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Subject Independent Automatic Facial Expression Recognition from Partially Occluded Still Images by Employing Appearance Based Feature Extraction Schemes

Naveen Kumar H N, Jagadeesha S

Abstract: ***Facial expression recognition is the process of identifying human emotion through expressions. The world around us is constantly changing and in this ever-changing scenario, development of a system which performs automatic detection and recognition of facial expressions in a given scene is of paramount importance, and at the same time highly challenging. It becomes even more challenging when the aforesaid scene is partially occluded, thus limiting the facial area which could be explored. As such, expression recognition from partially occluded images is still largely an unexplored area. The proposed work is an attempt towards subject independent automatic expression recognition from partially occluded images. Salient features of the proposed work involves careful approximation of contributions made by facial regions like eye, mouth, and nose towards recognition of each basic expression; determination of a particular region in face which contributes the most discriminative and abstract feature for recognition of a particular expression; identification of facial region wherein expression recognition is independent of any occlusion happening with respect to that particular region. The proposed work to begin with segments facial regions from a static facial image; discriminative and abstract features extracted from so segmented facial regions are experimented upon to better understand the contribution made by each region in recognition of a facial expression. Various appearance features such as HOG, LBP and OGBP have been incorporated in the experimentation, and results obtained thereby infer that mouth region convey lion's share of the information about probabilistic determinant of an expression and its intensity when compared to remaining regions. The proposed system outperforms holistic approaches in connection with facial expression recognition.***

Keywords**:** ***Feature extraction, Facial expression classification, Appearance features, Oriented gradients of binary pattern***

I. INTRODUCTION

In the past few decades, Automatic Facial Expression Recognition has made substantial progress owing to its emerging importance in applications involving but not limited to Human-Computer Interaction (HCI), Health Science, Security systems, Behavioral analysis, Entertainment and so on [1]. Emotion is a complex Psychophysiological experience that results in physical and psychological changes that influence an individual's behavior. Most of the times, Emotion is misunderstood with either mood or feeling. Emotion by definition is a short time effect, an immediate reaction to the external stimuli. Feelings happen as we begin to integrate those emotions, think about it or to "let it soak in." Mood by definition is a medium time effect, which may last for few hours or few days. In contrast, personality is something which is supposed to be stable over a long period of time. Human emotions are expressed through various means like facial expressions, tone of voice, body posture, eye gaze direction, body gesture and various other physiological signals. From basic emotion theory and postulates, it is found that much of the information conveyed between individuals during communication happens through facial expressions. Facial expression is an efficient and significant non-verbal mode of communication and as such includes rich information regarding an individuals' behavior. Sir Paul Ekman was the first person to describe each of the basic emotion in terms of a facial expression that universally and uniquely characterized that particular emotion [2]. As an example, Facial muscle activity represents characteristics of an induced expression [3]. Faces tend to be the most visible form of communication for conveyance of an emotion. Automatic expression recognition from human faces is an important and integral part of artificial intelligence systems. One of the main challenges facing modern AI systems lie in providing a user interface whose functionality is adaptive to user's capabilities, preferences, and requirements while also taking into account both context and emotional state of the user. Automatic Facial Expression Recognition (AFER) system, as the name itself suggests does exactly that, i.e.., automatic detection of expressions from a Human face; such expression detection is considerably easy if the face from which expression is to be detected is crystal clear, without any hindrances or intrusions. But it is not guaranteed that we will get a crystal clear image without any hindrances or intrusions. Most of the times we are required to deal with images which are in one way or the other compromised. Hence, designing a robust AFER system is the need of the hour wherein such robust systems must be made capable of handling variation in lighting, partial occlusion, pose variations, rigid head motions, subjects of any age, ethnicity, and also be able to differentiate all possible expressions along with its varied range of intensity [4-7].

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***Correspondence Author(s)**
Naveen Kumar H N, Department of ECE, S D M Institute of Technology, Ujire, Karnataka, INDIA
Jagadeesha S, Department of ECE, S D M Institute of Technology, Ujire, Karnataka, INDIA

