ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 5, Issue 7, July 2016

Emotion Recognition based on Gray- Level Co-Occurrence Matrix and Adaptive Genetic Fuzzy System

J. Suneetha, Dr. K. Sandhya Rani

***Abstract* -** Facial expressions provide an important behavioral measure for studies of emotion and which plays a vital role in human interaction and communication. Facial expressions are helpful in understanding the overall mood of the person in a better way. Facial expression recognition is one of the challenging and active research topic in the recent years and used in many application areas. This paper presents a new method for the recognition of facial expression from nose and mouth texture features of given image. The nose and mouth texture features are extracted using Gray-Level Co-Occurrence Matrix (GLCM) and extracted texture features are send to the expression recognition phase. Finally Adaptive Genetic Fuzzy System (AGFS) is applied for classification of the facial expressions.

Keywords: Feature Extraction, Classification, Gray Level Co-occurrence Matrix, Adaptive Genetic Fuzzy system.

I. INTRODUCTION

Facial expressions are a form of nonverbal communication, which plays a prominent role in interpersonal relations and social communications. Facial expressions denote important information about emotion of a person. Recent rapid progress of communication technology and computer science has made facial expression recognition as a vital role in human-machine interface and advanced communication. In recent years much research has been done on machine recognition of human facial expression. With the development of artificial intelligence and pattern recognition, researchers are giving more attention to facial expression recognition as it is an important technology of human-interactive interface. Facial expression recognition has wide range of applications in areas such as security, medical field, psychological studies, surveillance, virtual education system etc[1]. For example expression recognition system will help in creating this intelligent visual interface between the man and the machine. Humans communicate effectively and are responsive to each other's emotional states. The examples are chat-room, video conference and recent advances in robotics, especially humanoid robots. As robots begin to interact more and more with humans and start becoming a part of our living spaces and work spaces, they need to become more intelligent in terms of understanding the human's moods and emotions. Another example is in virtual class room where teachers can use facial expression analysis to adjust the difficulty of the exercise and learning steps of students [2].

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 human facial analysis and features are classified as permanent or transient. Eyes, lips, brows and cheeks which remain permanent are examples for permanent features where as facial lines, brow wrinkles and deepened furrows that appear with changes in expression are transient features.

Elman and Friesen classified expressions into seven universal emotions such as happy, sad, surprise, fear, disgust, anger, neutral and every emotion has a corresponding specific expression [3]. Eye movement is a key part of facial behavior because the eyes are invariably involved in facial displays and important features of eye are eye corners and eye lids. The nose part in a face reflects emotions like anger and disgust. The important features of nose are nose tip, nose furrows and nostrils. The mouth feature plays a vital role in the identification of expressions and primary features are corners of the lips, upper lip and lower lip. The combination of different features of a face like eyes, mouth, nose, cheeks and eyebrows contribute to express different types of emotion.

The automatic Facial expression analysis consists of three steps namely i) Face Detection and Preprocessing ii) Feature Extraction iii) Facial Expression Recognition. Face detection is the first stage of a facial expression recognition system in which face region is identified from the input image by using image processing techniques. Preprocessing is the most important step which is performed to obtain 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.

In feature extraction phase, the significant features of images which are having prominent role in the recognition of facial expressions are extracted for further processing. The final phase is Recognition phase where the significant features which are extracted in feature extraction phase are used as input. For the development of Recognition module, Statistical or Neural network models can be used to analyze and classify the different facial expressions. In this paper, a new method is presented for recognition of facial expressions by using nose and mouth texture features.

II. PROPOSED WORK

The proposed model consists of three phases such as preprocessing, feature extraction and facial expression recognition. In first phase the face image is preprocessed by using some prominent preprocessing techniques such as size normalization, skewing, noise removal, image enhancement and image segmentation. The preprocessing is the essential step for given input images. The output of first phase i.e. preprocessed image is send to next phase called feature extraction. In second phase the texture feature can be extracted using Gray-Level Co-Occurrence Matrix (GLCM) which is a popular statistical method of extracting textural feature from images. The four static parameters properties of Energy, Homogeneity, Correlation and Contrast are used to decrease the computational complexity. Texture features of nose and mouth extracted from given preprocessed image using GLCM. The static parameters of nose and mouth are calculated using GLCM. From the Nose part four important texture features and from Mouth part another four significant texture features are extracted and stored in a vector.

