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Shape and Texture based Facial Expression Recognition using Score Level Fusion

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Abstract: Expression is the most important mode of non-verbal communication between people. Facial expression carries significant information about the mental, emotional and even physical states of the conversation. Recognition of facial expressions has used in wide application areas like scientific, surveillance, medical, marketing etc. This paper proposed hybrid technique is called score level fusion. Initially preprocessing operations performed on the given image and the features are extracted. The proposed work consists of two important phases such as feature extraction phase and fusion phase. Shape features are extracted from the eyes and texture features are extracted from nose and mouth. The eye features are extracted by using Active Appearance Model (AAM) and the nose and mouth features are extracted by using Gray Level Co-occurrence Matrix (GLCM). With the help of the Artificial Neural Network (ANN) classifier one score value is calculated from extracted eye feature and in another case with the help of Adaptive Genetic Fuzzy System (AGFS) score value is calculated from the mouth and nose. The score values are given as input to the fusion phase in which simple-sum fusion method is used for the calculation of the final score. This final score is compared with a threshold value in order to classify the facial expressions.

Keywords: Facial Expressions, Active Appearance Model, Gray Level Co-occurrence Matrix, score value.

I. INTRODUCTION

A human face carries a lot of significant information while interacting with one another. Facial expression is one of the efficient ways to express emotions and feelings. Research demonstrates that facial expression supply to about 55% effect of general emotion expression through social communications [1].

In computer vision and pattern identification sector, one of the most recent research topics is to identify the human emotions from the facial expression. Facial expression recognition is one of the important methods attracted by many researchers because it is useful in many sectors such as human-computer interaction, medical, security, education, business and analysis of social interactions, and etc. Facial expressions are dynamic features which communicate the speaker's attitude, emotions, intentions, and so on. The face is the primary source of emotions. Facial features play an essential role in the human facial analysis and features are classified as permanent or transient. Ekman and Friesen have proposed a fundamental facial expression identification method which is used to categorize the given facial image into the common expression type such as happy, sad, disgust, surprise, fear, angry and neutral [2]. Facial expression analysis and recognition have been one of the fast developing areas due to its wide range of application areas such as emotion analysis, biometrics, image retrieval and is one of the subjects on which lots of research has been done through solving the problems occurring in recognition of the face expressions under different illuminations, orientations and numerous other variations [3]. In this paper, a new method is presented in recognition of facial expressions by using shape and texture features. An overview of the proposed methodology and system structure is given in section 2 of the paper. Section 3 describes the modules and techniques of proposed work and section 4 presents experimental results of the proposed work.

II. PROPOSED METHODOLOGY

The face is the primary source of emotions and facial features plays an essential role in the human facial analysis. Facial expression analysis deals with visually recognizing and analyzing different facial emotions and facial feature changes. Here, input dataset image is preprocessed and the features are extracted. Shape features are extracted from the eyes and texture features are extracted from nose and mouth. The eye shape features are extracted by using Active Appearance Model (AAM) and the nose and mouth texture features are extracted by using Gray Level Co-occurrence Matrix (GLCM). With the help of the Artificial Neural Network (ANN) classifier one score value is calculated from extracted eye feature and in another case with the help of Adaptive Genetic Fuzzy System (AGFS) one score value is calculated from the mouth and nose. The score values are given as input to the fusion phase in which simple-sum fusion method is used for the calculation of the final score. This final score is compared with a threshold value in order to classify the facial expressions. The System model of proposed work as shown in the following Fig 1.

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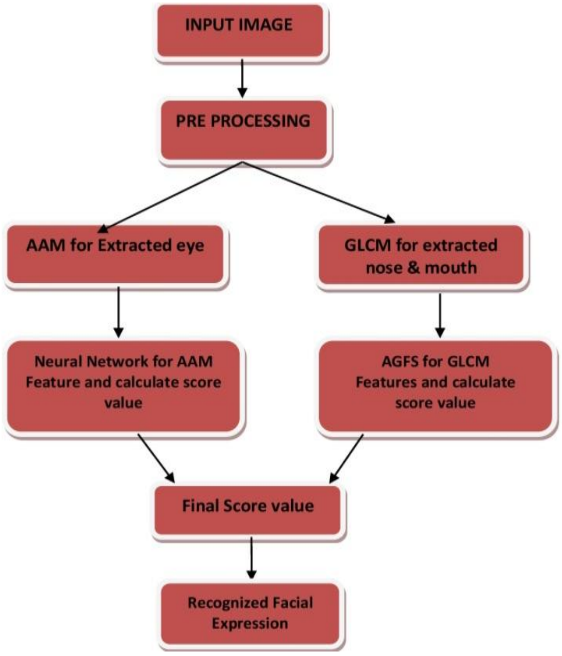

Fig 1. System model of Facial Expression Recognition System

III. MODULES

Facial expression analysis refers to a computer system that attempt to automatically analyze and recognize facial motions and facial feature changes based on visual information. A good face expression recognition system of the features are it must be fully automatic, robust, work with people from different cultures and different skin colors work in different lighting conditions, pose and occlusions. To find the facial expression recognition in the proposed model consists of three phases such as preprocessing, feature extraction and facial expression recognition.