The occlusions on face like presence of sunglass, hair or moustache, scarf, hat, hands, or as such any object covering the face degrade the performance of AFER system. Most of the existing works corresponding to expression recognition from image sequences demand no rigid head motion, no facial hair, no occlusion, first frame to be a neutral face and facial landmarks to be marked in the first frame, so as to achieve higher recognition accuracy [8-11]. But, aforesaid demands make the system user dependent and simply put cannot be trusted. More over when such demands are placed on the user, the word "automatic" tends to lose its meaning as expressions obtained are no more natural. The very essence of a true AFER system lies in the fact that it tends to capture a natural unadulterated expression and then go on and detect it; this happens to be the true definition of a real world situation. One of the major obstacles for expression recognition in real-world situations is presence of partial occlusion on the face as such occlusion may change authentic visual appearance of the face. Hence it becomes very difficult to extract discriminative and abstract features. In most of the existing holistic approaches, the whole face region is involved in the process of feature extraction and classification irrespective of the contribution made by individual facial regions towards robust and abstract feature for expression classification. Holistic feature extraction methods include Principal Component Analysis (PCA) [12], Linear Discriminant Analysis (LDA) [13], and Independent Component Analysis (ICA) [14]. Holistic approaches suffer from burden of redundant information which in turn increases memory consumption and adds timing complexity. Due to all this, Real time implementation of holistic approaches has become cumbersome.

II. METHODOLOGY

The block diagram of the proposed work is depicted in Fig. 1, proposed work comprises of training phase and testing phase. In the training phase viola jones algorithm is applied upon each image in order to detect the face [15]. Once detection of face is done, Facial region segmentation is carried out so as to extract eye, nose and mouth region from the detected face image. Next is feature extraction wherein necessary and contributing features are extracted from aforesaid eye, nose and mouth regions; later, so extracted features are separately used to train different classifiers respectively. During testing phase, face detection algorithm detects only the face from test image; facial region segmentation segments the so detected face into eye region, nose region and mouth region; features extracted from aforesaid facial regions are used individually to predict the expression of the test image. Viola-jones algorithm is employed for face detection and facial region segmentation.
This approach emphasizes the role of facial regions which are actively involved during the occurrence of a particular expression. The contribution of facial regions during emotion elicitation is an important analysis to be made before designing a model for expression classification. This work is an attempt towards determining from facial regions the most discriminative and abstract feature for expression classification. In an occluded face image if we could know that the occluded region has no contribution or very less contribution towards expression interpretation, we may conclude that said occlusion doesn't lead to any change in the expression identification. But in contrast, if a part of the facial region contributing the most discriminative feature in relation to expression recognition is occluded, it will lead towards degradation in recognition rate.

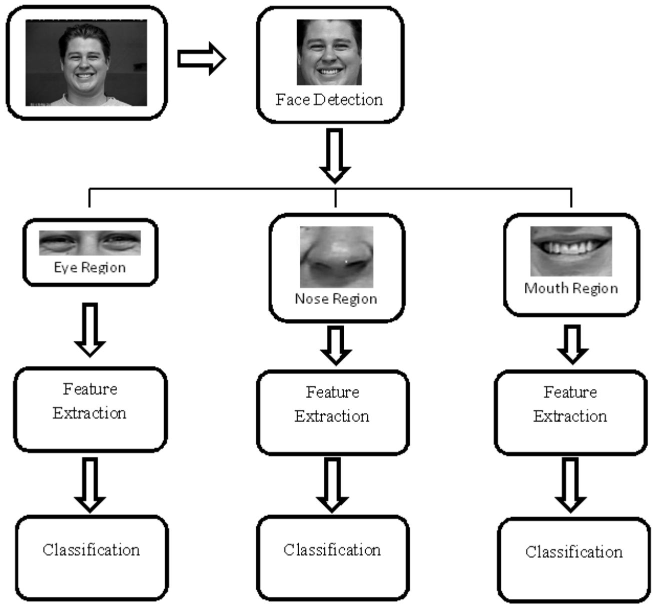

Fig.1.Block Diagram Of The Proposed Work

The appearance features considered in the proposed work are: The Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP) and Oriented Gradients of Binary Pattern (OGBP).

A. Histogram of Oriented Gradients (HOG)

HOG represents images by directions of the edges they contain; gradient operators extract local features across the image which is encoded as gradient magnitude and angle [16].
Gradient structure characteristics are better projected by HOG features. Herein low level features are robust to illumination variations. The HOG algorithm segments a static image into small spatial regions known as "Cells". Cells can be rectangular or circular. Orientation provides gradient feature vector for a single cell. Gradient feature vectors so obtained from each cell of a single image are concatenated to form feature vector for a single image. The feature vectors extracted from image regions representing different facial expressions are then used for training and testing phases of SVM classifier. Fig.2 depicts the HOG feature representation for prominent facial regions. HOG feature is extensively used as appearance feature for facial expression classification [17, 18].

