Facial Emotion Recognition using Hybrid Gabor-LBP Technique for Human Machine Interaction

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Abstract : ***Facial emotion recognition serves as the most important tool for an effective Human Machine Interaction (HMI). It plays a vital role in interpreting and communicating with the people who have speaking impairments as well as a medium to understand and communicate with infants who cannot emote their feelings verbally. In this paper, we propose a hybrid feature extraction technique consisting of Gabor filter combined with Local Binary Pattern (LBP).The features extracted were tested on standard classifiers such as Support Vector Machine (SVM) and K-Nearest Neighbourhood (KNN) classifiers. Facial images from JAFFE and Cohn-Kanade databases were utilized for training as well as testing. The work shows a very high facial emotion recognition rate of 94.8% and 88.4% with the proposed method for JAFFE and Cohn-Kanade databases respectively.***

IndexTerms - Feature Extraction Methods, Classification, Similarity measure, Confusion Matrix, Local Binary Patterns, Gabor Filter

I. INTRODUCTION

In the field of video analytics, human Facial Emotion Recognition (FER) is one of the most challenging tasks, mainly due to the variability and complexity in emotion representation. At the same time, there are vast implications of FER in the areas such as operator fatigue detection, Human-Computer Interaction (HCI), data-driven animation, etc. Due to these attributes and characteristics, the problem of human emotion recognition has been able to successfully capture the attention of researchers in recent times. As shown in the research performed by Mehrabian[1], non-verbal communication is more impactful tool for effective social interaction than verbal speech. The work done by Mehrabian[1] claims that for social communication,7% contribution is given by the verbal part,34% by vocal and the maximum i.e., 55% is contributed by the facial expressions. Thus we can clearly identify the importance effectiveness of facial emotions including fields like Behavioral science, Medicine, Pattern recognition, and Human-Machine interaction etc. Considering the above reasons, a lot of priority and significance has been given to the field of facial emotion recognition by the researchers. As illustrated in the work done by Ekman et al. [2] there are seven basic expressions for Human facial frontier. They had also quoted that all the other expressions are a mixture of these seven basic expressions (anger, fear, happiness, disgust, surprise, sadness and neutral). However, for the main task i.e., to recognize the facial emotions accurately, a very efficient and optimal method is required which is a complex, subtle, and difficult task. The method employed should be able to identify the emotion effectively to build up a better HMI platform.

The most important step inked for facial emotion recognition is the feature extraction from facial images. The algorithms involved in the literature for feature extraction in FER systems are distinguished as feature based and holistic based algorithms. Feature based methods bank on the shapes of the numerous elements of a face for extracting the facial features such as nose , eyes, , mouth, etc., whereas Holistic based methods depend entirely on the extraction of global features of the input image[3].There are distinctive methods applied for feature extraction using holistic approach such as Linear Discriminant Analysis (LDA) [4],Eigen-face approach [5],Independent Component Analysis (ICA), 2D-PCA, Gabor , 2D-LDA, wavelet general discriminant analysis[6], Discrete Cosine Transform(DCT),RBF neural network [7] and much more. Independent Component Analysis (ICA) and Principal Component Analysis (PCA) accord a poor recognition rate because the features extracted by these methods are sensitive to the illumination changes [3].Gabor filters utilized for feature extraction include the convolution of images with Gabor filters at different scales including spatial frequency and orientation to obtain features with very high discriminative attributes. But this method for feature extraction utilizes high computational penalty. Local Binary Pattern (LBP) [8] and the modified LBP [9] have been widely used for their robust performance in an unconstrained environment. LBP corresponds to binary values depending on the deviation of neighboring pixels intensities with the central pixel intensity in a 3x3 window. Here the intensity of the central pixel is treated as the threshold for all its neighboring pixel values [8].But the major shortcomings of LBP is that their performance is deteriorated when confronted with random noise and illumination changes, since it leads to variation in gray levels [10]. The Sobel-LBP [11] has proved to be a very effective and fruitful method for improving the feature extraction performance. In this method, at first, Sobel edge detector is tried on the input image for obtaining the edge information and then the output obtained is given to LBP for feature extraction. Local ternary pattern (LTP) [10] gained recognition after that, which works both on non- uniform and uniform regions thereby enhancing its performance compared to LBP. LTP produces a simple ternary code that adds an extra intensity discrimination level. The individual ternary patterns obtained are then disintegrated into positive and negative code. Separate histograms and similarity metrics are computed by treating these codes as separate channels of LBP descriptors. To end these computations finally the results obtained are combined. LTP as LBP yields to be computationally expensive as well. The major drawback with both LBP and LTP is that the central pixel information is under-utilized. Local Directional Pattern (LDP) [12] uses kirsch compass masks around a position instead of the gray levels of the pixel for getting the directional edge response. The feature extraction hence relies on the responses obtained from these masks. Local Directional Pattern (LDP) delivers improved recognition accuracies than LBP. LDP reckon on selecting larger edge directions but the patterns obtained are inconsistent at uniform and near-uniform regions [10]. Local Directional Number pattern (LDN) [13] exploits the directional information in place of gray level of the face textures. Kirsch masks are deployed in order to assess the direction of maxima and minima relying on the direction of its position for face recognition.

