, which determine the face space.
2. When a new face is encountered calculate a set of weights based on the input image and the eigenfaces by projecting the input image onto each of the eigenfaces.
3. Determine the image is a face at all by checking to see if the image is sufficiently close to "face space".
4. If it is a face classify the weight pattern as either a known person or as unknown.
5. Choose a threshold value ϵ that defines the maximum allowable distance from any face class. Optionally choose a threshold f that defines the maximum allowable distance from face space.
6. For each new face image to be identified, calculate its feature vector and compare it with the stored feature vectors of the face library members.
7. If the comparison satisfies the threshold for at least one member, then classify this face image as "known", otherwise a miss has occurred and classify it as "unknown" and add this member to the face library with its feature vector.
8. If the same unknown face is seen several times, calculate its characteristics weight pattern and incorporate into the known faces.
9. If the comparison satisfies the threshold for at least one member, then classify this face image as "known", otherwise a miss has occurred and classify it as "unknown" and add this member to the face library with its feature vector.

a. GENERATE THE EIGEN FACES

To generate the Eigen faces, sample faces are needed. These images will be used as examples of what an image in face-space looks like. These images do not necessarily need to be images of the people the system will later be used to identify however the image should represent variations one would expect to see in the data on which the system is expected to be used, such as head tilt/angle, a variety of shading conditions etc. Ideally these images should contain pictures of faces at close to the same scale, although this can be accomplished through pre-processing if necessary [3]. It is required that all of the images being used in the system, both sample and test images, be of the same size. The resulting Eigen faces will also be of this same size once they have been calculated. If a multitude of face images can be reconstructed by weighted sum of a small collection of characteristic features or Eigen pictures, perhaps an efficient way to learn and recognize faces would be to build up the characteristic features by experience over time and recognize particular faces by comparing the feature weights needed to approximately reconstruct them with the weights associated with known individuals. Therefore, each individual is characterized by a small set of feature or Eigen picture weights needed to describe and reconstruct them. This is an extremely compact representation when compared with the images themselves. All the images should be grey scale images with pixel intensity values ranging from 0 to 255. Images are thought

of as pixels, each having(x, y) coordinates with (0, 0) being at the upper left corner. Convert this to a column form, it can be done in either row or column major form. Then generate the Eigen faces by calculating the Eigen vectors of the covariance matrix. If the number of data points in the image space is less than the dimension of the space ($M < N^2$), there will be only M-1, rather than N^2 , meaningful eigenvectors. The remaining eigenvectors will have associated Eigen values of zero. We can solve for the N^2 dimensional eigenvectors in this case by first solving the eigenvectors of an $M \times M$ matrix such as solving 16×16 matrix rather than a $16,384 \times 16,384$ matrix and then, taking appropriate linear combinations of the face images. Images of faces, being similar in overall configuration, will not be randomly distributed in the huge image space and thus can be described by a relatively low dimensional subspace .

b. CLASSIFICATION OF A FACE IMAGE

The eigenface images calculated from the eigenvectors of L span a basis set with which to describe face images. Sirovich and Kirby evaluated a limited version of this framework on an ensemble of $M = 115$ images of Caucasian males digitized in a controlled manner, and found that 40 eigenfaces were sufficient for a very good description of face images [6]. With $M' = 40$ eigenfaces,RMS pixel by pixel errors in representing cropped versions of face images were about 2%.In practice, a smaller M' can be sufficient for identification, since accurate reconstruction of the image is not a requirement [6]. Based on this idea, the proposed face recognition system lets the user specify the number of eigenfaces (M') that is going to be used in the recognition. For maximum accuracy, the number of eigenfaces should be equal to the number of images in the training set. But, it was observed that, for a training set of fourteen face images, seven eigenfaces were enough for a sufficient description of the training set members. Identification becomes a pattern recognition task. The eigenfaces span an M' dimensional subspace of the original N^2 image space. The M' significant eigenvectors of the L matrix are chosen as those with the largest associated Eigen values.

IV. IMPLEMENTATION AND RESULTS

- **Read the faces and normalize them.**

Every time it is not possible to input the image with the same size and color contrast & brightness so the system will automatically convert the images into the format acceptable by the network.

