An Efficient Method for Automatic Emotion Detection from Facial Expression

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Abstract— The human face plays an important role for automatic recognition of emotion in the field of identification of human emotion and the interaction between human and computer for some real application like driver state surveillance, personalized learning, health monitoring, automatic music player, etc. In this article we have tried to design an automated framework for emotion detection using facial expression. Facial expression recognition system require to overcome the human face having multiple variability such as colour, orientation, expression, posture, texture and so on. Facial Expression Recognition is challenging problem up till now because of many reasons, moreover, it consists of three sub challenging tasks face detection, facial feature extraction and expression classification. PCA (Principal Component Analysis) analysis is used to detect the face from the captured image. Extended local binary pattern is used for feature extraction of the face. Emotion detection is done by calculating the Euclidian distance between the feature points. Emotions are classified into seven major categories viz. joy, sorrow, surprise, disgust, fear, anger, neutral.

Key words: Principal Component Analysis, Facial Expression, Extended Local Binary Pattern, Feature Extraction

I. INTRODUCTION

Facial expressions are one of the natural means to communicate the emotions and these emotions can be used in entertainment and Human Machine Interface (HMI) fields. The main objective of this work is to develop an intelligent system that can easily recognize the facial expression and accordingly perform the function of the system. The seven universally classified emotions are Happy, Sad, Anger, Disgust, Fear, Surprise and Neutral. Emotion recognition is useful to make smooth communication between human & computer interaction. The recognition of human emotion can have wide applications in heterogeneous field. "Your Face speaks louder than your voice", to support this sentence one communication research says that during face to face communication nonverbal communication have 55% impact on the message conveyed between two parties so analysis of facial expression and cognition is necessary for effective communication. Facial behaviour recognition is an application of computer vision that uses technology like image processing, and artificial intelligence, and expert knowledge of psychology. The algorithm that is used in developing the present system is Principal Component Analysis (PCA) which utilizes Eigen-faces to extract the facial features. The designed algorithm is very efficient due to less computational time taken hereby increasing the performance of the system. This work finds its applications in various domains like Human Computer Interaction (HCI).Spontaneous facial expression recognition is significantly more challenging than recognizing posed ones. In real time spontaneous facial expression recognition the main problem is that the geometric and appearance features of different expressions tend to overlap with each other. However, as new techniques are developed in the field of human computer interface, more research is necessary in order to find optimal algorithms with respect to automation, speed and accuracy. The first aim of this seminar is to incorporate anatomical grip for emotion recognition. Facial behaviour is represented using Facial Action Coding System (FACS). FACS couples the transient appearance changes with the action of muscles from anatomical perspective. FACS employs Action Units (AU) and AU represents the muscular activities to describe the facial expressions. Generally, a single muscle is invoked by most of the AU's. However, in some scenarios to express relatively autonomous activity of several segment of one specific muscle, two or more than two AUs are used. FACS has recovered overall 46 Action units which delivers a multifaceted procedure to express a large variety of facial behaviour.

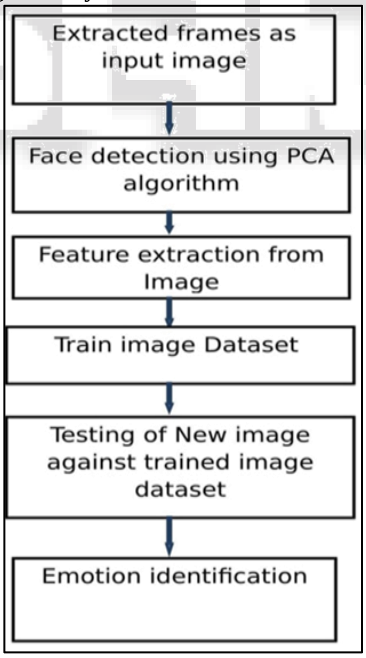

Fig 1

In rest of the section we have discussed the following- In Section II; we have tried to report and refer some of the influential work in the domain of emotional intelligence. In Section III, we have discussed about PCA analysis. In Section IV, we have described the use of Extended Local Binary Pattern for feature extraction. Section V focuses mainly on emotion detection using Euclidian distance. Finally Section VI and Section VII are the possible extension of our work and conclusion.

