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Emotion recognition from geometric facial patterns

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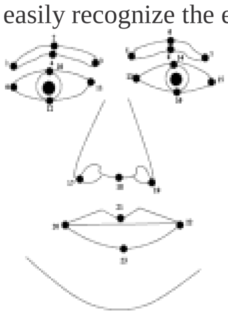
ABSTRACT
This paper presents emotion recognition model using the system identification principle. A comprehensive data driven model using an extended self-organizing map (SOM) has been developed whose input is a 26 dimensional facial geometric feature vector comprising eye, lip and eyebrow feature points. This paper thus includes an automated generation scheme of this geometric facial feature vector. MMI facial expression database is used to develop non-heuristic model. The emotion recognition accuracy of the proposed scheme has been compared with radial basis function network, and support vector machine based recognition schemes. The experimental result shows that the proposed model is very efficient in recognizing six basic emotions. It also shows that the average recognition rate of the proposed method is better than multi-class support vector machine. (SVM)
Keywords: Facial expression geometric facial features

I. INTRODUCTION

Generally on our daily life, communication plays important role. With the growing interest in human–computer interaction, automation of emotion recognition became an interesting area to work on. One kind of non verbal communication is Facial Expression. These are used for recognizing one's emotion, intentions and opinion about each other. Basically when people are communicating, 55% of the message is conveyed through facial expression, vocal cues provide 38% and the remaining 7% is via verbal cues. Ekman and Friesen stated that there are six basic expressions; such as **happiness, sadness, disgust, anger, surprise and fear**. The Facial Action Coding System (FACS) is a human observer based system, developed to detect the changes in facial features or facial muscles movements using 44 anatomically based action units. Determining FACS from images is a very laborious work, and thus, during the last few decades a lot of attention is given towards automating it. Automatic analysis of facial features requires feature extraction from either static images or video sequences, which can either be further classified into different action units or can be applied directly to the classifiers to give the respective emotion.. Generally, two common types of features are used for facial expression recognition: 1) geometric features data 2) appearance features data. Geometric features include shape and position of the feature; whereas appearance based features consist of information about the wrinkles, bulges, furrows, etc. Micro-patterns in appearance provide information about the facial expressions. But one disadvantage of appearance based methods is that it is difficult to generalize appearance features across different persons. Although geometric based features are sensitive to noise and the tracking of those features is rather difficult, geometric features alone can provide sufficient information to have accurate facial expression recognition. Humans have a very extraordinary ability to recognize expressions. Even in cartoon image having only some contours, we can easily recognize the expression.



Geometric features	Number of features	Description
Eyebrow	4x2	Two extreme corners, upper and lower mid points
Eyes	4x2	Two extreme corners, upper and lower mid points
Nose	3	Two nostrils and nose tip
Lip	4	Two extreme corners, upper and lower mid points

Fig. 1 shows - Facial points of the frontal image.

Emotion - specified facial expression. 1. Disgust 2. Fear 3. Joy 4. Surprise 5. Sadness 6. Anger

This paper introduces a completely automatic method of facial expression recognition using geometric facial features alone. The features extracted from the region of the eyes, eyebrows, lips, etc. play a significant role in providing sufficient information to recognize the presence of any of those six basic expressions. All the feature parameters are calculated as the ratio of current values to those of the reference frame. This includes methodologies for detection of different facial features, such as eyebrow contours, state of eyes, lip contour and key point's detection for each of the features. We also introduce methodologies to make the features rotation and illumination invariant. In order to come up with very accurate facial expression recognition results, a good classifier is extremely desirable. Kohonen Self-Organizing Map (KSOM) method is to classify the features data into six basic facial expressions. KSOM has an ability to arrange the data in an order that maintains the topology of the input data. The features data are first clustered using KSOM, and then the cluster centers are used to train the data for recognition of the basic different emotions. To evaluate the performance of the proposed classification method, we compare the proposed method with three widely used classifiers: Radial Basis Function Network (RBFN), 3 Layered Multilayer Perceptron (MLP3) and Support Vector Machine (SVM).

The remaining part of the paper is consisting of segmentation and key features extraction techniques of the most important geometric features while other Section describes the architecture of SOM and the methodologies involved in applying 26 dimensional data to the SOM network for clustering the features data into basic six emotion zones. The section is followed by system identification using self-organizing map that creates a model by solving least square error of a supervised training system.

II. PROPOSED RELATED WORKS

Facial expression analysis classified into three basic stages: face detection, facial features extraction, and facial expression classification. For decades, researchers are working on human facial expression analysis and features extraction.

