JOURNAL OF SOFTWARE ENGINEERING & INTELLIGENT SYSTEMS
ISSN 2518-8739
30th April 2019, Volume 4, Issue 1, JSEIS, CAOMEI Copyright © 2016-2019
www.jseis.org

ANALYSIS OF THE EFFECT OF ETHNICITY, COLOR AND GENDER ON MULTI VIEW FACE EMOTION RECOGNITION

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Academic Editor: Muhammad Jehanzeb, APCOMS, Rawalpindi, Pakistan.

Published: 30th April, 2019

Funding: Authors have no funds.

Article Type: Research Article

ABSTRACT

Based on existing literature, there are seven basic emotions that human can express. Human facial expression degree varies among different people. In this paper, real time face emotion recognition system is presented. The multi-view facial emotion recognition system works with frontal, non-frontal and side face view. A 3D face pose estimation algorithm detects head rotations of yaw, roll, and pitch for emotion recognition. UPM3D-FE and BU3D-FE databases were used in this research. After detecting the face, geometrical facial features combined with texture features are extracted automatically from specific areas of the face in a novel approach. The features are tested on different classifiers to determine the performance of the method. The results show improvement over existing approaches in neutral, happy, sad, disgust, anger and surprise when using the neural networks with GLCM texture operators. Moreover, a real time system is achieved. Other analysis about the role of ethnicity, gender, shows that gender has almost no effect on emotion recognition and in BU3DFE database, middle east, and southeast Asians achieve the highest accuracy of results and the lowest are black and white ethnicities.

Keywords: facial expressions; basic emotions; real time; 3D face pose; back propagation; texture operator;

1. INTRODUCTION

The first efforts toward automatic emotion recognition were done in 1978 [1] and the facial expressions were analysed in a sequence of pictures by using twenty facial points. Despite the introduction of the system in 1978, this line of work was not pursued until the 90s. The reason is that the face detection and tracking algorithms were still under development before this period. Moreover, inexpensive computing power became available only in the 1980s and 1990s. Since 1990s recognizing emotions in human has attracted great interest [2, 3].

There are many different emotions that humans experience. However, based on literature there are mainly seven basic emotions namely, anger, disgust, fear, happiness, sadness, surprise and neutral [4, 5]. The applications of automatic emotion recognition are in many different areas such as psychology, computer technology, robotics and security. The problem of emotion detection is particularly difficult since the solution tries to consider all the changes in the face such as pose, occlusions, illumination changes, and resolution in image and flexibility with regard to these changes. In addition, other factors such as the difference in age, race or having makeup are needed to be considered in finding emotions [3, 6]. Generally, there are two approaches to face emotion recognition; holistic approaches, and local features [2, 3, 7, 8].

The holistic approach to emotion recognition considers the whole image as input data, and the variations of all the pixels on face picture are used to recognize the emotion. In other words, holistic approach analyses the texture of face. Regarding examples of holistic methods, eigenfaces and fisherfaces [9], or LBP (local binary patterns) texture analysis [10] are some well-known examples. On the other hand, feature based approaches focus on particular points on the face and analyse a particular region of the face. For local features analysis methods LBP [10], and in case of finding the exact location of face points, ASM (active shape model) [11] or AAM (active appearance model) [12, 13] or DPM (deformable parts model) [14] can be used. Beside the two approaches of feature based and holistic for emotion recognition, the hybrid methods exist that make use of both approaches and combine them to recognize emotions [15, 16]. Summary of all methods for emotion recognition can be seen in survey papers [2, 3, 7, 8].

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This paper presents an automatic real-time system for multi-view face emotion recognition. This means that the emotion is detected from the face which is also rotated from -90º to +90º head rotation, and the results were tested for the unknown person (person independent). The selection of special features for emotion recognition causes the approach to achieve higher accuracy even in the case of multi view faces. In order to identify emotions in real time the face should be detected within a time frame, that is not noticeable to the human observer.

The role of gender, color, and ethnicity was analysed in [17] and it is mentioned that emotion recognition from specific ethnicity has higher accuracy than from all ethnicities. In this work, roles of gender, ethnicity, and color have been analysed in emotion recognition.

