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# Data Handling and Data Classification in Multi-View Facial Expression Recognition Using Local Binary Patterns

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**Abstract-** Facial expression recognition is an active research field in the application development sector which includes animation, sociable robots and neuro-marketing. Facial Expression recognition is not simple, because the layers of images can vary due to the mode of expression, background, pose and brightness. Analysis of Automatic facial expression recognition is a challenging problem and it is very significant application in many research areas like data driven animation and human computer interaction. In this article, we examine the facial representation depends on the Local Binary Patterns. To minimize the issue, preprocessing methodologies were used to extract only the expression of particular attributes from the facial images and explore the presentation order of samples at the training sample order. The proposed method attains better results when compared to the existing techniques and achieves 97% accuracy.

**Index Terms**—first term, second term, third term, fourth term, fifth term, sixth term

## I. INTRODUCTION

Facial expression plays a major role in human emotion recognition[1]. The facial changes show the person's emotional state, social communication and intension [2]. In recent days, automated facial expression recognition plays an essential role in many applications namely interactive games, data-driven animation, neuro-marketing and many interaction systems amongst human and computer. Recognizing the facial expression is effortless and rapid function for humans[3], but it is difficult for computers, recent techniques demonstrated with 95% of accuracies, sometimes it extended based upon its conditions and attributes. Many literature works does not contain the stable evaluation techniques and it gives misleading inaccuracy, also doesn't mention many facial expression recognition issues in real-time cases. Also Low accuracy had stated due to

uncontrolled database backgrounds and cross database valuations. To solve this problem, several researchers have tried to develop the methodology in the computer which reaches a similar precision of humans. Still, there is a problem with computers because it is not easy to distinguish human facial expressions and feature space. Some expressions like "sad and fear" shown to be more close in attribute space.

Methodologies to examine the facial expression recognition are mainly come under these cases of training and testing the images. Recognizing the system of facial expression can be categorized into two types: The first type is the persons who work with static images [4] -[9] and the other is the persons who work with dynamic image sequences [10] -[13]. The static based method comprises the data about the current input image merely. Dynamic image sequences contain the temporal data images to understand the facial expression taken from single or many frames. Recognition of Multi- View Facial Expression in an automated system gets the expected static image input or image sequence input. This methodology will highlight the static images and it will focus the six facial expression to seven facial expression sets such as surprise, sadness, fear, disgust, anger, joy and neutral. This work also predicts neutral expression.

The facial acquisition can be divided into two major categories: face detection [14] - [17] and head poses estimation [18] - [20]. Depending on Geometric attributes based technologies with location & space of facial attributes like eyes, eyebrows, mouth and nose. Feature vectors contain the Appearance-based strategies extracted from the entire face or particular sections[21]. Feature Learning, Selection of Features and Classifier Construction are three basic training procedures [22]. These

techniques are responsible for feature extraction associated with facial expression. Intra- class expression deviation should be reduced while increasing the inter-class deviation. Increasing the inter-class deviation is hard because the facial images of the same individual in various expressions may similar to each other in [23].

In this proposed work, face recognition depends on Local Binary Pattern attributes [24] -[26] for independent individual facial expression recognition. Local Binary Pattern [LBP] attributes used for the analysis of texture and introduced to denote the analysis of facial images [27] - [29]. The survey shows that it related to Gabor wavelets. Local Binary Pattern [LBP] attributes analyzed the raw image in a single scan and present in low dimensional attribute space also retain the discriminative data of facial images in compact depiction. The main goal of this research article is to examine the LBP attributes of independent individual face expression recognition. Various Machine Learning Strategies are exploited to categorize the expressions on huge databases. LBP attributes were used for the classification of facial expression in [30] and the LBP operator helps for feature extraction for recognizing the facial expression. A large number of Databases are used in this proposed system for recognizing facial expression. In this research article, we that proved LBP attributes give better performance and it gives promising outcomes for real-world applications.

