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# An RBF Network with Optimal Clustering for Face Identification

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***Abstract:*** Automatic face recognition is a challenging problem which has received much attention during recent years due to its many applications in different fields. This paper describes a robust and efficient method for face identification using Radial Basis Function (RBF) Network with Optimal Clustering Algorithm (OCA) for training units and Back Propagation (BP) Learning for classification. OCA clusters the preprocessed training patterns which are taken as input of the RBFN. Then a general approach, which determines the initial structure and parameter are presented. Then BP Learning Algorithm is presented which classifies the input person angles into person. The present method successfully recognizes faces with different angles and expressions. The method enjoys the general advantages of RBFN with OCA and BP Learning. The identification of different faces is fast. The experimental result shows a high identification rate with fast learning.

***Keywords:*** Machine learning, ANN, BP Networks, Classification, OCA, RBF

## 1. INTRODUCTION

Face recognition has drawn considerable interest and attention from in the field of pattern recognition for the last two decades. This is very important because of its potential application such as in the field of video surveillance, access control system, retrieval of an identity from a dataset for criminal investigation and person authentication.

Although many researchers have investigated a number of issues related to face recognition it is still difficult to design an automatic system for the job because

Facial images are highly variable in nature.

Sources of variability include individual appearance, three dimensional (3D) poses, facial expression, facial hair, makeup and so on and others factors from time to time. Furthermore the illumination condition, background, scale and occlusion are all present in facial image acquired under real world scenarios. This makes face recognition a great challenging problem [1], [10], and [3].
In our opinion two issues are central.
What feature can be used to represent “Face under environmental changes?”
How to classify a new face image using representation?

For (1) there are many face detection and feature extraction methods have been developed [4, 5, and 6]. Most of it is based on feature extraction technique. Our research paper focuses on Optimal Clustering Algorithm (OCA) [7], [2].

For (2) we use RBFN with OCA and BP learning to find a efficient and general way for face recognition.

In this paper, face recognition is implemented via RBFN [8]. In order to reduce the structural complexity and computational burden, two strategies are adopted.

First, face features are extracted by OCA through two processing modules, i.e. cluster the image sets according to the Euclidean distance with each other and the determine the central image of each cluster which will act as mean in RBFANN and calculate the standard deviation for each cluster.

Next Back propagation Learning is presented to train the RBF neural network for performing identification [9].

In section 2, OCA, BP Learning, RBFN neural network are briefly introduced. Algorithm of present technique is introduced in section 3.Experimental results based on database from FEI (fei.edu.br/~cet/facedatabase.html) are reported in section 4.Finally conclusion are drawn in section 5.

## 2. FORMULATION OF PROBLEM

Here we use the OCA [7, 2] to determine the cluster based on their affinity and central image of each cluster.

For this algorithm we only have to supply the maximum intra cluster distance of give pattern. Unlike the other supervised algorithm we do not have to supply the number of cluster to be formed.OCA forms the natural number of cluster.

***Algorithm for Optimal Clustering Algorithm***

Create a cluster containing first randomly selected data point; mean of the cluster is equal to the value of the object.

Begin
For each existing cluster $c_i$ do
Calculate the difference $d_i$ between any randomly selected object not yet clustered and the cluster means;
Let $d = \min(d_i)$
If d<= Th (Threshold)
Assign object to the cluster having difference $d$;
Update the cluster mean;
Else
Create a new cluster containing the object;
Mean of the new cluster is equal to the value of the object
End if
End for
End

The time complexity of the OCA is O ($k*(r/d)*n$), where "$k$" is the number of clusters formed, "$r$"= radius of the data set, "$d$"= length of a pixel and "$n$".

**Back Propagation Learning**

One of the most popular methods for training multilayer network is Back Propagation Learning Algorithm. The BP is powerful, useful and relatively easy to understand and many other training methods are modification of it. The BP network have two primary modes of operation: feed forward and learning.

Feed forward operation presents a pattern to the input unit and passes the signal through the network to yield output from the output units.

