ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 11, May 2015

A Novel Approach of Face Recognition Using Statistical Features and Neural Networks

[1]T.Chandrasekhar, [2] Dr.K.GIRIBABU , [3]Dr.Ch.Sumanth Kumar
[1,3] GITAM University, Visakhapatnam
[2]V.V.I.T, Nambur

Abstract:-Facial recognition systems are computer-based security systems that are able to automatically detect and identify human faces. Facial recognition has gained increasing interest in the recent decade. Over the years there have been several techniques being developed to achieve high success rate of accuracy in the identification and verification of individuals for authentication in security systems. This project experiments the concept of neural network for facial recognition that can differentiate and recognize face of image. This face recognition system begins with image pre-processing and then the output image is trained using Back propagation algorithm. Back propagation network learns by training the inputs, calculating the error between the real output and target output, and propagates back the error to the network to modify the weights until the desired output is obtained. After training the network, the recognition system is tested to ensure that the system can recognize the pattern of each face image. The purpose of this project is to recognize face of image for the recognition analysis using Neural Network. This project is mainly concern with offline facial recognition systems using purely image processing technique.

Key Words: **Face Recognition, Wavelet, PCA, Neural Network, Self-Organizing Map (SOM).**

I. INTRODUCTION

Face recognition is very important for our daily life. It can be used for remote identification services for security in areas such as banking, transportation, law enforcement, and electric industries, etc. For this security access project is aimed at demonstrating facial recognition techniques that could antiquate, substitute, or otherwise, supplement, conventional key, and can be used as an alternative to existing fingerprint biometrics method. A computerized system equipped with a digital camera can identify the face of a person and determine if the person is authorized to start the vehicle. This integrated system would be able to authorize a user before switching on the vehicle with a key. Whilst facial recognition systems are by now readily available in the market, the vast majority of them are installed at large open spaces, such as in airport halls. The focus of this project is, thus, to compare the extracted feature with face image database for the recognition analysis using Neural Network. Biometric identification is the technique of automatically identifying or verifying an individual by a physical characteristic or personal trait. Facial recognition is one of classical applications of the Artificial Neural Network. This recognition system use neural network approach to recognize the image according to the neural network, this project use backpropagation network. The back propagation learning is a technique discovered by Rumelhart, Hinto, and Williams in 1986 and it is a supervised learning that learns by propagating the signals through the network, computing the input and output using a feedforward network, then calculates the error values and propagates the error back through the network to adapt the weight during training. To perform this project, a simulator program, Matlab R2013a is applied in such a way that the image face can be able to assign an input pattern or to train the network. According to the Matlab software, there is a Neural Network Toolbox that helps this project to train the network.

A) Neural Networks: An artificial neural network is a non linear and adaptive mathematical module inspired by the working of a human brain. It consists of simple neuron elements operating in parallel and communicating with each other through weighted interconnections.

b) Model of neuron: A neuron is an information-processing unit that is fundamental to the operation of a neural network. In this case of artificial neural networks, the strength of the connection between an input and a neuron is defined as the value of the weight. Negative weight values correspond to inhibitory connections, while positive values correspond to excitatory connections. The adder sums up all the inputs modified by their respective weights. Finally, a transfer function controls the amplitude of the output of the neuron. An acceptable range of output is usually between 0 and 1, or -1 and 1 depending on the transfer function selected.

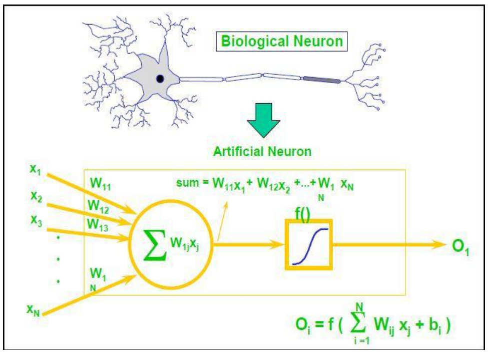

Fig.1 A typical model of an artificial neuron

II. EXISTING METHOD

Modified face image which is obtained in the Face recognition system, should to be classified to identify the person in the database. This is face recognition part of a Face Recognition System. Face recognition part is composed of preprocessing face image, vectorizing image matrix, database generation, and then classification. The classification is achieved by using FeedForward Neural Network (FFNN). Before classifying the face image, it should be preprocessed. Preprocessing operations are histogram equalizing of grayscale face image, resizing to 30-by-30 pixels, and finally vectorizing the matrix image. Histogram equalizing is used for contrast adjustment. After histogram equalization is applied, input face image is similar to faces in database. Input face image has a resolution about 110-by-130 pixels which is large for computation of classifier. So, dimension reduction is made with resizing images to 30-by-30 pixels image to reduce computational time in classification. After resizing, image matrix should be converted to vector because classifier does not work with two-dimensional input. Input vector size will be 900- by-1 vector to classifier. Neural Network is used to classify given images. Neural Network is a mathematical model that is inspired from biological neural network system. Neural network consists of neurons, weights, inputs and output.