The output of second phase i.e. nose and mouth texture features of image is send to the input of next phase. The final phase classification is performed by using Adaptive Genetic Fuzzy System (AGFS) model. The aim of innovative Adaptive genetic algorithm is employed to enhance with the help of the crossover and mutation operator. According to the fuzzy values for each feature that are generated in the fuzzification process, the fuzzy rules are also generated and trained.

The proposed method was carried out by taking the JAFFE database and database was obtained with photographs of each person at different expressions. These expressions can be classified into some discrete classes like happy, anger, fear, surprise, sad, disgust and neutral. The absence of any expression is considered as “neutral” expression. The various phases in Facial Recognition system are shown in the following Fig 1.

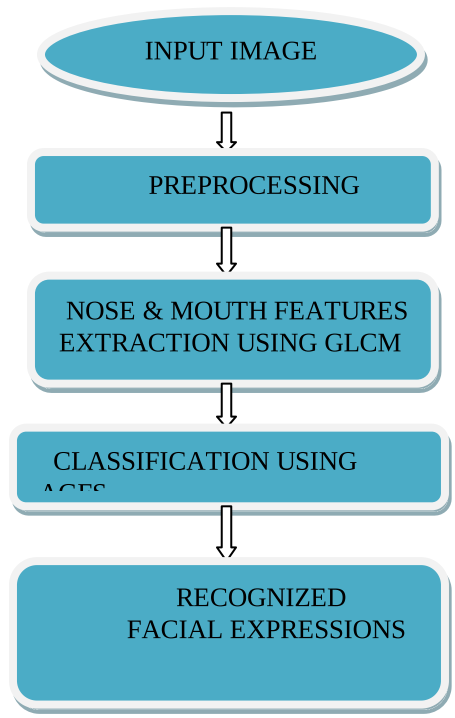

Fig 1: Phases in Facial Expression Recognition System

III. FEATURE EXTRACTION MODULE

After obtaining the preprocessed image of a face, the next step is to extract facial features. There are two types of features namely geometric features and appearance features. Geometric features represent the shapes and location of facial components such as eyebrows, eyes, nose, mouth etc. The facial components or facial feature points are extracted to form a feature vectors that represents the face geometry. The Appearance based features present the appearance (skin texture) changes of the face, such as skin color, eye color, wrinkles and furrows.

The proposed method exhibits the location of three facial features such as eyes, nose and mouth.

GRAY LEVEL CO-OCCURANCE MATRIX:

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. Gray Level Co-Occurrence Matrix (GLCM) is a popular statistical method of extracting textural feature from images. 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 to creating a GLCM, and then extracting statistical measures from this matrix. Here, the various aspects of images are extracted and stored in a matrix. One of the easiest matrix methods to extract the texture aspect is GLCM and it is used to extract various aspects of all the images in the database and the input image are saved for processing affine situation. The co-occurrence matrix is the arithmetical model, which is used to examine different image applications such as biomedical, remote sensing, industrial defect detection systems and etc. Depend on gray level value of pixel; gray level matrix is used to extract the image aspects[4].

A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels G in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, θ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (θ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, θ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. The four static parameters properties of Energy, Homogeneity, Correlation and Contrast are used to decrease the computational complexity [5].

i) ***Energy:*** This statistic is also called Uniformity or Angular second moment which measures the textural uniformity that is pixel pair repetitions and also provides the sum of squared elements in the GLCM. It detects disorders in textures and energy reaches a maximum value equal to one. High energy values occur when the gray level distribution has a constant or periodic form. The range is [0 1] and energy is 1 for a constant image.

ii) ***Homogeneity:*** This statistic is also called as Inverse Difference Moment. It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements and it is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. GLCM contrast and homogeneity are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. It means homogeneity decreases if contrast increases while energy is kept constant. The range is [0 1] and homogeneity is 1 for a diagonal GLCM.

iii) ***Correlation:*** Measures the joint probability occurrence of the specified pixel pairs and returns a measure of how correlated a pixel is to its neighbor over the whole image. The range is available in between[-1 1]. Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN for a constant image.

iv) ***Contrast:*** Measures the local variations in the gray-level co-occurrence matrix and it is the difference between the highest and the lowest values of a contiguous set of pixels. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies. Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image Range is [0 , (size(GLCM,1)-1)^2] and contrast is 0 for a constant image.

