

## FACIAL EMOTION RECOGNITION THROUGH GABOR FILTER AND RBF NETWORKS

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### ABSTRACT

*Human Emotion Recognition plays an vital role in the human-computer interaction (HCI). In this paper, the emotions are detected on segmented image by means of low dimension weighted Gabor filter bank. The segmentation reduces the space area and merely those facial features are paying attention that reflects expressions precisely. The classification of chosen features values classifies throughout a RBF network. This experimental outcome show that by the selection of best possible features, the computational complication reduces considerably.*

**Keywords-** Gabor feature extraction, RBF networks classification, Eigen vectors, Segmentation.

### 1. Introduction

The Human Emotion Detection is a bouncy research area during current years. It is the mixture of Computer Vision (CV), Human Computer Interface (HCI) and Pattern Recognition. Facial Expression plays a significant role in Human Computer Interaction. Emotions are displayed on the face during Facial Expression. Facial Expressions are due to the movements of muscles of the face. These movements replicate the emotional states of the person to the observer. Emotions are feeling or reply to particular state of affairs or environment.

In emotional classification there are two basic emotions are there, Love-fear. Based on this we categorize the emotion into positive and negative emotions. The six basic emotions are angry, happy, fear, disgust, sad, surprise. An additional expression is neutral. Further emotions are Embarrassments,

interest, pain, shame, shy, smile, laugh, sorrow, hunger, curiosity.

This meadow has been a research interest for scientists from numerous different tracks like computer knowledge, engineering, neuroscience and psychology [1]. In this paper, we propose an entire emotional classification via facial expression. The network is well trained with the different emotions of the face with diverse age group of people from different situation. When set an input, the RBF network with the aid of FLD, trained with various emotions of the face expression with that of training examples and produces the output.

An important problem in the emotion recognition field is the lack of agreed benchmark database and methods for compare different methods performance. Cohn kanade database is a pace in this direction [2]. This Existing research was developed by Paul Ekman [3]. It was a psychological perspective. In the early 1990s the engineering humanity started to use these results to build automatic methods of recognizing emotions from facial expressions in images or video [4] based on a variety of techniques of tracking [5]. Recent work on facial expression study and recognition [6] has used these “basic expressions” or a subset of them. In [7], Pantic and Rothkrantz present an in depth review of many of the research done in automatic facial expression recognition in recent years. The effort in computer-assisted quantification of facial expressions did not begin until the 1990s.

Mase [8] used optical flow (OF) to recognize facial expressions. He was one of the first to utilize image processing techniques to recognize facial expressions. Lanitis [9] used a elastic shape and

appearance model for image10 coding, person identification, pose healing, masculinity recognition, and facial expression recognition. Black and Yacoob [10] used limited parameterized models of image motion to recover non rigid movement. Previously recovered, these parameters were used as inputs to a rule-based classifier to recognize the six basic facial expressions.

Yacoob and Davis [11] computed optical flow and used comparable rules to classify the six facial expressions. Rosenblum, Yacoob, and Davis [12] also computed optical flow of regions on the face then apply a radial basis function network to classify expressions. Essa and Pentlands [13] used an optical flow region-based technique to recognize expressions. Donato et al. [14] tested different features for recognizing facial AUs and inferring the facial expression in the structure. Otsuka and Ohya [15] first computed optical flow, after that computed the 2D Fourier transform coefficients, which were used as feature vectors for a hidden Markov model (HMM) to classify expressions. The trained system was capable to recognize one of the six expressions near real-time (about 10 Hz). Moreover, they used the tracked motions to manage the facial expression of an animated Kabuki system [16]. Martinez [17] introduced an indexing approach based on the identification of frontal face images beneath different illumination conditions, occlusion and facial expressions.

Oliver et al. used lower face tracking to extract mouth shape features and used them as inputs to an HMM [20] based facial expression recognition system (recognizing neutral, happy, sad, and an open mouth). These methods are similar in that they first extract various features from the images, then these features are used as inputs into a classification system, and the result is one of the pre selected emotion categories.

Our method could solve the accuracy problem, and further improve the performance of facial expression recognition systems to a great level.

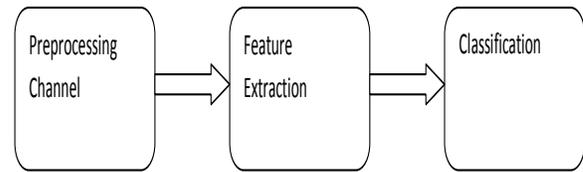


Figure 1: Basic block diagram of the proposed method



Figure 2: Examples of cropped facial emotions of Cohn-Kanade Database

## 2. Techniques Used

In our proposed algorithm, we use different techniques for different sections.