Substantial efforts were made during this period Major challenge was the automatic detection of facial features. Representation of visual information in order to reveal the subtle movement of facial muscles due to changes in expression is one of the vital issues. Several attempts were made to represent the visual informations accurately. Some of them are: optical flow analysis, local binary patterns, level set, active appearance model, geometric analysis of facial features. The major drawback with model based methods like AAMs and ASM is that they need prior information about the shape features. Generally, during the training phase of AAM and ASM, the shape features are marked manually. Moore et al. found appearance based features by dividing the face image into sub- blocks. They used LBPs and variations of LBPs as texture descriptors. Gu et al. used contours of the face and its components with a radial encoding strategy to recognize facial expansions. They applied self-organizing map (SOM) to check the homogeneity of the encoded contours

Many techniques have been proposed for classification of facial expressions, such as multilayer perceptron (MLP), radial basis function network (RBFN), support vector machine (SVM) and rule based classifiers.

III. AUTOMETED FACIAL FEATURES EXTRACTION

The most crucial aspect of automatic facial expression recognition is the accurate detection of the face and prominent facial features, such as eyes, nose, eyebrows and lips. There are total 23 facial points which can describe all six basic facial expressions in frontal face images. The 23 facial points are given in Fig. 1. We extract 26 dimensional geometric facial features using the concept of the analytical face model. The 26 dimensional geometric features are consisting of displacement of 8 eyebrow points, 4 lip points along x- and y-direction and projection ratios of two eyes. The displacement or movement of facial features is calculated using the neutral expression as reference where nose tip also plays the role in calculating the features displacement. All details are given in Lip mid-points and corner-points detection technique

3.1 FACE DETECTION

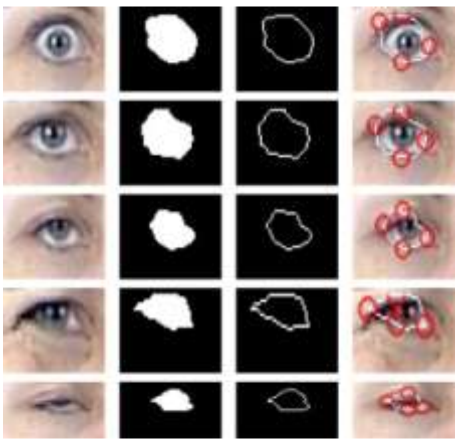
Face detection is one of the most complex and challenging problems in the field of computer vision, because of the large intra-class variations caused by the changes in facial appearance, pose, lighting, and expression. The first and most significant step of facial expression recognition is the automatic and accurate detection of the face. We use Paul Viola and Michael Jones' face detection algorithm to extract the face region. The face detection is 15 times quicker than any technique so far with 95% accuracy. They use simple rectangular features similar to Haar which are equivalent to intensity difference values and are quite easy to compute.

3.2 EYE DETECTION & EYE FEATURE EXTRACTION

Accurate detection of eyes is desirable since eyes' centers play a vital role in face alignment and location estimation of other facial features like lips, eyebrows, nose, etc. After the face is detected, we first estimate the expected region of eyes using facial geometry. In frontal face images the eyes are located in the upper part of the face. Removing the top 1/5th part of the face region we take the first 1/3rd vertical part as the expected region of eyes. We use Haar-like cascaded features and the Viola–Jones' object detection algorithm to detect the eyes.

The challenges in eye state detection is due to the presence of eyelashes, shadows between eyes and eyebrows, too little gap between eyes and eyebrows. Moreover, the eye corners are situated in the skin region and do not have any distinct gray scale characteristics. To overcome these problems, we propose an effective eye states' detection technique using horizontal and vertical projections applied over the threshold image of eye's non-skin region. It can be assumed that the extend of opening of the eye is directly proportional to the maximum horizontal projection. To threshold this transformed image, an adaptive thresholding algorithm is used, which is based on Niblack’s thresholding method, generally used for segmentation of images for optical character recognition. Threshold value given by Niblack’s method calculates the threshold value for every pixel using local mean and standard deviation. It yields effective results for document image segmentation but its performance is very poor in our case so slight modifications in algorithm gives good segmentation results.

Peer’s one of the simpler methods for skin classification is given below. It can be observed that the skin region is mainly dominated by the red color component compared to green and blue color. **Red, green and blue** components are extracted from the eye region. Since the red color component dominates the skin region, the normalized red component is obtained as follows. Normalization is necessary to eliminate the effect of brightness variation:



0.875

0.80

0.5714

0.3846

0.2857

Fig. 2. Examples of eye segmentation, key feature points detection and projection ratios.

Algorithm 1 – skin classification.

