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Compound Facial Expression Recognition through Gabor Filter and RBF Network

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ABSTRACT: Past researches on facial expressions of emotion has focused on the study of six basic categories—cheerfulness, surprise, annoyance, sadness, fear, and aversion. However, many more facial expressions of emotion exists and are used regularly by humans. This paper describes a significant group of expressions, which we entitle in compound emotion categories, i.e. combination of two basic emotions, for example: Happily Surprised, Sadly Surprised, etc. The emotions are detected on segmented image by using low dimension Gabor filter bank. The Process of segmentation reduces the space area and Concentration is paid to those facial features that reflects expressions specifically. The classification of chosen features values classifies throughout a RBF network

Keywords- Segmentation, Eigen vectors, Gabor Feature Extraction, RBF network classifier.

I. INTRODUCTION

Expression is an important mode of non-verbal conversation among people. Expression recognition technology fascinates people's attention in the field of image processing, computer vision, pattern recognition etc. Facial expression provides necessary information about the mental, sensitive and physical states of the discussion. It include much information

Regarding ones id as well as about mood and state of mind. Facial expression interactions typically applicable in social life, teacher-student interface, sincerity in frequent contexts, medicine etc. however people can simply recognize facial expression easily, but it is pretty hard for a machine to do this. To reach high degree of efficiency, to raise the speed of calculation, better consumption of memory, in terms of classification and recognition of facial expressions a lot of modification is required in the previously used algorithms. To meet the estimated goals, the main aim of this research paper is to develop a proficient algorithm for Facial Expression Recognition by the combination of two or more techniques.

In the presented paper we have used compound emotions which have been constructed by combining basic component categories and new emotions have been generated. For instance, happily surprised and angrily surprised are two distinct compound emotion categories. The present work defines 20 distinct emotion categories. Sample images of their facial expressions are collected from 200 human subjects. A Facial Action Coding System analysis shows the production of these 20 categories is different but persistent with the subordinate categories they belongs to (e.g., a happily surprised expression combines muscle movements and expression involved in happiness and surprised). In the paper, a method has been presented to design an Eigenvector based facial expression recognition system.

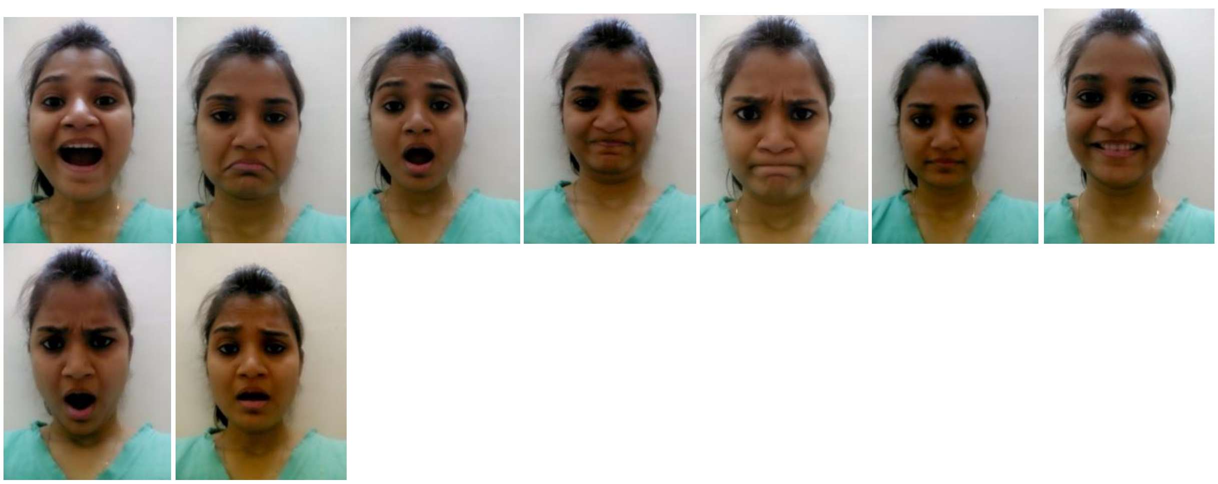


Figure.1. 6 basic and 3 compound emotions (i.e. happily surprised, sad, sadly surprised, disgusted, angry, neutral, happy, angrily surprised and surprised)

The Eigenvector base features are extracted from the images. In the training phase, a set of 200 images from Cohn-kanade database having the six basic expressions and additional 3 compound emotions from real time database are processed. In the testing phase, the Eigenvector of an image is calculated and the consequent Euclidean distance (EuD) of that image is computed. Euclidean distance between the Eigenvectors of the expression and the Eigenvectors of the test image is compared with the Eigenvectors of the other expressions and the one which measured minimum distance is classified as particular facial expression.

