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REAL TIME FACIAL EXPRESSION RECOGNITION IN THE PRESENCE OF ROTATION AND PARTIAL OCCLUSIONS

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ABSTRACT

In the real world, occlusion is considered as an important problem in the domain of emotion recognition. This study investigates the occlusion in real time using a fully automatic system. The features are extracted effectively from special areas of the face using both texture and geometrical features on the face. The system uses a trained backpropagation neural network to find the seven basic emotions. The experiments were conducted on normal, and with occlusions on forehead, eyes, and mouth. The proposed system was able to detect emotions with high recognition rates. The results are presented for near frontal and multi view faces using UPM3DFE and BU3DFE 3D facial expression databases.

Keywords: *Face Emotion Recognition, Neural Network, Backpropagation, Feature Extraction, Occlusion, 3DFE*

1. INTRODUCTION

Facial Expression Recognition (FER) is part of affective computing research area and it has become an active field of research in the recent years. The subject is a combination of different areas namely, physiology, psychology, computer vision, image processing, pattern recognition and other fields [1]. The applications range from robotics, health care, monitoring, and many other areas.

The facial expressions are normally classified into seven basic emotions (anger, disgust, fear, happiness, sadness, surprise and neutral) [2, 3]. In addition to the basic problem of emotion recognition, there are other issues that make the FER problem more challenging. These issues include dealing with changes in the pose, occlusions, illumination and different resolutions. Furthermore, the emotion recognition in actual world scenario is a real time task, since facial expressions can occur and change in small time intervals [4].

Most of the FER systems till date consider only images under constrained conditions. These conditions are mostly frontal faces that can have some facial accessories such as glasses, scarf or headwear. Moreover, numerous standard face databases have been developed for emotion recognition purposes. However, as mentioned earlier, in real world scenarios several conditions are required to be considered. For example, the occlusion problem occurs in many situations accidentally, and the system needs to be robust in dealing with it. In certain situations, occlusion is observed more frequently. Nguyen et al. [5] investigated the occlusion in facial expressions used in sign language communication (Figure 1).

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Figure 1: Occlusion during expression recognition in sign language [5].

During emotion recognition procedure, features are selected from the face, and these features contain information about the emotions. The features are geometric or texture features or a combination of both. In the case of occlusion features that are selected from local areas of face carry an advantage. This is because occlusion modifies the overall texture of face in a way that inhibits the emotion recognition. On the other hand, the features from local areas in occluded areas can be discarded, and features from non-occluded regions remain intact. These features could be used to classify the emotion.

In this paper, a combination of geometric (local) and texture features are used for facial expression recognition in occluded faces. The face is also rotated in yaw and pitch angles with imposing occlusions. For generating the rotated and occluded faces for this purpose, the Binghamton BU3DFE [6] and UPM3DFE [7, 8] face databases are used. The occlusion on the face is performed by inserting gray rectangles on facial parts. After this, a backpropagation neural network is trained to classify emotion in real time. The paper is organized as follows. In section 2 related works in facial expression recognition related with occlusion are discussed. Section 3 describes the proposed system. Section 4 manifests the experimental results. Finally, section 5 discusses conclusions and future works.

2. RELATED WORKS IN FER UNDER OCCLUSION

Facial expression recognition in the presence of occlusion has been studied in several works. However, the existing databases are mostly relying on frontal faces and live videos are not examined in these works.

Jiang and Jia [9] used RPCA to analyze the texture of facial emotions in JAFFE database [10]. PCA is based on reducing high dimensional data to much lower dimensions. RPCA is a modification of PCA to minimize the errors caused by occlusion. The aim of this method is to recover the low ranking matrix A from D = A + E, with E being the gross but sparse errors by solving equation 1.

$$\min_{A,E} \|A\|_* + \lambda |E|_1 , \ D = A + E \qquad (1)$$

The overall procedure for robust FER is displayed in Figure 2. At first, the eye and mouth occlusion is repaired with RPCA method. Later, the Eigenfaces and Fisherfaces are used to extract features, and finally, nearest neighbor and SVM are used to classify emotions.

