An Accurate Facial Expression Detector using Multi -Landmarks Selection and Local Transform Features

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Abstract— ***In the past few years, facial features detection and landmarks analysis plays a vital role in several practical application such as surveillance system, crime detector and age estimation. In this paper, we proposed a novel approach of recognizing facial expressions based on multi landmark detectors, local transform features and recognizer classifier. The proposed system is divided into four stages. (a) Face detection using skin color segmentation and ellipse fitting, (b) Plotting landmarks on facial features, (c) Feature extraction using euclidean distance, HOG and LBP. While, (d) SVM classification learner is used to classify six basic facial expressions like Neutral, Happy, Sad, Anger, Disgust, and Surprise. The proposed method is applied on two facial expression datasets i-e. MMI facial expressions dataset and Chicago Face dataset and achieved accuracy rates of 80.8% and 83.01%, respectively. The proposed system outperforms the state-of-the-art facial expression recognition system in terms of recognition accuracy. The proposed system should be applicable to different consumer application domains such as online business negotiations, consumer behavior analysis, E-learning environments, and virtual reality practices.***

Keywords—Face detection, landmark analysis, SVM classifier, facial expressions recognition

I. INTRODUCTION

Facial expressions are the dominating way of communicating with others. It has been narrated that true happiness is revealed by the eyes and lips and true sadness is revealed by the muscles of the chin. Over the past few decades, human facial expression recognition (FER) systems used advanced sensors [1,2] such as video cameras [36], eye trackers, thermal cameras, human vision component sensors[3,4], and stereo-cam[4] to intelligently recognize the human behaviors, gestures, emotions[1]. Existing methods of FER are generally categorized into 3 concepts: evoked-based FER systems, posed-based FER systems, and spontaneous-based FER systems. In evoked-based FER systems, person can artificially made different facial expressions detected by the systems. In posed-based FER systems, the candidates are asked to express each emotion intentionally resulting in more intense and less natural results. In spontaneous-based FER systems, participants' facial expressions are recorded secretly for recognition which are less intense and are unnatural [7]. Our proposed work lies in the concept of pose-based FER system. Highly encountered problems in facial expression recognition are pose variation, illumination condition, presence of hairs or glasses on face etc. Researchers are facing many challenges till now to overcome these problems.

Recently many researches have been carried out in facial expressions recognition. PCA and LDA [8] were used as a common tool for classification in expression recognition. In 2015, A.H Matamoros et al. [9] designed ROI segmentation and Gabor function to extract the features and recognize the facial expressions. Local fisher Discriminant analysis is used in Encrypted domain based facial expression recognition system which is proposed in [10]. In [11], Discriminative Filter based regression Method is used to classify the facial expressions. Recently, in [13], the author recognizes the emotions by the help of facial features movement. In [14], Facial expression recognition is done using PHOG and LPQ. Today both manual and automatic FER are prime focal areas for researchers. In manual FER, native coders examine the facial images and classify them by their own judgments concerning the state of expression. While, automatic FER evaluation relies on procedural techniques to extract features from images for facial expression detection. However, automatic FER is still a challenge and uses dynamic procedures to better understand facial expressions in both streaming and real time data [1]. This article is also focused on automatic FER.

This paper presents a novel method of detecting the face and plotting the landmarks on facial features like eye brows, eyes, nose, lips and chin to classify various facial expressions. The system successfully recognizes 6 basic facial expressions like Happy, Sad, Neutral, Disgust, Anger, and Surprise. In our proposed methodology, first, skin based facial detection is carried out using YCbCr color space and ellipse fitting is done to remove the neck area. Second, the landmarks are plotted on facial features like eye brows, eyes, nose, lips and chin by converting the RGB image to binary image and find the maximum connected components. The maximum connected regions found are bounded by a bounding box. Third, the feature extraction is carried out using HOG, LBP, and Euclidean distance. At last, training and testing is done using SVM classifier to predict the correct facial expressions.

The paper is organized as follows. Section II describes a novel proposed methodology used in our system to intelligently recognize the facial expressions. In Section III, performance

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evaluation is discussed in detail and Section IV discuss about conclusion.

