Face Recognition Based on Multi Scale Low Resolution Feature Extraction and Single Neural Network

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Summary

This research paper deals with the implementation of face recognition using neural network (recognition classifier) on multi-scale features of face (such as eyes, nose, mouth and remaining portions of face). The proposed system contains three parts, pre-processing, multi scale feature extraction and face classification using neural network. The basic idea of the proposed method is to construct facial features from multi-scale image patches for different face components. The multi-scale features of face (such as Eyes, Nose, Mouth and remaining portion of face) becomes the input to neural network classifier, which uses MLN (back propagation algorithm) and Radial Basis function network to recognize familiar faces (trained) and faces with variations in expressions, illumination changes and with spects. The crux of proposed algorithm is its beauty to use single neural network as classifier, which produces straight forward approach towards face recognition. The proposed algorithm was tested on FERET face data base for 500 images of 100 subjects (300 faces for training 200 for testing) and results are encouraging (99% recognition rate) compared to other face recognition techniques.

Key Words: *Radial Basis Function, Back Propagation, Neural Network, Multi Scale Resolution, Feature Extraction, Face Recognition.*

1. Introduction

Machine recognition of faces is gradually becoming very important due to its wide range of commercial and law enforcement applications, which include forensic identification, access control, border surveillance and human computer interactions [1,2]. Given that all human faces share the same basic features (i.e. eyes, nose and mouth) arranged in the same general configuration, the capacity to distinguish one face from another must depend on the fine-grained analysis of a face's components and holistic information. As component and holistic based face representations have complementary strengths and weaknesses, a well designed visual perception system should employ both types of representation for face recognition. Many recent works demonstrate that face recognition using PCA [4, 7] and LDA [5, 6, 7] good methods for face recognition. Generally PCA is not suitable for classification purpose as it does not use any class information and LDA has the risk of poor generalization ability.

Recently, work has been done on face recognition with large dimensional reduction (using low resolution and single neural network [1,2]) but recognition rate is only 90.25% for 40 Images. In Low Resolution Neural Network face has been resized to 400 samples using Bicubic Interpolation, these 400 samples are used as inputs to artificial neural networks. In this method as equal emphasis is given (Uniform Sampling is used in Image resizing) on all the parts of a face resulting in redundancy of the image data from discrimination point of view and hence suffers from unwanted equal weight age on whole face portion of the image resulting in low recognition rate.

2. Proposed Method

It is generally believed that we human beings put different emphasis on different parts of a face e.g. eyes, nose, cheeks, forehead and other remaining parts. The existing approaches put same emphasize on all the parts of a face resulting in low recognition rate. In our approach, we select four different observers – two eyes, nose, mouth and remaining portion of the face assuming that the eye coordinates are known. We then pass these patches (except the eyes) observed by different viewers through low pass (Gaussian) filter so as to smooth several parts of the image and reduce the effect of noises. The observed patches by different viewers are then combined into a single image vector. This image vector is then used as an input to the Artificial Neural Network and network is trained to recognize all the faces in image databases. We start with 2D face images which are normalized, zero mean and unit variances then four different observers are chosen, i.e. eyes, nose, mouth and remaining portions.

The flow chart shows the step by step procedure for obtaining the future vector for a given face image.

