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Comparative Analysis of ANFIS and NN Approach for Expression Recognition using Geometry Method

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Abstract— ***The area of Human Computer Interaction will be much more effective and natural if computers can automatically recognize and classify facial expressions for supplied face images and hence perceive about emotional state of human beings. The paper explains about comparative analysis of expression recognition using two approaches. Adaptive Neuro-Fuzzy Inference System (ANFIS) and Back propagation Neural network are used as classifiers for classifying the expressions of supplied face into seven basic categories like surprise, neutral, sad, disgust, fear, happy and angry. Facial Geometry method is used for facial feature extraction. Face portion segmentation and localization is achieved using series of morphological image processing operations. In geometry method, permanent facial features like eyebrows, eyes, mouth and nose are extracted using SUSAN edge detection operator and face geometry. Experiments are carried out on JAFFE facial expression database and gives better performance in terms of 100% classification accuracy for training set and 97.142% and 94.76% average recognition accuracy for test set using ANFIS and NN approach respectively for 30 test samples.***

Keywords— **HCI, ANFIS, Neural Networks (NN), Morphological Image Processing, Facial Feature Extraction**

I. INTRODUCTION

Due to technological advancements; there is an arousal of the world where human being and intelligent robots live together. Area of Human Computer Interaction (HCI) will be much more effective and useful if computer can predict about emotional state of human being and hence mood of a person from supplied images on the basis of facial expressions and will be considered as boon for vision community. Mehrabian [23] pointed out that 7% of human communication information is communicated by linguistic language (verbal part), 38% by paralanguage (vocal part) and 55% by facial expression. Therefore facial expressions are the most important information for emotions perception in face to face communication. For classifying facial expressions into different categories, it is necessary to extract important facial features which contribute in identifying proper expressions. Recognition and classification of human facial expression by computer is an important issue to develop automatic facial expression recognition system in vision community. In recent years, much research has been done on machine recognition of human facial expressions [3][10][20][28]. In last few years, use of computers for Facial expression and emotion recognition and its related information use in HCI have gained significant research interest which in turn given rise to a number of automatic methods to recognize facial expressions in images or video [30][13][17][1][33].

This paper presents comparative analysis of two models in the context of classification and recognition of facial expressions for human faces. Adaptive Neuro-Fuzzy Inference System (ANFIS) and NN model classify the expressions of supplied face into seven basic categories like surprise, neutral, sad, disgust, fear, happy and angry. For face area segmentation and localization, basic image processing operations like morphological dilation, erosion, reconstruction techniques are used. In geometry method, six permanent Facial features like eyebrows(left and right), eye (left and right) , mouth and nose are extracted using facial geometry distance measure and feature vector is formed considering height and width of left eye, height and width of left eyebrow, height and width of right eye, height and width of right eyebrow, height and width of nose and height and width of mouth along with distance between left eye and eyebrow, distance between right eye and eyebrow and distance between nose and mouth. Experiments are carried out on JAFFE facial expression database. The paper is organized as follows. Section 2 describes about review of existing methods, section 3 highlights on methodology followed, section 4 explains expression classification and recognition, section 5 gives experimental results and analysis, section 6 presents conclusion and future scope and last section gives references used.

II. REVIEW OF EXISTING METHODS

In recent years, the research of developing automatic facial expression recognition systems has attracted a lot of attention. A more recent, complete and detailed overview can be found in [29] [4] [11]. Accuracy of facial expression recognition is mainly based on accurate extraction of facial feature components. Facial features are located and extracted using approaches like SUSAN algorithm [21][12], selective feature rules[6],PCA and wavelet[16][5][26][22], EICA, FLDA,ICA,[22], LBP[34][35], cross correlation based optical flow[7], curvelet and SVD[9]. Many methods have been proposed for expression recognition such as KNN [16] discrete HMM [22], MANFIS [34], eigen spaces/modified PCA [5], RBF and fuzzy inference system [7], QNN [15], Neural networks [26], [19][2]. FACS was first developed by Ekman and Friesen [27] and is used to measure the facial behavior. FACS codes different facial movements into action units. There are 44 action units which are based on underlying

muscular activity and produces momentary changes in facial expressions. Thus facial expressions are recognized by correctly identifying the action units or combinations of action units. Approaches used in [18][19][32][36] used neural networks as classifier and achieved recognition accuracy ranging from 90.01-96.4 for different number of samples and in [34] use of MANFIS model has given the accuracy of 95.29% for 35 samples.

