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Optimization in Feature Extraction schemes on Static Images to Improve the Performance of Automatic Facial Expression Recognition Systems

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***Abstract*—** Automatic Facial Expression Recognition (AFER) systems are gaining importance in various emerging Human Computer Interaction (HCI) applications and affective computing applications. The abstract and robust features to interpret facial expressions and encode them as an emotion, still, remain as a challenge in the field of AFER. The objective of the proposed work is to analyze the performance of still image based AFER system with respect to various feature extraction schemes, and to optimize and thereby improving the recognition accuracy of AFER systems. Features such as; Histograms of Oriented Gradients (HOG), Local Binary Pattern (LBP) and a combination of HOG-LBP are used for the analysis of AFER system performance on feature extraction schemes. Various Parameters corresponding to features of interest are involved during the experimentation to understand the impact of a particular feature parameter on the recognition rate of AFER system. It's not a simple task to optimize parameters of a feature to achieve better recognition rates. The proposed work is implemented on Extended Cohn-Kanade (CK+) dataset for six expressions. Cell size parameter of the features experimented has shown improvement in performance. Experimental results demonstrate the effectiveness of the proposed work on still image based facial expression recognition by providing significant performance improvement over other methods under comparison.

***Keywords*—** Facial Expression Recognition, Feature Extraction, Feature combination, Image Classification, Texture Descriptor, Human Computer Interaction Component

I. INTRODUCTION

Automatic Facial Expression Recognition (AFER) has been and still is a challenging research area in the field of affective computing systems. AFER serves as a fundamental step in applications such as human-computer interaction, assistive health care technologies, interactive agent, fatigue measurement, lie detection and so on. The detailed information about one's experience can be communicated through facial expression. The aim of AFER system is to classify each given facial image into any one of six basic expressions (Anger, Disgust, Fear, Happy, Sad and Surprise) as defined by Ekman and Friesen [1]. Despite of recent progress and advancements in computer vision and machine learning, current AFER systems still suffer from lack of optimal performance due to complex deformation of face, illumination variations, occlusion, registration errors, person-specific face morphology, pose variations etc. Reliable and robust appearance information extraction still remains challenging in the process of facial expression recognition.

Depending on the type of information extracted, FER systems shall be categorized as Shape based methods, Motion based methods and Appearance based methods [2, 3]. Shape based methods rely on geometric information such as distance and angle between pupil and nostril, widening of mouth, widening of eyebrows etc. Active Appearance models are used to extract features from face geometry. Shape based methods demand crystal clear image of a face along with accurate landmark detection and localization. It is highly difficult to generalize an FER system which relies on shape based methods [4].

The contributions of the proposed work are:

1. Does feature combination improve accuracy?
2. To analyze the performance of FER system based on variations in the feature parameter.
3. Optimization in feature extraction schemes for improved performance.

The rest of the paper is organized as follows, Section I contains the introduction, Section II summarizes the related work on facial expression recognition, In Section III the methodology of the proposed work is addressed, Results and discussion of the proposed work are presented in Section IV and Section V concludes the proposed work.

II. Related Work

Motion based methods make use of spatial and temporal information for expression recognition which makes FER to be more dynamic. Facial Action Coding System (FACS) explicitly distinguishes facial actions and provides inference about what they mean. FACS investigator's guide, FACS interpretive database can be used to make emotion based inferences from FACS codes. Many algorithms that utilize FACS do not attempt to make the interpretive connection from Action Units (AUs) to a labeled facial expression [5].
The performance of motion based methods completely reliant on methods used for alignment of the face. As facial actions over time are different across subjects, it remains an challenging issue as to how a common temporal feature for each expression, among the population, can be effectively encoded while suppressing subject specific facial shape variations. It is assumed that training sequences begin with neutral expression and end with apex expressions. Motion based methods demand alignment at the beginning and ending stages. Manual labeling of eye positions is employed for the first frame and so labeled eye positions are used to determine the facial area of the whole sequence and also for normalization. In real time, an expression doesn't start with neutral stage and end with apex stage, it may occur with various offsets and at different paces, which induces a difficulty in the process of extracting suitable representations from spatio-temporal video patterns. There is no consensus on how to combine those representations flexibly enough, so as to generalize on unseen data and possibly unseen temporal variations.

