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Intelligent Facial Emotion Recognition System Using Linear Binary Pattern (LBP)

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ABSTRACT

Facial expression and recognition is one of the hot topic of recent time as it find application in One or other form such as Bio metric, emotion analysis, image retrieval etc. Different method and technique is adopted for facial and emotion recognition. Emotion recognition is done in basically two parts firstly, pre-processing and secondly post processing parts. Detection and extraction of images from the pre processing parts where as post processing parts aims to extract specific feature from pre-processed image and recognise the facial or emotion of human being. Our aim is to recognize the emotion of human being from seven categories of expression such Sadness, Happy, Fear, Surprise, Angry, Disgust and neutral. For this purpose we used LBP as method for feature extraction and Back propagation as classier for emotion recognition of face expression.

Keywords: Facial expression and recognition, LBP, Gabor Transformation, Haar Wavelet

I. INTRODUCTION

Facial recognition, being a central method of conveying human feelings, discovers its applications in human-PC cooperation (HCI), medicinal services, observation, driver wellbeing, trickery discovery and so forth. Colossal achievement being accomplished in the fields of face location and face acknowledgment, full of feeling processing has gotten considerable consideration among the specialists in the space of PC vision. Signals, which can be utilized for influence acknowledgment, incorporate outward appearance, paralinguistic components of discourse, non-verbal communication, physiological signs (e.g. Electromyogram (EMG), Electrocardiogram (ECG), Electrooculogram (EOG), Electroencephalography (EEG), Useful Attractive Reverberation Imaging (FMRI) and so on.)[4]. An audit of signs and techniques for full of feeling registering is accounted for in, as indicated by which, the majority of the examination on outward appearance investigation depend on recognition of essential feelings: Disgust, fear, sad, Happy, Angry, neutral and surprise. Various novel strategies for outward appearance acknowledgment have been proposed in the course of the most recent decade.

The emotional frontier is in fact the next obstacle to be surmounted in understanding humans. Facial expressions can be considered not only as the most natural form of displaying human emotions but also as a key non-verbal communication technique. If efficient methods can be brought about to automatically recognize these facial expressions, striking improvements can be achieved in the area of human computer interaction. Research in facial emotion recognition has being carried out in hope of attaining these enhancements. Moreover, there are other applications which can benefit from automatic facial emotion recognition. Artificial Intelligence has long relied on the area of facial emotion recognition to gain intelligence on how to model human emotions convincingly in robots. Recent improvements in this area have encouraged the researchers to extend the applicability of facial emotion recognition to areas like chat room avatars, video conferencing avatars.

The ability to recognize emotions can be valuable in face recognition applications as well. Suspect detection systems and intelligence improvement systems meant for children with brain development disorders are some other beneficiaries. Need for automation. Improve the classification accuracy.

II. LITERATURE REVIEW

A facial expression is one or more motions or positions of the muscles beneath the skin of the face. According to one set of controversial theories, these movements convey the emotional state of an individual to observers. Facial expressions are a form of nonverbal communication. They are a primary means of conveying social information between humans, but they also occur in most other mammals and some other animal species[13].Humans can adopt a facial expression voluntarily or involuntarily, and the neural mechanisms responsible for controlling the expression differ in each case. Voluntary facial expressions are often socially conditioned and follow a cortical route in the brain. Conversely, involuntary facial expressions are believed to be innate and follow a sub cortical route in the brain. Facial recognition is often an emotional experience for the brain and the amylase is highly involved in the recognition process. Basic facial emotions include happiness, anger, sadness, fear, surprise, and disgust. Previous evidence has revealed that patients with schizophrenia and their unaffected siblings exhibit cognitive and social cognition impairments, especially in identifying facial emotion. As a key component of social cognition, facial expression recognition is one of the hallmark deficits of schizophrenia. Some scholars have found that patients with schizophrenia are worse at recognizing facial emotion associated with anger and sadness[7]. Compared to negative emotions such as anger and sadness, people with schizophrenia are more accurate in identifying positive emotions such as happiness. In people with schizophrenia, such emotion-specific deficit is caused by aberrant neuronal processing in brain regions that specifically modulate negative emotion recognition.

