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Face Expression Recognition using Gabor Features and Probabilistic Neural Network

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Abstract: This paper describes an improved face emotion recognition (FER) system using Gabor Filter, Probabilistic Neural network (PNN) and Principal Component Analysis (PCA). For face part segmentation and localization, viola jones algorithm is applied. The facial features are extracted from face image by means of Gabor filters. The Probabilistic Neural network (PNN) is used as a classifier for classifying the expressions of supplied face into seven basic categories such as angry, happy, sad, surprise, disgust, fear and neutral. Experiments are conducted on JAFFE facial expression database and gives better performance in terms of 100% recognition rate for training set and 86.2% accuracy for test set. The experiments have highlighted the efficiency of the proposed method in enhancing the classification rate. At the end we have shown simulation results for the proposed technique and established that proposed technique is performing better than the existing work. The planned system is implemented in MATLAB version 8.1.604 R2013a.

Index Terms: Facial expression recognition, Gabor filters, Face regions, Feature extraction, Probabilistic Neural Network

I. INTRODUCTION

As pointed out by Mehrabian [1], While human communication, words conveys 7%, tone of voice conveys 38% and face emotion conveys 55%. Hence by Facial emotion recognition an important task in human computer interaction can be achieved. In this work, we investigate how to recognize facial expressions automatically.

Feature based Facial expression recognition uses three steps such as face detection, feature extraction and emotion recognition.

To recognize facial expressions a set of key parameters that best describe the particular set of facial expression needs to be extracted from the face image so that the parameters can be used to distinguish among expressions. This group of key parameters is called the feature vector of the image and the amount of information extracted from the image to the feature vector is the single most important factor of successful feature extraction technique. There are different kinds of methods to extract feature vector from facial images such as DCT[2], wavelet[2] ,LBP[3] PCA [4] and Gabor methods, amid Gabor features have been used widely after Lyons et al. [5]first projected that the Gabor representation shows a major degree of emotional plausibility. Due to this our work uses gabor filter for feature extraction from face image.

Artificial neural network (ANN) [6] is a influential tool of information processing. There are a variety of neural-network architectures [11] together with multilayer perceptron (MLP) neural network, radial basis function (RBF) neural network, self-organizing map (SOM) neural network, and probabilistic neural network (PNN). Because of easiness of training and a sound statistical basis in Bayesian estimation theory, PNN has become an efficient tool for solving numerous classification problems (e.g., [7]-[10]). Due to its strong ability of modeling linear and nonlinear relationship, it has been widely used in pattern recognition .Our proposed work uses PNN for emotion classification from feature vector.

Our conclusion points to that it is achievable to build a improved automatic facial expression recognition system based on a Gabor wavelet code and PNN together with PCA.

The rest of the paper is ordered as follows: Section 2 describes allied work on the design of FER. In Section 3, we propose emotion classification using Gabor filter and PNN. Validation of the proposed algorithm for facial features extraction is expressed in Section 4.In addition to finally, conclusion is drawn in Section 5.

II. RELATED WORK

Many techniques have been used for FER since 1978 .

Michael Lyons oret al[16] (1998) introduced Gabor filter in which facial expression images were coded using a multi-orientation, multi-resolution set of Gabor filters which are topographically ordered and aligned approximately with the face. They have proved possibility of constructing facial expression classifier with Gabor coding of the facial image.

M. Pantic et al. (2001)[17] used an expert system comprised of two main parts the Integrated System for Facial Expression Recognition (ISFER ISFER Workbench and HERCULES to perform recognition and emotional classification of human facial expression from a still face image which forms a framework for hybrid facial feature detection.

Maja Pantic et al(2004) [18] proposed a multidetector approach to extract ten profile-contour fiducial points and 19 fiducial points of the contours of the facial components. Based on these, 32 individual facial action units (AUs) occurring only or in grouping are recognized using rule-based reasoning. by means of each scored AU, the utilized algorithm associates a factor denoting the belief with which the pertinent AU has been scored. A recognition rate of 86% is achieved.

G.U.Kharat et al (2008) [19] used various feature extraction techniques such as Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT), Singular Value Decomposition (SVD) to extract the valuable features and used Support Vector Machine (SVM) for emotion recognition. and the performance of various feature extraction technique is compared.