Semantic level facial feature extraction for dynamic FER aims at establishing relationships between a sequence of latent states and high level features. To capture facial muscles complex relationship Wang et al. [6] integrates temporal interval algebra into a Bayesian network. Sikka et al. [7] proposes a novel latent ordinal model that allows weakly supervised learning. The dimensionality reduction techniques such as PCA or k-means clustering are explicitly required during training. In addition, training at sequence level reduces the quantity of available data for training, and testing, as compared to frame based approaches. These approaches require continuity of sequences for both training, and testing, and may lack the flexibility to handle failure cases.

Appearance based methods use textural information by considering pixels intensity value. Happy et al. [8] proposed the use of facial patches which are active during emotion elicitation, for expression recognition. These patches are further processed to obtain salient patches which contain discriminative features for classification of expressions. Appearance features from selected facial patches are used for expression recognition. Accurate detection of facial landmarks plays a vital role in the performance of the approach. The proposed work is an attempt to explore appearance based features for facial expression recognition to overcome the drawbacks of above said methods.

III. Methodology

A. The main objective of the proposed method is to analyse the performance of AFER systems based on feature extraction schemes and to find the optimal appearance feature, along with its parameters from still images to improve the performance of FER system. Viola jones algorithm is employed for face detection. The features taken into consideration are Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP) and a combination of HOG-LBP. Various parameters of both the features are taken into consideration, so as to study the impact of each feature parameter on the performance. Figure 1 depicts the block diagram of the proposed work.

Figure 1: Block diagram of the proposed method

B. Histogram of Oriented Gradients(HOG)

The directional change in intensity of pixels is known as gradients. An image gradient represents directions of the edges they contain. Gradient operators extract local features across the image which is encoded as gradient magnitude and angle. Gradient magnitude and angle histograms are extracted from cells, and combined across larger entities known as blocks. HOG feature projects Characteristics of local shape or gradient structure. Low level features are robust to illumination variations [9]. Local geometric and photometric transformations have no impact on HOG feature.

The various feature parameters involved in the experimentation are Cell size, Block size, Block overlap and Number of bins in the orientation histograms. Cell size of HOG feature is a 2 element vector that specifies the size of HOG cell in pixels. Block size of HOG feature is a 2 element vector that specifies the number of cells in a block. Block overlap is a 2 element vector that specifies the number of overlapping cells between adjacent blocks.

HOG feature algorithm divides static image of a face into small spatial regions known as "Cells". Cells can be rectangular or circular. The image is divided into cells of size N × N pixels and for each cell, gradients are computed using formulations as shown below.

Let $g(x,y)$ represent a single cell in face window.

$$Horizontal\ Gradient\ Operator: k_h = [-1\ 0\ 1] \quad (1)$$

$$Vertical\ Gradient\ Operator: k_y = [-1\ 0\ 1]^T \quad (2)$$

$$Horizontal\ Gradient\ of\ g(x,y): G_x = g(x,y) * k_h \quad (3)$$

$$Vertical\ Gardient\ of\ g(x,y): G_y = g(x,y) * k_y \quad (4)$$

$$Orientation = tan^{-1}\left(\frac{G_y}{G_x}\right) \quad (5)$$

$$T - Matrix\ transform\ and\ * - 2D\ Convolution$$

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. During training and testing phase the feature vectors extracted from images representing different facial expressions are used. Figure 2 depicts the HOG feature representation for various cell sizes.

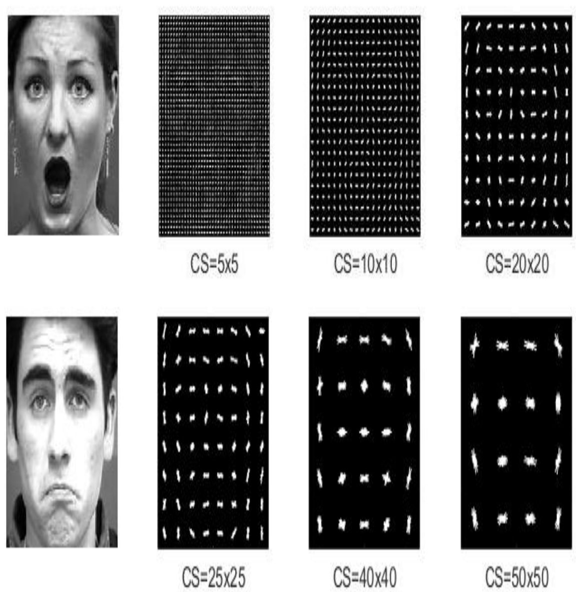

Figure 2: HOG feature representation of an image for various Cell Sizes (CS).

