



Facial Expression Recognition for Color Images Using Genetic Algorithm

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Abstract- Expressions are the voices that spell the mood of a person. To identify the emotions of the population and their underlying feelings like happy, sad, surprise, disgust need to be classified. The aim of this work is to recognize the emotions of people and classify them under the basic expressions categories. The research was carried on for color images for which segmentation based on a skin color helps to localize the face. The face is divided into three facial parts using horizontal and vertical projections. A Dataset is created by extracting the statistical features from each of the facial parts, and feature selection is implemented using a genetic algorithm based on the Root Mean Square Error (RMSE) that occurred while training the data with Naïve Bayes classifier. The algorithm has an accuracy of 92.31%.

Keywords-Statistical features, Horizontal projection, Genetic algorithm, Root Mean Square Error, Naives Bayes.

I. INTRODUCTION

The recent research in biometrics has expanded its application in medical, forensics, and for digital authentications. More researchers are on track to explore new ideas and techniques to use in this field. On such task, biometric like facial expression recognition makes a pathway to identify the difference between fake pain and genuine pain, posed and spontaneous expressions and intensity of each expression. Gwen Littlewort et.al has developed computer expression toolbox [1] and has automatically identified 30 actions from Facial Action Coding System (FACS) using data mining technique [2]. Seyed Mehdi Lajevardi, Zahir M. Hussain have applied high order local correlation and local binary operator for facial expression recognition [3]. Kwok-Wai Wong et.al have used a genetic algorithm for face detection [4]. Ahmed Bilal Ashraf has used Support Vector Machine and Active Appearance Models to identify the intensity of the pain [5]. Seyed Mehdi Lajevardi et.al has used Viola Jones for face detection and tensor perceptual color framework for facial expression recognition [6]. Mahdi Ilbeygi et.al have developed a fuzzy based facial expression recognition system for color images after detecting a face using skin color segmentation [7]. This work has resulted in developing a facial expression recognition system for color images.

II. PROPOSED METHOD

The proposed work of facial expression recognition system has different levels. The Block diagram of the proposed system is given in Figure 1.

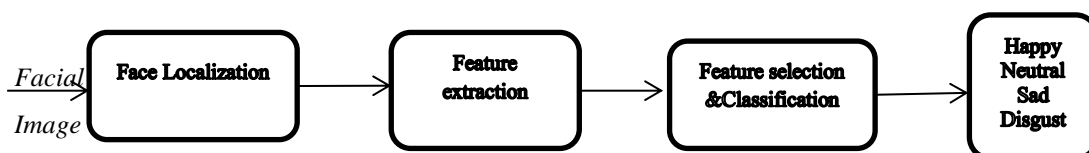


Figure.1. Block diagram of the proposed system



III. FACE LOCALIZATION

The input image as in figure 2 for the facial expression recognition is from the Indian face database[8] which consists of male and female images depicting four expressions happy, sad, neutral and disgust. The images are frontal face images with some background. To identify the facial expressions, the region of interest, face is localized using skin color segmentation. Viola et.al has developed robust face detection method [9] to detect the face from the images. M.Mahadevi et.al. has detected face based on L*a*b color using connected component analysis and template matching [10]. This algorithm utilizes the skin color segmentation [11] that was developed by M.Mahadevi et.al. The skin color segmentation developed was hybrid color model segmentation which combines the color components H and S from the HSV color model, the Chrominance component from the YCbCr color model and the Color component 'b' from the L*a*b color model. The separated components were converted to a binary image using Otsu's threshold, and a scalar product of the component binary images resulted in skin segmented face image as in figure 3.

IV. FEATURE EXTRACTION

A characteristic of an object that helps to discriminate it from other objects is called an image feature. Feature extraction is also a critical phase which generates features to help in the task of object classification. Features can be detected based on shape, edges, boundaries, moments and texture. To extract the features the cropped face image as in figure 5. is divided into three facial parts using horizontal and vertical projection. Horizontal projection is the sum of the row pixels, and vertical projection is the sum of the column pixels. The total value of the white pixels of the cropped face image helps to identify the boundary of the face. The cropped face image is divided into upper face region and lower face region by taking the peak value of the horizontal projection as the upper bound for the upper face. Further, the upper face region is divided into left and right face regions by taking the peak value of the vertical projection of the upper face as the upper bound for the left region. After splitting the face into three facial parts and Sobel edge operator is applied to the facial parts. An edge contains useful information about the object. So edges are used to measure the size of the objects in an image, and the edge detected facial parts are given in figures 6, 7 and 8. The dataset is created using spatial statistical features like mean, standard deviation, entropy, skewness which are used for classification. This work has calculated skewness, entropy, the mean and standard deviation for each of the facial parts. Four features of each image are extracted to form a feature vector with 12 features in it.