All the above methods discussed in the literature for feature extraction were sloppy in terms of accuracy. Therefore, in this paper we propose a competent feature extraction method which improves the accuracy of recognition compared to the methods discussed in the literature.

The organization of this paper is as presented below. Section II explains the overview of facial emotion recognition system. Section III presents the existing methods used for feature extraction. Section IV discusses the proposed feature extraction technique. Section V discusses about the various classifiers used in this work. Section VI shows the simulated results obtained with discussions and finally section VII discusses the conclusion of our work.

II. SYSTEM OVERVIEW

The proposed facial emotion recognition (FER) system consists of four modules. They are image preprocessing, ROI detection, feature extraction, and classification. A brief description for the FER system is given as follows. To begin with, in the preprocessing stage, the images taken from the database are enhanced and resized to make it less computationally expensive. Then, secondly, the region of interest is detected from the image and it is demarcated from the rest of the unutilized sections of the image. In this FER system the ROI basically consists of the eyes and lips. Next, after the ROI i.e., eyes and lips regions are partitioned out, we implement the feature extraction for these sections for all the training images of the database consecutively. For this we utilize the feature extraction techniques to compute the features and finally are stored as feature vectors for the distinct images of the database. Finally, the FER system exploits a minimum distance based classifier in order to recognize the facial emotion thereby comparing the test image features with the trained ones for peculiar class i.e., expression.

III. EXISTING METHODS FOR FEATURE EXTRACTION

There are a variety of existing methods for facial feature extraction as described in the literature mentioned above. In this work, we try to correlate our proposed method i.e., a mixture of Gabor and LBP for feature extraction combined with SVM and KNN independently for classification. Therefore, first we explain Gabor filter and Local Binary Patterns (LBP) briefly before explaining our proposed method. By comparison, we are trying to prove the efficiency and the robustness of our proposed work compared to the methods mentioned in the literature.

3.1 Gabor Filter

Gabor filters (also called Gabor wavelets or kernels) have proven themselves to be a powerful tool for facial feature extraction and robust face recognition. They represent complex band-limited filters with an optimal localization in both the spatial as well as the frequency domain. Thus, when employed for facial feature extraction, they extract multi-resolutional, spatially local features of a confined frequency band [14]. Like all filters operating in the scale-space, Gabor filters also relate to the simple cells of the mammalian visual cortex and are, hence, relevant from the biological point of few as well. In general, the family of 2D Gabor filters can be defined in the spatial domain as follows [15, 16, 17]:

$$\psi_{u,v}(x,y) = \frac{f_u^2}{\pi k\eta} e^{-((f_u^2/k^2)x'^2+(f_u^2/\eta^2)y'^2)} e^{j2\pi f_u x'} \tag{1}$$