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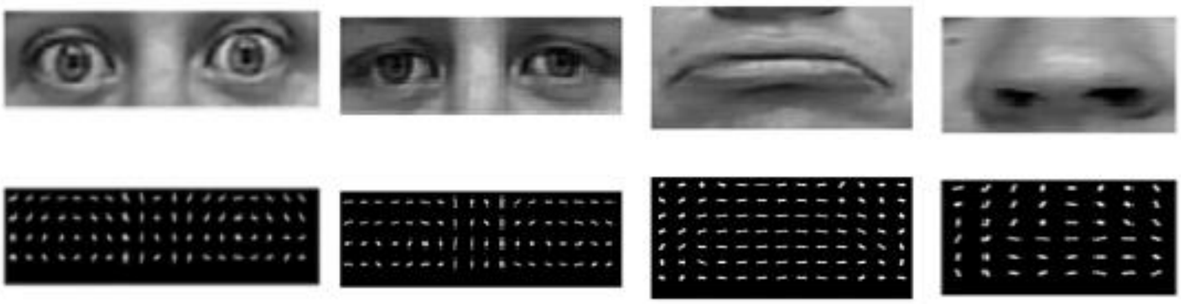

Fig.2.HOG feature representation of facial regions

B. Local Binary Pattern (LBP)

The computational simplicity and discriminative power of LBP algorithm has made it very popular. Local spatial patterns and surface textures are herein described by features. The facial image is segmented into several non-overlapping blocks. Features are computed by thresholding the neighborhood of each pixel with the center value. LBP histograms are computed for each block and finally the block LBP histograms are concatenated into a single vector. LBP texture descriptors are widely used for expression classification [19-23].

C. Oriented Gradients of Binary Pattern (OGBP)

Conventional LBP algorithm is applied upon facial regions in order to obtain LBP image. Oriented gradients are computed from LBP image representing a facial region. This is the novel feature taken into consideration in the proposed work for expression classification. Fig.3 depicts the extraction of oriented gradients from LBP image.

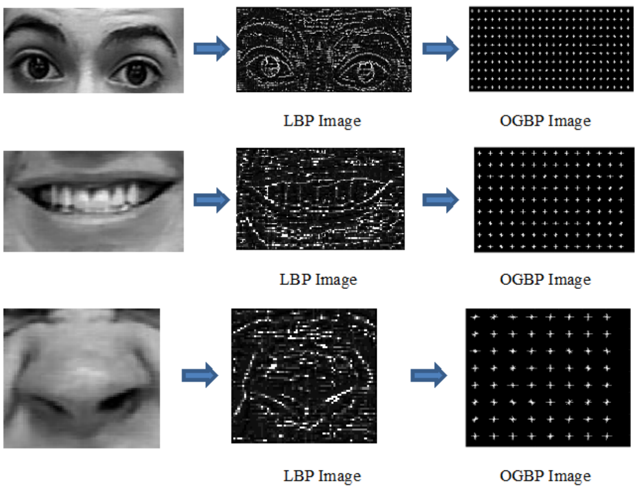

Fig.3.Extraction of oriented gradients from LBP Image.

D. Support Vector Machine (SVM) Classification

SVM is a popular machine learning algorithm which maps feature vector to a different plane, usually to a higher dimensional plane, through non-linear mapping, and then finds a linear decision hyper plane so as to classify two classes. Since SVM is a binary classifier, one versus all technique has been implemented for multi-class classification. In this technique k numbers of classifiers are used, where k represents number of classes [24].

III. RESULT AND DISCUSSION

All the experimental sessions have been carried out on Extended Cohn-kanade (CK+) dataset [25]. Cohn-Kanade dataset is publicly available and is specifically built for FER issues, and comprises of image sequences for all six basic expressions (anger, disgust, fear, happy, sad and surprise). Each image sequence starts with a neutral expression and ends with an expressive face. The dataset comprises of subjects of varying gender, age and ethnicity, which makes the dataset one of the most popular for evaluating the performance of FER systems. The subsets of images containing expressive faces were selected to form an image dataset for training and testing phase. Facial region segmentation is carried out to obtain facial parts from expressive faces. The sample dataset comprises of mouth, eye and nose regions are depicted in fig. 4, 5 and 6 respectively.