The purpose of this research is to develop NN and hybrid model for classifying facial expressions into different groups based on the geometric values of facial features and to make comparative analysis of both classification techniques and improve the % recognition accuracy. Geometry based feature extraction method is fully automatic i.e there is no need of model initialization or feature point initialization like fiducial points. Here one can show the features located graphically with the help of bounding box. Hence, the proposed facial expression recognition system aimed to use image preprocessing and geometry based techniques for feature extraction and a hybrid model ANFIS and Neural network for expression recognition for the frontal view face images.

III. METHODOLOGY

Fig. 1 shows block diagram for the methodology followed for Automatic Facial Expression Recognition.

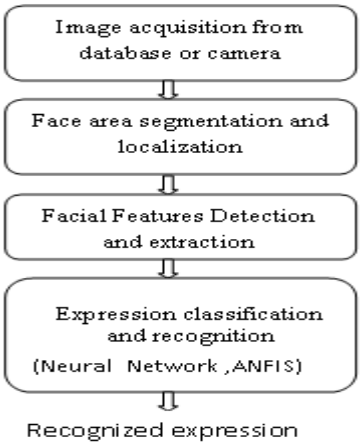

Fig. 1 Block diagram of AFER

A. Face acquisition, face area segmentation and localization

Face area and facial feature plays an important role in facial expression recognition**.** Better the feature extraction rate more is the accuracy of facial expression recognition. Precise localization of the face plays an important role in feature extraction, and expression recognition. But in actual application, because of the difference in facial shape and the quality of the image, it is difficult to locate the facial features precisely.

1) Data collection

Data required for experimentation is collected from JAFFE database [24-25] for implementation. JAFEE stands for The Japanese Female Facial Expression (JAFFE) Database. The database contains 213 images of 7 facial expressions (6 basic facial expressions + 1 neutral) posed by ten different Japanese female models. Sixty Japanese subjects have rated each image on 6 emotion adjectives. The database was planned and assembled by Miyuki Kamachi, Michael Lyons, and Jiro Gyoba with the help of Reiko Kubota as a research assistant. The photos were taken at the Psychology Department in Kyushu University. Few samples are shown in Fig. 2

Fig. 2 Few samples of facial expressions of person YM from

2) Face area segmentation and localization

JAFFE database contains low contrast images therefore images are first pre-processed using contrast limited adaptive histogram equalization operation and is used for enhancing contrast of an image. Face area is segmented using sequence of morphological image processing operations like dilation, erosion reconstruction, complementation, regional max and clear border (Fig. 3).

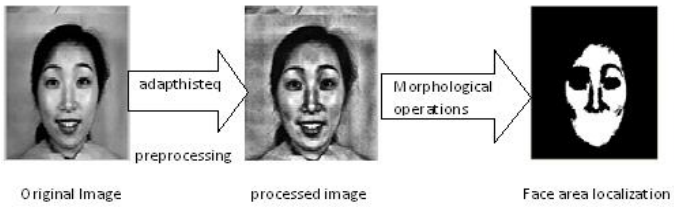

Fig.3 Face area segmentation and localization

B. Feature Extraction using Geometry Approach

In order to extract facial features, segmented face image (RoI) is then resized to larger size to make facial components more prominent. SUSAN edge detection operator [12] along with noise filtering operation is applied to locate the edges of various face feature segment components. Methodology described in our paper [31] is used for facial feature segment localization and extraction. Facial geometry shown in Fig. 4 is used to extract facial feature segments.

1) Formation of feature vector

Bounding box locations of feature segments obtained using steps in [31] are used to calculate the height and width of left eyebrow, height and width of left eye, height and width of right eyebrow, height and width of right eye, height and width of nose and height and width of mouth. Distance between centre of left eye and eyebrow, right eye and eyebrow and mouth and nose is also calculated. Thus total 15 parameters are obtained and considered as feature vectors (Fig.5).

