Experiment using ULBP and Edge Map based Facial Expressions Recognition system

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Abstract

This paper is present an algorithm based on Local Binary Patterns (LBP) for automatic facial expression recognition. Facial Recognition algorithm classifies given image into predefined classes of various expressions. The proposed algorithm first apply the Gaussian filter on the input image to remove unwanted noise and to smooth the image then it computes horizontal and vertical edges of an image to extract features of facial expression. Edges are the main component to recognize of facial expression generated by the movement of muscles that are better appeared in the form of edges. In the next step, the algorithm generates the histogram of the image by dividing into the different block. We have used Uniform patterns of LBP (ULBP) to reduce dimensions of LBP histogram which help the algorithm to be more efficient and less computationally expensive. We have trained and tested our algorithm on the standard data set of facial expressions like TFEID and JAFFE. In our experiments, we are able to achieve 90.2% recognition rate on TFEID data set using adaptive weights and on JAFFE dataset recognition rate is 89.6%.This paper is present an algorithm based on Local Binary Patterns (LBP) for automatic facial expression recognition. Facial Recognition algorithm classifies given image into predefined classes of various expressions. The proposed algorithm first apply the Gaussian filter on the

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input image to remove unwanted noise and to smooth the image then it computes horizontal and vertical edges of an image to extract features of facial expression. Edges are the main component to recognize of facial expression generated by the movement of muscles that are better appeared in the form of edges. In the next step, the algorithm generates the histogram of the image by dividing into the different block. We have used Uniform patterns of LBP (ULBP) to reduce dimensions of LBP histogram which help the algorithm to be more efficient and less computationally expensive. We have trained and tested our algorithm on the standard data set of facial expressions like TFEID and JAFFE. In our experiments, we are able to achieve 92% recognition rate on TFEID data set using adaptive weights and on JAFFE dataset recognition rate is 89.2%.

***Keywords*:** Facial Image Analysis, Sobel Operator, Uniform Local Binary Pattern. Facial Expression Recognition,

1. INTRODUCTION

Facial Expressions help human beings to communicate their emotions and intentions [1]. It has also great scope in human-computer interaction systems such as 2D or 3D face animation, intelligent computer systems, psychology research and cognitive research [2]. Facial expressions recognition is affected by many technical challenges such as (i) head pose (ii) face difference, etc. The effects due to head pose can be compensated by regularizing, but face difference is very difficult to remove by pre-processing. A number of methods have been presented in the literature for facial expressions recognition [3-9,]. Cohen et al [17] adopted Bayesian network classifier, and the quoted performance was 73%. In[18] authors have proposed two techniques for facial expression recognition; the first based on Gabor Wavelets and SVM with linear polynomial and second technique use RBF kernels

instead of a linear polynomial. The recognition rate of the two techniques is 84.8% and 86.9% respectively. Majha Pentic et al. [19] gives an analysis of various techniques previously used for facial expressions recognition. In [20] LBP based techniques are used for facial expressions recognition with the accuracy of 79% using template matching. Though a number of techniques have been proposed for facial expressions recognition, recognizing facial expressions with high accuracy is still a challenging task for research community due to the complexity and variety of facial expressions.

Local Binary Pattern (lbp) is widely used by many researchers as a facial image analysis technique. Initially, lbp was introduced as texture analysis technique [10, 11]. Later ahonen et al [12, 13] described lbp based methods for facial image analysis. In this paper, we use lbp of local areas as discriminative features for facial expressions recognition. The motivation for the proposed algorithm is that facial expressions are represented as the composition of micro patterns, which are efficiently handled by lbp. In the recommended algorithm, we use edge information of facial expression rather of using the whole image. Edge maps are low-level features that are used in many computer vision applications. These maps give important information for different facial expressions. Facial expressions are formed by the movement of facial muscles that can be efficiently represented by using edge maps, thus in the present work alternatively of directly applying lbp on the facial image, it is applied to the deduced edge maps. After calculating edge images the whole image is divided into non-overlapping blocks and lbp histogram are extracted from each block. The histograms are later concatenated to deduce an enhanced feature vector. To further reduce the length of feature vector only uniform characteristics are used for recognition determination.

2. EDGE MAP

Subjective research demonstrates that human beings can recognize line drawing as promptly and accurately as gray scale images [14]. As discussed earlier, facial expressions can be easily represented by edges. That can be used for facial expressions recognition. We use Sobel's operator for

edge detection because Sobel's operator is one of the mildest operators for extracting edge map, and it is regularly used in practice. An example of Sobel's edge exposure is shown in Figure 1..

