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Face Recognition by Bunch Graph Method Using a Group Based Adaptive Tolerant Neural Network

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Research Article

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Abstract

This paper presents a new method for feature extraction from the facial image by using bunch graph method. These extracted geometric features of the face are used subsequently for face recognition by utilizing the group based adaptive neural network. This method is suitable, when the facial images are rotation and translation invariant. Further the technique also free from size invariance of facial image and is capable of identifying the facial images correctly when corrupted with noise/ camouflage. The method shows a result of 97% correct result in facial database of 320 images of 10 classes. The technique can be extended easily to incorporate the rotational invariance of the images.

Keywords: Fiduccial points; bunch graph; neural network; group based classification;

1 Introduction

One of the most remarkable ability of human vision system is to recognize faces. It is important for several aspects of our social life. The problem of face recognition by machine was considered in the early stages of computer vision and is now again revived after nearly a decade. Many literatures are available in this area such as neural nets (Shalkoff, 1997), karhuneun'loeve expression (Bounelli, 1993), fuzzy relational moments (Karibasappa, 1999), (Todd et al., 1996), is density lines and auto-correlation method (Goudail, 1996; Karibasappa, 1998), etc. There are two distinct techniques applied to recognition of digital images (Bernd, 1997). The first technique is

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based on the template matching from the image database and the second technique emphasis the computation of a set of features from the picture of a face. The template matching is represented as a two-dimensional intensity value which is compared using a suitable metric such as Euclidean distance with a single template representing the whole face. There are different and more complex approaches to use a single template together with a qualitative prior model of face transformation from different viewpoints. This technique is popularly known as template matching (Bounelli, 1993). But this technique is cumbersome and time consuming and not at all robust. On the other hand in geometric feature base matching a face can be recognized even when the details of the individual features such as eye, nose, mouth, etc., are no longer resolved. The geometric information such as the relative positions of eye, nose, mouth, chin, etc. is extracted from the facial image at a very coarse resolution. This feature based matching is advantageous with respect to the memory space and computational time over head. Subsequently, various mathematical parameters which are extracted from facial image such as Eigen vectors, wavelets, and fiducial points have been utilized for the face recognition. In this paper, we have used the bunch graph (Wiskott, 1997) as the geometric features of the face. Let us now discuss briefly the face recognition system proposed in this paper, the schematic diagram of which is given in fig 1.. First is face is detected by a frame grabber. The fiducial points are selected manually and estimation of the vectors joining the fiducial points are done by a dedicated available software.

