Recognition of Facial Expressions using Local Binary Patterns of Important Facial Parts

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Abstract

Facial Expression Recognition is one of the exciting and challenging field; it has important applications in many areas such as data driven animation, human computer interaction and robotics. Extracting effective features from the human face is an important step for successful facial expression recognition. In this paper we have evaluated Local Binary Patterns of some important parts of human face, for person independent as well as person dependent facial expression recognition. Extensive experiments on JAFFE database are conducted. The experiment results show that person dependent method is highly accurate and outperform many existing methods.

Keywords: Facial Expressions, Local Binary Pattern (LBP), Histogram.

1. INTRODUCTION

Facial expression is one of the powerful and natural mean for human beings to communicate their emotions and intentions [1]. Facial expression carries crucial information about the mental, emotional and even physical state of a human being. It is a desirable feature of next generation computers, which can recognize facial expressions and responds accordingly and enables better human machine interactions.

Automated Facial Expression Recognition (AFER) is an interesting and challenging problem. Facial Expression Recognition requires both extraction of facial features and design of a classifier, as shown in figure1.

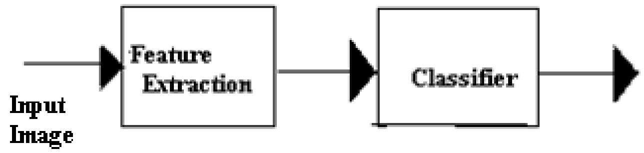

FIGURE 1: Facial Expression Recognition System.

Features (Real values) are extracted from the original face images which minimizes the within class variation of expression and maximizes the between classes variations. If improper features are used, even the best classifier could not recognize proper expressions. There are two main types of approaches to extract facial features: [22-23] geometric feature based methods [2-4] and the appearance based methods [5-9] [16-21]. Geometric feature based methods extract geometric information from the facial images. In appearance based methods, features are either extracted from the entire face or specific regions in facial images. Because of more effectiveness, we are choosing appearance based approach. Gabor wavelet appearance features were demonstrated to be more effective than geometric features [5]. However Gabor Wavelet representation is computationally expensive.

In this paper we make use of facial expression representation based on Local Binary Pattern (LBP) [8, 9, 14] [16-18]. LBP features were proposed originally for texture analysis [6, 7]. Ahonen et al [10, 11] presented LBP based methods for face detection and recognition. The most important properties of LBP features are their tolerance against illumination changes and their computational simplicity.

2. LOCAL BINARY PATTERNS (LBP)

LBP features were originally proposed for texture analysis, which have been recently used in face recognition and facial expression recognition due to its low computation and high discrimination capability. The original LBP operator labels the pixel of an image by thresholding the 3X3 neighborhood of each pixel with the value of the central pixel, and a binary value is assigned to neighborhood pixel on basis of the following function.

$$f(nh) = \begin{cases} 1, if\ v(nh) \geq v(c) \\ 0 \quad\quad otherwise \end{cases} \tag{1}$$

Where v (nh) is gray- scale value of the neighborhood pixel and v (c) is gray- scale value of the centre pixel. These neighborhood bits form a Local Binary Pattern (LBP) corresponding to central pixel.

This can be understood from an example. Suppose the values of a pixel and its eight neighbors are as follows.

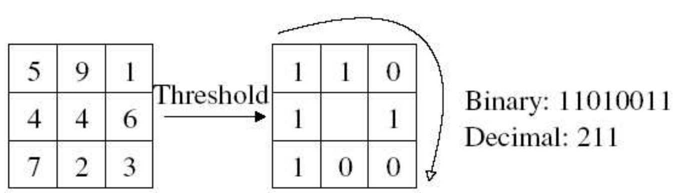

FIGURE 2: Local Binary Pattern.

The derived numbers (called LBP) represent different local patterns like edges, curves, flat regions and spots etc. Using LBP operator the whole image can be transformed to LBP image. An example of LBP image of a facial image is shown in figure 3.

