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EFFICIENT RECOGNITION OF FACIAL EXPRESSION USING COMPOUND LOCAL BINARY PATTERN WITH HISTOGRAM OF ORIENTED GRADIENTS

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Keywords:
Facial expression recognition (FER);
Gabor filter;
Gabor coefficients maps (GCM);
Compound local gabor binary pattern (CLGBP);
Histogram of oriented gradients (HOG);
k- Nearest Neighbor (k-NN).

Abstract

In recent years, automatically recognizing facial expression has essential real world applications. It remains a challenging problem and active research topic in computer vision. Many novel methods have been proposed to tackle the automatic facial expression recognition problem. One of the difficult issues for a successful facial expression recognition system is, to design a robust facial feature descriptor. A facial descriptor is proposed for automatic facial expression recognition. In the proposed method, Compound Local Gabor Binary Pattern (CGLBP) is used as descriptor for facial expression with Histogram of Oriented Gradients (HOG). For feature extraction the facial features are extracted in the following three steps: First Gabor Coefficients Maps (GCM) is extracted from the face image using the multi-scale and multi-orientation Gabor filters. The compound local binary pattern operator is

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performed on each GCM to extract the compound local gabor binary pattern. HOG is described on all compound local gabor binary patterns to obtain HOG sequence and the generatedHOGs are concatenated in to unique HOG. For feature classification, a simple machine learning algorithm known as k-Nearest Neighbor (k-NN) classifier is used and it classifies the facial expressions in to different classes. The experimental result demonstrates that, the recognition rate and the accuracy of the new method are more effective and higher than the other methods under comparison.

1. Introduction

Facial expressions of a human being can reflect the human emotion effectively and based on the emotion observation of one person, we can get some information about his or her mood, feeling etc. The facial expressions can be divided into six types, including the happiness, sadness, fear, disgust, surprise and fear. The facial expressions of smile, happiness, surprise and anger are investigated using the proposed method. The main objective is to recognize these four types of facial expressions effectively and efficiently. Ahmed F. and Kabir M., [1] proposed DTP, is used to quantizes the edge responses in three different levels in order to provide more consistency in both smooth and high-textured regions, even under the presence of noise. I. Buciu *et al*., [2] develop a hybrid system namely Independent Component Analysis (ICA) with Support Vector Machines (SVM) and Gabor Wavelet (GW) with SVM. Independent component analysis (ICA) decomposes a set of observations into a basis whose components are statistically independent. Caifeng *et al.*, [3] describe that, for appearance-based feature extraction Local Binary Pattern (LBP) and its variants have gained much popularity for their superior performances because LBP encoding scheme considers the sign of the difference between two gray values. Faisal Ahmed *et al*., [4] introduce the extension of original LBP called CLBP, that assign a *2P*-bit code to the center pixel based on the gray values of a local neighborhood comprising *P* neighbors. CLBP uses two bits for each neighbor in order to encode the sign as well as the magnitude information of the difference between the center and the neighbor gray values.

Hieu V.Nguyen *et al*., [5] describe a novel approach based on a combination of Gabor Filter, LBP and Whitened PCA (LGBPWP) to resolve "Single Sample per Person" (SSP) situation in face recognition since it is difficult to extract the features from only one image per person for facial expression recognition. This selection method is efficient when used together with whitened PCA, where the intrapersonal variation can be suppressed. Jabid .T *et al*., [6] proposed Local Directional Pattern (LDP) and Kabir. H *et al*., [7] proposed LDPv to encode the magnitude information, since LBP method only encodes the sign of the difference between two gray values and thus, discards the magnitude of the difference which is very important texture information. Pierluigi Carcagn *et al*., [8] describe Histogram of Oriented Gradients (HOG) in order to get the local information which is not given by normal histogram. In HOG, local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients or edge directions. C.P. Sumathi*et al.*, [9] analyze variousmethods to identify the facial expression and also describe about the facial parameterization using Facial Action Coding System (FACS) action units and the methods which recognizes the action unit parameters using facial expression data. Various kinds of facial expressions are present in human face which can be identified based on their geometric features, appearance features and hybrid features. The two basic concepts of extracting features are based on facial deformation and facial motion.

Tian Y *et al.*, [10] tell that, an automatic analysis of the facial expressions of people is highly important for automatic understanding of humans, their actions and their behavior in general. For expression recognition, based on the type of features used, it can be broadly divided into two categories, namely geometric feature and appearance feature. Facial feature extraction was mostly based on the geometric relationships between different facial components. Xinghua Sun*et al.*,[11]develop a descriptor with the combination of Gabor Filter (GF) and Local Binary Pattern (LBP) which is named as Local Gabor Binary Pattern (LGBP), to enhance the magnitude information of Gabor Filterby using LBP. First Gabor coefficient is extracted from face images and then LBP is applied to each Gabor features to obtain LGBP. Finally each face image is described by histogram sequence and resulted in LGBP histogram. Ying-li Tian *et al.,* [12] developan automatic system to analyze subtle changes in lower facial expressions based on both permanent and transient facial features in a nearly frontal image sequence. To measure both types of information, Ying-li Tian *et al.,* proposed a multistate facial component model and has high sensitivity and specificity for subtle differences in facial expression.

