

# GLOBAL JOURNAL OF ENGINEERING SCIENCE AND RESEARCHES

## DESIGN SUITABLE NEURAL NETWORK FOR PROCESSING FACE RECOGNITION

Luma. N. M. Tawfiq<sup>\*1</sup> and Wafaa. R. Hussein<sup>2</sup>

<sup>\*1,2</sup>Department of Mathematics, College of Education for pure science / Ibn Al-Haitham, University of Baghdad

### ABSTRACT

Face recognition technology using neural network is an attractive solution for the researchers who are working on the field of machine recognition, pattern recognition and computer vision, in this paper neural network is designed for face recognition using high performance training algorithms based on standard numerical optimization techniques. That is demonstrating how a face recognition system can be designed by artificial neural network.

**Keywords-** Artificial neural network, Face recognition, Training neural networks.

### I. INTRODUCTION

Face is one of the most desired physiological biometrics traits for automatic person identification. Applications of face recognition include access control to sensitive information/locations, border control and surveillance. Face recognition have been studied by a number of authors for example [1-7] and their references. Face recognition schemes work in two stages: the enrolment stage and the recognition stage [1]. Both stages consist of a number of processes: data capture; pre-processing; feature extraction; feature matching and classification [6]. In the enrolment stage a digital representation of the person's face is captured and pre- processed to correct for changes in face size and rotation. Feature extraction aims extract a set of discriminating features, commonly referred to as a feature vector, from the face image that can be used identify the person. These feature vectors are then stored either on a token or in a database that will be used later for recognition. The set of all feature vectors (also called templates) belonging to a set of users is often referred to as the Gallery. During recognition, a new face sample is presented for the system which is then pre-processed before extracting its feature vector. The new feature vector is then compared with those previously stored during the enrolment stage. There are two scenarios in recognition stage:

**Verification:** In this case, the person declares his/her identity to the system and the system compares the fresh feature vector with those of the claimed identity(i.e.1-to-1 matching) stored in the database or in the token and verifies if the claimed identity is true or false.

**Identification:** In this case, the person's identity is not declared or is unknown to the system. Therefore, the system compares the fresh feature vector with all templates in the biometric- database to determine to identity of the person concerned (i.e. 1- to- N matching) [8].

### II. FACES RECOGNITION APPROACH

Much of the previous work [2], [7], [9-10] on automated face recognition has ignored the issue of just what aspects of the face stimulus are important for face recognition.

This suggests the use of an information theory approach of coding and decoding of face images, emphasizing the significant local and global features, such features may or may not be directly related to our intuitive notion of face features such as the eyes, nose, lips, and hair.

In this paper we use artificial neural network (ANN) technique to determine the noise faces of the face images. Noise faces can be viewed as a sort of map of the variations between faces.

### III. DISGITAL IMAGE REPRESENTATION

An image may be defined as a two-dimensional function  $f(x, y)$  where  $x$  and  $y$  are spatial (plane) coordinates, and the amplitude for  $f$  at any pair of coordinates is called the *intensity* of the image at that point. The term *gray level* is used often to refer to the intensity of monochrome images. Color images are formed by a combination of individual images. For example, in the RGB color system a color image consists of three individual monochrome images, referred to as the *red* (R), *green* (G), and *blue* (B) *primary* (or *component*) *images*. For this reason, many of

the techniques developed for monochrome images can be extended to color images by processing the three component images individually [11].

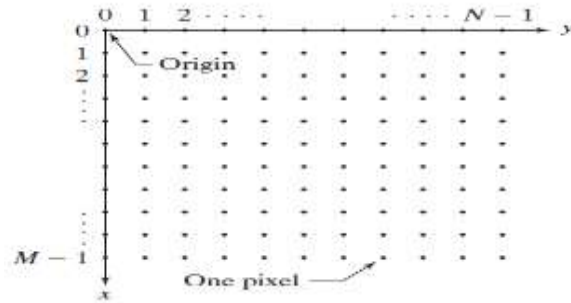


Figure 1: coordinate system

The coordinate system in Figure 1 and the preceding discussion leads to the following representation for a digitized image:

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,N-1) \\ f(1,0) & f(1,1) & \dots & f(1,N-1) \\ \vdots & \vdots & & \vdots \\ f(M-1,0) & f(M-1,1) & \dots & f(M-1,N-1) \end{bmatrix}$$

The right side of this equation is a digital image by definition. Each element of this array is called an *image element*, *pixel*, or *pel*. The terms *image* and *pixel* are used throughout the rest of our discussions to denote a digital image and its elements.

