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Illumination Invariant Face Recognition using Supervised and Unsupervised Learning Algorithms

Shashank N. Mathur, Anil K. Ahlawat, and Virendra P. Vishwakarma

Abstracts**—**In this paper, a comparative study of application of supervised and unsupervised learning algorithms on illumination invariant face recognition has been carried out. The supervised learning has been carried out with the help of using a bi-layered artificial neural network having one input, two hidden and one output layer. The gradient descent with momentum and adaptive learning rate back propagation learning algorithm has been used to implement the supervised learning in a way that both the inputs and corresponding outputs are provided at the time of training the network, thus here is an inherent clustering and optimized learning of weights which provide us with efficient results.. The unsupervised learning has been implemented with the help of a modified Counterpropagation network. The Counterpropagation network involves the process of clustering followed by application of Outstar rule to obtain the recognized face. The face recognition system has been developed for recognizing faces which have varying illumination intensities, where the database images vary in lighting with respect to angle of illumination with horizontal and vertical planes. The supervised and unsupervised learning algorithms have been implemented and have been tested exhaustively, with and without application of histogram equalization to get efficient results.

Keywords**—**Artificial Neural Networks, back propagation, Counterpropagation networks, face recognition, learning algorithms.

I. INTRODUCTION

THIS research paper compares the process of supervised and unsupervised learning of artificial neural networks on illumination invariant face recognition. A facial recognition is the process of automatically identifying or verifying a person from a digital image or a video frame from a video source and has been a recent area of research. Previously work of acquiring linear subspaces for face recognition in case of variable lighting has been published [1]. Various face recognition methodologies based on fitting 3D morphable model [2] and by fusing thermal infrared and visible imagery [3] have been proposed while there are other artificial neural network based recognition methods for real time [4] and upright frontal face detection [5]. In this paper, we have developed a supervised learning methodology for a bi-layered artificial neural network and a Counterpropagation network for implementing the unsupervised learning and have compared the results.

Artificial neural networks being mathematical or computational models based on biological neural networks have been widely used in various fields such as calandria tubes and pressure tubes contact detection in pressurized heavy water reactor [6], optical character recognition for Tamil text [7], consumer choice prediction [8], partial discharge pattern classification [9] and intelligent form based character recognition [10]. The artificial neural networks are adaptive systems, during the learning phase of supervised learning, the weight matrices are updates according to the set of input and target outputs that are provided. Incase of unsupervised learning methods, target outputs cannot be provided thus, an efficient clustering technique is developed which helps to group the various sets of inputs that are provided. Previously, comparison of unsupervised learning techniques like principal component analysis (PCA), self organizing maps (SOM) and Independent component analysis [11] has been carried out, but here we compare supervised and unsupervised learning methods.

Unsupervised learning has been carried out using the Counterpropagation networks which are a two stage hybrid network in which the first stage is of clustering followed by the application of Outstar rule in the second stage providing us a single output at the end, as it is a winner takes all system [12]. Counterpropagation networks have found application in areas such as solving flow problem [13] and character recognition systems [14]. The unsupervised learning methods do not have the knowledge about the target outputs for the given inputs, thus an efficient clustering methodology is described with the help of which clusters are developed on which application of Outstar rule provides accurate results.

Supervised learning has been carried out with the help of a bi-layered feed forward back propagation artificial neural network, which contains an input layer, two hidden layers and an output layer. The usage of two hidden layers has provided better results as compared to a single hidden layer unlike cases such as those of detection of road junctions in aerial images where one hidden layer provides efficient results [15]. The feed forward neural networks have been successfully implemented to synthesize multiple valued logic functions [16]. Though several very fast learning methods for neural networks have been published [17], we use the Gradient descent with momentum and adaptive learning rate back propagation with the knowledge of back propagation learning for systems [18] and successful application of momentum

Shashank Narain Mathur is with Department of Computer Science Engineering of Amity School of Engineering and Technology affiliated to Guru Gobind Singh Indraprastha University, New Delhi-110061 , India
(Email : shashanknarainmathur@yahoo.com)
Anil K. Ahlawat is with Department of Computer Science Engineering of Amity School of Engineering and Technology, Noida, India.
Virendra P. Vishwakarma is with Department of Computer Science Engineering of affiliated to Guru Gobind Singh Indraprastha University, New Delhi-110061 , India

back propagation neural network for air quality sensor system [19].