C. Local Binary Pattern Texture Descriptor

LBP texture descriptor is popular due to its ease of computation and discriminative power. LBP feature describes two dimensional surface textures through local spatial patterns and gray contrast. The use of uniform patterns reduces the feature vector size. In LBP descriptor the image pixels were labeled to obtain a binary code by thresholding the neighborhood of each pixel with the center value. The center pixel LBP value is obtained by binary to decimal conversion. The illustration of the basic LBP operator is shown in Figure 3. Based on the operator; the LBP code is used to label every pixel in an image. The density of each pixel is obtained by 256-bin histogram of the labels and for the region of interest it is used as texture descriptor. The occurrences of LBP code are composed into histogram and by simple histogram similarities, the classification is performed. A similar approach for facial image representation leads to loss of spatial information. Therefore, along with the texture information, one should also retain their locations. This can be achieved by using LBP texture descriptors so as to obtain several local descriptions of the face and finally combine them to obtain global description. Compared to holistic methods, local feature based methods are more robust to illumination variations and pose variations [10].

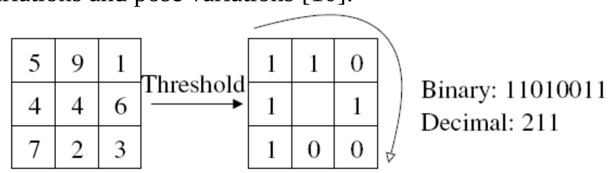

Figure 3: Computation of LBP.

In order to extract features, the face image is divided into non-overlapping blocks. Computation of LBP histograms and its concatenation forms single vector representation the face image. Ahonen et al. [10] proposed 59-element subset of uniform patterns to represent face images, which operates like edge detectors. The LBP feature histogram representation of a face is as depicted in Figure 4 [11]. The various feature parameters involved in the experimentation are Number of Neighbours, Radius, and Cell size. Number of neighbours in LBP is the set of neighbours selected from circularly symmetric pattern around each pixel. The radius of LBP in pixels is the circular pattern used to select neighbours of each pixel in image. Cell size of LBP is a 2 element vector that segments image into non-overlapping cells.

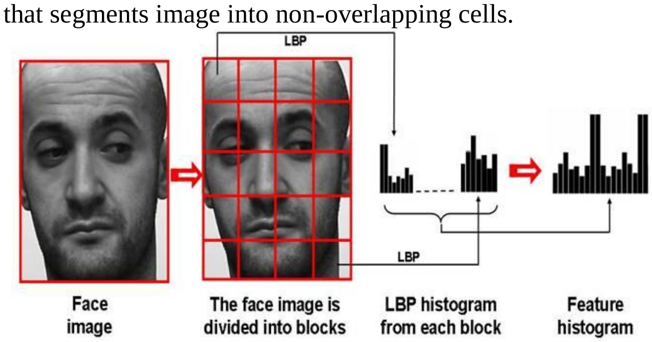

Figure 4: LBP histogram representation of face image.

D. Support Vector Machine Classification

SVM is a discriminative classifier defined through a separating hyper plane. SVMs are non-parametric and hence boost the robustness associated with Artificial Neural Networks and other nonparametric classifiers. The purpose of using SVM is to obtain acceptable results in a fast, accurate and easier manner. The model of SVM used in the proposed work is shown in Figure 5.

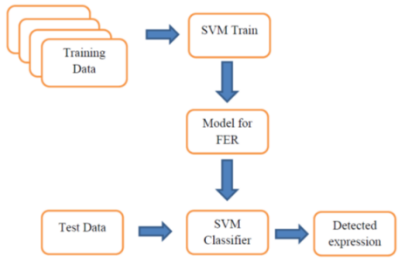

Figure 5: SVM classifier model.

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. In the proposed work six universally accepted facial expressions (Anger, Disgust, Fear, Happy, Sad and Surprise) were taken into consideration, so six classifiers are employed to classify the facial expression. The first classifier employed detects whether the features extracted from the test image infer anger expression or not, similarly the remaining classifiers detects whether the features extracted from the test image detects respective expression or not.

