© April 2016 | IJIRT | Volume 2 Issue 11 | ISSN: 2349-6002

SURVEY ON FACIAL RECOGNITIONS TECHNIQUES

Asia Mashkoor, Himani Gupta
SCSE, Galgotias University, Greater Noida

***Abstract*— Automatic recognition facial expressions and analysis of it has been an active topic for over decades. Different features extraction from salient features patches play a vital role in recognition of facial expression effectively. The critical step for recognition of facial expression recognition is to extract emotions features accurately. Facial expression recognition approaches consist of two main categories which are based on the type of features used in geometry-based features and appearance-based features. This paper shows the comparison in the performance of FER by automatically capturing facial movement features in static images based on distance features and expression recognition by using appearance features of selected facial patches.**

***Index Terms*— salient facial patches, Adaboost, face recognition, facial landmark detection, feature selection,**

I. INTRODUCTION

Facial expression recognition (FER) has been remarkably developing in recent years. It is a mode of communication of human emotion and having its applications in human and computer interaction, surveillance, robots control, deceit detection etc .Many technology has been accepted in this area for accurate extractions of features. Recognition of face is still challenging task if pose and illumination changes. Numerous methods have been proposed for solving such problem. This paper is about the discussion of various techniques used for recognition of face. Facial expressions are robust. However, to date, robust recognition of facial expressions from images and videos is still a challenging task due to the difficulty in accurately extracting the useful emotional features [2].

Facial features movements consist of position of features and shape changes are mostly caused by the movement of facial elements and muscles during the flow of emotional expression. As expressing emotions are changes then facial element will constantly change their positions. Large success has been achieved in the fields of face detection and recognition. Anger, happiness, sadness, surprise, fear, disgust are the basic emotions and are used for analyzing the facial expression. Effective expression analysis hugely depends upon the accurate representation of facial features. Facial Action Coding System (FACS) [3] represents face by measuring all visually observable facial movements in terms of Action Units (AUs) and associates them with the facial expressions. According to Whitehill et al. [4], the detection of all facial fiducial points are even more challenging than expression recognition itself Mostly existing algorithms are based on appearance based features and geometric based features. Geometric based algorithms tracing the shape and the size of the face and facial components such as lip corner, eyebrows, eyes etc. Some researchers in [5][6][7][8] use shape model algorithms on the set of characteristics point for classifying the expressions. But all these algorithms require accurate and reliable detection of the facial landmarks which is actually quite very difficult to achieve. There is variable distance between landmarks from person to person. In appearance based method [9], number of filters such as Gabor wavelets, local binary patterns etc are applied on specific face region or on the whole face for encoding the texture. In [4] reported that the appearance based methods shows superior performance from the method based on geometric based features. But the space cost and time are higher in appearance based methods. By dividing the face region into number of block for extracting the facial features, the researchers has achieved the better accuracy in [9][10][11][12][13][14][15] but these approaches get failed for the improper face alignment. Earlier works [16][2] on features extraction from specify face region mainly determines the facial regions which help in discrimination of expression that is based on training data. The size and positions of patches of face vary according the training data. For classifying the 6 basic emotions, the appearance features are fed to multi-class classifiers. With the lower number of histogram bins the appearance features are used for reducing the computation. The vast majority of the past work on FER does not take the dynamics facial movement features into account [17]. Identifications of salient patches is a significant task towards the classification of expression. Once the salient patches are selected, then the expression recognition becomes easier and irrespective of the data.

II. LITERATURE REVIEW OF FACE RECOGNITION TECHNIQUES

In[2] the proposed framework in the performance of FER by automatically capturing facial movement features in static images based on distance features, which is composed of pre-processing, training, and test stages. In pre-processing stage, taking the centre on nose and other facial components are also included, facial regions are manually cropped from database images and scaled to a resolution of 48 *48 pixels. Then, multi resolution Gabor images are attain by convolving eight scales, four-orientation Gabor filters with the scaled facial regions. In training stage, the extractions of set of patches are perform by circulating the number of patches across the train Gabor image that have different sizes. Then, operations of patches matching perform for converting the extracted patches to distance features. The minimum rule applied for finding the best match feature in the space. Adaboost, that is adaptive boosting used for selecting the "salient" patches. During test stage, new image taken randomly, and the same operation of patches matching was perform using the "salient" patches. For the recognition of six basic emotions that include anger, disgust, happiness, fear, sadness, surprise, the resulting distance features fed into multiclass support vector machine (SVM).