A large amount of evidence has shown that facial recognition impairment in a person with schizophrenia is not a specific cognitive deficit. It has a moderate relationship between emotion recognition and executive functioning. This has been suggested by a few studies elucidating the correlation of different degrees of facial emotion recognition and executive functions in people with schizophrenia. However, this correlation must be further investigated in future research studies as the conclusions of previous studies have not provided consistent results. Many studies are focusing on individuals (first degree relatives of the patients) that have a genetic-risk of developing schizophrenia[13]. Previous studies demonstrated that the deficits in facial emotion recognition of the first degree relatives might be potential markers of schizophrenia. A few studies have observed impaired facial emotion recognition in unaffected biological relatives and in individuals in a prodromal state, but another study found no noticeable problems in individuals at high risk of developing schizophrenia. The conclusion still needs to be further clarified as these studies have presented contradictory results. We hypothesized that people with schizophrenia and their siblings had different levels of facial recognition impairment, and the impairment was associated with deficits in their executive functioning as suggested by previous study. However, as the association has been shown to be in both the number of categories completed and preservative errors in some research, but just preservative errors in others, we also hypothesized that the previously contradictory results might be understood by investigating the degree or intensity of the emotion recognition impairment as this has rarely been considered in previous studies. Therefore, we designed a study of first episode people with schizophrenia and their siblings to explore facial emotion recognition and executive function in a genetic risk group. Each emotion was divided into three different intensity grades to allow detailed study.

III. METHODOLOGY

Facial feature extraction In this research, we propose an extended overlap LBP operator for feature extraction. As discussed earlier, about LBP operator first applies multi-scale and multi-orientation filters to decompose a face image. The proposed feature extraction process consists of four steps: pre-processing for illumination and noise invariance, face detection, and a modified

LBP based fine scale textural description. The original LBP operator was proposed by Ojala et al as a texture feature descriptor. It is created by thresholding the values of a 3×3 neighbourhood of pixels against the central pixel, and interpreting the result as a binary number. The LBP operator can be denoted as LBPs, r where s is the number of sampling points in the neighbourhood and r is the radius. The original LBP operator uses the (8,1) circular neighbourhood. Research findings showed that in a (8,1) neighbourhood, uniform patterns which contain more information than any other patterns, accounted for 90 percentage among all the patterns[13]. However, since LBP uses a circular neighbourhood, it is likely to lose information when shifting from one sub-region to another. To retrieve more discriminative information from texture, we further extend the LBP model by overlapping the sub-region selected by the LBP operator. We specifically overlap the neighbouring two LBP regions with the last column of the preceding region since we would like to retrieve information missing from the corners of each sub-region without increasing the size of the feature vector substantially. The overlapped sub-region is shown in Fig. 1. In this overlapped LBP operator, we use the standard size of 3×3 pixel in a (8, 1) neighbourhood for each sub-region. The detected face image in this research has a size of 100×100 pixel. By applying the standard

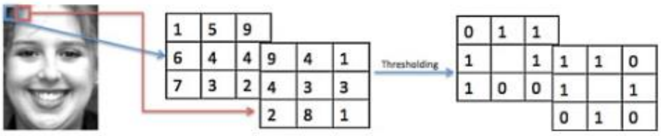

Figure 1: LBP operators

LBP operator, we obtain 1089 sub-regions, therefore 1089 histograms. However, after applying the overlap LBP operator, the number of sub-regions increases to 1156. The difference in the size of feature vector between the standard and overlap LBP operators is not too dramatic whereas the overlap LBP provides more discriminative texture information.

After labelling a image with the LBP operator, a histogram of the labelled image (x,y) (x,y)

Can be defined

$$H_i = \sum_{x,y} L(f_i(x,y) = i), i = 0, ..., n-1 \quad (1)$$

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

$$L(A) = \begin{cases} 1, \; if \; A \quad \text{is} \quad true, \\ 0, \; if \; A \quad \text{is} \quad false, \end{cases} \quad (2$$

A. Algorithm

Algorithm Direct similarity feature selection

Input:

Training images in the same emotion category

Accumulated statistic regarding to the significance of facial compartment

Parameter setting and termination criterion

Begin

Initialize (P);//P(S1, S2,,Sk) is a population of solutions of size k.