Similarly for recognizing Upper Face Action Units, an automated system called multistate facial component model was developed by Ying-li Tian *et al*., [13] to measure permanent and transient facial features. In this method, separately modeling non-additive AU combinations affords no increase in the recognition accuracy.Ying-li Tian*et al.,* [14] describe a real-time system to automatically recognize facial expressions in relatively low resolution face images. To handle the full range of head motion, the headis detected instead of the face. Then the head pose is estimated based on the detected head. For frontal and near frontal views of the face, the location and shape features are computed for expression recognition.Zhou H*et al.,* [15] develop a descriptor LBP, for representing salient micro-patterns of face images. Compared to Gabor wavelets, the LBP features can be extracted faster in a single scan through the raw image and lie in a lower dimensional space, whilst still retaining facial information efficiently. In the proposed method using the descriptor which is the combination of Gabor filter, Compound Local Binary Pattern and Histogram of Oriented Gradients, the effectiveness of the facial expression recognition system can be increased better than the other methods given in the above discussion.

2. Research Method

In the proposed method, a new facial expression analysis system is designed to automatically recognize facial expressions in real environments. Figure 1 shows the block diagram of the proposed method.

2.1 Feature Extraction

In the automatic recognition of facial expression, first the facial features are extracted by using the combination of three feature extraction descriptor namely Gabor filter, CLBP and histogram of oriented gradients.

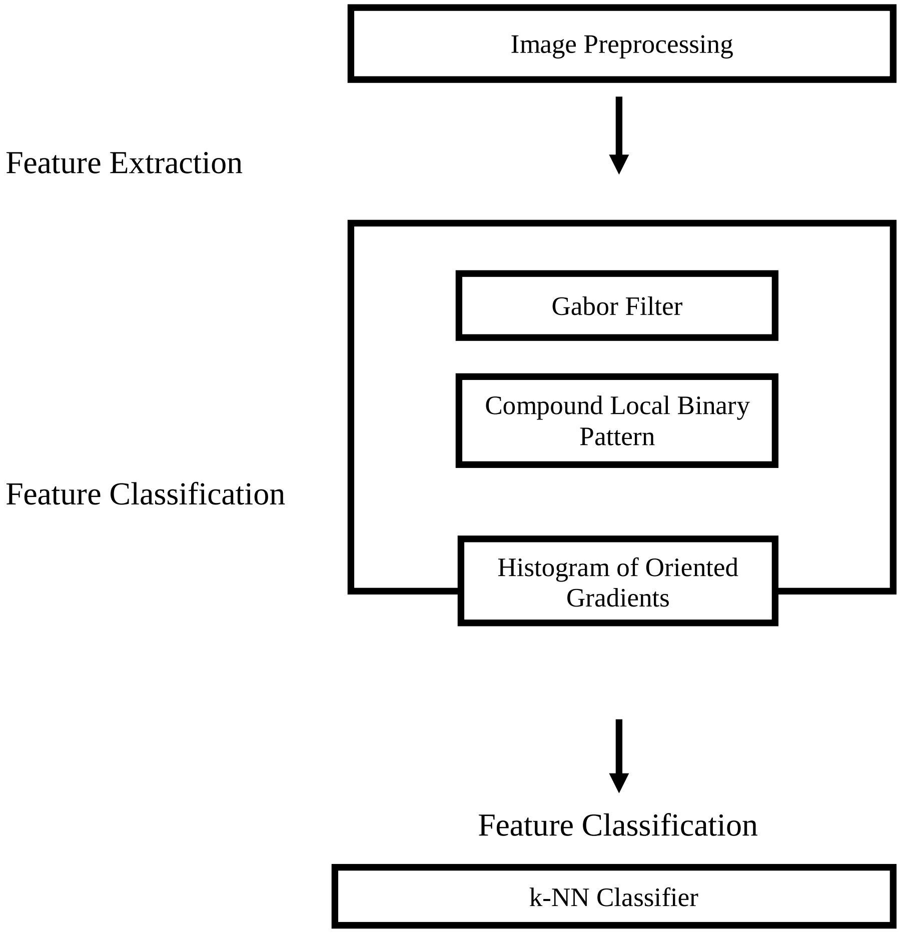


Figure1. Block Diagram of CLGBP with HOG

2.1.1 Gabor Filter (GF)

In Gabor filter, it is common to use the base points instead of the entire image, to extract the features of the given image. The 2D Gabor function is a product of a Gaussian and a complex plane wave. The Gabor Filter is a linear filter whose impulse response is defined as a harmonic function multiplied by a Gaussian function. The function of 2D Gabor Filter is defined as in equation 1,

$$G_k(x, y) = G_r(x, y) + iG_i(x, y) \quad (1)$$

where $G_r(x, y)$ is the real part of Gabor filter and $G_i(x, y)$ is the imaginary part of gabor filter.