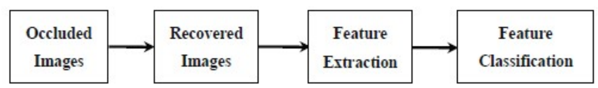

Figure 2: Occlusion during expression recognition in sign language [9].

The occlusions in images were acquired using black rectangles on eyes or mouth areas. Experimental images for this work are shown in Figure 3.

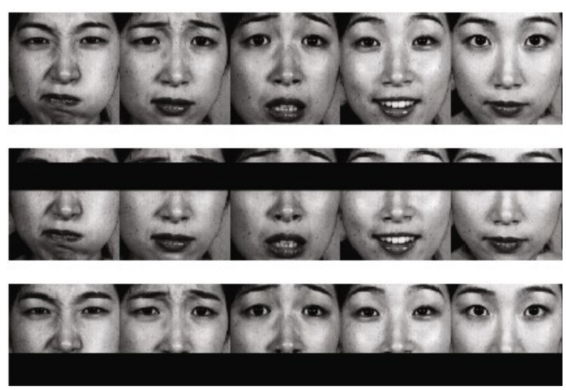

Figure 3: Top row original images, middle row eye occlusion, bottom row mouth occlusion [9].

Maximum results were achieved using Eigenface method for feature extraction and nearest neighbor for emotion recognition. 76.22% accuracy was achieved for eye occlusion and 72.38% for mouth occluded images.

Azmi and Yegane [11] used LGBP features (combination of LBP and Gabor) to extract features

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from JAFEE database images (Figure 4). Nearest Neighbor (NN) algorithm is later utilized for the classification of the emotion.

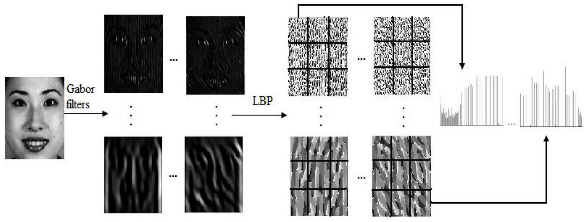

Figure 4: LGBP features extraction [11].

The result without occlusion shows a rate of 96.25% for recognition. With eye occlusion, the recognition rate is found to be 88.77%. For face recognition with mouth occlusion, the recognition rate is found to be 92.78%. Vyas and Hablani [12] have further experimented with JAFFE database images. They used uniform LBP for feature extraction from occluded images from JAFFE database. A LBP pattern is uniform, if the binary pattern contains at most two bitwise transitions from 0 to 1 or 1 to 0, if the pattern is read circularly. Selecting uniform patterns will reduce the length of LBP histogram and improves the classification.

In addition, this work examined the forehead and nose occlusion, which is also taken into consideration in this study (Figure 5).

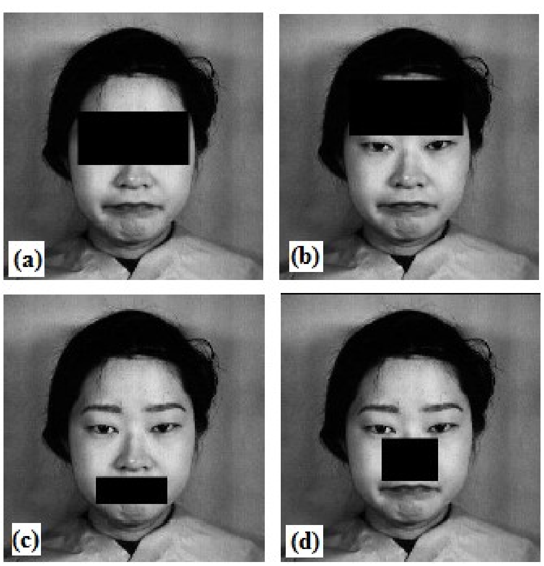

Figure 5: Different occlusion (a) eyes (b) forehead (c) mouth and (d) nose [12].

The result without occlusion shows 94.82% recognition rate. With forehead occlusion, the result is the same as no occlusion with 94.82% using this database. With eyes, nose and mouth in occlusion, the system achieved 93.10%, 91.37% and 89.67% recognition rate, respectively.