Mean: Mean of a region calculates the average value of the pixels within the range of pixel values in that region and is given by the equation.

$$\mu = \frac{\sum_{i=1}^n x_i}{n} \quad (1)$$

Where $x_1, x_2, x_3, \dots, x_n$ represent pixel values and n is a total number of pixels in that region.

Standard deviation: Standard deviation of a region is a statistical measure that quantifies the amount of dispersion of the pixel values around the mean, and the equation gives it.

$$\sigma = \sqrt{(1/n) \sum_{i=1}^n (x_i - \mu)^2} \quad (2)$$

Where μ is the mean of the facial part region, and 'n' is a total number of pixels in that region.

Entropy: Entropy of a region is a statistical measure of randomness that can be used to characterize the texture of the input image and is given by the equation.

$$\text{Entropy} = - \sum_j P_j \log_2 P_j \quad (3)$$

Where p_j is the probability, that the difference between 2 adjacent pixels is equal to 'j'.

Skewness: Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean and is given by the equation.

$$\gamma_1 = E \left[\left(\frac{X - \mu}{\sigma} \right)^3 \right] = \frac{\mu_3}{\sigma^3} = \frac{E[(X - \mu)^3]}{(E[(X - \mu)^2])^{3/2}} = \frac{\kappa_3}{\kappa_2^{3/2}}, \quad (4)$$

Where μ and σ are the average mean and standard deviation.

The feature vector of the proposed methodology is given in table. I.



TABLE.I FEATURE VECTOR

Feature Vector	Feature Number
Ulskew	1
Urskew	2
U skew	3
Ulent	4
Urent	5
Uent	6
UImean	7
Urmmean	8
Umean	9
Ulstdev	10
Urstd	11
Ustd	12

where UIm, Ulstd, Ulskew, Ulent are the mean, standard deviation, skewness, entropy of the upper left facial part. Urm, Urstd, Urskew, Urent, are the mean, standard deviation, skewness, entropy of the upper right facial part. Um, Ustd, Uskew, Uent are the mean, standard deviation, skewness, entropy of the lower facial part.

V. FEATURE SELECTION AND CLASSIFICATION

The algorithm uses Naïve Bayes classifier for classification and genetic algorithm for feature selection. As an initial step of classification, a Naive Bayes classifier object was created using the training data set, based on which classification accuracy is calculated. To improve the accuracy of the algorithm feature selection was performed using a genetic algorithm.

A. Naïve Bayes classifier

Naïve Bayes classifiers [12] are probabilistic classifiers based on Bayes theorem with independence between the features. It is stated that each of the attributes contribute equally to the classification problem. By analyzing the contribution of each of the independent attribute a conditional probability is determined and are classified based on the result that the different probabilities have on the prediction to be made. For a given training data the Naïve Bayes algorithm finds the prior probability of each class. For each attribute X_i , the number of occurrences of each attribute value is counted to determine $P(x_i)$. The probability $P(x_i/J_C)$ is calculated based on the number of times that value during training. The output is predicted from the probabilities of the training set. Estimation of a tuple 't' which has p independent attribute values $\{x_{i1}, x_{i2}, x_{i3}, \dots\}$ is given by the equation.

$$P\left(\frac{t_i}{c_j}\right) = \prod_{k=1}^p P\left(\frac{x_{ik}}{c_j}\right) \quad (5)$$

In this algorithm, a Naïve Bayes classifier object is created using a training dataset with 65 rows and twelve column values wherein the row contributes the observations from each image, and the columns contribute the features of the images. With the predicted class labels from the classifier object, the algorithm then classifies the test data based on the features that are selected during the feature selection stage.

B. Feature selection using genetic algorithm

Feature selection is required when there are 'n' number of features or when there are so many independent attributes. In this work since each of the attribute values are independent and contributes equally to the classification problem, feature selection is needed for best classification rate with minimum features. Hence, a genetic algorithm is used for feature selection.

Genetic algorithm [13] is an evolutionary algorithm that generates solutions to optimization problems using techniques such as mutation, crossover, and selection. In a genetic algorithm [14], a population of candidate solutions is generated which is optimized to a better solution. Parameters like mutation and crossover help in redesigning the population. The evolution starts with randomly generated individuals and is an iterative process. During each iteration, the population is evolved which is termed as a generation. During each generation, the best-fitted individual is selected for the next phase. The fitness function is to optimize an objective function. When the population satisfies the fitness, it passes through the next stage where mutation or crossover to be selected for the next iteration. So formed generations converge to an optimal solution for the problem. The convergence is realized either when maximum generations are generated, or when the satisfied fitness value is reached.

