Robust Facial Expression Recognition using Gabor Feature and Bayesian Discriminating Classifier

Yamini Piparsaniyan, Vijay K. Sharma, K. K. Mahapatra

***Abstract-* Automatic facial expression recognition is important for effective Human computer interaction (HCI) as well as autistic children for communication. In this paper, we propose emotion recognition using Gabor feature and simple Bayesian discriminating classifier based on principal component analysis (PCA) for emotion recognition. The multi class classification strategic has been applied based on highest value of log likelihood after training different emotions class. Facial expression images from JAFFE database have been used for training as well as testing. Very high accuracy (96.73 %) of emotion recognition has been obtained with proposed method.**

***Index Terms* −Bayesian classification, Computer vision, Emotion recognition, Gabor features, PCA.**

I. Introduction

Recognition of facial expression is important not only for children with autism to meet their daily communication needs, but also in natural interaction of users with the computer as in Human computer interaction (HCI) [1–4]. Facial expressions can be listed broadly under six categories namely, Anger, Disgust, Fear, Happy, Sad, and Surprise [5]. Neutral state can be one of the categories of facial expression.

Feature extraction is the first step in facial expression recognition (FER), followed by a classifier. Facial feature extraction is performed either by geometric-feature-based method or by appearance-based method. The former is difficult to accommodate, as it requires accurate detection and tracking of facial feature points [4, 5]. Appearance-based method utilizes the appearance changes in face image for feature extraction. Principal component analysis (PCA) is one of the methods used in this category for representation of a face images with reduced dimension (space reduction) [6].

For classification, Bayesian discriminating classification and support vector machine (SVM) can be used. Bayesian classification is a simple probabilistic method. It is used in [7] for face detection. SVM based classification has been used in [3, 5] for expression recognition.

Chakraborty *et al.* [2] used geometry based method in which facial features were analyzed by segmenting the individual frame into regions of interest. Smitha *et al.* [1] used PCA for feature extraction and then classified using Euclidean distance method. PCA alone cannot give good performance (in terms of accuracy) in case of expression recognition. In [8], Dynamic Bayesian Network has been used for facial feature tracking and facial expression recognition. Littlewort *et al.*[9] selected a set of Gabor features from among 5×8×48×48 features (5 scales, 8 orientations and at 48×48 pixels) using Adaboost algorithm. The selected features were used for training the SVM classifier for recognition. Zhang *et al.*[4] used Gabor filter banks at different patches in an image. Facial movement features were captured using distance features obtained after patch matching operation. Further, a subset of salient patches were selected using Adaboost. Emotions were classified using LIBSVM implementation of SVMs. SVM is a complex training system, not suitable for high speed applications.

This paper proposes a method for facial expression recognition using Gabor filter banks for feature extraction and efficient Bayesian discriminating classifier. The proposed method has very high emotion classification accuracy as compared to available recognizer and also simple Bayesian classifier is more suitable for faster implementation. The method is trained and tested using Japanese Female Facial Expression (JAFFE) database [10].

The remaining part of the paper is organized as follows. Gabor filter based feature extraction and classification using Bayesian discriminating classifier in reduced dimension space is explained in section II. Section III describes the proposed emotion recognition method. Experimental results and comparison with some existing emotion recognizer systems is given in section IV. Section V concludes the paper.

II. Gabor Feature Extraction and Classification

A. Gabor Wavelet Representation

For 2D data, Gabor wavelet is given by [11],

$$\left.\begin{aligned} \psi_{\Pi}(f,\theta,\gamma,\eta) &= \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}x_t^2+\frac{f^2}{\eta^2}y_t^2\right)} e^{j2\pi f x_t} \\ x_t &= x\cos\theta + y\sin\theta \\ y_t &= -x\sin\theta + y\cos\theta \end{aligned}\right\} \quad (1)$$

Here, f is sinusoidal frequency, θ is wavelet orientation, γ is the spatial width along the sinusoidal plane wave, η is the spatial width of wavelet which is perpendicular to the wave and x,y represents the coordinates of pixels. By varying the scale (f) and orientation (θ), a filter bank is created. The scale