The real part and imaginary part of GF is described in equation 2 and 3.

$$G_r(x, y) = \frac{K_v^2}{\sigma} \exp\left(-\frac{K_v^2(x^2+y^2)}{2\sigma}\right) * \left[\cos\left(K_v(\cos(Q_u).x + K_v \sin(Q_u).y) - \exp\left(-\frac{\sigma}{2}\right)\right)\right] (2)$$

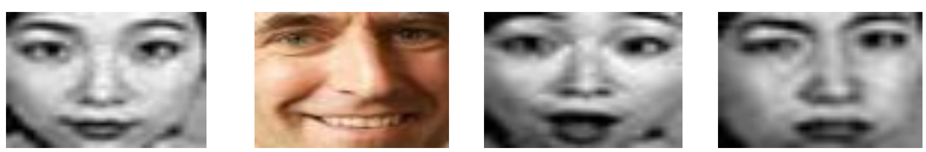
$$(x, y) = \frac{K_v^2}{\sigma} \exp\left(-\frac{K_v^2(x^2+y^2)}{2\sigma}\right) * \left[\sin\left(K_v(\cos(Q_u).x + K_v \sin(Q_u).y) - \exp\left(-\frac{\sigma}{2}\right)\right)\right]$$

(3)

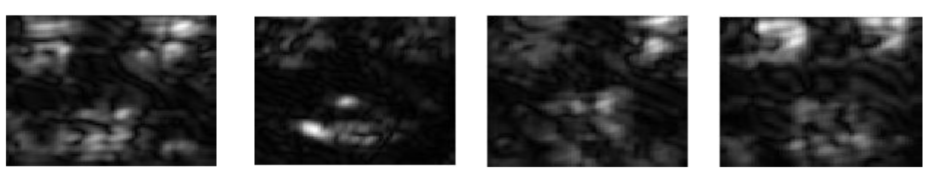
where $K_v = \pi exp\left(-\left(\frac{v+2}{2}\right)\right)$, $Q_u = \pi * \frac{u}{6}$.

In the equation (2) and (3), the factor K_v^2 ensures that, the filters tuned to the different spatial frequency bands have the approximately equal energies. The term $\exp\left(-\frac{\sigma}{2}\right)$ is subtracted to make the filters insensitive to the level of illumination. The terms Q_u and K_v have defined the orientation and scale of the Gabor wavelets respectively. The parameter σ is the ratio of the Gaussian window's width to the Gabor wavelets length and the parameter *u* is the orientation of Gabor wavelets and σ is set to be π /2.

Neutral Smile Surprise Anger



(a)



(b)

Figure2.Result of Gabor Filter (a) Input Image (b) Gabor Filtered Image(Jaffe database)

Neutral Smile Surprise Anger

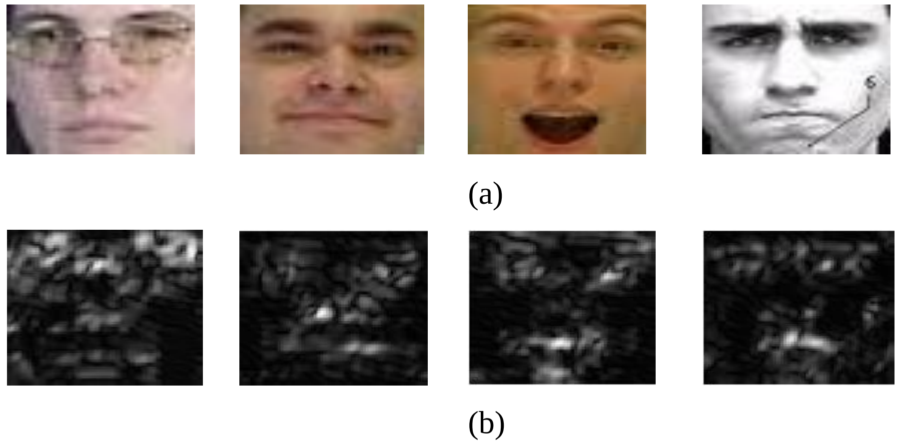


Figure3.Result of Gabor Filter (a) Input Image (b) Gabor Filtered Image(Cohn Kanade database)

The Gabor feature can be extracted by constructing a filter bank consisting of several Gabor Filters. Then, each filter is convolved with image to produce Gabor space. In this method, face image is convolved with Gabor Filter and the result is called Gabor Coefficient Map (GCM) and its corresponding equation is,

$$G(x, y, v, u) = G_k(x,y) * I(x,y) \quad (4)$$

where $G_k(x,y)$ is the GF and I (x , y) is the face image. Figure 2 and 3 shows the images of Gabor features obtained from the original image from two databases namely Cohn Kanade (CK) database and Jaffe database using Gabor Filter.