III. PROPOSED METHOD

Wavelet Transforms: The Wavelet Transform is a technique for analyzing finite-energy signals at multi-resolutions. It provides an alternative tool for short time analysis of quasi-stationary signals, such as speech and image signals, in contrast to the traditional short-time Fourier transform. The one dimensional Continuous Wavelet Transform CWT of f(x) with respect to the wavelet □(x) is defined as follows:

$$\psi_f(j,k) = \langle f, \psi_{j,k} \rangle = \int_{-\infty}^{\infty} f(x)\psi_{j,k}(x)dx$$

i.e. wavelet transform coefficients are defined as inner products of the function being transformed with each of the base functions j,k. The base functions are all obtained from a single wavelet function □(x), called the mother wavelet, through an iterative process of scaling and shifting, i.e.

$$\psi_{j,k}(t) = 2^{\frac{j}{2}}\psi(2^j t - k).$$

A wavelet function is a wave function that has a finite support and rapidly diminishes outside a small interval, i.e. its energy is concentrated in time. The computation of the DWT coefficients of a signal k does not require the use of the wavelet function, but by applying two Finite Impulse Response (FIR) filters, a high-pass filter h, and a low-pass filter g. This is known as the Mallat's Algorithm. The output will be in two parts, the first of which is the detail coefficients (from the high-pass filter), and the second part is the approximation coefficients (from the low-pass filter). For more details see. The Discrete Wavelet Transform (DWT) is a special case of the WT that provides a compact representation of a signal in time and frequency that can be computed very efficiently. The DWT is used to decompose a signal into frequency sub-bands at different scales. The signal can be perfectly reconstructed from these sub-band coefficients. Just as in the case of continuous wavelets, the DWT can be shown to be equivalent to filtering the input image with a bank of band pass filters whose impulse responses are approximated by different scales of the same mother wavelet. It allows the decomposition of a signal by successive high pass and low pass filtering of the time domain signal respectively, after sub-sampling by 2. Consequently, a wavelet-transformed image is decomposed into a set of sub bands with different resolutions each represented by a different frequency band. There are a number of different ways of doing that (i.e. applying a 2D-wavelet transform to an image). The most commonly used decomposition scheme is the pyramid scheme. At a resolution depth of k, the pyramidal scheme decomposes an image I into 3k +1 sub bands, {LLk, LHk, HLk, HHk, LHk-1, HLk-1,…, LH1, HL1}, with LLk, being the lowest-pass sub band, There are ample of wavelet filters that have been designed and used in the literature for various signal and image processing/analysis. However, for any wavelet filter, the LL subband is a smoothed version of original image and the best approximation to the original image with lower-dimensional space. It also contains highest-energy content within the four sub bands. The subbands LH1, HL1, and HH1, contain finest scale wavelet coefficients, and the coefficients LLk get coarser as k increases. In fact, the histogram of the LL1-subband coefficients approximates the histogram of the original image in the spatial domain, while the wavelet coefficients in every other subband has a Laplace .This property remains valid at all decomposition depth. Moreover, the furthest away a non-LL coefficient is from the mean in that subband, the more probable the corresponding position(s) in the original image have a significant feature. In fact the statistical properties of DWT non-LL subbands can be exploited for many image processing applications, including image/video compression, watermarking, content-based video indexing, and feature extraction.

The network will receive the 960 real values as a 960-pixel input image (Image size ~ 32 x 30). It will then be required to identify the face by responding with a 94-element output vector. The 94 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.

ISSN: 2277-3754
ISO 9001:2008 Certified
International Journal of Engineering and Innovative Technology (IJEIT)
Volume 4, Issue 11, May 2015

i) Architecture of neural network: The neural network needs 960 inputs and 94 neurons in its output layer to identify the faces. The network is a two-layer log-sigmoid/log-sigmoid network. The log-sigmoid transfer function was picked because its output range (0 to 1) is perfect for learning to output Boolean values

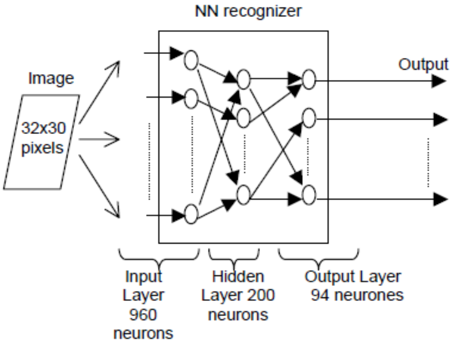

Fig. 2. Architecture of neural network

The hidden layer has 200 neurons. This number was picked by guesswork and experience. If the network has trouble learning, then neurons can be added to this layer. 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. 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. The network is trained on two copies of the noise-free database at the same time as it is trained on noisy images. The two copies of the noise-free database are used to maintain the network's ability to classify ideal input 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 both adaptive learning rate and momentum. The network is initially trained without noise for a maximum of 10 000 epochs or until the network sum-squared error falls below 0.1 (see figure.2).