The 2d Gabor filter apply and it is mathematically expressed as:

$$F(x\,,y) = \exp\left(-\frac{X^2+\gamma^2 Y^2}{2\sigma^2}\right) \times \cos\left(\frac{2\pi}{\lambda}\;x\right)$$

$$X = x\cos\theta + y\;\sin\theta\,,\;\; Y = -x\;\sin\theta + y\;\cos\theta,$$

Where θ represents the orientation, σ represents the effective width, λ represents the wavelength, and γ =¼ 0:3 the aspect ratio. SVM [32] is machine learning algorithms used most widely for the classification of problems.

The two main processes for building the distance features are feature extraction and patch matching operation. In feature extraction process of collecting the different 3D patches for all emotions, but in patch matching operation converts 3D patches to distance features that is used for capturing facial movement features. Four steps are involves in feature extraction algorithm. First, all training images are classified into 10 sets. For each emotion, there is Gabor scale for each, and each patch size. In [1] a Gabor image selected from all the emotions images. Then secondly, one patch moves across the column and row pixels of this Gabor image. Third, the matching area and matching scale was recorded. Finally, a set of patches is constituted by combining the extracted patches of all emotions, all scales, and all patch sizes. Another operation is patch matching operation, which is also, comprises of four steps. First, define the matching area and matching scale that are providing a bigger matching space. Second, the distances are obtained by matching these patches with all the other patches that are available in matching space in training images. Taken two patches as inputs and yields one distance value based on a distance metric. Third, the distance feature chosen minimum distance of the patch in the training image. Finally, all the distance features are combined into a final set. In [1] author proposed that for facial expression recognition the facial landmark detection is un-deniable. The essential step is face alignment and it mostly done by detecting the position of eyes. Facial landmark detection followed by features extraction. Accuracy is depending on the type of features extraction.