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and orientation are changed according to equations given by [11],

$$\left.\begin{aligned} f_g &= f_{\max} / \left(\sqrt{2}\right)^g, \\ \theta_h &= \frac{h}{8}\pi, \\ \psi_{g,h}(x,y) &= \psi_{\Pi}(f_g, \theta_h, \gamma, \eta) \end{aligned}\right\} \tag{2}$$

The value of parameters in Eq.(2) are given by $\gamma = \eta = \sqrt{2}$, $f_{max} = 0.25$ with $g \in \{0,\ldots,3\}$, $h \in \{0,\ldots,7\}$, generally. In the current work both scale and orientation are taken as $(g,h) \in \{0,\ldots,7\}$, to extract more discriminating features.

B. Feature Extraction from Gabor Wavelets

Each component of the 2D Gabor wavelet (at different scales and orientations) is convolved with the image given by Eq.(3). Downsampling is performed by a factor of 4 in rows and columns of the absolute value of the filtered image. The feature vector is obtained by rearranging the downsampled value. The

$$O_{g,h}(x,y) = I(x,y) * \psi_{g,h}(x,y) \tag{3}$$

$$F = (\mathrm{o}_{0,0}^T \mathrm{o}_{0,1}^T \cdots \mathrm{o}_{7,7}^T)^T \tag{4}$$

vector is normalized to have zero mean and unit variance. If $o_{g,h}$ denotes the feature vector from the filtered image at scale g and orientation h, then final feature (F) value in R^d is given by Eq.(4)[11]. For m×n image, the value of feature space dimension, d = m×n×g×h/(4×4).

C. Modeling the Classifier

Log likelihood, 'L', for extracted feature vector of test image with respect to a training class(w_k), is estimated using multivariate normal distribution of conditional density function, PCA and logarithmic of conditional density function and given by [7],

$$L_k = -\frac{1}{2}\left[\begin{aligned} &\sum_{i=1}^{M}\frac{u_i^2}{\lambda_i} + \frac{\|F-M_k\|^2 - \sum_{i=1}^{M} u_i^2}{\rho} + \ln\left(\prod_{i=1}^{M}\lambda_i\right) \\ &+ (N-M)\ln(\rho) + N\ln(2\pi) \end{aligned}\right] \tag{5}$$

where,

$$\rho = \frac{1}{N-M}\sum_{t=M+1}^{N}\lambda_t \tag{6}$$

$$U = \Phi_k^t (F - M_k) \tag{7}$$

Here, $M_k \in R^N$ is mean, λ_t's are eigen values, Φ is orthogonal eigenvector matrix, U is principal component vector with M components of a class (w_k), u_is are the components of U defined by Eq.(7), ρ is the average of N–M eigen values, F is feature of test image (obtained from (4)) and N is total number of eigen values from covariance matrix of d×d (N = d, from section II B). Bayes classification rule is applied on calculated log likelihoods of two classes (w_1 and w_2) to find whether a test image (I_t) belongs to w_1 or w_2 class [7] (Eq.(8)).

$$I_t \in \begin{cases} w_1, & if \quad L_1 > L_2 \\ w_2, & otherwise, \end{cases} \tag{8}$$

III. Proposed Method For Emotion Recognition

The block diagram of proposed method for facial emotion recognition is shown in Fig. 1 which consists of the following steps.

A. Pre-processing

Pre-processing of image means to find effective area of face contributing for feature extraction by removing background and lower face portion of body (if present). This can be done by using a face detection technique. In proposed work, face detection is done using Bayesian discriminating feature method [7]. Face images and a large number of non face images were taken for the training. After training the classifier, face detection is performed and detected faces were cropped and saved for the facial feature extraction. Example of cropped images is shown in Fig. 2 for JAFFE database [10].

B. Feature Extraction

The feature extraction method is performed using a Gabor filter bank of scales and orientations both equal to 8. The pixel coordinates *x, y* (in Eq.(1)) is taken as 39, 39 as in [12], and the final feature vector is given by Eq.(4).

