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Generation of Facial Expressions through Manipulating Facial Parameters

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Abstract

Extracting discriminative features from salient facial patches plays an important role in effective facial expression recognition. The accurate detection of facial landmark is needed to improve the localization of the salient patches on face images. This paper proposes framework for expression recognition by using appearance features of facial patches. By synthesis of emotional facial expressions through manipulating facial parameters, we aim to introduce facial emotions to a neutral facial image. For this, we perform a pre-processing process in which the face region is identified based on the skin colour segmentation method. Then face is located with the connected area identification process. The feature points in facial region are examined, extracted and stored. In this algorithm, bilinear transformation is used with in the mesh warping technique to manipulate the facial parameters. Thus, we could generate some standard set of expressions like happy, angry, sad, fear, surprise etc. However, the optimal implementation of the proposed framework will significantly improve the computational cost; and real-time expression recognition can be achieved with substantial accuracy. Further analysis and efforts are required to improve the performance by addressing some issues [1].

Keywords: *Facial expression analysis, facial landmark detection, feature selection, salient facial patches*

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INTRODUCTION

The area of human–computer interaction (HCI) will be much more effective if a computer can recognize the emotional states. Emotional states have a greater effect on the face which can tell about mood of the person. So, if we can recognize facial expressions, then we can know about the human's emotions and mood. This research focuses to develop automatic facial expression recognition system (AFERS); here the system takes input as human face and output as appropriate expressions. The expressions class are such as angry, disgust, fear, happy, neutral, sad, and surprise. This research focuses to increase both, the recognition accuracy and computational efficiency. Face localization, feature extraction and classification algorithms are used for arriving at a simpler approach to perform facial expression recognition and classification [2, 3]. Facial expressions are the facial changes with respect to a person's internal emotions, intentions, or social communications. Expressions are temporally deformed features generated by contractions of facial muscles. The changes of muscular activities to be brief lasting for a few seconds, rarely more than five seconds or less than 250. The classification of facial features in one of the six basic emotions such as: happiness, sadness, fear, disgust, surprise and anger [4].

Automatic facial expression recognition (AFER) system has application areas like lie detection, neurology, intelligent environments, clinical psychology, behavioural and multimodal human–computer interface (HCI). It uses the facial signals that cause interaction between human and computer in more robust, flexible and natural way [5].

RELATED WORK

Ishraque *et al*. describes facial expression recognition system by encoding the spatial structure and contrast information of facial expressions [6]. This method concentrates on integration of local edge response pattern and contrast information that makes it robust and insensitive to noise; and non-monotonous illumination changes maintain a high recognition rate with lower computational cost. Once trained, our system can be used in consumer products for human–computer interaction by facial expressions. Feature description transforms the aligned faces into some representation emphasizing that certain facial aspects are difficult [7].

Khandait *et al.* presents the combination of SUSAN edge detector, edge projection analysis and facial geometry distance measure, as best combination to locate and extract the facial feature for gray scale images in constrained environments and feed forward back-propagation neural network is used to recognize the facial expression [8]. For face portion segmentation, basic image processing operation like morphological dilation, erosion, reconstruction techniques with disk structuring element are used. Proposed method does not extract exactly six features parameters properly if there are hairs on the face [9].

Bouzerdoum *et al.* explains expression recognition that is based on fixed filters and adaptive filters connected in a cascading structure [1]. The fixed, directional filters extract primitive edge features, whereas the adaptive filters are trained to extract more complex features, which are then classified by SVMs. They also implemented and compared two feature selection methods to construct a FER system from a reduced number of features. Disadvantage is that there is a need to develop optimizational algorithms that allow the SVM in Stage-3 and the adaptive filters in Stage-2 to be trained simultaneously.

Pantic and Patras proposed AU detection based upon changes in the position of the facial points tracked in a video of a near profile view of the face [7]. This work provides automatic detection of AUs and their temporal segments in a face. This method assumes that the input data showing facial-displays always begin with a neutral state. In reality, such an assumption cannot be made; variations in the viewing angle should be expected. Also, human facial behaviour is more complex and transitions from one facial display to another do not have to involve intermediate neutral states.

