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A Human Facial Expression Recognition Model based on Eigen Face Approach

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Abstract

Emotion recognition through facial expression detection is one of the important fields of study for human-computer interaction. To detect a facial Expression one system need to come across various variability of human faces such as colour, posture, expression, orientation, etc. To detect the expression of a human face first it is required to detect the different facial features such as the movements of eye, nose, lips, etc. and then classify them comparing with trained data using a suitable classifier for expression recognition. In this research, a human facial expression recognition system is modelled using eigenface approach. The proposed method uses the HSV (Hue-Saturation-Value) colour model to detect the face in an image. PCA has been used for reducing the high dimensionality of the eigenspace and then by projecting the test image upon the eigenspace and calculating the Euclidean distance between the test image and mean of the eigenfaces of the training dataset the expressions are classified. A generic dataset is used for training purpose. The gray scale images of the face is used by the system to classify five basic emotions such as surprise, sorrow, fear, anger and happiness.

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Keywords: Facial expression recognition; Hue-Saturation-Value colour model; Principal Component Analysis; Eigenfaces; Euclidean Distance.

1. Introduction

A facial expression is one or more motions or positions of the muscles beneath the skin of the face. These movements

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are used to convey the emotional state of an individual to observers. Facial expressions are a form of nonverbal communication. Facial expression Human facial emotion recognition software if carefully equipped in an analysis centre, it can produce valuable outcomes. Recognition or emotion recognition is one of the new concept which is getting momentum in the field of research on intelligent systems.

Recognizing human emotion can have numerous applications in various contexts. While the most promising one is probably the man-machine interaction, patient monitoring, studying a suspect for anti-social motives etc. might be other useful areas for emotion recognition. With emotion recognition system the centre can analyse customer's reaction on seeing certain product or advertisement or upon receiving a particular piece of information or message. Based on the response whether they are happy or sad or disgusted, etc. the service centre can modify their approached.

In a generalized form of a facial expression recognition system, an input sensing device such as a webcam obtained the input image from a subject and then it communicates with the computer. After detection of the facial area, representative feature from the emotionally expressive face image are extracted, it is then pre-processed and a classifier is used to classify them into one of the emotion classes such as anger, fear, surprise, happy, neutral etc. There are several detection method as well as classifier algorithms that can be used in the detection and classification.

A dynamic model of emotions is presented in this research based on a comprehensive eigenspace based approach. Eigen space is a feature space that best encodes the variation in the eigenfaces. The eigenfaces may be thought of as a set of feature space which characterize the overall variations among face images. The rest of the paper is organized as follows. Section II describes the emotion taxonomy of various emotions. In section III the related work on emotion recognition is discussed. Section IV describes the system overview and implementation of the proposed approach. In section V we describe the results followed by conclusion and future work in section VI.

2. Emotion Taxonomy

Emotion theorists and psychologists have defined several models for emotion classification ranging from universally displayed basic emotions to culturally specific complex ones. Out of the various models in emotion research, there are two that have dominated facial expression research: Ekman's basic set of emotions[11], and Russell's circumflex model of affect[12].

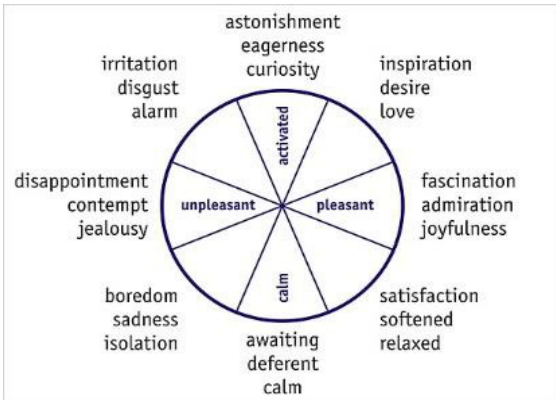

Fig. 1. The Circumflex Model of Russell

Ekman and Freisen in 1971[11] proposed six prototypical (basic) emotions - anger, disgust, fear, joy, sadness, and surprise - which are displayed universally among human beings and are recognized from human facial expressions. The universality of these basic emotions, having its roots in the universality thesis proposed by Charles Darwin, was further supported by the cross-cultural studies in[9]. This categorical description has gain popularity and possesses an advantage from the fact that facial expressions pertaining to basic emotions are easily recognized and described by humans. This model of emotion subspace has become the most prevalent model for measuring emotion, and the facial expressions associated with these basic emotions have dominated the studies related to facial expression recognition over the last four decades. An alternative description model of human emotion was proposed by Russel[12] where emotional states are represented by circle as in two dimensional bipolar space (Pleasantness-unpleasantness, arousal-sleep) rather than specific discrete categories. For example anger might be perceive as conveyance of extreme displeasure and moderately high arousal.

