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Human facial emotion recognition using Harris point and Support vector machine

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Abstract

This paper presents a novel facial emotion recognition model using the system identification approach.The results showed that the ability to recognize facial emotion develops with expression, with a developmental course that depends on the emotion to be recognized. This paper includes an automated generation scheme of this geometric facial feature vector. This also include a method like single input and single output, by giving single image as an input we can obtained a result of its specific expression which is observed, we also able to observe the key point descriptor of all the images which were used in training in which the overlapping of their expressions are given. This paper gives the provision of using tested images as an input test image.

Keywords: Facial expression emotions, Human Facial emotion recognition, Harris point, LBP and SVM.

I. Introduction

Facial expression is an advantageous and essential method for human communications. The mental research led by Mehrabian [1], nonverbal part is the most instructive direct in social correspondence.Verbal part contributes about 7% of the message, vocal – 38% and facial expression about 55%. Humans demonstrate and convey a lot of evident information visually rather than verbally. So face is a subject of study in many areas of science such as psychology, behavioral science, medicine and finally computer science. Face recognition is a biometric approach that employs automated method to verify or recognize the identity of a living person based on his/her physiological characteristics. In this manner facial expressions will assume a key part in future Human-Machine Interface (HCI) and propelled communications. Facial expression has various characteristics such as multi-resolution; inter connection among components, vagueness and subjectivity. To think about these qualities, specialists have utilized a great deal of

classification strategies to perceive facial expressions [2-5].

In this work, we address an important domain of human computer interaction (HCI), which is effective visual facial expression recognition [1, 2]. Facial expression provides information about affective states, that is, emotion [3] and perception. Another domain of application is human interaction with computers in smart environments. Automated systems need to be capable of adapting to particular situations.

Generally, such systems include automatic facial feature extractors and change trackers. In the past, many facial expression analysis approaches have been pursued, which analyze still images and video sequences as well as two dimensional (2-D) and 3-D data. In general, both 3-D and temporal data are considered to contain valuable information about facial expression. Wang et al. [4] presented an approach to analyze the curvature of the facial shape. However, although 3-D shape information is very useful, in general, it can only be provided with special sensors. Valstar and Pantic [5] analyzed facial changes occurring because of expressions. For this purpose, they recognized facial muscle action units and analyzed their correspondence in the temporal domain. Kumano et al. [6] proposed pose invariant facial expression acknowledgment utilizing variable power layouts over the entire face. With respect to facial expression classification, the state-of the-art techniques are often limited to frontal poses and small variations in skin colour. Further, they are often sensitive to global motion with resulting perspective distortions. In order to deal with these issues, we propose an automatic, real-time capable method for facial expression recognition that achieves independence from the current pose. It should also be noted that varying face sizes can be handled, which may occur due to head movements and rotations.

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II. Literature survey

Processing of facial emotions emerges early (e.g., Barrera & Maurer, 1981; Walker- Andrews, 1997), but full proficiency seems not to be acquired before 10 years of age. In spite of the fact that preschoolers can name facial feelings at above possibility levels (e.g., Markham and Adams, 1992; Russell & Widen, 2002; Widen & Russell, 2003), they are substantially less accurate than adults. The purpose of our study was to provide new evidence on development change in recognition of facial emotions during childhood. Few studies have investigated the developmental course of facial emotion recognition, contrary to face recognition abilities, and the results are often inconsistent, mainly because of the great variety of methods used. A study by Bruce et al. (2000) recommended that advancement of facial feeling acknowledgment relies upon undertaking requests. When children needed to point to which of two faces was happy, sad, angry, or surprised, they achieved nearly perfect accuracy by 6 years of age. However, when they needed to select which of two emotional faces expressed the same emotion as a third face, a good accuracy level was not reached until 10 years of age. In a comparable report in which kids expected to coordinate an enthusiastic photo to one of four potential outcomes (unbiased, astonishment, joy, or disturb), Mondloch, Geldart, Maurer, and Le Grand (2003) reported an increase in accuracy between 6 and 8 years of age, when performance reached the adult level. In a study by Kolb, Wilson, and Taylor (1992), children and adults were shown a single emotional photograph or a cartoon depicting an emotional situation and then needed to select from a panel of six different emotional photographs (happiness, sadness, fear, anger, disgust, and surprise) the face that expressed the same or correct emotion. Recognition of facial feelings enhanced in the vicinity of 6 and 8 years and in the vicinity of 8 and 10 years old, contingent upon the errand, and enhanced again between age 14– 15 yearsof age and adulthood. There is also evidence that the developmental pattern is not uniform across emotions.