1.1 General flow of work

This paper presents a real time face emotion recognition system, and the multi view person independent facial emotion recognition problem is considered. The results are evaluated with standard facial expression databases [18, 19], where subjects expressed the seven basic emotions. The images are taken from 3D viewing software Meshlab [20] and from different angles and resized to 320 × 240 images containing the face of the subject. The emotion detection is essentially a low-frequency task, hence, this size of images is sufficient for emotion recognition [16].

The general procedure is shown in Figure 1. In the first step, the face of the person is detected from the camera picture, and face landmarks are identified. In the second step, face pose is identified using a geometrical approach. After this, in step 3, the feature vector is made from geometrical, texture and rotation angles (roll, pitch, and yaw). Finally, at step 4, the feature vector is given to Neural Networks (or neuro-fuzzy classifier) to identify the emotion. The procedure is repeated from step 1 to step 5 for the person to display the emotion in real time for each frame captured from the camera. The details of UPM3DFE and BU3DFE database regarding the number of subjects, ethnicities, and format of the database are presented in Table 1.

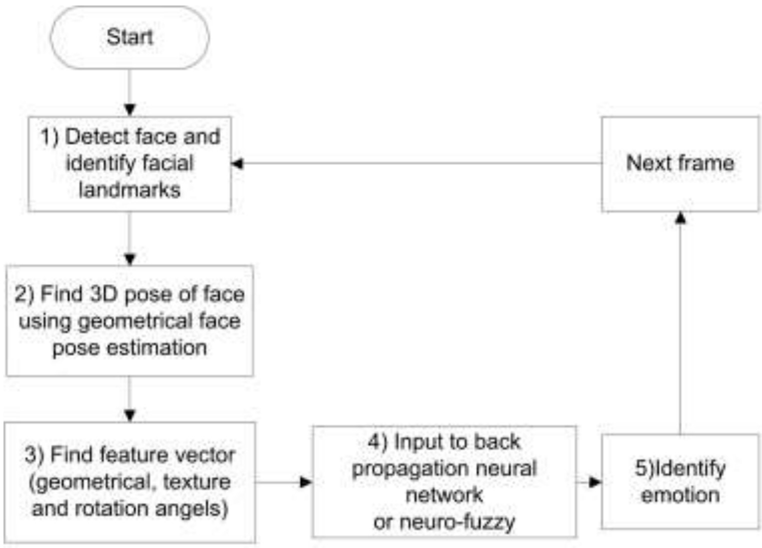

Figure. 1 Overall view of emotion recognition system using 3D face emotion database.

Table. 1 Comparison of BU3DFE and UPM3DFE facial expression databases

	BU-3DFE	UPM-3DFE
No of subjects	100	50
male-to-female ratio	44 by 56	30 by 20
Basic emotion	7	7
White	51.0	0.0
Blacks/Africans	9.0	18.0
Chinese/east-Asian	24.0	20.0
Indians	6.0	8.0
Middle-east Asian	2.0	26.0
Latino-Hispanic	8.0	0.0
south-east Asia	0.0	28.0
Format of database	Virtual Reality Modeling Language	.asc (x,y, and z) file and texture face picture

The number of subjects including rotations, emotions and emotion intensities for BU3DFE database is 37500 subjects and for UPM3DFE database is 5250 subjects.

The rest of paper is organized as follows, section 2 describes the methods used for achieving the FER system, including feature extraction and construction of feature vector using geometrical features, rotation angles, and texture features. Section 3 presents the experiments including BU3DFE experimental results of the method with GLCM. Moreover, the experiments on UPM3DFE and mixed BU and UPM database and results of ethnicity, color, and gender on each database and real time analysis are in this section. Finally, in section 4, conclusions of the results and limitations of work with suggestions for future improvements are presented.

2. METHODS

In this section, the methodology that is used, for emotion recognition, is presented. First, the method for finding and selecting features on the face is presented. In order to recognize emotions, a feature vector needs to be created with appropriate features for finding the emotions of the person. The feature vector consists of geometrical features which are distances or angles of facial parts and texture features and also face angle in comparison to frontal face. In order to successfully extract these features, the positions of facial points within face need to be found.