Nguyen and Ranganath [5] have worked on recognizing facial expressions in sign language. They used a Kanade-Lucas-Tomasi (KLT) point tracker to locate facial features in presence of occlusion (Figure 6). The likelihoods of facial feature movements were input to a neural network (NN) to identify four common sign language expressions, namely, Yes/no question (YN), Wh question (WH), Topic (TP), and Negation (NEG) (Figure 7).

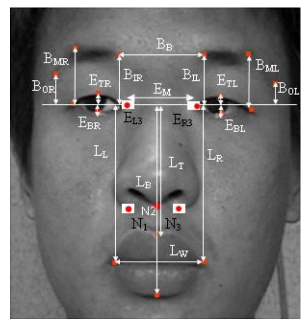

Figure 6: Facial features used to find sign language expressions [5].

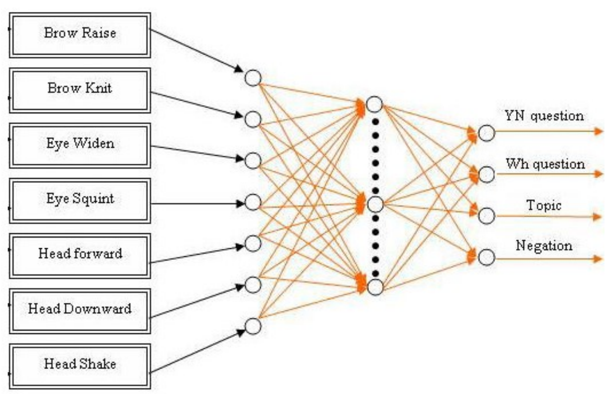

Figure 7: Neural network used for classification of four expressions [5].

The best results obtained using this method is 74% for the four expressions. The author claimed that this low rate, may be due to the fact that the video sequences represent natural signing where the different signers expressions did not follow main stream linguistic definition.

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3. PROPOSED SYSTEM DESCRIPTION

This paper presents an automatic real time facial expression recognition system which considers occlusion and head rotation. There are different steps for implementing this system. At first, facial landmarks are robustly identified on the face in presence of occlusion. Secondly, the 3D pose of the face is identified. Then the feature vector with geometrical and texture features of the face are identified. Finally, the emotion is identified using a backpropagation neural network. These steps are repeated for each new frame in the sequence.

The steps for this system are illustrated in Figure 8 at the end of the paper. The subsequent sections explain each step in detail.

3.1 Face landmarks detection

The first step for emotion recognition in each frame is face detection and facial landmarks localization. We use viola-jones trained cascades [13] for face detection in picture sequences. There are separate cascades for frontal and profile face in OpenCV. The HSV skin color detection is also used in case of false face detection[14].
Figure 9 shows the flowchart to detect different view faces on picture sequences.

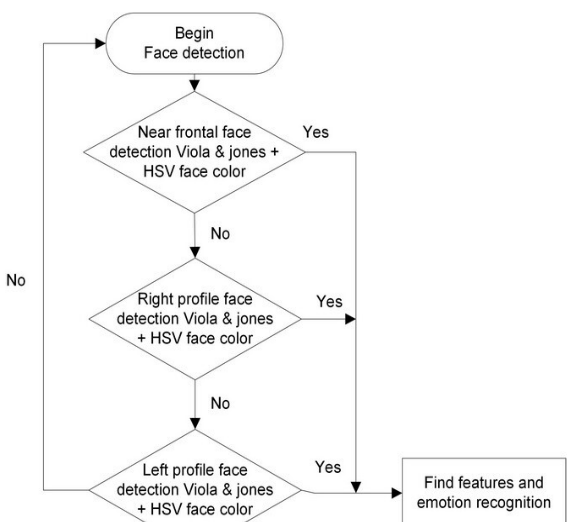

Figure 9: Face detection flowchart for multi view face detection.

In order to find geometrical features, it is necessary to locate facial landmarks. One approach is to use the separate detector for each facial area. This is done usually by training cascade classifiers using adaboost [13]. However, this approach fails to provide a robust estimation of landmarks locations. Moreover, this approach may result in having false detections.