3. Related work on Emotion Recognition

Although there is a vast literature on emotion recognition, it is still now considered a complex problem for the following reasons. First, the level of ambience of individuals differs significantly. Further, a subject experiencing similar emotions at different time is often found to have significant differences in his/her external manifestations of emotions. Naturally, identification of one's correct emotional state from the measurements of the physiological conditions is also difficult. More subjects excited with stimulus responsible for arousal of a specific emotion, have a manifestation for mixed emotions. Emotion recognition becomes more complex, when subjects arouse mixed emotions. Among interesting works on emotion recognition, the work by Ekman and Friesen[8] needs special mention. They forwarded a scheme for recognition of facial expression from different regions of face, e.g. cheek, chin, and wrinkles. It reports a direct correlation of facial expression with the eyes, the eye-brows, and the mouth. Pushpaja V. Saudagare and D.S Chaudhari[4] came forward with a technique to detect expression from emotions through neural networks. It reviews the various techniques of expression detection using MATLAB (neural network toolbox). Hamit Soyel and Hasan Demiral[5] also implemented the techniques of facial expression detection using 3D facial feature distances. They detected basic emotions such as anger, sadness, surprise, joy, disgust, fear and neutral which are successfully recognized with an average rate of 91.3%.Andrew Ryan[13] and six more scientists also came up and developed an Automated Facial Expression Recognition System (AFERS) which is basically used to detect the presence of deception during the interview process. Mandeep Kaur, Rajeev Vashisht and Nirvair Neeru[7] developed a facial expression recognition system using Pricipal Component Analysis and Singular Value Decomposition techniques. Muid Mufti and Assia Khanam[10] developed a fuzzy rule based emotion recognition technique using facial expression recognition. In[1] Local Binary Pattern has been extracted from static images to classify facial expression using PCA. In[2], based on the reconstruction error after the projection of each still image into orthogonal basis directions of different expression subspaces, the facial expression is recognized.

4. System Overview and Implementation

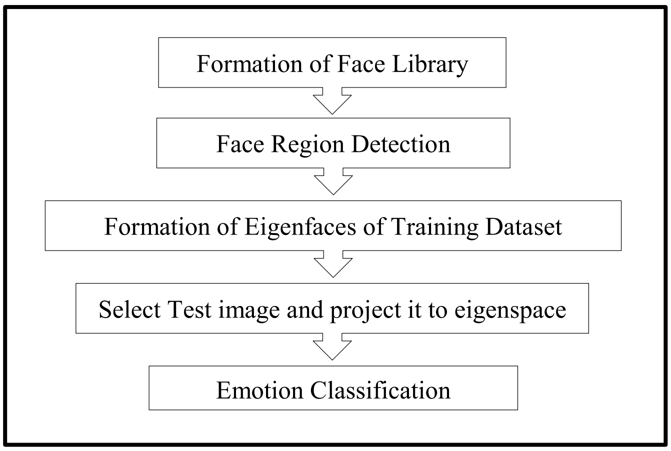

Fig. 2. Proposed Methodology

4.1. Face Detection

The first objective of the system is to detect the face region for which we have used the HSV (Hue-Saturation-Value) color model to extract the skin region of the persons image and then segmented the face region from it by elimination the unnecessary parts of the skin region and further converting the face region to gray scale image for further processing. The skin region detection is performed on the HSV (Hue-Saturation-Value) color model. Two parameters, namely x and y are identified[3] based on the following formula (1) and (2).

$$x = 0.148 \times H - 0.291 \times S + 0.439 \times V + 128 \quad (1)$$

$$y = 0.439 \times H - 0.368 \times S - 0.071 \times V + 128 \quad (2)$$

For each pixel the computation is done based on the above equation. A pixel is said to be a skin pixel provided the values for parameters x, y and H of the pixel satisfies the following inequalities, which are $140 < y < 165$, $140 < x < 195$ and $0.02 < H < 0.1$.

As the skin region detection is based purely on the colour value matching, apart from the face and neck portion other parts of the body present in the image are also included in skin regions.