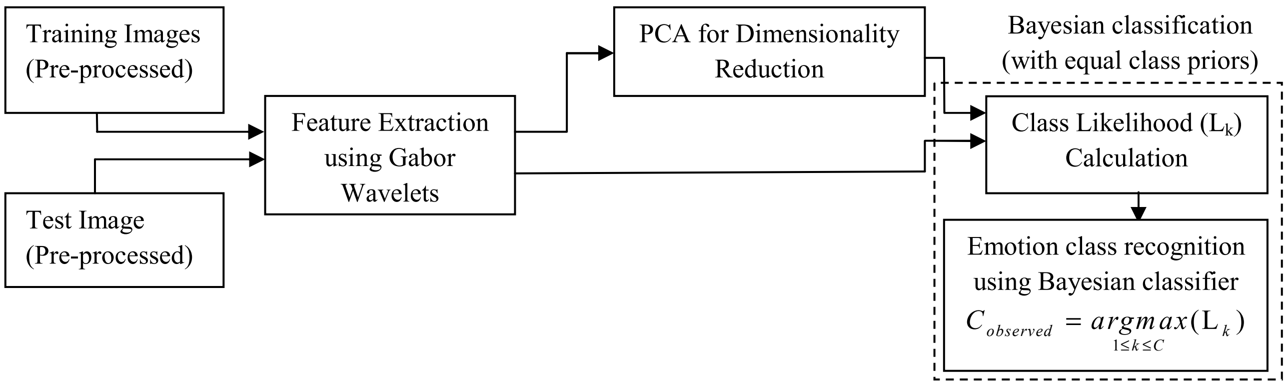

Fig.1. Block diagram for proposed facial expression recognition method

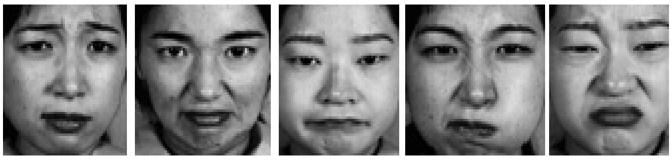

Fig.2. Example of pre-processed test images from JAFFE dataset

C. *Modeling*

Feature vector of training images, belonging to same emotion class is estimated using Eqs.(1)– (4), and are grouped together to form particular class feature vector. If emotions are categorized in 'C' number of classes, class feature vectors, w_k, for each class (k=1 to C) are obtained to get covariance matrix of d×d. Similarly feature vector (F) of test image is estimated using Eqs.(1)– (4) and substituted in Eq.(5) to find likelihood (L_k) with each class w_k.

D. *Classification*

To classify the estimated likelihoods, L_k, (k=1 to C), proposed method extends the binary Bayes classifier (with equal class priors), discussed in [7], to multi class classifier for recognition of emotion of test image, such that,

$$C_{observed} = \underset{1 \le k \le C}{argmax}(L_k) \tag{9}$$

Eq.(9) recognizes the emotion class '$C_{observed}$' as the emotion label of the test image. Prior probabilities of each emotion class are equal, as equal number of training images in each class has been taken.

IV. Experimental Results and Comparisons

The proposed method is tested for accuracy using JAFFE database [10]. Images from JAFFE databases have been pre-processed and resized to 16×16 for training as well as testing. JAFFE database have 210 images of frontal face showing seven emotions (Anger, Disgust, Fear, Happy, Sad, Surprise and Neutral) posed by 10 Japanese female models. Each emotion class has 30 images. Out of 30 images in each class, 20 have been used for training and rest of 10 images for testing the accuracy. In three different rounds, different training and test sets have been used. The principal components taken is 10 (i.e., M=10). Performance result of proposed emotion recognition method is shown in Table I. The columns represent the classified emotion for the desired emotion in corresponding rows. Anger is classified with 100 % accuracy. The lowest accuracy is obtained in case of fear class.

