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Completed Robust Local Binary Pattern Texture Descriptor for Classification of Facial Expression

Nagaraja S.

Department of Computer Science, Karnatak Science College, Dharwad, Karnataka, India

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Abstract: In this paper, we presented a method for representing facial expressions by extracting texture features from Completed Robust Local Binary Pattern (CRLBP). Completed Robust Local Binary Pattern, which is resistant to noise and changes in lighting conditions, is used to generate consistent texture features. These features are then combined to create a feature vector that represents facial expressions. The suggested approach is assessed by conducting facial expression recognition using a standardized database like JAFFE. The process of identifying facial expressions is carried out by using a chi-square distance measure along with a nearest neighbor classifier. The findings from our experiment demonstrate that our method is more effective than other widely used LBP approaches.

Keywords: Facial expression, CRLBP, Local Binary Pattern, Texture Descriptor.

I. Introduction

The act of using facial expressions is crucial for humans to convey their emotions and intentions effectively. The subject of facial expression recognition is both fascinating and difficult within the fields of Digital Image Processing and Computer Vision. The objective is to detect mental activity, facial movement, and changes in facial features from both photos and videos, and categorize them into abstract groups solely based on the visual data. This is feasible because human facial expressions have similarities. Recognizing facial expressions from static images is harder compared to image sequences due limited information about expression actions. The main components of a basic system for recognizing facial expressions are face pre-processing, extraction of expression features, and classification of expressions. Recently, there has been growing interest in the process of feature extraction of facial expression, which is considered to be a significant milestone. Facial expressions have been examined by various professionals including clinical and social psychologists, medical practitioners, actors, and artists. Nevertheless, towards the conclusion of the 20th century, animators and computer scientists became intrigued by the investigation of facial expressions due to the progress made in robotics, computer graphics, and computer vision.

A survey on automatic facial expression analysis was carried out by Fasel and Luettin [5]. This survey presents the most notable methods and systems for automatic facial expression analysis that have been presented in previous research. The paper discusses various approaches and methods for extracting facial motion and deformation, as well as for classifying them. These approaches and methods are considered in relation to face normalization, the dynamics of facial expressions, and the intensity of facial expressions. Additionally, their ability to withstand changes in the environment is also explored. Tian et.al.[2] conducted the research. A face analysis system was created that can automatically analyze facial expressions by considering both permanent and temporary characteristics. The system is capable of accurately identifying six upper face action units and ten lower face action units. They created a face component model for their feature extraction system, consisting of different states. For instance, their lip model includes three states: open, closed, and tightly closed. In the same way, the eyes, eyebrows, and cheeks all have their own unique models with multiple states. Cohen et.al.[3] A face tracker was employed to identify the face, tracking the changes in facial characteristics. Every facial distortion corresponds to a specific characteristic and is known as motion units. Bartlett et.al.[4] A system was created that can automatically and instantaneously recognize seven emotions and up to seventeen action units. The optimal outcomes are achieved by their system, which is based on machine learning. It works by using a particular group of Gabor filters in combination with AdaBoost. Additionally, they train support vector machine classifiers using the filtered outputs from AdaBoost.

X. Feng et al [1] divide the face area of the face image into small regions, from which the LBP histograms are extracted and concatenated into a single feature histogram that represents facial expression descriptor. In [6] region based local descriptors are used to recognize facial expressions in image sequences using spatiotemporal LBP. C. Shan et al. [7] extract most discriminant LBP features from Boosted-LBP and achieve good recognition rate using support vector machine classifier. S. Zhang et al. [8] proposed a method for facial expression recognition based on LBP and local fisher discriminant analysis. Initially, LBP features

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are extracted from the original images and reduced the feature dimension of LBP features using local fisher discriminant analysis. Support vector machines classifier is used for recognition of facial expression. In [9] LBP is applied to face image and then LBP image is divided into 3x5 non overlapping blocks, calculate the LBP histogram of each block and concatenating it. Laplacian Eigenmaps is used for feature dimensionality reduction and support vector machine classifier is used for classification. X. Wu et al. [10] used to curvelet transform to extract features from face images for face and facial expression recognition. The literature survey reveals that, the combination of curvelet transform with LBP yields good feature descriptor than using curvelet transform alone. The curvelet based LBP texture operator is a good feature extractor. A. Saha et al. [11] proposed the combination of curvelet transform and LBP for recognizing the facial expression from still images. Recently a study conducted by Anirudha B Shetty etal. [12] compared two face recognition methods, specifically Haar Cascade and Local Binary Pattern, to evaluate their effectiveness in classification. The Haar Cascade method produces a high recognition rate in comparison to the Local Binary Pattern (LBP) method. Padmashree and Karunakar [13] proposed a method for recognition of face using Local Binary Pattern Histogram and achieved good recognition rate in normal condition. Completed Robust Local Binary Pattern (CRLBP) was introduced by Y.Zhao et al. [14] for texture classification. In CRLBP, the image local differences are decomposed into three components i.e., signs, magnitudes and central information, in which the gray value of centre pixel in a 3x3 local area is replaced by its average local gray value.

