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Facial Expression Detection using Pattern Analysis and Machine Intelligence

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Abstract:* Emotion is a mental state that happens spontaneously rather than through conscious attempt and it is accompanied by physical changes. Human computer interaction can be automated by using emotions and the accompanied physiological changes. The computers not only respond to human commands, they also try to mimic the human behavior. Automatic recognition of human facial expression and emotion takes the computer one step near the above said task. Human emotion recognition is an interesting and challenging problem. In order to translate facial expressions to emotions, an emotion assessment technique are required. Emotion assessment is difficult task even users are not always able to express their emotion with words all the time and the self-reporting emotions have a high probability of false emotions. In this work, initially the human face will be detected. Then the facial features will be extracted and classified into different expressions. The features extracted from the image will be quantified and will be used as training set for the pattern recognizing neural network. The trained neural network in future will classify the images according to the emotions expressed by the person.

Keywords:* Facial Expression Recognition, Pattern Recognition Neural Network, Feature Extraction.

I. INTRODUCTION

As the proverb 'Face is the index of the mind' rightly suggests, facial expression reflects the feeling and emotions felt by a person.

For efficient detection of spatial expression, many algorithms have been proposed. Ghimire et. al [2] proposed extraction of local region specific features and support vector machines for classification of the facial expression. Classification accuracy of 97% was achieved. Shan et. al [3] applied support vector machine classifiers on the boosted local binary pattern features obtained from different image data sets. The accuracy obtained for jaffe image data set was 81%. Cohn-Kanade database of video signal is classified by Siddiqi et. al [4] using Hidden Conditional Random Fields and a classification accuracy of 93% is achieved. Happy and Routray [5] implemented facial expression recognition from jaffe and ck images by determining facial patches.

Zhong et.al [1] also determined facial patches and used them for multitask sparse learning) framework. But facial patches vary for different sets of faces. Kotsia and Pitas [6] used geometric deformation features and support vector machines for facial expression detection of Cohn-Kanade database and obtained a classification accuracy of 99.7%. Huang and Tai [7] used key point descriptors for determining the features and classified the expression using weighted majority voting classifier. The accuracy obtained for jaffe image data set was 93.33%. Chi et.al [8]suggested a cloud model of images for expression recognition. The effectiveness of the suggested method is not mentioned. Sarode and Bhatia [9] extracted intransient facial features and detected four facial expressions. An average accuracy of 81.5% is obtained for four classes of jaffe image data set. Shruti Bansa1 and Pravin Nagar [10] used Bezier curves for determining emotions. The accuracy obtained was 70%.

Numerous attempts were made for effective recognition of emotion from the facial images. Mostly jaffe image dataset or Cohn-Kanade database were used for carrying out the research. From the literatures it has been found that the maximum accuracy obtained for jaffe data set is 93.33% which is lesser than that of Cohn-Kanade database. Hence for our work, jaffe image data set is chosen. The geometrical features are extracted from images and ANN is used as classifier for emotion detection.

The rest of the paper is organized as follows. The feature extraction from facial images is described in section II. Section III presents a detailed insight into the artificial neural networks applied for facial expression recognition. In Section IV the performance of automatic facial expression recognition system is analyzed. In Section VI concluding remarks are given.

II. PROCESSING STEPS

A. Determination of Input-Target Pair for Training:

1. Let n be the no. of images in each set of facial expression
2. Let m be the no. of facial expressions
3. Let i =1
4. Let j=1
5. Input the jth image for Expression(i)
6. Enhance the image
7. Extract the features from the face (eyebrows, eyes and lips)
8. Determine the following values for extracted eyes, eyebrows and lips

   Feature:

   Area

   Orientation

   Perimeter

   Solidity

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MajorAxisLength
MinorAxisLength
Centroid

9. Increment j
10. If j<n Repeat steps 5-10
11. Convert the calculated values into vectors and assign the target value as (i) for all the vectors.
12. If i<m Repeat steps 4-12

B. Training the Neural Network:

1. Initialize no. of layers
2. Initialize no. of hidden neurons
3. Set the activation function for each layer
4. Train the neural network with input-target pairs

C. Testing the Neural Network:

1. Input the test input to trained neural network
2. Obtain the output. From the output value determine the facial expression

