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LBP Based Facial Expression Recognition Using k-NN Classifier

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ABSTRACT

Facial expression is one of the common, immediate and natural means for human beings to communicate their emotions and intensions. Facial expression analysis finds its major applications in human computer interaction and data driven animations etc., In this paper, we evaluate facial representation based on some statistical local features, Local Binary Patterns, for facial expression analysis. Different machine learning techniques were deployed and thoroughly verified for JAFFE data base. A wide-ranging work and experiments shows LBP based feature extraction is very effective and efficient, and the best recognition performance is obtained by using k-NN classifier i.e. 84%.

Keywords: **Facial expression recognition, Local Binary Pattern (LBP), k-Nearest Neighbour(k-NN), Japanese Female Facial Expressions(JAFFE).**

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I. INTRODUCTION

Facial expression is one of the most means for human beings to communicate mutually between each other to distribute their emotional intensions. There has been continued research interest in enabling computers to identify expressions and to use the emotional information rooted in them in human-machine interfaces. Automation in facial expression recognition has been a theme of research in the last years due to the great number of potential day-to-day applications

Facial expression analysis is an challenging and much scoped area and finds major applications in real time, Thus it attracted many attentions in these recent years [1 - 3].

Deriving an effective facial representation from the original images is a major step for successful analysis of facial expression recognition. For extracting features from an image, generally there are two regular approaches: geometric feature based methods and appearance based methods [4]. In this paper, we empirically study and analyze facial expression representation using Local Binary Pattern (LBP) features for facial expression recognition. LBP features have been actually introduced for texture analysis and recently found it been useful to represent faces in facial images analysis [5]. LBP is resistive to illumination changes, rotation invariant and computational simplicity [6], we examined *k*-NN based machine learning technique for better classification of images and found its the best eminent classifier for LBP based feature extraction. Moreover LBP features perform stably and robustly over a constructive range of low resolutions of face images, and yield capable performance in compressed low-resolution.

II. LITERATURE SURVEY

William James gives the important theory of physiological emotions In 19th century, that is in a person emotions are deep-seated in the physical experience. First we perceive the object then response occurs and then emotions appear. For example, when we notice a lion or other danger we begin to sprint, i.e., a sign of emotional intension. Each emotion has its own characteristics and appearance information. Six basic emotional intensions are seen i.e. fear, surprise, sadness, happiness, anger and disgust are accepted universally. These basic emotional intensions can be distinguished as negative and positive emotions.

Ekman and Friesen [7] designed the Facial Action Coding System (FACS) to code facial expressions where movements on the face have been described by a set of action units (AUs). Each AU has some related muscular foundation. By following a set of prescribed rules this system of coding facial expressions is done manually. facial expressions images are taken as input. This process is very time-consuming. many researchers were inspired by Ekman's work to analyze facial expressions by means of image and

video processing. Facial features were tracked and the amount of facial movement was measured to categorize different facial expressions. ‘‘Basic expressions’’ or a subset was recently used to work on facial expression analysis and recognition [8].

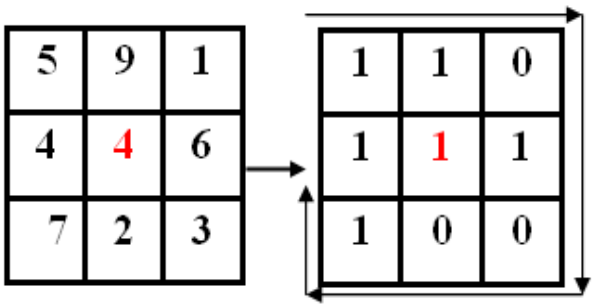
Recently C. Shan et al. [9] made a attempt to recognize facial expressions at low resolutions using LBP feature extraction and SVM classifier. In this work, we demonstrate LBP features for low-resolution facial expression recognition using k-NN classifier. However, these existing works were conducted on a very small database (JAFFE) using an individual classifier. In contrast, here a study of LBP features for facial expression recognition with *k*-NN classifier on JAFFE database to investigate LBP features for low-resolution facial expression recognition, a critical problem but seldom addressed in the present work. We not only perform evaluation on different features provide just as good or better performance. So our project is very promising for real-world applications.