IV. Results and Discussion

The experimental set up comprises of Intel Core i3 processor, Windows 8 operating system and MATLAB R2016a. All the experimental sessions have been carried out on Extended Cohn-kanade (CK+) dataset and JAFFE dataset. These datasets are publicly available and are specifically built for FER issues, and comprises of image sequences for all six 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 dataset one of the most popular for evaluating the performance of FER systems. The subsets of images, containing expressive face, were selected to form an image dataset for training and testing phase. Dataset used in the experimentation comprises of images from 40 female subjects and 24 male subjects exhibiting all six facial expressions. 4-fold Cross validation approach is employed, wherein complete dataset is randomly divided into 4 subsets. Four trails of experiments are conducted on the said dataset. During each trail, a single subset is preserved as the validation data for testing and remaining 3 subsets are employed for training. This approach is repeated 4 times, with each of the 4 subsets used exactly once for testing. The 4 results are then averaged to produce a single estimation. Leave one out cross validation is also experimented, wherein one subset is preserved as the validation data for testing and remaining subsets are employed for training. Single trail experimentation is carried out in leave one out approach. The various experiments carried out are summarized below.

A. Experiments Carried on HOG Feature

The various HOG feature parameters involved in the experimentation are Cell size, Block size, Block overlap and number of bins in the orientation histograms. Variations in Block size, Block overlap, and number of bins of a feature have not shown a promising improvement in the performance. However, variation in cell size parameter of HOG feature has shown considerable improvement in the performance. Six different cell size values (5, 10, 20, 25, 40, and 50) are used during the experimentation. Average result of four trails of the experimentation (4-fold cross validation) for each cell size is tabulated in the form of confusion matrix as shown in Figure 6. The cell size 10x10, 20x20, 25x25 provide good recognition rate when compared with all other experimented cell sizes.

	AN	DI	FE	HA	SA	SU
AN	**62.92**	21.5	0	0	15.5	0
DI	6.7	**91.35**	0	0	1.9	0
FE	22.3	9.2	**42.33**	6.7	19.4	0
HA	5.7	0	7.4	**86.88**	0	0
SA	20.3	11.3	15.7	0	**52.62**	0
SU	0	2.6	6.7	0	0	**90.67**

(a) Cell Size: [5 5]

	AN	DI	FE	HA	SA	SU
AN	**64.95**	19.3	1.8	0	13.9	0
DI	3.5	**96.46**	0	0	0	0
FE	19.5	6.3	**55.47**	0	18.7	0
HA	1.3	0	7.7	**90.91**	0	0
SA	14.2	4.9	14.4	0	**66.46**	0
SU	0	0	4.5	0	0	**95.43**

(b)Cell Size: [10 10]

	AN	DI	FE	HA	SA	SU
AN	**70.65**	17.26	0	0	12.05	0
DI	4.43	**95.57**	0	0	0	0
FE	18.3	7.5	**62.11**	2.7	9.3	0
HA	1.78	0	4.67	**93.52**	0	0
SA	17.58	0	13.48	0	**68.92**	0
SU	0	1.8	2.39	0	0	**95.81**

(c)Cell Size: [20 20]

	AN	DI	FE	HA	SA	SU
AN	**62**	20.6	0	0	17.4	0
DI	4.9	**95.06**	0	0	0	0
FE	21.6	6.5	**54.48**	0	17.4	0
HA	1.5	0	5.7	**92.8**	0	0
SA	14.2	0	15.3	0	**70.46**	0
SU	0	0	4.1	0	0	**95.81**

(d)Cell Size: [25 25]

	AN	DI	FE	HA	SA	SU
AN	**56.92**	21.3	3.6	0	18.1	0
DI	3.2	**94.86**	0	0	1.9	0
FE	21.9	7.9	**51.87**	0	18.3	0
HA	2.1	0	6.2	**91.7**	0	0
SA	16.7	8.9	17.5	0	**56.9**	0
SU	0	3.1	9.4	0	0	**87.5**

(e)Cell Size: [40 40]

	AN	DI	FE	HA	SA	SU
AN	**53.52**	21.8	6.3	0	18.3	0
DI	9.7	**82.88**	0	0	7.4	0
FE	24.8	11.3	**43.11**	0	20.7	0
HA	6.7	0	9.3	**84**	0	0
SA	17.1	10.8	17.3	0	**54.77**	0
SU	0	5.3	11.7	0	0	**83**

(f)Cell Size: [50 50]

Figure 6: Confusion matrices of AFER system based on HOG feature: (a)-(f) the experimental results corresponding to six cell sizes (5, 10, 20, 25, 40, and 50).