where $x' = x \cos\theta_v + y \sin\theta_v$, $y' = -x \sin\theta_v + y \cos\theta_v$, $f_u = f_{max}/2^{(u/2)}$, and $\theta_v = v\pi/8$. As can be seen from the filters definition, each Gabor filer represents a Gaussian kernel function modulated by a complex plane wave whose center frequency and orientation are given by f_u and θ_v respectively. The parameters κ and η determine the ratio between the center frequency and the size of the Gaussian envelope and, when set to a fixed value, ensure that Gabor filters of different scales behave as scaled versions of each other [151]. It should also be noted that with fixed values of the parameters κ and η, the scale of the given Gabor filter is uniquely defined by the value of its center frequency f_u. While different choices of the parameters determining the shape and characteristics of the filters define different families of Gabor filters, the most common parameters used for face recognition are $\kappa = \eta = \sqrt{2}$ and $f_{max} = 0.25$ [14, 15, 16, 17].When using the Gabor filters for facial feature extraction, researchers typically construct a filter bank featuring filters of five scales and eight orientations, that is, $u = 0, 1, . . . , p - 1$ and $v = 0, 1, . . . , r - 1$, where $p = 5$ and $r = 8$.

Let I(x, y) stand for a grey-scale face image of size a×b pixels and, moreover, let $\psi_{u,v}(x, y)$ denote a Gabor filter given by its center frequency f_u and orientation θ_v. The feature extraction procedure can then be defined as a filtering operation. The real parts of the Gabor filter bank commonly used for feature extraction in the field of face recognition. Given face image I(x, y) with the Gabor filter $\psi_{u,v}(x, y)$ of size u and orientation v [15, 16, 17, 18], that is

$$G_{u,v}(x, y) = I(x, y) * \psi_{u,v}(x, y) \tag{2}$$

where $G_{u,v}(x, y)$ denotes the complex filtering output that can be decomposed into its real ($E_{u,v}(x, y)$) and imaginary ($O_{u,v}(x, y)$) parts:

$$E_{u,v}(x, y) = Re[G_{u,v}(x, y)] \tag{3}$$

$$O_{u,v}(x, y) = Im[G_{u,v}(x, y)] \tag{4}$$

Based on these results, the magnitude ($A_{u,v}(x, y)$) and phase ($\varphi_{u,v}(x, y)$) responses of the filtering operation can be computed as follows:

$$A_{u,v}(x,y) = \sqrt{E_{u,v}^2(x,y) + O_{u,v}^2(x,y)} \tag{5}$$

$$\varphi_{u,v}(x,y) = \arctan\left(\frac{E_{u,v}^2(x,y)}{O_{u,v}^2(x,y)}\right) \tag{6}$$

When deriving the Gabor (magnitude) face representation from a given facial image, the first step is the construction of the Gabor filter bank. As we have pointed out already, most of the existing techniques in the literature adopt a filter bank comprising Gabor filters of five scales (u = 0, 1, . . . , 4) and eight orientations (v = 0, 1, . . . , 7). Next, the given face image is filtered with all 40 filters from the filter bank resulting in an inflation of data dimensionality to 40 times its initial size. Even for a small face image of, for example, 128 × 128 pixels, the 40 magnitude responses reside in a 655360 (128 × 128 × 40) dimensional space, which is far too expensive for efficient processing and storage. Thus, to overcome this dimensionality issues, down sampling strategies are normally exploited. The down sampling techniques reduce the dimensionality of the Gabor magnitude responses, unfortunately often at the expense of valuable discriminatory information. One of the most popular down sampling strategies relies on a rectangular sampling grid superimposed over the image to be sampled. In the down sampled image only the values located under the sampling grid's nodes are retained, while the rest is discarded. The down sampling procedure is applied to all magnitude responses, which are ultimately normalized using a properly selected normalization procedure and then concatenated into the final Gabor (magnitude) face representation or, as named by Liu and Wechsler [15], into the augmented Gabor feature vector. (Note that typically zero-mean and unit variance normalization is applied at this step. However, as other normalization techniques might be superior to the zero mean and unit-variance scheme, the issue of selecting the most appropriate normalization procedure will empirically be investigated in the experimental section.) If the down sampled Gabor magnitude responses are denoted in vector form at the u^{th} filter scale and v^{th} orientation by $g_{u,v}$, then the augmented Gabor (magnitude) feature vector x can be defined as follows [15, 16, 17, 18]:

$$X = (g_{0,0}^T, g_{0,1}^T, g_{0,2}^T, \ldots, g_{4,7}^T)^T \tag{7}$$

It should be noted that in the experimental section, we use images of size 128 × 128 pixels and a rectangular sampling grid with 16 horizontal and 16 vertical lines, which corresponds to a down sampling factor of ρ = 64.