A. Preprocessing

Preprocessing is the most important and the required step of the image processing. It is performed to get uniform and noise free image for further processing. Preprocessing image commonly involves removing low-frequency background noise, poor contrast, normalizing the intensity of the individual particles images and masking portions of images. The image preprocessing consists of operations like size normalization, noise removal, skewing and contrast adjustment and other image enhancement operations [4]. In the first phase the face image is preprocessed by using some significant preprocessing techniques such as size normalization, skewing, noise removal, image enhancement and image segmentation. For the region area of the eye portion, mouth, and nose features are segmented from the preprocessed image.

B. Feature Extraction

After preprocessing, the next step is to extract facial features and in classification process the feature extraction plays a vital role. If inadequate and insignificant features are used, then it may not be possible to achieve better recognition accuracy even though good classifiers are used for recognition. Geometric feature based methods and appearance based methods are widely used approaches to extract facial features. A feature vector which represents the face geometry is formed by extracting facial components or facial feature points where as the appearance features represent the appearance changes of the face like wrinkles and furrows. The proposed method exhibits the location of three facial features such as eyes, nose and mouth. The eye shape features are extracted by using Active Appearance Model (AAM) and the nose and mouth texture features are extracted by using Gray Level Co-occurrence Matrix (GLCM).

C. Gray Level Co-Occurrence Matrix for Mouth and Nose Texture Feature Extraction

Texture is one of the important characteristics used in identifying objects or regions of interest in an image which contains important information about the structural arrangement of surfaces and in general, texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts [5]. It is a statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co-occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. The GLCM method is a way of extracting second order statistical texture feature. According to the co-occurrence matrix fourteen textural features measured from the probability matrix to extract the characteristics of images are defined by Haralick. In this thesis work, four important features such as Angular second moment(energy), Inverse different moment(Homogeneity), Contrast, Correlation are considered in order to decrease the computational complexity of the process [6]. In extraction phase the texture features such as Angular second moment (energy), Inverse different moment (Homogeneity), Contrast, and Correlation are extracted from nose and mouth using Gray-Level Co-Occurrence Matrix (GLCM). Finally the extracted features are placed in a feature vector which consists of four texture features from mouth and another four texture features from the nose. This feature vector is the input for the recognition of facial expression phase.

D. Active Appearance Model (AAM) for Eye Shape Feature Extraction

Shape is one of the most important visual attributes in an image. In fact, the human visual system is able to extract and abstract shapes from very complex scenes. The concept of shape is invariant to translations, rotations, and scaling, the shape of an object is a binary image representing the extent of the object [7]. Due to these considerations shape presentation is one of the most

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challenging aspects of computer vision. Active Appearance Model (AAM) is a statistic model incorporating both shape and intensity information and extracting the prominent geometric features from the preprocessed image. In the proposed model, shape feature of the eyes are extracted using Active Appearance Model. In AAM the shape of a segmented input image is represented by a vector consisting of the positions of the landmark points. Active Appearance Model (AAM) is a computer vision algorithm, used template matching a statistical model for building shape and appearance of facial features, by automatically locating landmark points that define the shape and appearance of objects in an image [7]. Edwards, et al., first introduced an AAM in 1988 , and this is widely used in the facial expression analysis. AAM combines a powerful model of joint shape and texture with a gradient-descent fitting algorithm, it provides a better matching for image texture, and has a more robust method for tracking facial movements and appearance than alternative active shape model (ASM). Matching to an image involves finding model parameters which minimize the difference between the image and a synthesized model example, projected into the image. In order to realize these benefits, the model of object appearance should be as complete as possible to synthesize a very close approximation to any image of the target image. AAM is particularly suited to the task of interpreting faces in images. Faces are highly variable, deformable objects and manifest very different appearances in images depending on pose, lighting, expression and identity of the person. Interpretation of such images requires the ability to understand this variability in order to extract useful information [8].

A different vector δI can be explained as:

$$\delta I = I_i - I_m$$

Where I_i is a vector of gray level value in the image and I_m is the vector of gray level value for the current model parameters.