Fig.4.Sample dataset of mouth region

Fig.5.Sample dataset of eye region

Fig.6.Sample dataset of nose region

4-fold Cross validation approach is employed, wherein complete dataset is randomly divided into 4 subsets. Subject independency is introduced by employing an approach wherein expressive face parts belonging to the same subject are not being used for both training and testing phase. Four trails of experiments are conducted on the said dataset. During each trail, one of the subset is retained as the validation data for testing and remaining 3 subsets are used for training.

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This approach is repeated 4 times, with each of the 4 subsets used exactly once for testing. Thus obtained 4 set of results are then averaged to produce a single estimation. Numerous experiments of same kind have been carried out and results of the same are discussed in the following section.

A. Experiment conducted on HOG feature

The confusion matrix of the experiments carried out on mouth and eye region of the face by employing HOG feature extraction scheme is tabulated in the table I and II respectively (AN-Anger, DI-Disgust, FE-Fear, HA-Happy, SA-Sad, SU-Surprise).

Table-I: Confusion matrix of the experiment carried out on eye region using HOG feature extraction scheme (%)

Eye Region	AN	DI	FE	HA	SA	SU
AN	**37.5**	9.4	13.2	7.4	32.5	0
DI	11.8	**77.9**	9.1	0	1.2	0
FE	5.7	7.9	**38.7**	13.9	7.2	26.6
HA	0	5.5	9.3	**69.7**	10.2	5.3
SA	17.3	13.5	14.9	0	**45.9**	2.4
SU	1.3	0	5.2	0	3.7	**89.8**

Table-II: Confusion matrix of the experiment carried out on mouth region using HOG feature extraction scheme (%)

Mouth Region	AN	DI	FE	HA	SA	SU
AN	**78.5**	8.6	0	0	12.9	0
DI	4.7	**84.6**	0	3.3	6.3	1.1
FE	0	4.6	**86.1**	9.3	0	0
HA	0	1.8	3.6	**94.6**	0	0
SA	3.4	6.8	0	0	**85.1**	4.7
SU	0	4.7	0	7.3	2.1	**85.9**

With reference to Table I and Table II, following inferences can be made. Recognition rate is better for disgust, happy and surprise expressions when only eye region is employed for expression recognition. Recognition rate is found to be good for all the expressions when only mouth region is employed for expression recognition. The comparison of recognition rates obtained by employing HOG feature extraction scheme on mouth region, eye region, nose region, and whole face region is tabulated in Table III and graphical representation of the same is depicted in Fig 7. With reference to Table3, recognition accuracy is found to be poor for most of the expressions (except disgust) when only nose region is involved in expression recognition. However, there is found to be significant improvement in recognition rate of anger, fear and sad expressions if only mouth region is involved as compared to experiments carried out on whole facial region. In addition, the recognition accuracy is found to be good for disgust and surprise expression upon extraction of HOG feature from the whole face region. The results of the experiments carried out infer the relation between facial regions and possibility of occurrence of expressions. In totality, we can summarize that detection of disgust and surprise expression demands whole face for feature extraction, whereas detection of anger, fear, happy and sad expressions demand only mouth region for feature extraction. Thus, any sort of mouth region occlusion may severely degrade the performance of AFER systems. It may be taken in to account that occlusion with respect to nose and eye region has a negotiable impact on the performance of AFER system.

Table-III: Comparison of recognition rates obtained by employing HOG feature extraction scheme on different facial regions (%)

HOG feature	AN	DI	FE	HA	SA	SU
Eye region	37.5	77.9	38.7	69.7	45.9	89.8
Mouth region	78.5	84.6	86.1	94.6	85.1	85.9
Nose region	22.3	73.2	27.5	57.8	37.5	43.6
Whole face	58.9	94.9	57.3	89.6	57.7	95.5

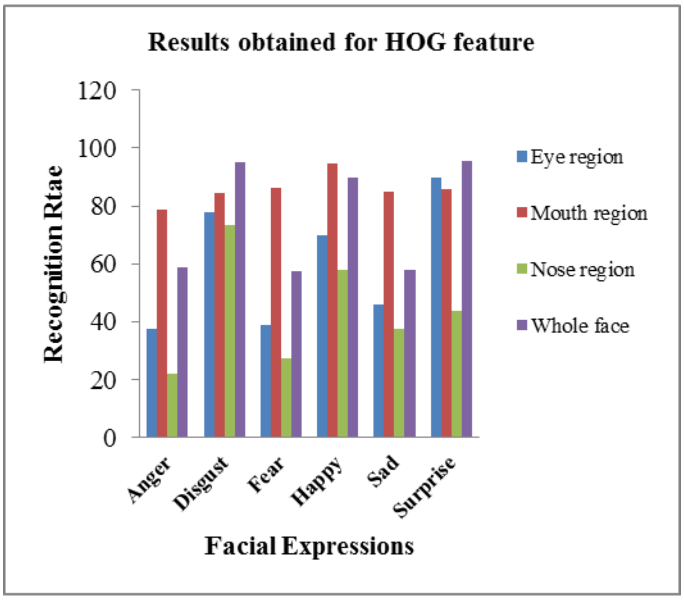

Fig.7.Comparison Of Recognition Rates Obtained By Employing HOG Feature.