In [18], for accurate tracking facial components an active Infrared illumination along with Kalman filter is used. By using both geometric and appearance features performance can be improved. Initially, facial landmark positions are detected by using face geometry. Tian et al. [19], the relative distance (lip-corner, eye, brow etc) and transient features (wrinkles, furrows etc) used for recognizing AUs present in lower face. Uddin et al. [20] used image difference method for detecting the changes in expression. The landmarks selection are major issues that is carried out by matching the eye and mouth regions. In [21] relative geometrical distance based technique was proposed by the author which using the Gabor filters for detecting the landmark. SUM and HMM models was used as classifiers. Performance model is a popular model used for detecting of facial landmark to fit into new data instances. Active shape model used for determining the shape, scale and by fitting an appropriate point distribution model to the object of interest. In Active Appearances Models (AAM) [22], both shape and texture models are combine for representing the object. Hence, it providing the superior result to the Active Shape Models (ASM). AAM is widely used [23] [24] [25] [26] 27] for detection and tracking of non-rigid facial landmarks. However, it having a poor performance in a person independent scenario. It is tedious and time-consuming task for manually placing the landmark point in training the data for construction of the model. Cristinace et al. [28] propose the Constrained Local Model (CLM) framework for proving the better tools for the person independent of facial landmark detection. Saragih et al. [29] modified the CLM algorithm and proposed the Regularized Landmark Mean Shift (RLMS) algorithm. Asthana et al. [30] proposed the Discriminative Response Map Fitting (DRMF) method for CLM framework. Satisfactory result has been obtained by using these deformable models. Chew et al. [31] proposed the fact that, even with small alignment error, the appearance based models work robustly as it works for perfect alignment. Therefore if slightly errors occur, it will not hamper the purpose for detecting the landmarks. For the superior performance [32, 33], Gabor wavelets representations are used for face image analysis. Local Binary Pattern (LBP) has also show remarkably result in facial image analysis [10][34][35]. Jabid et al. [11] get the better performance LBP features by using local facial descriptor, which is based on local description pattern code. Dhal et al. [36] also reported remarkable performance by using local face quantization in facial expression recognition. In [12], Local Directional Pattern Variance (LDP) is proposed which encodes contrast information using local variance of directional responses. However, Shan et al. [37] found LBP features to be robust for analysis of low-resolution images. Therefore, we used the LBP histograms asappearance features PCA [38][39] and LDA [40] [41][42] are used as tools for the reduction in dimension and also for the classification in expression recognition. In [43] PCA-LDA has shows the higher performance. In [44], for the recognition of facial expression and every encrypted domain based system to propose for achieving the higher accuracy as in normal images, local fisher discriminant analysis are used. In [45] author explains that there is subspace which is consist of same expression and if new expression is generated from one image by projecting it into different emotion subspace. Full-face image is mostly used in proposed method while very few use extraction of features from spatial facial patches. In[13] face image division is perform into several sub regions (7×6) and local features[7×6×59] dimension features are extracted. For the extraction of sub region (7×6×59 dimensional features) face images division is perform into several sub regions. Adaboost technique use for removing the outliers are also use for the selection of discriminative LBP histogram bins. In [14] [15] and [46] similar approaches are also used. In such cases if small misalignment occur, it increase the error in classification, as it would causes the displacement of the sub region locations. Moreover, there is a different size and shape in found from person to person so it cannot assume that one particular block always have the same facial position. Hence in [1] author adopted the local patch selection based approaches are used. In [47] authors divided the face in 64 sub regions, finding the common facial patches which are found to be active mostly for all expression and spatial faces patches which are found to be active for rare expression. In[2] features are extracted from image by using Gabor filter then these features of different scales are trained by using Adaboost for removing outliers and extracting the salient patches. When extracting patches are trained with different database then the size and position of the salient patches are different. Therefore, for the recognition of expressions in unknown images, unique criteria cannot be established. In most of the literatures, the size and the position of facial patches are found to be different for different data base. In [1] author attempts experiment for identifying the salient facial areas which are having generalize discriminative features for expression classification.

III. LATEST WORK

When the facial expressions change the expansion and contradiction occur in the muscles of face, which lead to the change in position of facial landmarks. If facial muscles change then the textures of the area also are changed. In [1] author shows that the different facial area having large contributions in order to recognize the expressions automatically. In other words, we can say that, in [1] author explore the facial patches that lead to the generation of different features for effective separations of two expressions. In [16][2] author suggested that appearance features extraction and accurate detection of facial landmark from active regions improve the quality of facial expressions recognitions. Therefore the first step is to localize the face that performed by the detection of the landmarks. The eyes and the nose in the face area detected by learning free approach and coarse region of interest [ROI] around nose and eye would be marked. From the region of interest, lip and eyebrow corner are detected. With respect to the landmarks locations, active patches locations are defined. Evaluations of active facial patches are performed in training stage and the expression having maximum variation in features are elected.

DETECTION OF FACIAL LAND MARK

Different expressions of face, which make different facial patches active, these facial patches study, proposed in [47].

During selection of all basic expressions, it is reported that the some facial patches are found to be common and some are confined to a single expression. The active patches area found to be active below the eyes, the area around the eyebrows, around the nose and corner of mouth.

EXTRACTION OF PATCHES FROM FACE IMAGE

It is necessary to locate the facial components first and performed patches around these organs. Unzueta et al. [48] author proposed the method for facial organs localization and the method was robust, light weight generic face model fitting and learning free. Local gradients analysis method used for finding the facial patches and for the adjustment of deformable face model then project an image will lead to the matching of features points of face. In [1] learning free approaches has been adopt for the localization of facial landmark. With respect to the lip corner nose, eyes, eyebrows the process of extraction of active facial patches is perform and the geometrical statistics of the face are used.

