FACIAL EXPRESSION RECOGNITION USING ENHANCED LOCAL BINARY PATTERNS

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ABSTRACT- Facial expression, a non-verbal communication, is a means through which humans convey their inner emotional state, thus playing an important role in social interaction and interpersonal relations. Facial expression recognition plays a significant role in human-computer interaction as well as various fields of behavioral science. There are six known classes of emotional state which are anger, disgust, fear, happiness, sadness and surprise, associated with their respective facial expressions, according to Ekman's studies. Humans recognize facial expressions almost effortlessly and without delay, but this is quite challenging for digital computers. The paper presents facial expression recognition using local binary patterns. The main contribution of the paper is the feature selection applied, in which the high variance LBP pixels are selected to represent faces. By selecting the high variance pixels based on LBPs, the recognition rates were improved significantly. The tests are completed on the BU-3DFE database. The experiments show that after applying feature selection, the recognition rates are improved by 11%.

Keyword: expression recognition, BU-3DFE, feature extraction, enhanced local binary pattern, variance, feature selection.

1. INTRODUCTION

Facial Expression Recognition (FER), is one of the important topics in computer vision. Although much progress has been made in respect to 2D images, it is still a challenging problem in computer vision and pattern recognition [1][2] [3]. Facial expression on the other hand is a visible exhibition of emotion, intention, cognitive activity and psychopathology of an individual [4]; by means of adjusting the facial muscles for each level of facial expression. Humans can easily understand each facial expression, whereas it is difficult for machines to recognize faces or face expression. Advancements in the field achieved significant results in identifying, classifying and recognizing emotional expressions from digital images.

Conventional algorithms apply the stages of image acquisition, registration, normalization, feature extraction, classification and recognition. Besides the recognition of the expressions, their intensity levels are also a direction to research. Researchers are making effort to extract different facial feature from different expression level, but their recognition performance generally depend upon the reliability of the extracted features [5]. For this reason, this paper made use of the popular algorithm, Local Binary Patterns (LBP) for feature extraction and classified using distance classifier. Since the LBP has recently gained attention in the field of facial recognition, so it is worthwhile, using it in facial expression recognition applications [3] [6].

However, the major aspect we are most concerned about when dealing with FER is the expression on the face [4]. This is due of the challenging fact that the human faces carry a lot more information such as the identity of an individual, we therefore need to find a way to remove the personal identity while working with expression recognition.

FER has application in areas such as human computer interaction, computer vision and pattern recognition due to its application in several areas such as customer satisfaction framework, in security system for verification and authentication and some robots have been developed to benefit from the ability to recognize facial expressions [7]. Also, the behavioral science or medicine are key areas that can take advantage of the application of facial expression analysis [4].

The paper describes the LBP operators in section 2. It is followed by the section 3 that presents extraction of facial features based on LBP. Section 4 explains the face recognition methodology used. Simulation results and conclusions are given in the sections 5 and 6 respectively.

2. LOCAL BINARY PATTERNS

LPB is a popular non-parametric texture descriptor which was originally proposed by [8] to be

978-1-5090-5001-7/17/$31.00 ©2017 IEEE
DOI 10.1109/CICN.2017.12

computationally simple [9]. LBP is a very simple and powerful way of representing texture and model of digital images [10] and has been used over the last decade in the area of facial recognition and recently in facial expression recognition, age estimation and gender classification [11]. It has the ability to handle variations such as pose variations and illumination changes. When LBP is running on a digital image, it produces code that describe the local textural patterns of that image by normalizing the intensity values in each pixels' neighborhood [2] and considers the generated results as binary numbers [12].

The LBP texture pattern is created by thresholding the neighborhood the 3x3 pixels by the gray value of its center. The code generated in this way is known as the LBP code. The LBP operator has also been extended, so that it can now be applied at different radius sizes in the circular neighborhood [13] [12]. In situations where a neighborhood pixel poses equal or greater pixel value compared to the center pixel, a "1" is assigned to such pixel, otherwise, a lower logical bit of "0" [11] is assigned. The LBP code for the center pixel is made up of the aggregated sum of weighted results to 8-bits of 1's or 0's to a binary code [2] (Figure 1).