B. Experiment conducted on LBP feature

The confusion matrix of experiments carried out on mouth and eye region of the face by employing LBP feature extraction scheme is tabulated in the Table IV and V respectively. With reference to Table IV and Table V, Recognition rate is found to be poor for most of the expressions when only eye region is involved in the expression recognition and it is found to be good for most of the expressions when only mouth region is involved in the experimentation.

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Table-IV: Confusion matrix of the experiment carried out on eye region using LBP feature extraction scheme (%)

Eye Region	AN	DI	FE	HA	SA	SU
AN	**36.5**	20.2	12.4	10.7	13.9	6.3
DI	10.6	**57.3**	10.6	14.9	3.3	3.3
FE	10.6	13.1	**20.7**	18.8	7.7	26.1
HA	4.2	8.6	8.6	**47.9**	9.4	21.3
SA	12.2	4.4	8.9	17.8	**33.6**	23.1
SU	0	7.5	12.1	10.6	7.5	**62.3**

Table-V: Confusion matrix of the experiment carried out on mouth region using LBP feature extraction scheme (%)

Mouth Region	AN	DI	FE	HA	SA	SU
AN	**70.3**	5.3	14.5	2.3	5.3	2.3
DI	2.8	**62.8**	4.2	5.4	13.1	11.7
FE	5.3	3.3	**49.8**	19.7	7.6	14.3
HA	5.6	5.6	7.7	**81.1**	0	0
SA	3.4	6.3	3.4	4.6	**80.5**	1.8
SU	5.1	7.2	3.1	13.8	3.1	**67.7**

The comparison of recognition rates obtained by employing LBP feature extraction scheme on mouth region, eye region, nose region, and whole face region is tabulated in Table VI and graphical representation of the same is depicted in Fig. 8. With reference to Table VI, Nose region is the one which is contributing significantly towards extraction of abstract and robust feature for disgust expression compared to other facial regions. The recognition rate is found to be poor for most of the expressions (except disgust) when only nose region is involved. The recognition rates obtained from mouth and eye region can be averaged in case of surprise expression. Recognition rate of experiments where only mouth region is involved is found to be most accurate for anger and sad expressions when compared to other facial regions. The above result indicates the relation between facial regions and possibility of occurrence of expressions, and furthermore this relation could be utilized in order to detect particular expression of interest.

Table-VI: Comparison of recognition rates obtained by employing LBP feature extraction scheme (%)

LBP feature	Anger	Disgust	Fear	Happy	Sad	Surprise
Eye region	36.5	57.3	20.7	47.9	33.6	62.3
Mouth region	70.3	62.8	49.8	81.1	80.5	67.7
Nose region	27.5	76.5	18.9	37.2	28.7	33.7
Whole face	62.8	77.5	57.4	87.1	56.9	91.5

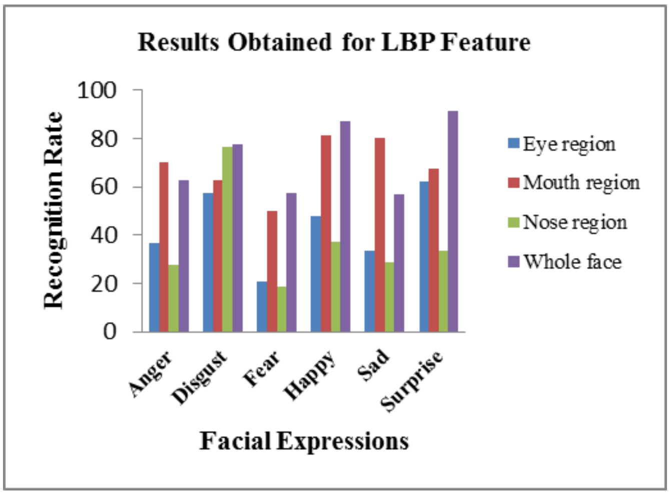

Fig.8.Comparison Of Recognition Rates Obtained By Employing LBP Feature

C. *Experiment conducted on OGBP feature*

The confusion matrix of experiments carried out on mouth and eye region of the face by employing OGBP feature extraction scheme is tabulated in the table VII and VIII respectively. With reference to Table VII and Table VIII, Recognition rate is found to be poor for anger, fear and sad expressions when only eye region is involved in the expression recognition and it is found to be good for most of the expressions when only mouth region is involved in the experimentation.