Results indicate that smallest cell size 5x5 and largest cell size 50x50 fails to achieve good recognition rate, which intern shows the impact of HOG cell size parameter on recognition rate of a FER system. Selection of larger cell size to extract large scale spatial information leads to loosing of small scale detail which deteriorates the performance of FER system based on HOG feature. The selection of smaller cell size leads to over fitting of data which intern deteriorates the performance of FER system. It's highly challenging to predict the optimal cell size parameter of HOG feature to achieve higher recognition rates. The impact of variation in cell size of a HOG feature on FER system recognition rate is shown in Figure 7. Compared to variations in block size, block overlap and number of orientation bins of HOG feature, the variation in cell size of a feature has provided good results. The best recognition rates are achieved for median cell size values compared to smaller and larger cell size values.

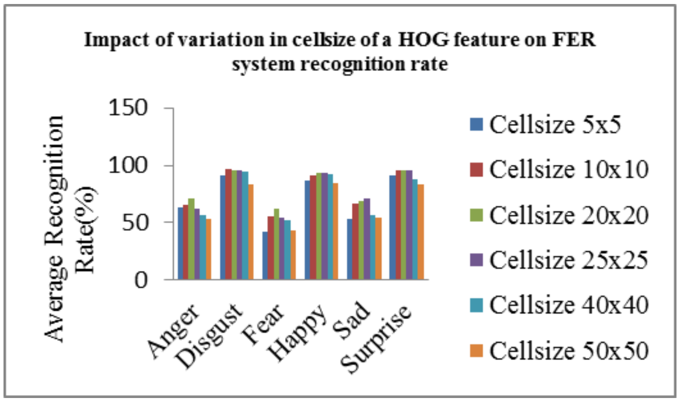

Figure 7: The average recognition rates of six different facial expressions on Extended Cohn-kanade database for six different cell sizes of HOG feature.

The best recognition rates achieved by experiments carried on HOG feature using cross validation and leave one out approach are tabulated in Table 1 and Table2 respectively. Recognition rate is slightly improved in both the approaches for HOG feature with median cell size values compared to the conventional HOG feature. This performance improvement indicates that cell size parameter of HOG feature has marked its importance over other feature parameters. The 4-fold cross validation approach performance is better compared to one leave out approach.

Table 1: Performance of HOG feature in Cross-validation approach

	AN	DI	FE	HA	SA	SU
HOG	58.9	94.9	57.3	89.6	57.7	95.5
HOG CS:20x20	70.6	95.6	62.1	93.5	68.9	95.9
HOG CS:25x25	62	95.1	54.5	95.8	70.5	95.8

Table 2: Performance of HOG feature in leave one out approach

	AN	DI	FE	HA	SA	SU
HOG	38	98.4	70.5	86.5	61.9	98.6
HOG CS:20x20	42	100	78.7	97.9	52.4	98.5
HOG CS:25x25	38	100	73.8	96.9	61.9	100

B. Experiments Carried on LBP Feature

The various LBP feature parameters involved in the experimentation include Number of Neighbors used to compute LBP, Radius, and Cell size. A variation in number of neighbors, along with variation in radius fails to provide improvement in the performance. However, cell size parameter of LBP feature has shown some improvement in the performance. Six different cell size values (5, 10, 20, 25, 40, and 50) are used during the experimentation. Average results of 4 trails (4-fold cross validation) of the experimentation for each cell size is tabulated in the form of confusion matrix as shown in Figure 8. The cell size 10x10, 20x20 and 25x25 provide good recognition rates compared to all other cell sizes experimented.

	AN	DI	FE	HA	SA	SU
AN	**57.16**	15.7	7.3	0	19.8	0
DI	0	**78.32**	8.2	0	13.4	0
FE	8.5	19.4	**45.41**	3.2	23.4	0
HA	9.7	4.3	2.7	**83.26**	0	0
SA	10.2	26.7	12.3	0	**50.8**	0
SU	2.4	0	5.9	0	0	**91.6**

(a) Cell Size: [5 5]

	AN	DI	FE	HA	SA	SU
AN	**65.42**	13.3	2.9	0	18.3	0
DI	0	**85.15**	6.1	0	8.7	0
FE	3.2	23.9	**48.7**	3.7	20.4	0
HA	5.7	4.3	0	**89.96**	0	0
SA	4.6	26.3	13.9	0	**55.13**	0
SU	1.3	0	3.9	0	0	**94.78**