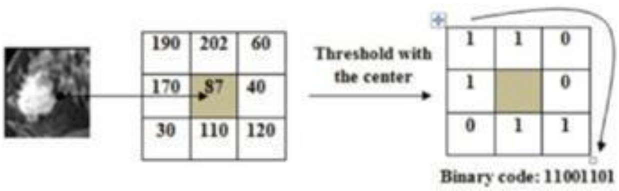
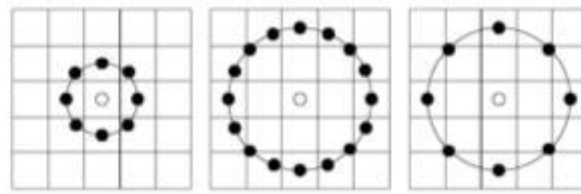


Figure 1: Basic LBP Operator.

The values in the Binary matrix (see Figure 1 above) are obtained after using Equation 3.1 in order to extract the LBP feature for the center pixel.

$$S(k) = \begin{pmatrix} 0 & if\ T(i)<0; \\ 1 & if\ T(i)>=0 \end{pmatrix} \quad 3.1$$

LBP codes have been enhanced in such a way that it allows more accurate codes. This computing process enhanced by generating extra-interpolated neighborhood pixels. In other to achieve this process, it is assumed that a circle with radius R and a center pixel P are computed on the border of the center circle. With the interpolation process, extra point from the neighborhood pixel is generated. Figure 2 below demonstrates the three different sets of P and R values.



(P=8, R= 1) (P=16, R= 2) (P=8, R= 2)

Figure 2: Three neighbor-sets for different values of P and R

An LBP is said to be uniform if the circular binary pattern (clockwise) is made up of at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. For example, the patterns 00000000 (0 transitions), 00001111 (1 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001110 (3 transitions) and 11001001 (4 transitions) are not [12] [14]. For patterns with two transitions are P (P −1) combinations possible. For uniform patterns with P sampling points and radius, R the notion $LBP^{u2}_{P,R}$ is used. Accumulating the non-

uniform patterns into a single bin eventually yields an LBP operator with less than 2p labels, For instance, the number of labels with the neighborhood of 8 pixels is 256 for the standard LBP but only 59 for $LBP^{u2}_{P,R}$ [1] while deduction from Ojala et al's [8]

experiment that, the LBP histogram makes sense to assign individual bins to the uniform patterns and to group less representative pattern (non-uniform) in one unique bin. One of the most import benefits of uniform LBP as pointed out by Ojala et al [8], is that LBP^{u2} identifies just the important local textures patterns, like spots, line ends, edges and corners. Another reason why uniform LBP is prefered over non-uniform LBP is because of its staitististical robustness. [15] reported that making use of uniform patterns instead of all the available patterns has produced better recognition results in quite an number of applications.

3. EXTRACTION OF LBP BASED FEATURES

LBPs are used to describe the texture patterns in an image. Its computational simplicity make it a preferred choice for feature representation [13]. The bits related to local neighboring matrix generates the 8 pixels around every pixel. These 8 bits form a binary number which is then converted into decimal form.

LBP coding style is invariant to many alterations on the pixels' actual values, but since the code does not apply accordingly, the order among the pixel values are maintained [2].

Using LBP, the binary code that defines local texture patterns are generated by normalizing the intensity values in bordering pixel. The face descriptors are defined by LBPs extracted from the face image. The method of feature extraction here considers the local parts of the image as shown in Figure 3, then extracts LBP patterns for each region. This process is followed by histogram calculations for each region. After that, the histograms, let say LBP histograms for each region are concatenated to obtain a single face vector defining the whole face image. This part is without feature selection. After feature selection, which is described in Section 4 in details, this face vector is formed with the concatenation of the selected LBP codes.

This global description forms the feature vector that represents texture of the image and hence used to measure the similarity between the images, by calculating the distance between them using distance classifiers. Figure 4 shows the feature extraction method.

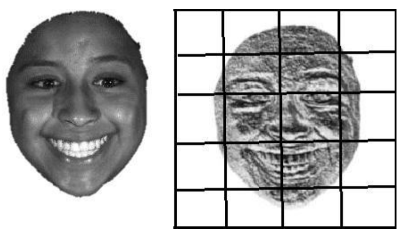


Figure 3: Subdivision of the face image into local regions.