Ira Cohen et al. (2003) [20] proposed a new architecture of hidden Markov models (HMMs) for automatically segmenting and recognizing human facial expression from video sequences. They explored both person-dependent and person-independent recognition of expressions and compare different methods.

Jun Wang, Lijun Yin (2007) [21] used topographic analysis that treats the image as a 3D surface and labels each pixel by its terrain features. Topographic context (TC) captures the distribution of terrain labels in the expressive areas of a face. It characterizes the distinctive facial expression while conserving abundant expression information and disregarding most individual characteristics. Experiments conducted using two public databases (MMI and Cohn–Kanade database) proved that TC was a good feature representation for recognizing basic prototypic expressions and achieved the best correct rate at 82.61% for the person-independent facial expression recognition

Caifeng Shan et al. (2009)[22] formulated Boosted-LBP to extract the most discriminate LBP features, and used Support Vector Machine for recognition and obtained the best recognition performance by using Support Vector Machine classifiers with Boosted-LBP features. They proved that LBP features perform stably and robustly over a useful range of low resolutions of face image of video sequences captured in real-world environments

Luiz S. OLiveira et al. (2011) [23] used 2 Dimension Principal Component Analysis for feature extraction and K-Nearest Neighbor for classification. They tried to solve some problems of the PCA which effect recognition problem. As PCA works on vector image while 2DPCA works on the whole image. But in 2DPCA coefficient are more so, we need to select feature for classification. The performance of the system was about 91%.

Jaimini Suthar(2014)[24] have surveyed various feature extraction methods, like Gabor Filter, Principal Component Analysis (PCA), Local binary patterns (LBP), Linear Discriminate Analysis (LDA), with different classifiers like Support Vector Machine (SVM), Artificial Neural Network (ANN), and fuzzy logic, which are used to recognize human expression in various conditions on different databases.

Happy, S.L et al, (2015) [25] proposed a novel framework for expression recognition by extracting few prominent facial patches which are active during emotion elicitation. These active patches are further processed to obtain the salient patches which contain discriminative features for classification of each pair of expressions. They have proved thel consistency of their work in different resolutions,

Reoruah, D et al (2015) [26] proposed a method to detect face regions automatically including mouth, eyebrow and eye where a nominal deformation of face muscle is observed. And facial features from the face regions which are based on relative displacement of face muscles are extracted. Then using Hidden Markov Model (HMM) for expression classification is done.

