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Facial expression recognition using Eigen face approach

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***Abstract*---**Emotion recognition via identification of face emotion is the primary areas of research between human and the machine communication. In order to identify facial emotion, one device must locate different variabilities of human face including color, stance, emotions, direction, and so on. Initially, the human facial expressions are recognized by the various features such as eye, nose, mouth, etc. must be detected and then classified using an appropriate expression recognition classifier compared to the qualified results. In this analysis a method of identification of human facial expression is modeled on its own hands. The approach proposed uses the color model HSV (Hue-Saturation-Value) to identify the facial image. Principal Component Analysis reduce the size of the space, later the test image is projected on the space. The Euclidean distance between the test image and the mean individual of the training data and categorized the phrases. For testing purposes, a standardized dataset is used. The device uses the gray representations of the face to categorize five simple emotions including surprise, sadness, anxiety, indignation and satisfaction.

***Keywords*---**facial expression, Eigen face, emotion recognition, hue saturation value.

Introduction

The Facial gestures are identified by the movement of the muscles and the texture of the skin. The movements are used to transmit an individual's emotional state to observers. Types of nonverbal contact are facial gestures. Expression of the face Human facial expression detection program will yield useful results, if

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carefully equipped in an examination center. Acknowledgement or emotional understanding is one of the latest concepts that are gaining ground in intelligent machine science. Human emotion detection may have various uses in diverse situations. Although the most promising is possibly human-machine contact, hospital observation, the prosecution of an anti-social suspect etc. may be other places helpful to emotionally remember. The emotional processing technology allows the center to analyze the response of customers when they see certain products or advertising or when they get certain details or message. The service center will change their response depend on the reaction.

The input is collected using the webcam in an image format and then processed by the machine for further analysis. After the facial region has been detected, representative elements are removed from the emotionally expressive face picture, pre-processed and classified to include them into one of the emotional groups, such as indignation, anxiety, surprise, happiness, neutrality and so on. Different detection techniques, as well as classifier algorithms, are available for detection and classification. In this study, a complex emotional model is provided focused on a systematic self-space methodology. Eigen space is a function space which codes the variation in the individual faces most effectively. The characterization of total variations of the face images can be seen as the collection of functional spaces. The remainder of the document is arranged accordingly. Section II describes the different kind of emotions. Section III discusses the associated with the emotional recognition. Section IV outlines the description of the framework and its execution. In Section V, we explain the findings and potential work in Section VI.

Emotion taxonomy

Emotional philosophers identified many emotional classification models varying from commonly shown simple emotions to culturally nuanced ones. Two types of emotional analysis many facial expression research: Ekman's simple emotional set [11] and Russell's circumflective affect model [12]. In 1971 [11], Ekman and Freisen suggested six prototypical (fundamental) emotions – wrath, disgust, terror, excitement, sadness and surprise – that are commonly expressed by humans and understood by human face expressions. The universality of these essential feelings, focused on Charles Darwin's universality thesis, was further confirmed by intercultural studies [9]. This categorical description is can in prominence and has the benefit of being readily understood and identified by men as facial expressions concerning fundamental emotions. In the past four decades, this emotional subspace paradigm has been the most predominant emotion measurement model, and experiments on facial expression perception have controlled the facial expressions correlated with these fundamental emotions. Russel [12] suggested an alternate classification paradigm of human emotion, where emotional conditions are described by circles as in bipolar double dimensional spaces, rather than by strict discreet categories. For eg, wrath may be seen as a transmission of intense displeasure and relatively high enthusiasm.

Related work

While there is a large literature on emotional recognition, for the following reasons it is still considered a complicated issue. First, the degree of atmosphere of people is substantially different. Furthermore, a topic with identical feelings also has considerable variations in the outward expressions of emotions at various times. Of course, it is often impossible to identify one's right emotional status from physiological tests. More subjects aroused by stimulus liable for the excitement of a certain emotion exhibit mixed emotions. When topics awaken mixed feelings, emotional recognition becomes more complicated. The study by Ekman and Friesen requires special mention among important studies on emotional recognition. They sent a scheme to recognize facial expression in various areas of the face such as jaw, chin and wrinkles. It reports a clear association between face expression and the eyes, eyebrows and lips. A technique was developed by Pushpaja V. Saudagare and D.S Chaudhari [4] to identify transmission of emotions via neural networks. It reviews different speech recognition techniques using MATLAB (neural network toolbox). HamitSoyel and HasanDemiral [5] have both used 3D facial distances to track facial speech. They detected simple emotions, such as frustration, sorrow, surprise, excitement, disgust, fear and neutrality, which are recognized effectively at an average 91.3% pace. Andrew Ryan [13] and six other scientists have also created an Automated Facial Expression Recognition System (AFERS), mostly used for detection of disappointment during the interview phase. Mandeep Kaur, Rajeev Vashisht, and NirvairNeeru [7] built a method for facial expression by using the techniques of Primary Component Analysis and Singular Meaning Decomposition. Muid Mufti and AssiaKhanam [10] have used facial recognition to create a fluid rule-based emotional recognition technique. In1 Local binary patterns from static photographs were derived for the classification of facial expression using PCA. In [2] the face expression is known based on the reconstruction error after the projection of each still picture into the orthogonal position of various subspaces.