2.1.2 Compound Local Binary Pattern (CLBP)

The LBP operator considers only the sign of the difference of two gray values and hence the LBP operator fails to generate binary codes consistent with the texture property of a local region. To overcome this failure, CLBP operator is proposed.The CLBP operator assigns a 2P-bit code to the center pixel comprising P neighbors. The proposed method uses two bits for each neighbor in order to encode the sign as well as the magnitude information of the difference between the center and the neighbor gray values. Here, the first bit represents the sign of the difference between the center and the corresponding neighbor gray values. The other bit is used to encode the magnitude of the difference with respect to a threshold value, which is the average magnitude M_{avg} .

The CLBP operator sets the first bit to 1 if the magnitude of the difference between the center and the corresponding neighbor is greater than the thresholdM_{avg}. Otherwise, it is set to 0. The CLBP descriptor can be defined by the function given in equation (5).

$$s(i_p, i_C) = \begin{cases} 00 & i_p - i_C < 0, |i_p - i_C| \le M_{avg} \\ 01 & i_p - i_C < 0, |i_p - i_C| > M_{avg} \\ 10 & i_p - i_C \ge 0, |i_p - i_C| \le M_{avg} \\ 11 & \text{otherwise} \end{cases} \quad (5)$$

where, $i_c$is the gray value of the center pixel, $i_p$is the gray value of a neighbor pixel p, and M_{avg} is the average magnitude of the difference between $i_p$and $i_c$in the local neighborhood. The CLBP operator can be described as shown in figure 5. Here, the CLBP code can be written as, (1010101010111111).

65	65	90
65	60	90
70	70	90

10	10	11
10	C	11
10	10	11

Figure4. Illustration of generation of CLBP

10	10	11
10	C	11
10	10	11

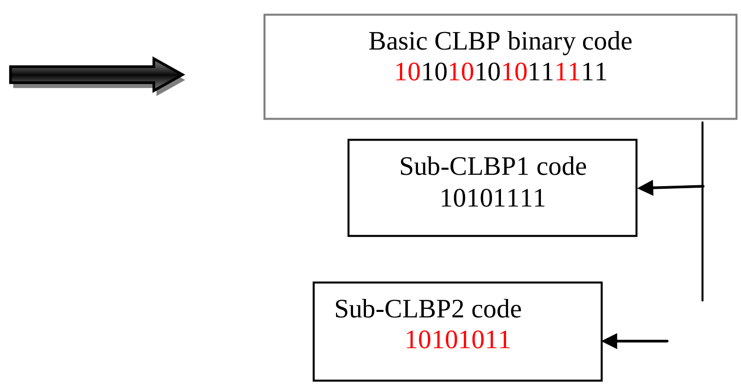
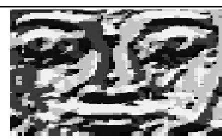
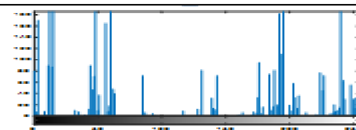
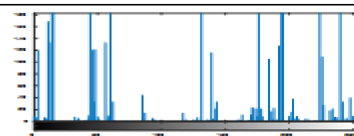
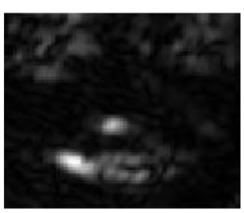
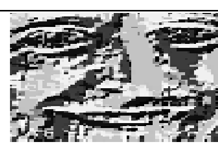
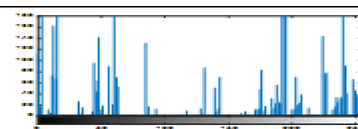
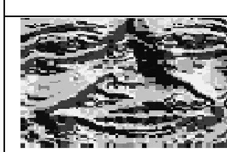
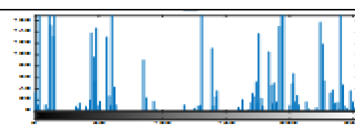
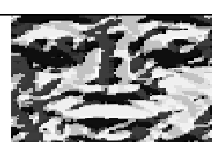
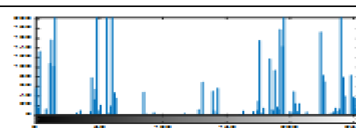
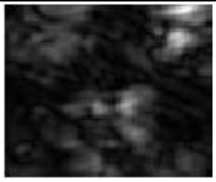
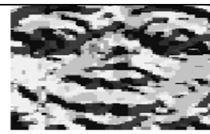
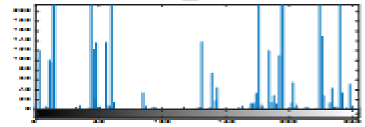
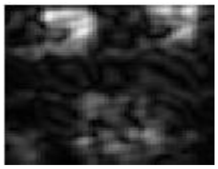
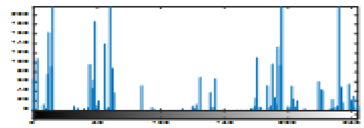
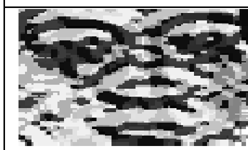
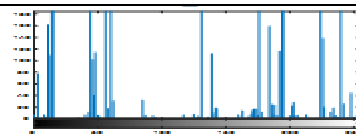