The output of second phase i.e texture features of image send to the input of next phase. The Third phase classification is done using Adaptive Genetic Fuzzy System (AGFS) model. The aim of innovative Adaptive genetic algorithm is employed to optimize the weights. The conventional genetic algorithm is enhanced with the help of the mutation operator. In this included the fuzzy layer in to the adaptive genetic algorithm. According to the fuzzy values for each feature that are generated in the Fuzzification process, then the fuzzy rules are also generated and trained.

IV.EXPRESSION RECOGNIZATION MODULE

Facial Expression Recognition is to analyze and detect the expressions from given input images or video sequences. The input to the classifier is a set of features which were retrieved from face region in the previous stage. The set of features is formed to describe the facial expression. The facial expression recognition methods are divided into two categories such as Frame-based recognition and Sequence-based recognition. The Frame-based recognition method is based on static images and sequence-based recognition method is based on dynamic video images.

ADAPTIVE GENETIC FUZZY SYSTEM (AGFS):

The adaptive genetic fuzzy system is effectively used to recognize the facial expressions. Firstly, the rules are created in accordance with the fuzzy system. Now, the input for the fuzzy system is the extracted features of nose and mouth from the given input image and the output of the fuzzy system is the number of rules. Finally, the optimal rules are chosen by means of the adaptive genetic algorithm.

Fuzzy system:

The design of the novel fuzzy technique is achieved through three vital steps such as the fuzzification, fuzzy inference engine and the defuzzification. Fuzzification process effectively adapts the crisp input to a linguistic variable with the membership function gathered in the fuzzy knowledge base. Fuzzy inference engine adapts the fuzzy input into the fuzzy output based on If-Then type fuzzy rules. Defuzzification has the function of adapting the fuzzy output of the inference engine to the crisp with the help of the membership functions analogous to those employed by the fuzzifier. Further, the crisp rules are fuzzified in the inference system by means of the triangular membership function and the fuzzification is highly essential as a degree of membership function is specified for each member of set and the fuzzy system is capable of predicting the outcomes further accurately by means of the membership function[6,7].

Fuzzy Membership function: The membership function is achieved by choosing the proper membership function. Now, the triangular membership function is chosen to change over the data into the fuzzified value. The Triangular membership function is home to three vertices such as a, b and c in a fuzzy set (a: lower limit and c: upper limit where membership degree is zero, b: the centre where membership degree is one).

The formula employed to estimate the membership values is depicted as follows.

$$m(f)=\begin{Bmatrix} 0 & if\ f\le p \\ \dfrac{f-p}{q-a} & if\ \ p\le f\le q \\ \dfrac{r-f}{r-q} & if\ q\le f\le r \\ 0 & if\ f\ge r \end{Bmatrix}$$

Now, It is crystal clear that at (p) and (r) the value is zero and it regularly achieves a maximum of value one at the centre point (q) between the (p) and (r). The triangular membership function is elegantly exhibited below.

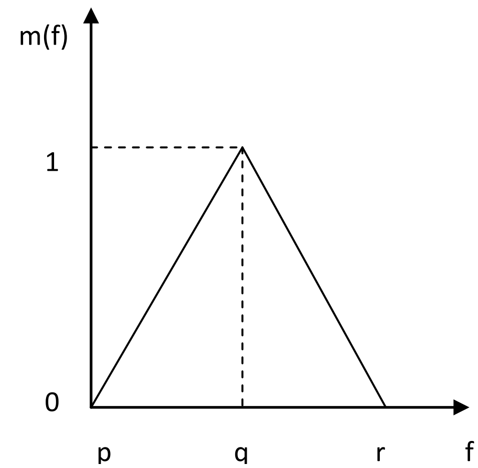

Fig.4: Triangular membership function

Rule Base: The rule base encloses a set of fuzzy rule in the form of: If A and B then detect C. By employing the fuzzy system the features of nose and mouth is carried out. The number of rule is equivalent to the number of features chosen from the input image and set of rules are the input for the adaptive genetic algorithm. At last, the best rules are chosen by means of the adaptive genetic algorithm. Now, the conventional genetic algorithm is improved with the help of the mutation rate. In accordance with the AGA algorithm the optimal rules are chosen. The detail explanation of adaptive genetic algorithm is given below

Adaptive Genetic Algorithm:

Genetic Algorithms are methods of optimization used to find optimal solutions of several complex problems and the conventional genetic algorithm is enhanced with the 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[8].