A digital image can be represented as a MATLAB matrix:

$$f = \begin{bmatrix} f(1,1) & f(1,2) & \dots & f(1,N) \\ f(2,1) & f(2,2) & \dots & f(2,N) \\ \vdots & \vdots & & \vdots \\ f(M,1) & f(M,2) & \dots & f(M,N) \end{bmatrix}$$

where  $f(1,1) = f(0,0)$  (note the use of a monospace font to denote MATLAB quantities). Clearly, the two representations are identical, except for the shift in origin. The notation  $f(p,q)$  denotes the element located in row  $p$  and column  $q$ . For example,  $f(6,2)$  is the element in the sixth row and second column of matrix  $f$ . Typically, we use the letters  $M$  and  $N$ , respectively, to denote the number of rows and columns in a matrix.  $A_{1 \times N}$  matrix is called a *row vector*, whereas  $A_{1 \times 1}$  matrix is a *scalar*.

#### IV. THE EXPERIMENT DATABASE

Three distinct subjects of ORL database; each subject has 10 different images. The images were taken at different times and different modest facial pose (frontal, tolerance for some tilting), facial expressions (open or closed eyes, smiling or non-smiling) and facial details (glasses or no glasses). The images are of size (112×92) pixels were taken with a tolerance for some tilting and rotation of the face of up to 20 degrees. All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position. Thus the total number of images is 30 images. Figure 2 illustrate images for three subjects [12].



Figure 2: Image sample

### V. EXPLANATION OF THE PROBLEM

The suggested design of ANN is to be trained to recognize the persons of the database. An imaging system that converts each face image centered in the system’s field of vision is available. The result is that each face image is represented as a 112 by 92 matrix of real values, that is, image size (112×92).

The 10304-pixel input images are defined as a matrix of input vectors, that is, image size (112×92) depending on the results in. The target vectors are also defined with variable called targets. Each target vector is a 112-element vector with a 1 in the position of the face it represents, and 0’s everywhere else. For example, the face number one is to be represented by a 1 in the first element (as this example is the first face of the database), and 0’s in elements two through ninety-two [10].

### VI. SUGGEST DESIGNED OF NEURAL NETWORK

The ANN will receive the 10304 real values as a 10304-pixel input image, i.e., image size (112×92). It will then be required to identify the face by responding with a 112-element output vector.

The 112 elements of the output vector each represent a face. To operate correctly the network should respond with a 1 in the position of the face being presented to the network all other values in the output vector should be 0.

In addition, the network should be able to handle noise. In practice the network will not receive a perfect image of face which represented by vector as input.

Specifically, the network should make as few mistakes as possible when classifying images with noise of mean 0 and standard deviation of 0.2 or less.

### VII. ARCHITECTURE OF SUGGESTED NEURAL NETWORK

We suggest neural network consist three layers the first layer is input layer contained 112 inputs neurons, the hidden layer has 112 neurons with tan.sigmoid transfer function was picked because its output range (-1 to 1) is perfect for learning to output (see Figure 3). The third layer is output layer contained 112 neurons to identify the faces.

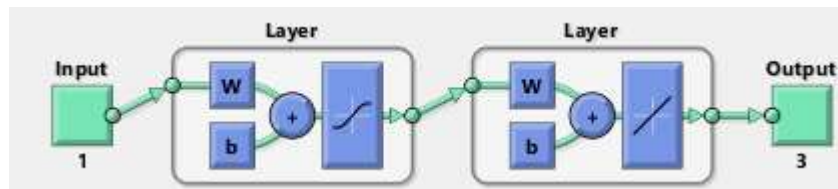


Figure 3: Architecture of suggest ANN

The network is trained to output a 1 in the correct position of the output vector and to fill the rest of the output vector with 0’s. However, noisy input images may result in the network not creating perfect 1’s and 0’s. After the network has been trained the output will be passed through the competitive transfer function.

This function makes sure that the output corresponding to the face most like the noisy input image takes on a value of 1 and all others have a value of 0. The result of this post-processing is the output that is actually used.

### VIII. TRAINING SUGGEST NEURAL NETWORK

To create a neural network that can handle noisy input images it is best to train the network on both ideal and noisy images. To do this the network will first be trained on ideal images until it has a low sum-squared error. Then the network will be trained on 10 sets of ideal and noisy images. Unfortunately, after the training described above the network may have learned to classify some difficult noisy images at the expense of properly classifying a noise free image.

Therefore, the network will again be trained on just ideal images. This ensures that the network will respond perfectly when presented with an ideal face. All training is done using back propagation with improve Levenberg-Marquardt (trainlm).