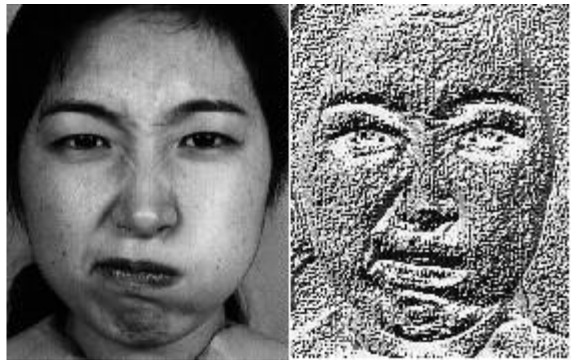

FIGURE 3: An Example of LBP Image for a Facial Image.

The limitation of original binary pattern is its small 3X3 neighborhood, which cannot capture the dominant features. The basic LBP Operator was extended to the neighborhood of different sizes [12]. Using circular neighborhood and bilinear interpolation, the neighborhood of any radius with different number of pixels can be used. See Figure 4 for extended LBP operator.

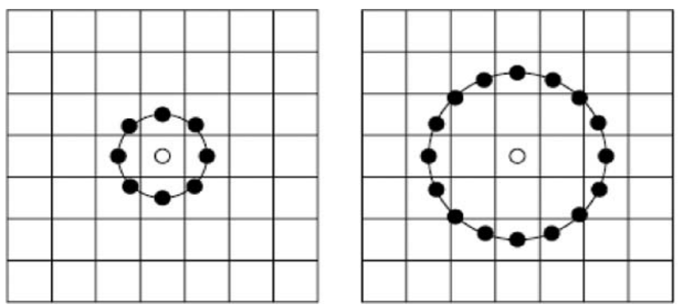

FIGURE 4: Local Binary Patterns of Circular Radius 1 and 2 with 8 and 16 Pixels.

The notation $LBP_{P,R}$ is used to denotes the Extended LBP with P pixels and R radius. It has been shown that certain patterns contain more information than others [12]. Therefore it is advantageous to use only those patterns which contain more information. Ojala et el [12] called these patterns as uniform patterns. A Local Binary Pattern is called uniform if it contains at most two bitwise transitions either from 0 to 1 or from 1 to 0. For example, 01111111 is a uniform pattern but 10001101 is not, as it has three bitwise transitions. It is observed that about 90% of the patterns in (8, 1) neighborhood and about 70% of the patterns in (16, 2) neighborhood are uniform patterns in texture images [12]. The LBP operator that accumulates only uniform patterns is denoted by $LBP^{U2}_{P,R}$. The number of patterns for $LBP^{U2}_{8,1}$ is only 59 as compared to number of patterns for standard $LBP_{8,1}$, which is 256.

After applying LBP operator to each pixel of an image, the Histogram of LBP operator values is formed as follows.

$$Hi = \sum_{x,y} I(LBP(x,y) = i) \qquad i = 0,1,\ldots..n-1 \tag{2}$$

Where n is the different possible values (Labels) produced by the LBP operator, and

$$I(x) = \begin{cases} 1 & if\ x\ is\ True \\ 0 & if\ x\ is\ False \end{cases} \tag{3}$$

This LBP histogram of an image contains the information about local micro patterns like edges, curves, flat regions and spots etc present in the image. LBP histogram is shown in figure 5.

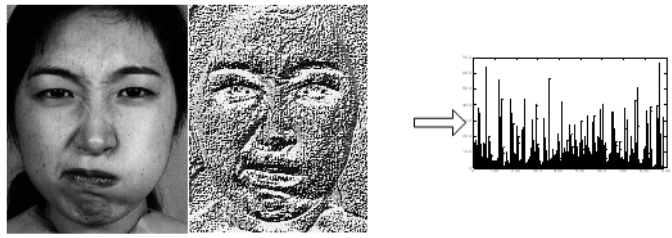

FIGURE 5: LBP Histogram of a Facial Image.