2.1 Geometrical features and face pose estimation

As a prerequisite for finding geometrical features, it is necessary to locate facial landmarks. One approach is to use a separate detector for each facial area. This is done usually by training cascade classifiers using Adaboost [21]. But this approach fails to provide a robust estimation of landmarks locations, also it may result in having false detections. This can be compensated by considering geometrical positions of landmarks. In this approach first, the candidate points, for each landmark, are found with individual detectors and secondly, the landmark configuration with the highest similarity to the geometrical configuration is selected. The deformable parts model (DPM) further improves the algorithm by considering a single model for local appearance model, and the geometrical constraints.

Equation 1 shows the method for estimating positions of facial points. The first term (q) is local appearance model estimating the landmarks on position ‘s’ and input image I. The second term (g) is the deformation cost considering the relative positions of neighbouring landmarks i and j (Figure 2). The appearance model can be the normalized intensity value, or derivatives of intensity values which are Sobel edge detection values, or multi scale LBP (local binary patterns). The multi scaled LBP is used due to outperforming other algorithms [14]. The learning of model parameters is done by Labelled Faces in the Wild (LFW) database [22].

DPM considers facial landmarks as vertices in an acyclic graph and the link between points as edges of the graph, and the landmark positions are simultaneously estimated by a single scoring function [24]. In order to find geometrical features, the facial points are localized with DPM and using Flandmark library under opencv. Figure 2 shows that 8 facial points are localized [14].

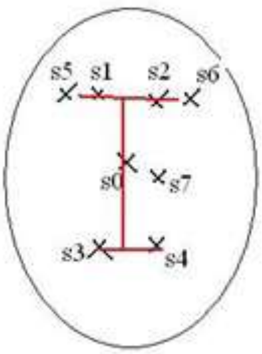

Figure. 2 Facial feature points. s5 and s1 left eye corners, s2 and s6 right eye corner, s7 tip of the nose, s3 and s4 mouth corners, and s0 center of the face.

From the seven points, the three rotation angles are determined geometrical equations, and the rotation angles of yaw and pitch are computed [23]. Finding the head pose is a computer vision problem and available methods can be found in chutorian and trivedi survey [24]. This paper implements a geometrical approach for pose estimation. The head pose is determined in 15º intervals, meaning that yaw and pitch are measured from -45º to +45º by 15º steps. Experiments show that the current method has a lower mean absolute error in comparison with other approaches [23].

After finding the seven facial points using the trained model with DPM, more points are being located on face in order to be able to determine all geometrical features related to the emotions. The points are eyebrow centers (s12, s13), upper and lower lip (s14, s15) and upper and lower eyes (s8, s9) and (s10, s11), and they are mainly detected from Sobel edged image of face and positions of previous points (Figure 3). In the case of the rotated face or bad illumination or partial occlusion, some of the points for example eyebrows may not be detected. In such a case, the symmetry of face is used and the corresponding detected point height (for example eyebrow height) is given to the other similar point.

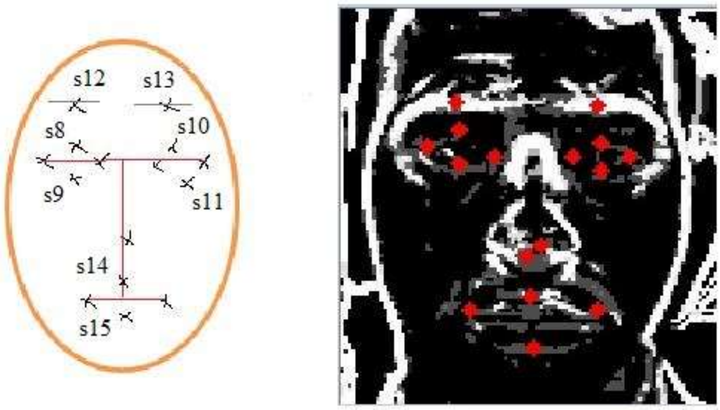

Figure. 3 Added Facial feature points for eyebrow centers (s12, s13), upper and lower lip (s14, s15) and upper and lower left eye (s8, s9), and upper and lower right eye (s10, s11).

Table 2 shows important attributes that can be seen in seven basic emotions partially from [25]. These characteristics are used to select important geometrical features to identify emotions.