The supervised and unsupervised learning algorithms have been implemented and have been trained and tested with the help of a facial image database "Yale database", provided by the Yale University which comprises of 63 images of 10 subjects each, having been grouped into five subsets, each subset having different Illumination conditions. The illumination varies with respect to the horizontal and vertical planes such that incase of subset 1, the illumination angles are such that front of the face is illuminated while in case of subset 5, the illumination appears to come from the back of the face, making it difficult to recognize. In case of both the learning methods Subsets 1 was used for training the networks while the other four subsets were used for testing the methods.

Fig. 1 One image each of the 10 subjects of the Yale Database that have been used.

In Addition to the normal training and testing of the artificial neural networks and Counterpropagation networks, Histogram equalization was applied to the input training and testing images with the help of which normalization of images took place, which helped in making the images of subset 5 easier to recognize, but led to the distortion of images of subset 4 where the illumination appears to come from the sides of the image making the recognition lesser. The application of histogram equalization provided another set of valuable information which has led to exhaustive comparison of the supervised and unsupervised learning algorithms.

The paper presents a comparative study of application of supervised and unsupervised learning methods for illumination invariant face recognition. The implementation of supervised learning has been carried out with the help of a bi-layered artificial neural network while the unsupervised learning has been carried out with the help of a Counterpropagation network. The comparison has been done exhaustively, such that efficient results are obtained for both the recognition methods with and without application of histogram equalization, thereby providing us with multiple sets of results for the illumination variant face recognition problem.

II. METHODOLOGY

An illumination invariant face recognition method for supervised and unsupervised learning methods is proposed. Given a face image with an arbitrary illumination direction, it can complete recognition in a uniform way with high performance without knowing or estimating the illumination direction. The supervised learning algorithm is implemented using a bi-layer feed forward back propagation neural network while the unsupervised learning method uses a Counterpropagation network.

A. Supervised Learning Algorithm

The supervised learning algorithm is developed in which during the training, input as well as corresponding outputs are provided. Thus there is update of weight matrices according to which results can be obtained at the time of testing.

1) Architecture

A bi-layer feed forward back propagation artificial neural network is used to implement the supervised learning algorithm. The learning algorithm used in case of supervised learning is Gradient descent with momentum and adaptive learning rate back propagation. The various parameters involved with the artificial neural network used are described in the Table 1. The facial image database has images of size 192x168 pixels which are reduced to one-fourth and are converted into column vectors, thus the architecture includes an input layer of 8064 neurons. There are two hidden layers in the network with hyperbolic tangent sigmoid transfer function which improve the performance of the network as compared to a single hidden layer network. The output layer contains 10 neurons, one corresponding each to a subject.

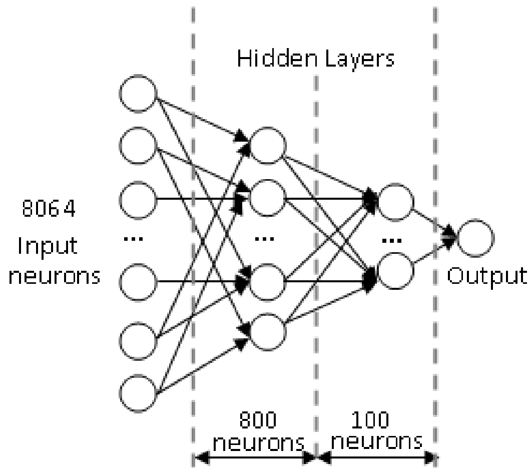


Fig. 2 Architecture of Artificial Neural Network used.

TABLE 1
PARAMETERS USED IN ARTIFICIAL NEURAL NETWORK

Name of Parameter		Artificial Neural Network used
Number of neurons	Input layer	8064
	Hidden layer 1	800
	Hidden layer 2	200
	Output layer	10
Training Algorithm		Gradient descent with momentum and adaptive learning rate back propagation
Number of epochs		5000
Training goal		0.005
Learning rate		0.01
Momentum constant		0.9
Performance function		Mean Square Error
Transfer function	Hidden layer 1	Hyperbolic tangent sigmoid transfer function
	Hidden layer 2	Hyperbolic tangent sigmoid transfer function
	Output layer	Linear transfer function

2) Preprocessing of images

The Yale Database used contains 630 facial images for 10 subjects distributed into 5 subsets of varying illumination intensity. The image size is 192x168 pixels which is reduced to 96x84, i.e. one-fourth of its original size, such that on conversion of the image back to original size, there is negligible loss of vital information from the image. The image obtained after resizing is converted into a column vector of size 8064x1 which can be used to train the images as well as for testing the network after training.