Thus-

$$F_v=\{H_1,W_1,H_2,W_2,H_3,W_3,H_4,W_4,H_n,W_n,H_m,W_m,\ D_1,D_2,D_3\} \quad (1)$$

Where,

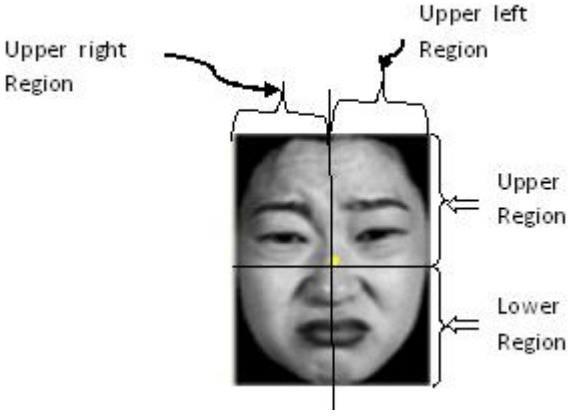

Fig. 4 Facial Geometry for extracting facial feature segments

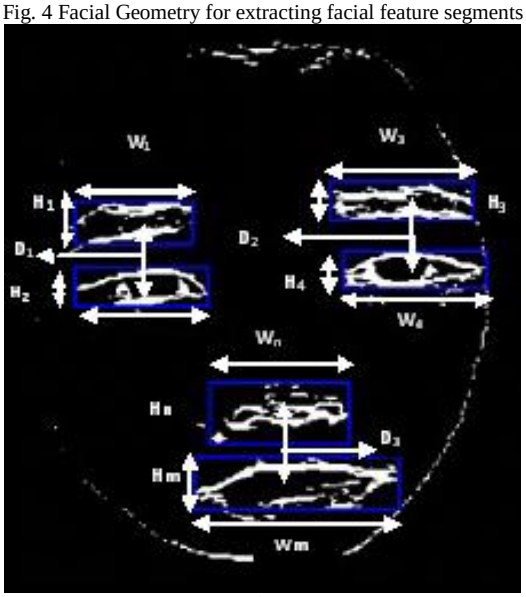

Fig. 5 Feature vector for Expression recognition

H_1= height of left eyebrow, W_1= width of left eyebrow,
H_2= height of left eye, W_2= width of left eye
H_3=height of right eyebrow, W_3= width of right eyebrow,
H_4= height of right eye, W_4= width of right eye
H_n= height of nose, W_n= width of nose,
H_m= height of mouth, W_m= width of mouth
D_1 = distance between centre of left eyebrow and left eye,
D_2 = distance between centre of right eyebrow and right eye,
D_3 = distance between centre of nose and mouth

The parameters are calculated using the following formulae –

$$H_i = x_{2i}-x_{1i} \quad , i = 1,6 \qquad (2)$$

$$W_i = y_{2i}-y_{1i} \quad , i = 1,6 \qquad (3)$$

D_1 = $\frac{(x_2 - x_1)}{2}$ of Left eye - $\frac{(x_2 - x_1)}{2}$ of Left eyebrow (4)

D_2 = $\frac{(x_2 - x_1)}{2}$ of right eye - $\frac{(x_2 - x_1)}{2}$ of right eyebrow (5)

D_3 = $\frac{(x_2 - x_1)}{2}$ of mouth - $\frac{(x_2 - x_1)}{2}$ of nose (6)

IV. EXPRESSION CLASSIFICATION AND RECOGNITION

Back propagation Neural Networks (BPNN) and hybrid model (ANFIS) are used to recognize and classify facial expressions.

A. BPNN model for Expression Recognition

NNs are developed to solve demanding pattern processing problems, like speech and image processing. Fig. 6 shows the model of neural network. Back propagation learning algorithm is performed in two stages [8]: feed-forward and feed-backward. In the first phase the inputs are propagated through the layers of processing elements, generating an output pattern in response to the input pattern presented. In the second phase, the errors calculated in the output layer are then back propagated to the hidden layers where the synaptic weights are updated to reduce the error. This learning process is repeated until the output error value, for all patterns in the training set, are below a specified value.

