International Journal of Electrical and Power Engineering 1 (3): 286-294, 2007

Implementation of Echostate Neural Network for Facial Recognition

[1]Srinivasa Rao Madane, [2]Wahidha Banu, [3]Purushothaman Srinivasan and [4]Srinivasa Rao Madane
[1]Department of Electronics and Communication Engineering,
Vinayaka Mission University, Selam, Tamil Nadu, India
[2]AC Technology College of Engineering, Karaikudi, Tamil Nadu, India
[3]Raja Rajeswari Engineering College, Chennai, Tamil Nadu, India
[4]Department of Electronics and Communication Engineering,
Vinayaka Mission University, Selam, Tamil Nadu, India

Abstract: Facial recognition plays an important role in the field of forensic science. Different methods have been proposed by many researchers. In the present day, intelligent facial recognition is very much required. This is due to the fact that, facial masks are used by culprits. After extracting features of a face, intelligent algorithms like artificial neural network can be used to correctly identify a true face. The neural network algorithm proposed is Echostate Neural Network (ESNN). The inputs for the ESNN are the outputs obtained after processing the following methods especially, principal component analysis, Fisher's Linear Discriminant Function (FLD). The recognition performance of ESNN has been compared with that of Radial Basis Function (RBF). In spite of the normal performance exhibited by RBF, ESNN gives promising results when the inputs are distorted.

Key words: Echostate Neural Network (ESNN), Radial Basis Function (RBF), Fisher's Linear Discriminant Function (FLD), Principal Component Analysis (PCA), Artificial Neural Network (ANN)

INTRODUCTION

Facial recognition systems, one of the oldest forms of recognition, measure characteristics such as the distance between facial features (from pupil to pupil, for instance) or the dimensions of the features themselves (such as the width of the mouth). Most developers employ either neural network technology or statistical correlations of the face's geometric shape. Many have had difficulty in achieving high levels of performance when database sizes increase to the tens of thousands or more.

There have been reports of medical concerns associated with the use of some biometrics. The recently growing interest in facial biometrics is the most obvious and non-intrusive tool for secure authentication. Biologists believe that a significant part of human cognitive function evolved to provide efficient ways of recognizing other people's facial features and expressions. But the ability to recognizing friends' faces doesn't extend well to identifying strangers by photo identity. Hence the need to automate the process of face recognition.

A number of facial recognition/identification systems have been developed with a various degree of success. The most common such system is based on the concept of eigenface that is based on Principal Component Analysis (PCA). Most existing biometrics based identification systems are designed for specific purposes and may not be particularly suitable for mass use in mobile/smartcard platforms. Smartcard and mobile system applications, pose serious challenges due to cards constrained memory, limited computational powers and slow transmission rate..

A multi resolution facial profiling system is being researched for identification / authentication in smartcard applications. Elements of the intended facial profiling system arose from an ongoing medical related research project on measuring facial muscle movement during speech. Although computational efficiency is not a serious concern in that research, working with raw image/ video data (i.e., in the spatial domain) is made much more cumbersome as a result of data size. Instead, a multi resolution image-decomposition provides the potential to represent patterns as well as anomalies in the decomposed images.

The research revealed a very interesting property that is satisfied by facial features at all resolutions, which provides the necessary elements for fast and efficient facial profiling systems. Associated with each facial feature (eyes, nose, mouth, chin, etc.) in a face image and at each resolution, there are a small numbers of parameters that can be computed efficiently. These parameters can be

Corresponding Author: Srinivasa Rao Madane, Department of Electronics and Communication Engineering, Vinayaka Mission University, Selam, Tamil Nadu, India

used to automatically detect the boundaries and location of the main facial features and thereby providing a powerful and efficient tool to validate the profile data for each feature. Preliminary results also indicate that these parameters are sufficient, on their own, for face recognition/identification. This result may also be used to support any other known biometric-based facial identification system. The efficiency of computing the profiling data, together with its small size makes it suitable for smartcard/mobile applications and in particular for identification/authentication purposes. The research also reveal great potentials for new efficient face recognition systems that are based on modified principal component analysis of multi-resolution decomposition of facial images. Indeed, a number of plausible ways to develop multiresolution versions of eigenface concept for authentication is done.