#### 8.1. Training Without Noise (network1 "net")

The network is initially trained without noise for a maximum of 100 000 epochs or until the network sum-squared error falls below 0.0001, see Figure 4.

##### Training performance

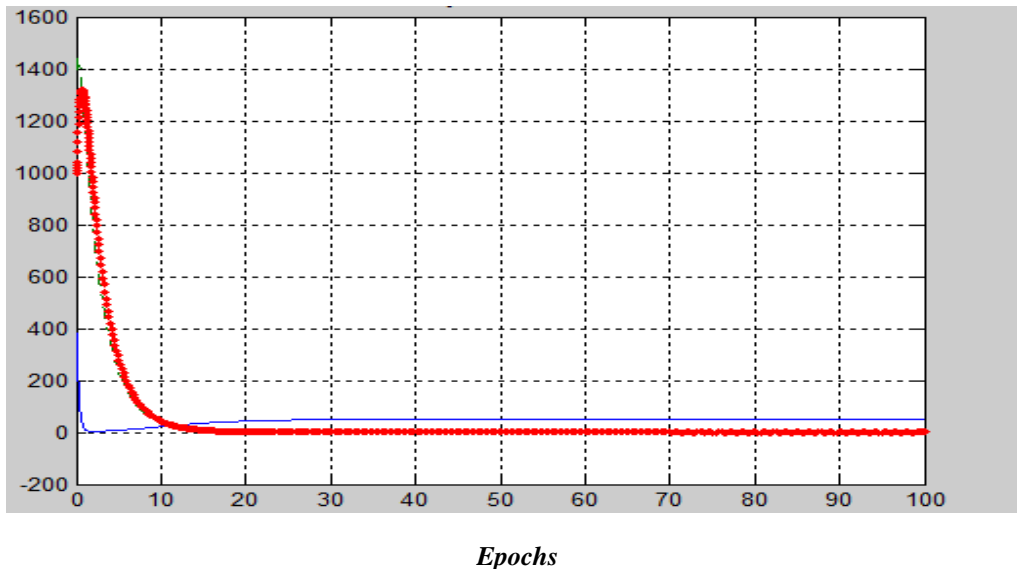


Figure 4: Training Results

#### 8.2. Training With Noise (network 2 "netN")

To obtain a network not sensitive to noise, we trained with ideal copies and noisy copies of the images in database. The noisy images have noise of mean 0.1 ( $\epsilon = 0.1$ ) and 0.2 ( $\epsilon = 0.2$ ) added to them.

This forces the neurons of network to learn how to properly identify noisy faces, while requiring that it can still respond well to ideal images. To train with noise the maximum number of epochs is reduced to 30000 and the error goal is increased to 0.006, reflecting that higher error is expected due to more images, including some with noise, are being presented.

#### 8.3. Training without Noise Again

Once the network has been trained with noise it makes sense to train it without noise once more to ensure that ideal input images are always classified correctly.

### IX. PERFORMANCE OF SUGGEST DESIGN

The reliability of the suggest design of neural network is measured by testing the network with some input images with varying quantities of noise. We test the network at various noise levels and then graph the percentage of network errors versus noise. At each noise level 10 presentations of different noisy versions of each face are made and the network's output is calculated. The output is then passed through the competitive transfer function so that only one of the 112 outputs, representing the faces of the database, has a value of 1. The number of erroneous classifications is then added and percentages are obtained.

The network did not make any errors for faces with noise of mean 0.00 or 0.05, when noise of mean 0.10 was added to the images both networks began to make errors. If a higher accuracy is needed the network could be trained for a longer time or retrained with more neurons in its hidden layer.

Finally, the network could be trained on input images with greater amounts of noise if greater reliability were needed for higher levels of noise, see Figure 5.