Pantic and Rothkrantz propose a new automatic recognition of facial gestures i.e., facial muscle activity is now days becoming an area of intense interest in the research field of machine vision [10]. Here, we present an automated system to recognize facial gestures in colour face images. Multi-detector approach to facial feature localization is utilized to sample the profile contour and the contours of the facial components such as the eyes and the mouth**.**

PROPOSED METHODOLOGY

The overview of the proposed method is shown in Figure 1. Observations from the figure suggest that accurate facial landmark detection and extraction of appearance features from active face regions improve the performance of expression recognition. Therefore, the first step is to localize the face, followed by detection of the landmarks. Here, the eyes and nose are detected in the face image as a coarse region [5].

The lip and eyebrow corners are detected from respective ROIs. Locations of active patches are defined with respect to the location of landmarks. Figure 1 shows the steps involved in automated facial landmark detection and active patch extraction. In training stage, features of maximum variation between pairs of expressions are selected. These selected features are further projected into lower dimensional subspace and classified into many expressions using a multi-class classifier [11, 6, 8]. The training phase consists of: pre-processing, selection of facial patches, extraction of appearance features and learning of the multi-class classifiers.

In an unseen image, the process first detects the facial landmarks, then extracts the features from the selected salient patches, and finally classifies the expressions.

PROPOSED ALGORITHM

Perform a Human Face Check Operation: It is done by finding a ratio of height to width in the provided image. The criterion for it to be a human face is as follows:

Ratio >=1.0 Ratio <=2.0. It should provide a standard height and width for the image.

Pre-processing: To enhance the quality of inputted image, perform a contrast function.
i. Invert filter;
ii. Grayscale filter;
iii. Brightness filter; and
iv. Contrast.

With the help of skin colour detection method and connected component method, the facial region is located from the inputted image.

Skin Colour Segmentation: Based on RGB colour model, we could obtain the normalized image.

r=R/(R+G+B)
g=G/(R+G+B)

In primary colours, blue colour comes less frequently as skin colour. So, we could avoid blue colour normalization. We convert an input RGB image into gray scale image. A pixel with an intensity value greater than or equal to the universal threshold is set to black.