This shortcoming 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. DPM considers facial landmarks as vertices in an acyclic graph. Moreover, the link between points is detected as edges of the graph, and the landmark positions are simultaneously estimated by employing a single scoring function [14].

Equation 2 shows the method for estimating positions of main facial points. The first term is local appearance model estimating the landmarks on position s and input image I. The second term is the deformation cost considering the relative positions of neighboring landmarks i and j (as shown in Figure 10).

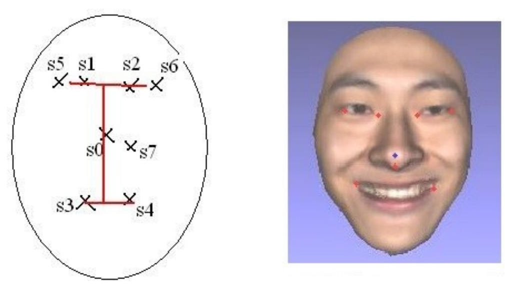

Figure 10: Main Facial feature points.

$$f(I,s)=\sum_{i=0}^{M-1} q_i(I,s_i)+\sum_{i=1}^{M-3} g_i(s_0,s_i)$$
$$+g_5(s_1,s_5)+g_6(s_2,s_6)+g_{67}(s_0,s_7) \qquad (2)$$

The multi scaled LBP is used for appearance model due to outperforming other algorithms [15]. The learning of model parameters is done by Labeled Faces in Wild (LFW) database [16].

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After finding fiducial facial points, more points are being located on face to be able to determine all geometrical features for the emotion recognition. 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 3.15).

For detecting these secondary points the seven main points were used together with Sobel edged face image (Figure 11). Simply the distance is traveled in vertical or sloped line until the next (thick enough) white or grey pixel group on the edged image.

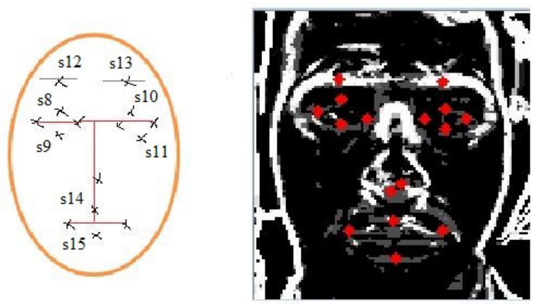

Figure 11: Added Facial feature points for eyebrow centers, upper and lower lip and upper and lower left eye, and upper and lower right eye.

The facial points graph can be changed for profile or side view face using the same method. Uřičář et al have extended the method for other face angles. Since we use face color detection to compensate or facial features loss due to face rotation, we only use profile face and frontal face models, and half profile face model is not used (refer to pose estimation section 3.2).

Figure 12 shows the facial points graph in side view faces. Only the underlined points are considered for feature extraction for emotion recognition. The points are double checked (similar to detecting secondary points in near frontal faces, Figure 11) with image processing method using edge detected and skin color images.

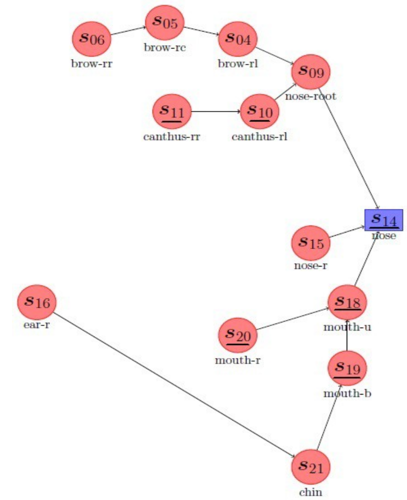

Figure 12: Facial feature points graph on profile face [17].

In case of occlusion, even with the presence of occluded parts of face the facial points are detected, however the locations of points maybe wrong, so we use an intelligent algorithm to use the other correctly found facial points to identify the emotion. Figure 13 shows face from BU3DFE database with occlusion in the forehead area. The occlusion in this area is created by superimposing a gray rectangle.