II. SYSTEM METHODOLOGY

This section illustrates the phases involved in facial expression recognition in RGB images. The methodology consists of several steps depicted in Fig.1. The system architecture is mainly divided into four main steps. First, YCbCr color space and ellipse fitting is used to detect the face. Second, the face is cropped and landmarks are plotted on facial features by converting the cropped image into binary image and finding the maximum connected components on face. Third, the feature extraction is carried out using HOG, LBP, and Euclidean distance. At last, SVM classifier is applied to classify the six basic expressions.

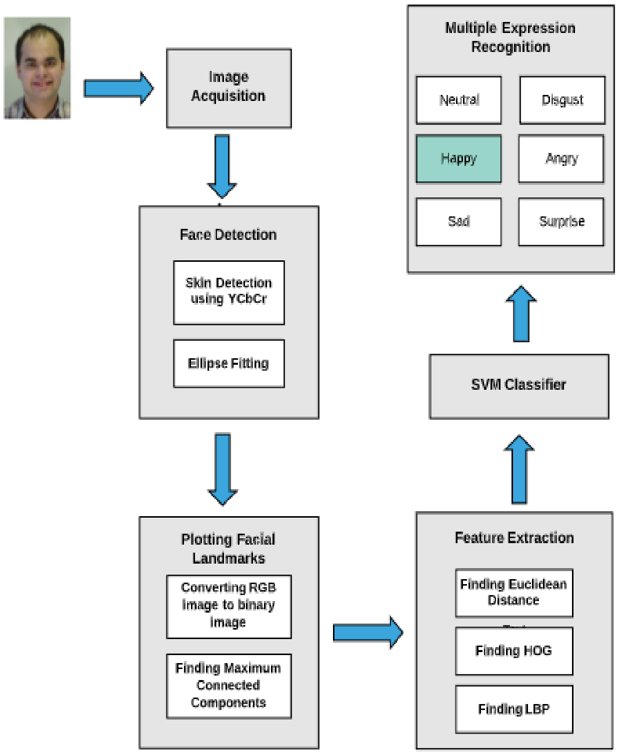


Fig. 1. System architecture of proposed FER

A. *Skin color segmentation and Face Detection*

Skin color base face detection is very popular nowadays in the field of computer vision. Many government organizations are using this technique for security purpose in order to track humans. Likewise, this technique is also used to detect faces by using some pixel color intensities. In this system, face can be detected using YCbCr color space. Since the skin color of the humans varies from person to person and the color of the skin cannot be distinguished in RGB color channels. Therefore, in order to detect the face parts in images, the RGB image is converted into YCbCr color space by empirically thresholding skin pixels [16]. It is concluded in various researches that YCbCr provides good coverage of different skin color types and distinguish easily between skin and non-skin pixels.

In YCbCr color space, the Cb ad Cr defines the chrominance components and are not affected by the illumination variation. In YCbCr, the chrominance components are represented by the values of Cb and Cr. Thus, skin color model is derived from these values.

After applying skin model, a bounding box is appeared on face to segment the skin pixels from non-skin pixels. Fig.2 shows the detection of face using YCbCr.

Fig. 2. Skin color model used for face detection using YCbCr

The problem arise in face detection is that bounding box appears on face as well as on neck because YCbCr is detecting the skin region. Therefore, in order to discard the neck part, geometric parameters are applied in order to detect the elliptical shape of face. The ellipse is determined by the mass center *(p, q),* orientation of face θ and length *a* and *b* of the minor and major axis. For each connected region *Z*, the calculation of an ellipse can be given by [13].

$$\overline{(p,q)} = \left(\frac{1}{A}\sum_{(p,q)\in Z} p_i, \frac{1}{A}\sum_{(p,q)\in Z} q_1\right) \tag{1}$$

$$\theta = \frac{1}{2}\arctan\frac{(2u_{1,1})}{(u_{2,0}-u_{0,2})} \tag{2}$$

where *A* is the area of connected area *Z*, after the ellipse is fitted. Some parameters of the shape of each connected region *Z* can be used to remove the components that are not the part of the face. The determination rule of ellipse are mentioned below [13]:

1) After the skin color segmentation, some holes are inevitably formed on face region. Only the region is considered having only one hole in it i-e h ≥ 1 can be identified as face.

2) The ratio of ellipse is set in a certain range **r** where 1 ≤ r ≤ 2. Fig. 3 shows the face detection after ellipse fitting.