In the last 25 years, face authentication has received growing interest, in response to the increased number of real world applications requiring detection and recognition of humans, as well as the availability of low-cost hardware. Although human faces have generally the same structure, they are at the same time very different from each other due to gender, race and individual variations. In addition to these variations, facial expressions can change their appearance. A robust detection-authentication system must also overcome variations due to lighting conditions, rotations of the head, complex background, etc.

The majority of face recognition techniques employ two-dimensional (2-D) grayscale or color images (Chellapa *et al*., 1995). Although the three-dimensional (3-D) structure of the human face intuitively provides highly discriminatory information and is insensitive to environmental conditions, only a few techniques have been proposed that are based on range or depth images. This is mainly due to the high cost of available 3-D digitizers that makes their use prohibitive in real-world applications. Furthermore, these devices often do not operate in real time (e.g., time of flight laser scanners) or produce inaccurate depth information (e.g., stereo vision).

One of the main problems in face recognition (Moses *et al*., 1994; Brunelli and Poggio, 1993) is that facial appearance is distorted by, for example, seasonal changes (aging, hairstyle, usage of cosmetics, etc.), rotation, harsh or heterogeneous illumination and occlusions caused by glasses, scarves, etc. This problem may be partly alleviated by recording a rich training database containing representative variations. Such an approach is shown to lead to improved recognition/ authentication rates (Murase and Nayar, 1996).

Face classification aims to identify individuals by means of discriminatory facial attributes extracted from one or more images belonging to the same person. The challenge is, therefore, in the selection of appropriate features and their efficient matching. Face classification techniques can be roughly divided into two main categories: Global approaches and feature-based techniques. In global approaches, the whole image serves as a feature vector, while in local feature approaches, a number of fiducial or control points are extracted and used for classification. Global approaches model the variability of the face by analyzing its statistical properties based on a large set of training images. Representative global techniques are eigenfaces, Linear/Fisher Discriminant Analysis (LDA) (Etomad and Challappa, 1996) Support Vector Machines (SVM) and Hidden Markov Models (HMMs). Feature-based techniques, on the other hand, discriminate among different faces based on measurements of structural attributes of the face. More recent approaches include elastic graph matching and dynamic link architecture.

Problem definition: The problem is to find out a better method to identify a person even with distorted information of the face, under poor lighting, under different unusual posture. Different methods have been evolved during the past research work that include the varieties of intelligent methods. The proposed work involves estimation of the per
son's identity from the given facial photograph using ESNN. The network learns the facial feature obtained from fishers linear discriminant plane. The research involves in comparison of the performance of the Radial Basis Function (RBF) (Meng *et al*., 2002; Turk and Pentland, 1991) with ESNN.

Echo State Neural Network (ESNN): An Artificial Neural Network (ANN) is an abstract simulation of a real nervous system that contains a collection of neuron units, communicating with each other via axon connections. Such a model bears a strong resemblance to axons and dendrites in a nervous system (Purushothaman and Srinivasa, 1994, 1998). Due to this self-organizing and adaptive nature, the model offers potentially a new parallel processing paradigm. This model could be more robust and user-friendly than the traditional approaches. ANN can be viewed as computing elements, simulating the structure and function of the biological neural network. These networks are expected to solve the problems, in a manner which is different from conventional mapping. Neural networks are used to mimic the operational details of the human brain in a computer. Neural networks are made of artificial 'neurons', which are actually simplified versions of the natural neurons that occur in the human brain. It is hoped, that it would be possible to replicate some of the desirable features of the human brain by

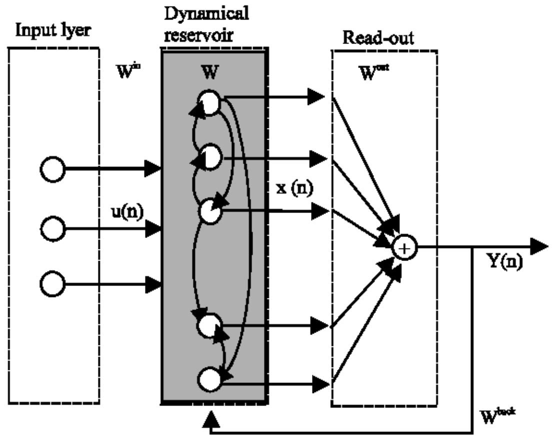

Fig. 1: An Echo State Network (ESN)

constructing networks that consist of a large number of neurons. A neural architecture comprises massively parallel adaptive elements with interconnection networks, which are structured hierarchically.