i)Generation of chromosomes

The initial solutions are created arbitrarily and each solution is known as the gene and the individual genes are integrated as chromosomes and it is known as the solution set. The numbers of genes are integrated with the chromosomes and the solution set for the population is generated. The population of genetic algorithm consists of chromosomes and the population size is initialized as permanent. The numbers of solutions are initialized ohm accordance with the standard genetic algorithm. In this case, the initial solutions are known as the weight.

ii) Fitness function

In fitness calculation we are introducing a fuzzy to generate a fitness function then we will perform a crossover and mutation. In this work we are calculating a fitness function using layer generation in fuzzy. In cross over, the two parent chromosomes are selected so as to exchange their genes between them. The example given below shows the parent chromosomes parent 1 and parent

1	**2**	**3**	**1**	2	3	1	2

Parent 1

3	2	1	3	**2**	**1**	**3**	1

Parent 2

In parent 1 & 2 chromosomes, the bold lettered are kept unchanged in their positions and the residual gene of the chromosomes is swapped between the parent chromosomes. After the crossover, the chromosome appears as shown below.

1	2	3	1	**2**	**1**	**3**	2

New chromosome 1

3	**2**	**3**	**1**	2	1	3	1

New chromosome 2

After the crossover, the new chromosome is mutated for enhancing the efficiency of the solution and the bold illustrates the mutated gene of the chromosome. In the innovative mutation, the identical order is chosen within the offspring and it is swapped from its position to other place for yield the most excellent optimal solution. The shift changing mutation technique is employed in the mutation operation and the orders of each chromosome are shifted to left one step and substituted by the new order. After the shift the changes within the off-spring is illustrated as follows.

1	2	3	1	**2**	**1**	**3**	2

Mutation process

From the above the gene of the off spring is shifted one step left and the optimized new solution is getting by the mutation process. The optimal solution is obtained after the mutation function and it shows the final output of the result with their minimal optimized time and it gives the minimum make span time[9,10].

When the mutation function is completed, the new chromosomes are generated for the new solution sets. Later on, the fitness value is found out for the new solutions. The solution which furnishes the best value is selected and deemed as the optimal solution. Otherwise, steps mentioned above are repeated for the new solution sets. The testing data with diminished attribute is specified to the fuzzy logic system, where the test data is adapted to the fuzzified value as per the fuzzy membership function. Subsequently, in accordance with the membership function, the fuzzified input is including with the fuzzy rules defined in the rule base. Thereafter, the output is specified to the defuzzification. The performance analysis of our proposed technique is shown in below section.

iii) Updation

When the mutation function is completed, the new chromosomes are generated for the new solution sets. Later on, the fitness value is found out for the new solutions. The solution which furnishes the best value is selected and deemed as the optimal solution. Otherwise, steps cited above are repeated for the new solution sets.

The testing data with diminished attribute is specified to the fuzzy logic system, where the test data is adapted to the fuzzified value as per the fuzzy membership function. Subsequently, in accordance with the membership function, the fuzzified input is harmonized with the fuzzy rules defined in the rule base. Thereafter, the output is specified to the defuzzification, now the fuzzified value is converted to the crisp value and the evaluation is performed. The fuzzy score is created after the defuzzification procedure. The performance analysis of our proposed technique is shown in below section,

V. RESULT AND DISCUSSION

The proposed method is implemented in MATLAB platform and performance of the proposed system measures through 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

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

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.

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

Accuracy

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

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

Expression	Specificity	Sensitivity	Accuracy
Angry	68	63	80
Disguise	66	66	78
Fear	64	66	82
Happy	64	73	82
Sad	83	76	77
Surprise	78	85	87
Neutral	73	74	82

Table I: Comparison results for the image classification in Specificity, Sensitivity, and Accuracy