III. FEATURE EXTRACTION

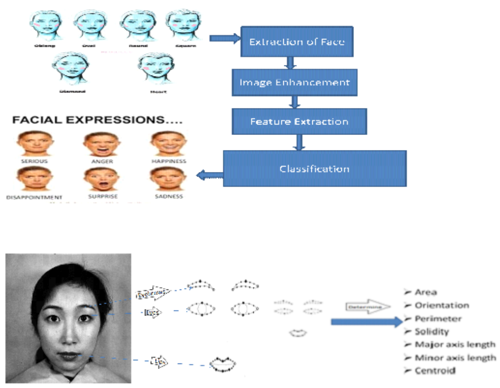
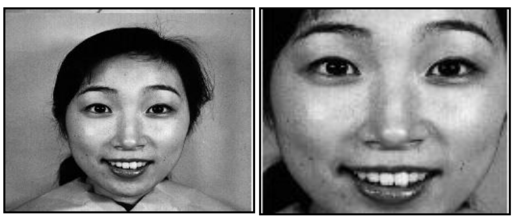
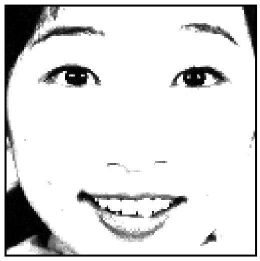


Fig. 1. Processing Steps

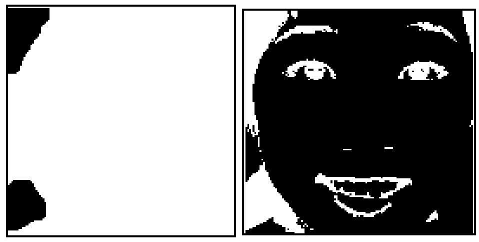
Initially the human face features are detected from the original image by removing the neck and part of hair. This is achieved by cropping the image. The cropped image is fed as input to image enhancement unit. In this, contrast adjustment is carried out. Gamma correction is performed. By ANDing the mask with the enhanced image facial features are obtained by their orientation and size. The facial features extracted are eyes, mouth and eyebrows. For the extracted features the geometrical feature values viz. area, orientation, perimeter, solidity, major axis length, minor axis length and centroid are determined.



(a) Original Image (b) Cropped Image



(c) Preprocessed Image



(d) Mask (e) Enhanced Image

(f) Facial Features

Fig. 2. Outputs of Feature Extraction Steps

The outputs of feature extraction steps are shown in Figure 2. Then the facial features are classified into different expressions. The facial features include the change in the shape and size of eyebrows, eyes and lips. The features extracted from the image are quantified and are used as training set for the neural network.

IV. FEEDFORWARD NEURAL NETWORK (FFNN)

A feedforward neural network is a biologically inspired classification network. In this, information is passed in the forward direction only (Simon Haykin 1999)[11]. In a feedforward network neurons are formed in layers, where the first layer takes inputs and the last layer delivers the outputs. The middle layers which have no association with the outside world are called hidden layers. Each neuron in one layer is connected to every neuron in the next layer. As information is constantly "fed forward" from one layer to the next these networks are called feed forward networks. There is no connection between neurons in the same layer.

The hidden layer neurons of a Feed Forward Neural Network take sigmoid activation function. The sigmoid activation function is given by,

$$F(n) = \frac{1}{1+\exp(-*n)}$$

Linear activation function for the output layer has been used. These neurons give the output directly proportional to their input. i.e. the input and output have linear relationship. Back propagation learning algorithm is used for training.

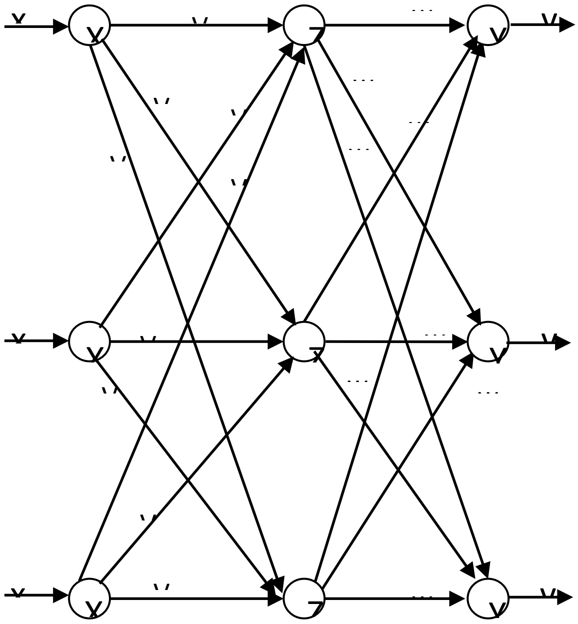


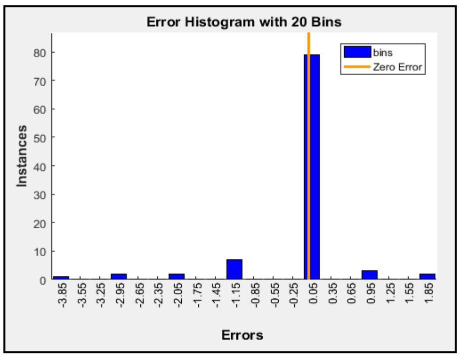
Fig. 3. Feedforward Neural Network

Figure 3 shows the Feed Forward Neural Network. The network is assumed to have n inputs denoted by x_i where i varies from 1 to n, m outputs denoted by y_k where k varies from 1 to m. There are n input neurons and m output neurons. The hidden layer has p neurons. The connection between layers and their weights are shown in figure. The weights of the input to hidden layer connections are marked as v and the weights of hidden layer to output layer links are marked as w.