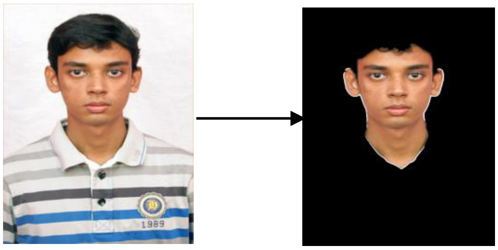

Fig. 3. Extraction of Skin Region

4.2. Segmentation of the face region

In order to filter out the unwanted skin regions, the column wise sum is obtained for all the columns. Then the non-zero-column-sum windows are marked by grouping the adjacent columns having non-zero column sum value. Similar operations are carried out row wise on the new image to find out the maximum row window (based on non-zero-row-sum values). In this way, the glitches and unnecessary skin patches are eliminated.

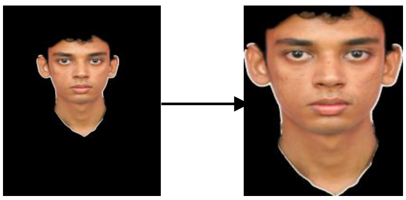

Fig. 4a. Segmented Face Region

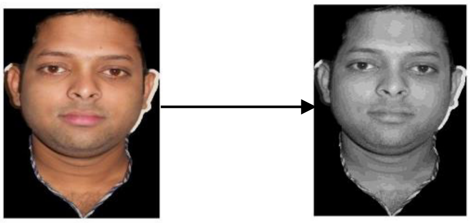

Fig. 4b. Conversion of Face Region to gray scale

4.3. Implementation of Principal Component Analysis

The principal components of certain distribution among faces are the eigenfaces. As we know, images are very high dimensional signal and dealing with eigen space of image vector dimension is a computationally expensive task. Thus, to reduce the dimension of data, PCA (Principal Component Analysis) is used taking in account the various dependencies present among the feature vectors. This is done to represent it in a form where much information is not lost. PCA helps to find K principal axes which capture most of the variance in data by defining an orthogonal co-ordinate system and K should be big enough to retain enough information to build the eigenspace. Then the approximation of each face image is done using a subset of the eigenfaces those having the largest eigen values.

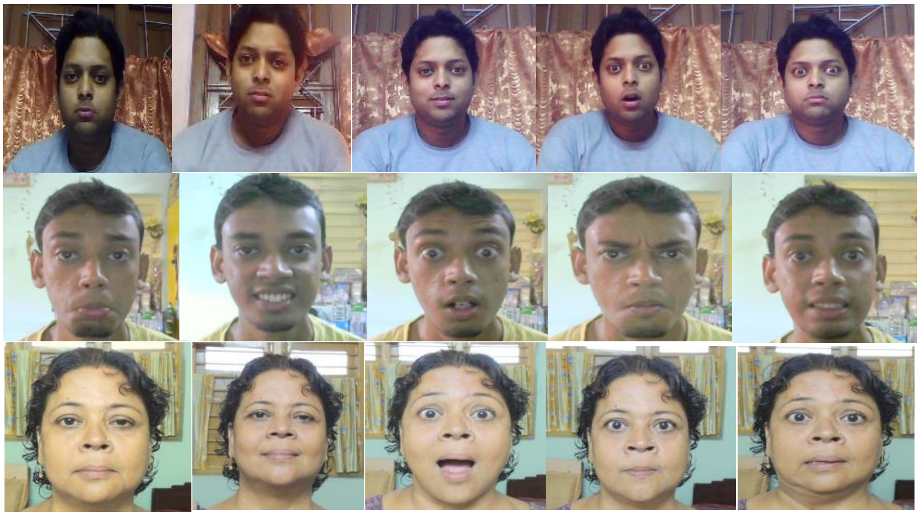

Fig. 5. A part of the training dataset

Therefore the sum of weights of eigenfaces represent the face. The PCA training is used to generate the eigen faces. A database is created for the eigenface formation which consists of 30 images of faces representing expressions such as surprise, anger, fear, sorrow and happiness. An $M \times N$ dimension space is created using the covariance matrix of these 30 images which later reduced to K dimension using PCA. Fig 4 represents 15 images from the training dataset of expressions. The procedure for training the expression dataset is as below:

Step 1: Every face image is being transformed to vectors of dimension ($h \times$ w, 1) where h and w are height and width respectively of the face image and value 1 represents a single face image.

Step 2: Computation of mean feature vector.

Step 3: Subtracting mean feature vector from each feature vector.

Step 4: The covariance matrix is estimated to find the eigen directions in order to find the eigenvectors.

Step 5: K eigen vectors representing the K largest eigen values from each class are chosen.