3) Implementation of Supervised Learning

The weight matrices of the artificial neural network developed are updated by training the network with the subset 1 images of all the 10 subjects, thus training the system with 60 images with known target outputs. Each image is converted into a column vector of size 8064x1 and along with its target output; it is subjected to the network with the help of which a weight update takes place. Gradient descent with momentum and adaptive learning rate back propagation can train any artificial neural network as long as its weight, net input and transfer functions have derivative functions. Back propagation is used to calculate derivatives of performance p with respect to the weight and bias variables x.

$$dX = \gamma * dXp + \alpha * \gamma * dp/dX \quad (1)$$

Where,

γ is momentum constant

α is learning rate
dXp is the previous change to the weight or bias.

For each epoch, if performance decreases toward the goal, then the learning rate is increased by the factor of ratio to increase learning rate. If performance increases by more than the factor maximum performance increase, the learning rate is adjusted by the factor ratio to decrease learning rate and the change, which increased the performance, is not made.

B. Unsupervised Learning Algorithm

The unsupervised learning algorithm, Counterpropagation network is developed in which during the training process only the inputs are provided which are clustered without the knowledge about the corresponding outputs. The clustering is followed by application of Outstar rule.

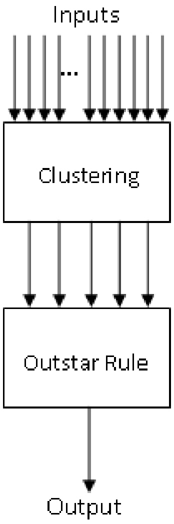


Fig. 3 Architecture of Counterpropagation Network used.

1) Architecture

The Counterpropagation algorithm has been implemented for unsupervised learning for illumination invariant face recognition. The Counterpropagation network is a hybrid two layer network, in which the first stage is the process of clustering followed by the application of Outstar rule and thus providing us with a single output, implementing winner takes all. The first stage of Counterpropagation network is clustering, each facial image of the subject is converted into a row vector of size 32256x1,since we are training the networks with subset 1 of the database used, we carry out the clustering by using subset 1 of all the 10 subjects to develop a matrix of size 32257x60, where the first column of each row indicates the cluster to which the image belongs and the next 32256 are the gray level values of the image. Once the cluster matrix is developed, the Outstar rule can be applied and a recognized output is obtained.

2) Implementation of Supervised Learning

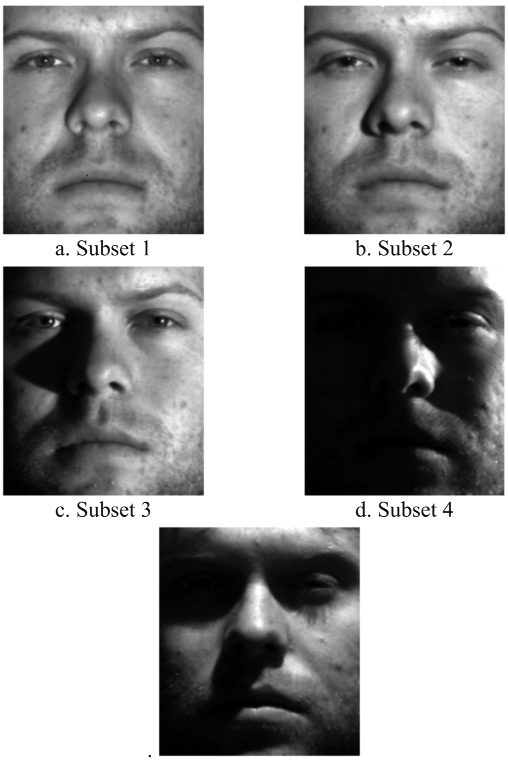
The facial image database taken has images of size 192x168 pixels, thus there are large number of pixel values each of which is important for recognition in case of unsupervised learning, thus resizing of the image to a smaller size does not give efficient results and thus original sized image is used. The inputs that are required at the time of clustering are supposed to be in the form of row vectors, with the help of which a cluster matrix can be made. The cluster matrix that is made contains 6 images of each subject along with the corresponding cluster numbers, which are according to the number of the subset. After the cluster matrix is made, we can compare any input image with it using the Outstar rule and can correctly recognize the input image. When an input image is taken for recognition, we convert it into a row vector of size 32256x1. The correlation index for resulting vector and the image pixel values in the clustered matrix are calculated for all the row vectors and the five highest correlation indexes along with the cluster numbers are selected. After the five cluster values with maximum correlation indexes are found, the Outstar rule is applied. The application is shown as below:

$$\Delta c = c_d - c_c \quad (2)$$

$$r = (1 + \Delta c)/c_d \quad (3)$$

Where,
C_d is correlation with default image,
C_c is correlation index calculated,
r is Outstar coefficient