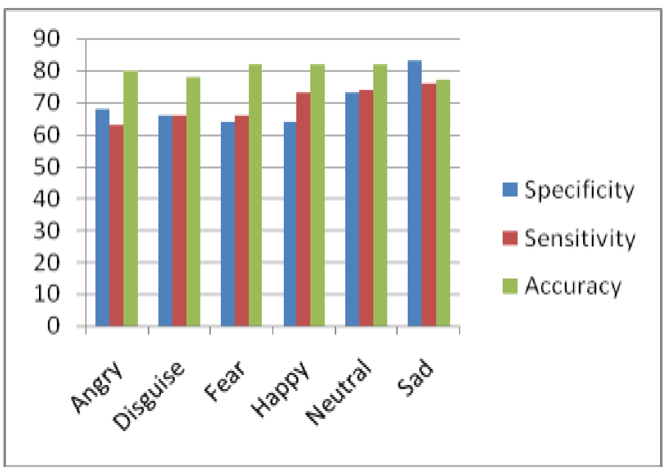

Fig 3: Graphical representation of evaluation metrics

The proposed work provides good emotion classification result and which gives improved accuracy outcomes. The above Table I gives information about comparison results for the image classification in specificity, sensitivity, accuracy. The accuracy for the AGFS are 80% of angry, 78% of disgust, 82% of fear, 82% of happy, 77% of sad, 87% of surprise and 82% of neutral. Therefore, the proposed work accuracy is 81% obtained by using AGFS Model.

VI. CONCLUSION

The main objective of this paper is to present a novel method to analyze the facial expressions from given image by focusing on certain regions of a face such as nose and mouth. Initially extract the Energy, Homogeneity, Contrast and Correlation texture of given image are extracted by using Gray-Level-Co occurrence–Matrix. A model is developed in classify the facial expressions such as happy, angry, fear, disguise, sad, surprise and neutral. For the development of this model, Adaptive Genetic Fuzzy System is adopted and satisfactory result is obtained. Therefore, the propose work accuracy is 81% obtained by using AGFS Model.

REFERENCES

[1] G.Hemalatha, C.P.Sumathi, "A Study of Techniques for Facial Detection and Expression Classification", *IJCSES, Vol- **5**,No.**2**,April **2014**.*

[2] S L Happy, Aurobinda Routray, "Automatic Facial Expression Recognition Using Features of Salient Facial Patches", In Proceedings of *IEEE Transaction on Affective Computing*, Vol. 6, No. 1, 2015.

[3] P. Ekman, W.V. Friesen," Constants across cultures in the face and emotion", *Journal of Personality Social Psychol*. 17(2) , (1971**)** ,Page No-124-129.

[4] Bino Sebastian V, A.Unni Krishnan and kannan Balakrishnan, "Gray Level Co-Occurrence Matrices", *International Journal of Computer Science and Information Technology(IJCSE)*,Vol 2,No.2, April 2012.

[5] P.Mohanaih, P. Sathyanarayana, L.Gurukumar, "Image Texture Feature Using GLCM Approach", *International Journal of Scientific Research Publications*, Vol 3,Issue 5,May 2013.

[6] Amir Jamshidhazhad,Jam Md Nordin, A heuristic model for optimizing fuzzy knowledge base in pattern recognition system", *Journal of scientific & industrial research,* Vol7,may 2012,PP 341-347

[7] Sanjay Singh Pal, Muzammil Hasan,, " Facial Recognition using fuzzy Logic**",** *International Journal of Science &Research,* ISSN 2379-7064

[8] Kunjal Mankad, Priti Srinivas Sajja, Rajendra Akerkar, " Evolving Rules using Genetic Fuzzy Approach-Education case study", International Journal on Soft Computing (IJSC), Vol.2, No.1, February 2011.

[9] Jorge Casillas Æ Brian Carse, " Genetic Fuzzy system: Recent development and future directions", Soft Computing (2009) 13:417–418.

[10] Asli Celikyilmaz, I. Burhan Turksen, " A Genetic Fuzzy system based on Improved Fuzzy functions", journal of computers, vol. 4, no. 2, february 2009

AUTHORS PROFILE

J.SUNETHA received the B.Tech. Degree in Computer Science from Jawaharlal Nehru Technological University, Hyderabad and M.Tech. Degree in Computer Science from Sathyabhama University, Chennai. She is Research Scholar at Sri Padmavathi Mahila Viswa Vidyalayam, Tirupathi, Andhra Pradesh, India. Her field of interests includes Pattern Recognition, Biometrics and soft computing.

Dr.K.Sandhya Rani, M.Sc, M.Tech, Ph.D is presently working as Computer Science Professor in Sri Padmavati Mahila Visvavidyalayam (SPMVV), Tirupati. She is having 30 years of teaching experience & 18 years of research experience in SPMVV and published more than 50 papers in reputed National and International journals. Her thrust areas of research are Pattern Recognition, Data Mining and Big Data Analytics.