Fig. 3. Ellipse fitting base on connected region for face detection.

B. *Image Binarization*

In image binarization, the RGB cropped facial region is converted into binary values. It replaces all the pixels in the input image having greater luminance with value 1(white) and other pixels are replaced by 0(black). A certain threshold is given when converted an RGB image to binary image so that that the 2 levels are allotted to pixels that are above and below of the given threshold. The binary images using Otsu thresholding are shown in Fig.4.

$$\sigma_B^2(k) = \frac{[\mu_T \omega(k) - \mu(k)]^2}{\omega(k)[1 - \omega(k)]} \tag{3}$$

where μ is the certain threshold value. Fig. 4 shows the binarization values of facial images.

Fig. 4. Binary images of cropped RGB face images

C. *Multi-landmarks Selection*

After the face has been detected and converted into binary image. The next step is to find the maximum connected components inside the face region in order to find the face features, i-e eyes, eyebrows, nose and mouth. The pixels that are mostly connected inside the face are the black areas and denoted by 0. The image is scanned from left to right finding the maximum number of connected pixels and is marked by a bounding box. As a result, 5 bounding boxes are obtained on each facial features in which two bounding boxes are on left and right eye brows, 2 are on left and right eyes and one bounding box is on lips. The next step is to plot the landmarks on facial features. For this, the midpoints of the edges of the bounding box are plotted. As a result, 4 points are obtained on each bounding box. Then, the mid-points between these 4 points on each bounding box are plotted. Meanwhile, a total of 8 points on each facial feature are retrieved.

Let *a, b, c,* and *d* are the edges of the bounding box, then the midpoint found of each edge is calculated as:

$$p_1 = \frac{a}{2}\ ;\ p_2 = \frac{b}{2};\ \ p_3 = \frac{c}{2}\ ;\ p_4 = \frac{d}{2} \tag{4}$$

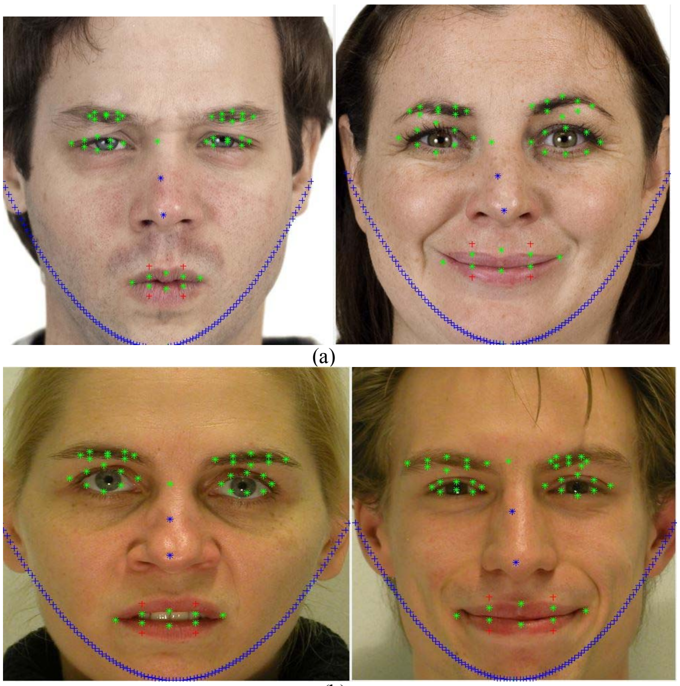
The midpoints between the above four points can be calculated as;

$$p_n = \frac{(p_i + p_j)}{2} \tag{5}$$

The nose is found by using the cascade algorithm. In order to localize the nose, first we find the midpoint of the bounding box appeared on nose using the Cascade algorithm. Then, midpoints between the extreme right point of the right eye and extreme left point of the left eye can be determined and plotted. At the end, midpoint between the nose tip and eyes point can be determined and plotted, so we can get a total of 3 landmarks on nose.

For lips landmarks, despite of the previous 8 landmarks additional 4 points are marked on upper and lower lips to recognize the movement of lips and classify the expressions based on lips movement.

The chin landmarks are plotted by detecting the skin range from face central point to left, right and center part of chin. The two landmarks are plotted on left and right side. Third point is plotted at chin by detecting the skin from face central point towards chin. Fig. 5 shows the overall landmarks positions of different facial datasets.