Table. 2 Attributes of basic emotions partially from [25]

Expression	Texture information
Anger	The inner eyebrows go downward and come together and wrinkle. The eyes are open. The lips are pressed against each other or opened to expose the teeth.
Sadness	The inner eyebrows are bent upward. The eyes are slightly closed. Corner of the mouth is bent downward.
Surprise	The eyebrows are raised. The eyes are wide open, the lower mouth relaxed. The mouth is opened.
Happy	The eyebrows are relaxed. The mouth is open and the mouth corners pulled to either side of the face (mouth width is increased).
Disgust	The eyebrows and eyelids are relaxed. The upper lip is raised and curled. Often nose is wrinkled
Fear	The eyebrows are raised and pulled together. The inner eyebrows are bent upward. The eyes are open and alert.

The list of geometrical features used to determine emotions are brought in Table 3. As can be seen in the Table, the distances or values are normalized by face size in the case of bigger face picture in the frame when a subject is near or far from the camera.

Table. 3 Geometrical features for emotion detection

Feature	Description
Normal mouth to nose	Distance mouth to nose, normalized by dividing to face height.
Normal mouth width	Lip width normalized by dividing to face width.
Normal mouth height	Mouth height normalized by dividing to face height.
Happy	The eyebrows are relaxed. The mouth is open and the mouth corners pulled to either side of the face (mouth width is increased).
Dist eyebrow	Eyebrows distance from eye line.
Eye value	Value showing how much eye is visible to determine eye close or open.
Down mouth muscle	Value showing the below lip corner muscle.

2.2 Appearance features

The face texture also varies in the presence of different emotions. The change in skin texture with emotions can also be studied from Table 2. For appearance or texture features, the GLCM texture algorithm and LBP (Local binary patterns) are used [26, 27]. Applying the texture algorithm on the whole image in many cases cannot give conclusive results to determine the emotion. This is because it considers all the skin areas and possible shadow or different background portions of the rectangle containing face image. Therefore, the skin texture features from five areas of the forehead, left and right mouth areas, nose, and eyebrow constriction on the face are taken separately for emotion detection (Figure 7).

For example, the image I with the size of n × n the co-occurrence matrix P can be defined in Equation 1, i and j are the pixel values and x and y are the spatial positions in the image. The (i,j) th value of the co-occurrence matrix gives the number of times the i and j pixel values occur in the relation considering the displacement. Also, the GLCM matrix can be computed in different angles, 0, 45 and 90 and 135 degrees in a 2D image. For this research 0 and 90 degrees are selected, as they consider all changes in vertical and horizontal directions. From GLCM matrix a number of texture features can be extracted. The four texture features used in this research, they are namely, contrast, correlation, energy, and homogeneity.

$$P(i,j) = \sum_{x=1}^{n} \sum_{y=1}^{n} \begin{cases} 1 & if\ I(x,y) = i\ and\ I(x+\Delta x, y+\Delta y) = j \\ 0 & otherwise \end{cases} \quad (1)$$

In the five regions of the face, 4 texture features are taken in horizontal and vertical directions. This makes a total of 40 texture features from the face. We combine the geometrical features also with texture, which gives us 49 features for emotion detection.

2.3 Multi-view Features for emotion recognition

The face detection task will be done using Cascade of the face and HSV skin color detection. The normal face cascades can detect yaw angle variation from -50 to 50 degrees or even more, but in the case of completely side view faces, or profile face this cascade is not applicable. Therefore, in face detection phase firstly the normal face cascade is used and only faces detected within HSV skin color area are held as valid. After this, the algorithm searches for left side view faces using cascade for profile face and if there is no result in this case also the right side view face is sought for. In case, where neither near frontal nor left or right side view faces are found, the process is repeated (Figure 4).