This work designs the chromosomes as a binary string data type. The randomly generated population is a set of chromosomes which is of binary string data type with 0's and 1's as the value. Each value of '1' means that that specific feature will be selected for classification. The number of features is chosen to be the length of the



chromosome. In this algorithm, the number of features is twelve and sample structure of chromosome is given as in Figure 9 which is of length 12.

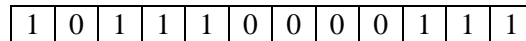


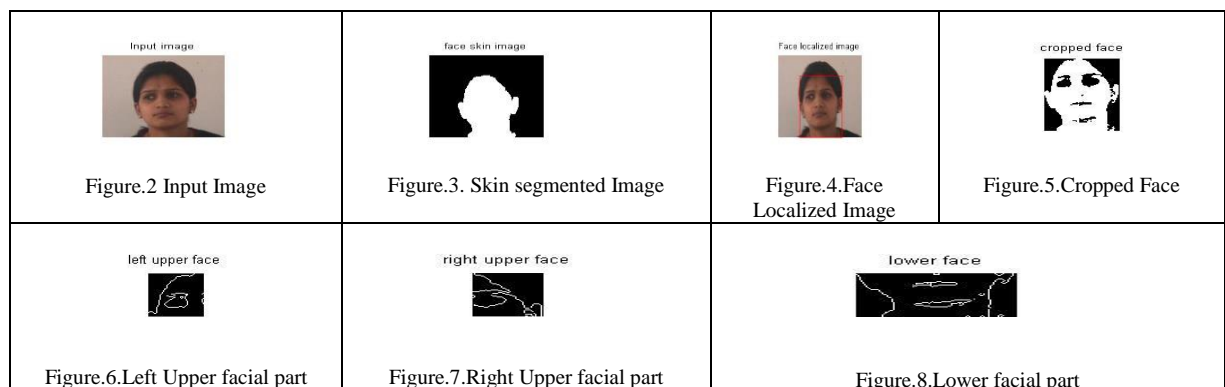
Figure.2 Structure of a Chromosome

The fitness function considered for classifying the training dataset is the minimization of the Root Mean Square Error (RMSE). RMSE is defined as the sample standard deviation of the differences between predicted values, and observed values [15] and is given by the equation(6).

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (\hat{y}-y)^2}{n}} \tag{6}$$

VI. PROPOSED ALGORITHM

- 1 Input the RGB image as in figure 2.
- 2 The RGB input image is converted to HSV, YCBCR, and L*a*b color models.
- 3 The color components H and S from HSV model, Cb component from YCBCR and ‘a’ and ‘b’ color components from L*a*b are separated from the image.
- 4 Each of the color components from the color models is converted to a binary image using Otsu’s threshold value.
- 5 The resulted binary images are combined using a scalar product which produces a skin segmented image as in figure 3.
- 6 Then finally a bounding box is drawn over the image to localize the face as in figure 4, and it is cropped as in figure 5.
- 7 The resulted image as in figure 5 is ready for feature extraction stage. Using the peak value of the horizontal projection the cropped face image is divided into lower and upper face.
- 8 The upper face image is further divided into left and right face regions based on the peak value of the vertical projection of the upper face.
- 9 Sobel edge operator is applied to left, right upper face regions and to lower face region and is given in figure 6, figure 7, and figure 8.
- 10 Statistical features are calculated for the face regions. Four features of each face regions (three regions) which contributed to twelve features were extracted as Feature vector as in table I, and a sample dataset is tabulated in table II.
- 11 Dataset size of 65 rows is trained with twelve features using Naïve Bayes classifier.
- 12 The resulted Root Mean Square Error after classification for the twelve features using Naïve Bayes was taken as a fitness function for the genetic algorithm.
- 13 For each run different features were selected and was given as input by the genetic algorithm.
- 14 For each generation run the classification accuracy and RMSE are calculated and the individual that best fits the fitness function is selected for next generation.
- 15 65 images were trained using genetic algorithm and the RMSE plot is given in figure 10.
- 16 65 images were tested using Naïve Bayes classifier and a confusion matrix is tabulated in table IV.