Figure5. Illustration of generation of sub-CLBP

In proposed method, a different approach has been presented where all the CLBP binary patterns are split into two sub CLBP patterns. In other words, a 16-bit CLBP pattern is split into two 8-bit CLBP patterns, where the first CLBPpattern is obtained by concatenating the bit values corresponding to the neighbors in the north, east, south, and west directions, respectively and the second CLBP pattern is obtained, by concatenating the bit values corresponding to the neighbors in the north-east, south-east, south-west, and north-west directions, respectively.After splitting 16-bit CLBP binary pattern in to two 8-bit CLBP patterns, the corresponding encoded image representation is obtained for two CLBP patterns. Then, histogram is applied to each 8-bit CLBP pattern and all the generated histograms are concatenated to form unique histogram called CLBP histogram. The obtained CLBP histograms function as a feature representation for recognizing facial expression. Figure 6 illustrates the generation of two 8-bit CLBP codes in eight different directions. The first CLBP code is obtained based on north-east, north-west, south-east, and south-west directions and second CLBP code is obtained based on north, south, east, and west directions respectively.

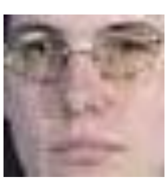
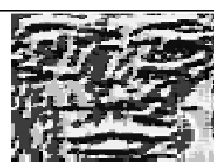
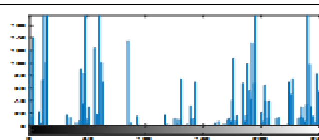
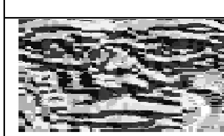
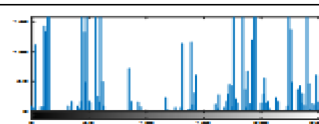
Table 1: CLBP Images with Histogram of Jaffe database

