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Performance Comparison of Neural Classifiers for Face Recognition System Using GLCM Features

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Abstract—**Neural network basedclassifiers can combine both statistical and structural information and achieve better performance than the simple minimum distance classifiers.Hence they have been widely used in pattern recognitionapplications. The performance of neural network based classifier depends on the input feature selection and neural network architectures.Gray-level co-occurrence matrix (GLCM) features are used to build theFRS. The architectures used in this paper are feed forward neural network and single neuron cascaded architecture. For comparison the network complexity has to be maintained constant and hence the neurons used in hidden layers are maintained constant. To reduce computational complexity Tansigmoid function is replaced by Elliot function and the performance is compared. Three different databases namely ORL, YALE, and JAFFE are used for performance comparison.**

Index Terms—**Artificial neural network, Cascade neural network, Face recognition, Feed forward neural network,GLCM**

I. INTRODUCTION

Face recognition has attracted significant attention because of its wide range of applications. The problem of face recognition is the fact that different faces could seem very similar therefore; a discriminating task is required, which is complex. Even though human beings can easily identify the faces with little effort, building an automated system is very challenging due to varying illumination conditions, position and facial expression. However, in the presence of such issues, distinct feature extraction techniques combined with classifiers having good classification capability improves the performance of FRS.

Feature extraction is very important in building an FRS. The extracted features contain relevant information about the face image. Different techniques have been used for extracting features. Some of the promising feature extraction techniques available in literature arePrincipal component Analysis (PCA)[1]-[3], Linear Discriminant Analysis (LDA) [4]-[7], Scale Invariant FeatureTransform (SIFT), Gabor, Local binary pattern(LBP)[9],wavelet transform and gray-level co-occurrence matrix(GLCM).

In literature GLCM is used to extract the textural features. GLCM is the simple matrix method to extract texture features. Texturefeature describes the pattern of information or arrangement of the structure found in image. Texture can be measured from a group of pixels. Texture feature is extracted can be classified into spatial textural feature and spectral texture feature extraction methods. For the former approach, texture features are extracted by computing the pixel statistics or finding the local pixel structures in original image, whereas the latter image is transformed into frequency domain, then fromthe transformed image features are calculated.Statistical approach such as co-occurrence matrix will help to provide valuable information about the relative position of the neighboring pixels in an image. GLCM [10] is a statistical method that describes the occurrence of the gray level pixel of an image. The extracted features from GLCM are contrast, correlation, energy, homogeneity, sum of squares, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measure of correlation (IMC), dissimilarity, autocorrelation, cluster, prominence, cluster ,shade and maximum probability. In this paper GLCM features are fed to different Neural Networks(NN)for classification.

The second key aspect of face recognition method is the choice of the classifier. TheNN can be trained to perform complex functions so it is one of the most successful classifier in the field of pattern recognition [11]-[14].

The NN performance depends on the network architecture, activation functions, and learning algorithms. The network architecture is the method of interconnection between the neurons and determines the capability of a network. In literature different neural architectures are proposed. The popular architectures are single/multilayer feed forwardnetwork [15] and cascade neural networks. Computational complexity of the network depends on the excitation function. In this paper the complex tan sigmoid function is replaced by a simpler Elliot function and the performance is compared.

The objective of this paper is to analyses performance of the two different NN based classifier for FRS. Extensive simulation studies are carried out to analyses the performance of the neural network in term of recognition accuracy.

To analyses theperformance NN based FRS three bench mark databases are explored. These databases havedifferent

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characteristics in termsvarying scale (ORL), illumination (YALE) and facial expressions (JAFFE).

II. GLCM Based Feature Extraction

GLCM is a statistical method that considers the spatial relationships of pixels of the image also known as the gray-level spatial dependence matrix. The features describes about the distribution of intensities and relative positions of neighboring pixels. It is calculated how often a pixel with gray-level (gray scale intensity) value i occurs with adjacent pixel value k. Each element (i,k) specifies the number of times that the pixel with value i occurred adjacent to a pixel with value k. The adjacency can be defined to take place in each of four directions 0º, 45 º, 90 º and 135 º.