Supervised learning consists of presenting an input pattern and changing the network parameters to bring actual (network) outputs to the target outputs.

Given an adequate number of hidden units, three or more layer network can implement any arbitrary decision boundaries. The BP training is of two types: stochastic training and batch training.

***RBF Neural Network:***

RBF Neural Networks have attracted massive research interest in the field of neural network because:

They are universal approximator [11];

Their learning speed is fast because of local tuned neurons[12];

They have more compact topology than other neural networks [13];

They possess the best approximation property [14].

The basic structure of RBF neural network shown in Fig. 1

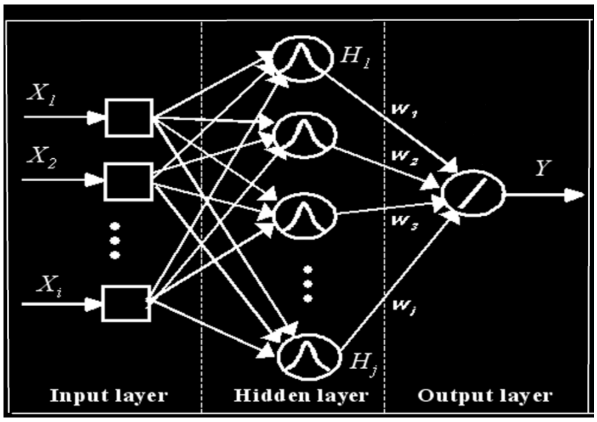


**Fig. 1. RBF Neural Networks**

The output of the k^th^ RBF unit $H_k(X) = H_k\left[\frac{\|X-\mu_k\|}{\sigma_k}\right]$ k=1, 2...j (1)

Where X is an $i$ dimensional input vector, $\mu_k$ is a vector with same dimension as X. $j$ is the number of hidden units and $H_k(.)$ is the RBF unit. Typically $H_k(.)$ chosen as a Gaussian function

$$H_k(X) = exp\left[-\frac{\|X-\mu_k\|^2}{2\sigma_k^2}\right] \quad (2)$$

‖.‖ is the Euclidean Distance between input image and central image.

The $j^{th}$ output $Y_j$(X) of RBF neural network is

$$Y_j(X) = b(j) + \sum_{i=1}^{n} H_i(X)\times w_2(j, i) \quad (3)$$

Where $w_2$(j, i) is the weight of the $i^{th}$ respective field to the $j^{th}$ output and $b(j)$ is the bias of $j^{th}$ output.

In the following analysis, the bias is not considered in order to reduce the network complexity. Hence, the $j^{th}$ output

$$Y_j(X) = \sum_{i=1}^{n} H_i(X)\times w_2(j,i) \quad (4)$$

## 3. ALGORITHM OF PRESENT TECHNIQUE:

***A. Preprocessing***

The image has to be pre processed before learning or identification. There are several steps in pre-processing.

**Noise Elimination:** The first step of pre processing is to eliminate the noise of sample patterns in the "faces" training database.

**Image Normalization:** This process normalizes all image patterns into 100*75 pixels and stores into the training database.

***Histogram Equalization and Image Binarization:***

The third step is to convert training database or test database of 100*75 pixels into grey image. Thereafter histogram equalization for training or test images are performed to compensate for imaging effects due to illumination, brightness etc. Lastly the image is converted into binary image.

Conversion of 2D matrix image files into 1D matrix:

The last step is to convert training database or test database of 2D matrix pixels (100*75). This set is the input to the different training and testing system.

***B. Computation of the Mean Image and Width Estimation from The Cluster with OCA***

The OCA computes the mean of each cluster on its own.We calculate width or Standard Deviation of each cluster by the formula

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_i - \mu_i\right)^2} \quad (5)$$

Where $N$ is the number of data points in each cluster; $X_i$ is the data point in each cluster; $\mu_i$ is the mean image of that particular cluster.

***C. Classification with BP Learning Algorithm***

The adjustment process of the weight $w_2$ is a linear one. Here we use BP learning algorithm to adjust the weight.