3. FEATURE EXTRACTION FROM FACIAL PARTS

LBP histogram computed from the whole face image tells about the occurrences of the micro-patterns without any indication of their locations. An alternative of this is as follows: first divide the whole face image into sub regions, find out the histogram of each sub region and concatenate all histograms to get a LBP histogram of face. We know that each sub region does not contain the equal amount of information about facial expressions, so we choose some important parts of the face for above purpose. We have chosen eight important sub regions of a face as shown in figure 6, those are two parts of left eye, two parts of right eye, two parts of nose and two parts of mouth. After experimenting with different LBP operators, we have chosen $LBP^{U2}_{8,2}$.The number of bins for each region is 59 , so the size of a final feature vector is 472.

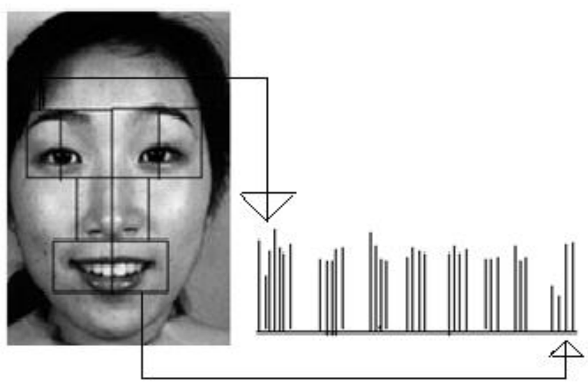

FIGURE 6: Important Facial Parts and Their Histograms of LBP's.

4. FACIAL EXPRESSION RECOGNITION USING LBP

We evaluate the performance on JAFFE (Japanese Female Facial Expression) [13]. JAFFE is a very popular database for facial expression recognition, in which in total 213 facial expression images with 10 Japanese women are involved. Each individual has three or four images with seven kinds of facial expressions, including anger, disgust, fear, happy, sadness, surprise and neutral,. Figure 7 shows seven expression image examples selected from JAFFE database.

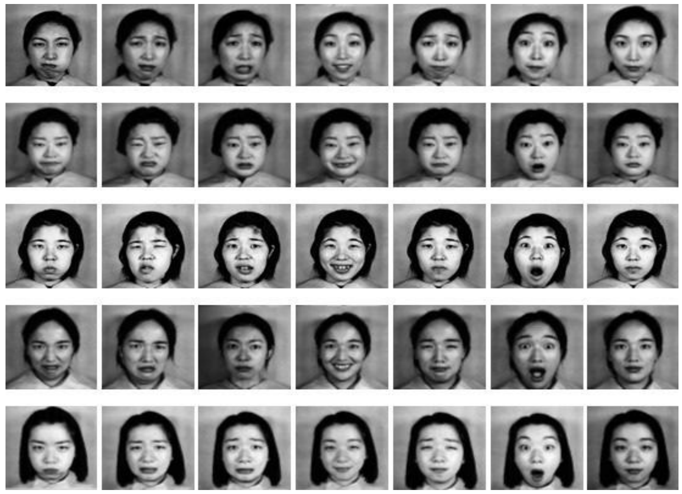

FIGURE 7: Some Sample Images from JAFFE Dataset.

In this section, we perform person-independent as well as person dependent facial expression recognition using LBP features along with template matching as a classifier. Template matching was used in [14] to perform face recognition using LBP-based features: a template is formed for each class of face, and then the nearest neighbor classifier is used to match the test image with the closest template. Here we adopt the template matching for classification of facial expressions. We adopt two types of template matching, one is the person independent template matching and the other is person dependent.