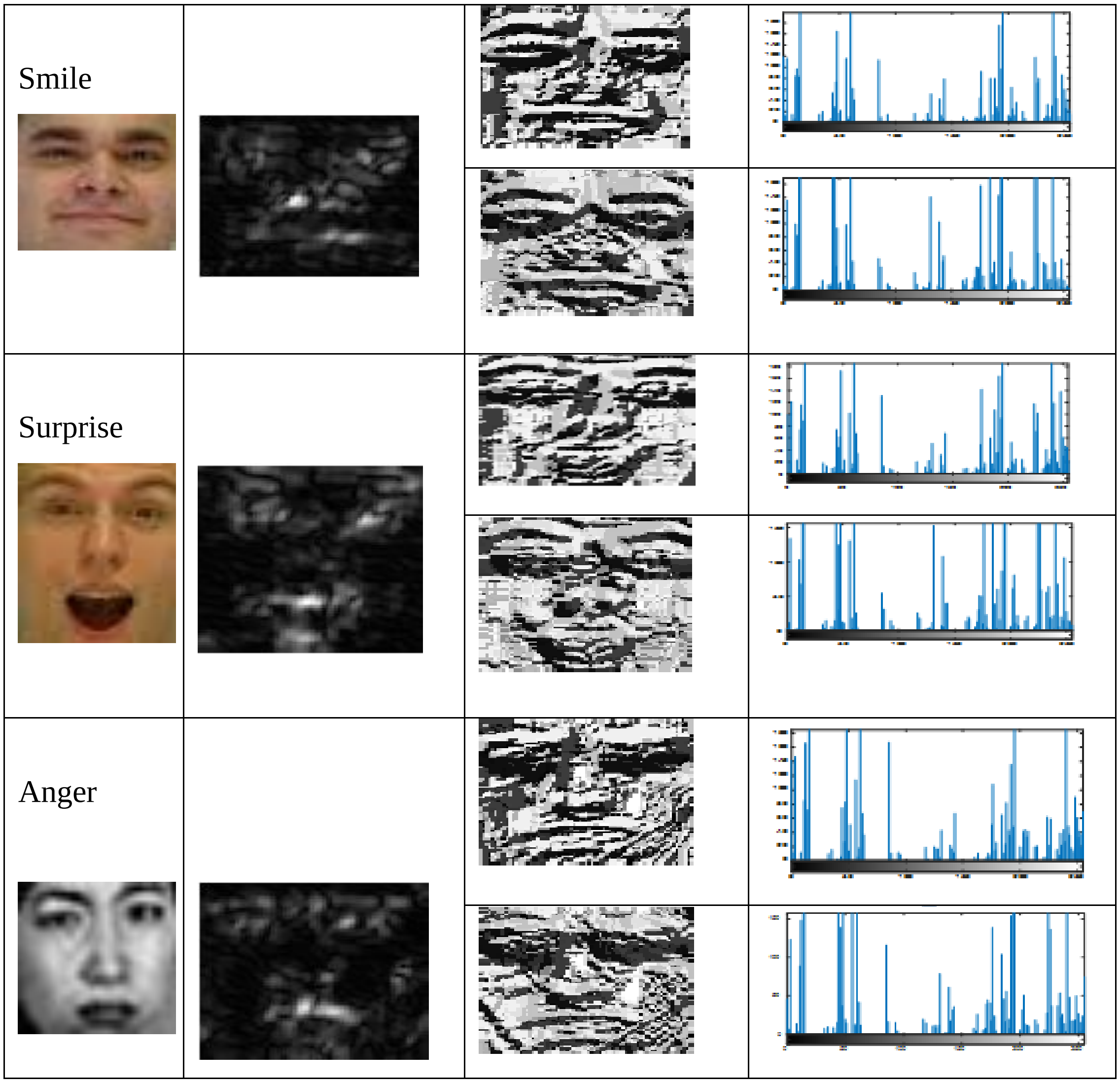
Expression	Gabor Filtered Image	CLBP Image	Histogram
Neutral 			
			
Smile 			
			
Surprise			

			
Anger 			
			

In the proposed method, the GCM is obtained from the input image using Gabor filter. After obtaining GCM, the CGLBP descriptor is applied to GCM to obtain CLGBP binary codes. The obtained code is partitioned in to two CLGBP patterns, to obtain features in different directions. Then, the HOG is applied on each CLGBP to obtain the histogram in different directions and orientations. Finally, all the obtained HOG is concatenated to produce unique histogram of oriented gradients. Table 1 and 2 describes the Gabor features, sub-CLBP patterns and CLBP histogram for the original images of Cohn Kanade database and Jaffe database respectively.

Table2. CLBP Images with Histogram of Cohn Kanade database

Expression	Gabor Filtered Image	CLBP Images	Histogram
Neutral 			
			



2.1.3 Histogram of Oriented Gradients

HOG descriptor is based on the accumulation of gradient directions over the pixel of a small spatial region referred as “cell”. HOG descriptor is characterized by using two main parameters, the cell size and the number of orientation bins. Cell size represents the dimension of the patch involved in the single histogram computation. The number of orientation bins refers to the quantization levels of the gradient information. After applying CLBP operator and splitting 16-bit CLBP pattern into two 8-bit binary codes, two encoded image representations are obtained for the corresponding two sub-CLBP patterns. Then for each sub-CLBP pattern, HOG descriptor is applied. In HOG descriptor, the image is divided into the cells of size N x N pixels and the orientation of the gradient in each pixel is computed. The rule for computing orientation is given by,

$$\theta_{x,y} = \tan^{-1}\frac{L\,(x,y+1)-L\,(x,y-1)}{L\,(x+1,y)-L\,(x-1,y)} \qquad (6)$$

where *L* is an intensity (gray scale) function describes the image to be analyzed and $\theta_{x,y}$ is the orientation. The HOG is more effective for facial expression recognition, because histogram of each sub-CLBP codes can be obtained in different directions and orientations. Therefore, features of subtle changes in facial expression can also be extracted using HOG. Thus, after computing HOG for each sub-CLBP pattern, all the computed histograms of oriented gradients are concatenated into unique HOG histogram. Finally,the HOG features vectors are then given as input to a k-NN classifier for feature classification.