In stochastic training patterns are chosen randomly from the training set and the network weights are updated for each pattern representation. This method is stochastic because the training data can be considered as a random variable.

In batch training all patterns are presented to the network before the training takes place.

begin
Initialize w, $\eta$, m←0;
Do
m←m+1
$x_m$← sequentially chosen pattern
calculate the error
$w_{ji}=w_{ji}+\eta$.error
Until $w_{ji(t+1)} \approx w_{ji(t)}$
Return w
End

In our presented method, for face recognition we set the number of inputs equals to that of features (i.e., dimension of input space), while number of outputs sets to the number of classes.

It is cumbersome to select the hidden nodes. Different approaches revolving around increasing and decreasing the complexity of the architecture have been proposed [15]-[22].

Many researchers have illustrated that the number of hidden units depends on the geometrical properties of the training pattern as well as type of activation function. Nevertheless this is still an open issue in implementing RBF neural networks. Our presented approach we assume that number of hidden units is equal to the number of cluster formed by OCA.

## 4. EXPERIMENTAL RESULT

Experimental results are carried out on the FEI database.

The training example set is comprised of four different faces each of which is having three different angles and each angle have three different poses. Fig. 2 and Fig. 3 show a set of nine unidentifiable faces.

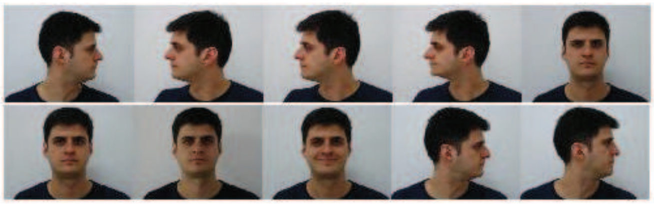

**Fig. 2. First training example set**

**Fig. 3. First testing example set**

After clustering with OCA we are getting three clusters per person.OCA classify the different angle of the person as a different cluster as their Euclidean distance in plane is quite high.

Next we pass the cluster data and central image and standard deviation into the RBF neural network. We get Gaussian output in the hidden layer.

We choose random value as layer 2 weight for BP Learning. The output is compared to the target value provided in the system. Thus the weight is updated.

$\Delta w_{ij}=w_{ij} + \eta$. Error

The learning is saturated when $w_{ij} \approx w_{ij}+\Delta w_{ij}$ $\eta$ is assumed 0.1.

The recognition rate is defined as the ratio of the total number of correct recognition by the method to the total no of images in the test set for a single experimental run. Therefore, the average recognition rate, $R_{avg}$, of the method is defined as follows:

$$R_{avg} \frac{\sum_{i=1}^{q} n_{cls}^{i}}{q.n_{tot}} \qquad (6)$$

where $q$ is the number of experimental runs. The $n^{i}_{cls}$ is the number of correct recognition in the $i^{th}$ run and $n_{tot}$ is the total number of faces under test in each run. Consequently, the average error rate may be defined as 100-$R_{avg}$.

Our test database contains 180 colour images of 20 persons. Each person has 9 images, each having a resolution 100x75. Images of the individual have been taken varying light intensity, facial expressions and facial details. All the images taken against a homogeneous background, with rotation up to 90 $^{0}$. Sample face image of a person shown in Fig.

***Performance Analysis of the System:***

The test dataset contains 180 faces of 20 person with different facial expression and 20 unknown test face. Therefore a total of 180 faces are used to train and another 200 faces are used to test the RBFNN. It should be noted that there is no overlap between the training and test images. The best average recognition rate is 93.34%.

## 5. CONCLUSION

An RBF neural network using OCA and BP Learning has been designed and developed for face recognition .These are partially independent of angel and expression of the given data images. The identification rate for the optimal network with the optimal number of RBF units is considerably high, although the network size is small. And the recognition with limitation is nearly perfect. Also the learning to perform recognition is fast.

Some limitation of the present system is that the number of identifiable person is finite and face recognition is possible, if the test images are only changed to a limited number of angels and expressions.

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