## II. PROPOSED WORK

In this proposed work, facial expression recognition works in two main stages. The first stage is the training stage and the next stage is the testing stage. We used Cohn-Kanade database for our tests and trials [31]. 23 facial displays were done by the instruction of subjects that focused on prototypic emotions. Fig. 1 displays some training facial images from Cohn-Kanade database.

### a. Image Preprocessing

In this work, we picked image sequences from different databases. The main selection principle was that sequence of the image could be labeled under one of the six facial expressions id. In the Image Pre -Processing section, we have to focused on noise removal, face detection, background subtraction, constraining the size of the image and face alignment by Region of Interest (ROI).



Figure 1: Facial Expression Images from Cohn-Kanade database

After this process, these face images are used for feature extraction. With the help of Linear Discriminant Analysis and Principal Component Analysis, these techniques have been processed. Then the vectors of the extracted attributes are fed into training and testing process.

At the training stage, the proposed system gives training data including grayscale facial images with its expression id, train a set of network weight and eye center locations. It needs to confirm that the presentation order of the facial image samples should not affect the training performance. New images are synthetically created to maximize the size of the database in the training stage. Then the rotation correction takes place as the horizontal axis. At the same time, the image is cropped to eliminate background data also holds particular expression attributes. The result of the training stage is the set of network weight that gains the best result with the evaluation of data after the various orders of training rounds. The testing stage used spatial normalization, cropping, intensity normalization and down sampling. The output contains the six facial expressions id. The facial expressions are mentioned as (0- surprise, 1- sadness, 2- fear, 3- disgust, 4- anger, 5- joy, 6- neutral).

In this process, the three peak frames and neutral face helps prototypic recognition of expression in each sequence. To examine the performance of generalization to the subjects, cross-validation of 10-fold testing was adopted in our work. Databases are randomly and precisely portioned into 10 groups of same subject numbers. Training data includes 9 groups to train the classifier; consequently, other groups were used for data testing. This process was continual at 10 times for each group. Then the

recognition outcome needs to be reported on testing sets.

Fixed distances amongst the two eyes have been normalized[32] and labeled the location of the eyes manually to examine the LBP features for no facial registration errors. Face detection and localization of the eye attains the automatic registration of face [33]. From the original frames, 110 to 150-pixel facial images were cropped depending upon the location of the eye. Fig. 2. Displays the sample of the original facial expression image and cropped facial expression image.

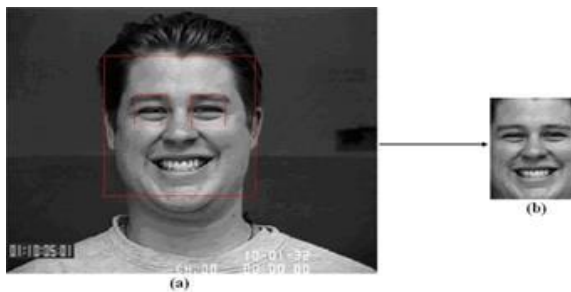


Figure 2: Illustration of (a) Original Image to (b) Cropped Image

### b. Local Binary Patterns

Ojala introduced the novel Local Binary Pattern [LBP] operator[34] and showed powerful texture description. The operator tags the image pixels by  $3 * 3$  neighborhood thresholding of each pixel linked with the center value and considering the binary number results. Fig. 3. Demonstrates as an instance. Also 256 histogram bin labels were computed over a region which acts as a texture descriptor. It derived the LBP codes (Binary Patterns) that codify the curved edges, flat areas, spots and other local primitives as demonstrated in Fig. 4. In Fig. 4, Ones are represented by white circle and Zeros are represented by black circle. Hence each LBP code has observed as micro texton [35].

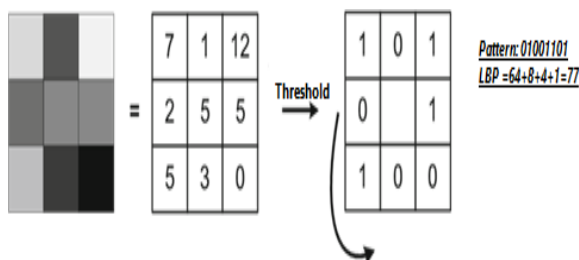


Figure 3: The Basic Structure of LBP Operator

Bi-linearly interpolating and Circular Neighborhoods are used to permit any number and radius of the neighborhood pixels. In Fig. 5, the notations of P and R mentioned the P neighborhood, the sampling points are equally spaced on the circle radius R that create a neighbor dataset of the symmetric circle.