III. Feature Extraction

Facial Expression Database

Collection of images that associates with an facial expression experiments is a Database. Thus to train our classifier we used JAFFE (Japanese female facial expressions) data base.

Which consisted of 10 female subjects with 7 different emotions. Each expression of an individual female subject consists 4-5 images with different resolutions and these has to be resized to a smaller resolution for better results, and thus there are total 213 images of 10 female subjects.



Binary: 11010011
Decimal: 211

Fig.1. The basic LBP operator

We used JAFFE database in experiment to a classifier. Initially we performed person dependent experiments, in which part of the data for each subject was used as training data, and another part as testing data. The training data set consists of 75% and testing data set consists 25% of data i.e., An individual female subject each expression consists 5 images in which 4 images are put in training data set and remaining 1 image is put into testing data set, this is similarly did for all 10 female subjects respectively.

The JAFFE data base which we got from the JAFFE official website[10] are available with the proper expression and respective name of an female subject such as KA.AN1,KL.AN1,KMAN1,KR.AN1 etc, these are renamed for our convenience in a numerical sequence manner such as 1,2,3,……214.

The data base is an actual back end of an system which supports the requirements needed for facial expression classification, the proposed system how an actual trained or testing data set available is as shown in fig.2.

These images after resizing into a smaller resolution i.e., say 128 X 128, the data sets of training and testing are separately combined respectively according to the expressions in the order Anger, Disgust, Fear, Happy, Neutral, Sad, Surprise to get a combine result of all training and testing images.

The output of respective data sets is a large image which is in the matrix format, now the matrix is stored for feature process (i.e., instead using large image we can directly use the matrix form of it to access the elements of individual image)

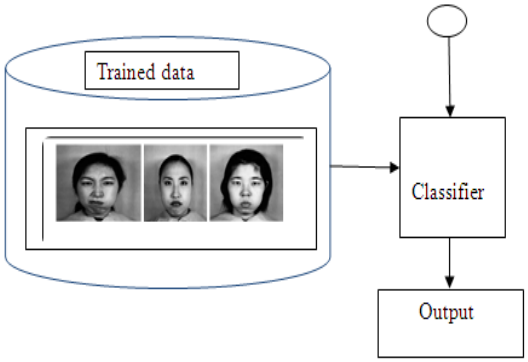


Fig.2. Block Diagram of proposed data set available at backend

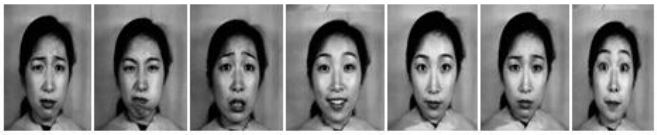


Fig.3. Samples of an individual from JAFFE data base with various expressions

Local binary Pattern(LBP)

The feature extraction is done by LBP, Ojala et. al. introduced a LBP which is used to train the classifier based on the feature extraction the original LBP operator [6], and was proved a powerful means of texture description. The pixels of an image is labelled by thresholding a 3x3 neighbourhood with the centre value of each pixel and considering the results as a binary number (see Fig. 1 for an illustration), and a 256-bin histogram of the LBP labels which is computed over a region is considered as a texture descriptor.