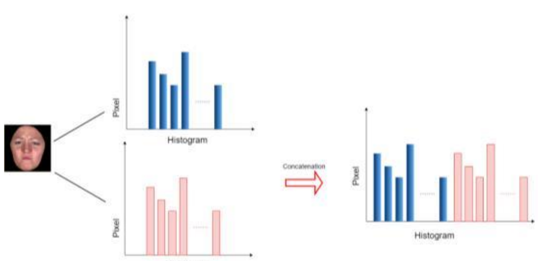


Figure 4: Basic feature extraction using LBP histograms.

4. FEATURE SELECTION

The most significant part of this study is the application of feature selection on the most frequently occurred patterns of LBP. This is obtained by generating a general binary matrix that is used as reference for useful pixels from both the training images for all expression classes and test images. The main idea here is to point out which LBP codes are varying according to expressions. Thus, an LBP code with high variance indicates and informative code. On the other hand, an LBP code with low variance indicates almost a static code which is not informative during expression deformations of the face. This is motivated by the studies done on the face geometry in [20], [21] and [22].

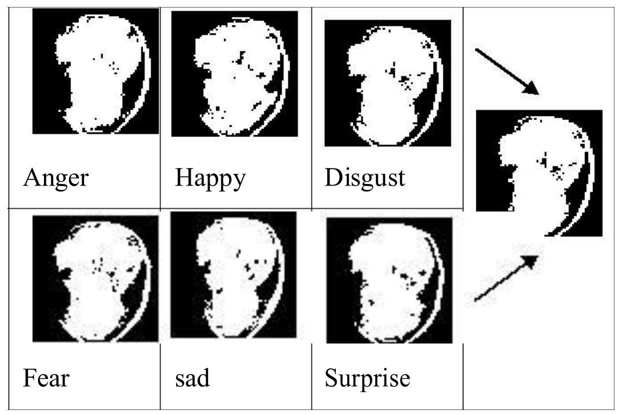


Figure 5: Common binary is extracted from all image classes.

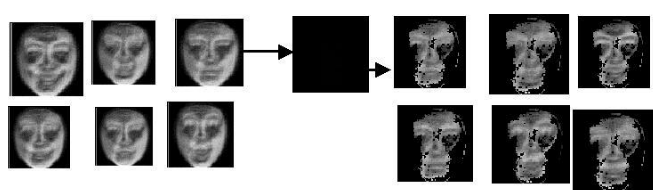


Figure 6: Common binary is used to extract selected LBPs.

The feature selection algorithm derives the LBP images for all the available images. Then, we divide these LBP images into groups of facial expressions. For each expression group, for example for the anger images, each pixel's variance is measured. The variances are calculated for each pixel, using all the LBP images of that group or class. Then, the pixels having the variance above the average variance is depicted as high variance code. By this way, the method points high and low variance pixels for each expression class, based on LBPs. This information is then converted into a binary matrix, where a white pixel shows high variance pixel, and a black pixel shows low variance pixels. Considering the union of these binary images, we say a common binary image is generated which is then used as a reference image in feature selection. This is illustrated in Figure 5. Figure 6 shows how the common binary reference image is used to select LBPs.

5. STRUCTURE OF FER SYSTEM

FER is a system that identifies the expression of a person from a digital image and it is conventionally achieved by comparing facial features from known images and the unknown images. This process can be analyzed in three main components which are registration and normalization, feature extraction and classification as shown in Figure 7..

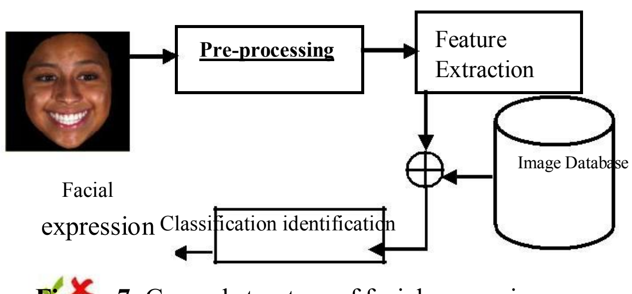


Figure 7: General structure of facial expression recognition system.