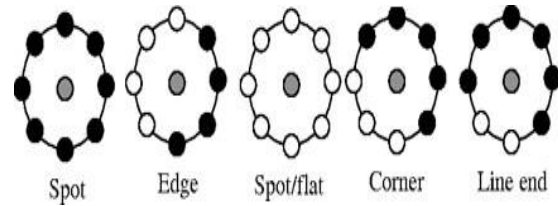


Figure 4: Sample of Primitive textures detected by LBP

Subsequently labeling the facial image with LBP operator, a labeled image histogram  $Hl_i$  can be noted as

$$Hl_i = \sum_{a,b} I\{f_i(a,b) = i\}, \quad i = 0,1,2, \dots, m \quad (1)$$

Where  $m$  is denoted as different labels numbers generated by LBP operator

$$I(X) = \begin{cases} 1 & X \text{ is } t \\ 0 & X \text{ is } f \end{cases} \quad (2)$$

The composition of Micro-patterns contains the Facial Images which can be well-defined by LBP histograms. Hence, it is an initial process to use LBP attributes to describe the facial images [36].

The entire facial images are computed by LBP histogram which encodes the occurrences of micro-patterns without any denotation about the locations. Facial images are evenly separated into small regions as  $sr_0, sr_1, sr_2, \dots, sr_n$  for extracting the LBP histograms. The extraction of the LBP attributes from sub-region are concatenated in a form, which spatially improved the attributes in the histogram that denoted as

$$Hl_i = \sum_{a,b} I\{f_i(a,b) = i\} I(a,b) \quad (3)$$

Where  $i = 0, 1, 2, \dots, m - 1, j = 0, 1, 2, \dots, m$

Also we performed the recognition of independent individual facial expression using LBP attributes. Template matching is used to recognize facial expressions.

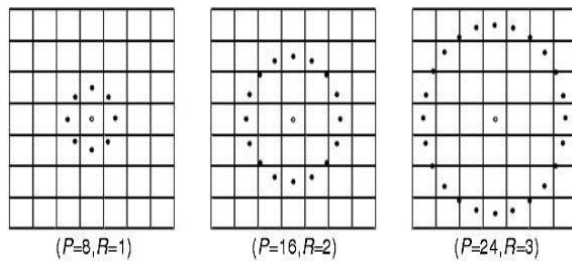


Figure 5: Samples of three extended Local Binary Patterns

### c. Data Classification

Convolutional Neural Network (CNN) used in the facial expression recognition for the learning process. The proposed CNN architecture contains two CNN channels that separate the eyes and mouth. Each CNN channels obtains the grayscale input image of 32 \* 64 pixels. Each CNN channels is generated as 2 max pooling layers, 2 convolution layers, 1 output layer and 1 full connection layer. 5\*5 convolution layer with 2\*2 max pooling layer are used to minimize the image size in the first CNN layer. Five attribute maps of new convolution from first layer is applied in second CNN layer that uses 5 \* 5 various filters with 2 \* 2 max – pooling filter size. Classification is done with maximum probability.