Given an image I with size of $N \times N$,the co-occurrence matrix C can be written as

$$C_{(i,k)} = \sum_{y=1}^{N} \sum_{z=1}^{N} \begin{cases} 1, \text{if } I(y,z)=i \text{ and } I(y+\Delta_y, z+\Delta_z)=j \\ 0, \text{ otherwise} \end{cases} \quad (1)$$

Where Δ_y and Δ_z indicates the pixel of interest and its neighbor. These offset makes the co-occurrence matrix to be sensitive to rotation. It can be avoided by using set of offsets sweeping through 180 º at the same distance parameter Δ to achieve a degree of rotational invariance (i.e. [0 Δ] for 0°,C is horizontal [-Δ Δ] for 45°, C is right diagonal [-Δ 0] for 90°, C is vertical, and [-Δ -Δ] for 135° C is left diagonal. Various features are extracted from GLCM.Some of the important features used in this work is calculated fromGLCM are

$$\text{Contrast} = \sum_{i,k} |i-k|^2 c(i,k) \quad (2)$$

$$\text{correlation} = \sum_{i,k} \frac{(i-\mu_i)(j-\mu_k)C(i,k)}{\sigma_i \sigma_k} \quad (3)$$

$$\text{energy} = \sum_{i,k} c(i,k) \quad (4)$$

$$\text{Homogenity} = \sum_{i,k} \frac{c(i,k)}{1+|i-k|} \quad (5)$$

$$\text{cluster shade} = \sum_{i,k} (i-\mu_y+j-\mu_z)^3 C(i,k) \quad (6)$$

$$\text{cluster prominence} = \sum_{i,k} (i-\mu_y+j-\mu_z)^4 C(i,k) \quad (7)$$

III. Neural architecture for face recognition system

The performance of various NN based classifiers for real time FRS applications depends on the architecture. This has motivated the performance analysis of different neural network architectures to determine the most compact and accurate NN architecture using GLCM features.The FFNN and single neuron cascaded architecture is designed and compared. The uniformity is maintained among the models by adopting the same number of neurons in thehidden layers, learning algorithm, trainingand testing data. All NN models use GLCM features and linear activation function for output layer .The architectures are briefly described.

A. Feed Forward Neural Network

Multilayer Layer Feed-forward Neural Network (MLFF-NN)architecture consists of an input layer, one or more hidden layers, and an output layer. Each neuron model in the architecture includes a nonlinear activation function and those in output layer use pure-linear function. The training algorithm used is LM[16] algorithm. The design of a multi layer network consists of identifying the number of hidden layers and the number of neurons in each hidden layer. The number of inputs depends on the feature extraction method and the number of outputs depends on the number of persons in the data base. There is no systematic approach to design. The number of hidden layers and the number of neurons in each layer are obtained by trial and error. In this paper the number of neurons in the first hidden layer is increased till no further distinct improvement is observed. Then another hidden layer is introduced and neurons added. The process is done for a fixed number of hidden neurons. Total number of neurons was identified for each database. TheFFNN was built for ORL,YALE and JAFFE database.

B. Single Neuron Cascaded architecture with Tan sigmoid/Elliot function as activation function

The Cascade architecture consists of an input layer, hidden layers, and an output layer. The first hidden layer receives only external signals as inputs. Other layers receive external inputs and outputs from all previous 1ayers. A cascade NN can have any number of neurons in each layer and the cascading of inputs improves its mapping capability. Initially, a hidden layer with only one neuron between the input and output is trained till the performance index is reached. In this paper a single neuron is used in every hidden layer so as to obtain single neuron cascaded architecture. Single neuron cascaded network isself-organizing and inherits the advantages of cascaded the inputs. The tan-sigmoid activation function is used for all hidden layers and pure-linear function is used for output layer. The complexity of computation is increased by the nonlinear tan sigmoid activation function. To reduce the complexity a new nonlinear Elliot function [17] is used instead of tan sigmoid function. The number of tan-sigmoid function used is thirty are replaced by thirty Elliot functions which is computationally less complex.The tangent sigmoid function is shown in equation (8) and Elliot's function is shown in equation (9).In this paper the performance of single neuron cascaded architecture with Elliot function as activation function (SNCET) is compared with single neuron cascaded architecture with Tan-sigmoid function (SNCTS) as activation function and FFNN.The number of input depends on the feature extraction method and the output depends on the number of classes on the databases.