Artificial neural networks are computing elements which are based on the structure and function of the biological neurons. These networks have nodes or neurons which are described by difference or differential equations. The nodes are interconnected layer-wise or intra-connected among themselves. Each node in the successive layer receives the inner product of synaptic weights with the outputs of the nodes in the previous layer. The inner product is called the activation value. The activation value is passed through a non-linear function. When the vectors are binary or bipolar, hard-limiting non-linearity is used. When the vectors are analog, a squashed function is used. Some of the squashed functions are sigmoid (0 to 1), tanh (-1 to +1), Gaussian, logarithmic and exponential.

A network with two states of a neuron (0 or 1 and -1 or 1) is called 'discrete' and the same with a continuous output is called 'analog'. If, in a discrete network at a particular time 't', the state of every neuron is updated, the network is said to be synchronous. If the state of only one neuron is updated, the network is said to be asynchronous. A network is feed forward, if there is no closed chain of dependence among neural states. The same network is feed backward, if there is such a closed chain. When the output of the network depends upon the current input, the network is static (no memory). If the output of the network depends upon past inputs or outputs, the network is dynamic (recurrent). If the interconnection among neurons change with time, the network is adaptive; it is called non-adaptive. The synaptic weight updation of the networks can be carried out by supervised methods, or by unsupervised methods, or by fixed weight association networks methods. In the case of the supervised methods, inputs and outputs are used; in the unsupervised methods, only the inputs are used; and in the fixed weight association networks methods, inputs and outputs are used along with pre-computed and pre-stored weights. Some of the supervised learning algorithms are the perceptrons, decision-based neural networks, Adaptive Linear Element (ADALINE), multi layer perceptron, temporal dynamic models and hidden Markov analysis. The various unsupervised learning algorithms are neo-cognition, self-organizing feature map, competitive learning, Adaptive Resonance Theory (ART) and the principal component analysis. The fixed weight networks are hamming net, hopfield net and the combinatorial optimization. The total pattern recognition system constitutes instantiation space, feature extraction, training the network and the testing the network.

Dynamic computational models require the ability to store and access the time history of their inputs and outputs. The most common dynamic neural architecture is the Time-Delay Neural Network (TDNN) that couples delay lines with a nonlinear static architecture where all the parameters (weights) are adapted with the backpropagation algorithm. Recurrent Neural Networks (RNNs) implement a different type of embedding that is largely unexplored. RNNs are perhaps the most biologically plausible of the Artificial Neural Network (ANN) models. One of the main practical problems with RNNs is the difficulty to adapt the system weights. Various algorithms, such as backpropagation through time and real-time recurrent learning, have been proposed to train RNNs; however, these algorithms suffer from computational complexity, resulting in slow training, complex performance surfaces, the possibility of instability and the decay of gradients through the topology and time. The problem of decaying gradients has been addressed with special Processing Elements (PEs).

The Echo State Network (ESN), Fig. 1, with a concept new topology has been found by Jaegr (2002b), Jager and Hass (2004). ESNs possess a highly interconnected and recurrent topology of nonlinear PEs that constitutes a "reservoir of rich dynamics" and contain information about the history of input and output patterns. The outputs of these internal PEs (echo states) are fed to a memory less but adaptive readout network (generally linear) that produces the network output. The interesting property of ESN is that only the memory less readout is trained, whereas the recurrent topology has fixed connection weights. This reduces the complexity of RNN training to simple linear regression while preserving a