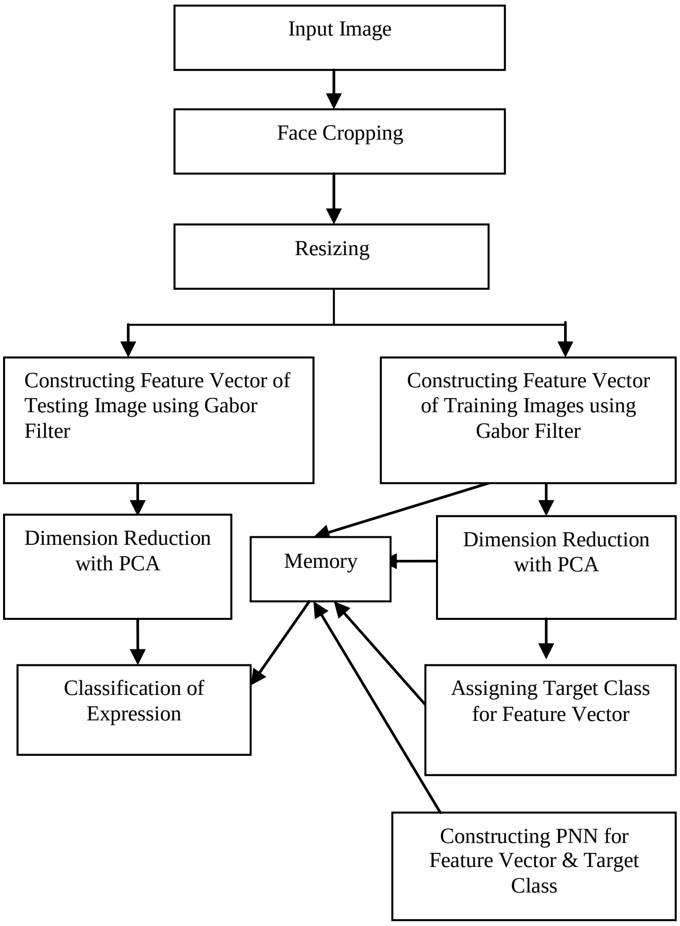

Figure.3.1 Block Diagram of Proposed System

III. PROPOSED SYSTEM DESIGN

Figure 3.1 shows the proposed system design. The procedure of the entire system consists of four parts

a. Image Preprocessing
b. Feature Extraction
c. Dimension Reduction
d. Recognition with ANN

A. Preprocessing:

In preprocessing, the input image is cropped and resized.

a. Cropping: The input image is cropped to get the face image using viola jones algorithm [27] as in fig.3.2 & 3.3

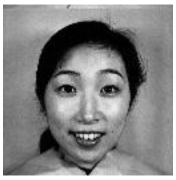

Figure.3.2 Input image

Fig.3.3.Cropped face image

b. Resizing: The face image is resized to a uniform size (256×256) after cropping the faces images to train easily.

B. Feature Extraction With Gabor Filter:

To extract features from the grayscale face image, Gabor filter [5][15] is applied to the grayscale face image with 8 orientation and 5 scales (size of 40) in the following equation (1)

$$g_{\lambda,\theta,\varphi,\sigma,\gamma}(x,y) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\varphi\right) \quad (1)$$

$$x' = x\cos\theta + y\sin\theta$$

$$y' = -x\sin\theta + y\cos\theta$$

The parameters used in Eq. (1) are as follows. Wavelength (λ); is the wavelength of the cosine factor of the Gabor filter kernel, Orientation (θ); is the orientation of the normal to the parallel stripes of a Gabor function. Its value is represented in degrees. Valid values are real numbers between 0 and 360.The Phase offset (φ) in the argument of the cosine factor of the Gabor function is specified in degrees with real numbers as valid values between -180 and 180.The Aspect ratio (γ), specifies the ellipticity of the support of the Gabor function, and we can compute wavelength of Gabor filter using Bandwidth (b) in eq. 2.

$$\frac{\sigma}{\lambda} = \frac{1}{\pi}\sqrt{\frac{ln2}{2}}.\frac{2^b+1}{2^b-1} \quad , \quad b = log_2\frac{\frac{\sigma}{\lambda}\pi+\sqrt{\frac{ln2}{2}}}{\frac{\sigma}{\lambda}\pi-\sqrt{\frac{ln2}{2}}} \quad (2)$$

Figure3.1 & 3.2 shows real and magnitude parts of gabor filter with 8 orientations and 5 scales. So each pixel is then represented by 40 Gabor features. A well designed Gabor filter bank can capture the relevant frequency spectrum in all directions

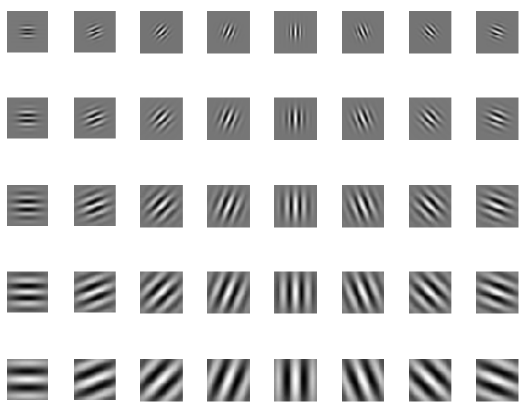

Figure.3.4.Real parts of gabor filter

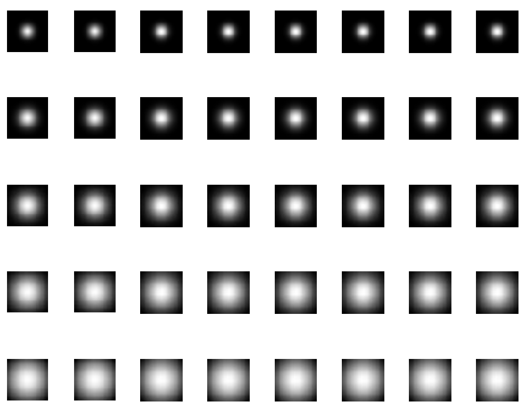

Figure.3.5 Magnitude parts of gabor filter

The Gabor feature representation of a grayscale face image is obtained by convolution of the face image and a Gabor filter as in the following equation (3):