After labelling a image with the LBP operator, a histogram of the labelled image f1(x,y) can be defined as :

$$H_i = \sum_{x,y} I\,(f1\,(x, y)) = i \qquad (1)$$

Where i=0…n-1

Where n is the number of different labels produced by the LBP operator and

$$I\,(A) = \begin{cases} 1 & \text{A is true;} \\ 0 & \text{A is false;} \end{cases} \qquad (2)$$

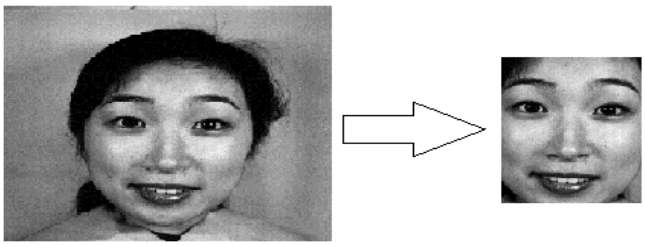


Fig.4. The original face image and the detected face image.

IV. CLASSIFIERS

The word classifier [11] is defined loosely to a computer program that implements a specific procedure for image classification. Many classification strategies has devised by the scientists over the years. The classifier that will best accomplish a specific task should be selected as alternatives by the analyst. At present there is no possibility to state that a given classifier is a "best" for every situation, because characteristics of each image and the circumstances for each study vary. Hence it is very much essential for an analyst to understand the alternative strategies for image classification.

A. A primitive method of classification mainly follows two approaches:

1. Unsupervised: The classifiers which do not utilize training data as the basis for classification is said to be Unsupervised Classifier. This family of classifiers involves algorithms which examines the unknown pixels in an image and make them into a number of classes based on the natural groupings. It performs very well in cases where the values given within a cover type in measurement type are close together, data in different classes are comparatively well separated.

2. Supervised: Process of using Pixels of known identity is used to classify pixels of unknown identity is supervised classification. Pixels located within training areas are the samples of known identity. Pixels located within these areas are used to train samples assigning specific spectral values to appropriate informational class. The steps involved in A typical supervised classification procedure are:

- The training stage
- Feature selection
- Selection of appropriate classification algorithm
- Accuracy evaluation.

A. k-Nearest Neighbour (k-NN) Classifier:

The method for classifying objects based on closest training examples in the feature space is *k*-Nearest neighbour classifier. The k-nearest neighbour algorithm is simplest where classification of an object is done by majority vote of its neighbours (*k* is a positive integer, naturally small). If *k*= 1, then the object assigned to class its nearest neighbour. The nearest-neighbour method predicts the class of a test example. The training phase is simple, i.e., to predict first example and then to compute its distance with every training example. Then, by keeping the *k* closest training examples, where $k \geq 1$ is a unchanging integer. This basic method is called the *k*-NN algorithm.

$$d(x, y)=(\sum^{m}_{i=1} (x_i-y_i)^2)^{1/2}$$

B. Confusion matrix

A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix.

The entries in the confusion matrix have the following meaning in the context of our study:

1. *A* is the number of **correct** predictions that an instance is **negative**.
2. *B* is the number of **incorrect** predictions that an instance is **positive**.
3. *C* is the number of **incorrect** of predictions that an instance **negative**, and
4. *D* is the number of **correct** predictions that an instance is **positive**.

The following table shows the confusion matrix for a two class classifier.

Several standard terms have been defined for the 2 class matrix:

1. The accuracy (AC) is the proportion of the total number of predictions that are correct. It is calculated using the equation
(3)
2. The true positive rate (TP) is the proportion of positive cases that are correctly identified, as calculated using the equation
(4)
3. The false positive rate (FP) is the proportion of negatives cases that are incorrectly classified as positive, as calculated using the equation
(5)
4. The true negative rate (TN) is defined as the proportion of negatives cases that were classified correctly, as calculated using the equation
(6)
5. The false negative rate (FN) is the proportion of positives cases that were incorrectly classified as negative, as calculated using the equation
(7)
6. Finally, precision (P) is the proportion of the predicted positive cases that were correct, as calculated using the equation
(8)

TABLE I. Confusion matrix for a two class classifier

		Predicted class	
		Negative	***Positive***
Actual Class	***Negative***	A	B
	Positive	C	D

V. PROPOSED METHOD

The proposed method shows an overall architecture of an facial expression recognition system which is explained clearly with the flow of diagram as shown below.