The performance of proposed method is compared with existing highly accurate facial emotion recognition models listed below and comparison chart is shown in Fig.3. The method proposed in [2], based on fuzzy relational approach

TABLE I

Percentage of Correct and Erroneous Emotion Recognition With Training Database and Test Images from JAFFE Database

Desired Emotion	**Recognized Emotion**						
	Anger	Disgust	Fear	Happy	Neutral	Sad	Surprize
Anger	100	0	0	0	0	0	0
Disgust	0	96.77	3.22	0	0	0	0
Fear	0	3.22	93.54	0	0	3.22	0
Happy	0	3.22	0	96.77	0	0	0
Neutral	0	0	0	0	96.77	0	3.22
Sad	0	3.22	0	0	0	96.66	0
Surprize	0	0	3.22	0	0	0	96.77
Overall Accuracy		96.73%					

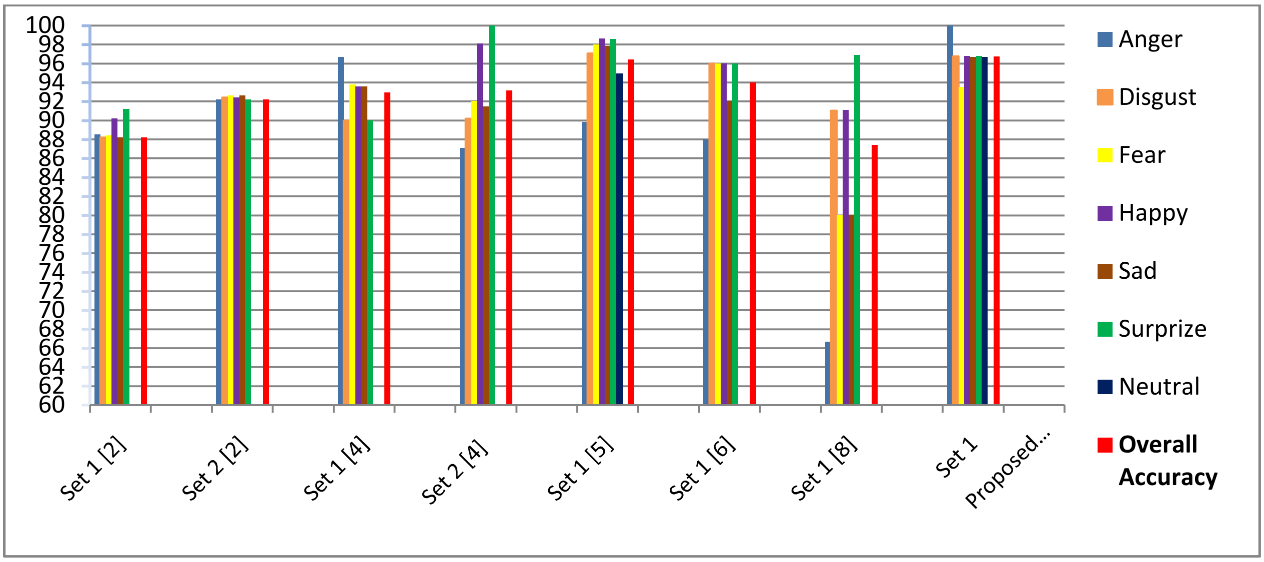

Fig.3. Emotion recognition performance comparison chart of proposed method with existing methods

shows overall 88.2 % accuracy when tested on Set1,containing images of 100 Indian male showing 6 emotions (except neutral). It shows 92.2 % accuracy when tested on Set2, contains images of 100 Indian female showing 6 emotion (except neutral).The method proposed in [4], which is based on facial movement analysis, shows 92.92 % accuracy when tested on Set1 containing 180 images from JAFFE database showing 6 emotions (except neutral) and 93.14 % accuracy when tested on Set2, containing 800 images from Cohn-Kanade database showing 6 emotions. Method proposed in [5] based on local directional number pattern, shows 96.68 % accuracy when tested on Set1, contains images from Cohn-Kanade database showing all 7 emotions. In [6], 94 % accuracy is obtained by using Hidden Markov Model method for recognition. Facial action units based method in [8], which is, shows 87.43% accuracy when tested on Set1, contains images from Cohn-Kanade database showing 6 emotions (except neutral).

V. CONCLUSION

A method for facial emotion recognition based on Gabor based feature and efficient Bayesian classifier for multi class classification is proposed. The proposed method shows overall accuracy of 96.73% for JAFFE database, which is higher than accuracy of existing facial emotion recognition methods. The simple Bayesian classifier is suitable for real time implementation.

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