Randomly select non-replaceable solutions, NR, from P;

GA (P);//GA operation on P

while termination criterion not met

// Stage 1

while cascade loop in stage 1 not reached

if 1st cascade loop

Q1:=Select q1 number of best candidates from P;

else

Q1:=Select q1 number of best candidates from Pmicro1;

end if

Pmicro1:=merge (Q1, NR);//create micro population, Pmicro1, by

merging Q1 and NR;

GA (Pmicro1);//GA operation on Pmicro1

end while//stage 1 cascade loop

Replace poor candidates from P with NR and q1 number of best

candidates from Pmicro1;

Q2:=randomly select q2 number of candidates from P;

Pmicro2:=merge (Q2, Best candidate in Pmicro1);

//create micro population Pmicro2

// Stage 2

while cascade loop in stages 2 and 3 not reached

for each SiPmicro2;

Separate Si to upper (Ui) and lower layer (Li);

Fix (Ui);

Initialize Li based on accumulated probability of occurrence;

GA (Li);//GA optimization in the lower layer;

Return best lower layer representatives that _t upper layer;

// Stage 3

Fix (Li);

Initialize Ui based on accumulated probability of occurrence;

GA (Ui);//GA optimization in the upper layer;

Return best upper layer representatives that _t lower layer;

end for

end while//stages 2 and 3 cascade loop

Replace poor candidates from P with NR and all updated candidates Si from Pmicro2;

GA (P);//GA operation on P

end while//for termination criterion

Return the best candidate from P;

End

Output: A best feature subset to represent an emotion category.

IV. EXPERIMENTS AND RESULTS

A Experiment

In this experiment we use LBP for feature extraction, for feature selection direct similarity feature selection is used and neural network is used as classifier. In LBP each pixel is compared with its eight neighbour by subtracting the central pixel. The resulting strictly take the value with 0 and other with 1.

B Parameter settings

Matrix m * n represent the facial compartments S_i it is defined by

$$S_i = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \end{bmatrix}$$

The fitness is of S_i is evaluated by number of correct indication of training dataset in the same expression category.