IV.CONCLUSION

Face recognition is challenging problems and there is still a lot of work that needs to be done in this area. Over the past ten years, face recognition has received substantial attention from researchers in biometrics, pattern recognition, computer vision, and cognitive psychology communities. 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. We have demonstrated how a face recognition system can be designed by artificial 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 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. In this chapter we have reviewed face recognition schemes, and in particular we advocated the use of wavelet-based face recognition. The fact that a wavelet-transform of face image into a number of different subbands representing the face at different frequency range and different scales, has been exploited to develop several single-stream face recognition schemes one for each wavelet subband.

REFERENCES

[1] Rein-Lien Hsu, "Face Detection and Modeling for Recognition," PhD thesis, Department of Computer Science & Engineering, Michigan State University, USA, 2002.

[2] Tom Mitchell, '' neural net & Face images", Home work 3, CMU, Carnegie Mellon University, Pittsburgh, USA, October 1997.

[3] David J.Beymer,''Pose-Invariant face Recognition Using Real & Virtual Views'', PhD thesis, MIT, USA, 1996.

[4] Encyclopaedic,©1993-2002 Microsoft Corporation, Collection Microsoft® Encarta® 2003.

[5] Réda Adjoudj , ''Detection & Reconnaissance des Visages En utilisant les Réseaux de Neurons Artificial'', Thèse de MAGISTER, Spécialité Informatique, Option Intelligence artificielle, Université de Djillali Liabès, department d'informatique, SBA, Algeria, October 2002.

[6] Henry A.Rowley ,''Neural Network-based face detection'' PhD thesis, Carnegie Mellon University, Pittsburgh, USA, May 1999.

[7] Jeffrey S. Norris,'' Face Detection and Recognition in Office Environments'', Submitted to the Department of Electrical Engineering and Computer Science in Partial Fulfillment of the Requirements for the Degree of Master of Engineering in Electrical Engineering and Computer Science at the Massachusetts Institute of Technology, M.I.T, USA, May 21, 1999.

[8] Ying-Li Tian & Takeo Kanade,'' Recognizing Action Units For Facial Expression Analysis'', Carnegie Mellon University, Pittsburgh, USA, 1999.

[9] Howard Demuth, Mark Beale, "Neural Network Toolbox User's Guide for Use with MATLAB", by The MathWorks, Inc.1998.

[10] John Daugman, ''Face and Gesture Recognition: Overview'' IEEE PAMI, vol.19, no.7, July 1997. [11]. D. L. Swets and J. J. Weng, "Using discriminant eigenfeatures for image retrieval," IEEE Trans. PAMI., Vol. 18,No. 8, 831-836, 1996.

[11] A. J. O'Toole, H. Abdi, K. A. Deffenbacher and D. Valentin,"A low-dimensional representation of faces in the higher1993.

[12] A. K. Jain," Fundamentals of digital image processing,"pp.163-175, Prentice Hall, 1989.

[13] B Moghaddam, W Wahid and A pentland, "Beyondeigenfaces: Probabilistic matching for face recognition, "Proceeding of face and gesture recognition, pp. 30 –35, 1998.

[14] A.I. Wasserman."Neural Computing: Theory and Practice"– New York: Van Nostrand Reinhold, 1

[15] Golovko V., Gladyschuk V." Recirculation Neural Network Training for Image Processing," Advanced Computer Systems. -1999. - P. 73-78.

[16] L. Harmon, "The recognition of faces," Scientific American, Vol. 229, 71-82, 1973.

[17] I. Daubechies, "Ten Lectures on Wavelets, CBMS-NSFseries in Applied Mathematics," Vol. 61, SIAM Press, Philadelphia, 1992.

[18] I. Daubechies, "The wavelet transform, time-frequency localization and signal analysis," IEEE Trans. Information Theory, Vol. 36, No. 5, 961-1005, 1990.

[19] A. Pentland, B. Moghaddam and T. Starner," View-basedand modular eigenspaces for face recognition," Proc. IEEE Conf.Computer vision and Pattern Recognition, Seattle, June, 84-91, 1994.

[20] H. A. Rowley, S. Baluja and T. Kanade, "Neural network based face detection," IEEE Transaction on PAMI, Vol. 20, No.1,23-38, 1998.

[21] E.M.-Tzanakou, E. Uyeda, R. Ray, A Sharma, R.Ramanujan and J. Dong, "Comparison of neural network algorithm for face recognition," Simulation, 64, 1, 15-27, 1995.