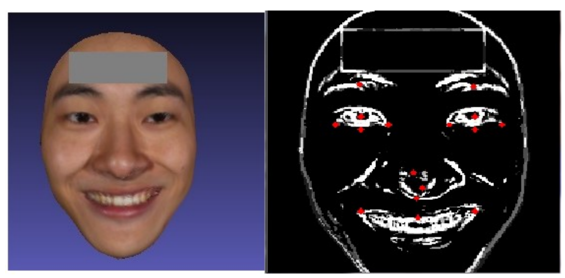

Figure 13: Face from BU3DFE database and the Facial feature points detected in presence of forehead occlusion

3.2 Pose estimation

For pose estimation problem a geometric approach is used. The pose information is used as features for emotion recognition. In the first step, the flowchart in Figure 9 is executed to find if the detected face is near-frontal or side view face. After this, the 7 facial feature points (Figure 10) are used to find the three rotation angles of head, yaw, pitch, and roll.

Equations 3 to 5 are used to determine the three face rotations.

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$$Yaw \propto \frac{(s_5(y)-s_1(y))}{(s_5(x)-s_1(x))} \quad (3)$$

$$Roll = Arc\tan(\frac{s_2(y)-s_1(y)}{s_2(x)-s_1(x)}) \quad (4)$$

$$Pitch \propto \frac{\mathrm{Dist}(s_1\ s_2)\ \mathrm{to}\ (s_7)}{FaceHeight} \quad (5)$$

Regarding yaw angles rotation, if the face is rotated much to the left or right corners, the corners of eyes are not visible and are detected wrongly. So we use skin color to move back the false detected points back to the face area (Figure 14).

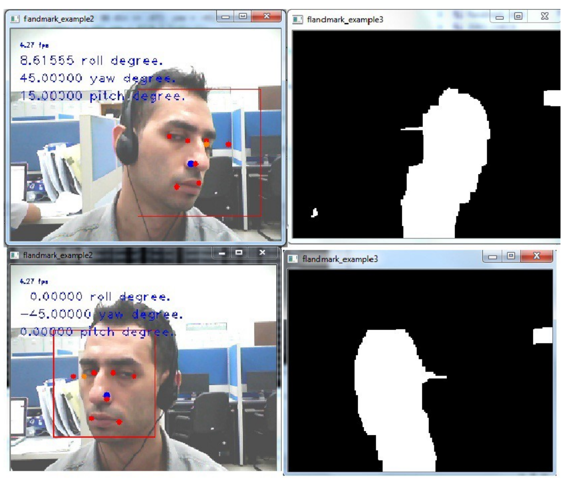

Figure 14: Landmark correction using face color for asserting the facial points fall within face boundary.

For details of pose estimation algorithm refer to the work by the author for face pose estimation [18].

3.3 Emotion recognition

Using the facial landmarks obtained in previous part, the geometrical and texture features are selected in order to find the emotion. Table 1 shows the geometrical features (distances and pixel values) used for emotion recognition.

Table 1: 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.
Distance eyebrow	Eyebrows distance from eye line.
Eye value	Value from the edged image showing how much eye is visible to determine eyelid is close or open.
Down mouth muscle	Value showing the below lip corner muscle.

The texture of skin also varies during different emotions. Regarding the texture values, The texture is obtained from important areas of the face using GLCM texture algorithm [19]. The GLCM features can be taken in a different direction. In this research, only the horizontal and vertical directions are chosen for GLCM, due to the fact that these directions cover all the variations of the skin. The four texture features of contrast, correlation, energy, and homogeneity were considered for features. Figure 15 displays the texture areas on the face that are considered for texture analysis.

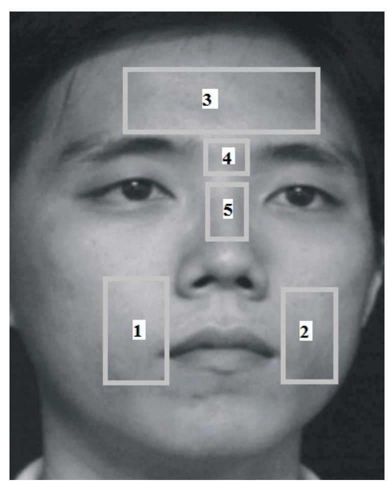

Figure 15: Areas on face used for texture analysis.