After the application of equation 2, the Outstar coefficients are calculated for the five maximum correlation coefficient valued images. The resultant recognized image is the one with the minimum Outstar coefficient.



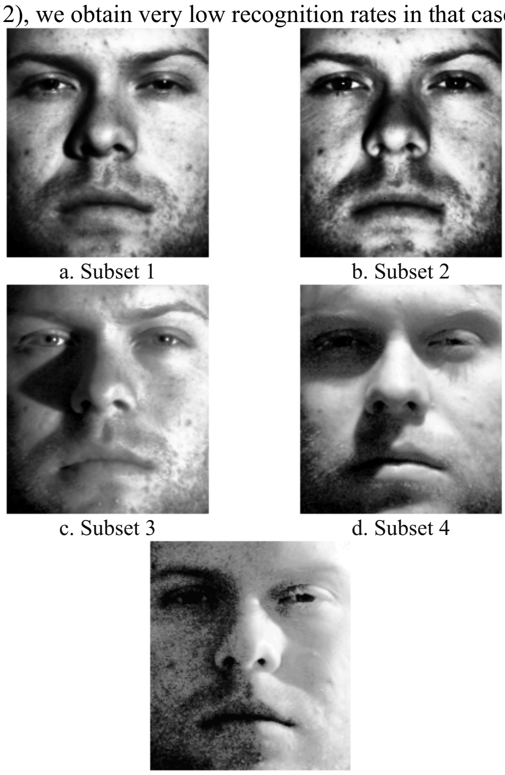
a. Subset 1 b. Subset 2 c. Subset 3 d. Subset 4 e. Subset 5.

Fig. 4 Sample images for each subset from Yale database for subject 1.

III. RESULTS AND DISCUSSIONS

We present the comparative results obtained for supervised and unsupervised learning on illumination invariant face recognition. The supervised learning algorithm gradient descent with momentum and adaptive learning rate back propagation was implemented using a feed forward back propagation artificial neural network and unsupervised learning algorithm was developed using Counterpropagation networks. The networks were trained with the help of subset 1 of the Yale database containing 6 images for each of the 10 subjects. The testing was carried out using the 57 images (Refer to Table 2) from the subset 2-5 for each of the 10 subjects. The training of the networks was carried out with and without application of histogram equalization. The supervised and unsupervised learning algorithms were implemented successfully using MATLAB 7.0 and trained and simulated on a Pentium-IV (3.4 GHz), 1GB RAM to provide valuable results.

The images of subset 5 for each of the subject have an illumination in which the light comes from the rear of the person, thus when histogram equalization is applied, the face can be distinguished and easily recognized, whereas the images of subset 4 where the illumination appears to come from the side, the images are distorted, thus there is a fall in recognition rate of subset 4 with application of histogram equalization as compared to recognition without its application. It should be noted that without the application of histogram equalization, the images of the subset 5 are ambiguous for recognition even by human vision, and since the number of images in subset 5 are maximum (Refer to Table 2), we obtain very low recognition rates in that case.



a. Subset 1 b. Subset 2 c. Subset 3 d. Subset 4 e. Subset 5

Fig. 5 Images of figure 3 obtained after histogram equalization

The results in Table 3 have been obtained without the application of histogram equalization, thus we obtain lowest recognition rates in subset 5 and highest recognition rate in subset 2. The recognition rates obtained for subset 3, 4 and 5 in case of unsupervised learning are far more than those obtained for the supervised learning. We observe that the recognition rates of both the supervised and unsupervised learning algorithms are similar in case of subset 2, since the illumination intensities are similar to those of subset 1 with which the networks have been trained, thus there is a very high rate of recognition in that case. The error graph obtained for reaching the goal during the training of the artificial neural network with the help of supervised learning is shown in Fig.6.