IV. Experimental results and discussions

This section describes about the performance analysis of two different NN based classifier for face recognition system. To evaluate the performance, experiments are carried out on three different databases. GLCM features are extracted for each image in the databases. The extracted forty-four GLCM features are fed as input to the neural network classifiers. To investigate the recognition capability different number of training and testing sample per subjects are taken and the recognition accuracy is calculated. The recognition accuracy is the ratio between the numbers of correct recognized images to the total number of test images. All the images not used for training were used for testing. To compute the standard deviation different combinations of training and testing dataset are taken.

A. Experimental results on ORL database

The performance of the different architectures is compared in terms of recognition accuracy. Different number of training and testing sample per subjects are taken and the recognition accuracy is obtained.

The ORL database contains 400 face imagesfrom 40individual's.The totalnumber of images for each person is 10. For comparison, the samenumber of hidden neurons is used for all the architectures. Different combinations of training and testing images are used to compute the recognition accuracy with standard deviation.

The number of subjects per class is increased from lower value to the maximum value and the recognition accuracy is observed. The network performance is further investigated using different combinations of training and testing data sets to compute the standard deviation. The standard deviation indicates the accuracy range irrespective of any combination of training and testing data set.The recognition accuracy of all the three NN is shown in Table.1. This is represented in a bar graph in Fig. 1. From the highest recognition accuracy achieved is 89.0±6.3for SNCET, 87.3±3.5 for SNCTS and 65.5±6.6for FFNN.From the Table it is observed that the performance of the SNCET is as good as SNCETS and outperforms FFNN.

Table1: Performance Comparisonof different Networks for ORL database

Number of images trained	Number of images tested	FFNN Recognition accuracy(%)	SNCTS Recognition accuracy(%)	SNCET Recognition accuracy(%)
20	80	28.5±13.1	49.0±2.3	57.3±5.0
30	70	39.3±6.7	57.8±9.3	61.4±2.2
40	60	46.9±5.2	71.4±6.0	71.9±2.0
50	50	52.4±7.5	81.8±4.0	75.3±1.5
60	40	58.1±5.6	84.5±4.9	83.6±4.2
70	30	58.8±6.8	85.2±2.4	87.3±2.7
80	20	59.3±5.3	87.3±3.5	88.2±4.3
90	10	65.0±6.6	85.0±3.5	**89.0±6.3**

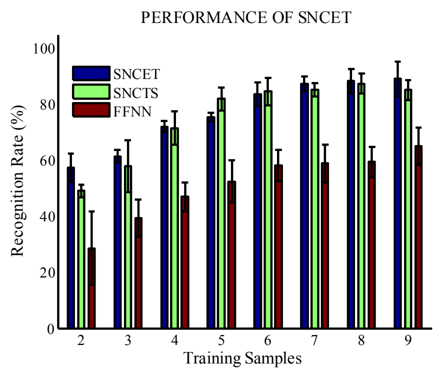

Fig 1: Comparison of proposed method with existing methods for ORL database

B. Experimental results on YALE database

YALE database consists of total number of 165 images. There are 11 images per subject, which is in GIF format. The overall recognition rate with a standard deviation of the all NNs is shown in Table 2. The recognition accuracy for SNCT, SNCTS and FFNN with error bar is shown in Fig.2.