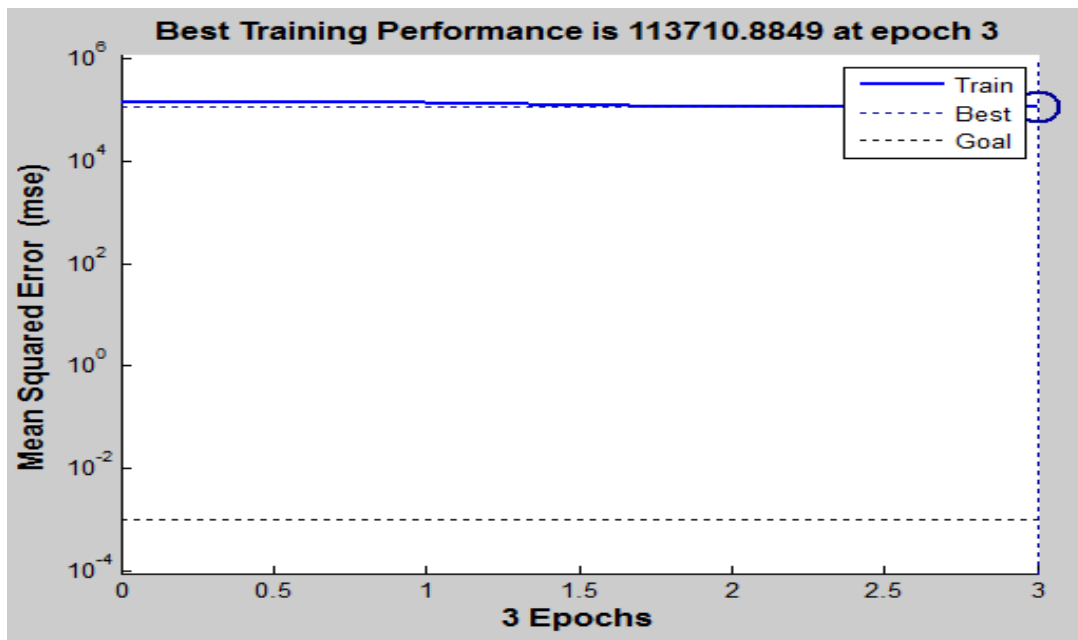


Figure 5: Training results without noise

### X. TEST SUGGEST DESIGN OF NEURAL NETWORK

The efficiency of the suggested design for the pattern recognition can be measured by testing the network with sample of hundreds input images with different quantities of noise images. We test the suggested network with different noise levels to measure the efficiency of suggested network.

Firstly, select noise image and added to the set of input images, for each noise level 10 presentations of different noise for each image are made and then calculate the output of network. Then calculate the transfer function of this output, so that only one of the 10 outputs, representing the ideal image of the database, and has a

value of 1. The number of erroneous classifications is then added. Figure (6) illustrates the efficiency for the network tested with and without noise.

Finally, if greater efficiency is needed for higher levels of noise then, the network must be tested by input images with greater amounts of noise.

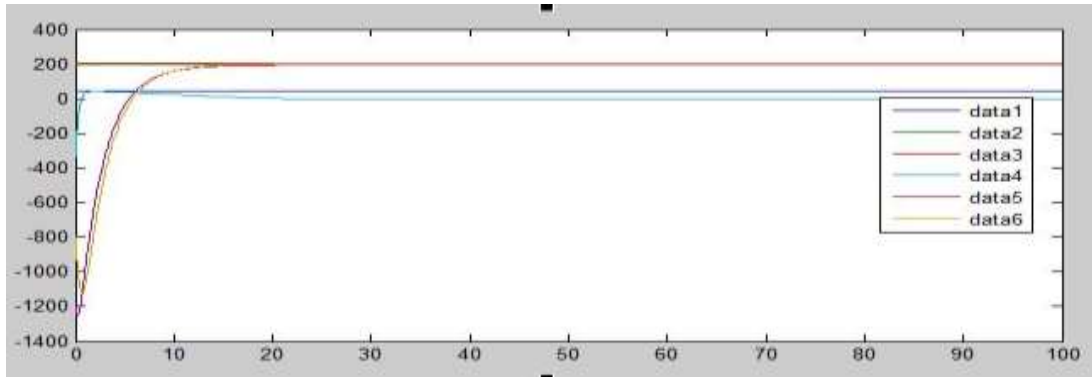
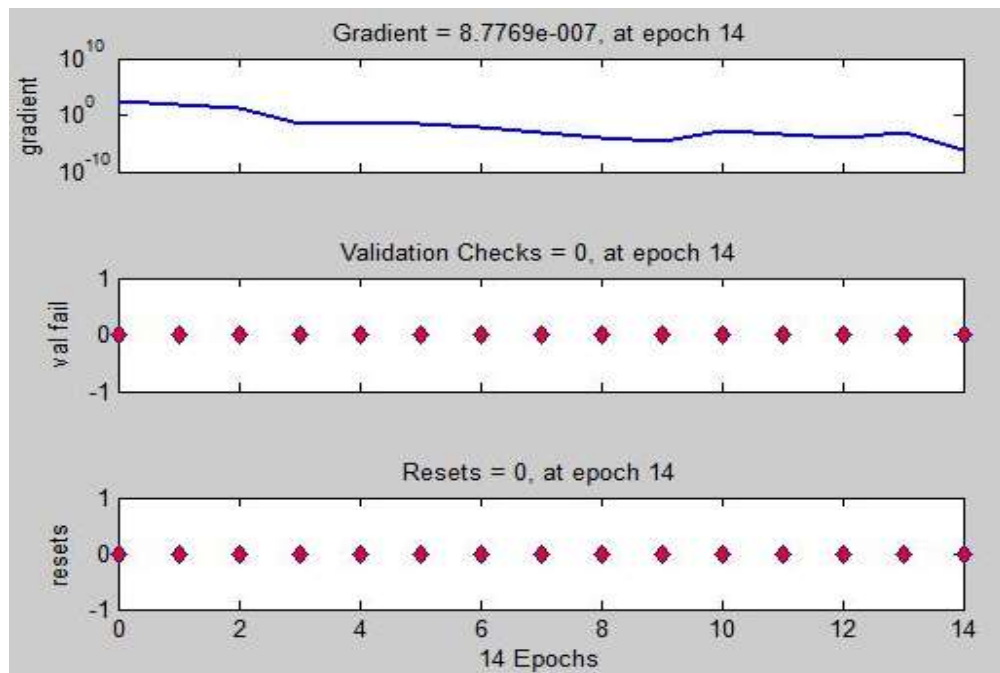