II. RELATED WORK

In emotional recognition of face, a notable advancement has been observed in the field of neuroscience, cognitive and computational intelligence. In general, emotion recognition is a two steps procedure which involves extraction of significant features and classification. Feature extraction determines a set of independent attributes, which together can portray an expression of facial emotion. For classification in emotion recognition the features are mapped into either of various emotion classes like anger, happy, sad, disgust, surprise, etc. For the effectiveness calculation of a facial expression identification model both the group of feature attributes which have been taken for feature extraction and the classifier that is responsible classification are equivalently significant. For a badly picked collection of feature attributes, in some cases, even a smart classification mechanism is not able to produce an ideal outcome.

Thus, for getting the high classification accuracy and qualitative outcome, picking of superior features will play a major role. Since last five decades, this model with six basic emotion has begun to be the most popular and usual model for estimating the emotions and detection of emotion from their respective facial expression. After certain time a different model of emotion was presented by Russell where emotional states are depicted by a ring having two pole in two dimensional space instead for categorizing each of the emotion distinctly. In this paper Principal Component Analysis (PCA) is used to detect emotion using facial expressions. Extended LBP is used for feature extraction and these features are used to classify and detect the emotions.

III. PRINCIPAL COMPONENT ANALYSIS (PCA)

Principal component analysis (PCA) is a statistical approach used for pattern recognition and signal processing to reduce the number of variables in face recognition technique. PCA technique has enormous potential as a feature extractor and is one of the approaches to improve the reliability of the recognition systems. By projecting the test image on the subspace spanned by the Eigen faces, the recognition of the facial expression is performed and then the further classification is carried out by a distance measure method known as Euclidean distance.

Following are the steps involved to recognize the facial expressions using PCA approach:

A. Prepare the Data

A 2-D facial image can be represented as a 1-D image by concatenating each of its row (or column) into a thin vector. A set of images with M vectors of size N is considered.
Training set of face images T1, T2, and T3 …TM-

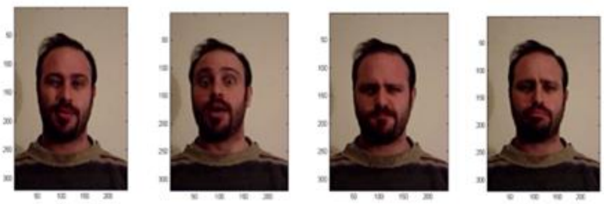

Fig. 2: Face Analysis

B. Subtract the Mean

The average grid is to be figured and subtracted from the first faces, and the result obtained is put away in a variable x

– Average Face of Image : $\Psi = 1/M * (\sum_{i=1}^{M} Ti)$; M – no. of images

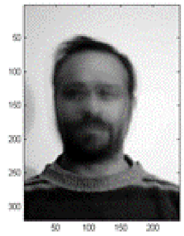

Fig. 3: Ψ average face

C. Calculate Eigen faces

$$\Phi i = Ti - \Psi$$

Calculate Eigen faces

D. Calculate the Co-Variance Matrix

After the above step, the covariance matrix of x is calculated.

E. Calculation of the Eigenvectors and Values of Covariance Matrix

Now, the eigenvectors and the subsequent eigenvalues of particular images are calculated

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = AA^T$$

Where A is,

$$A = [\Phi_1 \; \Phi_2 \; . \; . \; . \; \Phi_M].$$

λk Eigen value

$$\lambda_k = \frac{1}{M} \sum_{n=1}^{M} (\mathbf{u}_k^T \Phi_n)^2$$

C= λk Uk

F. Classifying the Faces

The new image is changed into its Eigen face segments. The weight vector is shaped from the subsequent weights. The distance between two weight vectors gives comparability measure between the consequent images i & j.

IV. EXTENDED LOCAL BINARY PATTERN

Local Binary Pattern (LBP) features have performed very well in various applications, including texture classification and segmentation, image retrieval and surface inspection. The original LBP operator labels the pixels of an image by thresholding the 3-by-3 neighbourhood of each pixel with the centre pixel value and considering the result as a binary number. The 256-bin histogram of the labels computed over an image can be used as a texture descriptor. Each bin of histogram (LBP code) can be regarded as a micro-texton. Local primitives which are codified by these bins include different types of curved edges, spots, flat areas, etc.