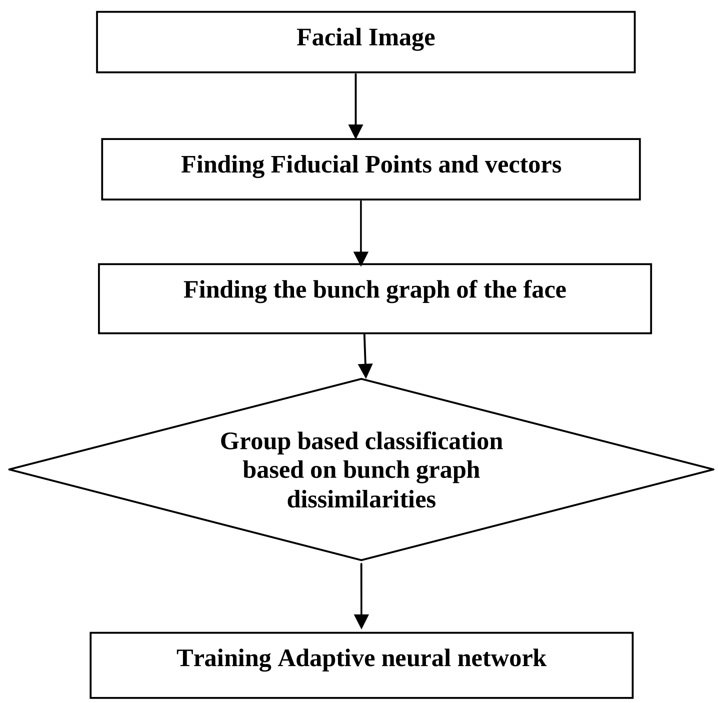

Fig. 1. Face recognition system by using a group based Adaptive neural network

After getting these fiducial vectors (Chaddah, 1996), the rotation invariable facial images are grouped under a particular class where it is being trained by an adaptive neural network. In this experiment we have taken 10 facial images of a person from a fixed distance, fixed illumination with face rotated from 45^0 left to 45^0 right. These faces are being trained with a number of neural networks in the group. The fiducial points are extracted and vectors are estimated as mentioned above. Based on the dissimilarity measurement of the facial geometric symmetry, it's class is determined and the parameters are fed to that particular neural network (Terry Caelli, 1977). The output of individual NN is passed to a AND/OR node, which gives the nearest matched image.

During the test phase, the fiducial points are extracted from the facial image and the vectors and dissimilarity measurements are done in the same way. Then based on the dissimilarity measure, it is fed to one or two neural networks in the group based adaptive NN. After getting the outputs from the NN, are fed to the AND/OR node from which the output is derived, which is the nearest matched facial image.

This paper has been classified into five sections. Section II of the paper covers the methods of feature extraction using bunch graph method (Wiskott, 1997). In section-III of the paper, group based adaptive neural network has been explained to model the recognition process. We have proposed an architecture which combines the geometric features extracted by bunch graph method with group based adaptive neural network. Simulation and results are being presented in section IV and Conclusions and future directions have given in section V.

2 Feature Extraction by Bunch Graph Method

A bunch graph G represents a face that consists of 'n' nodes connected by E edges. The nodes are located at facial land marks x_n , where n=1,2,….N, called 'Fiducial points', i.e. the pupils of the eye, the corner of the mouth, the tip of the nose and bottom of the nose, top and bottom of the ears etc., The edges are labeled with two dimensional distant vectors $\Delta x_e,=x_n-x_m$, e=1,2,……E. where edge 'e' connects node n and m. In order to extract bunch graph automatically for a face of geometrical relationship and intuitively selected geometric relationship is suggested to find out the relative positions of the node points.

While considering the features of a face, one will definitely encounter few interesting constraints that can be exploited in the process of feature extraction. It is obvious that every face has two eyes, one nose, one mouth, two ears, with very similar layouts. This is considered as the first constraint in the feature extraction. The second important constraint is the bilateral symmetry of the facial feature. These two constraints are used here for the classification for taking a particular neural network, which we will be discussing in the next section. We have used bunch graph method to find out the relative positions of facial landmarks (here after called fiducial points).

Fig. 2. Fiducial points such as starting and end points of eyebrow, eye pupil, tip and side points of nose, two end points of mouth and tip of chin etc., and the edges joining these points

Here the important features of the face such as starting and endpoint of eye brow, eye pupil, tip of the nose and bottom points of nose, tip of the lip, two end points of the mouth, tip of the chin, top point of the forehead etc., are taken into consideration as shown in fig. 2. Mathematically, it is represented by x_n, n=1,2,……N. Then the face is represented by a face graph consisting of the fiducial points x_n and the edges which are labeled with two dimensional distant vector $\Delta x_e=x_n-x_m$, where e=1,2,…..E. and edge 'e' connects node n and m of the geometrical structure of the graph. Graphs for different head pose differ in geometry and local features. In order to extract image graphs automatically for new faces, one needs a general representation rather than models of individual faces. The representation should cover a wide range of possible variation in the appearance of faces, such as differently shaped eyes, mouths, or noses, different types of beards, variations due to sex, age and race etc. The automatic representation of the fiducial points of a general face is a big challenge and it is still an open problem.