$$F_{\mu,v}(z) = I(z) \times \psi_{\mu,v}(z) \quad (3)$$

Where, × denotes the convolution operator and F(z) is the Gabor filter response of the image with orientation u and scale v. For a 256x256 image, the size of transformed image is 256x256x5x8.So the convolution output produce feature vector which has 16380 features for each image.

The real and magnitude part of Gabor feature vectors with eight orientations and five frequencies is given in Fig.3.3, 3.4.

C. Dimension Reduction with PCA:

As a consequence of Gabor filter, a high dimensional feature vector is obtained. Therefore, it is mandatory to reduce the dimensionality of the feature vector. Principal component analysis PCA

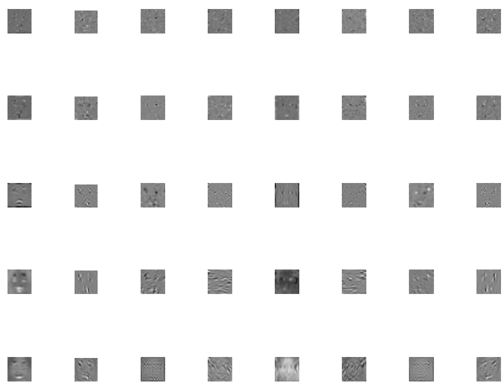

Figure.3.6.Real parts of gabor feature vector

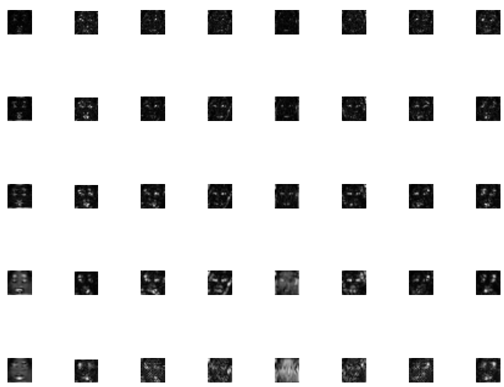

Figure.3.7 Magnitude parts of gabor feature vector

[4] is a technique used to lesser the dimensionality of a feature space that takes a set of data points and constructs a lower dimensional linear subspace that best describes the variation of these data points from their mean.

In effect of this some principal components can be removed because they give details only a small amount of the data, whereas the largest amount of information is contained in the other principal components. Dimensionality reduction of PCA is as follows in equation (4):

$$Y = P \times X \quad (4)$$

Where Y defines lower dimensional feature vector, P = [P1P2… Pn] consists of the n eigenvectors corresponding to leading eigenvalues of the matrix of X. The lower dimensional vector Y captures the most expressive features of the original data X. In our work the lower dimensional feature vector has 3200 features for each face image.

D. Recognition With PNN:

Probabilistic neural network is a kind of radial basis network suitable for classification problems. Probabilistic neural network (PNN) was developed by Specht [12]. It features a feed-forward architecture and supervised training algorithm similar to back propagation. However, a back-propagation neural network has to be trained for a long time to learn the relationship between input and output variables. furthermore, a sufficient dataset must be available to partition the data into a training set, a test set and a validation set to avoid over fitting[6].An alternative method is probabilistic neural network. Instead of adjusting the input layer weights using the generalized delta rule, each training input pattern is used as the connection weights to a new hidden unit. PNN offers several advantages over back-propagation network. Training is much quicker, usually a single pass. Moreover, PNN allows true incremental learning where new training data can be added at any time without requiring retraining of the entire network . The PNN also possesses some useful characteristics as the back-propagation algorithm such as generalization ability.