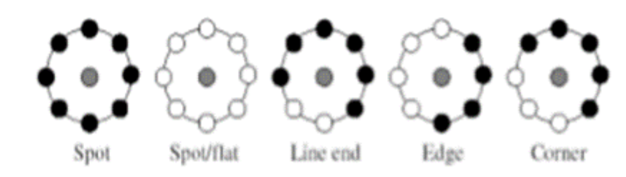

Fig. 4: Extended Local Binary Pattern

The LBP operator has been extended to consider different neighbour sizes. For example, the operator LBP4, 1 uses 4 neighbours while LBP16, 2 considers the 16 neighbours on a circle of radius 2. In general, the operator LBPP, R refers to a neighbourhood size of P equally spaced pixels on a circle of radius R that form a circularly symmetric neighbour set. LBPP, R produces 2P different output values, corresponding to the 2P different binary patterns that can be formed by the P pixels in the neighbour set. It has been shown that certain bins contain more information than others. Therefore, it is possible to use only a subset of the 2P LBPs to describe the textured images. Ojala et al. defined these fundamental patterns as those with a small number of bitwise transitions from 0 to 1 and vice versa. For example, 00000000 and 11111111 contain 0 transitions while 00000110 and 01111110 contain 2 transitions and so on. Accumulating the patterns which have more than 2 transitions into a single bin yields an LBP descriptor. The most important properties of LBP features are their tolerance against monotonic illumination changes and their computational simplicity.

A. LBP based facial representation

Each face image can be considered as a composition of micro-patterns which can be effectively detected by the LBP operator. Ahonen et al. introduced a LBP based face representation for face recognition. To consider the shape information of faces, they divided face images into M small non-overlapping regions R0, R1... RM (as shown in Figure 4). The LBP histograms extracted from each sub-region are then concatenated into a single, spatially enhanced feature histogram defined as:

$$H_{i,j} = \sum_{x,y} I(f_l(x,y) = i) I((x,y) \in R_j)$$

Where, i = 0... L-1, j = 0... M-1. The extracted feature histogram describes the local texture and global shape of face images.

V. EMOTION DETECTION USING EUCLIDIAN DISTANCE

Euclidean distance is used to calculate the distance between various feature points. If the features have n-dimensions then the generalized Euclidean distance formula between the feature points (x, y) is given by Euclidean Distance(x, y) =

$$\sqrt{(x1 - y1)2 + (x2 - y2)2 + \cdots \ldots + (xn - yn)2}$$

Using this we also calculate other distances between any features points.

Detection of emotions is based on the calculation of distances between various features points. In this step comparison between distances of testing image and neutral image is done and also it selects the best possible match of testing image from train folder. It also detects the emotions on the basis other distances calculated. And the final results are displayed.

VI. FUTURE WORKS

It will be very fascinating if we contemplate by considering both the auditory & visual information and some more attributes like EEG signal, facial colour etc. together, for processing with the expectation that this kind of multi-modal information processing will become a datum of information processing in future multimedia era. We can even improve the accuracy by taking the principal component of each individual portion of the face like eye, nose, lips, forehead, cheek, etc. and then compare with the experimented image. All current face recognition algorithms fail under the vastly varying conditions under which humans need to and are able to identify other people. Next generation person recognition systems will need to recognize people in real-time and in much less constrained situations. Because of the nature of the problem, not only computer science researchers are interested in it, but neuron scientists and psychologists also. Face recognition systems used today work very well under constrained conditions, although all systems work much better with frontal mug-shot images and constant lighting.

VII. CONCLUSION

Human emotions are expressed in many ways which are facial expressions, physiology, vocal and gesture, signal recognition, etc. In facial expressions, there are lots of methods that were considered. In this paper, a new LBP approach is introduced which extracts the feature from the face. First a sequence of pre- Processing tasks such as Principal Component Analysis is done. Then Euclidean distance between some landmark points on the face is calculated and those values are compared with those in the training data set to predict the emotion.

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