[1]. IMAGE AQUISITION**:** Initially the images are acquired from training and testing dataset as formed and explained in chapter 5 where each images is of 256x256 resolution gray scale image.

[2]. IMAGE PREPROCESSING**:** image preprocessing includes 2 steps

I. **Face detection:** The image acquired may contain background other than only face region. For accurate classification of human expression only face part has to be detected and for this requirement we go for viola Jones method [12],[13] for face detection.

II. **Image resizing:** The images from dataset considered for both testing and training is of size 256x256. Each images are resized to 32x32 for compatibility of classifier.

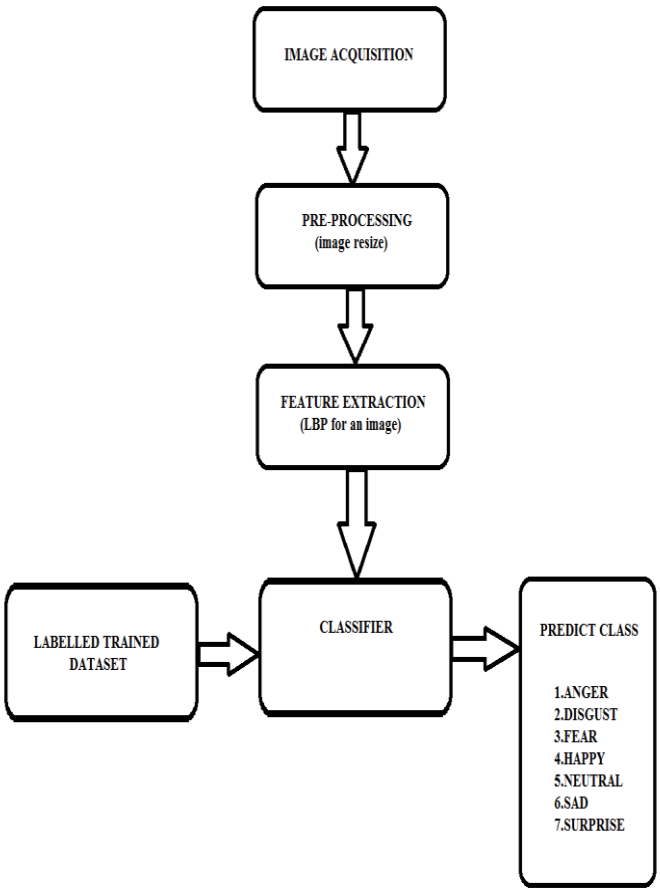


Fig.5. Flow Diagram Of Facial Expression Recognition

[3]. FEATURE EXTRACTION**:** After detecting and resizing the images, the features are to be extracted for further processing, which includes

i. **Step 1**: The image sized 256x256 is been resized to 32 x 32 pixels as explained previously. Each image is been divided into 4x4 and 8x 8 size of 64 and 16 blocks respectively. The same is as shown below

f(x, y)=[out_ i], i = 1……N

Where, N = number of blocks

f(x, y) = detected face.

out_ i = each block of size 8x8 or 4x4

ii. **Step 2**: The LBP's(Local Binary Patterns) is extracted for each block separately as discussed in chapter 3 and is mathematically represented as

$\mathbf{L_i = LBP\ (out\_i)}$ i= 1……N

Where, N = number of blocks

LBP = LBP operator

iii. **Step 3**: After extracting LBP, the histogram for each block is evaluated. Mathematically it is given as

$\mathbf{k_i = hist\ (L_i)}$ i=1……N

Where, N is number of blocks

hist is histogram operator

iv. **Step 4**: Each block for which is histogram is computed is concatenated to form a feature vector and the mathematical representation for this is given below

$\mathbf{FV= [k_1, k_2, k_3, k_4 \ldots\ldots\ldots\ldots\ k_N]}$

Where, FV= Feature vector.

v. **LABELLED TRAINED DATASET**: After extracting the feature vector from the training and testing dataset, the training dataset has to be labeled with the facial expression classes for supervised learning, so that an unseen facial expression can be classified according to the label. The labeling is as shown below.