It is a well known fact that it is too expensive to cover each feature combination by a separate graph. Instead a combination of representative set of M individual model graphs is generated like a stack-like structure, called a *Bunch Graph*. It is represented by G^{Bm} (m=1,…, M). Each model graph has the same grid structure and the nodes refer to identical fiducial points. A set of lines referring to one particular fiducial point is called a bunch. An eye bunch, for instance, may include lines from closed and open eyes to cover these local variations. The corresponding bunch graph ***B*** is then given the same grid structure as the individual graphs, its nodes are labeled with the bunches of lines J_n^{Bm} and its edges are labeled with the averaged distances $\Delta \vec{x}_e^{\,B} = \sum_m \Delta \vec{x}_e^{\,Bm} / M$. During the location of fiducial points in a new image of a face, the procedure described below selects the best fitted lines, from the bunch dedicated to each fiducial point. Thus, the combination of lines in the bunch graph is available, covering a much larger range of facial variation. After finding out these 2D distant vectors, they are normalized to form a normalized distant vector.

In our experiment, we have considered the following fiducial points, which can always be expanded.

F1= Top forehead midpoint;
F2= mid point of the two eyebrows;
F3= Left eyebrow starting point;
F4= Left eyebrow end point;
F5= Right eyebrow starting point;
F6= Right eyebrow end point;
F7= Nose bridge point;
F8= Left end of the nose;
F9= Nose Tip point
F10=Right end of the nose;
F11= Left chin point;
F12= Right chin point;
F13= Left eye pupil point;
F14= Right eye pupil point;
F15= Left eye end point;
F16= Right eye end point;
F17= Left end of the lip;
F18= Right end of the lip;
F19= Ear bridge point;
F20= Ear end point;

The coordinates of the points shown are extracted from the facial image, considering lower left corner of the image as the origin. The procedure for the feature extraction is highlighted below.

Procedure: Feature Extraction by Bunch Graph Method

Begin (for i =face 1 to face n)
Take the facial image from the database (BMP image) as input
A facial image is converted into a intensity image
Pertinent fiducial points are selected from the facial image manually
Vectors joining the fiducial points are extracted and normalized
Normalized vectors are stored in the form of a graph
End

These fiducial points and joining vectors are being used for grouped in a specific orientation class.

3 Group Based Adaptive Neural Network

Face recognition becomes difficult for a shift invariant and rotation invariant faces. When a face is shifted or rotated, face recognition becomes considerably more difficult. To solve this, a translation-invariant face recognition technique was developed. For this all shifted and rotated faces in two dimensions has to be included as training examples for the neural network node (Shalkoff, 1997). Thereby after training, the ANN group-based node is able to recognize shifted and rotated faces in tow dimensions.

To take decision for a complex pattern such as translation invariant face recognition is very difficult. A single neural network is not capable of simulating this type of complex function very well. But on the other hand if we can use a set of adaptive neural networks in place of single neural network, it will be capable for pattern recognition involving a large number of classes along with noisy input. This has led to use multiple classifiers to improve classification performance. The choice of an individual classifier is typically ranked on the basis of confidence level. Here it is to be noted that the faces are grouped on the vector of the fiducial points. Now the question is how to combine this ranking. There are many classifier fusion based on decision regions, voting methods, predication by top choice by combinations. But in this paper we have used a correct multiple classifier structure for the translation invariant face recognition. Here a number of standard multilayer feed forward neural networks with continuous bounded and non constant activation function are used with reference to uniform distance. The classification is based on the dissimilarity measurement of the symmetrical parameter of the fiducials points. After classification the bunch graph parameters are passed on to any one of the adaptive neural network (Zhang.M. 1996), these neural networks are being trained on geometrical parameters of the facial features grouped on a particular orientation of the face. It has been shown vide fig.3. The outputs of these networks are passed on to a AND/OR group operator, which finally gives decision about the face recognition. The individual neural networks are standard feed forward neural networks (Shalkoff, 1997).