In this paper, we proposed a technique for identifying facial expressions by extracting texture features from CRLBP. These texture features of facial expression contribute to the formation of the feature vector. Our experiments indicate that using these texture features greatly benefits facial expression recognition. We used a nearest neighbour classifier and achieved a commendable recognition rate in comparison to alternative approaches.

II. Completed Robust Local Binary Pattern(CRLBP)

The Completed Robust Local Binary Pattern (CRLBP) descriptor was introduced by Y.Zhao et al.[14]for texture classification. The CRLBP to overcome, the demerits of LBP, LTP and CLBP, in which the value of each center pixel in a 3x3 local area is replaced by its average local gray level. Compared to the centergray value, the average local gray value is more robust to noise and illumination variants. Zhao et al. introduced Weighted Local Gray Level (WLG) for replace the traditional gray value of the center pixel to make CRLBP more robust and stable.

2.1 Robust Local Binary Pattern (RLBP)

The RLBP produces code, which is invariant to monotonic gray scale transformation and insensitive to noise. The gray value of centre pixel in 3x3 local area is replaced by its average local gray value of the neighbourhood pixel values instead of the gray value of centre pixel value, in which the RLBP is calculated. The Average Local Gray value (ALG) is defined as

$$\mathrm{ALG} = \frac{\sum_{i=1}^{8} g_i + g}{9}, \qquad (1)$$

where g is the gray value of the centre pixel and g_i (i=0,1,…8) represents the gray value of the neighbor pixels. ALG is the average gray level of local area, which is obviously more robust to noise than the gray value of the centre pixel. The LBP process is applied by using ALG as the threshold instead of the gray value of central pixel, named as Robust Local Binary pattern (RLBP). This can be defined as

$$\mathrm{RLBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - \mathrm{ALG}_c)2^p = \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + g_c}{9}\right)2^p, \qquad (2)$$

where g_c is the gray value of central pixel and g_p(p=0,1,…P-1) represents the gray value of the neighbor pixel on 3x3 local area of radius R, P is the number of neighbors and g_{ci}(i=0,1,…8) is the gray values of the neighbour pixel of g_c. Average local gray level of pixel is used as threshold, therefore RLBP is insensitive to noise and also two different patterns with same LBP code may have different RLBP code, because that neighbors of each neighbour pixel are also considered. The RLBP can overcome mentioned demerits of LBP.

Sometimes specific information of the central pixel is needed, but ALG ignores the specific information of individual pixel. In order to defined Weighted Local Gray Value (WLG) to balance between anti-noise and information of individual pixel. The WLG is defined as follows

$$\mathrm{WLG} = \frac{\sum_{i=1}^{8} g_i + \alpha g}{8 + \alpha}, \qquad (3)$$

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where g and g_i are defined in Eq. (1), α is a parameter set by user. If α is set to 1, WLG is equivalent to ALG. The RLBP is calculated as follows

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - WLG_c)2^p = \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + \alpha g_c}{8+\alpha}\right)2^p \,, \quad (4)$$

where g_p, g_c and g_{ci} are defined Eq. (2), α is a parameter of WLG.

2.2. Completed robust local binary pattern (CRLBP)

For differentiating the confusing patterns of LBP, RLBP inherits the effective framework of CLBP. The magnitude m is usually defined as follows:

$$m_p = \left|WLG_p - WLG_c\right| = \left|\frac{\sum_{i=1}^{8} g_{pi} + \alpha g_p}{8+\alpha} - \frac{\sum_{i=1}^{8} g_{ci} + \alpha g_c}{8+\alpha}\right| \quad (5)$$

Where g_p, g_c, g_{ci} are defined in Eq. (2) and $g_{pi}(i = 0, \dots, 8)$ denotes the gray value of the neighbour pixel of g_p and α is the parameter of WLG. CRLBP-Magnitude (CRLBP_M) measures the local variance of WLG. As a result, CRLBP_M as defined follows

$$CRLBP_{M_{P,R}} = \sum_{p=0}^{P-1} s(m_p - c)2^p \,, \quad (6)$$

where c is the threshold is set as the mean value of $m_p$of the whole image. The center pixel, which expresses the image central gray level, also has discriminative information. Thus, also defined an operator named CRLBP-Center (CRLBP_C) to extract the local central information as follows:

$$CRLBP_{C_{P,R}} = s(WLG_c - c_I) \quad (7)$$

where threshold c_I is set as average local gray level of the whole image.