C. Results

The following results were obtained

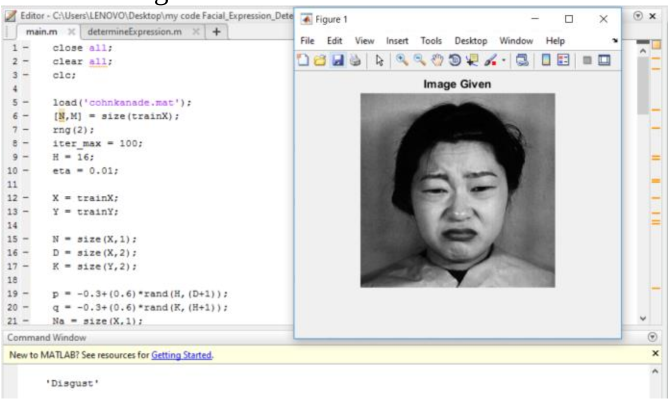

Figure 2: This photo show disgust

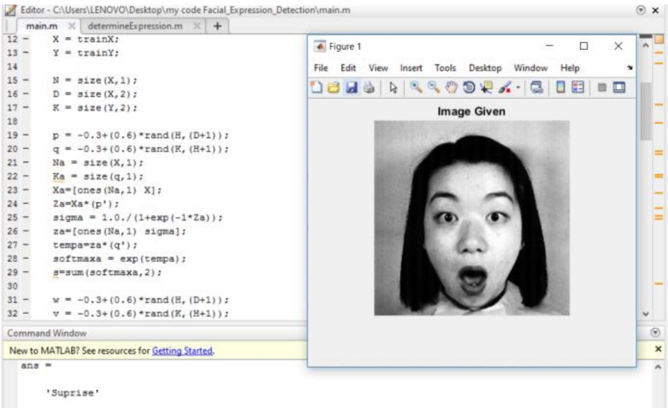

Figure 3: This photo show surprise

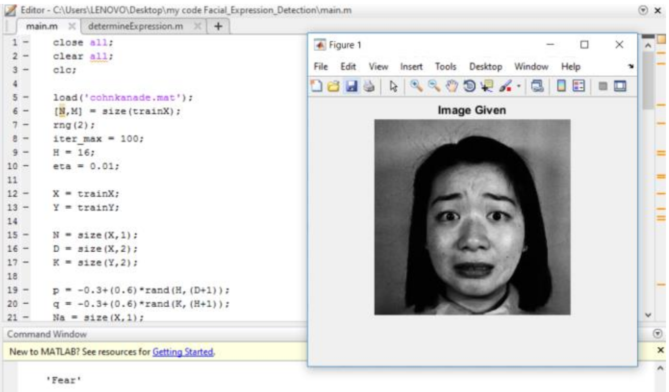

Figure 4: This photo show fear

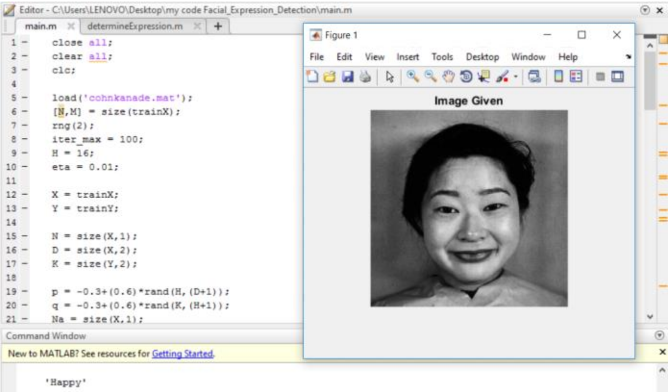

Figure 5: This photo show happy

Figure 6: This photo show neutral

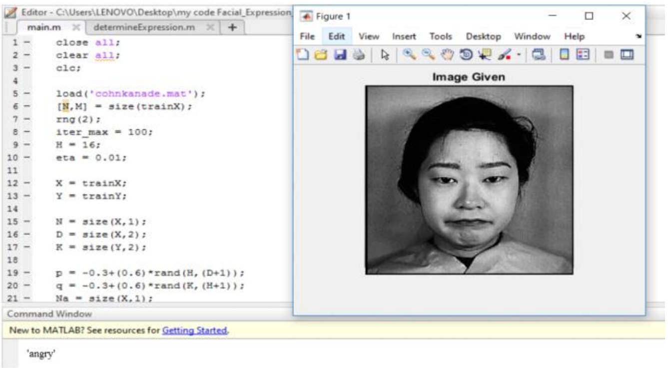

Figure 7: This photo show angry

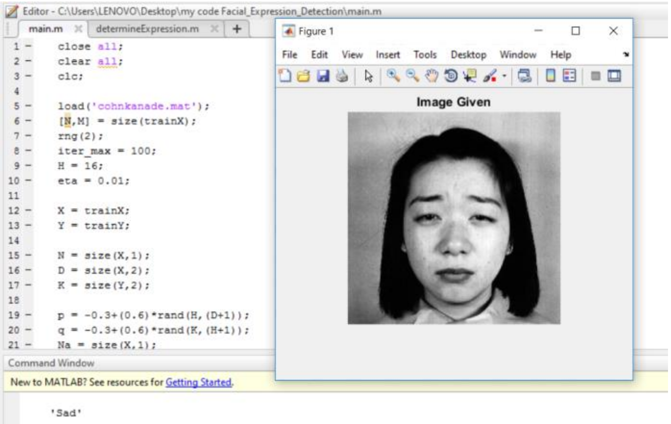

Figure 8: This photo show sad

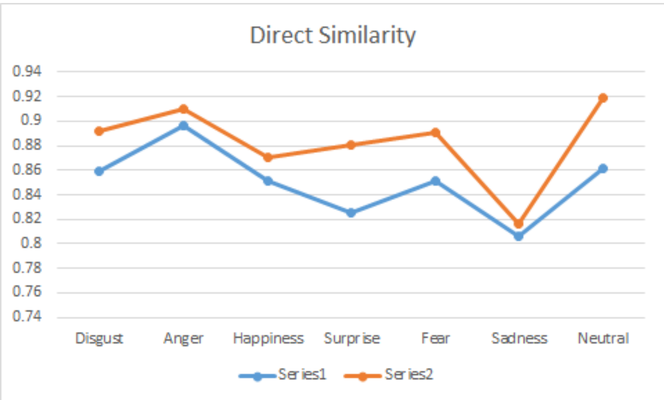

Figure 9: This photo show Comparison in terms of accuracy LBP and Gabor series in terms ofaccuracy with series 1 showing Gabor and series 2 represent LBP

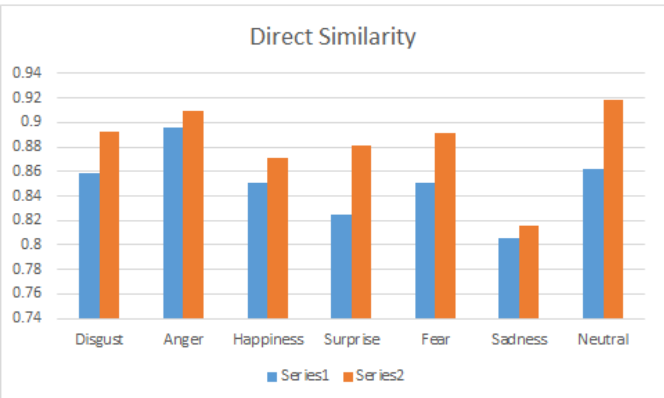

Figure 10: This photo show Comparison of LBP and Gabor series for different emotion