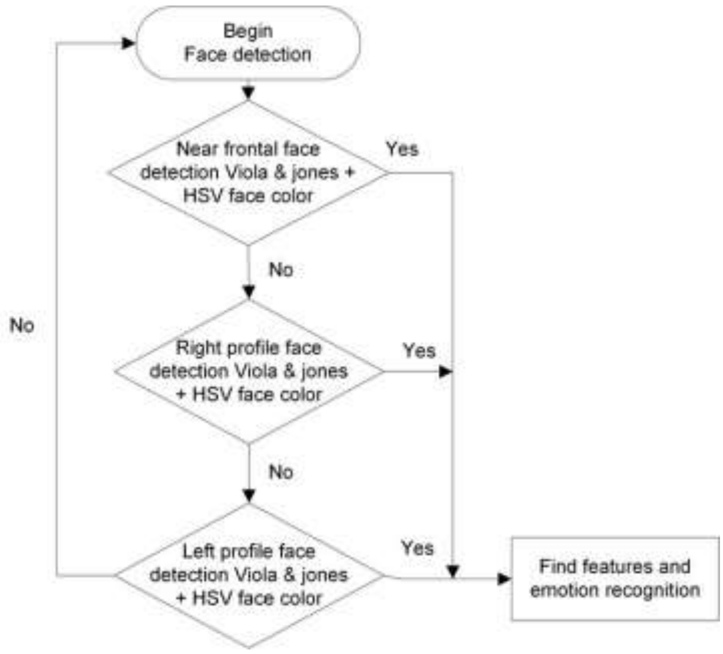

Figure. 4 Flowchart for multi view face detection

For side view faces, first the rectangle containing face is found by profile face cascade and HSV color detection. The left and right side view face detection has been explained in the flowchart in Figure 4. Next, the necessary facial points are correctly calculated by side-view PDM model. The model detects 13 points on the side-view face, but only 7 points are used for emotion recognition. They are upper and lower mouth points, mouth corner, tip of the nose, corners of eye and eyebrow point.

The features in case of frontal face and profile face are shown in Figure 5. They are namely eyebrow distance, corner of mouth to nose tip distance, lip opening and the texture areas in mouth corner, nose and forehead area. The hidden features in profile face are given the value of '-1' for other facial features.

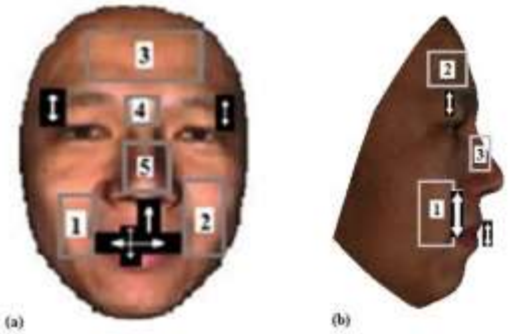

Figure. 5 Features selected for (a) near frontal, and (b) profile face images.

The setup for performing emotion recognition in real time consists of a high quality web camera, so the captured picture quality should not be blurry or dark. In this work, an HD (high definition) web camera capable of working with a resolution of 720p has been chosen and utilized.

The features extracted from the face are used to detect the emotions with the help of a back propagation neural network with one input, one hidden layer, and one output layer. The Neural network is trained using scaled conjugate gradient function method (SCG) [28]. This makes it considerably faster than standard back propagation. It uses activation function tan-sigmoid and performance function is MSE (mean of squared errors). To overcome the problem of over-fitting in the neural network, a ten-fold cross validation method is used. 90% of the data is used for training and the remaining 10% is equally divided into validation and testing. The experiment is repeated 10 times on all the folds of the data and average results are reported.

All features are tested with a supervised method to test the redundancy, using the supervised method of minimum Redundancy Maximum Relevance(mRMR) [29]. This algorithm approximates the maximum dependency to the target class of the features when mutual information between a feature and target class c defined as in Equation 2. In practice, incremental steps procedure to select features is used (Equation 3).

$$I(S_m, c) = \int\int p(S_m, c) log \frac{p(S_m,c)}{p(S_m)p(c)} dS_m d_c \quad (2)$$

$$max(x_j \in X - S_{m-1}) \left[I(x_j, c) - \frac{1}{m-1}\sum_{x_i \epsilon S_{m-1}} I(x_j; x_i)\right] \quad (3)$$

After finding the rank of features in order of importance, the features are tested for misclassification error for each number of features. The results show that all the features are important for emotion recognition and adding the features would continually decrease misclassification error. Figure 6 shows the misclassification error for each different number of features in case of the neural network.

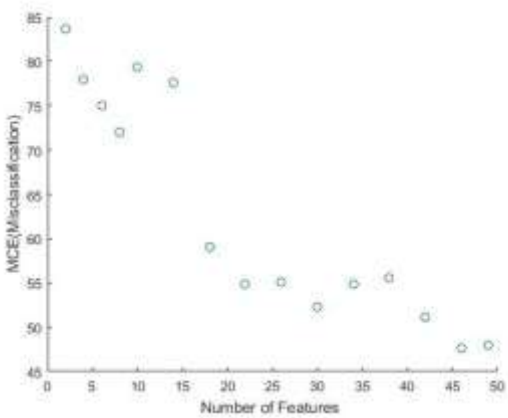

Figure. 6 Graph of misclassification error for emotion recognition against number of features.