The three operators, CRLBP_S, CRLBP_M, and CRLBP_C, combined (Z. Guo et al., 2010 [19])in two ways, jointly or hybridly. In the first way, similar to the 2-D joint histogram, we can build a 3-D joint histogram of them, denoted by CRLBP_S/M/C. In the second way, a 2-D joint histogram, CRLBP_S/C or CRLBP_M/C is built first, and then the histogram is converted to a 1D histogram, which is then concatenated with CRLBP_M or CRLBP_S to generate a joint histogram, denoted by CRLBP_M_S/C or CRLBP_S_M/C.

III. Facial expression Recogntion

The images are first edited by removing the excess parts to isolate the face in the image. Histogram equalization is performed to enhance the contrast of the image before extracting the facial features from it. We obtained texture characteristics by applying CRLBP to face images that have been normalized. Finally, we extract robust and noise free texture features from the face images, which represents the expression of the face.The histogram of 255 labels for CRLBP is computed using the class labels from the face images. The training template Z^c for a specific facial expression class is created by grouping feature vectors with the same class labels together. consequently,

$$Z^c = \{z_1^c, z_2^c, z_3^c, \dots, z_n^c\}, \quad (8)$$

where n denotes number of training samples available for the corresponding class. The representative feature set of the class c is the cluster center of template Z^c and is calculated as

$$M^c = \frac{1}{n}\sum_{i=1}^{n} z_i^c. \quad (9)$$

Nearest neighbor classifier is used for classification with Chi-Square metric.

$$\chi^2(S, M^c) = \sum_{i=1}^{N} \frac{(S_i - M_i^c)^2}{S_i + M_i^c} \,, \quad (10)$$

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where S is the feature vector of length N extracted from the test image.

IV. Experimental Results

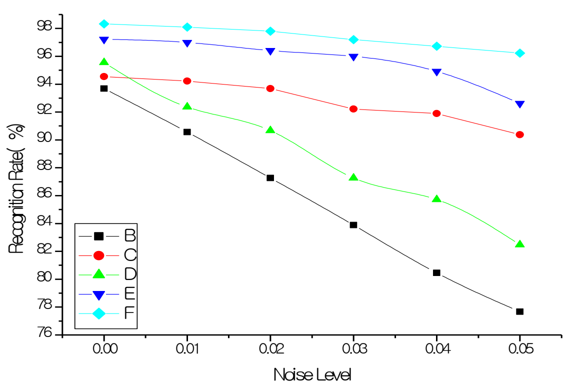
In order to assess the efficiency of our proposed method, we conducted tests using Matlab r2015b and core i5 Dell Inspiron laptop on JAFFE [15] dataset. This dataset comprises multiple instances of the six basic facial expressions, along with a neutral facial image for each individual. There is a total of 213 image featuring 10 individuals, with each image size is 256x256 pixels.

At the beginning, all the images from the JAFFE database are resized to 110x150 pixels in order to isolate and extract the face from each image. Afterwards, we apply histogram equalization to normalize the face image and enhance its contrast. Ten sets of normalized face images are used for 10-fold cross validation. Ten rounds of testing were performed, each time utilizing a different combination of nine sets for training while reserving one set for testing purposes. The final recognition rates are calculated by averaging the recognition rates of ten tests.We have performed numerous tests on the JAFFE database in order to determine the most suitable parameters, such as discovering the best possible settings. Using the Nearest Neighbourhood (NN) classifier, we determine the values of α, R, and P for CRLBP. The histogram, which represents the facial feature vector of the face expressions, is calculated in all tests. The $CRLBP_{8,2}$ produces favourable outcomes when compared to other combinations for a 6-class expression. The same combination also produces positive outcomes for facial expressions consisting of 7 classes.