Table-VII: Confusion Matrix of the experiment carried out on eye region using OGBP feature extraction scheme (%)

Eye Region	AN	DI	FE	HA	SA	SU
AN	**38.7**	18.9	0	0	42.4	0
DI	9.6	**72.8**	0	17.6	0	0
FE	10.1	13.7	**18.4**	20.3	11.8	25.7
HA	5.6	5.6	10.6	**65.5**	0	12.7
SA	14.5	22.7	18.6	11.1	**25.3**	7.8
SU	12.7	0	17.6	0	0	**69.7**

Table-VIII: Confusion Matrix of the experiment carried out on mouth region using OGBP feature extraction scheme(%)

Mouth Region	AN	DI	FE	HA	SA	SU
AN	**70.9**	14.3	7.4	0	7.4	0
DI	10.8	**48.3**	9.7	9.7	13.9	7.6
FE	4.7	13.8	**67.2**	5.1	7.9	1.3
HA	0	2.3	4.5	**90.9**	0	2.3
SA	4.4	8.9	10.2	0	**72.7**	3.8
SU	3.1	9.2	7.5	3.1	5.3	**71.8**

The comparison of recognition rates obtained by employing OGBP feature extraction scheme on mouth region, eye region, nose region, and whole face region is tabulated in

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Table IX and graphical representation of the same is depicted in Fig.9. With reference to Table IX, Nose and eye regions are the ones which are contributing significantly towards extraction of abstract and robust feature for disgust expression when compared to other facial regions. The recognition rate is found to be poor for most of the expressions (except disgust) when only nose region is involved. The recognition rates obtained from mouth and eye region can be averaged in case of surprise expression, and likewise, recognition rates obtained from nose and eye region can be averaged in case of disgust expression. Recognition rate of the experiments where only mouth region is involved is found to be most accurate for most of the expressions (except disgust) when compared to other facial regions. The relation between facial regions and expressions can be better understood by the above results. Detection of expressions such as disgust and surprise demands whole face region, whereas other expressions demands only mouth region.

Table-IX: Comparison of recognition rates obtained by employing OGBP feature extraction scheme (%)

OGBP feature	Anger	Disgust	Fear	Happy	Sad	Surprise
Eye region	38.7	72.8	18.4	65.5	25.3	69.7
Mouth region	70.9	48.3	67.2	90.9	72.7	71.8
Nose region	17.3	68.7	27.5	23.9	20.3	33.7
Whole face	57.8	75.7	46.9	76.5	38.9	78.3

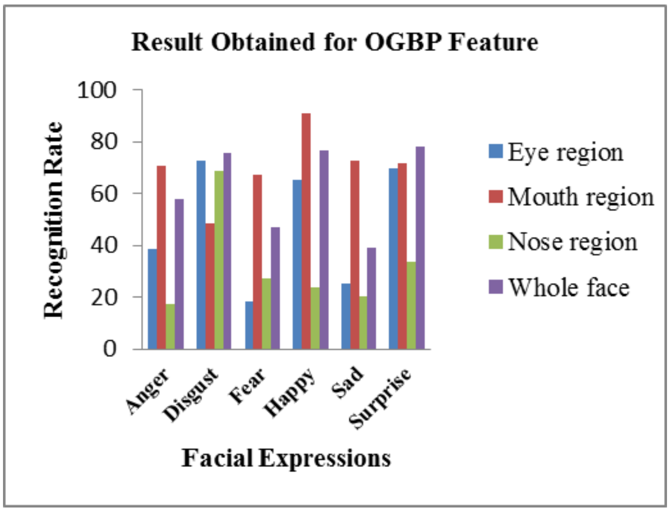

Fig.9.Comparison Of Recognition Rates Obtained By Employing LBP Feature

The result of the experiments carried out reveal that mouth region is the one which is significantly contributing towards robust and abstract feature for expression recognition when compared to eye and nose region. In the entirety of the experiments carried out, the recognition rate is found to be superior for most of the expressions (except disgust and surprise) when only mouth region is taken into consideration compared to the whole face. Thus, considering a part of face instead of whole face seems ideal and also has its own advantages in terms of processing such as reduced computation time and optimum resource usage. The nose and eye region occlusion has very little impact on the performance of automatic FER system. Mouth region occlusion severely degrades the performance of FER systems. Result of experiments conducted on mouth region by employing HOG, LBP and OGBP feature extraction schemes is tabulated, and is as shown in Table X. With reference to Table X, we can conclude that performance of HOG is superior when compared to LBP and OGBP for all the expressions.