The number of hidden neurons is typically between number of the input layer neurons and the output layer. Therefore, a different number of neurons is tested in the hidden layer and generalization or testing error is calculated. For each number of hidden neurons, the neural network is tested for three times and the average error is considered. The process is repeated in all folds to find the optimal number of hidden neurons. The graph in Figure 7 shows two minimum errors at 17 and 30 neurons, but the lowest error occurs in 30 hidden layer neurons.

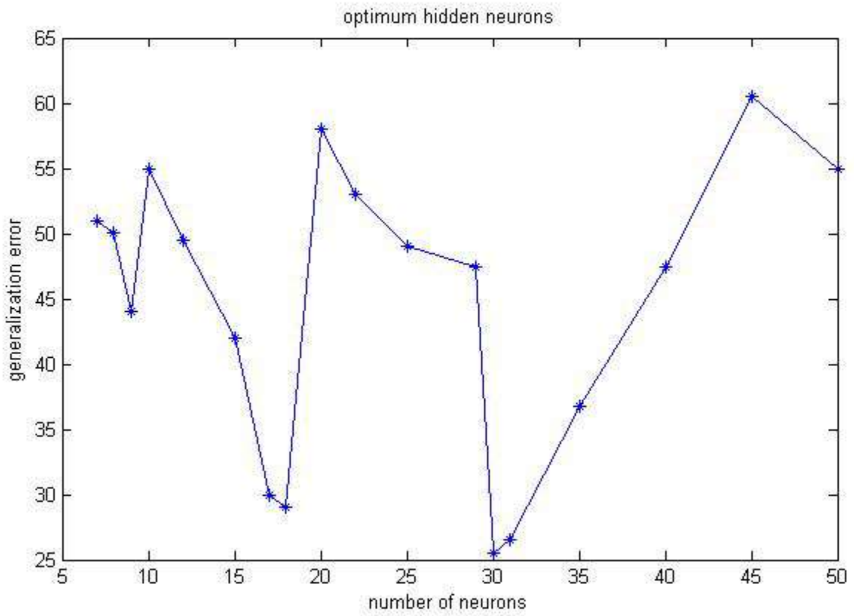

Figure. 7 Graph of the number of hidden layers with respect to generalization error for emotion recognition neural network.

3. MULTI-VIEW FACE EMOTION RECOGNITION EXPERIMENTS

In this section experimental results for emotion recognition and effects of color, ethnicity and gender are presented.

3.1 BU3DFE with GLCM texture features and neural networks

If we exclude fear from emotions with GLCM texture operator, we have 87.5% for person independent in near frontal face images. In case of multi view faces, the accuracy rate is 84%. In case of including the fear emotion and seven emotions for near frontal images, the accuracy is 80.61% for person independent (Figure 8). For multi view faces the accuracy rate is 77.48% for (Figure 9).

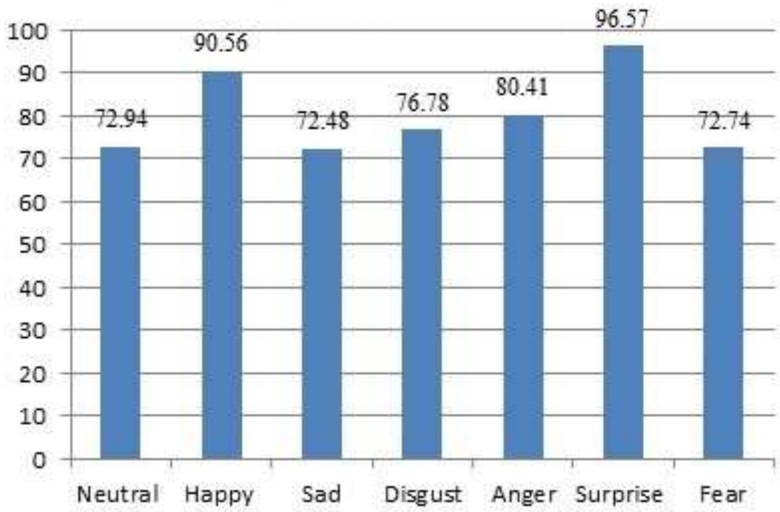

Figure. 8 Emotion recognition chart for seven emotions BU3DFE with GLCM for near frontal