Table1: Recognition rate of our approach for different R and P for CRLBP

Different R and P for CRLBP	Recognition Rate (%)
CRLBP(8,1)	95.56
CRLBP(8,2)	98.03
CRLBP(16,2)	93.25
CRLBP(16,3)	90.85

In addition, experiments have been conducted on images with noise to observe the robustness of CRLBP against both noise and variations in lighting conditions. The images used in the test were altered by adding random Gaussian noise. The noise had an average value of 0 and varied between 0 and 0.05. CRLBP achieves a superior recognition rate compared to LBP, Curvelet + LBP, CLBP, and Curvelet + CLBP. However, when it comes to normal face images, LBP has a lower recognition rate compared to CLBP. As shown in the figure 1, CRLBP has a much higher recognition rate in noisy situations.



B: Curvelet + LBP, C: CLBP, D: Curvelet + CLBP, E: RLBP, F: CRLBP

Figure 1: Recognition rate (%) of our approach for various noisy conditions

Table2: Comparison result of our approach for JAFFE database

Methods	Recognition Rate (%)
Eigenface	65.83

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Modified Eigenface	84.16
LDA	82.61
Kernel LDA	82.90
LBP	85.57
Curvelet + LBP	93.69
Curvelet + CLBP	95.56
RLBP	97.22
CRLBP	**98.03**

The confusion matrices are computed by employing the $CRLBP_{8,2}$ method for both the 6-class and 7-class facial expression datasets. The confusion matrix displays the percentage of instances, where any expression displayed in a row is incorrectly identified as another expression in the corresponding column. The Table 3 displays the confusion matrix for the 6-class expression recognition in the mentioned combination, while Table 4 presents the confusion matrix for the 7-class expression recognition in the same combination. It has been noticed that identifying Happiness and Surprise expressions is easy to do with great accuracy. However, in the case of Anger, Fear, and Sadness expressions, there is often confusion with other emotions in the 6-class category. For the 7-class category, it is observed that Surprise, Happy, and Fear can be identified with a high level of accuracy. However, the accuracy in recognizing Anger, Disgust, Neutral, and Sad is relatively lower.

The suggested method is evaluated in comparison with Eigenface and Modified Eigenface [18], LDA and Kernel LDA [19], LBP based approach[16], the curvelet with LBP approach [11], and the CLBP approach[17]. The outcomes are presented in Table 2. The Chi-square based nearest neighbor classifier is utilized in all of the experiments. The method we used resulted in a recognition rate of 98.03%, while the LBP method achieved a recognition rate of 85.57%. Additionally, the Curvelet based LBP approach had a recognition rate of 93.69% and the curvelet with CLBP approach had a recognition rate of 95.56%. As a result, our method surpasses the performance of Eigenface, Modified Eigenface, LDA, Kernel LDA, LBP, curvelet based LBP, and CLBP approach. This is because the curvelet transform retains the important edge details and other changes that happen in the face when expressing emotions. Moreover, the CRLBP algorithm effectively captures features from facial images that are resistant to both noise and varying lighting conditions.

V. Conclusion

This paper introduces a novel method for identifying facial expressions by using CRLBP. The robust and invariant features from CRLBP are used to extract features from still images, taking into account factors such as noise and illumination. Our methods were tested on the JAFFE database and the results of the experiment show that our methods have a higher recognition rate when compared to the recognition rates of Eigenface, Modified Eigenface, LDA and Kernel LDA, LBP, curvelet based LBP, and CLBP methods. This happens because the CRLBP is capable of extracting strong and resilient features from facial images, regardless of any interferences from noise or changes in lighting.

Table3: Confusion matrix of 6 class facial expression recognition using CRLBP on JAFFE Database

Expressions	Anger %	Disgust %	Fear %	Happy %	Sad %	Surprise %
Anger	96.67	3.33	0	0	0	0
Disgust	0	100	0	0	0	0
Fear	3.33	0	96.67	0	0	0
Happy	0	0	0	100	0	0
Sad	3.33	0	0	0	96.67	0
Surprise	0	0	0	0	0	100

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Table4:Confusion matrix of 7 class facial expression recognition using CRLBP on JAFFE Database

Expressions	Anger %	Disgust %	Fear %	Happy %	Sad %	Surprise %	Neutral %
Anger	88.23	2.94	2.94	0	2.94	0	2.94
Disgust	5.88	88.23	5.88	0	0	0	0
Fear	2.94	2.94	91.17	0	2.94	0	0
Happy	0	0	2.94	91.17	0	0	5.88
Sad	2.94	2.94	8.82	0	85.29	0	0
Surprise	0	0	0	2.94	0	94.11	2.94
Neutral	0	0	5.88	2.94	0	0	91.17

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