(a)

(b)

Fig. 5. Total landmarks plotted on faces of (a) Chicago Face Dataset and (b) MMI facial expressions dataset respectively

D. *Facial Features Extraction*

The extraction of facial features is a very important step in recognizing the facial expression. In this section, three methods are described such as Histogram Oriented Gradient (HOG), Local Binary Pattern (LBP) and Euclidean distance. It is calculated between the points plotted on facial features.

1) Histogram Oriented Gradient

Histogram Oriented Gradient (HOG) is a very popular method of extracting the features. Divide an image into small i-e 8x8 pixels cells and blocks of 4x4 cells. Each cell contains a fixed amount of gradient information. Normalize the obtained results using the block wise patterns and returns a descriptor of each cell [14]. Fig. 6 shows the extraction and plotting of HOG features.

2) Local Binary Pattern

Local Binary Pattern (LBP) is combined with Histogram Oriented Gradient (HOG) to improve the performance of feature extraction. It labels the image pixels by thresholding every neighbored pixel and convert it into binary [14].The average LBP calculated against each landmark is shown in Fig.6

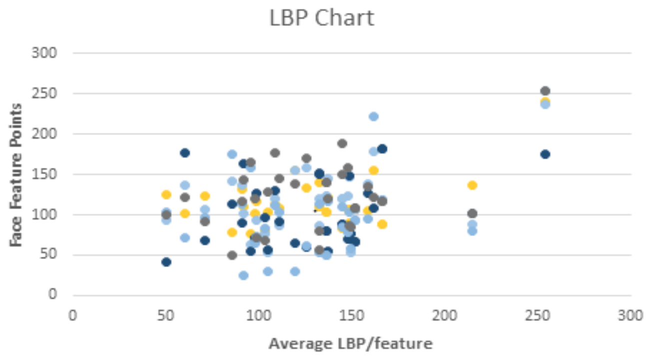


Fig. 6. LBP chart shows average calculated LBP against each landmark point.

3) *Euclidean Distance*

The Euclidean distance is the distance between two points calculated as;

$$d(a,b) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2} \qquad (6)$$

where a and b are the points whose Euclidean distance can be calculated and n is the number of points.

In this paper, the Euclidean distance is calculated among two point and the distance are saved in a metric. Similarly, the Euclidean distance is calculated between all landmarks and these points are used to extract the features. These points are further used in classification of facial expressions.

E. Facial Expression Classifier

Support Vector Machine is a discriminative classifier used in this paper to classify the six expressions [19]. It is a supervised machine learning algorithm that can solve linear problems. It uses a kernel trick to transform the data and creates a hyperplane which separates the data into classes. Fig. 7 shows the SVM model of our proposed system.

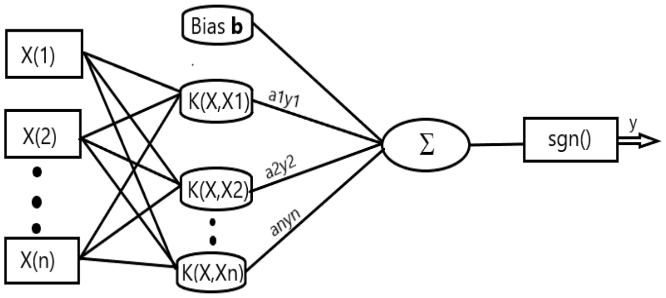


Fig.7. SVM model of proposed system

III. Performance Evaluation

In order to evaluate the performance, the system is trained, tested and validated on two publicly available datasets i-e Chicago Face Dataset and MMI facial expressions dataset. All these experiments are performed in Matlab 2017 using Intel Pentium Dual Core (2.5 GHz) with a RAM capacity of 8 GB. The experiments are performed on these datasets one by one and we calculated the mean accuracy rate of each dataset. Fig. 8(a) shows the Chicago Face Dataset images [39, 40, 41] and 8(b) shows the images of MMI Facial Expressions dataset.