2.2 Feature Classification

In feature classification stage, the facial features obtained from feature extraction descriptors are given as input set for k-NN classifier and different classes of expression can be classified by using k-NN classifier.

2.2.1 k-NN Classifier

k-Nearest Neighbor algorithm is among the simplest of all machine learning algorithms. K-NN classifier is also known as case based reasoning or memory based reasoning. If k=1, the object is simply classified as the class of the object nearest to it. When there are only two classes, k must be an odd integer. However, when performing multiclass classification k must be an odd integer. After we convert each image to a vector of fixed-length with real numbers, the most common distance function known as Euclidean distance is used for k-NN classifier.

$$d\,(x\,,\,y) = \|x-y\|^2 = \sum_{i=1}^{k}(x_i-y_i)^2 \qquad (7)$$

The object of interest is compared to every sample in the training set, using a distance measure, a similarity measure, or a combination of measures. The unknown object is then identified as belonging to the same class as the closest sample in the training set. This is indicated by the smallest number if using a distance measure, or the largest number if using a similarity measure. This process is computationally intensive and not very robust. The Nearest Neighbor method can be made more robust, by selecting not just the closest sample in the training set, but by consideration of a group of close feature vectors. This is called the k-Nearest Neighbor method.

3. Results and Analysis

To evaluate the effectiveness of the proposed method, two well-known databases namely CK database and JAFFE database are used. The output results are compared between the two databases in this experiment. For better results, the input image is divided in to two different sub regions namely 2×2 and 3×3.

3.1 Jaffe (Japanese Female Facial Expression) Database

The Jaffe database contains 213 images of 7 facial expressions posed by 10 Japanese female models. Each image has been rated on 6 emotion adjectives by 60 Japanese subjects. The CLGBP descriptor was trained and tested on Jaffe database to achieve an excellent recognition rate for four class expression datasets. The input images of four expressions such as neutral, smile, surprise and anger are collected from the Jaffe database. Then, each image is divided into two sub regions namely 2×2 and 3×3 and for each region the dataset is created and stored for further process.

Neutral Smile Surprise Angry

Figure6. Input Images of Jaffe database

3.1.1 Ten- Fold Cross-Validation Scheme

A ten-fold cross-validation scheme is proposed, to evaluate the effectiveness of the CLGBP descriptor and to measure the recognition rate. In this scheme, the entire dataset fetched from Jaffe database is divided in to ten subsets. From the ten subsets, one subset is used as the testing set and the remaining nine subsets are used for training the classifier. The above process is repeated for ten times and the average of all ten recognition rate is calculated to evaluate the effectiveness of the proposed method.

3.1.2 Performance on Histogram Based Features

The histogram is applied to the CLGBP, since histogram technique has many good characteristics. But it loses some information, when histogram is applied to the entire image. To avoid the loss of information, histogram is applied only after the image is partitioned in to number of sub-regions. However, it does not provide appearance and shape features of the image. Hence, to increase the recognition rate the HOG descriptor is used.A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The confusion matrix itself is relatively simple to understand the effectiveness of the proposed technique. The table 3 shows the confusion matrix of JAFFE database for 2×2 images and 3×3 images and it indicates the performance rate of facial expression recognition. From the confusion matrix, it is concluded that the recognition rate of facial expression for 3×3 is higher than 2×2 images. From the table 3 it is concluded that, the recognition rate is better for surprise expression (65% for 2×2 and 75% for 3×3) than the other three expressions.

Table3. Histogram based Confusion Matrix 2×2 and 3×3 of Jaffe database

Expression	2×2				3×3			
	Neutral	Smile	Surprise	Anger	Neutral	Smile	Surprise	Anger
Neutral	58%	17%	13%	12%	62%	13%	15%	10%
Smile	14%	63%	16%	7%	10%	70%	20%	0%
Surprise	15%	10%	65%	10%	15%	10%	75%	0%
Anger	25%	13%	22%	40%	17%	8%	15%	60%

3.1.3 Performance on HOG Based Features

HOG is applied to the output of CLGBP descriptor to extract appearance and shape features from the face image to recover the failure of histogram. The features of small changes in face can also be extracted using HOG, because of the usage of HOG in different directions and orientations. In HOG descriptor, the image is divided in to the cells of size of N× N pixels and HOG is obtained for each region. Hence, all HOG is concatenated in to unique HOG. From the given table 4 recognition rate of confusion matrix of size 3×3 is higher than the confusion matrix of size 2×2. It is also concluded that the recognition rate of HOG based features for 3×3 is better than the histogram based features. The recognition rate of neutral is 88%, smile is 90%, surprise is 83% and anger is 85%.