V. PERFORMANCE EVALUATION

System performance is tested with the jaffe image dataset.

A. Error Histogram:



The dispersion of the system errors is depicted by the error histogram plot. This histogram is a measure of anomalies. The anomalies are the data points where fit between the original class and the target class significantly worse than the majority of data.

The error histogram of FFNN system is shown in Figure. . In this case of SVM, it can be seen that the maximum errors fall between 0.05 and 0.1, The error span is from -4 to 2 which shows that some of the expressions are wrongly recognized.

B. Confusion Matrix:

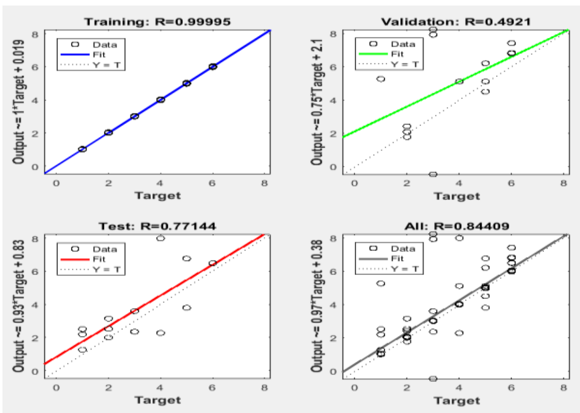
The performance of a classifier is better evaluated by the confusion matrix. It is an error matrix portrayed by a table layout which helps in visualizing the performance of classifier. The columns of the confusion matrix represent the instances in the output class whereas the rows represent the instances in the actual class.

	A	B	C	D	E	F
A	0.833	0.056	0.056	0.000	0.056	0.000
B	0.000	0.867	0.133	0.000	0.000	0.000
C	0.059	0.059	0.706	0.059	0.000	0.118
D	0.000	0.077	0.000	0.769	0.077	0.077
E	0.000	0.000	0.000	0.125	0.750	0.125
F	0.000	0.000	0.000	0.000	0.000	1.000

Figure shows the confusion matrix of FFNN system. It is seen that 83.33% of class A are correctly classified as class A whereas 16.67% are wrongly classified as belonging to class B,C and E. Class C data is correctly classified. Similarly, other expressions are also wrongly classified. Only the last expression is properly identified.

C. Regression Plot:

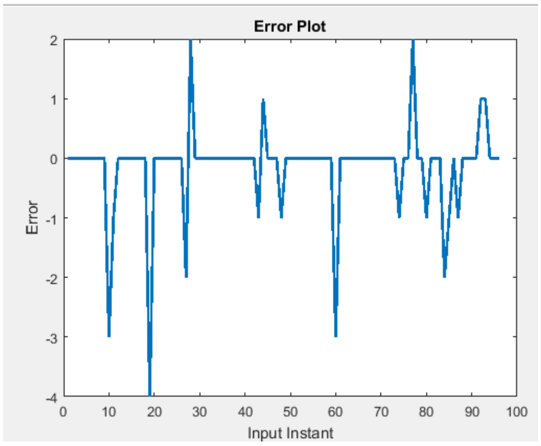
The regression plot is drawn between the system outputs and actual classes. It shows the regression between them. The R value of 1 indicates perfect fit.



In FFNN system during training, the regression curve almost fits which is indicated by the R value 0.99995. In case of validation, the regression is more. While testing it is somewhat improved to the R value of 0.77144. The regression plot of entire data indicates an acceptable regression value of 0.84409.

D. Error Plot:

Error plot is the plot between error and the input instant. It shows the error at each instant of time. For FFNN system the error plot is shown in Figure. The error varies from -4 to 2. The horizontal line indicates zero error.



E. Mean Absolute Error (MAE):

Mean absolute error is a measure of error between the output class of data points and the actual class of the same. It is represented by

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y(i) - t(i)|$$

where y(i) is the output class of the ith data point and t(i) is the target class of the same.

For feedforward network the mean absolute error is found to be 29.17%.

VI. CONCLUSION

A novel feature extraction algorithm based on image processing is applied. The algorithm created a mask from the enhanced image and the mask is utilized for extracting facial features. The facial features are then converted to geometric values and used for training the neural networks. Feedforward as well as feedback neural network are used for expression recognition. The expressions chosen are happy, angry, normal, sad, afraid and disgusted. The FFNN system showed a mean absolute error of 29.17%.. Though this result is remarkable, the future work will involve the expression identification from real time images.

VII. REFERENCES

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