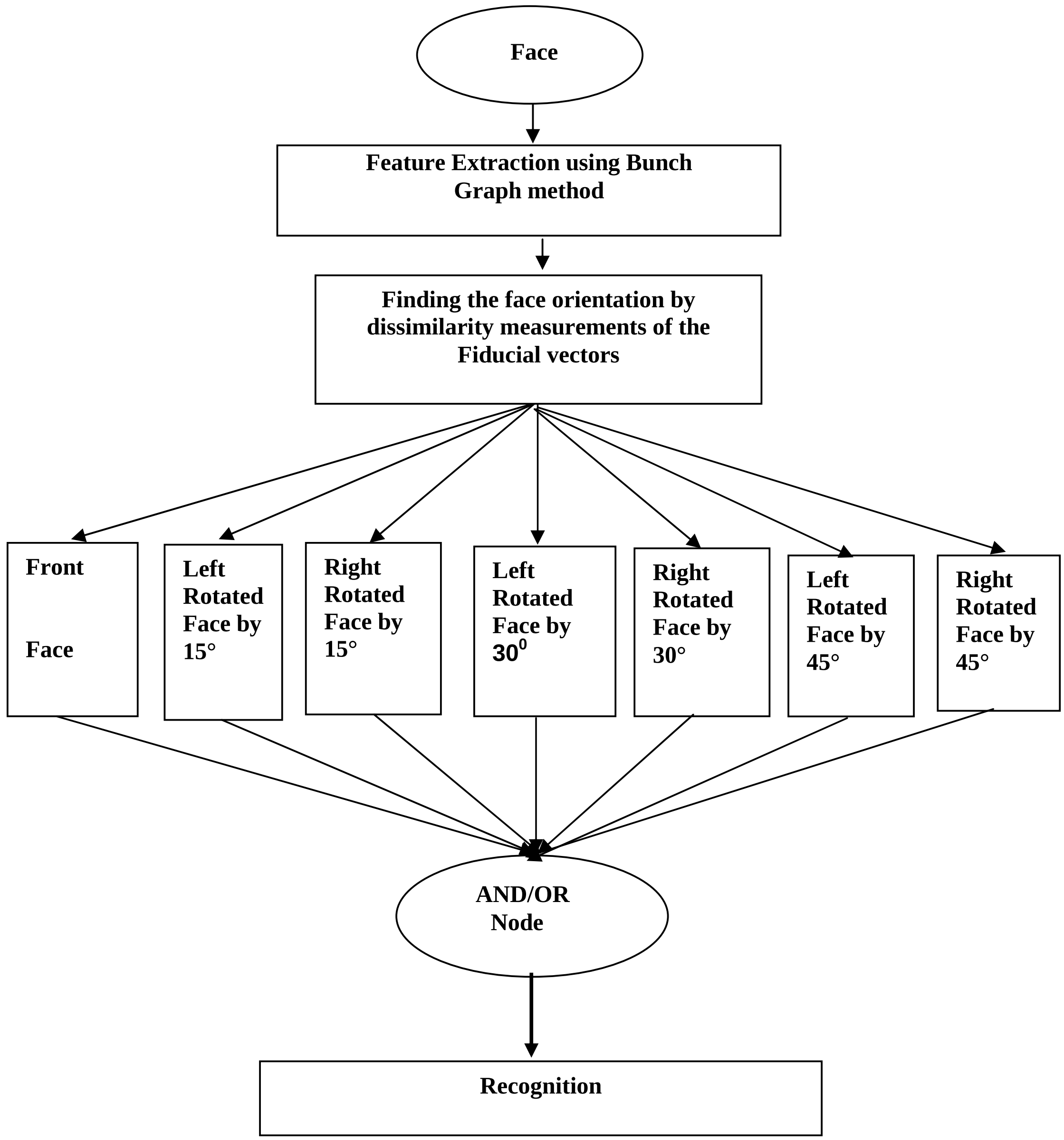

Fig. 3. **Face Recognition System for Rotation invariant facial images**

Once the facial bunch graph is extracted from the facial images from different angles and orientations, it has to be grouped in various clusters/ category. This group based classification of the maps corresponds to a separate category.