Table-X: Comparison of recognition rates obtained by employing various feature extraction schemes on mouth region only (%)

Mouth region	Anger	Disgust	Fear	Happy	Sad	Surprise
HOG	78.5	84.6	86.1	94.6	85.1	85.9
LBP	70.3	62.8	49.8	81.1	80.5	67.7
OGBP	70.9	48.3	67.2	90.9	72.7	71.8

IV. CONCLUSION

The proposed work is an attempt made towards understanding individualistic contribution of facial regions towards facial expression recognition. The three prominent facial regions (Mouth, Eye and Nose), coupled with three feature extraction schemes (HOG, LBP and OGBP) have been considered for experimentation. Depending upon the expression of interest to be detected, selection of facial region for feature extraction plays a prominent role. Results of the experiments carried out on extended Cohn-kanade database reveals that there is significant contribution from mouth region towards abstract and robust feature extraction with regard to expression classification. It is interesting to note that result of the experiments conducted on mouth region not only dominates the result of the experiments conducted on other facial regions but also the results of the experiments conducted on whole face region. The features extracted from mouth region are sufficient to detect anger, fear, happy and sad expression instead of features from whole face. The proposed work outperforms the traditional holistic approaches for facial expression recognition. In addition, the dependency in performance of an FER system with respect to occurrence of occlusion in relation to various parts of the facial region is also examined. The occurrence of occlusion with respect to mouth region severely degrades the overall performance of FER system; occlusion on nose region has little impact on recognition rate of one particular expression, i.e.., disgust, and occlusions with respect to eye region has very little impact on overall performance of FER system. From aforesaid observations, we can infer that to achieve better recognition rates occlusion with respect to mouth region must be avoided. The relation between expression of interest and facial regions is conveyed in a better way through the proposed work. The HOG feature extraction scheme dominates LBP and OGBP feature extraction schemes with respect to performance.

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In future, the proposed work can be carried out on JAFFE, KDEF and Faces DB datasets to test its robustness. In addition, various other feature extraction and classification techniques could be experimented upon so as to improve recognition rates.