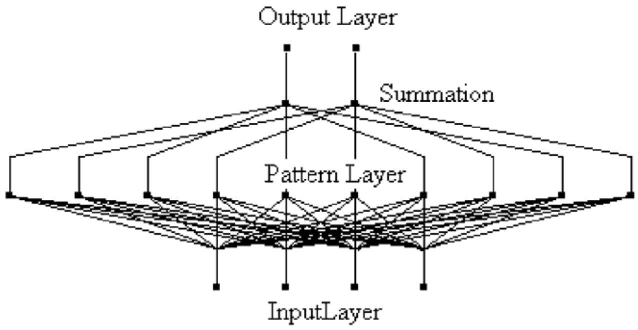

Figure. 3.8. Diagram of a three-layer probabilistic neural network

An example of a probabilistic neural network is shown in Fig.3.5. It has three layers [12]. The network contains an input layer, which has as many elements as there are separable parameters needed to describe the objects to be classified. It has a pattern layer, which organizes the training set such that an individual processing element represents each input vector. And finally, the network contains an output layer, called the summation layer, which has as many processing elements as there are classes to be recognized. Each element in this layer combines via processing elements within the pattern layer which relate to the same class and prepares that category for output. The transfer function is radial basis function for the first layer and is competitive function for the second layer. Only the first layer has biases. Training of the probabilistic neural network is much easier than with back-propagation. It can be simply finished by setting the weights of the network using the training set. Our work constructed PNN with 3200 input units and 7 hidden unit and 7 output units.

The results showed that the predictive ability of the probabilistic neural network is stronger than the others in this study.

IV. RESULTS AND DISCUSSION

Data required for experimentation is collected from JAFFE database [13] (Lyons et al., 1998; Zhang et al.) for neural network training and testing. JAFEE stands for The Japanese Female Facial Expression (JAFFE) Database. The database contains 213 images of 7 facial expressions (6 basic facial expressions + 1 neutral) posed by ten different Japanese female models. Fig.3.6. shows few samples of facial expressions of person KA.

Fear sad surprise happy Angry Neutral disgust

Figure.4.1. Sample Facial expressions of KA from JAFEE data base

It was observed from the work of Shishi et al [14] that the images in the range 134–154 (all belong to the expresser UY) and 199–219 (all belong to expresser NA) were difficult to interpret and highly erratic. Hence expressers NA a UY were considered to be outliers. The problem apparently is in the expressers expressing the expressions. So Experiments were carried out by removing these two expressers from the data set.

By not including 42 images belong to two unreliable expressers from the data set, generalized recognition rate of 86.2% for test data and 100% for training data is achieved as shown in table 1.

Table 1 .Confusion Matrix For 7-Classes Of Facial Expressions

	happy	**sad**	**fear**	**disgust**	**surprise**	**anger**	**Neutral**
Anger	90	0	0	0	5.2	0	0
Disgust	0	75	4.5	0	0	0	0
Fear	0	0	77	4.1	0	0	0
Happy	0	0	2.5	90	0	0	0
Sad	3.6	0	0	0	90	0	0
Surprise	0	0	0	0	0	91	0
Neutral	0	0	0	0	0	0	91

Table 2. Comparison of proposed algorithm

Expression	**happy**	**sad**	**fear**	**disgust**	**surprise**	**anger**	**Neutral**	**Total**
Gabor+LVQ	90	75	75	90	85	90	90	85
Gabor+PNN	90	75	77	90	90	91	91	86.2

In Table II the result of the study is compared with earlier work in which the experimental settings are comparable to ours where LVQ [14] is used instead of the PNN. It shows that the approach presented here is equally good in discriminating expressions. Compared with the previously reported work on 7-class facial expression recognition tasks our work reported an accuracy of 86.2%.

V. CONCLUSIONS AND FUTURE WORK

The present study effectively used PNN for facial expression recognition and Gabor filter banks and PCA as the feature extraction tool. The result is hopeful enough to discover real-life applications of facial expression recognition in fields like surveillance and user mood evaluation. Adaptation of the present approach is being studied to sense mixed-emotions (for example, happiness and surprise, fear and disgust) that may arise in the human face.

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