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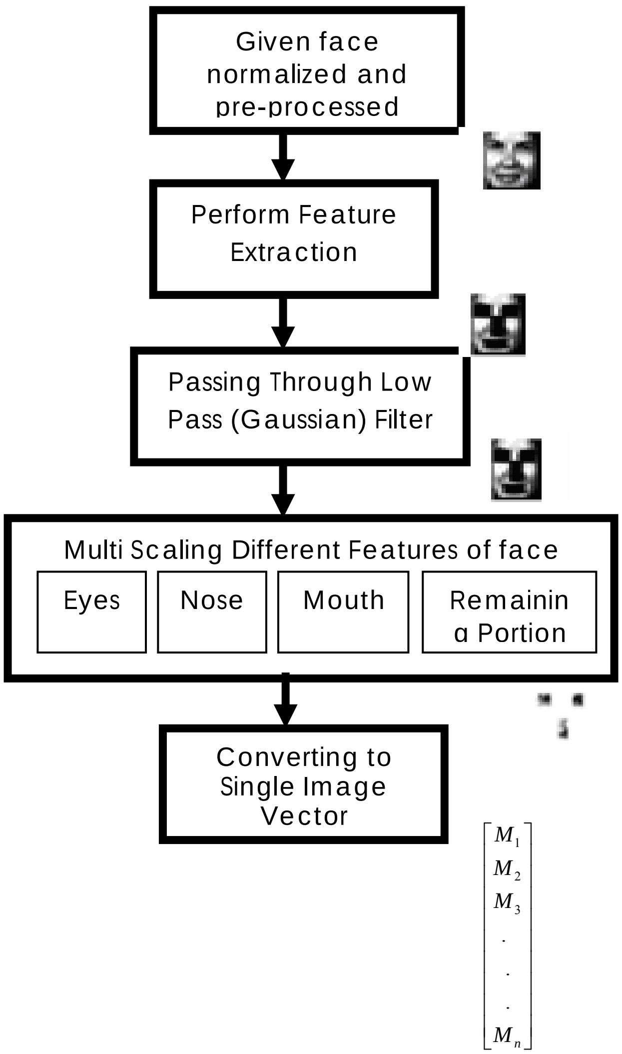
Fig-1 Flow chart for Multi Scale Feature Exaction



Dimensionality of these face components are then reduced by simple down sampling techniques (Eyes 1:1, Nose 1:2, Mouth 1:4, Remaining portion of face 1:8). These 2D face images patches can be represented by a matrix $A = [\bar{a}_1, \bar{a}_2, ...\bar{a}_T]$, where a_i represents a one-dimensional image-column obtained from the two-dimensional image patches scanned in lexicographical order and writing them to a column vector. T is the number of training images. We have used different dimensionality reduction for different face components the size of the final image column vector is $N \times 1$, where N is the total number of pixels obtained from all the four image patches, which is much less than the original full image data

3. Implementation

The algorithm is described in the following steps:

1. Given any face image normalized and pre-processed with known eye coordinates.

2. Based on eye coordinates estimate the size of left eye and right eye. Keep the original image resolution for eye observers.

3. Apply a low pass (Gaussian) filter to the whole image.

4. Crop the Nose patch and Mouth patch from the above image. The locations of the Nose and Mouth patches are kept same for all images.

5. For nose observer reduce the image resolution to half. Select one pixel for every two pixels. For mouth keep one pixels for every four pixels. Apply to both x and y dimensions.

6. Using the above patches extract the remaining portion of the face. Keep only one pixel for every eight pixels. Apply to both x and y dimensions.

7. Convert the above image patches obtained in (2), (5) and (6) into a single image vector of dimension $N \times 1$ (In this case it is 336 x 1- it changes with resolution)

This image column vector is given as input to the trained artificial neural network for recognition.

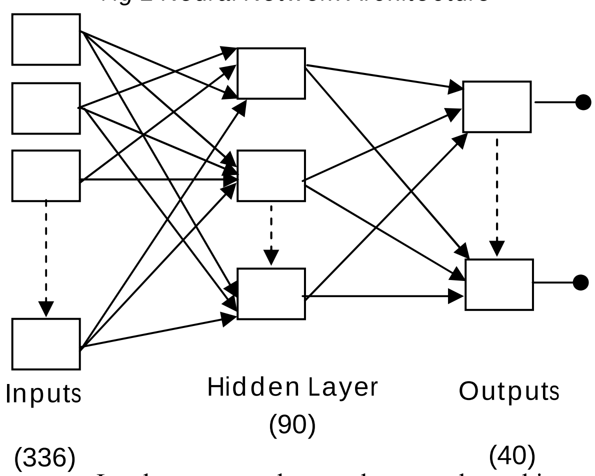
4. Artificial Neural Network

Artificial neural network is a branch of artificial intelligence which has fast emerged with wide range of applications in pattern recognition and data processing.It is popular because of its adaptive learning, self organising, real time operations and fault tolerance via redundant information coding. There are many efficient algorithms using which we can implement ANN, but we made use of multi layer neural network (back propagation algorithm) and Radial Basis Function network

4.1 Back Propagation

Back propagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks [10,11] and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors are used for training.