We can observe the results listed in Table 4, which have been obtained for supervised and unsupervised learning with the application of histogram equalization. As previously mentioned, in subset 5, illumination appears to come from the rear. The application of histogram equalization helps to extract structural information which is otherwise not visible to human vision and thus we obtain higher recognition rates for subset 5, but the recognition rates for subset 4 are reduced, since they have illumination from sides, which on application of histogram equalization leads to distortion of image. When histogram equalization was applied to the set of images used for training the artificial neural network with the supervised learning algorithm, the error graph obtained for reaching the goal is shown in Fig.7.

TABLE II
SUBSET WISE IMAGE DISTRIBUTION IN YALE DATABASE

Subset	Number of images
1	6
2	12
3	12
4	14
5	19

TABLE III
RESULTS OBTAINED WITHOUT THE APPLICATION OF HISTOGRAM EQUALIZATION

Subset	Percentage of recognition	
	Supervised Learning	Unsupervised Learning
1	100.00	100.00
2	100.00	100.00
3	76.81	95.83
4	48.42	71.42
5	17.28	15.78

TABLE IV
RESULTS OBTAINED WITH THE APPLICATION OF HISTOGRAM EQUALIZATION

Subset	Percentage of recognition	
	Supervised Learning	Unsupervised Learning
1	100.00	100.00
2	100.00	100.00
3	72.46	97.71
4	27.27	34.68
5	46.92	57.31

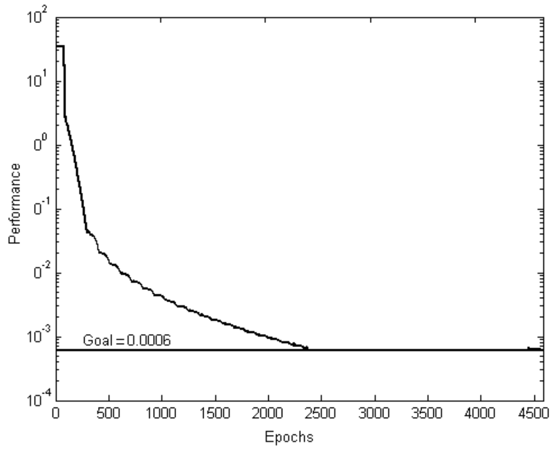


Fig. 6 Error graph obtained during training of Artificial Neural Network with the application of histogram equalization

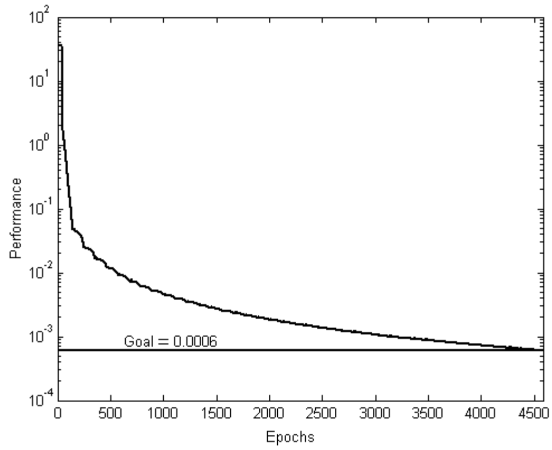


Fig. 7 Error graph obtained during training of Artificial Neural Network without the application of histogram equalization

IV. CONCLUSION

The paper has presented a comparative study of supervised and unsupervised learning algorithms and their application on illumination invariant face recognition. The supervised learning algorithm gradient descent with momentum and adaptive learning rate back propagation and unsupervised learning algorithm, Counterpropagation networks have been instrumental in the face recognition process in case of varying illumination intensities. The supervised learning algorithm was implemented using a bi-layered feed forward neural network with 8064 input neurons and it was noted that the recognition results obtained were lesser as compared to the ones obtained by the Counterpropagation network which followed a methodology of clustering and application of Outstar rule. We note that the artificial neural networks using supervised learning are not able to provide recognition rates higher than those obtained by unsupervised learning. It would be correct that with unsupervised learning it is possible to learn larger and more complex models than with supervised learning. This is because in supervised learning one is trying to find the connection between two sets of observations, thus it is not successful in recognizing the facial images which have similar structure but different illumination intensity. Results obtained for supervised and unsupervised learning in which illumination does not vary as in case of subset 2 are same, thus we can conclude that complex problems of recognition can be carried out with much higher efficiency with the help of unsupervised learning algorithms.

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