Figure 1: (a) Gray image (b) Horizontal edge map (c) Vertical edge map (d) Average of Horizontal & Vertical

In prior work, Sobel's edge maps are used for encoding into binary images [15, 16] thus leads to loss of significant image information. In the recommended algorithm, we use non-binary edge maps to extracts LBP characteristics.

3. Local Binary Pattern

LBP texture representation operator was, firstly, presented by Ojala et al [10] for texture analysis. Presently, LBP is used broadly in a number of applications like face recognition, pattern matching, template matching, etc. LBP is a non-parametric operator, which represents the local spatial structure of an image, at a given pixel position (xc, yc). It designates the pixels of an image by thresholding the neighborhood of each pixel with the center value and reflecting the result as a binary number as shown in Fig. 2. The decimal form of the resulting 8-bit word (LBP code) can be represented as follows::

$$\mathrm{LBP}(x_c, y_c) = \sum_{n=0}^{7} \mathrm{s}(i_n - i_c)\, 2^{\mathrm{n}}$$

Where i_c represents the gray value of the center pixel (x_c, y_c), i_n represents gray values of 8 surrounding pixels and function s(x) is defined as:

$$s(x) = \begin{cases} 1, if\,(x \geq 0) \\ 0, if\,(c < 0) \end{cases}$$

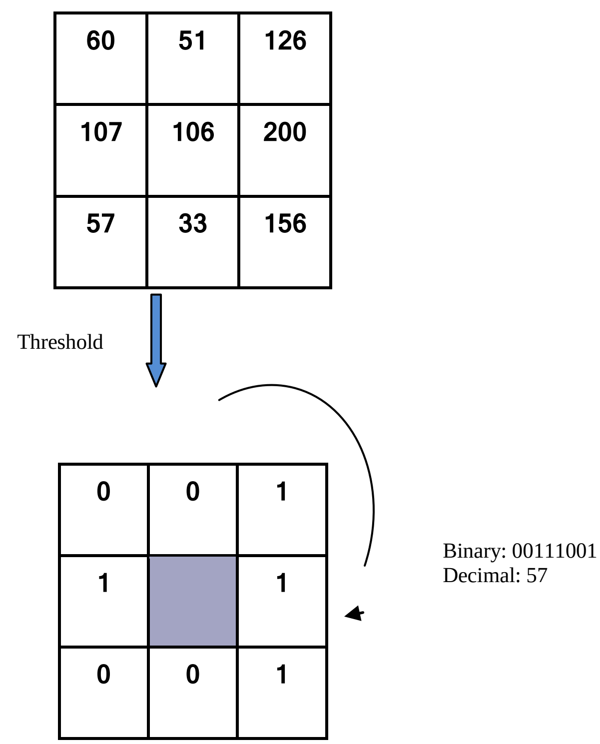

Figure 2: Illustration of LBP operator

Initially, LBP used a 3X3 operator later LBP operator was stretched to use neighborhood of different sizes [11]. Multi-resolution LBP operator allows any radius and number of pixels in the neighborhood. Which is denoted as LBP (P, R), Where P denotes sampling points on a circle of radius of R.

Another branch of LBP is the use of uniform patterns [11]. A Local binary pattern is called uniform if it includes at most two bitwise transitions from 0 to 1 or vice versa when the binary string is examined circular. For example, 00000000, 00111000, 11100001 are uniform patterns. It is remarked that uniform patterns account for nearly 90% of all patterns in (8, 1) neighborhood and for about 70% in the (16, 2) neighborhood in the texture image [11].

In the suggested work, we use uniform LBP operator LBPu2(P, R), Where the superscript u2 indicates using only uniform patterns, which have at the most 2 transitions. And then histogram can be interpreted as:

$$H_i = \sum_{x,y} I\{f(x,y) = i\}, \qquad i = 0, \dots, n-1$$

Where *n* is the number of different labels produced by the LBP operator and:

$$I\{A\} = \begin{cases} 1, & A \text{ is true} \\ 0, & A \text{ is false} \end{cases}$$

. R_m. As shown in Figure 3.