(b)Cell Size: [10 10]

	AN	DI	FE	HA	SA	SU
AN	**68.82**	12.54	0	0	18.61	0
DI	0	**83.32**	0	6.7	9.9	0
FE	2.1	23.6	**51.2**	5.3	17.8	0
HA	2.6	6.1	0	**91.3**	0	0
SA	10.8	19.7	5.17	0	**64.33**	0
SU	0	0	2.7	0	2.9	**94.3**

(c)Cell Size: [20 20]

	AN	DI	FE	HA	SA	SU
AN	**66.88**	11.2	9.3	0	12.6	0
DI	0	**80.74**	5.9	0	13.3	0
FE	8.1	18.3	**52.8**	0	20.7	0
HA	1.4	5.7	3.3	**89.6**	0	0
SA	7.8	23.1	7.2	0	**61.86**	0
SU	1.8	0	5.4	0	0	**92.8**

(d)Cell Size: [25 25]

	AN	DI	FE	HA	SA	SU
AN	**59.57**	13.4	8.3	0	18.5	0
DI	0	**71.74**	6.8	0	21.4	0
FE	8.1	20.6	**52.2**	3.8	15.3	0
HA	4.5	7.2	1.3	**86.87**	0	0
SA	7.1	28.7	7.3	0	**56.9**	0
SU	2.3	0	5.2	0	2.3	**90.15**

(e)Cell Size: [40 40]

	AN	DI	FE	HA	SA	SU
AN	**58.56**	9.7	6.9	0	24.8	0
DI	4.1	**64.97**	5.4	6.9	18.6	0
FE	10.2	19.5	**45.48**	8.2	16.6	0
HA	13.7	4.9	0	**81.36**	0	0
SA	9.8	31.3	6.4	0	**52.42**	0
SU	2.23	0	8.7	0	4.23	**84.84**

(f)Cell Size: [50 50]

Figure 8: Confusion matrices of AFER system based on LBP feature: (a)-(f) the experimental results corresponding to six cell sizes (5, 10, 20, 25, 40, and 50).

C. Combination of HOG & LBP

The feature concatenation of HOG and LBP is also experimented on Cohn-Kanade dataset. The best result of the experiments conducted using 4-fold cross validation and leave one out approach are tabulated in Table 3 and Table 4 respectively. Improvement in recognition rate is observed in both the approaches for the trails of the experimentation where Cell Size (CS) parameter is taken into consideration. The HOG feature extracted from LBP image is also experimented as one of the feature extraction scheme, but as such fails to provide promising results for expression recognition.

Table 3: Performance of HOG-LBP feature combination using Cross-validation approach (CS: Cell Size)

	AN	DI	FE	HA	SA	SU
HOG-LBP	58.9	95.3	57.3	89.9	58.3	95.5
HOG-LBP CS :20x20	66.1	92.9	57.6	94.3	65.9	95.5
HOG-LBP CS :25x25	69.7	92.5	58.5	94.1	70.1	95.5

Table 4: Performance of HOG-LBP feature combination using leave one out approach (CS: Cell Size)

	AN	DI	FE	HA	SA	SU
HOG-LBP	38	100	70.5	86.5	61.9	98.6
HOG-LBP CS :20x20	38	98.4	85.2	94.8	73	98.6
HOG-LBP CS :25x25	44	100	85.3	93.8	61.9	98.6

V. CONCLUSION AND FUTURE SCOPE

The proposed work is an attempt towards improvement in performance of AFER systems by considering multiple features and its parameters. HOG, LBP and combination of HOG-LBP are the different feature extraction schemes used for the experimentation, with various feature parameters. The experimental results reveal that performance of AFER system is improved for variation in cell size compared to variation in other feature parameters. Various cell size values are used in the experimentation; however, best results are achieved for median cell size values compared to smaller and larger cell size values. Results of the experiments conducted suggest that cell size parameter of a feature shall be taken into account in order to improve the performance of FER systems. It can also be further inferred that 4-fold cross validation scheme performance is better when compared to one leave out scheme. HOG feature and combination of HOG-LBP outperforms LBP and geometric feature for expression recognition from still images. In future, the experiment shall be extended to accommodate more and differing cell size parameter values, in order to decide on optimal cell size parameter, so as to enhance the performance of an AFER system. The proposed work shall be carried out on various datasets (MMI, RAFD etc), partially occluded and pose varied images to test its robustness.

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