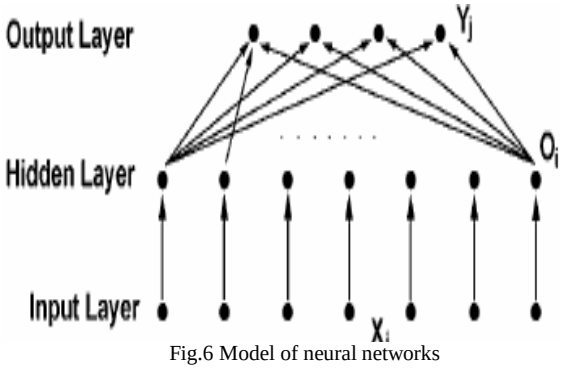

Fig.6 Model of neural networks

Fifteen values obtained in the subsection III.B.1) are given as an input to the BPNN model which uses an input layer, two hidden layer with 15 and 7 neurons each and an output layer. Transfer function used at hidden layer1 is tansig, hidden layer 2 is tansig and at output layer is linear.

B. ANFIS model for Expression Recognition

ANFIS proposed by Jang [14] are a class of adaptive networks that are functionally equivalent to fuzzy inference systems. ANFIS represent Sugeno Tsukamoto fuzzy models and uses hybrid learning algorithm.Fig.7 shows the detailed architecture of ANFIS model for expression recognition using geometry approach. Fifteen values so obtained in the subsection *III.B.1*) are given as an input to ANFIS model. Three ANFIS models are used which takes 5 inputs each for geometry method. Three Gaussian bell membership functions are associated with each input to model the variations of feature values for different facial expressions, so the input space is partitioned into fuzzy subspaces. In all 243 rules are generated for an ANFIS model.

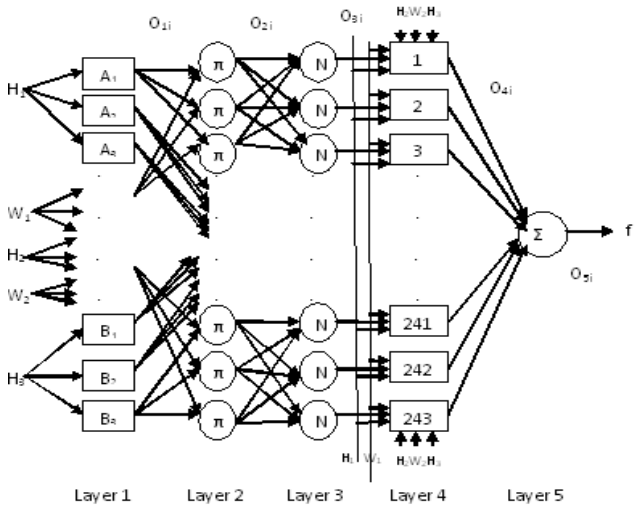

Fig. 7 Architecture of ANFIS model for expression recognition

Output of layer 5 of each model is given as input to maximum occurrence finder (Fig.8) which finds the maximum occurrence value of particular expression.

Thus for Geo-ANFIS approach

$$F = Maximum\ occurence(f_1, f_2, \ldots, f_n) \quad , n = 3 \qquad (7)$$

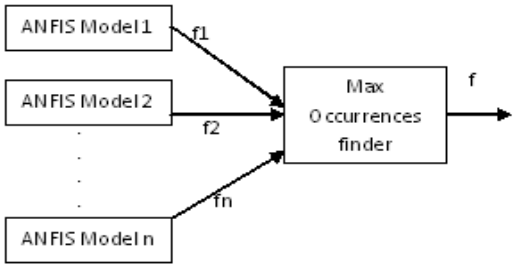

Fig. 8 ANFIS model o/p predictor for expression recognition

V. Experimental Results and Analysis

BPNN and ANFIS model is constructed for JAFEE Face Database for frontal view facial images. Fig. 9 shows the results of facial feature extraction using geometry approach. 15 feature values obtained are given as input to neural networks and ANFIS model.

Training Phase: In this work, supervised learning is used to train the back propagation neural network and ANFIS model. The training samples are taken from the JAFFE database. Each network is trained for different number of samples (145, 132, 120, and 100) for all expressions. After getting the samples, supervised learning is used to train the network. NN model is trained three times and shown good response in terms of reduction of error signal (Fig. 10) and gives 100% average classification accuracy. Plot of Fig.10 shows that the network learns gradually and reaches towards the goal. Fig.11 shows membership function before and after training for geometry-ANFIS method. Model is trained and shown good response in terms of reduction of error signal (Fig. 12.)