To test for redundancy [20], all the features are tested with MRmr (Maximum relevance minimum redundancy) algorithm. The forty texture features together with six geometrical features and three

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head pose features make a total of 49 features for emotion recognition. These features are given to a trained backpropagation neural network to find the emotions. Figure 16 shows the neural network architecture used for emotion recognition. The hidden layer neurons number is tested to have the lowest generalization error at 30 neurons.

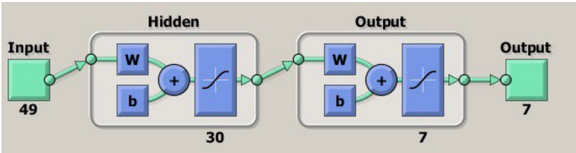

Figure 16: Neural Networks architecture for emotion recognition implemented in Matlab.

4. EXPERIMENTAL RESULTS

The experiments were conducted on BU3DFEE [6] and UPM3DFE [7] 3D databases. These databases are both standard database which contains male and female subjects from different racial backgrounds (White, middle eastern, Asian, Black, Indian and Latino). The neural network is trained with 70 subjects posing for 7 emotions. These subjects are divided with 70% for training data, 15% for validation data and 15% for testing. Two networks were trained for near frontal and multi view faces. Moreover, the results were analyzed for near frontal and multi view cases.

Firstly, the experiments are performed without any occlusion. Images are prepared as in Figure 17. Results for frontal and multi view are presented in Tables 2 and 3.

Table 2: Confusion matrix for near frontal and seven emotions.

	NE	HA	SA	DI	AN	SU	FE
NE	67.0	4.5	5.5	10	3.0	0.0	10
HA	2.0	83.5	0.0	5.5	0.0	0.0	9.0
SA	4.5	0.0	80.3	10.5	0.0	0.0	5.0
DI	0.0	2.0	3.7	83.3	11.0	0.0	0.0
AN	1.7	0.0	3.0	12.0	83.3	0.0	0.0
SU	0.0	13.4	5.0	0.0	0.0	66.6	15.0
FE	8.0	8.0	8.0	20.0	0.0	0.0	56.0

Table 3: Confusion matrix for mutil view and seven emotions.

	NE	HA	SA	DI	AN	SU	FE
NE	60.5	3.0	5.5	12.0	8.0	0.0	11.5
HA	6.0	75.0	7.0	9.5	5.0	0.0	2.0
SA	6.0	0.0	65.0	12.0	5.0	0.0	12.0
DI	5.0	2.0	3.0	75.0	15.0	0.0	0.0
AN	3.0	0.0	4.0	13.0	75.0	0.0	5.0
SU	0.0	12.0	7.0	0.0	0.0	65.0	16.0
FE	11.0	5.0	9.0	15.0	10.0	0.0	50.0

The results show 74.28% recognition rate for near frontal face and 67% for multi view faces in case of no occlusion.

After this, experiments are conducted on the face with eye occlusion. Both eyes are covered with two gray circles (Figure 18). As a result of using this method for eye occlusion, the eyes are covered with minimum face occlusion. Therefore the automatic face detection will work properly. Results for eye occlusion in case of frontal and multi view are presented in Tables 4 and 5.

Figure 17: An image from BU3DFE [6] with No Occlusion

Figure 18: An image from BU3DFE with eye Occlusion

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Table 4: Confusion matrix for near frontal with eye occlusion.

	NE	HA	SA	DI	AN	SU	FE
NE	65.0	4.5	7.5	10	3.0	0.0	10
HA	2.0	83.5	0.0	5.5	0.0	0.0	9.0
SA	14.5	0.0	70.3	10.5	0.0	0.0	5.0
DI	0.0	2.0	3.7	83.3	11.0	0.0	0.0
AN	1.7	0.0	3.0	12.0	83.3	0.0	0.0
SU	0.0	13.4	5.0	0.0	0.0	66.6	15.0
FE	8.0	8.0	8.0	20.0	0.0	0.0	56.0

Table 5: Confusion matrix for multi view with eye occlusion.