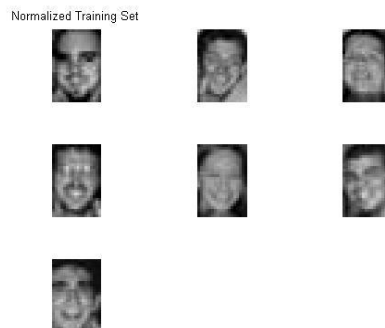


Figure 6: Normalized faces

- **Calculate Eigen faces.**

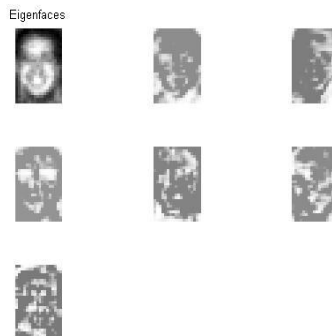


Figure 7: Calculated Eigen faces

- **Calculate weight and Euclidian distances.**

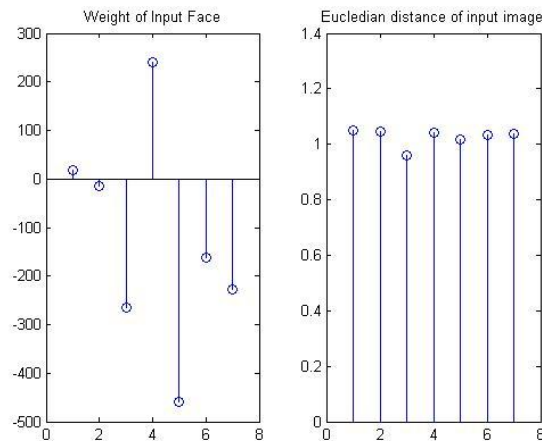


Figure 8: Calculated weight and Euclidian distance

- **Finally recognize the face and detect the location where the input face is present.**

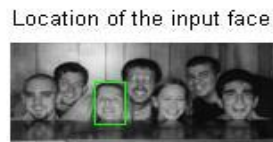


Figure 9: Detected location of the input face

This paper is implemented in Mat lab in a graphical environment allowing face detection in a database. Images are taken from Internet database.

V. COMPARISIOPN WITH OTHER METHODS

- The present approach is better in terms of speed and simplicity than feature based face recognition.
- Unsupervised learning capability makes it superior than feature based and other face recognition methods.
- By using PCA method using Eigen faces the performance of the recognition accuracy was 90% and it has improved to 100% using Gabor filters with neural networks [11].
- Using cross correlation technique the recognition accuracy was 85%.
Simply Eigen face method is not robust to the illumination changes but if combined with Gabor wavelets then it is robust to the illumination changes.
- In the sparsity enforcing method for learning face features resampling of features is needed but while resampling some important features can be lost and it takes time to resample the features [16].
- It shows better results than elastic graph matching procedure due to simple matching procedure and low computational cost.

The proposed method is tested on ORL face database. Each image has the size of 27 x 18 pixels. When it is compared with other techniques it shows the following result in terms of recognition rate in table1 and execution time in table2.

Method	% Recognition Rate
PCA	91.42
Eigen face	66.67
NN	93.33
PCA +NN	97.018
LDA based Curvelets with RBFN	98.60
Proposed approach	100

Table 1: Comparision of recognition rates with different methods.

Method	Execution time in seconds
PCA	74
PCA+BPNN	67
LDA +RBFN	67
Proposed approach	72

Table 2: Comparison of execution times with different methods.

VI. CONCLUSION

Generally face recognition is used for two primary tasks: Verification(one-to-one matching), Identification(one-to-many matching).The numerous applications are Security,Surveillance, Criminal justice systems, Image database investigations, “Smart Card” applications , General identity verification In this paper a new approach to face detection with Gabor wavelet and feed forward neural network along with Eigen face scheme is presented. Proposed method is also robust to illumination changes as a property of Gabor wavelets. Eigen face approach uses information theory concept and recognize faces on a small set of image features that best approximates the set of known face images. In a large database of faces it may be preferable to find a small set of likely matches to present to the user. The concept of face space allows the recognition system the ability to learn and subsequently recognize new faces in an unsupervised manner. If multiple faces are matched to the given input image then by increasing the threshold level we can achieve higher performance .When this scheme used with the Gabor filters and ANN for detection it shows better results in terms of accuracy and presents the detected face in few seconds.

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