Figure 6: The efficiency for the network tested with and without noise.

### XI. VALIDATION SUGGEST NEURAL NETWORK

To avoid the early stopping and over fitting problems, must be validation the system, a noise image can be presented to the network then create the network. Figure (7) illustrates the error for validation set with noise, for many epochs.



*Figure 7: The performance of network for validation at 14 epoch.*

## XII. CONCLUSION

Face recognition is challenging problems and there is still a lot of work that needs to be done in this area. This common interest in facial recognition technology among researchers working in diverse fields is motivated both by the remarkable ability to recognize people and by the increased attention being devoted to security applications. Applications of face recognition can be found in security, tracking, multimedia, and entertainment domains.

In this paper, we have demonstrated how a face recognition system can be designed by neural network. Note that the training process did not consist of a single call to a training function. Instead, the network was trained several times on various input ideal and noisy images (perturbation parameter) of faces. In this case training a network on different sets of noisy images forced the network to learn how to deal with noise, a common problem in the real world.

It shows the neural network performed pleasingly for all of the tested application domains. Even, this combination achieves a recognition rate of 96.5% with zero noise level ( $\epsilon = 0$ ).

## REFERENCES

- [1] Meng, J. Er, S. Wu, J. Lu, and H. L. Toh, "Face Recognition With Radial Basis Function (RBF) Neural Networks", *IEEE transactions on neural networks*, vol. 13, no. 3, may 2002.
- [2] Jeffrey S. Norris, "Face Detection and Recognition in Office Environments", MSc Thesis, Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, M.I.T, USA, May 21, 1999.
- [3] M. K. Dhar, Q. M. H. Haque, and Md. Tanjimuddin, 2013, "Face Recognition by Radial Basis Function Network", *International Journal of Computer Applications*, Vol. 78, No.3, pp: 21-26.
- [4] Rein-Lien Hsu, "Face Detection and Modeling for Recognition", PhD thesis, Department of Computer Science & Engineering, Michigan State University, USA, 2002.
- [5] Wang, Y., Jiar, Y., Hu, C., & Turk, M, "Face recognition based on kernel radial basis function networks". *Asian Conference on Computer Vision*, Korea. (2004, January 27-30).
- [6] V. Radha, and N. Nallammal, "Neural Network Based Face Recognition Using RBFN Classifier", *Proceedings of the World Congress on Engineering and Computer Science*, 2011, Vol I WCECS 2011, October 19-21, 2011, San Francisco, USA.
- [7] Tawfiq. L. N. M., and Al-Abraheme. K. M., "Using Neural Network and Singular Perturbation Problems in Face Recognition", *International Journal of Modern Computer Science & Engineering*, 2015, 4(1): 1-11.
- [8] Maiorana, E. and Ercole, C., (2007), "Secure Biometric Authentication System Architecture Using Error Correcting Codes and Distributed Cryptography", *GTTI*.
- [9] Rein-Lien Hsu, "Face Detection and Modeling for Recognition", PhD thesis, Department of Computer Science & Engineering, Michigan State University, USA, 2002.
- [10] H. A. Rowley, "Neural Network-based face detection", PhD thesis, Carnegie Mellon University, Pittsburgh, USA, May 1999.
- [11] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, 2009, "Digital Image Processing Using MATLAB", Second Edition, Gatesmark Publishing.
- [12] (website:<http://www.cam-orl.co.uk/facedatabase.html>, 2002).