Decision regarding a specific class is made by the dissimilarity measurement of the fiducial vectors of the symmetrical features of the face. Elaborately, for example if the image is a frontal face, the two eye brow vectors will be identical. For example, say the face is left rotated, then right eye brow vector is larger/greater than the left eyebrow vector and so on. Here the decision functions for complex patterns are invariably non-continuous and non-smooth. Single neural networks are not capable of simulating non-continuous, non-smooth functions very well. Pattern recognition using single class is difficult for problems involving large numbers of classes and/or noisy inputs. This group based neural network approach on the other hand is capable to do the rotation invariant for recognition. This problem has led some ideas to use multiple classifiers in an attempt to improve classification performance. Choices arrived at by individual classifiers are typically ranked on the basis of confidence level. The problem then becomes one of how to combine these rankings. It has already proved that a multiple classifier system is a powerful technique for solving difficult pattern recognition problems involving large noise class sets. This problem of face recognition determines the correct multiple classifier structure, which has the ability to handle patterns which involve large class numbers and noisy inputs.

As the multilayer feed forward networks are capable to approximate, any piecewise continuous function to any degree, this group based NN model can do the needful for such type of rotation invariant face recognition. Hence this model is proposed to recognize small numbers of ‘people of interest’ or a generalized face which is translation and rotation invariant.

4 Simulation and Results

This experiment has been carried out in the environment, listed in Table 1. The facial 256 gray levels with an ambient lighting condition 60^0 lux were taken.

Table 1. Experiment environment

Conditions	Training Images	Test Images
Lighting conditions	Fixed	Variable
3D moments	Yes	Yes
Expression	Variable	Variable
Distance from camera	Fixed	Fixed
Spectacles	Yes	Yes
Beards	No	No
Mustaches	No	No
Hair style changes	No	No
Background	Fixed	Fixed

In the experiment we have taken 32 numbers of classes. Typical images are shown in fig 4. Seven numbers of images out of ten per class has been taken for training the group based adaptive neural network and three numbers were kept for testing. The average age of the class is between 18 to 25 years.

Fig. 4. Examples of images used in our experiments

The central front face, 15^0 left rotated, 15^0 right rotated, 30^0 left rotated, 30^0 right rotated, 45^0 left rotated and 45^0 right rotated training cases have been taken for training the group based adaptive neural networks. For testing the algorithm the same person's facial images are taken into consideration. These image templates are then converted into intensity image and the geometrical parameters, which were described in section II were estimated. After getting the vectors for facial images the dissimilarity vector is estimated. Then it is fed to the appropriate neural network based on that vector. After the training phase is over these neural network parameters are used for any test image for recognition.

In our experiment we have achieved 97% of result. The lack of result is due to the manual extraction of the fiducial points and finding the fiducial vectors.

4 Conclusion and Future Direction

The face recognition system presented in this paper is a general approach combining facial bunch graph techniques and a group based adaptive neural network. It shows a very good result of 97% accuracy with a class size of 32. Further investigation says that it can be designed for recognizing members of a known class of faces of size varying maximum up to 256. A moderate number of typical faces can be considered to build up the bunch graph and store it as individual geometric feature and can be used for classifying the face into a subclass of particular orientation and also for subsequent training of that particular neural network. The bunch graph technique has been used fairly to determine facial attributes from single images. In this paper we have used manual steps for selection of fiducial points of the facial images. Further, this manual process can be replaced by grouping salient points on the basis of common motion. In future, the automatic extraction of the bunch graph is possible, which will speed up the face recognition process and make it more robust.

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