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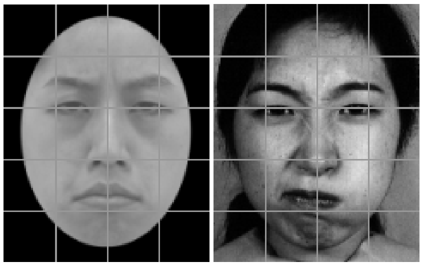

Figure 3: Facial Expression image (a). TFEID (b).
JAFFE are divided into 5X4 sub-region.

By arranging the whole image into blocks, the labels are summed over small domains to provide information on a provincial level and the regional histograms are concatenated to build a global representation of the face [12] .

I. PROPOSED ALGORITHM

Following are the main steps of the proposed algorithm.

1. **Application of Sobel Operator to find the two edge maps horizontal and vertical, i.e. G_x and G_y. and absolute edge map i.e. given by,**

$$G_A = \sqrt{{G_X}^2 + {G_Y}^2}$$

2. Distributing the edge maps into fixed sized blocks or regions. In our work, each block is of size 30 X30 .

3. Uniform feature is extracted by performing LBP on each sub block of edge images and allocate distinct weights to each block according to the fixed or adaptive mechanism.For facial expression recognition algorithm, we adopt following distance measuring methods as classifier.

1. Euclidian Distance

$$E.D. = \sqrt{\sum_{i=0}^{n} (\mathrm{x_i} - \mathrm{y_i})^2}$$

2. Chebyshev Distance

$$D_{\text{Chebyshev} \quad (\mathrm{p,q})} = Max_i(|p_i - q_i|)$$

3. Taxicab Distance

$$d_i(p,q) = \left||p - q|\right| = \sum_{i=1}^{n} |p_i - q_1|$$

As addressed in Step 3 two various weight mechanisms are used for employing weights to separate blocks of the image. Also, different weights are distributed to different parts of the face. The reason for that is; facial expressions affect specific regions of the face rather of the whole face. For example, an area around eyes, eye brows, lips, contributes further to the different facial appearances than the forehead, cheeks, etc. Accordingly, different weights can be allocated to the various face regions according to the meaning of the information it carried. The two weight mechanisms are explained as follows.

A. ***Fixed Weight:***

While applying fixed weight various regions of the face image are assigned with the several weight according to the magnitude of the area around the region. The following figure exhibits the weight assigned to the different blocks.

0	1	1	0

1	4	4	1
1	2	2	1
2	4	4	2
0	4	4	0

Figure 4: The weights set for the different regions.

B. *Adaptive Weight:*

As we pioneer discussed, facial expressions can be clearly represented by edges in the facial image. And in the submitted work, we apply LBP operator on the average of both vertical and horizontal edge map, as shown in the next Figure.

Figure 5: (a) Absolute edge map (b) LBP image of edge map.

While using adaptive weight we assign the weights to the various block according to the edge information. In other words, we can say that the weight depends upon the edge knowledge.

4. EXPERIMENT AND RESULTS

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The algorithm is evaluated using TFEID (Taiwanese Facial Expression Image Database) database (http:/ / bml.ym.edu.tw/ tfeid/). This database included 336 images of 8 different expressions. All images in databases comprise rim. The rim around the images is used to remove all irrelevant information like ear, hairs etc. which does not play any role in facial features. These images contain an only valuable region of the face such as eyes, lips, eyebrows, four head, and nose. Based on these regions, the algorithm selects all the features and able to distinguish one image's facial expression from other.

For Training the algorithm we have used following a number of images in each category. Training images took randomly from the database. Following tables shows different experiments on available database.

Table 1: Random Training Set

Sno.	Image Expression	Total images
1.	Anger	34
2.	Disgust	40
3.	Fear	40
4.	Happiness	40
5.	Neutral	39
6.	Sadness	39
7.	Surprise	36

Accuracy Calculated from Full Images shown in Table 2,3,4 respectably.

Table2: Using Arithmetic Mean and Euclidean Distance

	Smile	Anger	Disgust	Netural	Sad	Fear	Surprise	Total	Accuracy
Smile	13		4		1	2		20	65
Anger		15		1			2	18	83.33333

Disgust	8		3	3	3	3		20	15
Netural			2	7	7	4		20	35
Sad	1		1	4	10	3	1	20	50
Fear	2		7		6	4	1	20	20
Surprise		2		5	1		9	17	52.94118

Table 3: Results Using Arithmetic Mean and Chebyshev Distance

	Smile	Anger	Disgust	Netural	Sad	Fear	Surprise	Total	Accuracy
Smile	13		4		1	2		20	65
Anger		15		1			2	18	83.33333
Disgust	8		3	4	2	3		20	15
Netural			2	7	7	4		20	35
Sad	1		1	4	10	3	1	20	50
Fear	2		7		6	4	1	20	20
Surprise		2		4	2		9	17	52.94118