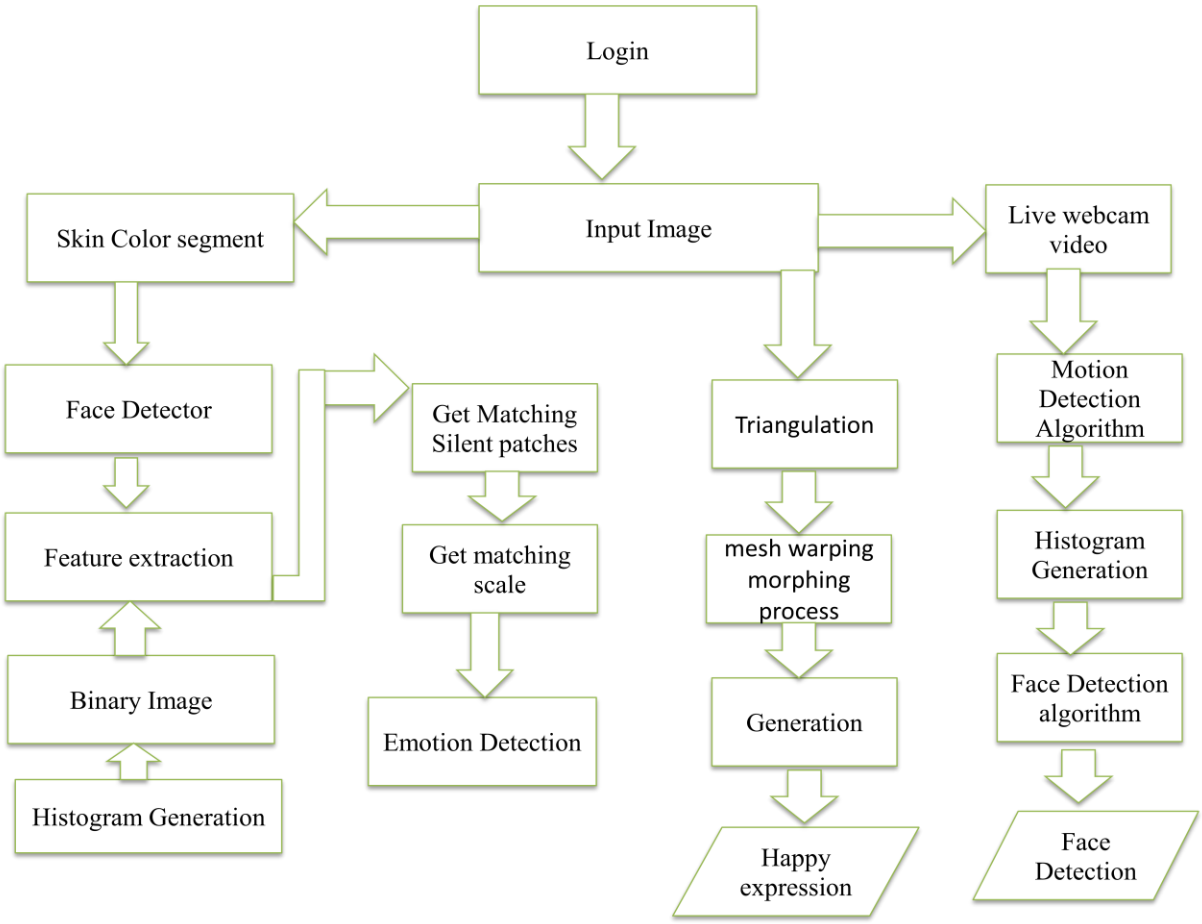

Fig. 1: *Architectural Diagram.*

Facial Salient Patch Feature Extraction: With an efficient feature extraction method, we could extract the facial features such as eyes, lips.

Given: aligned face ROI and nose position;
1. select coarse lips ROI using face width and nose position;
2. apply Gaussian blur to the lips ROI;
3. apply horizontal sobel operator for edge detection;
4. apply Otsu-thresholding;
5. apply morphological dilation operation;
6. find the connected components;
7. remove the spurious connected components using threshold technique to the number of pixels;
8. scan the image from the top and select the first connected component as upper lip position;
9. locate the left and right most positions of connected component as lip corners.

During the testing phase facial expression can be recognized using salient facial patch features by repeating the process using different expressions of the same person or image.

- Recording matching area;
- Recording matching scale;
- Emotion detection.

Pre-processing

A low pass filtering was performed using a 3×3 Gaussian mask to remove noise from the facial images followed by face detection for face localization. We used Viola-Jones technique of Haar-like features with Adaboost learning for face detection. Using integral image calculation, it can detect face, regardless of scale and location in real time. The localized face was extracted and scaled to bring it to a common resolution [12]. This made the algorithm shift invariant, i.e., insensitive to the location of the face on image. Histogram equalization was carried out for lighting corrections of the facial patches which are active during different facial expressions. The results indicate that these active patches are positioned below the eyes, in between the eyebrows, around the nose and mouth corners [9]. Using local gradient analysis, this method finds the facial features and adjusts the deformable 3D face model so that its projection on image matches the facial feature points. We have extracted the active facial patches with respect to each feature using the geometrical statistics of the face.

Skin Colour Segmentation

For skin colour segmentation, first we contrast the image and then perform skin colour segmentation. Then, we have to find the largest connected region and check the probability to become a face of the largest connected region. If the largest connected region has the probability to become a face, then it will open a new form with the largest connected region [11]. If the largest connected region's height and width is larger or equal than 50 and the ratio of height/width is between 1 and 2, then it may be a face.

Face Detection

For face detection, first we convert RGB image to a binary image. For converting binary image, we calculate the average value of RGB for each pixel. If the average value is below than 110, we replace it by black pixels and otherwise we replace it by white pixels. By this method, binary image is obtained. Then, we find the forehead from the binary image [12]. We start scanning from the middle of the image. Then find the maximum width of the white pixels by searching vertically, both left and right. Then we cut the face from the starting position of the forehead and its high will be 1.5 of its width. Then we will have an image which will contain only eyes, nose and lips.