III. Methodology

Propose Facial Expression Recognition System

The proposed programmed facial expression recognition framework can consequently identify human faces, extricate facial features, and perceive facial expressions.The inputs to the proposed automatic facial expression recognition algorithm are a sequence of images since dynamic images can provide more information about facial expressions than a single static image.

3.1 Face Detection

The first step for facial expression recognition is to solve the face detection sub-problem. Face detection determines the locations and sizes of faces in an input image. Automatic human face detection is not a trivial task because face patterns can have significantly variable image appearances due to many factors such as hair styles, glasses, and races. In addition, the variations of face scales, shapes and poses of faces in images also hinder the success of automatic face detection systems. Several different approaches have been proposed to solve the problem of face detection.

Each approach has its own advantages and disadvantages. In this paper, we adopt the method proposed by Viola and Jones to detect faces from images [34]. This face detection method can minimize computational time while achieving high detection accuracy.

3.2. Facial Feature Extraction

After the face in the first image frame has been detected, the next step is to extract necessary information about the facial expression presented in the image sequence. Facial features can be categorized into many different classes. In general, there are two types of facial features can be extracted: geometrical features and appearance features. While the appearance features can be extracted on either the whole face or some specific regions via some kinds of filters geometrical features focus on the extraction of shapes furthermore, areas of in transient facial features (e.g., eyes, eyebrows, nose, and mouth). In our framework, geometrical features are separated for facial expression recognition.

The movements of the facial features such as eyebrows, eyes, and the mouth have a strong relation to the information about facial expressions; however, the reliable extraction of the extract locations of the intransient facial features sometimes is a very challenging task due to many disturbing factors (e.g., illumination factor, noise). Even if we can accurately locate the facial features, we still encounter another problem about the extraction of the motion information of the facial features.

One simple approach to solve the aforementioned two problems is to place a certain number of landmark points around the located facial feature regions and then use a tracking algorithm to track those landmark points to compute the displacement vectors of those points. However, this approach has to break some bottlenecks. The first bottleneck is that how and where to automatically locate the landmark points.

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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 identified, we first gauge the normal locale of eyes utilizing facial geometry. In frontal face images the eyes are located in the upper part of the face. Removing the top $1/5^{th}$ part of the face region we take the first 1/3rd vertical part as the expected region of eyes.

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).

3.4 Nose Features Detection

For a frontal face image, the nose lies below the eyes. 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 threshold image to extract all the contours within the eyebrow region.

3.6 Proposed approach

Here we propose the utilization of Harris corner detection to identify features, for example, the eyes in a face picture. The Harris corner detection method seeks to find points in an image that are corners by the definition that moving in any direction from that point should provide a gradient change. The approach is to use a sliding window to search for the corner points by examining gradient changes when sliding across that area.We utilize the way that the eyes in a face picture will be extremely non-uniform in respect to whatever remains of the face. There white portion of the human's eye is surrounded by skin that is darker, and the pupil and iris in the center of the eye is almost always darker as well. When viewing a face image with varying pixel intensities, some of the strongest corners are in the eye region.