E. Classification using Neural Network for Eye

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationship. Artificial Neural Networks (ANN) have been proved to be very powerful tools for pattern recognition and have successfully been used in the automated classification of acoustic signals including natural patterns. A neural network is a set of interconnected layers, in which the inputs lead to outputs by a series of weighted edges and nodes. The weights on the edges are learned when training the neural network on the input data. The direction of the graph proceeds from the inputs through the hidden layer, with all nodes of the graph connected by the weighted edges to nodes in the next layer. To compute the output of the network for any given input, a value is calculated for each node in the hidden layers and in the output layer. For each node, the value is set by calculating the weighted sum of the values of the nodes in the previous layer and applying an activation function to that weighted sum [9]. The neural network multi-layer function, structure as shown in the following Figure 2.

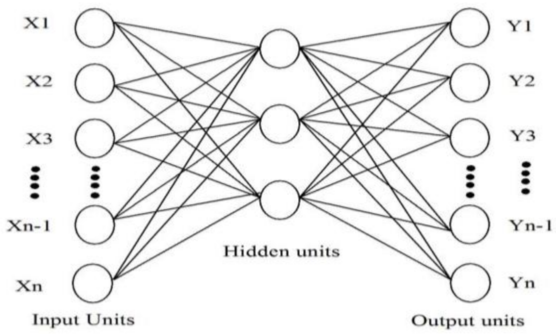

Figure. 2: Neural Network multi layered function

The input and output functions are
Y= ML(x,W), with x=(x_1,x_2,…x_n) and y=(y_1,y_2,---y_m)
W is the set of parameter $\{W_{ij}^L, W_{i0}^L\}, \forall i, j, L$
For each unit i of layer L of the ML. Integration

$$S = \sum_i y_j^{L-1} w_{ij}^L + w_{i0}^L \quad (1)$$

Transfer: $y_j^L = f(s)$, where

$$f(s) = \frac{1}{1+e^{-t}} \quad (2)$$

On the input layer $(L=0): y_j^L = x_j$

On the output layer $(L=L): y_j^L = \hat{y}_j$

The Multi layer network uses the algorithm of Gradient Feed Forward Neural Network (GFFBNN) for training and calculated score value.

F. Adaptive Genetic Fuzzy System for Mouth and Nose

The Adaptive Genetic Fuzzy System is a hybridization of Fuzzy Logic with Genetic Algorithm (GA) offers advantages of both the fields. In such systems, knowledge in the form of linguistic variables, fuzzy membership function parameters, fuzzy rules, a number of rules, etc. can be converted into suitable candidate solutions through the generic code structure of the GA. The use of Genetic Algorithms for designing Fuzzy Systems allows us to introduce the learning and adaptation capabilities. The input for the fuzzy system is the extracted features of the given input image. Initially, the rules are generated in accordance with the fuzzy system. The output of the fuzzy system is the number of rules and these rules are used as the input for the adaptive genetic algorithm and to find optimal rules.

Genetic Algorithms are methods of optimization used to find optimal solutions of several complex problems and the conventional genetic algorithm is enhanced with the

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help of the mutation operator. In this approach, the population is generated arbitrarily and two individuals are thereafter chosen in accordance with the fitness. Suppose A possesses fitness higher than that of B, then A will be selected and B ignored. However, they will reproduce to generate one or more offspring. Subsequently, the offspring is mutated arbitrarily. The procedure is carried on till an appropriate solution is arrived at or a specified number of generations have passed, in accordance with the requirements of the user. In the proposed work considered the evolutionary with Pittsburgh approach of the knowledge Base (KB) of an Fuzzy Logic Controller (FLC)[10]. The detail explanation of an adaptive genetic algorithm is given below.

Adaptive Genetic Algorithm

Step 1: Start with an initial population of solutions that constitutes the first generation(P(0)).

Step 2: Evaluate P(0)

a) Take each chromosome KB from the population and introduce it into the FLC.
b) Apply the FLC to the controlled systems for an adequate evaluation period and
c) Evaluate the behavior of the controlled system by producing a performance index related to the KB.

Step 3: While the Termination Condition is not met, do

a) Create a new generation (P(t+1)) by applying the evolution operators to the individuals in P(t).
b) Evaluate P(t+1) and
c) t = t+1

Step 4: Stop.

The fuzzy system is designed with the help of fuzzy rules and the fuzzy membership function. In proposed work, Mamdani Fuzzy inference system is used for implementation of the fuzzy inference mechanism. The output of the fuzzy system is the number of rules and these rules are used as the input for the adaptive genetic algorithm in order to obtain optimal rules. In Adaptive genetic algorithm, the initial solutions are generated based on a number of rules and fitness is evaluated. The fitness is measured with max accuracy. After the evaluation of the solutions, the cross over and mutation functions are applied [11]. The optimal rules are achieved after the mutation function.The rule inference procedure is used to obtain the linguistic value that is converted into a crisp value by using centered method.