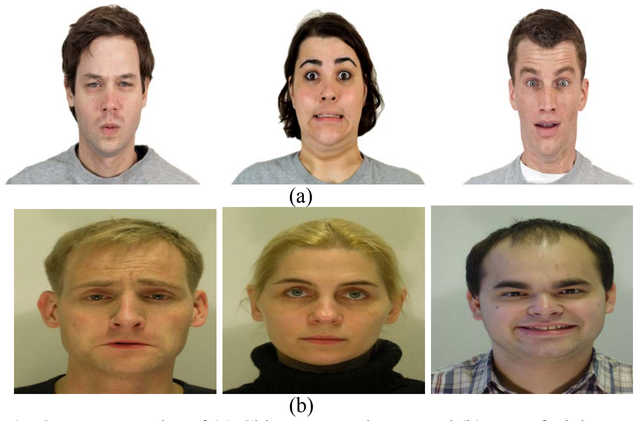


Fig. 8. Few examples of (a) Chicago Face dataset and (b) MMI facial expressions dataset.

A. Experimental Settings and Results

Table I and II show the experimental results obtained by using the Chicago Face Dataset and MMI face datasets. Both these datasets contain six basic expressions. Mean accuracy of Chicago Face dataset is 83.01% and accuracy achieved by MMI facial expressions dataset is 80.80%. Table III shows the comparison of different facial expressions recognition methods with the proposed method.

TABLE I. Mean Recognition Accuracy of Chicago Face Dataset

Expression	*Neutral*	*Happy*	*Sad*	*Angry*	*Disgust*	*Surprise*
Accuracy	89.4	88	80	72	73.3	95.4
Mean FER	**83.01%**					

TABLE II. Mean Recognition Accuracy Of MMI Facial Expressions Dataset.

Expression	*Neutral*	*Happy*	*Sad*	*Angry*	*Disgust*	*Surprise*
Accuracy	88.2	80	80	73.3	80	83.3
Mean FER	**80.80%**					

TABLE III. Comparison of different FER Methodologies with the Proposed System

Method	*Chicago Face Dataset*	*MMI facial expression dataset*
Deep Belief Network [15]	-	71.43
Score-Level Fusion [16]	-	68.35
Spatial CNN	-	60.45
Proposed approach	**83.01%**	**80.80%**

TABLE IV. Confusion Matrix of the Chicago Face Dataset

Expressions	**N**	**H**	**SD**	**A**	**D**	**SP**
N	**89.4**	4.8	3.3	1.6	0.9	0
H	6.4	**88**	1.3	2.7	1.2	0.4
SD	5.9	0.2	**80**	8.6	5.3	0
A	9.8	0	0	**72**	13.5	4.7
D	2.3	6.1	9.2	2.7	**73.3**	6.4
SP	0	0.5	0.1	1.5	2.5	**95.4**
Mean Recognition Rate = **83.01%**						

N=**Neutral; H**=Happy; **SD**=Sad; **A**=Angry;**D**=Disgust;**Sp**=Surprise

TABLE V. CONFUSION MATRIX OF THE MMI FACIAL EXPRESSIONS DATASET

Expressions	N	H	SD	A	D	SP
N	**88.2**	7.8	3.1	0.1	0.8	0
H	6.3	**80**	2.4	2.7	1.2	7.4
SD	5.6	2.1	**80**	8.5	3.8	0
A	9.8	0	3.2	**73.3**	7.5	6.2
D	2.3	1.1	9.2	0	**80**	7.4
SP	0	6.7	0	1.5	8.5	**83.3**
Mean Recognition Rate = **80.80%**						

IV. CONCLUSION

In this paper, we have introduced a novel method of recognizing the facial expressions by using the landmarks analysis. In our proposed methodology, face is detected using YCbCr color space and ellipse fitting. Multi-landmarks are plotted on facial features. After that features are extracted using HOG, LBP and Euclidean distance. At last SVM classifier is used to train and recognize the six basic expressions correctly. Our proposed system is tested on two publicly available dataset i-e CHICAGO face Dataset and MMI facial Expression dataset. We achieved an an accuracy of 83.01% and 80.80%, respectively.

In future, we will focus on classification of the other facial expressions in different face alignment and poses. We will also recognize expressions of multiple faces at a time.

ACKNOWLEDGMENT

This research was supported by Basic Science Research Progra m through the National Research Foundation of Korea (NRF) funded by Ministry of Education (No. 2018R1D1A1A0208564 5).

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