

Facial Expression Recognition Based On Local Binary Patterns Using BBO

Deepak Saxena¹, Anil Kumar², Rajesh Kumar Upadhyay³

Mangalayatan University, Aligarh, India

Abstract— This paper describes the project of Facial expression recognition based on local binary patterns . There are many channels or ways of conveying human emotions like behaviours, actions, poses, facial expressions and speech. Facial expressions have a higher importance as they can be easily recognized. In this project, we are working on a system which can automatically recognize the emotions represented on a face. With the help of image processing, the system can classify between the universal emotions: Happiness, Sadness, Anger, Disgust, Surprise and Fear. Automatic facial expression analysis is an interesting and challenging problem which impacts important applications in many areas such as human-computer interaction and data driven animation. Deriving effective facial representative features from face images is a vital step towards successful expression recognition. In this paper, we evaluate facial representation based on statistical local features called Local Binary Patterns (LBP) for facial expression recognition. Simulation results illustrate that LBP features are effective and efficient for facial expression recognition. A real-time implementation of the proposed approach is also demonstrated which can recognize expressions accurately at the rate of 4.8 frames per second.

Keywords—Facial expression recognition, Local Binary patterns, Support vector machine, Biogeography based optimization (BBO).

I. INTRODUCTION

Facial expression recognition is an attractive and difficult issue, and effects vital applications in numerous zones, for example, human-computer connection and information driven movement. Removing the ideal components from pictures is continuously needed in face acknowledgment calculation to accomplish high precision. In this paper we have displayed a proficient facial representation and face acknowledgment calculation in view of Biogeography Based optimization (BBO). To start with we separate the elements utilizing the principal Component Analysis (PCA) in the wake of applying Gabor channels and afterward we apply BBO to get the most alluring highlights. The Execution investigation is performed utilizing Cohn Kanade face database. Execution results demonstrate that biogeography based face acknowledgment calculation produces preferable results over the SVM using LBP.

There is a great deal of exploration parkways in the field of face acknowledgment because of difficulties present in the field. The objective of face acknowledgment is to match a given picture against an expansive database of pictures to check its vicinity. Outward appearance is a standout amongst the most intense, normal and prompt means for people to impart their feelings also, intensions. Facial expression recognition is an attractive and difficult issue, and effects essential applications in numerous territories, for example, human-computer connection and information driven movement. The face acknowledgment has been connected to two generally vital applications i.e check (coordinated coordinating)

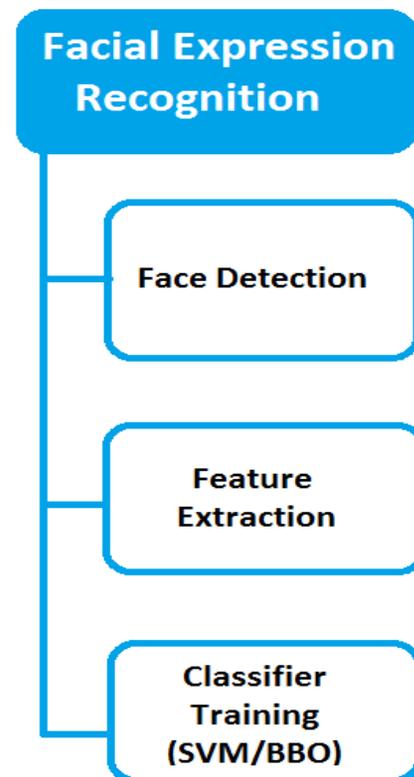


Fig. 1: Facial expression recognition system

and recognizable proof (one to numerous coordinating). Scientists have displayed a ton of methods for face acknowledgment. These systems can be ordered as all encompassing coordinating strategy for e.g Principal Component Analysis (PCA) and neighborhood highlight coordinating technique.