Our method has solve the accuracy problem, and also has improved the performance of facial expression recognition systems to a great level. The suggested system is designed in a way that it first performs face recognition and once the face is recognized then the particular expression is recognized. In case the face is not recognized, the expression can still be recognized and this feature make proposed algorithm more flexibility and user friendly.

The experimenter taking the subject’s pictures suggested a possible situation that may cause each facial expression, e.g., disgust would be expressed when smelling a bad odor. This is crucial to correctly produce compound emotions. For example, happily surprised is produced when receiving wonderful, unexpected news, whereas angrily surprised is expressed when a person does something unexpectedly wrong to you. Rather, subjects were encouraged to express each emotion category as clearly as possible while expressing their meaning (i.e., in the example situation described by the experimenter). A verbal definition of each category accompanies the sample picture.

II. Techniques Used

In our proposed algorithm, Different techniques have been used for different sections. For face detection, segmentation has been used. In this process facial image is segmented (behind region of interest is located) into small grid. If the input image is of size M x N then single module is about of size M/2 x N/2. The main concept behind the segmentation is to separate face regions so that the main facial features like eyes, eyebrows and mouth can be focused more than others.
For feature extraction from face, we use Gabor filter bank. As the global Gabor filter has high dimension, it requires more computation time and when combined with other feature extraction and algorithms becomes complicated.

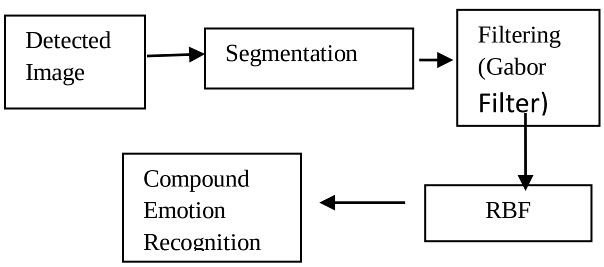


Figure.2. Basic block Diagram for Compound Emotion Recognition

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 and 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.

III. Methodology

The plans and implementation of the Emotion classification using facial expression System can be subdivided into four main parts: Image Detection, Facial Feature Extraction, Weighted value Calculation and then result of classification of images.

A. Image Detection

Most systems detect face under controlled conditions, such as without facial hair, glasses, any rigid head movement. Locating a face in a generic image is not a trouble-free task, which continues to challenge researchers. Once detected, the image region containing the face is extracted and geometrically normalized. We used real time database instead download the images from existing databases to avoid noisy data. We are using Radial basis function network which is capable of handling noisy images also. Its gives better result than back propagation neural network.

B. Facial Feature Extraction

The face image is converted into a feature vector that contains information about a face. The feature vectors are used to differentiate emotion classes. The major techniques for feature extraction are: feature-based and appearance-based. In feature-based, geometric features or facial points or shapes of facial components or spatial locations are used to extract features. In Appearance-based, the textures of the facial image, including wrinkles and furrows (local feature) are used to extract features. Gabor Filter is used for feature extraction. Gabor being band pass filters are most commonly used in image processing for feature extraction. In our structure the Gabor filters are combined with Eigenvectors to enhance the performance and accuracy.

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

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

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 σ is π for the image of resolution 256 X 256. Eighteen different Gabor filter represents excellent texture information of image with three spatial frequencies (k= π /4, π/8, π/16) and six orientations from 00 to 1800. In this experiment the value of σ = π and k= π / 4, π/8, π /16 and the center frequency is at the origin. A well designed Gabor filter bank can capture the relevant frequency spectrum in all directions.

C. ***Weighted Value Calculation***

Instead of averaging all the pixel values in the window, closer-by pixels are rated as higher weight and far-away pixels addressed as lower weight.

$$g(m,n) = \sum_{l=-L}^{L}\sum_{k=-L}^{L} h(k,l)s(m-k,n-l)$$

This type of operation for arbitrary weighting matrices is generally called “2-D convolution or filtering”. When all the weights are positive, it corresponds to weighted average. Weighted average filter retains low frequency and suppresses high frequency. The highest energy frequency in spatial domain has highest weighted value. All the highest weighted values are extracted from input images and stored into train dataset.