Table4. HOG based Confusion Matrix 2×2 and 3×3of Jaffe database

Expression	2×2				3×3			
	Neutral	Smile	Surprise	Anger	Neutral	Smile	Surprise	Anger
Neutral	66%	19%	15%	0%	88%	0%	0%	12%
Smile	12%	75%	13%	0%	10%	90%	0%	0%
Surprise	14%	9%	68%	9%	8%	9%	83%	0%
Anger	13%	0%	17%	70%	0%	7%	8%	85%

3.2 Cohn Kanade Database

The CK database comprises 100 university students who were around 18 to 30 years old at the time of image acquisition. Among them, 65% were female, 15% were African-American, and 3% were Asian or Latino. The CLGBP descriptor is trained and tested using CK database. The CLGBP descriptor, using CK database achieves higher recognition rate of facial expression than the Jaffe database for four class expression datasets. The four class expressions are neutral, smile, surprise, and anger.

Neutral Smile Surprise Anger

Figure7. Input Images of Cohn Kanade database

3.2.1 Ten-Fold Cross-Validation Scheme

In the ten-fold cross-validation scheme, entire dataset fetched from CK database is divided in to ten subsets. From the ten subsets, one subset is used as the testing set and the remaining nine subsets are used for training the classifier.

3.2.2 Performance on Histogram Based Features

The histogram is applied to the CLGBP since histogram technique has many good characteristics. To avoid the loss of information, histogram is applied only after the image is divided in to many sub regions. The table 5 shows the confusion matrix of CK database for 2×2 images and 3×3 images. From the confusion matrix of two regions, it is concluded that, the recognition rate of facial expression for 3×3 region is higher than 2×2 region.. From the given table, the recognition rate of surprise (74% and 90%) is better than the other expression in both 2×2 and 3×3 confusion matrix.

Table5. Histogram based Confusion Matrix for 2×2 and 3×3of Cohn Kanade database

Expression	2×2				3×3			
	Neutral	Smile	Surprise	Anger	Neutral	Smile	Surprise	Anger
Neutral	65%	21%	14%	0%	75%	13%	0%	12%
Smile	15%	72%	13%	0%	0%	86%	14%	0%
Surprise	13%	13%	74%	0%	10%	0%	90%	0%
Anger	16%	0%	14%	70%	0%	6%	15%	79%

3.2.3 Performance on HOG Based Features

HOG is used at the output of CLGBP descriptor trained with CK database. In HOG descriptor the image is divided in to the cells of size of N× N pixels and using the two parameters cell size and orientation of bins, HOG is obtained for each region. After that, all HOGs are concatenated in to unique HOG. The table 6 of confusion matrix given belowshows that, the recognition rate is better than the confusion matrix of histogram based features. It is also concluded that, recognition rate of confusion matrix for region 3×3 is higher than the confusion matrix for region 2×2 and efficient than the histogram based features for both 2×2 and 3×3 sub regions. The recognition rate of neutral is 96%, smile is 94%, surprise is 95% and anger is 97%.

Table6. HOG based Confusion Matrix for 2×2 and 3×3of Cohn Kanade database

Expression	2×2				3×3			
	Neutral	Smile	Surprise	Anger	Neutral	Smile	Surprise	Anger
Neutral	80%	20%	0%	0%	96%	4%	0%	0%
Smile	8%	83%	9%	0%	0%	94%	6%	0%
Surprise	15%	0%	85%	8%	3%	0%	97%	0%
Anger	12%	0%	13%	75%	0%	0%	5%	95%

From the tables 3, 4, 5 and 6 it is concluded that, the recognition rate of facial expression is higher for 3×3 sub-region which can be understand from the given confusion matrix. The results also prove that, the recognition rate is better only for CLGBP with HOG descriptor than the CLGBP with histogram descriptor. Among the four expressions, the recognition rate of surprise expression (97% for 3×3 sub-region of Cohn Kanade database) is high in all the cases. Hence, from the two well-known databases the Cohn Kanade database shows the increased recognition rate than the Jaffe database.

4. Conclusion

The proposed descriptor, Compound Local Gabor Binary Pattern was constructed for recognition of facial expression effectively. In facial expression recognition system, two steps namely feature extraction and feature classification is involved. The proposed method CLGBP for feature extraction provides both sign and magnitude information of difference between center and neighboring gray values and utilizes Gabor filter with CLBP codes and hence achieved increased recognition rate. Experimental results proved that, CLGBP operator was an efficient and effective approach for facial expression recognition system. It is also proved that, CLGBP operator is superior to other existing similar methods. The high performance depends on the variability of Gabor filters and hence, the proposed method has increased robustness. k-NN classifier used for feature classification, classifies the input image into four classes of expression namely neutral, smile, surprise, and anger. The CLGBP trained facial expression recognition system, can be used for human computer interaction, recognizing malicious intensions of a thief, safety driving etc.

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