System overview and implementation

Face detection

The first aim is to identify the facial region where HSV color model was used to remove skin region from the image of the individual and segment it then by eliminating unwanted regions like hair and transforming the face image for grayscale image. Skin part is detected by the HSV (Hue-Saturation-Value) color model. There are two arguments, namely x and y3 dependent on formula (1) and (2).

$$X=0.148xH-0.291xS+0.439xV+128 \quad (1)$$
$$Y=0.439xH-0.368xS-0.071xV+128 \quad (2)$$

The calculation is dependent on the above equation for each pixel. A pixel has been defined as a skin region given that the values for x and y parameters of a pixel satisfy $140 < y < 165$, $140 < x < 195$ and $0.02 < H < 0.1$. Since the detection of the skin is dependent exclusively on the corresponding color attribute, other body sections of the picture are often used in skin areas aside from the face and neck portions.

Segmentation

Unnecessary skin region are removed by the column wise total for the entire columns is obtained. The non-zero columns are identified by clustering the neighboring columns with a value of non-zero columns. The latest image is done in a similar manner to display the full row which depends on non-zero-row sum values. This eliminates bugs and unwanted skin spots.

Principal component analysis

Their own faces are the primary part of a facial detection. It is conscious that image are incredibly broad and that working with the picture vector dimension of its own space is a computationally costly activity. Therefore PCA (Principal Component Analysis) is used to minimize the data dimension taking into consideration the different dependencies that occur in the function vectors. This is required to reflect it in a way that does not lose any detail. It helps in identifying the K main axes that capture variations of data by specifying an orthogonal coordinate, and K is sufficiently huge to hold more details in order to construct the space. Each image is estimated from the subset of individual faces with the highest values of their own.

The number of the weights of the mask thus represents the facial image. The PCA preparation is used to create the facial image. For the creation of an individual, a database is developed consisting of 30 photographs of faces depicting the emotions like surprise, rage, terror, sorrow and happiness. The covariance matrix of these 30 images generates MxN dimension space that was reduced by PCA into k-dimension. 15 photos from the expressions training dataset. The protocol for the formation of the data collection is as follows:

- Phase 1: Each face image is converted into dimensional vectors (hxw, 1) where h is the height of image, w is the width of the face image and value 1 denote a single face image.
- Stage 2: Medium function vector computing.
- Step 3: Each vector is subtracted from the mean vector.
- Step 4: Its own path and its vector are calculated from the covariance matrix.
- Step 5: k own vectors are chosen to reflect the largest k own values in each class.

Projecting test image upon Eigenspace

The test picture is expressed by the linear mixture of these orthogonal pictures are obtained by the own faces. Equation (3) used to obtain the K elements weight vector for all individual image.

$$W=\gamma^{T}\text{xI} \quad (3)$$

Where W is the individual emotion weight matrix, Ț is the individual face vector matrix and I is the vector for testing images. T is the dimension of hwx30, where h reflects the heights of the props, w the width of the props, and 30 the number of props. I dimension is hwx1, resulting in the vector length K x 1 that is the weight matrix in the test case.

Emotion classification

The main goal of this work is to classify the people emotions into one of the essential emotions like pleasure, sadness, anxiety, surprise, etc. The Euclidean distance is determined from the average of the training dataset properties after the image has been chosen. And the distance between Euclides is related to its own values, i.e. the distances between the particular aspects of the training image data set and their image dataset. The difference in image distance are measured with different kinds of emotions such as happiness, grief, fear, surprise and anger in training period. Euclidean images and the average images matches the distances between the average images and training date set, the emotion is categorized and named according to the marked pictures. Equation for the calculation of euclidean distances of two points p and q in euclidean n-space (4).

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

The Euclidean distance from the mean image of the test images given as input. The training dataset matches the test image chosen, by calculating the Euclidean length of the training dataset is a minimum of the 25th place in the X-axis from the 30 pictures.

Result analysis

This work is analyzed for different kind of emotions like surprise, sadness, anxiety for validation. The algorithm has been validated and applied, and fits well for emotions like Surprise, Sadness, Anxiety, Rage and Satisfaction.

Table 1
Result Matrix represent the outcomes of the testing images represented in percentages

Test Image	Surprise	Sorrow	Fear	Anger	Happiness
Surprise	93	0	0	1.2	6.4
Sorrow	0	76.5	9.2	6.3	0
Fear	0	18.6	74.2	4.2	0
Anger	1.1	3.5	3.8	91.7	0
Happiness	7.5	0	0	0.77	94.2

The above table (table 1) represents the individual's happiness rates best at 94.2%, surprise at 93%, sorrow at 76.5%, fear at 74.2% and anger at 91.7%.

Conclusion

Detection of Facial expression is a complex challenge in the image processing area that gained much research in recent years because of its multiple uses within different fields. This paper proposed a model for the recognition of facial expression based on the Euclidean distance between the input image and the mean properties. The testing dataset contains photographs of numerous individuals and provides adequate outcomes when checked, but there is a resemble between sorrow and anxiety that can be used as a potential job and strengthened by many training dataset. In future, speech recognition can be processed to identify the emotions from the tone of their voices.

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