4.1 Person Independent Template Matching

A template is formed for each class of face expression by averaging the LBP histograms of a particular expression. In the training phase, these seven templates are stored. In the testing phase, a test image is compared with all stored templates. We have selected the Chi square test (X^2) as similarity measure.

$$X^2(\mathbf{S}, \mathbf{M}) = \Sigma_i \, (Si-Mi)^2 / (Si+Mi) \qquad (4)$$

Where **S** and **M** are two LBP histograms of template and test images respectively. Person independent template matching has achieved the generalization performance of 73.61% for 7 category classification. The Confusion matrix for 7-class facial expression recognition is shown in Table1.

Table1: Confusion Matrix for 7-class Person Independent Facial Expression Recognition.

	Anger %	**Disgust %**	**Fear %**	**Happy %**	**Neutral %**	**Sad %**	**Surprise %**
Anger	60	10	0	10	10	10	0
Disgust	0	50	10	20	10	10	0
Fear	0	0	54.5	9.1	9.1	9.1	18.2
Happy	0	0	0	91	9	0	0
Neutral	0	0	0	0	90	10	0
Sad	0	0	10	0	10	80	0
Surprise	0	0	10	0	10	0	80

Note that happy, neutral, sad and surprise expressions can be recognized with high accuracy (about 80-90%), but anger, fear and disgust are easily confused with other expressions.

4.2 Person Dependent Template Matching

Facial expressions may be expressed differently by different people [15], so low accuracy is achieved in the above method. Therefore, we propose a method that is person dependent. Instead of developing person independent seven templates- one for each expression- we propose to form templates that are person dependent. For each person, seven templates are formed- one for each expression- so total of 70 templates for 10 persons are formed. These 70 templates are stored in training phase. In the testing (Recognition) phase a test image is compared with all stored templates. The one with minimum distance is declared as a recognized expression. The person dependent template matching has achieved a very high generalization performance of 94.44% for 7 category classification. The Confusion matrix for person dependent facial expression recognition is shown in Table2.

Table2: Confusion Matrix for 7-class Person Dependent Facial Expression Recognition.

	Anger	**Disgust**	**Fear**	**Happy**	**Neutral**	**Sad**	**Surprise**
Anger	90	0	0	0	0	10	0
Disgust	0	100	0	0	0	0	0
Fear	0	0	90	0	0	10	0
Joy	0	0	0	100	0	0	0
Sad	0	0	0	0	100	0	0
Surprise	0	0	10	0	0	90	0
Neutral	0	0	0	0	0	10	90

Another benefit of this approach is that along with the recognition of an expression, it also recognizes with expression belongs to which particular person. The time taken to recognize an expression with our approach is, on an average, 11.5 milli seconds.

Person dependent template matching has achieved an average performance of 94.44% for JAFFE database, and has outperformed other methods as listed in Table3.

Table3: Comparison Between Different Methods for 7-class Recognition.

Method(features + classifier)	**Recognition Rate (%)**
LBP +Template Matching [1]	79.1
Geometric Features +TAN[24]	73.2
LDA+NN[1]	73.4±5.6
LBP+SVM(RBF)[1]	88.9±3.5
Gabor +SVM(RBF)[1]	86.8±3.6
Proposed method(Person Independent)	73.61
Proposed method(Person Dependent)	94.44

5. CONCLUSION AND FUTURE WORK

In this paper, we have extracted features based on Local Binary Pattern. As every part of the face does not contribute equally in face expression recognition, we have chosen some important facial parts like sub parts of eyes, nose and mouth. With the templates of extracted facial features, template matching was used to classify the expression. Experimental results show that the proposed approach is better than approaches that use the whole face image. The proposed method integrates person identity to perform better than conventional expression systems. The proposed person dependent approach achieves higher recognition rates than those of other approaches. Chi square distance is used as measure of similarity; for classification, we will use neural network and Support Vector Machines (SVM). Manual detection of face and its important parts will be enhanced by automatic detection. Performance evaluation will be extended from JAFEE to other databases.

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