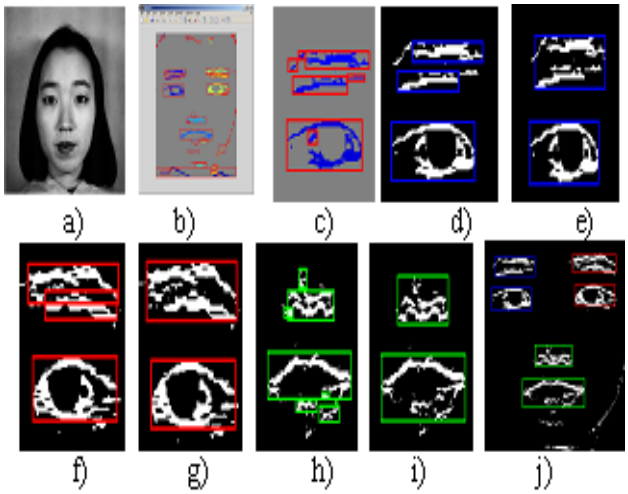

Fig.9 Facial Feature extraction results

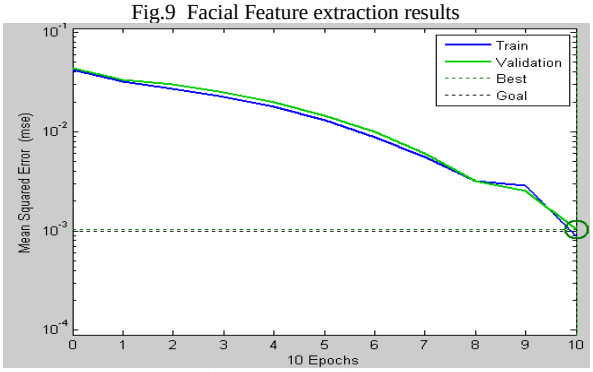

Fig. 10 Performance plot of neural network

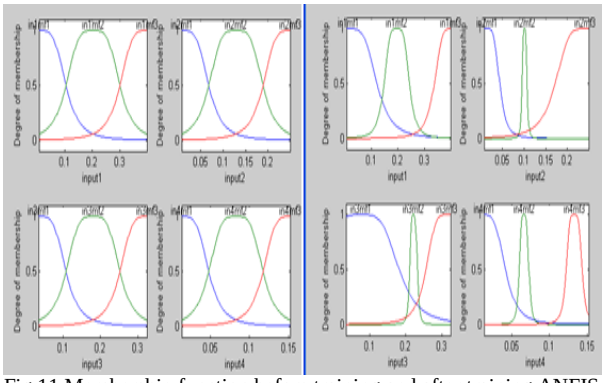

Fig.11 Membership function before training and after training ANFIS

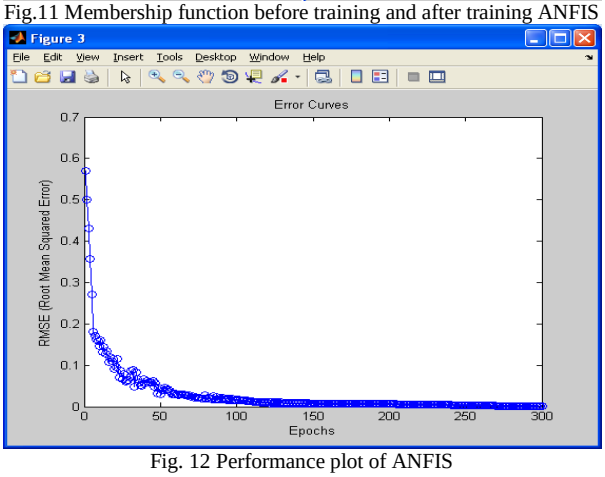

Fig. 12 Performance plot of ANFIS

Testing Phase: The proposed system is tested with JAFFE database for different number of samples (30, 43, 55, and 75) for all of the facial expressions. Fig. 13 shows the GUI for displaying the results of face localization, extracted permanent facial features with bounding box and its recognition and classification for geometry-NN and geometry-ANFIS approach and exhibits sad (SA) expression and Happy (HA) expression respectively. Fig.14 shows the plot depicting relationship between overall % recognition accuracy and number of samples of testing dataset for proposed approaches (Facial Geometry Approach(FGA)+ANFIS and FGA+NN/BPNN method).