	NE	HA	SA	DI	AN	SU	FE
NE	60.5	3.0	5.5	12.0	8.0	0.0	11.5
HA	6.0	75.0	7.0	9.5	5.0	0.0	2.0
SA	16.0	0.0	55.0	12.0	5.0	0.0	12.0
DI	5.0	2.0	3.0	75.0	15.0	0.0	0.0
AN	3.0	0.0	4.0	13.0	75.0	0.0	5.0
SU	0.0	12.0	7.0	0.0	0.0	65.0	16.0
FE	11.0	5.0	9.0	15.0	10.0	0.0	50.0

The results show 72.6% recognition rate for near frontal face and 65% for multi view faces in case of eye occlusion. We find out that eyes play not very important rule in emotion recognition.

After this, the occlusion is done on the forehead. The forehead is covered with a gray rectangle (Figure 19). Results for forehead occlusion in case of frontal and multi view are presented in Tables 6 and 7.

Figure 19: An image from BU3DFE with forehead Occlusion

Table 6: Confusion matrix for near frontal with forehead occlusion.

	NE	HA	SA	DI	AN	SU	FE
NE	67.0	4.5	5.5	10	3.0	0.0	10
HA	2.0	83.5	0.0	5.5	0.0	0.0	9.0
SA	4.2	0.0	80.3	15.5	0.0	0.0	5.0
DI	0.0	2.0	3.7	83.3	11.0	0.0	0.0
AN	1.7	0.0	3.0	12.0	83.3	0.0	0.0
SU	0.0	6.8	5.0	0.0	0.0	60.0	15.0
FE	8.0	8.0	8.0	20.0	0.0	0.0	56.0

Table 7: Confusion matrix for multi view with forehead occlusion.

	NE	HA	SA	DI	AN	SU	FE
NE	60.5	3.0	5.5	12.0	8.0	0.0	11.5
HA	6.0	75.0	7.0	9.5	5.0	0.0	2.0
SA	6.0	0.0	65.0	12.0	5.0	0.0	12.0
DI	5.0	2.0	3.0	75.0	15.0	0.0	0.0
AN	3.0	0.0	4.0	13.0	75.0	0.0	5.0
SU	0.0	12.0	7.0	0.0	0.0	61.0	19.0
FE	11.0	5.0	9.0	15.0	10.0	0.0	50.0

The results show 71.62% recognition rate for near frontal face and 65.9% for multi view faces in case of forehead occlusion. This shows that forehead has little effect on emotion recognition and this occlusion mostly show itself on surprise emotion.

Finally, the occlusion is done on the mouth area. The forehead is covered with a gray rectangle (Figure 20). Results for mouth occlusion in case of frontal and multi view are presented in Tables 8 and 9.

Figure 20: An image from BU3DFE with mouth Occlusion.

Table 8: Confusion matrix for near frontal with mouth occlusion.

	NE	HA	SA	DI	AN	SU	FE
NE	67.0	4.5	5.5	10	3.0	0.0	10
HA	3.0	70.0	7.0	5.5	5.0	0.0	9.0
SA	9.2	0.0	66.0	15.5	4.0	0.0	10.0
DI	0.0	2.0	3.7	80.0	11.0	0.0	3.3
AN	1.7	0.0	3.0	12.0	83.3	0.0	0.0
SU	0.0	13.4	5.0	0.0	0.0	66.6	15.0
FE	8.0	8.0	8.0	20.0	0.0	0.0	56.0

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Table 9: Confusion matrix for multi view with mouth occlusion.

	NE	HA	SA	DI	AN	SU	FE
NE	60.5	3.0	5.5	12.0	8.0	0.0	11.5
HA	16.0	55.0	12.0	9.5	10.0	0.0	2.0
SA	6.0	5.0	55.0	12.0	10.0	0.0	12.0
DI	5.0	2.0	3.0	75.0	15.0	0.0	0.0
AN	3.0	0.0	4.0	13.0	75.0	0.0	5.0
SU	0.0	12.0	7.0	0.0	0.0	65.0	16.0
FE	11.0	5.0	9.0	15.0	10.0	0.0	50.0

The results show 69.8% recognition rate for near frontal face and 62.2% for multi view faces in case of mouth occlusion. We find out that mouth plays a significant rule in emotion recognition.