3.2 Local Binary Pattern

Local Binary Pattern (LBP) concept is applied to area like face recognition [19], dynamic texture recognition [20] and shape localization [21]. The LBP method is widely used in 2D texture analysis. The LBP operator is a non-parametric 3x3 kernel which describes the local spatial structure of an image. It was first introduced by Ojala et al [22] who showed the high discriminative power of this operator for texture classification. At a given pixel position (x_c, y_c), LBP is defined as an ordered set of binary comparisons of pixel intensities between the centre pixel and its eight surrounding pixels. The decimal values of the resulting 8-bit word (LBP code) leads to 28 possible combinations, which are called Local Binary Patterns abbreviated as LBP codes with the 8 surrounding pixels. The basic LBP operator is a fixed 3 x 3 neighbourhood as in Fig 3.1

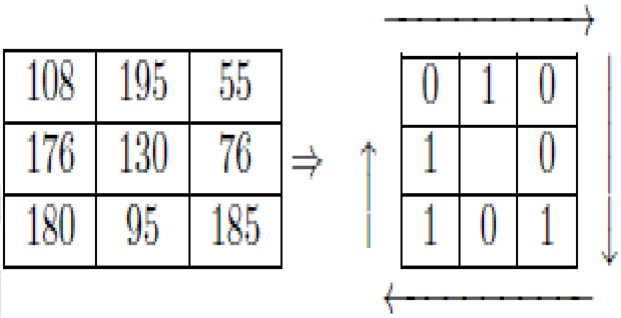

Fig 3.1 Basic Local Binary Pattern operator

The LBP operator can be mathematically expressed as

$$LBP(x_c, y_c) = \sum_{n=1}^{8} s(I_n - I_c)2^n \tag{8}$$

Where I_c corresponds to the gray value of the centre pixel (x_c, y_c), I_n to the gray values of the 8 surrounding pixels and function s is defined as,

$$s(x) \leftarrow \begin{Bmatrix} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{Bmatrix} \tag{9}$$

IV. PROPOSED FEATURE EXTRACTION METHOD

The basic structure of the proposed system involves a hybrid feature extraction technique utilizing Gabor filter and LBP. So at first; we extract the face region from training images using Viola-Jones method [24] which has been abundantly utilized in the field of face detection and face recognition using Matlab built-in functions. Then the face region extracted is converted into the required size of 256x256.Then the regions of the eyes and mouth are detected by means of Adaboost algorithm [25]. This region of interest (ROI) extracted from the images is then fed to the Gabor filter module which produces features for individual images. The obtained matrices are then reformed to produce column vectors, and they are normalized finally.

In part 2, the features obtained are converted back to an image. Actually, here we employ the resultant matrix obtained in the previous section instead of the total number of images as the input data to LBP. This modification ensures a better and a much better efficient system compared to the previous ones.

This process is repeated for all training images first and the final features extracted for each trained image is stored as a database with the corresponding class being labeled for individual expressions. For testing we consider one image at a time and the features are extracted by the proposed method. The features are tested to check the similarities with any of the features of an expression. The similarity index is calculated using classifiers explained below.

V. CLASSIFICATION

Classification here is done using two of the well known classifiers i.e., Support Vector Machine (SVM) and k-Nearest Neighbour (KNN) classifier. These classifiers help us in picking out the elements of the same class as well as different classes which in turn gives the recognition rates obtained individually by them. We in our work focus on utilizing these standard classifiers for checking the response of our proposed feature extraction method testing it on the standard classifiers.

SVM [26] is a machine learning method which maps on the available data to a feature plane and it then proposes a linear hyper plane which basically segregates the different classes by separating the pertinent data points. The Kernel linked with SVM is the polynomial Kernel with degree 1 and 2 which are used to classify the sets into different classes. But in this method Kernel with degree 1 is utilized for classification. The main objective here is to discover the similarity measure for the features of the test image by comparing it with the features of all other trained images of the databases.