$X_j = [FV_i, y]$

Where j = Number of samples in Training dataset which varies from 1…..138

FV = feature vector,

y = Class label as shown below

4) CLASSIFICATION**:** The labelled training dataset so formed is now given to classifier for training to produce a trained model which can further predict the class of test images.

VI. RESULTS

The facial expression recognition system using *k*-NN classifier and LBP with JAFFE data base was carried out under two phases.

1. Training phase: Under training phase, for all the images from the training dataset the features are extracted, labeled and given to the classifier for training. During the process of training, the classifier learns under supervision to generate the classifier model.

2. Testing phase: The trained classifier model is tested using the testing data set and further, the performance of the classifier can be evaluated.

***Case 1*:** The images from training data base (each data base) is divided into 4x4 sized cells to obtain a total of 64 blocks. Each cell is applied with LBP and finally feature vector is obtained.

The feature vectors along with class label are given as input to *k*-NN classifier for training. The k-NN classifier is trained by varying the values of *k* (i.e.=1,2,3,4). After the process of training for all the images present in the testing data set the feature vectors are obtained .These feature vectors are now given as input to trained k-NN classifier which is able to predict the class of each one of the image present in the testing data set, the results of k-NN classifier is as shown in Table II.

Table II. Classification accuracy obtained by varying k for 64 blocks

Accuracy In % For Individual Expression									Overall Accuracy
Classifier		Anger	Disgust	Fear	Happy	Neutral	Sad	Surprise	
K-NN Classifier	1	80	81.81	76.92	83.33	81.81	89	70	79.12
	2	80	81.81	83.33	83.33	90	72.72	70	80.17
	3	80	72.72	75	75	81.81	72.72	60	73.80
	4	80	72.72	50	50	90	72.72	60	72.68

Table III. Classification accuracy obtained by varying k for 16 blocks

Accuracy In % For Individual Expression									Over All Accuracy
Classifier		Anger	Disgust	Fear	Happy	Neutral	Sad	Surprise	
K-NN Classifier	1	100	81.81	83.33	83.33	80	81.82	70	82.89
	2	100	81.81	83.33	83.33	80	81.82	70	82.89
	3	100	72.72	75	75	80	81.82	80	80
	4	100	90.90	75	75	80	81.82	80	84.21

***Case 2*:** Subsequently the same process of facial expression recognition was carried out on the database by dividing the image into 8x8 cell of 16 blocks, the results for individual facial emotions are tabulated as shown in Table III.

As compared to 4x4 cells of total 64 blocks, we got higher accuracy for 8x8cells of total 16 blocks, which are experimentally tabulated as shown in Tables II and Table III respectively.

Finally, the performance comparison was made using classification accuracy on 16 and 64 blocks. The results are as depicted in figures shown below.