Determining a successful facial representation from unique face pictures is a key stride for fruitful outward appearance acknowledgment. There are two basic ways to deal with concentrate facial elements: geometric highlight based techniques and appearance-based routines. Geometric components display the shape and area facial segments, which are removed to shape a component vector that speaks to the face geometry. As of late have shown that geometric component based systems give comparable or preferred execution over appearance-based methodologies in real life Unit acknowledgment. On the other hand, the geometric component based strategies more often than not requires exact and solid facial element identification and following, which is hard to suit in many situations. With appearance-based routines, picture channels, for example, Gabor wavelets, are connected to either the entire face or particular face-areas to concentrate the appearance changes of the face. Because of their unrivaled execution, the real chips away at appearance-construct techniques have concentrated in light of utilizing Gabor-wavelet representations. On the other hand, it is both time and memory escalated to convolve face pictures with a bank of Gabor channels to concentrate multi-scale and multi-orientational coefficient.

II. FAST FACIAL EXPRESSION RECOGNITION

Face recognition methods can be categorize into feature based and holistic method for intensity images. One of the methods of holistic technique is Principal Component Analysis. PCA is a standard technique; it is used to extract features from a given image. Although many techniques are present for feature extraction and PCA is one of the most common techniques. It is use to extract desirable feature from an image. It results in eigen faces which represent all the images in database, which reduce the dimensions of images. Since in PCA raw images cannot be taken as input so for that we use gabor kernel for proper alignment and smoothing the images.

2.1 Face Detection

In the first stage, the system acquires an image from the system web camera and performs some image processing techniques on it in order to find the face region. System can operate on static images, where this procedure is called face localization or videos where we are dealing with face tracking.

Major problems which can be encountered at this stage are different scales and orientations of face. They are usually caused by subject movements or changes in distance

from camera. Significant body movements can also cause drastic changes in position of face in consecutive frames what makes tracking harder. What is more, complexity of background and variety of lightning conditions can be also quite confusing in tracking. For instance, when there is more than one face in the image, system should be able to distinguish which one is being tracked

2.2 Feature Extraction

After the face has been located in the image or video frame, it can be analyzed in terms of facial expression. There are two types of features that are usually used to describe facial expression: geometric features and appearance features. Geometric features measure the displacements of certain parts of the face such as eyebrows or mouth corners, while appearance features describe the change in face texture when particular action is performed The task of geometric feature measurement is usually connected with face region analysis, especially finding and tracking crucial points in the face region. Possible problems could be occurrences of facial hair or glasses.

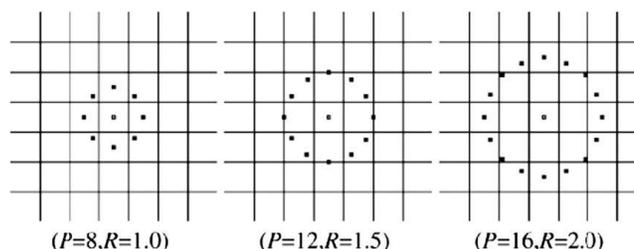


Fig.2:Examples of extended Local binary pattern

Fig. 2 shows various possible combinations to form a circularly symmetric neighbor set LBP(P,R), where P is the number of neighboring pixels and R is the radius of operation. In (1), B(i) represents the binary bit at the neighboring pixel i, and I(c) represents the intensity at the center pixel c of the block, then the LBP transform of the ith neighbor is given by

$$B(i) = 1; \text{ if } I(i) \leq I(c) \\ 0; \text{ otherwise} \quad \dots(1)$$

III. LOCAL BINARY PATTERNS (LBP)

Local Binary Patterns were introduced by Olaja et al. as effective texture descriptors. Input image is transformed into LBP representation by sliding window technique where value of each pixel in the neighborhood is thresholded with value of central pixel. Central pixel is encoded with LBP code (binary or decimal) in corresponding LBP image pixel.

Facial expression is most natural and immediate means for communicate.



Fig.3: Facial expression

The operator labels the pixels of an image by thresholding a 3×3 neighborhood of each pixel with the center value and considering the results as a binary number and the 256-bin histogram of the LBP labels computed over a region is used as a texture descriptor. The derived binary numbers (called Local Binary Patterns or LBP codes) codify local primitives including different types of curved edges, spots, flat areas, etc (as shown in Fig. 5), so each LBP code can be regarded as a micro-texton . The limitation of the basic LBP operator is its small 3×3 neighborhood which can not capture dominant features with large scale structure.