For face detection, we use segmentation process. In our loom a facial image is segmented (behind region of interest is located) into small grid. If the input image is of size  $M \times N$  then single module is about of size  $M/2 \times N/2$ . The main concept behind the segmentation is to separate face regions so that the mainly contributed facial features like eyes, eyebrows and mouth can be focused more quite than others. This reduces the search space, and the features of the region of interest can be extracted.

For feature extraction from face, we use Gabor filter bank. In the planned method, Gabor filter bank is used for facial feature extraction. As the global Gabor filter has high dimension, it requires more computation time and when combined with other feature extraction algorithms becomes complicated.

And for classification process, we use radial basis function networks. It's a two layer hybrid feed forward learning network. It is utterly connected

network. This is becoming a rising popular neural network with diverse applications and is possibly the main competitor to the multi layered preceptor. Much of the motivation for RBF network has come from traditional numerical pattern classification techniques. It's mainly used as classification tool.

### 3. Methodology

The block diagram shows planned method for recognizing the emotions. The working of each block is explained complete in the following sections:

#### 3.1. Preprocessing

Pre-processing of the facial image is measured as important step in facial emotion recognition so that the images might have equality in size, scaled, normalized intensity and restricted face region commencing the clutter background.

Firstly we detect the face with the use of segmentation process, in which we use watershed technique for getting better result.

#### 3.2. Facial Feature Extraction

Facial feature extraction is a vital process in facial emotion recognition and can affect the classification results. This technique is ended by extracting the necessary information from facial images so that only inherent features are selected for classification of the emotions.

Gabor filter bank is used for facial feature extraction. The general 2D Gabor function for facial feature extraction

$$g(x, y) = -\frac{k^2}{\sigma^2} \exp\left(-\frac{kx^2}{2\sigma^2}\right) \left[ \exp(ik \cdot x) - \exp\left(-\frac{\sigma^2}{2}\right) \right]$$

Where (x, y) is the spatial domain variables, k is the wave-factor that defines the range and direction of Gabor function,  $\frac{k^2}{\sigma^2}$  factor covers all spatial frequency bands by means of equal energy,  $\frac{\sigma^2}{2}$  subtract the DC component of Gabor filter.

The value of  $\sigma$  is  $\pi$  for the image of resolution 256 X 256. Eighteen different Gabor filter represents excellent texture information of image with three spatial frequencies ( $k = \pi/4, \pi/8, \pi/16$ ) and six orientations from 00 to 1800. In this experiment the value of  $\sigma = \pi$  and  $k = \pi/4, \pi/8, \pi/16$  and the center frequency is at the origin.

Also we do weighted value calculation after feature extraction. It gives the highest weighted values for the system. The highest energy frequency in spatial domain has highest weighted value and all the highest weighted values are extracted from input images.

#### 3.3. Classification

RBF model is used in our work because it can maps the data through nonlinearly into the advanced dimension space. Therefore, it can control the case when the class label and its attributes are nonlinear. Radial basis Function is a two-layer fully network connected classification tool. The hidden layer contains a basis function. The base function has the parameters- center and width. The output depends on the distance of input from the center.

Outputs layers

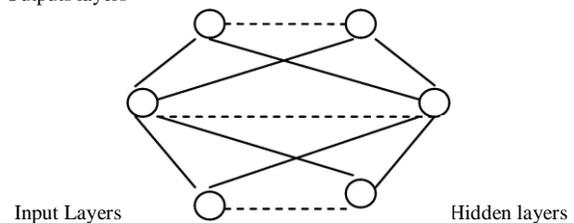
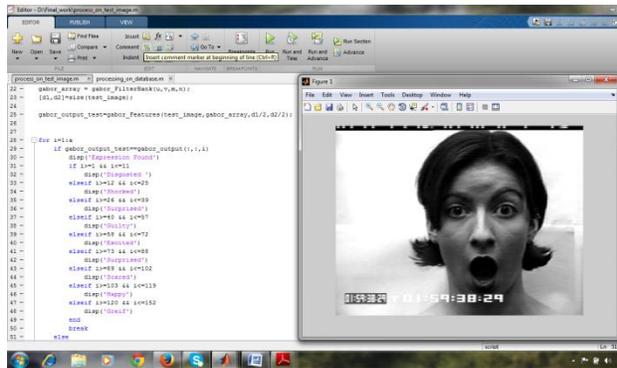