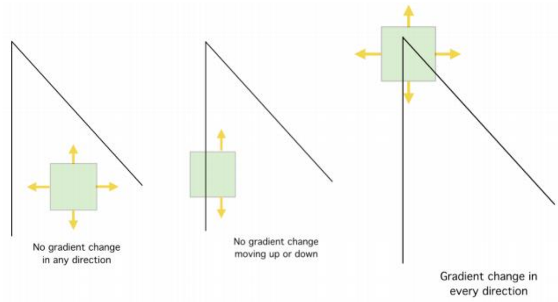

Figure 1: Framework of Harris point detector

In many texture analysis applications it is desirable to have features that are invariant or robust to rotations of the input image. As the LBPP,R patterns are obtained by circularly sampling around the center pixel, rotation of the input image has two effects: each local neighborhood is rotated into other pixel area, and inside every area, the inspecting focuses on the circle encompassing the middle point are turned into an alternate introduction.

Another extension to the original operator uses so called uniform patterns. For this, a consistency measure of a pattern is utilized: U ("pattern") is the quantity of bitwise transitions from 0 to 1 or the other way around when the bit pattern is considered circular.

A local binary pattern is called uniform if its uniformity measure is at most 2.

For instance, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform while the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are most certainly not. In uniform LBP mapping there is a separate output label for each uniform pattern and all the non-uniform patterns are assigned to a single label. Along these lines, the quantity of various yield marks for mapping for patterns of P bits is$P(P - 1) + 3$. For instance, the uniform mapping produces 59 output labels for neighborhoods of 8 sampling points, and 243 labels for neighborhoods of 16 sampling points.

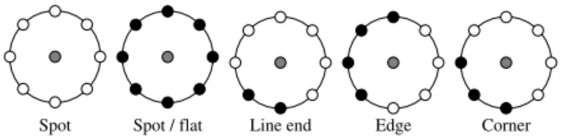

Figure 2: Different texture primitives detected by the LBP

During the training phase of machine learning algorithms, a model from the received input is build. And finally it provides a hypothesis function that can be used to predict result for the further input data. There has been an unexpected increment in the operation of SVM's for elite pattern arrangement.

IV. RESULTS

This section presents the results of features detection and classification of facial expressions intofive basic emotions Neutral (N), (happiness (H),Anxiety (A), disgust (D), fear(F)) demonstrating the accuracy of the proposed methodologies. In our experiments, we used 15different images. The directional displacement along x- and y-coordinate of each facial point is used as input feature for training the SVM. First the SVM is classifyingto ordered zones. The performance of the detection results is evaluated by comparing them against the ground truth (marked feature points).

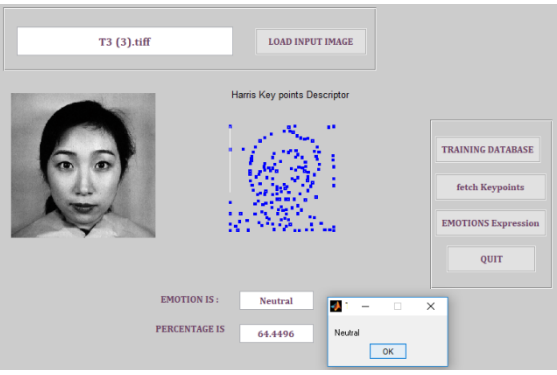

Figure 3: Neutral human face expression

We have obtainedspecific progressing experimentations for classifying emotional facial gestures using still images. We have used SVM classifiers. Its test results have verified to be acceptable.

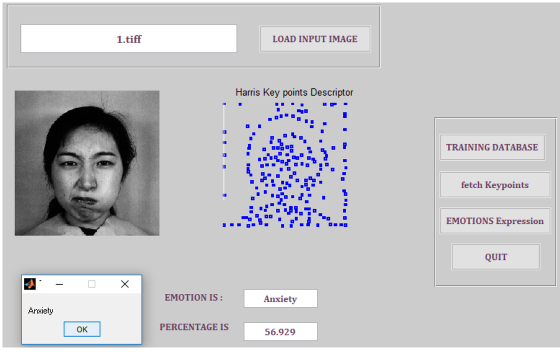

Figure 4: Anxiety human face expression

We have worked on our image database by manually extracting the prominent facial features from the image and henceforth training the SVM’s for classification of each emotion.