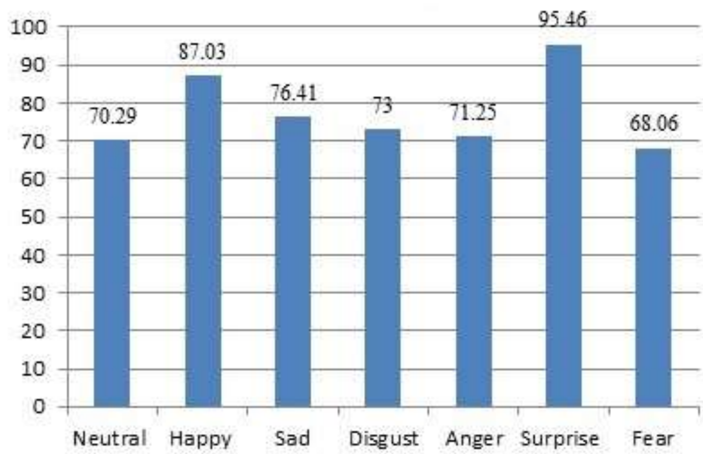

Figure. 9 Emotion recognition chart for seven emotions BU3DFE with GLCM for multi view.

The confusion matrices for neural network with GLCM textures for emotion detection seven emotions are manifested in Tables 5 and 6 (near frontal and multi view faces). It can be seen from the accuracy results for emotions in Figures 8 and 9 that surprise has the highest recognition rate. In multi view case fear has lower accuracy than other emotions and in near frontal faces, sad emotion has slightly lower than fear emotion. The sad emotion could be confused mostly with disgust, or disgust could be confused mostly with anger. This is in accordance with human perception. Moreover, in 7 emotions, the surprise and happy could be misidentified as fear. The comparison of other works with the proposed method [30-33] is presented in Figure 10. Our approach shows an improvement over other methods in recognition of nearly all emotions.

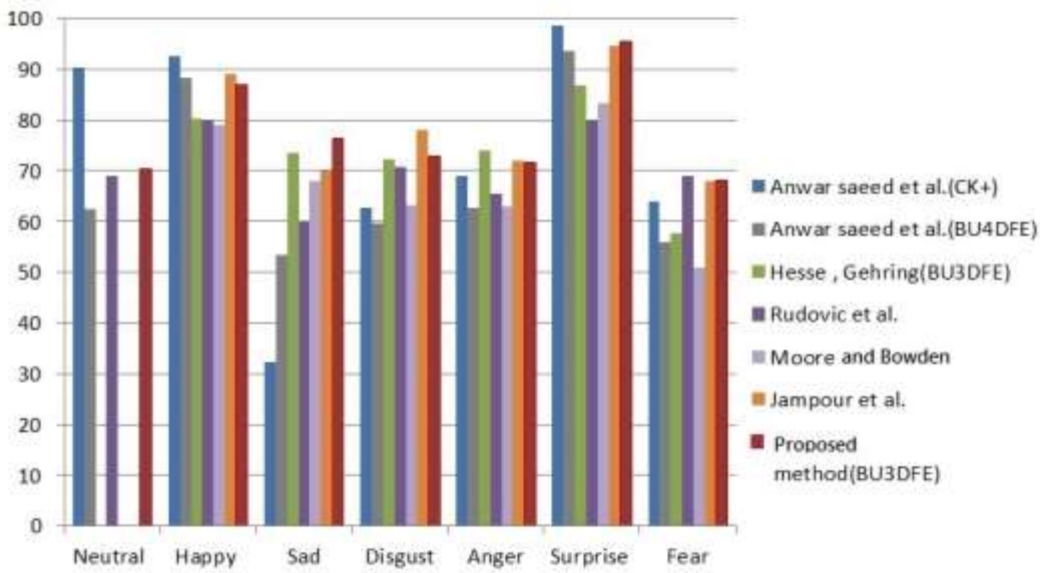

Figure. 10 Graph comparing different methods for person independent emotion recognition using 2D capturing camera. Method 1, Saeed et al used manual facial points and methods 3 (Hesse et al) and 4(Moore et al) did not include neutral to emotions.