REFERENCES

1. P. Weinberg, W. Gottwald, “Impulsive consumer buying as a result of emotions,” Journal of Business research, 10 (1) (1982) 43–57.
2. P. Ekman and W. Friesen, “Constants across cultures in the face and emotion,” Journal of personality and social psychology, Vol.17 no.2, p-124, 1971.
3. P. Ekman and W. Friesen, “The Facial Action Coding System (FACS): A Technique for the Measurement of Facial Movement”, Consulting Psychologists Press, San Francisco, 1978.
4. Maja Pantic, Leon J. M. Rothkrantz, “Automatic analysis of facial expressions: the state of the art,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.22, No. 12, 2000.
5. Z.Zeng, M.Pantic, G.I.Roisman and T. S. Huang,”A survey of affect recognition methods: Audio, visual and spontaneous expressions,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.31 no. 1, pp. 39-58, 2009.
6. Xiaoming Zhao and Shiqing Zhang, “A Review on Facial Expression Recognition: Feature Extraction and Classification,” IETE Technical Review, Vol. 33 Issue- 5, 2016.
7. Evangelos Sariyanidi, Hatice Gunes, and Andrea Cavallaro, “Automatic Analysis of Facial Affect: A Survey of Registration, Representation, and Recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 37, No. 6, June 2015.
8. I. Kotsia and I. Pitas, "Facial Expression Recognition in Image Sequences Using Geometric Deformation Features and Support Vector Machines," in IEEE Transactions on Image Processing, vol. 16, no. 1, pp. 172-187, Jan. 2007.
9. Zhang,Y.,Ji,Q., “Active and dynamic information fusion for facial expression understanding from image sequences”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27,699–714.
10. S L Happy and Aurobinda Routray, “Automatic facial expression recognition using features of salient facial patches”, IEEE Transactions on Affective Computing.
11. Maja Pantic, Ioannis Patras, “Dynamics of Facial Expression: Recognition of Facial Actions and their Temporal Segments from Face Profile Image Sequences,” IEEE transactions on systems, man, and cybernetics, Vol. 36, No. 2, April 2006.
12. Turk M A, Pentland A P, “Face recognition using eigenfaces,” J Cognitive Neuroscience 1991;3(1):72–86.
13. Belhumeur PN, Hespanha JP, Kriegman DJ. Eigenfaces vs. fisherfaces: recognition using class specific linear projection”, IEEE Transactions on Pattern Analysis and Machine Intelligence, 1997; 19(7):711–720.
14. Bartlett M, Sejnowski T J, “Independent components of face images: a representation for face recognition,” 4th Annual Joint Symposium on Neural Computation; La Jolla (CA); 1997.
15. Viola, P. & Jones, M., “Robust real-time face detection” International Journal of Computer Vision (2004) 57: 137.
16. Navneet Dalal, Bill Triggs, “Histograms of Oriented Gradients for Human Detection”, International Conference on Computer Vision & Pattern Recognition (CVPR '05), Jun 2005, San Diego, United States. pp. 886-893.
17. Cigdem Turan, Kin-Man Lam, “Histogram-based local descriptors for facial expression recognition (FER): A comprehensive study”, Journal of visual communication and image representation, 55(2018) 331-341.
18. P. Carcagn, M. Coco, M. Leo, C. Distante, “Facial expression recognition and histograms of oriented gradients: a comprehensive study, Springerplus 4 (1) (2015) 1. doi:10.1186/s40064-015-1427-3.
19. T. Ahonen, A, Hadid, and M. Pietikainen, “Face description with local binary patterns: Application to face recognition”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.28, pp. 2037-2041, 2006.
20. Xiaoming Zhao and Shiqing Zhang, “Facial expression recognition using local binary patterns and discrimant kernel locally linear embedding”, EURASIP Journal on Advances in Signal Processing 2012.
21. Caifeng Shan a, Shaogang Gong, Peter W. McOwan, “Facial expression recognition based on Local Binary Patterns: A comprehensive study, Image and Vision Computing 27 (2009) 803–816.
22. Zhao G, Pietikainen M, “Dynamic texture recognition using Local Binary Patterns with an application to facial expressions”, IEEE Trans Pattern Analysis and Machine Intelligence 2007; 29(6):915–928.
23. Shan, Sh. Gong, P. W. McOwan, “Facial expression recognition based on local binary patterns: a comprehensive study”, Image and Vision Computing, vol. 27, no. 6, pp. 803-816, 2009.
24. W. Hsu and C.-J. Lin, "A comparison of methods for multiclass support vector machines", IEEE Transactions on Neural Networks, vol. 13, no. 2, pp. 415-425, 2002.
25. P. Lucey, J.F. Cohn, T. Kanade, J. Saragih, Z. Ambadar and I. Matthews, "The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression", in the Proceedings of IEEE workshop on CVPR for Human Communicative Behavior Analysis, San Francisco, USA, 2010.

AUTHORS PROFILE

Naveen Kumar H N has received the B.E degree in Electronics and Communication Engineering and M.Tech degree in Digital Electronics and Communication from Visvesvaraya Technological University, Belagavi, Karnataka. Currently, he is working as an assistant professor in the department of Electronics and Communication Engineering at Shree Dharmasthala Manjunatheshwara Institute of Technology, Ujire, Karnataka. His research interests include Signal Processing, Image Processing and Computer Vision, Pattern Recognition, Facial Expression Analysis, Expression Recognition from partially occluded images, Facial Region Segmentation, Pain Expression Recognition, and Micro Expression Recognition. He has published 5 peer review research articles in the field of facial expression recognition.

Dr. Jagadeesha S has received the B.E degree in Electronics & Communication from Kuvempu University and M.E degree in Power Electronics from Gulbarga University, Karnataka. He has received Doctor of Philosophy (Ph.D) in the Department of Applied Electronics from Gulbarga University, Gulbarga. Currently, he is working as a Professor in the department of Electronics and Communication Engineering at Shree Dharmasthala Manjunatheshwara Institute of Technology, Ujire, Karnataka. His research interests include Micro Strip Antennas, Patch Antennas, Wireless communication, Signal Processing, Image Processing & Computer vision, Pattern Recognition and Facial Expression Recognition. He has published more than 20 peer review research articles.

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