- (R; G; B) is classified as skin if R >95;
- and G>45 and B>20 and max(R; G; B) _ min(R; G; B)>15;
- and |R _ G| >15 and R >G and R>B.

Algorithm 2 - Eye feature point’s detection technique.

Using contour detection algorithm gathers all the contours from the threshold image.

- Retrieve the largest contour and save the contour 'data into an array.
- Find the two extreme x-coordinate values of the largest contour, i.e., largest and smallest x coordinate values. Get the corresponding y-coordinates. The obtained point as left and right extreme feature points.
- To detect upper and lower midpoints of eyes, get the expected x-coordinate as X =(X1+X2)/2, where X1, X2 are two extreme points. Then, find the nearest x-coordinate values to the expected x-coordinate value. Set a constraint within the search region for both x-direction and y-direction to keep the search within the ROI.
- Among the two points, consider the lower midpoint as the point with larger y-coordinate value and upper midpoint as the point with smaller y-coordinate value.

3.3 EYEBROW FEATURE EXTRACTION

It consists of: eyebrow location estimation, pseudo-hue plane extraction, segmentation, contour extraction and, finally, key points detection. The objective of this process is to obtain a set of key points which describes the characteristics of the eyebrow and can be further used to recognize facial expression.

Eyebrow location is estimated using basic facial geometry. As we are using frontal or nearly frontal face images, the eyebrow region will be found slightly above the eye region. Taking each eye region as a reference, we estimate the expected eyebrow region (which will take into account the possible movements of eyebrow in sequential frames). Height of the eyebrow ROI is estimated at 1.5 times the eye ROI height.

3.3.1 EYEBROW PSEUDO-HUE PLANE EXTRACTION

The new eyebrow segmentation method based on color is very significant method and improvement over other reported methods. It is well known that eyebrow hair consists of two types of pigments called eumelanin and pheomelanin. Pheomelanin is found to be there in all human beings and comprises red color information. We extract a pseudo-hue plane of the eyebrow region, based on this fact which tells us to expect that the eyebrow hairs have more of red color information than green. Fig. 4 shows an example of pseudo-hue images obtained after applying the algorithm. A clear distinction between eyebrow and non-eyebrow regions can be observed in the pseudo-hue images obtained.

a) b) c) d)

Fig.4. Eyebrow features' detection steps: a) the pseudo-hue image obtained from as till image, b) thresholded image of the plane, c) the largest eyebrow contour d) four key points extracted.

Algorithm 3 – extraction of pseudo-hue plane of eyebrow region.

- Get the eye brow ROI.
- Split the RGB image of eyebrow ROI into HSI component planes. Enhance the contrast of the region by applying histogram equalization over the intensity plane.Merge backs all the planes.
- Extract the red, green and blue components of the image obtained
- Obtain the Pseudo hue plane of eyebrow as h=r/g+b for all pixel where r,g,b are red,green,blue component of each pixel
- For an image of size MXN
- For i=0 to M-1
- For j=0 to N-1
- Nomalization and psedo hue plane is scaled to an 8 bit image representation by multiplying hnorm with 255
- End for

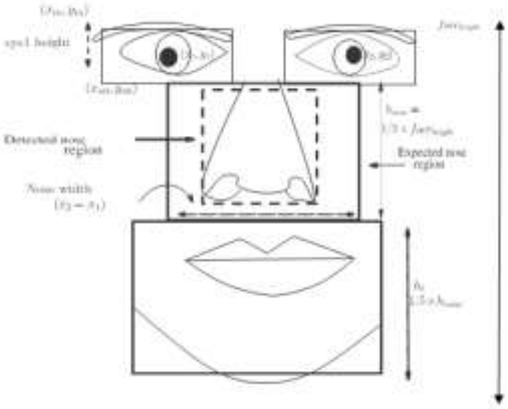


fig 5 Estimated location for nose and lip

3.3.2 EYEBROW SEGMENTATION, CONTOUR EXTRACTION AND KEY POINTS DETECTION

The pseudo-hue plane extracted in previous section shows a clear distinction between eyebrow and skin regions. The plane is normalized to eliminate the effect of intensity variation. The normalization method is explained in Algorithm. The adaptive thresholding algorithm is applied to the pseudo-hue plane. A window of size 7X7 is taken to calculate the threshold iteratively. The thresholding method uses summation of global mean and constant k time's local standard deviation to calculate the threshold. k is chosen as 0.5.