4. CONCLUSIONS

In this paper, a method for recognizing emotions in real time has been presented. The method extracts geometrical and texture features from special areas of face automatically, and we are able to effectively to find the emotion. We have tested our method experimentally both on frontal and multi view faces using standard BU3DFE and UPM3DFE databases.

Experimental results show that the method is able to find the emotion from occluded faces with high recognition rate, and the results have improved the existing methods in finding emotion on the multi view faces in case of occlusion.

We have achieved 72.6% recognition rate for near frontal faces and 65% for multi view faces in case of eye occlusion, and 71.6% recognition rate for near frontal faces and 65.9% for multi view faces in case of forehead occlusion. In case of mouth occlusion which plays a significant role in emotion detection, the high recognition rate of 69.8% for near frontal faces and 62.2% for multi view faces was achieved. The results manifest that the correct features were selected for finding emotions on the face.

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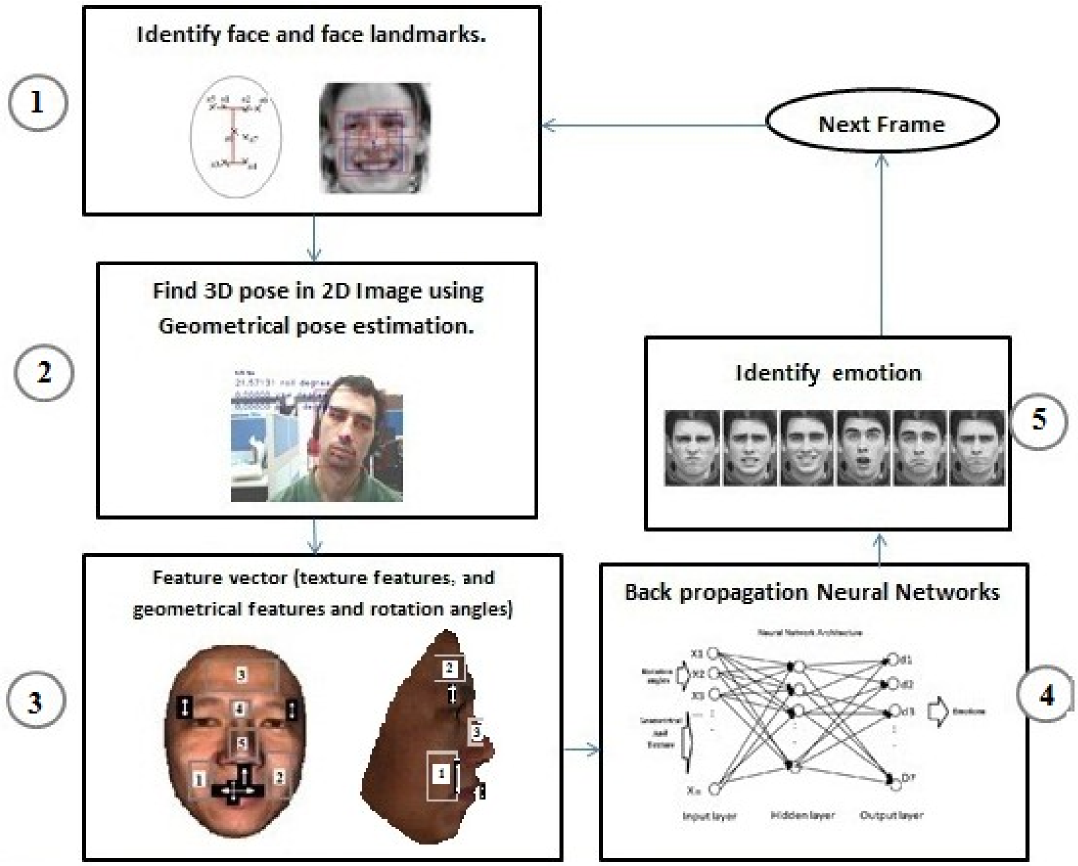

Figure 8: Real time emotion recognition system steps.