4.4. Projecting Test Image upon Eigenspace

Once the eigenfaces are acquired, a linear combination of these orthogonal images is considered to express the test image. Therefore a weight vector of K elements for each image is obtained using the equation (3).

$$\boldsymbol{W} = \gamma^{T} \times \boldsymbol{I} \tag{3}$$

where W is the weight matrix for each emotion to be identified, $\boldsymbol{\gamma}$ is the eigenface vector matrix and I is the test image vector. Dimension of $\boldsymbol{\gamma}$ is $hw \times 30$ where h represents height of eigenfaces, w represents width of eigenfaces, 30 is the number of eigenfaces. Dimension of I is $hw \times 1$ which results in vector length $K \times 1$ which is the test case weight[6] matrix.

Fig 6. Eigenfaces of a part of the training dataset

4.5. Emotion Classification

The final phase of the system is to classify the emotions of the person in one of the basic emotions such as Happiness, Sorrow, Fear, Surprise, etc. The classification of emotions is done in the following manner as discussed.

After the eigenface of the selected test image is obtained, its Euclidean distance is calculated with the mean of the eigenfaces of the training dataset. Then the Euclidean distance is compared with the eigenvalues of the eigenvectors i.e. the distances between the eigenfaces of the training dataset and their mean image. The training images corresponding to various distances from the mean image are labelled with expressions like happy, sorrow, fear, surprise and anger and when the Euclidean distance between the test image eigenface and mean image matches the distances of the mean image and training dataset's eigenfaces, the emotion is classified and named as per the labelled train images. The Equation to measure Euclidean distance between two points p and q in Euclidean n-space is given by equation (4).

$$\sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \tag{4}$$

The Euclidean distance of the input test image from the mean image is shown in Fig 7. The test image being selected here resembles maximum with the 25th image of the training dataset, so the Euclidean distance is minimum which corresponds to the 25th position in the *X*-axis in Fig 7 out of the 30 images of the training dataset.

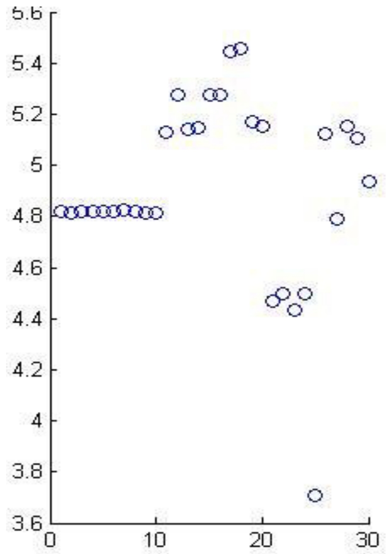

Fig. 7. Euclidean distance of the input test image

5. Results

The algorithm has been implemented and tested and it works well with emotions such as Surprise, Sorrow, Fear, Anger and Happiness. It is tested upon our self-made expression dataset and gives the result as shown in Table I. The result matrix is created based on the method we discussed earlier that the Euclidean distance between the test image and the mean of the training images is obtained and thereafter compared with the distances between the eigenfaces of the training dataset and their mean image. It is seen here that Happiness has the best recognition rate of 93.1 %, Surprise and Anger also has a very good recognition rate of 91% and 86.2% respectively and Sorrow and Fear has a fair recognition rate of 78.9% and 77.7% respectively and also Fear resembles sorrow and vice-versa by 15.4% which can be considered as a point of concern for the model and can be improvised by a much stronger training process.

Table 1. Result Matrix

Test Image	Surprise	Sorrow	Fear	Anger	Happiness
Surprise	91%	0%	1.2%	2.4%	5.3%
Sorrow	0%	78.9%	15.4%	5.7%	0%
Fear	1.2%	15.4%	77.7%	5.7%	0%
Anger	2.4%	5.7%	5.7%	86.2%	0%
Happiness	5.3%	0%	0%	1.6%	93.1%

6. Conclusion

Facial expression recognition is a challenging problem in the field of image analysis and computer vision that has received a great deal of attention over the last few years because of its many applications in various domains. This paper proposes a human facial expression recognition model based on eigenface approach in which the various emotions are recognized by calculating the Euclidean distance between the input test image and the mean of the eigenfaces of the training dataset. The training dataset consists of images of different people and when tested gives satisfactory results but there exists a resemblance between Sorrow and Fear to some extent which can be thought of as a future work and can be improved by more extensive training. The field of research in expression recognition is an area which can be further explored and improved.

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