Morphological operations, erosion followed by dilation are applied on the threshold image for 2–3 iterations to remove classification-induced near the eye region and boundary region. A contour detection method is used on the thresholded image to extract all the contours within the eyebrow region. The eyebrow feature points are detected by a process similar to the one described in eye detection. Fig. 4 shows an example of the eyebrow pseudo-hue plane, threshold image of the plane, contour extracted from the threshold image and four key points extracted from the largest contour.

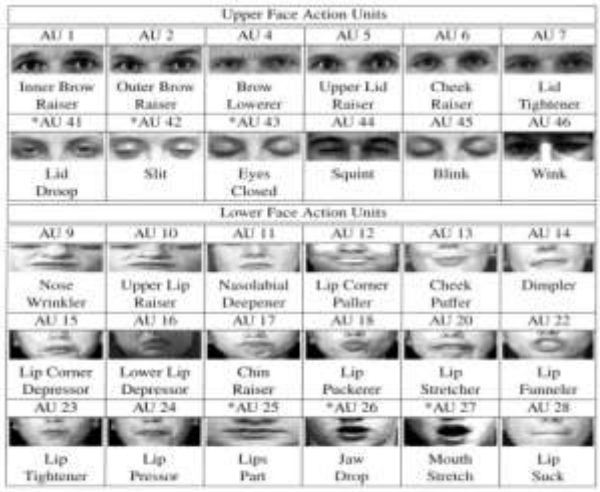
3.4 NOSE FEATURES DETECTION

For a frontal face image, the nose lies below the eyes. Fig. 5 shows a pictorial description of its approximate nose position. Using this information of facial geometry, we estimate the nose position.

It is observed; generally the nostrils are relatively darker than the surrounding nose regions even under a wide range of lighting conditions. We apply a simple thresholding method on the gray image of nose ROI followed by conventional morphological operations that remove noises and thus, have a clear distinction between two nostrils. The contour detection method is applied to locate two nostrils contours. The centers of these two contours are considered as the two nostrils.

3.5 LIP FEATURES EXTRACTION

A color based transformation method is used to extract lip from the expected region.The method was originally proposed by Hulbert and Poggio to the presence of hair and eye lids near the boundary region A contour detection method is used on the thresholded image to extract all the contours within the eyebrow region. Fig. 4 shows an example of the eyebrow pseudo-hue plane, threshold image of the plane, contour extracted the lip segmentation result obtained after applying the equation gives a clear distinction between red and green components within lip region and non-lip region. The obtained transformed plane is normalized to make it robust to change in intensity.



Algorithm 4 : Steps to estimate lip region.

- Get the eye centers (x1; y1) and (x2; y2) after detecting face and eye using Haar-like cascaded features.
- Detect nose using Haar-like cascaded features within the estimated nose region. Denote the height of the nose as n height.
- Estimate mouth region as follows:
- The mouth rectangular region can be given as Rect(xl ; yl ; hl ; wl), where xl and yl are the x and y coordinates of left upper corner point, hl is the height and wl is the width of the rectangle.
- hl is taken as 1.5 times to that of the height of the nose nheight taking into consideration that the expected lip movements will be covered within the region.
- Width wl is taken as (x2- x1) i.e., distance between two eye's centers along x-axis. The xl and wl are increased with certain values so that it will cover the area when the person smiles or for any kind of mouth expansion.

3.5.1 COMPARISON OF PROPOSED APPROACH WITH SNAKE ALGORITHM

The snake algorithm is a well established method. But in practice, it is very difficult to fine tune its parameters and as a result it often gets converged to a wrong lip contour. Preservation of the lip corners is also difficult with snake algorithm. Beyond all these drawbacks, use of snake algorithm needs proper initialization of the starting contour (i.e., an initial contour must be set closer to the actual lip shape which is in reality often unknown to us). Moreover, it is highly computationally expensive as it may need much iteration to actually converge to the lip contour. Fig. 6 shows an example of snake applied over a still image taken from the FEI database. The parameters are chosen as $\alpha = 0{:}01$, $\beta = 1{:}0$ and $\gamma = 0{:}1$ for both (a) and (c) with initial contours taken slightly different from each other. The results of the snake are shown in (c) and (d). The parameters are chosen after several trial and errors. The result shows how the accuracy of snake depends on the choice of initial contour. In the first row of Fig. 7 we show some of the snake results obtained after applying the snake algorithm on a video (taken from MMI database the white colored contour is the initial contour given to the snake algorithm and the yellow colored contour is the resultant lip contour. The second row of the figure shows the lip contour found by using our proposed lip contour detection algorithm.