D. Radial Basis Function Network

A *radial basis function (RBF)* is a real-valued function whose value depends only on the distance from the origin, so that

$\phi(\mathbf{x}) = \phi(\|\mathbf{x}\|)$; or alternatively on the distance from some other point *c*, called a *center*, so that

$\phi(\mathbf{x},\mathbf{c}) = \phi(\|\mathbf{x}-\mathbf{c}\|)$. Any function ϕ that satisfies the property

$\phi(\mathbf{x}) = \phi(\|\mathbf{x}\|)$ is a radial function. The norm is usually Euclidean distance, although other distance functions are also possible.

Sums of radial basis functions are typically used to approximate given functions. RBFs are also used as a kernel in support vector classification.

Radial basis functions are typically used to build up function approximations of the form

$$y(\mathbf{x}) = \sum_{i=1}^{N} w_i\,\phi(\|\mathbf{x}-\mathbf{x}_i\|),$$

where the approximating function $y(\boldsymbol{x})$ is represented as a sum of N radial basis functions, each associated with a different center $\boldsymbol{x}_i$, and weighted by an appropriate coefficient w_i. The weights w_i can be estimated using the matrix methods of linear least squares, because the approximating function is linear in the weights

$$y(\mathbf{x}) = \sum_{i=1}^{N} w_i \, \phi(\|\mathbf{x} - \mathbf{x}_i\|),$$

The sum can also be interpreted as a simple single-layer type of artificial neural network called a radial basis function network, with the radial basis functions taking on the role of the activation functions of the network, it can be shown that any continuous function on a compact interval can in principle be interpolated with arbitrary accuracy by a sum of this form, if a sufficiently large number N of radial basis functions is used.

The approximant y(x) is differentiable with respect to the weights w_i. The weights could thus be learned using any of the standard iterative methods for neural networks. Using radial basis functions in this manner yields a reasonable interpolation approach provided that the fitting set has been chosen such that it covers the entire range systematically (equidistant data points are ideal). However, without a polynomial term that is orthogonal to the radial basis functions, estimates outside the fitting set tend to perform poorly.

Each hidden neuron has a symmetric radial basis function as an Activation Function. The purpose of the hidden neurons is to cluster the input data and reduce dimensionality. Train input data in order to minimize the sum of square errors and find the optimal weights between hidden neurons and output nodes. These optimal weights can classify effectively the test data into correct classes. Figure 3 describes the basic architecture of RBF network.

The RBF kernel on two samples x and x', represented as feature vectors in some input space, is defined as

$$K(\mathbf{x}, \mathbf{x'}) = \exp\left(-\frac{||\mathbf{x} - \mathbf{x'}||^2}{2\sigma^2}\right)$$

$||x-x'||^2$ may be recognized as the squared Euclidean distance between the two feature vectors. σ is a free parameter. An equivalent, but simpler, definition involves a parameter $\gamma = -\frac{1}{2\sigma^2}$:

$$K(\mathbf{x}, \mathbf{x'}) = \exp(\gamma||\mathbf{x} - \mathbf{x'}||^2)$$

Since the value of the RBF kernel decreases with distance and ranges between zero (in the limit) and one (when x = x'), it has a ready interpretation as a similarity measure. The feature space of the kernel has an infinite number of dimensions; for $\sigma = 1$, its expansion is:

$$\exp\left(-\frac{1}{2}||\mathbf{x} - \mathbf{x'}||^2\right) = \sum_{j=0}^{\infty} \frac{(\mathbf{x}^\top \mathbf{x'})^j}{j!} \exp\left(-\frac{1}{2}||\mathbf{x}||^2\right) \exp\left(-\frac{1}{2}||\mathbf{x'}||^2\right)$$