The accuracy was evaluated in various ways to permit a good comparison of existing methods. Accuracy is calculated by the average as  $C_{mclass}$ , and the accuracy expression of n- class as  $C_{mclass Ex}$ .

$$C_{mclass} = \frac{\sum_1^m C_{mclass}}{m} \quad (4)$$

$$C_{mclass Ex} = \dots \quad (5)$$

Where  $H$  is the total number of hits in the Expression  $Ex$  and Total number expression sample is mentioned as  $H$  and number of expressions is noted as  $m$ . Then, each expression performed one vs all classification by one binary classifier[37]. In this technique, the images are denoted as  $m$  binary classifiers. Here  $m$  is the classification number of expressions. If the image comprises a particular expression, then each Classifier attains to answer “yes”, else it answers “no”. If the image comprises the anger expression, then the anger classifier mentioned as yes and all the other five classifiers retain “no”. The facial image accuracy is evaluated by  $C_{binary}$ , average and accuracy of the single binary classifier expression as  $C_{binary Ex}$ .

$$C_{binary} = \frac{\sum_1^m C_{binary}}{m} \quad (6)$$

$$C_{binary Ex} = \frac{Hit_{Ex} + Hi}{T_{Ex}} \quad (7)$$

Where  $H$  is the total number of times the classifier  $Ex$  answered “yes” in the Expression

$Ex$ . is the expression of Tested image.

$Hit$  is the total number of times the classifier answered as “No” in the expression  $Ex$ .  $T$  is denoted as Total Tested images and  $m$  is denoted as the number of expressions.

## III. RESULTS

To prove that the proposed methodology coped up with all databases and unknown database environments. The instances with other datasets also follow the same techniques that the Cohn–Kanade (CK+) database. The network was trained in the cross-database instance with Cohn–Kanade (CK+) datasets and the accuracy was evaluated. The image-database was divided into eight categories of non-overlapping subjects. We made 10-fold cross validation techniques. For that we performed 10 times of attribute training for each validation configuration and testing the subjects which change the training image presentation order[38].

Table 1 : Classifier Accuracy For Six Facial Expression on CK+ database

Classifier	Surprise	Sadness	Fear	Disgust	Anger	Joy
$C_{6class Ex}$	99.28	87.32	96.50	99.90	96.43	98.58
$C_{binary Ex}$	98.83	98.29	99.54	99.87	98.27	98.78
<b>Average of <math>C_{6class Ex}</math></b>		<b>96.337</b>				
<b>Average of <math>C_{binary Ex}</math></b>		<b>0.07</b>				
		<b>98.937</b>				
		<b>0.02</b>				

The validation group helps to pick the finest epoch for each process in feature training datasets and to pick the process with the top presentation-order. Depending on the presentation order and finest epoch, the network weights are picked to evaluate the test of data set accuracy. By using this trial

configuration, the network training is done about 960 times (i.e., eight groups (8) \*twelve subjects for each groups (12) \* ten runs of presentation order (10)). The feature training time for per process acquired 2 minutes, hence the total feature training period of the process takes (2 \* ten runs (10)) 20\_mins. The overall process will take 32hrs which consist of the entire mixture of feature training, validation& testing process. The outcome of this process has calculated an average of 96\_runs. Hence the total period is evaluated based on 8\_folds \* twelve subject for each group (12) \* one best- pattern out of ten runs (10).

Table 2: Parameters Used For Training Process

Parameter	Value
Epochs	10,000
Gaussian Standard Deviation	3
Loss Function	<i>SoftmaxWithLoss</i>
Learning Rate	0.01
Momentum	0.95
Synthetic Samples Count	80

Table 3: Confusion Matrix Of Six- Facial Expression

	Surprise	Sadness	Fear	Disgust	Anger	Joy
Surprise	250	2	2	0	1	2
Sadness	6	74	0	1	2	0
Fear	2	1	73	0	1	0
Disgust	0	1	0	77	0	1
Anger	0	2	0	1	126	2
Joy	0	0	1	0	2	208

Table 1. demonstrates the best result attained using both synthetic samples and normalizations for  $C_{6class}$  and  $C_{binary}$ . It proves the binary classifier techniques maximize their accuracy. The methodology of binary- classifier was active to permit a better comparison with some existing

techniques that just noted their results.  $C_{6class}$  is the six class classifier technique that contains better evaluation technique. If we were concerned about a particular expression, then  $C_{binary}$  classifier technique is effective. Depending on all subject runs, the standard deviation is noted in Table 1. The parameter values of training datasets attain the results displays in Table 2. We can use the same parameter values for other databases.