Table 2. Performance Comparisonof different Networks For YALE database

Number of images trained per class	Number of images tested per class	FFNN Recognition accuracy(%)	SNCTS Recognition accuracy(%)	SNCET Recognition Accuracy(%)
2	9	35.1±12.9	41.6±6.3	46.3±7.0
3	8	45.6±11.2	57.7±5.6	58.2±6.6
4	7	58.3±5.9	62.1±4.8	63.1±4.0
5	6	59.1±5.2	70.7±5.2	68.7±7.8
6	5	65.6±7.3	70.9±3.0	74.0±4.9
7	4	68.7±10.8	80.0±8.9	77.1±6.6
8	3	71.6±7.9	80.4±9.2	81.0±7.9
9	2	81.3±13.7	89.3±5.5	88.0±5.6
10	1	86.7±6.7	93.3±4.7	**96.0±3.7**

From the Table the highest recognition accuracy achieved is 96.0±3.7for SNCET, 93.3±4.7 for SNCTS and 86.7±6.7 for FFNN.From the results it is observed that the Single neuron cascaded architectures outperformsFFNN.

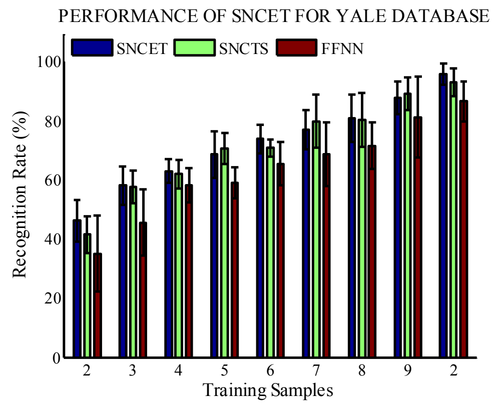

Fig 2: Comparison of proposed method with existing methods for YALE database

V. EXPERIMENTAL RESULTS ON JAFFE DATABASE

JAFFE database has 213 images of female facial expressions. Resolution of each image has 256 x 256 pixels. The number of images consists of seven expression namely neutral, happiness, sadness, anger, disgust, and fear. The images are in the tiff format. The performances of all the networks are shown in Table 3. From the results the highest recognition accuracy is 96.7±5.8 for sad expression is achieved by both SNCET and SNCTS.The highest recognition accuracy achieved by FFNN is80±10.The SNCET is shown to be as good as SNCTS and superior than FFNN.The recognition accuracy for SNCT, SNCTS and FFNN with error bar is shown in Fig. 3

Table 3. Performance comparison of different networks for JAFFE database

EXPRESSIONS	FFNN Recognition Accuracy(%)	SNCTS Recognition Accuracy(%)	SNCET Recognition Accuracy(%)
ANGER	73.3±11.5	83.3±15.3	86.7±5.8
DISGUST	80.0±17.3	93.3±5.8	90.0±0.0
FEAR	63.3±25.2	83.3±5.8	86.7±5.8
HAPPY	76.7±15.3	83.3±11.5	83.3±5.8
NEUTRAL	83.3±5.8	86.7±15.3	86.7±5.8
SAD	80.0±10.0	**96.7±5.8**	**96.7±5.8**
SURPRISE	63.3±20.8	80.0±10.0	93.3±5.8

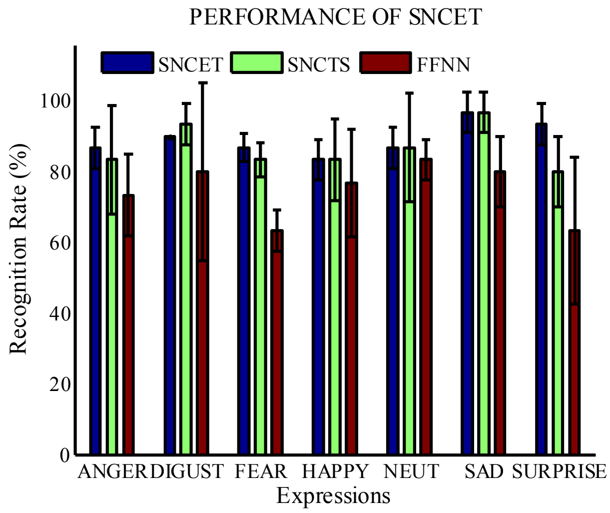

Fig 3: Comparison of proposed method with existing methods for JAFFE database

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