Figure 3: Structure of Radial Basis Function

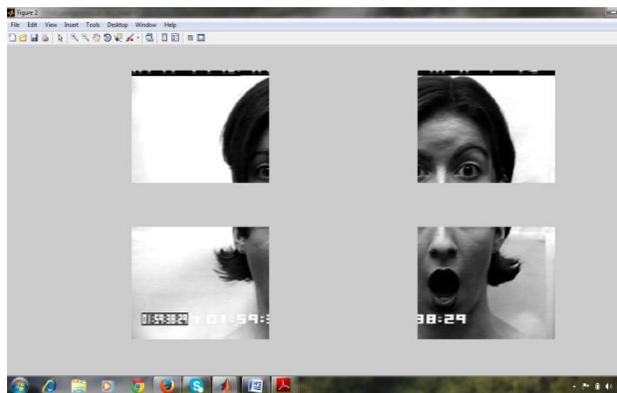
### 4. Experimental Analysis

#### 4.1. Database Used

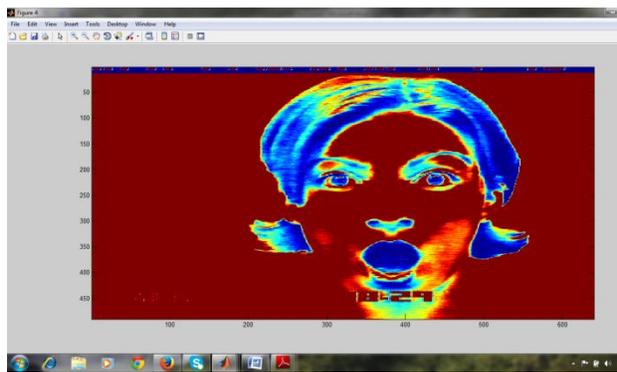
In this proposed work, we use 8 different types of emotions i.e. happy, disgusted, shocked, grief, surprised, excited and scared. From extended Cohn-Kanade database, 280 images in train dataset and 63 images in test dataset.



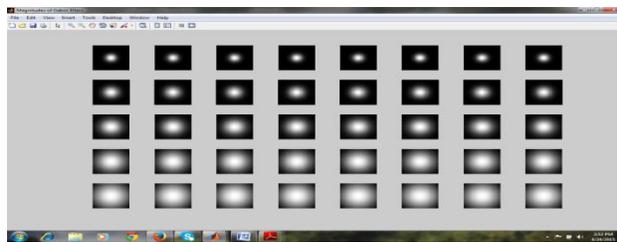
(a)



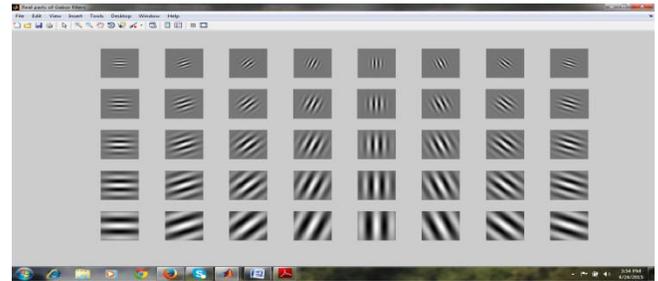
(b)



(c)



(d)



(e)

Figure 4: Snapshot of a) random database of Cohn-Kanade, b) segmented image, c) 2D magnitude Response, d) magnitudes of Gabor Filter and e) real parts of Gabor filter.

#### 4.2. Performance Analysis

The main practical statistical measurement that is used to estimate performance of our emotion detection system is

$$\text{Recognition rate} = \left( \frac{\text{correct}}{\text{correct} + \text{incorrect}} \right) * 100$$

Where, correct identify the correctly recognized label of test dataset, incorrect identify the incorrectly recognized label of test dataset.

In our proposed work we get 94.8% recognition rate which is much better than the previous work.

### 5. Conclusion

In present work a better emotion detection method for segmented image using weighted Gabor filter and radial basis function kernel has been discussed. The selected filters are considered on the selected feature space domain to decrease the computational complexity without scarifying concert. First face is detected from entire image and then segments the face region to obtain selected features from face (eyes, eyebrow and mouth). These modules of the face are then introduced to Gabor-based method. Then the output feature vectors are classified via the RBF network.

In future scope plan to work on compound emotions i.e. combination of two basic emotions for example happily Surprised, Angrily disgusted, etc.

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