Fig 2 Neural Network Architecture



In the proposed neural network architecture,, multi - layer network is considered with a hidden layer of size - 90, the number of input nodes are equal to number of face features -336(it changes with Resolution), number of outputs nodes are equal to number of faces to be recognized, in this case it is - 40, logsig and purelin transfer functions are used with goal error equal to 0.0001.

4.2 Radial Basis Function Network

A radial basis function network [12] is an artificial neural network, which uses radial functions as activation functions. A radial basis function (RBF) is a real- valued function whose value depends only on the distance from the origin.RBF networks are claimed to be more accurate than those based on Back- Propagation (BP), and they provide a guaranteed, globally optimal solution via simple, linear optimization. One advantage of radial basis networks over back propagation is that, if the input signal is non-stationary, the localized nature of the hidden layer response makes the networks less susceptible to phase include the learn rate and tolerance for errors.

5. Results and Discussion

We conducted our experiments on the FERET face image database. The images are acquired under variable illumination, facial expressions, with and without spects during different photo sessions and sizes of the face also vary. we have created the database of total 500 frontal images i.e. for 100 subjects each with 5 variations. Out of 500 images 300 (each subject with 3 variations for 100 subjects) are chosen randomly for training and remaining 200 (each subject with 2 variation for 100 subjects) are kept aside for testing.

Fig :3 – Sample of faces of a subject considered in our work

After Multi-Scale Feature Extraction, the original image size of 192X128 is drastically reduces to a column vector of size 336X1(it changes with resolution). Such image vectors of all the images are collected and given as input to the neural network, which is used as classifier for actual face recognition. It has been observed that the efficiency and accuracy have increased consistently because of the use of artificial neural networks.

We investigated the performance of this technique for face recognition based on the computation of two of its types- Multi-layer network using Back Propagation and RBF networks. We focus on the difficult problem of recognizing a large number of known human faces with variations in expressions.

A multi-resolution system achieves a recognition rate of 96% for Back Propagation and 99.% for RBF neural network.

Fig: 4 – Training of neural networks

-performance goal met

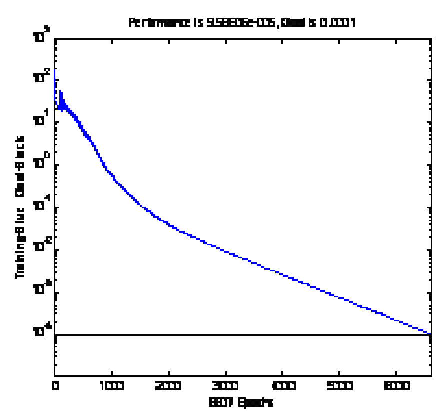


TABLE:1 Type of neural network vs. Recognition rate (for the resolution of eye 1:1, nose 1:2, mouth 1:4, remaining portion 1:8)

Type of network	% of Recognition
Multi layer network (Back propagation)	96
Radial basis function	99

We have done the analysis of our project by considering two types of neural networks – The multi layer network (back propagation) and RBF network. As can be seen in Table:1. 96% of the testing images have been recognized by multi –layer network (back propagation) while, 99% of them have been recognized by the RBF network. This implies that, the performance in terms of recognition rate is higher when implemented using RBF networks than Multi – Layer Network using back propagation. This recognition rate is very much higher compared to other techniques (1,2) and eigen feature technique (3).