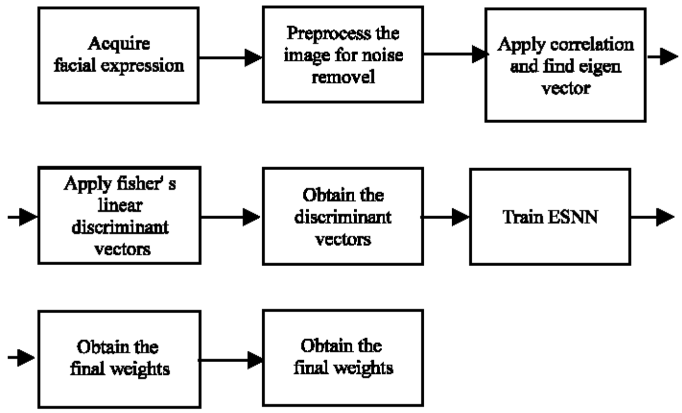

Fig. 2: Schematic diagram of the ESNN facial recognition

recurrent topology, but obviously places important constraints in the overall architecture that have not yet been fully studied.

The echo state condition is defined in terms of the spectral radius (the largest among the absolute values of the eigenvalues of a matrix, denoted by the reservoir's weight matrix ($\| W \| < 1$). This condition states that the dynamics of the ESN is uniquely controlled by the input and the effect of the initial states vanishes. The current design of ESN parameters relies on the selection of spectral radius. There are many possible weight matrices with the same spectral radius and unfortunately they do not all perform at the same level of Mean Square Error (MSE) for functional approximation.

ESN is composed of two parts: A fixed weight ($\| W \| < 1$) recurrent network and a linear readout. The recurrent network is a reservoir of highly interconnected dynamical components, states of which are called echo states. The memory less linear readout is trained to produce the output. Consider the recurrent discrete-time neural network given in Fig. 1 with M input units, N internal PEs and L output units.

The value of the input unit at time n is

$$u(n) = [u_1(n), u_2(n), \ldots, u_M(n)]^T, \tag{1}$$

The internal units are

$$x(n) = [x_1(n), x_2(n), \ldots, x_N(n)]^T \text{ and} \tag{2}$$

output units are

$$y(n) = [y_1(n), y_2(n), \ldots, y_L(n)]^T. \tag{3}$$

The connection weights are given

- In an ($N \times M$) weight matrix $W^{back} = W_{ij}^{back}$ for connections between the input and the internal PEs,
- In an $N \times N$ matrix $W^{in} = W_{ij}^{in}$ for connections between the internal PEs
- In an $L \times N$ matrix $W^{out} = W_{ij}^{out}$ for connections from PEs to the output units and
- In an $N \times L$ matrix for $W^{back} = W_{ij}^{back}$ the connections that project back from the output to the internal PEs.

The activation of the internal PEs (echo state) is updated according to

$$x(n+1) = f(W^{in} u(n+1) + Wx(n) + W^{back} y(n)), \tag{4}$$

Where $f = (f_1, f_2, \ldots, f_N)$ are the internal PEs' activation functions.

Here, all f_i's are hyperbolic tangent functions

$$\frac{e^x - e^{-x}}{e^x + e^{-x}}$$

The output from the readout network is computed according to

$$y(n+1) = f^{out}(W^{out} x(n+1)), . \tag{5}$$

Where $f^{out} = (f_1^{out}, f_2^{out}, \ldots, f_L^{out})$ are the output unit's nonlinear functions the readout is linear so f^{out} is identity.

Proposed method for facial recognition using ESNN: In this research, much concentration is done for the best recognition of face by implementing an ESNN. Figure 2 illustrates the sequence of steps involved in intelligent recognition of facial expression.

IMPLEMENTATION

Training

- Decide number of persons.
- Take three facial expression of each person.
- Calculate the Principal Component Vector by

$$Z=Z * Z^T$$

Where
Z = Intensities of image

- Find Eigen Vector of the Z matrix..
- Calculate the Phi_ And Phi_2 Vectors as follows.