The result shows the improved accuracy of our algorithm compared to the snake algorithm. The frames are given the same initial parameters (α=0:01, β=1:0 and γ=0:1) and with initial contours very close to the actual lip contour (shown by the white line). The yellow (darker) line shows the corresponding snake results obtained. The results could have been improved by changing the parameters, but in general, when we are tracking lip movements in a video clip, we cannot change the parameter, as the nature of the outcome is unknown to us in each video frame. With the use of our proposed lip contour detection method, such problems are entirely eliminated and we get reasonably accurate lip contours without depending on any kind of initial parameter inputs or contour initialization.

3.6 LIP MID POINTS AND CORNER POINTS DETECTION TECHNIQUES

Lip key-points, i.e., two lips corners and upper and lower mid points of the lip are extracted using a similar method to that used for eyebrow key point extraction .The displacement of each of the feature point wrt its location in neutral frame is considered as displacement data. These displacements data contains information about facial muscle movement which will turn indicate the facial movement. The extended KSOM uses this displacement data as input vector to train the N/W to classify different facial expression.

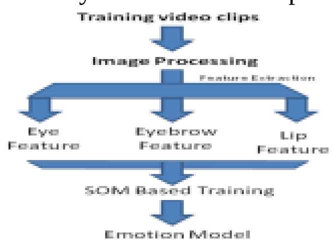


Fig. 8. System diagram of the proposed training approach

Calculation of displacement data at each feature point

- A reference along y-axis taken as (x = (x1+x2)/2, y) to measure movement of eyebrow feature points along horizontal direction. Two references along x-axis are taken as y1 and y2 to measure vertical movement of left and right points respectively, where (x1; y1) and (x2 ; y2) are the two eye's centers.
- Horizontal distances of the neutral frame's eyebrow feature points are calculated from the references. (x browptx) and (browptx-x) for left eyebrow features and right eyebrow features respectively. Similarly, vertical distances are calculated as (y1- browpty) and (y2- browpty), where (browptx ; browpty) are coordinates of each eyebrow feature points.
- Using the similar method given in step 2 the horizontal (hdist) and vertical (Vdist) distances of feature points in subsequent frames are calculated. Finally, the relative displacements of the feature points are measured as the difference between neutral frame's distances to the successive frames' distance from the reference.
- The displacement data are multiplied with a scaling factor (x scale/y scale) where x scale is given as standard x-scale divided by distance between two eye's centers (xstandard/(x2-x1)). And y scale is given as (ystandard/(noseh)), where nose h is the height of the nose which is given as y-coordinate of nose tip subtracted from the average of two eye's y-coordinates. X standard and y standard are chosen as 72 and 46 respectively.
- Considering the nose tip as a reference point, the above procedure is followed to measure the displacement of lip feature points in both vertical and horizontal directions

IV. SOM BASED FACIAL EXPRESSION RECOGNITION

Kohonen self-organizing map (KSOM) has an extra ordinary capability of clustering the data in an order that maintains the topology of input data. Because of this property of KSOM, the features data of similar facial expressions (small changes in features) get clustered into closer zones. This in turn makes the classification much better. This property of KSOM motivates us to use it for classifying the features data into six basic expressions. From the ontological prospective, the emotion space may not be topologically related. But in feature space there might exist topological relationship. Our present experimental results suggest this. Fig. 8 shows the flow diagram of the proposed SOM based facial expression recognition system. The normalized feature vector X ∑R26 is used to train KSOM network for classifying data into six basic emotion classes. A pictorial description of KSOM is shown in Fig. 9. KSOM discretizes the input and output spaces into several small zones, which also creates a linear mapping between input and output space. Since we want the output space to be discrete in nature, a logistic sigmoid function has been introduced after network output. The output of sigmoid function is further thresholded to yield either_1 or1.Foragiveninputvector x, say if the desired output is for happiness data, we set the desired output as {1 _1 _1 _1 _1 _1}. It means, the first bits that represent shappiness is true and others are false.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section present result of feature detection and classification of facial expression into 6 basic emotion happiness (H), sadness (Sa), disgust (D), anger (A), surprise (Sur), fear (F) Some examples of the facial features detection results are displayed in Fig. 11.

VI. CONCLUSION

Recognition of facial action units and their combinations rather than more global and easily identified emotion-specified expressions.

- A completely automated system for facial geometric features detection and facial expression classification is proposed. We introduce different techniques to detect eyebrow features, nose features, state of eyes and lip features.
- The proposed eye state detection method gives a clear distinction between different state of eye opening.
- A new mechanism is introduced based on 2D KSOM network to recognize facial expression that uses only a 26 dimensional geometric feature vector, containing directional displacement information about each features point.

- The KSOM network parameters are updated simultaneously to train the model for six basic emotions as a function of 26 directional displacement data.

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