G. Score level fusion

The recognition of facial expression using the proposed hybrid technique is called score level fusion and the aim of score level fusion is to effectively recognize facial expressions recognition with the help of score values. In Score level fusion, the scores of the individual systems are generated and the scores are fused together for recognition. The eye shape features are extracted by using AAM and the nose and mouth texture features are extracted by using GLCM. Optimally chosen with the help of the neural network calculate eye feature score value and with aid of AGFS calculate another score value of mouth and nose feature. The simple sum weighted fusion was used as a score fusion strategy and the fusion scores (S) is computed as follows

$$S = s_1 w_1 + w_2 s_2$$

Here s1 is neural network score value and s2 is AGFS score value where as the weights w1 and w2 are varied over the range [0, 1], such that the constraint w1 + w2 = 1 is satisfied. Based on score values, then the final score value is calculated and compared with a threshold value in order to classify the facial expressions.

IV. EXPERIMENTAL RESULTS

The proposed method is implemented in MATLAB platform with Japanese Female Facial Expression(JAFEE) database. The database contains 213 images of 7 facial expressions. Some of the images are used for training and some of the images are used for testing. The performance of the system is calculated by the sensitivity, specificity and accuracy. The fundamental count values of as True positive (TP), True negative (TN), False Positive (FP), False Negative (FN) are used for the measures of sensitivity, specificity and accuracy. Both the emotion classification and the classification by efficiency are analyzed by our projected techniques which are explained in detail in the next section.

A. Performance Evaluation

The effectiveness of the classifier is analyzed by the measures of Sensitivity, Specificity and Accuracy.

Sensitivity

The metrics of the sensitivity is the proportion of actual positives which are accurately recognized. It is related to the capability of test to recognize positive results. Here TP-True positives, TN-True Negatives, FP-False Positives, FN-False Negatives

$$\text{Sensitivity} = \frac{\text{Number of TP}}{\text{Number of TP} + \text{Number of FN}} \text{X100}$$

Specificity

The measure of the specificity is the proportion of negatives which are accurately recognized. It is related to the capability of test to recognize negative results.

$$\text{Specificity} = \frac{\text{Number of TN}}{\text{Number of TN} + \text{Number of FP}} \text{X100}$$

Accuracy

We can calculate the metric of accuracy from the metric of sensitivity and the specificity as declared below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Above equations are as well appropriate for finding the efficiency of classification of the signals.

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B. Result of Classification Evaluation

Table I: Represents the performance result of Evaluation metrics

Expression	Accuracy (%)	Sensitivity (%)	Specificity (%)
Angry	92	87	84
Disgust	96	86	86
Fear	92	86	92
Happy	94	91	94
Sad	98	98	93
Surprise	98	97	93
Neutral	95	94	95

The outcomes of facial expression classification are viewed with the metric values from the table I. The facial expression classification of our proposed work presents improved accuracy outcomes of 92% of angry, 96% of disgust , 92% of fear , 94% of happy , 98% of sad , 98% of surprise , and 95% of neutral respectively. The graphical representation experimental results are shown in following Figure 3.

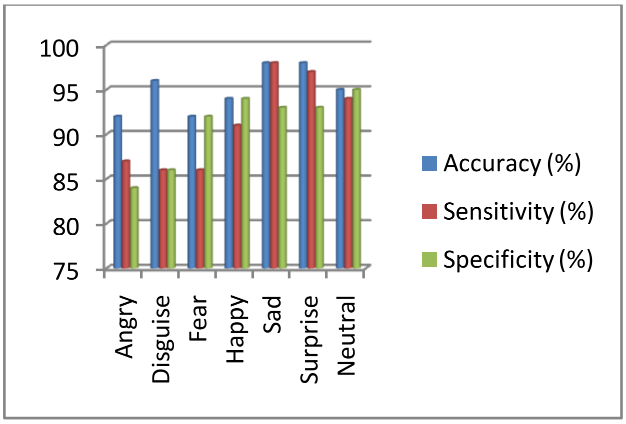

Fig 3. Graphical representation of evaluation metrics

V. CONCLUSION

Emotion is a state of feeling like thoughts, psychological changes and expressions. In this paper, a novel method is developed to recognize the facial expressions using score level fusion. The proposed method is implemented in MATLAB platform with Japanese Female Facial Expression(JAFEE) database. The database contains 213 images of 7 facial expressions. Some of the images are used for training and some of the images are used for testing. In this proposed work, accuracy is 91% by using score level fusion.

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