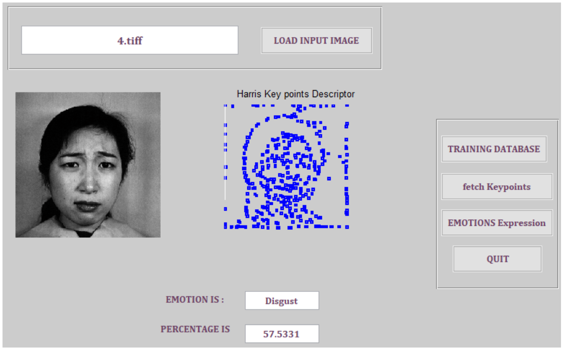

Figure 5: Disgust human face expression

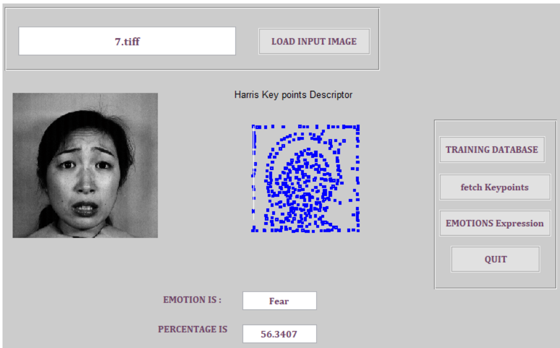

Figure 6: Fear human face expression

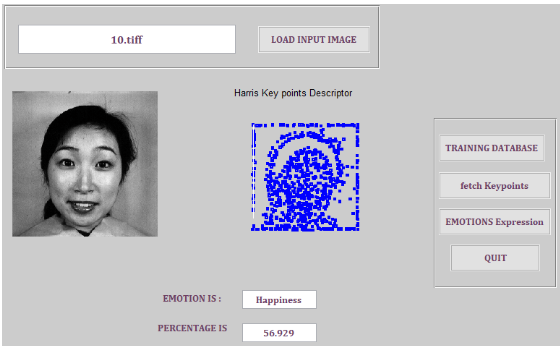

Figure 7: Happiness human face expression

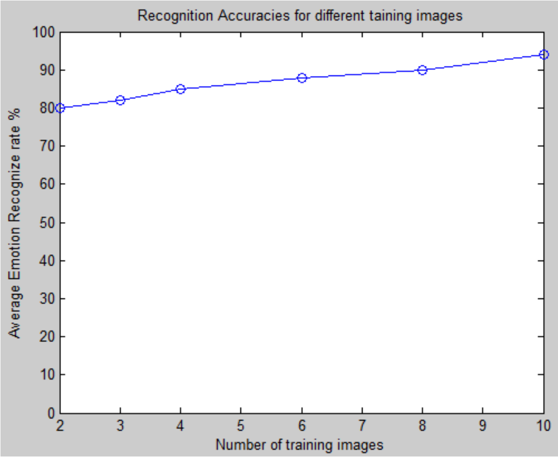

Figure 8: Average emotion recognize rate %

V. Conclusion

Facial Emotion recognition has become one of the most active research areas due to its contribution to human computer interaction analysis. In this paper a hybrid algorithm of Harris point and SVM was proposed in order to extract emotions from different datasbase images. It is an improvement over previous techniques as it takes into consideration the obstructed features of a human face and it demonstrates high recognition rates and also the errors were small as compared with the conventional method. The newly proposed and implemented algorithm evaluated on 15 images is much faster and has given much better results for extraction of emotions from the human face.

The possible extensions that can be made to the application are that it can be made to work with a greater number of and more complex emotion categories. Could for instance train the SVM with 'happy, sad, angry, and surprised' and then query it with a new sample belonging to one of these four categories (multi-class classification).

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