VII. RESULTS AND DISCUSSION

The proposed algorithm for facial expression classification used an Indian face database which contains frontal images of men and women in different postures and four expressions. The feature vector created during the feature extraction stage contains 12 features. The sample dataset values for different images are given in Table II.

TABLE.II STATISTICAL FEATURES OF FACIAL REGIONS

Ulskew	Urskew	Uskew	Ulent	Urent	Uent	Ulmean	Urmean	Umean	Ulst	Urstd	Ustd
-0.0669	-0.6272	0	2.3172	3.2324	2.6075	0.5736	0.4624	0.5194	0.5771	0.5051	0.5349
0.0946	-0.9642	-0.76	2.2004	2.4497	2.0765	0.5519	0.5485	0.4901	0.6444	0.498	0.4728
0	0.5072	0	1.5591	1.6404	1.4416	0.5612	0.3567	0.4923	0.6687	0.4813	0.4669
-0.9653	0	0	1.4441	1.5103	1.5585	0.6923	0.5993	0.458	0.5593	0.4894	0.493
-1.7162	0	-1.243	2.2281	1.6909	1.9782	0.7326	0.1891	0.4329	0.7225	0.3925	0.4501

With all the independent features considered for classification, Naïve Bayes classifier object was created. The algorithm was tested with 65 images (disgust-12, happy-24, neutral-16, sad-13). Since the features are independent, feature selection was performed by genetic algorithm and Naïve Bayes classification was applied to find the performance of the algorithm. A genetic algorithm is applied to minimize the number of features required to classify the expressions.

Genetic algorithm starts with randomly generated population, and each individual of the population is checked with the fitness function value RMSE. The best individual is the one that bests fit the fitness function in that generation, and that is moved on to the next iteration of creating the child chromosome. The next child chromosome is created by mutation and crossover which is the population of the next generation, and again the same procedure of checking the population with the best fitness value is executed. The features are selected when the total number of generations is exceeded or when there is a minimal average change in the fitness value. This algorithm trains and tests the dataset with ‘resubstitution’ method where both training and test data are the same.

With 65 images as the training dataset and with the genetic algorithm parameters as in table III, the average and best fitness individual is plotted as a graph in the figure 10.

TABLE.III GENETIC ALGORITHM PARAMETERS

Parameters	Values
Population Type	Bit String
Population Size	20
Generations	50
Stall Generation Limit	10
Mutation	Uniform
Cross Over	Cross over Arithmetic

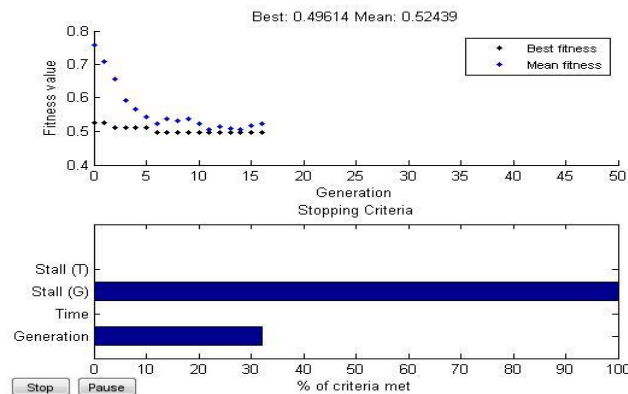


Figure.10 Best Fitness Plot and Stopping Criteria Plot

Figure 10 shows the best and mean fitness value of the training dataset. From the graph, it is clear that the RMSE started from 0.7 and gradually got minimized to a value of 0.49614 after generations. Also, the genetic algorithm had stopped when it met with the minimal average change in the fitness value. Those features that resulted with a minimum RMSE is selected for classification. The selected features are 1,3,5,7,10,11 which are Ulskew, Uskew, Uent, Urmean, Urstd, and Ustd. When these features are given as input to the Naïve Bayes classifier object, it resulted in a classification accuracy of 92.31% and the resulted confusion matrix for the selected 6-feature and 4 class labels is given in Table IV.



TABLE.IV CONFUSION MATRIX

	Disgust	Sad	Neutral	Happy
Disgust	10	1	0	1
Sad	0	12	1	0
Neutral	1	1	14	0
Happy	0	0	0	24

VIII. CONCLUSION

In this paper face localization has been implemented using skin color segmentation, and statistical extracted from different facial parts. About 12 features for a set of training images were calculated out of which six features were selected using a genetic algorithm. A Naive Bayes classifier was used to classify the facial expressions and four basic expressions of disgust, happy, neutral and sad were classified with an accuracy of 92.31%. In future, the system can also be extended to include many frequency domain features and classify the expression.

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