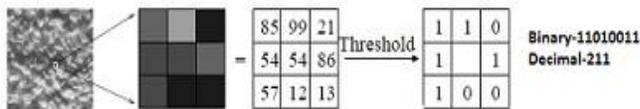


Fig.4: Basic LBP operator

The LBP operator $LBP_{P;R}$ produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the P pixels in the neighbor set. It has been shown that certain bins contain more information than others . Therefore, it is possible to use only a subset of the 2^P Local Binary Patterns to describe the texture of images. Ojala et al. called these fundamental patterns as uniform patterns. A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular. For example, 00000000, 001110000 and 11100001 are uniform patterns. It is observed that uniform patterns account for nearly 90% of all patterns in the (8,1) neighborhood and for about 70% in the (16,2) neighborhood in texture images [28]. Accumulating the patterns which have more than 2 transitions into a single bin yields an LBP operator, denoted LBP_{u2} $P;R$, with less than 2^P bins. For example, the number of labels for a neighborhood of 8 pixels is 256 for the standard LBP but

59 for LBP_{u2} . After labeling a image with the LBP operator, a histogram of the labeled image $f(x,y)$ can be defined as-

$$H_i = \sum_{xy} I(f(x,y)=i) , i=0.....n \quad \dots(2)$$

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

$$I(A) = \begin{cases} 1 & A \text{ is True} \\ 0 & A \text{ is false} \end{cases} \quad \dots(3)$$

This LBP histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the whole image, so can be used to statistically describe image characteristics.

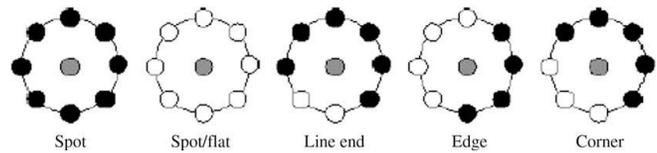


Fig. 5: Various edge textures detected using LBP(8;1)

It is a very powerful primitive texture descriptor which can identify various types of edges, flat areas, spots, etc. as shown in Fig. 5. A uniform LBP contains at most two bitwise transitions from either 0 to 1 or 1 to 0. It has been shown that these patterns account for over 90% of all patterns in the $LBP(8,1)$ neighborhood . Computing LBP histogram over an image only gives the occurrence frequency of each pattern without any information on the regional variations, therefore it is beneficial to take into account the face shape in localizing these primitive patterns.

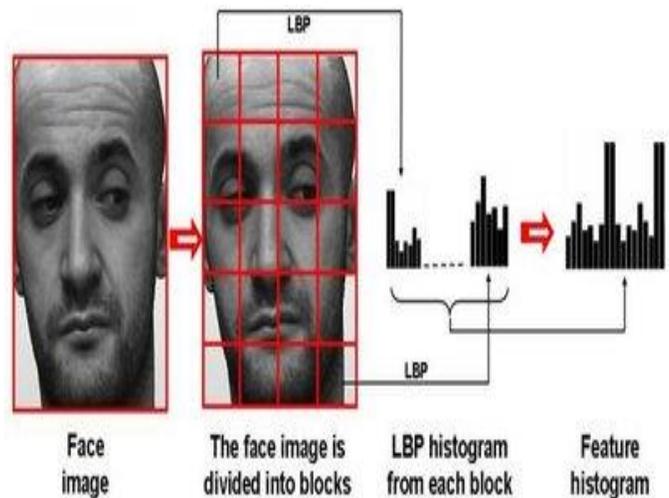


Fig.6: LBP Histogram

LBP features, therefore in order to generate a simple feature vector a sample face image from JAFFE database was divided into regions containing the two eyes and the mouth as shown in Fig. 6. The LBP features extracted from the two eyes’ sub-region were concatenated into a feature histogram and then averaged by two. The LBP features extracted from mouth region are appended to this histogram. Uniform LBP(8,1) operator was used to obtain the 59-bin histogram features for each region. Thus the final LBP histogram had a length of 118.