3.2 Ethnicity, color and gender effects on emotion recognition

After training each database (BU3DFE and UPM3DFE), the results for genders, color, and ethnicity were tested with subjects from the other database that was not used for training. Table 4 shows the result of each gender (male or female) after testing in all folds of cross validation on emotion recognition.

Table. 4 Gender effect in multi view 7 emotion recognition in each database

Classifier	Male	Female
BU3DFE	48.28%	59.21%
UPM3DFE	70.40%	66.09%

This information manifested that gender has almost no effect on emotion recognition because in case of BU3DFE female subjects have more accuracy (59.21%) and in case of UPM3DFE male subjects show better accuracy (70.4%).

Furthermore, the BU3DFE and UPM3DFE were examined for subjects of different colors and ethnicities from the other database, not used in training. In reporting the results, all views of subjects are considered, and the results after testing with cross validation are in Table 5. The subjects for testing the ethnicity were not used for training since they are from the other database.

Table. 5 Color and ethnicity in multi view 7 emotion recognition for each database

Classifier	White	Black	South-east Asian	Indians	Middle East	Latino
BU3DFE	-	45.01%	50.2%	56.6%	49.36%	-
UPM3DFE	57.3%	54.54%	69.1%	61.3%	66.6%	64.64%

In the case of BU3DFE classifier being tested on UPM3DFE subjects, the best results were achieved for Indians and South east Asian (56.6% and 50.2%) subjects. This is because east Asian subjects constitute the most number of subjects, after white subjects (24%), and Indian are in third place after black subjects with 6% of all subjects in BU3DFE (Table 1). The Middle Eastern and black subjects have the lowest rates. This is because in black subjects the facial points are detected with more error, due to less visibility in facial features such as lips, eyes, and eyebrows. Also, in the case of Middle East subjects, the number of middle east subjects is only 2% of the BU3DFE database.

In case of UPM3DFE classifier being tested on BU3DFE subjects, the best results were achieved for Middle East and southeast Asians subjects (66.6% and 69.1%), since the southeast Asian subjects constitute the most number of subjects (26%) and Chinese Asian form 20% in training UPM3DFE classifier. The lowest results were achieved in the case of black and white ethnicity groups. Regarding the black subjects, the reason is difficulty in finding facial features and in the case of white subjects the reason is that no white subjects used in training of UPM3DFE database.

4. CONCLUSIONS

In this paper, a real-time system for emotion recognition has been presented. A 10-fold cross validation has been performed to present the results. After testing the method on BU3DFE, UPM3DFE databases, the results show higher accuracy for BU3DFE database. The method of GLCM operators is tested as texture features, and a back propagation neural network has been used as a classifier. It has been shown that the emotion recognition system works with a high accuracy of 77.48% for multi view and 80.61% for near frontal when neural networks and GLCM features are used.

The method has improved the detecting of almost all emotions because it searches in special areas of skin where these emotions affect skin texture. Moreover, experiments with the neural network have shown in cases where subject shows mixed emotions, the neural approach is able to detect this and output the dominant emotion as output. The role of ethnicity with extra subjects was tested on both databases. It has been shown that ethnicities that have larger numbers in databases show better recognition rates, however, black subjects have low recognition rates in both databases, as a result of having more errors at facial points detection.

This system automatically finds facial landmarks and identifies emotions from the face. The system with Intel Core i5 CPU, 3.4 GHz with 8 Gigabyte RAM, runs at almost 0.17 fps (or at around 170 ms delay per frame). The face and emotions can be detected from -90 to 90 degrees, yaw and -45 to 45 pitch. Part of the error rates in detecting emotion can be shown to be from the displacement of facial points, and if manually chosen the emotion detection is improved [33]. Developing methods to estimate facial points with a minimum error at different pose angles can also further improve the overall accuracy of system. Some works in this area obtain good results also in non-frontal cases but they are not responding in real-time or require special hardware for real-time [34]. Recently there have been efforts to use deep learning algorithm to effectively achieve the tasks of multi view face detection and pose estimation [35]. Similar approaches could be used for finding the landmarks on the face in different views.

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