Fig.6. Comparison of Anger for k=1,2,3,4

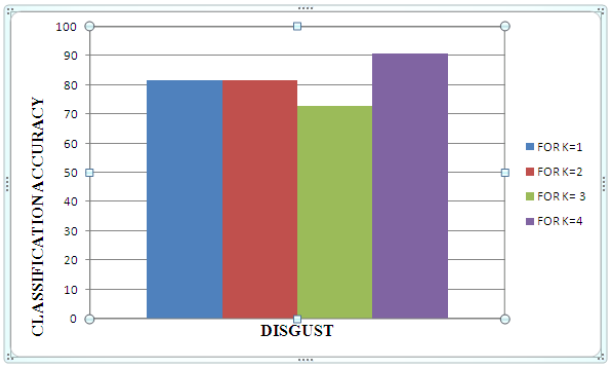


Fig.7. Comparison of Disgust for k=1,2,3,4

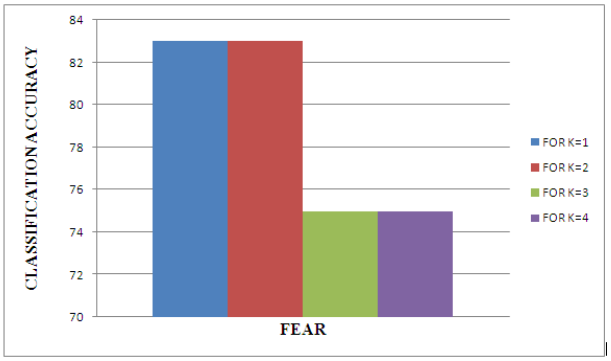


Fig.8. Comparison of Fear for k=1,2,3,4

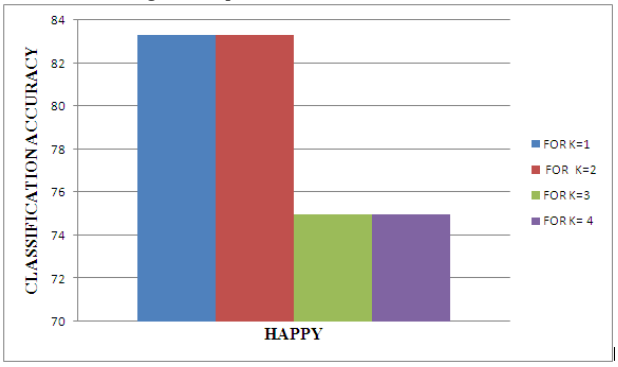


Fig.9. Comparison of Happy for k=1,2,3,4

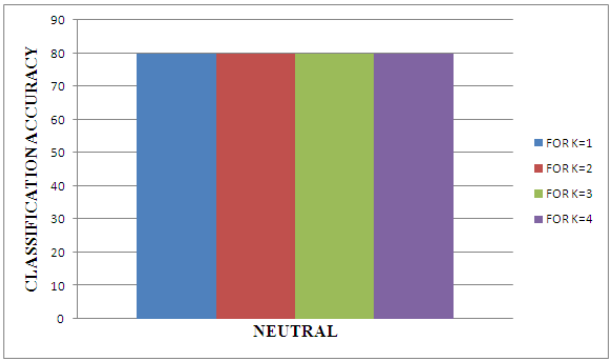


Fig.10. Comparison of Neutral for k=1,2,3,4

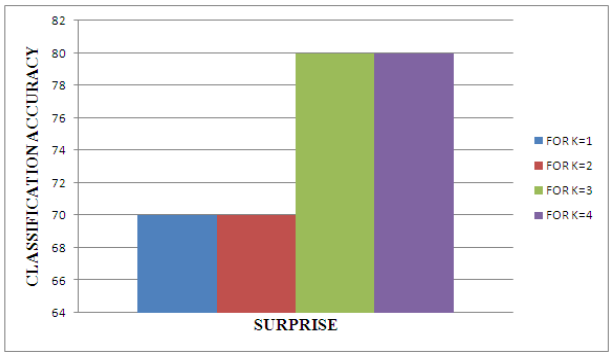


Fig.12. Comparison of surprise for k=1,2,3,4

VII. CONCLUSION

The accuracy obtained by using *k*-NN classifier for facial expression recognition according to our experimental results are higher than the accuracy obtained by using SVM classifier (The SVM classifier results from the base paper of C.shan.et.al [15] are compared with our project)i.e., the accuracy obtained by SVM is 75% and by using *k*-NN was 84%.

Further accuracy can be increased with fusion of various classifiers that gives more accuracy and using various feature extraction methods.

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