Table 4: Classifier Accuracy For Seven Facial Expression On Ck+ Database

Classifier	Surprise	Sadness	Fear	Disgust	Anger	Joy	Neutral
$C_{7class}$ Ex	98.82	83.62	92.50	99.32	91.23	99.58	95.28
$C_{binary}$ Ex	98.89	98.09	99.34	99.57	97.57	99.32	97.53
<b>Average of <math>C_{7class}</math> Ex</b>		<b>95.33</b>					
<b>Average of <math>C_{binary}</math> Ex</b>		<b>0.06</b>					
		<b>98.71</b>					
		<b>0.01</b>					

With the help of Table 1, the confusion matrix was created for six-class classifier which is shown in Table 3. Depending on the outcomes of the six-classifier, we can have mentioned that Surprise, Sadness, Fear, Disgust, Anger, and Joy attain an accuracy rate of more than 98%. When the facial expression of fear and anger was about 96%. The facial expression of sad attains the smallest recognition rate was only 87%. Observing the Confusion Matrix, the facial expression of sad and surprise expression was confused at many times. This displays the attributes of sad and surprise expressions are not properly divided in the pixel's space.

Moreover, we differentiate the neutral expression. It made changes in the classifier for recognizing the seven types of facial expressions. By using the similar type of six-class classifier, the outcome of the seven class classifier to the CK+ databases are demonstrated in Table 4. The standard deviation noted in the Table 4 shown the track amongst all subjects.

Table 5: Confusion Matrix Of Seven Facial Expression

	Surprise	Sadness	Fear	Disgust	Anger	Joy	Neutral
Surprise	250	6	2	0	1	1	2
Sadness	8	74	1	1	1	0	0
Fear	2	1	73	0	1	0	0
Disgust	0	1	0	77	0	1	3
Anger	0	1	0	1	120	2	9
Joy	0	0	1	0	1	206	0
Neutral	1	0	1	2	10	1	295

From the table, it can be clearly shown that the binary- classifier technique decreases a bit from 98.93 to 98.71. Also, the seven class classifier was also decreased from 96.33 to 95.33. Due to addition of one more network, these changes occurred. But, in the binary class technique, the values did not change due to the insertion of new classifier. Table 5 shows the seven facial expressions of the confusion matrix.

Table 6: Comparison of Classifiers with Six Facial Expressions and Seven Facial Expressions with Proposed Methodology

	Classifier	Six Facial Expression	Seven Facial Expression
Rivera et al.[39]	$C_{mclass}$	-	89.30
	$C_{binary}$	-	-
M. Liuet al. [40]	$C_{mclass}$	93.70	-
	$C_{binary}$	-	-
Lee etal. [41]	$C_{mclass}$	94.90	-
	$C_{binary}$	-	-
Caifeng Shan et al.[42]	$C_{mclass}$	95.10	91.40
	$C_{binary}$		
<b>Proposed Work</b>	$C_{mclass}$	<b>96.33</b>	<b>95.33</b>
	$C_{binary}$	<b>98.93</b>	<b>98.71</b>

For cross-database instances, comparisons of the proposed work with existing methodologies are demonstrated in Table 6. It displays the outcome of the CK+ database with validation techniques of training, testing and validation data sets were explained. Here a comparison amongst the proposed method and existing surveys are used to determine the performance of cross-validation techniques of K-fold and assure that the matching- subject is not included in feature training datasets and testing

groups. Table 8 proved that the proposed method attains the best outcome in CK+ database of all the instance cases.

## IV. CONCLUSION

In this research article, we proposed the multi-view facial expression recognition depends on LBP. Various types of classification techniques are examined. The main contribution of this work is to derive an efficient facial recognition from the original face image. We examine the LBP attributes to label the appearance in the variations of facial expression. The normalization techniques enhance the importance of accuracy methods. Moreover, it takes minimal time to train the data and recognize the images in real-time. Also, the instances in the cross base database shows that the proposed approach can able to work in unknown data environments, where the acquisition of the facial image testing conditions and subjects are different from the training of facial expression images.

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