For Discriminating various persons.

$$Phi\_1 = eigenvector(S_b * S_w^{-1})$$

$S_b = \Sigma(PCV_i - M_0) (PCV_i - M_0)^T / N$

Where

PCV_i (i = 1,2,3,…n)

PCV_1 = Principal Component Vectors of Person each person

M_0 = Average of ($PCV_1 + PCV_2 + PCV_3$)

$S_w = \Sigma (PCV_i - M_i) / N (PCV_i - M_i)^T$

where

M_i =1 , 2 , 3,….n

M_i = Average of PCV_i

- Calculate Phi_2 Vector.

$$Phi\_2 = eigenvector (Q S_b S_w^{-1})$$

$$Q = I - ((Phi\_1 * Phi\_1^{-1} * S_w^{-1}) / (Phi\_1^t * S_w^{-1} * Phi\_1))$$

- Transfer for M,N Dimensional Vector into two Dimensional Vector.

$$U = Phi\_1 * PCV_{i\,(1,2,3,\ldots n)}$$

$$V = Phi\_2 * PCV_{i\,(1,2,3,\ldots n)}$$

- Apply Echostate Neural network as follows.

Testing

- Read test image.
- Calculate the Principal Component Vector b.

$$Z=Z * Z^T$$

Where Z = Intensities of image

- Find Eigen Vector of the Z matrix by applying Eigen process.
- Connect to the database.
- Update the table respective to the Person's image.
- Display the Person's Name which is get updated in the database.

Echostate training of facial features: Decide the input features of the registered image
Fix the target values
Set no. of inputs=2;
Set no of reservoir = 20;
Set no. of output = 1
Create weight matrix (no of reservoirs,no.of inputs)= random numbers -0.5
Create weight backup matrix (no.of outputs, no of reservoirs)= (random numbers -0.5)/2
Create weight not (w0)(no.of reservoirs, no of reservoirs)= (random numbers -0.5)
Create temp matrix (te)(no.of reservoirs, no of reservoirs)= random numbers
Calculate w0 = w0.* (te <0.3)
Calculate w0 = w0.* (w0 <0.3)
Follow the heuristics

```
v = eig (w0)
lamda = max (abs(v))
w1= w0/lamda
w = .9* w1
```

Create network training dynamics

```
state = zeros (no_reservoir,1)
desired = 0;
for loop
    input = x (i:i+nipp-1)
    F=wt_input* input'
    TT=w*state
    TH=wt_back' * desired
    next_state = tanh ( F+TT + TH)
    state = next_state
    desired = x (i+nipp-1)
    desired_1 = desired
end
```

Testing-4 ESNN Network testing

```
input = x(i:i+nipp-1);
    F = wt_input* input';
    TTH=wt_back' * output_d;
next_state = tanh (F + w*state + TTH);
state = next_state;
output(i) = (wout'*state);
```

RESULTS AND DISCUSSION

Different orientations of persons have been considered to implement the ESNN for the facial recognition. The various postures have been shown in Fig. 3.

Fig. 3: Facial expressions of different persons

Sample image pixel matrix

147	148	153	155	152	154	159	161	163	163
149	149	156	158	158	163	162	164	164	164
151	152	157	157	161	161	163	165	166	169
155	157	159	159	160	163	164	167	167	168
153	158	161	161	162	162	164	168	170	170
156	160	163	162	164	165	166	167	172	170
158	162	161	162	166	166	168	170	172	170
160	161	164	164	168	165	167	171	175	172
159	161	164	167	170	168	170	175	175	179
161	162	165	167	167	168	174	173	171	174

Correlation matrix

3078745	2773595	2555539	2367792	2258210	2139709	2113195	2103348	2036330	193086
2773595	2682993	2500483	2331402	2232712	2114552	2083707	2048782	1990069	188762
2555539	2500483	2442523	2311269	2216606	2100021	2064694	2019620	1974854	188231
2367792	2331402	2311269	2272284	2189300	2074773	2037447	1998668	1960587	187250
2258210	2232712	2216606	2189300	2165827	2066828	2026552	1992738	1956568	187226
2139709	2114552	2100021	2074773	2066828	2046545	2015895	1982751	1949807	186665
2113195	2083707	2064694	2037447	2026552	2015895	2011248	1985045	1953431	186956
2103348	2048782	2019620	1998668	1992738	1982751	1985045	1990493	1955644	187084
2036330	1990069	1974854	1960587	1956568	1949807	1953431	1955644	1953017	187617
1930868	1887621	1882311	1872507	1872265	1866657	1869566	1870840	1876170	185118