The second classifier utilized here for classification is the k-Nearest Neighbour classifier abbreviated as KNN [23]. This classifier is described by non-parametric statistics and it presumes that the data is non-characteristic in its structure and has no parameters as well. Classification is performed based on the height of similarity between the test and train sample patterns in the feature space. The classification here is dependent on the votes of its neighbours. If k = 1 then the sample is assumed to be of the same class as of its nearest neighbour. The objective is to carry out the comparison of the coded feature vector of a testing sample from one feature vector with the remaining candidate's feature vectors of the testing sample with the help of a new similarity measure technique. This similarity measure between two feature vectors of train and test images, of length N is given by:

$$d_s = \sum_{i=1}^{N} \frac{|Train_i - Test_i|}{Train_i + Test_i} \tag{10}$$

The feature vector in lieu of the lowest distance value d_s indicates the recognition of the expression class.

VI. RESULTS AND DISCUSSION

In order to study and understand the performance of our proposed system, we have used two standard databases namely JAFFE database [27] and Cohn-Kanade Database [28] to evaluate the performance of our facial emotion recognition system i.e., we imposed our algorithm on these databases to understand the efficiency achieved by our proposed work. The databases utilized in this work are the standard databases used by a lot of researchers to prove the efficiency of their algorithms for facial emotion recognition as well as for face recognition. Training and testing sets were formed with a ratio of 90:10 for both JAFFE as well as Cohn-Kanade databases. First, the features were extracted from the training images and the feature vectors thus obtained were stored and then the same process was repeated for test image i.e., after extracting the features of test image, these test image features were consecutively compared with the features of the trained images. The test feature which resembles similar to the feature of a train image is said to be of the same class to the class of the trained image.

Table 6.1: Confusion Matrix of Proposed Method+ KNN tested On JAFFE Database for Maximum Accuracy

Desired Emotion	Recognized Emotion						
	Anger	*Disgust*	*Fear*	*Happy*	*Neutral*	*Sad*	*Surprize*
Anger	**100**	0	0	0	0	0	0
Disgust	4.4	**95.6**	0	0	0	0	0
Fear	0	0	**98.6**	0	1.4	0	0
Happy	0	0	1.9	**98.1**	0	0	0
Neutral	0	0	0	0	**86.9**	13.1	0
Sad	0	0	8.2	0	0	**91.8**	0
Surprize	0	0	0	7.4	0	0	**92.6**
Overall Accuracy		**94.8%**					

Fig.6.1 and Fig.6.2 shows the evaluated performance of Gabor filter when tested with SVM and KNN classifiers respectively. We then evaluate the performance of LBP when tested with SVM and KNN classifiers as depicted in the same figures as discussed above and finally we evaluate the performance of combined Gabor and LBP with SVM and KNN classifiers as shown in the same figures.

The simulated results shown in Fig 6.1 and Fig 6.2 also prove that all the feature extraction methods used for carrying out this work performed better when tested with KNN rather than on SVM. For JAFFE database, when Gabor filter was used as feature extraction method, the recognition rate was 82.1% and 85.4% when tested with SVM and KNN respectively. Similarly when LBP was used as feature extraction method, the recognition rate was 85.9% and 86.8% when tested with SVM and KNN respectively. But with the proposed feature extraction method the recognition rate rises to 93.8% and 94.8% when tested with SVM and KNN respectively. For CK database, when Gabor filter was used as feature extraction method, the recognition rate was 76.6% and 79% when tested with SVM and KNN respectively. Similarly when LBP was used as feature extraction method, the recognition rate was 78.7% and 80.6% when tested with SVM and KNN respectively. But with the proposed feature extraction method the recognition rate rises to 86.7% and 88.4% when tested with SVM and KNN respectively.

Since KNN performs much better as a classifier with our proposed feature extraction method, therefore the confusion matrix for the proposed feature extraction method when tested with KNN for JAFFE database is shown in Table 6.1 and similarly the confusion matrix for the proposed feature extraction method when tested with KNN for CK database is shown in Table 6.2.