TABLE 2: Resolution ratio VS Recognition rate For MLN (Back Propagation) without change in facial expressions

Left Eye	Right Eye	Nose	Mouth	Remaining portion of Face	% of Recg
1:1	1:1	1:2	1:4	1:8	96
1:1	1:1	1:4	1:8	1:16	94
1:2	1:1	1:4	1:8	1:8	91
1:2	1:2	1:8	1:8	1:16	86

TABLE 3: Resolution ratio VS Recognition rate For MLN (Radial Basis Function) without change in facial expressions

Left Eye	Right Eye	Nose	Mouth	Remaining portion of Face	% of Recgn
1:1	1:1	1:2	1:4	1:8	99
1:1	1:1	1:4	1:8	1:16	96
1:2	1:1	1:4	1:8	1:8	93
1:2	1:2	1:8	1:8	1:16	88

Change in the resolution ratio of the discriminated features of the face (Left eye, right eye, nose, and mouth and remaining portion of the face) can also influence the changes in recognition rate .We have done this analysis using the MLN (Back Propagation) and Radial Basis Function network on image with no facial expression changes. When we observe the first and last recordings in TABLE: 2, we can see that the recognition rate has drastically reduced from 96% to 86% (it changes 99% to 88% in the case of RBF network). Here we have observed two important aspects.

The first one is that, changing the resolution ratio of eyes from 1:1 to 1:2 saw comparatively drastic decrease in recognition rate. This is because the entire implementation of our project is based on position of eyes and its resolution ratio.

Second important aspect, is that for faces without any facial expression changes, change in resolution ratio for remaining portion of the face doesn't contribute much to decrease of recognition rate. The change in recognition rate changes with the contribution of components of face towards face recognition system. The more is its contribution that more its change will influence the recognition rate. The percentage of recognition has decreased (as shown in table 4 and 5) with variation in facial expressions.

TABLE: 4 Resolution ratio VS Recognition rate For MLN (Back Propagation) with variation in facial expressions

Left Eye	*Right Eye*	Nose	Mouth	Remaining portion of Face	% of Rrecg
1:1	*1:1*	1:2	1:4	1:8	95
1:1	1:1	1:4	1:8	1:16	93
1:2	1:1	1:4	1:8	1:8	90
1:2	1:2	1:8	1:8	1:16	82

TABLE 5: Resolution ratio VS Recognition rateFor MLN (Radial Basis Function) with variation in facial expressions

Left Eye	Right Eye	Nose	Mouth	Remaining portion of Face	% of Recg
1:1	1:1	1:2	1:4	1:8	94
1:1	1:1	1:4	1:8	1:16	92
1:2	1:1	1:4	1:8	1:8	89
1:2	1:2	1:8	1:8	1:16	81

Percentage of recognition has been reached to consistent value, once the number of faces for training in data base is increased to 500(Table-6)

Table – 6 : % Recognition Vs Number of faces (Resolution of eyes 1:1, nose 1:2, mouth 1:4, remaining parts 1:8)

Subjects	Number of Faces	MLN (Back Propagation)	Radial bases
10	50	91	92
20	100	92	94
30	150	93	95
40	200	95	98
50	250	96	98
100	500	96	99

6. Conclusion and Future Work

In this paper, we have proposed a methodology for putting dissimilar emphasis on different components of face images based on the human knowledge about the human face, which results in dimensionality reduction or coarse-level feature extraction in the first stage. In the second stage, dimensionalities are further reduced by using artificial neural network where only trained networks weights need to be stored to recognize the face in data base, thus it further reduces dimensionality. The proposed methodology therefore extracts face features by combining the human knowledge about the discriminating features in human face and the statistical results drawn from the training data. This combination is necessary and useful because neither the current human knowledge about what the discriminating face features are nor the limited number of training data (comparing to the high dimension of the face image vector) can be fully trusted. Therefore, it is not a surprise that the recognition accuracy is consistently improved by the merge of the human knowledge and the knowledge drawn from the training data. Indeed, the experiments on the large face data base (Table-6) show the consistent accuracy improvement of the proposed approach for different resolution of face futures and different neural networks (Table-2 to Table -5). Further research is to find the connection between the visual similarity/differences of two persons when viewed holistically and component wise. This will answer the question of how to arbitrate between these two viewing approaches.

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