Eigenvector matrix

0.0831	0.0580	-0.1477	-0.0771	-0.1397	-0.0354	0.0134	0.0765	0.0845
0.0735	0.0447	-0.0103	0.1179	0.0601	0.1065	0.0247	0.0718	0.0403
-0.1618	0.0294	-0.0263	0.0555	0.0842	-0.0805	0.1065	0.0446	0.0854
0.1353	0.1675	0.1356	0.1062	-0.1016	-0.0707	0.1735	0.1651	0.0349
-0.0148	0.0642	-0.0026	-0.1232	0.0386	0.0328	-0.3047	-0.2422	-0.0870
-0.0318	0.0194	-0.1203	-0.0771	-0.0975	-0.0215	0.0115	-0.0387	-0.1402
-0.0292	-0.1180	0.2274	0.0882	-0.0971	0.2704	-0.0232	0.1302	0.0491
0.0538	-0.1386	-0.1496	0.0230	0.0165	-0.1151	-0.0613	-0.1367	0.1269
-0.0501	0.1916	0.1572	-0.0139	0.1230	0.0571	0.0267	-0.1290	-0.2960
0.0660	-0.0328	0.0466	0.0596	0.1765	0.0078	-0.0520	0.0269	0.2466

Eigenvalue matrix

0.4407	0	0	0	0	0	0	0	0	0
0	0.8801	0	0	0	0	0	0	0	0
0	0	2.2042	0	0	0	0	0	0	0
0	0	0	3.7260	0	0	0	0	0	0
0	0	0	0	5.9275	0	0	0	0	0
0	0	0	0	0	9.2362	0	0	0	0
0	0	0	0	0	0	10.2134	0	0	0
0	0	0	0	0	0	0	12.6412	0	0
0	0	0	0	0	0	0	0	20.4903	0
0	0	0	0	0	0	0	0	0	30.3254

Diagonal values of eigenvalue matrix

Columns 1 through 12											
	0.4407	0.8801	2.2042	3.726	5.9275	9.2365	10.2134	12.6412	20.4903	30.3254	34.6929
Columns 13 through 20											
	52.5256	60.6881	77.9464	97.0914	129.1984	141.546	156.3125	171.4565			
Sorted value											
Columns 1 through 12	0.4407	0.8801	2.2042	3.726	5.9275	9.2365	10.2134	12.6412	20.4903	30.3254	34.6929
Columns 13 through 20	52.5256	60.6881	77.9464	97.0914	129.1984	141.546	156.3125	171.4565			
Column chosen 100 eigenvector chosen											
Columns 1 through 12	0.1138	0.1036	0.0978	0.0927	0.0903	0.0882	0.088	0.0884	0.087	0.0842	0.0832
Column 13 through 20	0.0822	0.084	0.0842	0.0872	0.089	0.0913	0.0916	0.0929			
Projection vector phi_1 and phi_2											
K>>phi_1(1:30)											
ans =											
Columns 1 through 12	0.0964	-0.0742	-0.0649	-0.0524	-0.0474	-0.038	-0.0282	-0.0234	-0.0123	-0.0071	-0.0024
Column 13 through 24	0.0091	0.0154	0.0223	0.0229	0.0322	0.0397	0.0396	0.0406	0.0375	0.0387	0.0501
Column 25 through 30	0.059	0.0654	0.0657	0.0685	0.0562	0.0568					
K>>phi_2(1:30)											
ans =											
Columns 1 through 12	-0.2251	0.0768	0.0707	0.0744	0.0689	0.0699	0.0689	0.0632	0.0638	0.0711	0.07
Column 25 through 30	0.036	0.0231	0.0108	0.0068	0.0056	0.006					

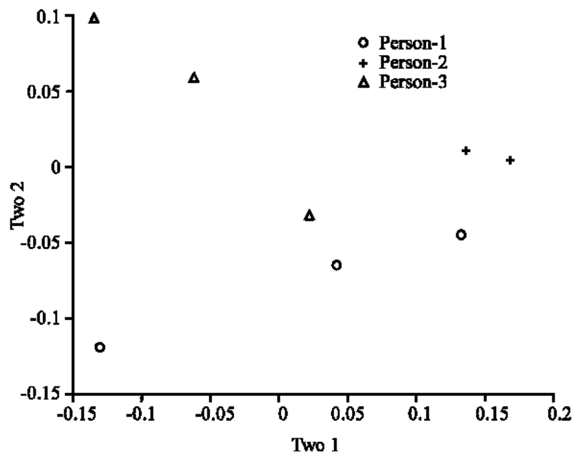

Fig. 4: Facial expressions

Table 1: Classification of the expressions of three persons

	Classification			Total classification
	Expression 1	Expression 2	Expression 3	
Person 1	CL	CL	CL	3
Person 2	CL	CL	NCL	2
Person 3	CL	Cl	CL	3
				8 / 9 =88.88%