Table 6.2: Confusion Matrix of Proposed Method+ KNN Tested On Cohn Kanade Database for Maximum Accuracy

Desired Emotion	Recognized Emotion						
	Anger	*Disgust*	*Fear*	*Happy*	*Neutral*	*Sad*	*Surprize*
Anger	**99.2**	0	0	0	0.8	0	0
Disgust	0	**87.1**	12.9	0	0	0	0
Fear	0	0	**85.6**	0	14.4	0	0
Happy	0	0	0	**83.1**	0	0	16.9
Neutral	0	0	0	0	**84.2**	15.8	0
Sad	0	9	0	0	0	**91**	0
Surprize	0	0	0	13.4	0	0	**86.6**
Overall Accuracy		**88.4%**					

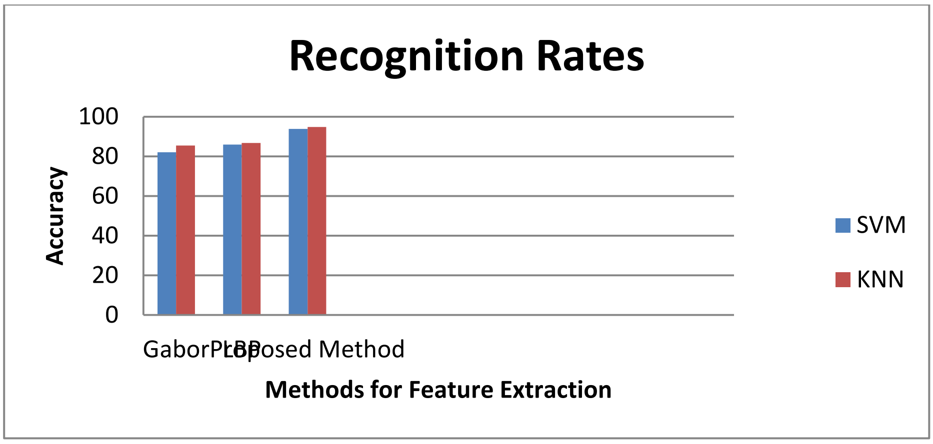

Fig.6.1: Results for feature extraction techniques tested with JAFFE database

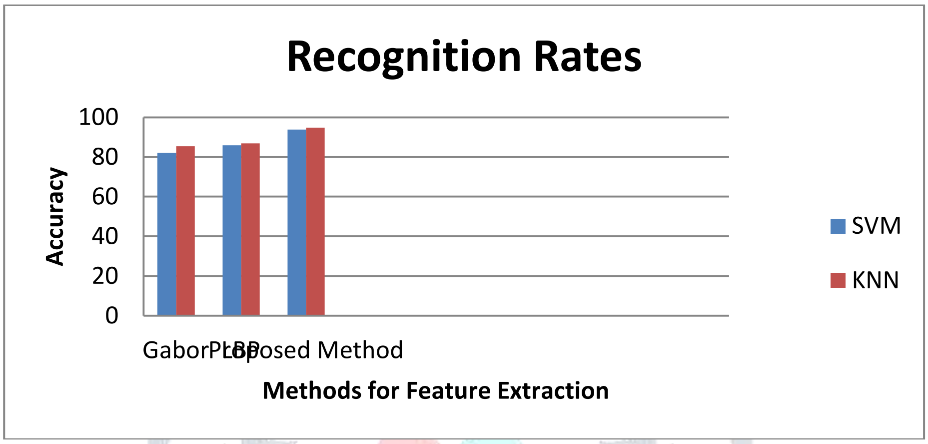

Fig.6.2: Results for feature extraction techniques tested with CK database

Hence, the simulated results obtained thus illustrates that our proposed method is able to obtain very high recognition rates of 93.94% and 91.8% for JAFFE and Cohn-Kanade database respectively in comparison to the existing methods. The existing methods which were discussed in the literature had good recognition rates for facial emotion analysis but our proposed method surpasses the rest. The comparison is illustrated in the figures given above where the results are meant to prove the effectiveness of our proposed method.

VII. CONCLUSION

Human emotion recognition plays an important role in identifying and understanding a person's state-of mind and sometimes it helps to understand their intentions as well. It has a wide scope in the field of robotics .In this paper, a human facial emotion recognition system using Gabor filter embedded with LBP has been proposed. The results obtained from the simulated results proves that this proposed method has proved to be better in terms of recognition rates as compared to its counterparts such as Gabor and LBP when used for feature extraction and KNN proved to be a better classifier for our proposed feature extraction method compared to SVM.

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