In a facial expression recognition system, image is first acquired as input, preprocessing is done, feature vector is extracted and compared to all available models by means of a similarity. In our study, a minimum distance classifier is employed. The input face will be identified with a simple distance classifier [15], [16]–[18], [1] between input image and the image database, which forms the basic facial expression recognition structure shown in Figure 8.

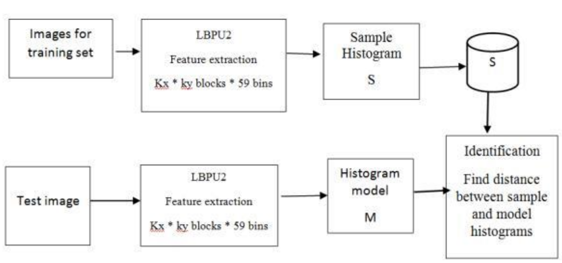


Figure 8: Proposed facial expression recognition framework.

performance is 66.67%, which brings a significant improvement after selecting the features.

6. PERFORMANCE ANALYSIS

The experiment of the proposed LBP based facial expression recognition as presented in this paper is implemented using MATLAB programming environment. The tests were performed on BU-3DFE dataset which includes 6 basic expressions which are anger, disgust, fear, happiness, neutral, sadness and surprise. There are 4 level of intensity in each facial expression, where level 1 being the lowest intensity and level 4, the highest intensity. The dataset contains 100 subjects. For each subject it involves facial images for each intensity level, 400 for each expression class and 100 for the neutral faces. In total, we have 2500 facial images [19]. In our experiments, in order to test the performance of the proposed feature selection method, we only use intensity level 4 which are the highest level of intensity for each expression. The images we use are originally colored and in 512x512 resolution, but during the preprocessing stage, the images were resized to 64x64 and converted into grayscale. Figure 9 shows sample facial images from BU-3DFE dataset.

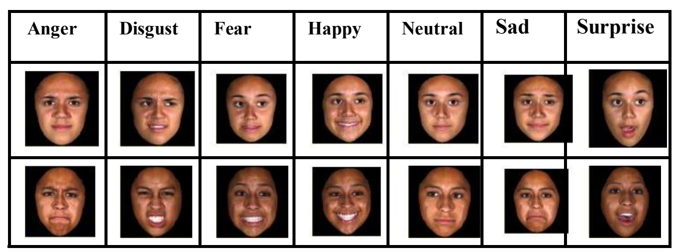


Figure 9: Sample faces from the BU-3DFE dataset.

70 percent of the images in each expression class were used for training and the remaining 30 percent for testing. All are converted into features using LBP in other to make a fine scale textural description of the image. We obtained a common binary vector, composed of the pixels of interest, and then selected corresponding features from the pixels of training set. During testing, features from the test images are selected and tested using distance classifier. Table 1 presents the recognition rates for the expressions.

The experiments were conducted in 3 stages. The first stage involved the classification of the average images without applying LBP and the test set, which produced an overall recognition rate of 49.17%. In the second stage, classification after applying LBP gave an overall recognition rate of 55%. In the third stage of the experiment, classification after applying LBP and the proposed feature selection method is applied. The results show the overall recognition rate of 66.67% As the Table 1 suggests, the overall

Table 1: Recognition Rates After Applying Feature Selection.

Expression	Recognition Rate (%)
Anger	65
Disgust	60
Fear	60
Happiness	65
Sadness	60
Surprise	90
Overall	**66.67**

The experiments show that the feature selection method increases the recognition rates significantly. The main aim of this study is to test the proposed feature selection method. Although a simple distance classifier used in the tests, the method show itself. Furthermore, using a better classifier that can train the selected features will significantly carry the recognition rates in that of the highest standards. Table 2 shows the experimental results before and after applying the proposed feature selection method.

Table 2: Summary of Recognition Tests.

Method	Overall Recognition Rate (%)
Without LBP	49.17
With LBP	55
With LBP + Feature Selection	66.67

7. CONCLUSION

The paper presents a FER system using selected LBPs. A novel feature selection algorithm is proposed based on LBP features. The proposed method generates LBP maps which can be used to select the most discriminative features for the expression recognition problem. Although the classifier used is a basic and simple one, it shows the contribution of the feature selection method proposed. The next direction is to use a strong classifier that can train the known faces described by the feature selection method. Another direction will be the generation of different maps for each facial expression.

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