Fig.13 GUI for classification and recognition of facial expression using Geo-NN and Geo-ANFIS approach

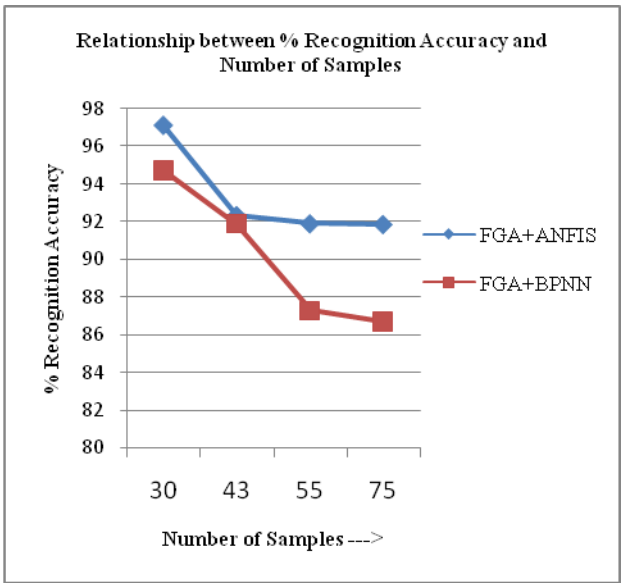

Fig.14 Relationship between Number of Samples and % Recognition accuracy for Geo+ANFIS and Geo+BPNN

Table I and Table II shows confusion matrices for testing dataset with geometry-ANFIS/NN based Facial Expression recognition respectively for 30 samples. In Geo-ANFIS approach, out of 30 samples, 29 samples are correctly classified and one sample (angry) is misclassified as sad. In Geo-NN approach, out of 30 samples, 28 samples are correctly classified and two samples are misclassified.

TABLE I
CONFUSION MATRIX FOR GEOMETRY-ANFIS METHOD

Expression	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise	Accuracy Rate
Angry	4	0	0	0	0	1	0	80.00
Disgust	0	3	0	0	0	0	0	100.00
Fear	0	0	4	0	0	0	0	100.00
Happy	0	0	0	4	0	0	0	100.00
Neutral	0	0	0	0	4	0	0	100.00
Sad	0	0	0	0	0	5	0	100.00
Surprise	0	0	0	0	0	0	5	100.00
Average recognition accuracy (%)								97.142

TABLE II
CONFUSION MATRIX FOR GEOMETRY-BPNN METHOD

Expression	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise	Accuracy Rate
Angry	4	0	0	0	0	1	0	80.00
Disgust	0	3	0	0	0	0	0	100.00
Fear	0	0	4	0	0	0	0	100.00
Happy	0	0	0	3	0	0	0	100.00
Neutral	0	0	0	0	4	0	0	100.00
Sad	0	0	0	0	0	5	0	100.00
Surprise	0	0	0	0	0	1	5	83.33
Average recognition accuracy (%)								94.76

VI. CONCLUSION AND FUTURE SCOPE

Machine recognition of facial expression is a big challenge even if human being recognizes it without any significant delay. The combination of SUSAN edge detector and facial geometry distance measure is best combination to locate and extract the facial feature for gray scale images in constrained environments if the images are frontal view and clear images without any obstacle like hair. 100% average classification accuracy is achieved for training sets with geometry-NN/ANFIS based approach and 97.142% and 94.76 % average recognition accuracy is achieved for test sets of JAFFE database with geometry-ANFIS and geometry-NN approach respectively which is promising.

Proposed combination method for feature extraction does not extract exactly six features parameters properly if there are hairs on face area, mixing of eyes and eyebrow portion. Therefore in future an attempt can be made to develop an approach which can handle such problems and will be suitable for different databases.

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