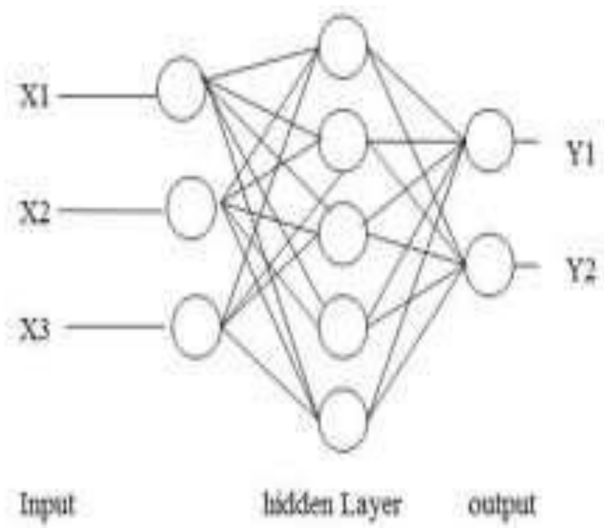
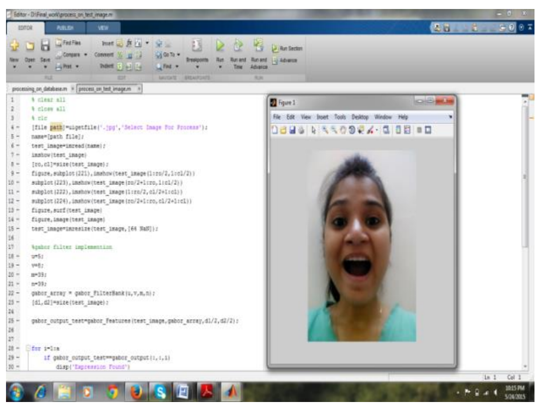


Figure.3. Radial Basis Function Network

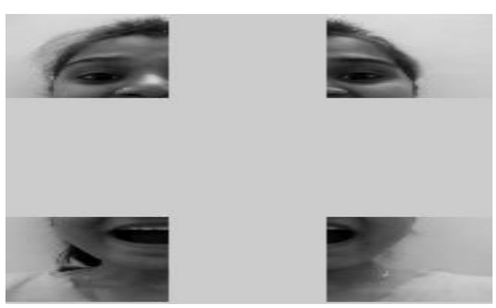
IV. Experimental Analysis

a. Database Used

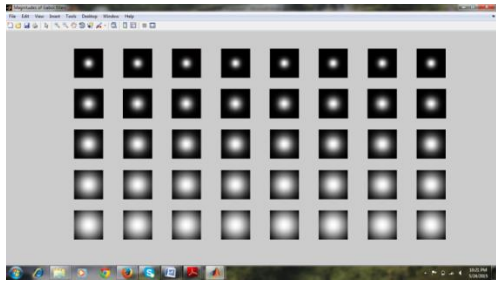
In this proposed work, we use 3 different types of emotions i.e. happily Surprised, Sadly surprised, Angrily Surprised. From extended Cohn-Kanade database, 152 images in train dataset and 48 images in test dataset.



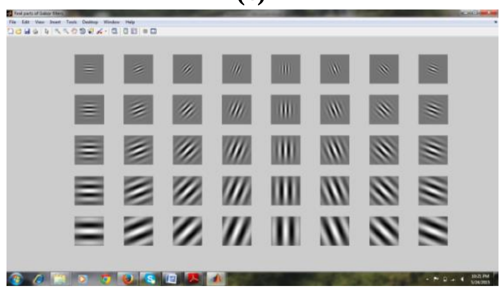
(a)



(b)



(c)



(d)

Figure.4. Snapshot of (a) Random image from compound emotions, (b) Segmentation, (c) Magnitude of Gabor filter, (d) Real part of Gabor filter

b. Recognition Analysis

The main practical geometric measurement that is used to approximation performance of our emotion detection system is

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

Where, **correct** identify the properly recognized label of test dataset, **incorrect** identify the wrongly recognized label of test dataset.
In our proposed work we get 82.8% recognition rate which is better than the earlier work.

V. Conclusion and Future Work

We conclude that to move the state of the art ahead, face recognition research has to hub on a topic that has received little attention in recent years—precise, complete detection of faces and facial features. Even though we have focused our study on the recognition of facial expressions of emotion, we suppose that the results concern to most face recognition tasks.

This work is designed to recognize emotional expression in human faces using the average values calculated from the training samples. We evaluated that the system was able to identify the images and evaluate the expressions accurately from the images. The experimental results show the efficiency of our proposed method, primarily used for recognition of the face following the six basic expressions and 3 compound emotions.

In the present work we have summarized the development of a model of the perception of facial expressions of humans. A key idea in this model is to linearly combine a set of face spaces defining some basic emotion categories.

The model is constant with our current considerate of human perception and can be successfully exploited to achieve great recognition results for computer vision and HCI applications.

In future, we plan to apply these techniques of basic emotions as well as compound emotions for video images or unstable images.

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