Two dimensional vector for three persons and three expressions

K>> two _1		
two_1=		
	0.1323	-0.0459
	0.0414	-0.0649
	-0.1317	-0.1163
K>> two _2		
two_2=		
	0.1362	0.0102
	0.1678	0.0039
	0.1678	0.0039
K>> two _3		
two_3 =		
	-0.1325	0.0981
	-0.0625	0.0586
	0.0349	-0.0319

The outputs of two_1 , two_2 and two_3 are plotted in Fig. 4 for understanding if there is any overlapping of expressions of different persons in order to get better classification of given expression of a particular person. Distribution of the facial expressions.

Testing the image randomly

Testing with the trained inputs: For testing the inputs of trained images or with image that was not used for training most of the steps of training have to be followed followed by using the final weights for final classification of the expressions.

The classification done by the program developed is given in Table 1.

In practice all the nine expressions of three persons should be correctly classified. However there is one misclassification. This may be due to noise in the expression.

CONCLUSION

The project is implemented for recognition of face using the extracted features of the face. An artificial neural network with radial basis function is used as an intelligent method for recognition of given orientation of the face. ESNN is a methodological analysis for face recognition. The principle firstly implemented for face recognition is Principal Component Analysis (PCA). Further it was developed by Fisher's Linear Discriminant (FLD), to over come the dimensional features in face recognition.

The faces of 5 persons with different orientations are considered for the project. Each orientation was trained using PCA, FLD and ESNN. Testing was done with the final weights obtained during training. A set of final weights was obtained. These weights are used for testing the existing face and detecting new face. The accuracy with which the project works is 96.5%.

REFERENCES

Brunelli, R. and T. Poggio, 1993. Face Recognition: Features versus templates, IEEE. Trans, Pattern and Machine Intell., 15: 1042-1053.

Chellapa, R., C.L.Wilson and S.Sirohey, 1995. Human and machine recognition of faces: A survey, Proc. IEEE., 83: 705-740.

Etemad, K. and R. Chellappa, 1996. Face Recognition Using Discriminant Eigenvectors, In: Proc. IEEE. Int. Conf. Acoust., Speech, Signal Proc., 4: 2148-2151.

Jaeger, H. and H. Hass, 2004. Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication. Science, 304: 78-80.

Jaeger, H., 2002b. Tutorial on training recurrent neural networks, covering BPPT, RTRL, EKF and the "echo state network approach (Tech. Rep. No. 159). Bremen: German National Research Center for Information Technology.

Meng Joo Er, Shiqian Wu and Hock Lye Toh, 2002. Face Recognition With Radial Basis Function(RBF) Neural Networks (Actions on neural Networks. 13: 3).

Moses, Y., Y. Adini and S. Ullman, 1994. Face Recognition: the Problem of Compensating for Changes in Illumination Direction, In: Proc. Eur. Conf. Comput. Vision, pp: 286-296.

Murase, H. and S.K. Nayar, 1996. Learning by a Generation Approach to Appearance-based Object Recognition, In: Proc. 13th Int. Conf. Pattern Recognition, 1: 24-29.

Purushothaman, S. and Y.G. Srinivasa, 1994. A back-propagation algorithm applied to tool wear monitoring, International Journal of M/C Tools and Manufacturing, 34: 625-631.

Purushothaman, S. and Y.G. Srinivasa, 1998. A procedure for training artificial neural network with the application of tool wear monitoring, Int. J. Prod. Res., 36: 635-651.

Turk, M.A. and A.P. Pentland, 1991. Eigenfaces for recognition, J. Cognitive Neurosci., 24: 211-219.