Feature Extraction and Classification

Some expressions share similar movements of facial muscles, features of such patches are redundant while classifying the expressions. First, the active patches are extracted, then we selected the salient facial patches. These salient patches are responsible for discrimination between each pair of basic expressions. A facial patch is considered to be discriminative between two expressions, if the features extracted from this patch can classify the two expressions accurately. Not all active patches are salient for recognition of all expressions. The patches that result maximum discrimination were selected for representing the expressions. The LBP histogram features in lower resolution images are sparse in nature because of the smaller patch area. LDA was applied for projecting these features to the discriminating dimensions and to choose the salient patches according to their discriminative performance. LDA finds the hyperplane that minimizes the intra-class scatter (Sw), while maximizing the inter-class scatter (Sb). It is also used as a tool for interpretation of importance of the features. Hence, it can be considered as a transformation into a lower dimensional space for optimal discrimination between classes.

EXPERIMENTAL RESEARCH AND ANALYSIS

The Cohn-Kanade database contains both male and female facial expression image sequences for the six basic emotions. In our experiments, the last image from each sequence was selected, where the expression is at its peak intensity. The number of instances for each expression varies according to its availability. In our experiments on CKþ database, we used

329 images in total: anger, disgust, fear, happiness, sadness, and surprise. Figures 2–4 show the identification of facial expression by extracting the active facial patches.

Fig. 2: *Input Image.*

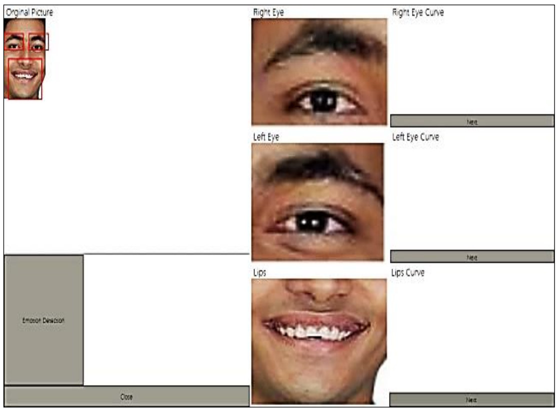

Fig. 3: *Feature Extraction.*

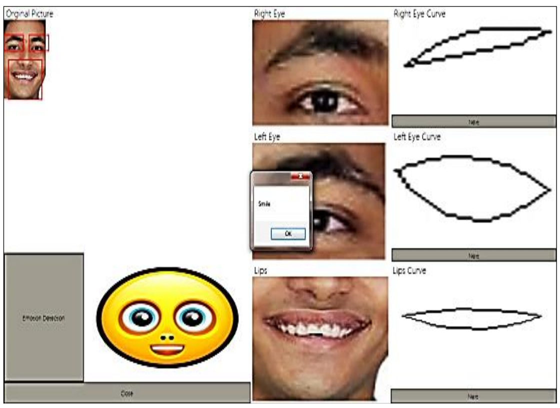

Fig. 4: *Expression Recognition.*

CONCLUSION AND FUTURE WORK

This paper explores the issue of facial expression recognition using facial movement features. The effectiveness of the proposed approach is testified by the recognition performance, computational time, and comparison with the state-of-the-art performance. The results also demonstrate significant performance improvements due to the consideration of facial movement features and promising performance under face registration errors. Different emotions have different salient areas; however, the majority of these areas are distributed around mouth and eyes.

The salient patches are distributed across all scales with an emphasis on the higher scales. The proposed approach can be potentially applied into many applications, such as patient state detection, driver fatigue monitoring, and intelligent tutoring system. In future work, we will extend our approach to a system by combining patch-based features with motion information in multi-frames, to generate realistic facial expression images from a neural facial image. We generated a particular expression with the help of bilinear transformation with in the mesh warping technique. We will also investigate effects of using a reduced number of features for classification and also plan to conduct extensive experimental studies using other available face databases.

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