V. CONCLUSION

Although many approaches are there we have used LBP for feature extraction in order to get better performance than Gabor method used for feature extraction. The above algorithm is of direct similarity and other is of back propagation. Direct similarity is used for recognizing feature selection and back propagation is used for classification purpose. In order to verify the effectiveness of LBP used for the feature extraction we need to compare it with Gabor method in feature extraction we used LBP along with discriminative feature selection using direct similarity and expression recognition using neural network classifier. We have evaluated the efficiency of the proposed system using frontal image extraction respectively from the ck+ database.

We have proposed a facial expression system which can recognized the different human emotion. At initial stage we prepared dataset and trained that dataset using neural network back propagation. The trained data set is used for identifying the given image. We have used LBP for feature extraction. The above figure 9 and Figure 10 shows that LBP used for feature extraction has better performance than the Gabor method used for feature extraction.

VI. FUTURE SCOPE

LBP accuracy can be considerably increased when it is used with other feature extraction technique. We also aim to explore the possibility of integrating other multi-objective evolutionary algorithms such as NSGA II etc. We can use different classifier in place of back propagation such

VII. REFFRENCES

[1] Tao Chen and Mikio Takagi. Image binarization by back propagation algorithm. International Archives of Photogrammetric and Remote Sensing, 29:345{345, 1993.

[2] Ryszard S. Choras. Feature extraction for cbir and biometrics applications. In Proceedings of the 7th Conference on 7th WSEAS International Conference on Applied Computer Science

Volume 7, ACS'07, pages 1{9, Stevens Point, Wisconsin, USA, 2007. World Scientific and Engineering Academy and Society (WSEAS).

[3] Dewan Md. Farid, Li Zhang, Alamgir Hossain, Chowdhury Mo_zur Rahman, Rebecca Stra-chan, Graham Sexton, and Keshav Dahal. An adaptive ensemble classifier for mining concept drifting data streams. Expert Systems with Applications, 40(15):5895 { 5906, 2013.

[4] S. L. Happy and A. Routray. Automatic facial expression recognition using features of salient facial patches. IEEE Transactions on A_ective Computing, 6(1):1{12, Jan 2015.

[5] N. A. Mahmon and N. Ya'acob. A review on classi_cation of satellite image using artificial neural network (ann). In 2014 IEEE 5th Control and System Graduate Research Colloquium, pages 153{157, Aug 2014.

[6] Angelos P. Markopoulos, Sotirios Georgiopoulos, and Dimitrios E. Manolakos. On the use of back propagation and radial basis function neural networks in surface roughness prediction. Journal of Industrial Engineering International, 12(3):389{400, 2016.

[7] Siew Chin Neoh, Li Zhang, Kamlesh Mistry, Mohammed Alamgir Hossain, Chee Peng Lim,Nauman Aslam, and Philip Kinghorn. Intelligent facial emotion recognition using a layered encoding cascade optimization model. Applied Soft Computing, 34:72 { 93, 2015.

[8] O. Nikisins and M. Greitans. Local binary patterns and neural network based technique for robust face detection and localization. In 2012 BIOSIG - Proceedings of the International Conference of Biometrics Special Interest Group (BIOSIG), pages 1{6, Sept 2012.

[9] M. Owayjan, R. Achkar, and M. Iskandar. Face detection with expression recognition using artificial neural networks. In 2016 3rd Middle East Conference on Biomedical Engineering (MECBME), pages 115{119, Oct 2016.

[10] Ebenezer Owusu, Yonzhao Zhan, and Qi Rong Mao. An svm adaboost facial expression recognition system. Applied Intelligence, 40(3):536{545, 2014.29

[11] Buse Melis Ozyildirim and Mutlu Avci. Generalized classifier neural network. Neural Networks, 39:18 { 26, 2013.

[12] A. Verikas and M. Bacauskiene. Feature selection with neural networks. Pattern Recognition Letters, 23(11):1323 { 1335, 2002.

[13] Z. Wang and Z. Xie. Infrared face recognition based on local binary patterns and kruskal-wallis test. In 2014 IEEE/ACIS 13th International Conference on Computer and Information Science (ICIS), pages 185{188, June 2014.linear regression classifier etc.