Table 4: Results Using Arthmatic Mean and Taxicab Distance

	Smile	Anger	Disgust	Natural	Sad	Fear	Surprise	Total	Accuracy
Smile	11		1	2	4	2		20	55
Anger		16		1		1		18	88.88889
Disgust	3		8	3	4	2		20	40
Natural	1	3		8	7	1		20	40
Sad	5	1	1	7	3	3		20	15
Fear	3			1	5	10	1	20	50
Surprise				2			15	17	88.23529

Accuracy Calculated from 20 sub imagers using Fixed -Weight shown in table 5,6,7 respectably.

Table 5: Results Using Arithmetic Mean and Euclidean Distance

	Smile	Anger	Disgust	Natural	Sad	Fear	Surprise	Total	Accuracy
Smile	17			1		2		20	85
Anger		14		2	2			18	77.77778
Disgust			18			1	1	20	90
Netural		2		15	1	2		20	75
Sad		1		2	12	4	1	20	60
Fear	1		1	2	3	13		20	65
Surprise		1		1	1		14	17	82.35294

Table 6: Results Using Arithmetic Mean and Chebyshev Distance

	Smile	Anger	Disgust	Natural	Sad	Fear	Surprise	Total	Accuracy
Smile	12	4		1		3		20	60
Anger		12	4		2			18	66.66667
Disgust	1	3	7	2	1	4	2	20	35
Netural	1	4	1	7	4	3		20	35
Sad		1	1	1	10	4	3	20	50
Fear	2		2		7	9		20	45
Surprise		2			3		12	17	70.58824

Table 7: Results Using Arithmetic Mean and Taxicab Distance

	Smile	Anger	Disgust	Natural	Sad	Fear	Surprise	Total	Accuracy
Smile	20							20	100
Anger		16		2				18	88.88889
Disgust			19			1		20	95
Netural				19		1		20	95
Sad				2	17	1		20	85
Fear	2			1	2	15		20	75
Surprise							17	17	100

Accuracy calculated from 20 Sub-Images using Adaptive Weights shown in table 8,9,10

Table 8: Results using Asthmatic Mean and Euclidean Distance

	Smile	Anger	Disgust	Natural	Sad	Fear	Surprise	Total	Accuracy
Smile	17			1		2		20	85
Anger		14		3	1			18	77.77778
Disgust			17	1	1	1		20	85
Netural			1	16		3		20	80
Sad				3	15	2		20	75
Fear	4		1	2	3	10		20	50
Surprise			1	1			15	17	88.23529

Table 9: Results Using Asthmatic Mean and Chebyshev Distance

	Smile	Anger	Disgust	Natural	Sad	Fear	Surprise	Total	Accuracy

Smile	14	1		2		3		20	70
Anger		12		2	1		3	18	66.66667
Disgust	2	1	12	3			2	20	60
Netural	2		1	9	4	4		20	45
Sad			1	3	13	1	2	20	65
Fear	3		1	4	5	7		20	35
Surprise		2		2	1	1	11	17	64.70588

Table 10: Using Arithmetic Mean and Taxicab Distance

	Smile	Anger	Disgust	Natural	Sad	Fear	Surprise	Total	Accuracy
Smile	20							20	100
Anger		16		2				18	88.88889
Disgust			19			1		20	95
Netural				20				20	100
Sad				1	18	1		20	90
Fear	2			1	2	15		20	75
Surprise							17	17	100

Conclusion

The suggested research work shows that the normalization of images is an important step for facial expression recognition. By promoting the normalization process it will produce better with greater recognition rate. We know that each human being manifests a particular expression differently or in its own way, but the photographs of the database show their individualized facial appearances. Since our training set is limited, it is challenging to form trained features for appropriate expression that containing comprehensive expression features for all human beings. As a result, when expression of an experiment set is different from that in the training set, it may be inadequately recognized. So, if a valid and complete training set can be obtained, the recognition precision will be enhanced. We have tested proposed system on different distance classifiers like Euclidean distance, Chebyshev Distance, and Taxicab Distance also known as Manhattan distance. Manhattan distance is simple as compared to popular euclidean distance but yielded great results. In future work, we will try to compare these classifiers with more sophisticated classifiers like SVM, Neural Networks.

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