IV. CLASSIFIER DESIGN

Different machine learning techniques including SVM and BBO were examined to recognize expressions. SVM has been used successfully to classify facial expressions. It is a powerful machine learning technique for data classification which tries to find a linear separating hyperplane with the maximal margin to separate data in a higher dimensional space. BBO learns the classification by selecting only those individual features that can best discriminate among classes by training several weak classifiers sequentially.

Table-1: Developed feature matrix for training of classifier

	Happy	Sad	Surprise	Anger	Disgust	Fear
Neutral	1	1	1	1	1	1
Happy	1	0	0	0	0	0
Sad	0	1	0	0	0	0
Surprise	0	0	1	0	0	0
Anger	0	0	0	1	0	0
Disgust	0	0	0	0	1	0
Fear	0	0	0	0	0	1

Table-2: Cofusion matrix (%) of 7-class facial expression recognition using BBO with LBP features

	Neutral	Happy	Sad	Surprise	Anger	Disgust	Fear
Neutral	90	05	00	00	05	00	00
Happy	10	90	00	00	00	00	00
Sad	10	00	70	00	10	10	00
Surprise	10	00	00	80	00	00	10
Anger	00	00	10	00	80	10	00
Disgust	10	00	10	00	00	80	00
Fear	20	00	00	00	00	00	80

V. CONCLUSION

In this paper, a facial expression recognition algorithm based on LBP was proposed. For a 7-class (Neutral, Happy, Sad, Surprise, Anger, Fear and Disgust) system, a recognition

accuracy of 80% was achieved. The complexity of the existing techniques was also reduced while maintaining the recognition accuracy to enable human emotion recognition on realtime video sequences.

REFERENCES

- [1]. G. Zhao and M. Pietikainen, "Dynamic texture recognition using local binary patterns with an application to facial expressions," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 29, no. 6, pp. 915–928, 2007.
- [2]. M. Valstar, I. Patras, and M. Pantic, "Facial action unit detection using probabilistic actively learned support vector machines on tracked facial point data," in Computer Vision and Pattern Recognition - Workshops, 2005. CVPR Workshops. IEEE Computer Society Conference on, June 2005, p. 76.
- [3]. R. E. Schapire and Y. Freund, "Boosting the margin: a new explanation for the effectiveness of voting methods," The Annals of Statistics, vol. 26, pp. 322–330, 1998.
- [4]. N. R. Howe, "A closer look at boosted image retrieval," in In ACM Transactions on Multimedia Computing, Communications. Springer-Verlag, 2003, pp. 61–70.
- [5]. P. Viola and M. J. Jones, "Robust real-time face detection," International Journal of Computer Vision, vol. 57, pp. 137– 154, 2004.
- [6]. X. Feng, M. Pietikinen, and A. Hadid, "Facial expression recognition based on local binary patterns," Pattern Recognition and Image Analysis, vol. 17, pp. 592–598, 2007.
- [7]. S. Liao, W. Fan, A. Chung, and D.-Y. Yeung, "Facial expression recognition using advanced local binary patterns, tsallis entropies and global appearance features," in Image Processing, 2006 IEEE International Conference on, Oct. 2006, pp. 665 –668.
- [8]. C. Shan, S. Gong, and P. W. McOwan, "Facial expression recognition based on local binary patterns: A comprehensive study," Image and Vision Computing, vol. 27, pp. 803 – 816, 2009.
- [9]. M. Lyons, J. Budynek, and S. Akamatsu, "Automatic classification of single facial images," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 21, no. 12, pp. 1357 –1362, Dec 1999.
- [10]. D. S. Bolme, J. R. Beveridge, M. Teixeira, and B. A. Draper, "The csu face identification evaluation system: Its purpose, features and structure," in In International Conference on Vision systems. ICVS, 2003, pp. 304–311.

AUTHORS



I, Deepak Saxena received his Bachelor’s Degree in electronics and instrumentation engineering from UPTU, Lucknow (U.P), India. Now he is pursuing his M.Tech. in Electronics and Communication engineering from Mangalayatan University, Aligarh, Uttar Pradesh.