PREPOCESSING

For removing the noise from facial images, low pass filtering is applied by using 3×3 gaussions mask. In [1], Viola-Jones technique [49] of Haar like features with Adaboost learning for face detection. It having the low computational complexity and this technique is sufficient for accurate detection of near upright and near frontal face images. Integral image calculation used for detection of face, independent of scale and location in real time. The extraction is apply for localization of face and scaling for bringing it to the common resolutions. Further, the features selected are projected into the lower dimensional sub-space. The projection of selected features into the lower of these selected features into different expressions. The training phases include the extraction of appearance of features , pre-processing, selection of facial patches and learning about the multi class classifiers in an unseen images dimensional subspace are perform and by using multiclass classifier, the classification. The first process is the detection of landmarks, then extraction of features from the selected salient patches and finally classification of expressions. Algorithm becomes insensitive for the location of the image. For light corrections, histogram equalisation carried out.

LOCALISATIONS OF NOSE AND EYE

For the selection of coarse of regions of interest (ROI) around nose and eyes are perform by geometrical position of face. It remains fix whether the expression will change or not. For upright face alignment the position of eyes were detected.

DETECT OF LIP CORNER

ALOGORITH FOR DETECTION OF LIP CORNER

Given : Aligned the nose position.
Step 1 : Selected area of interest around lips by using width of face and position of nose.
Step 2 : Gaussian are apply to area of interest near lips.
Step 3 : For edge detection, horizontal Sobel operator are apply.
Step 4 : Otsu threshold is apply
Step 5 : morphological ...operation are apply
Step 6 : Then finding the components that are connected to each other
Step 7 : Removing the unnecessary connected components by using threshold technique.
Step 8 : Scan the image from the top and select the first connected component as upper lip position
Step 9 : locate the left and right most positions of connected components lip corners.

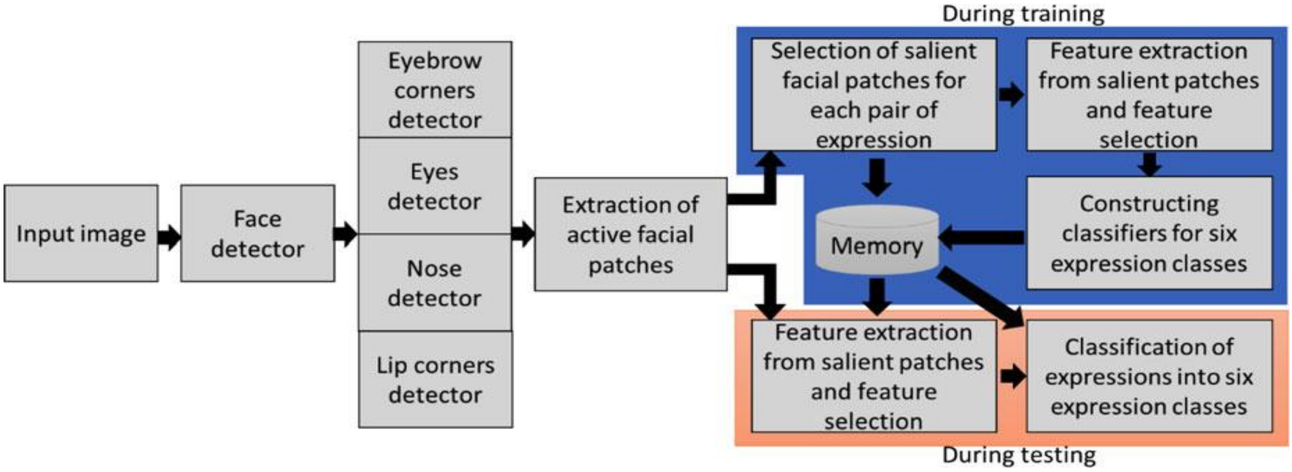

Fig 1 shows the overview of the proposed system in [1]

Reduces the computational complexity and false detections rate. Haar classifiers are used for the detection of both eyes this technique is trained for each eye. Mean of these vertices decided the centre of eyes. Haar technique gives vertices of the selected rectangular area around detected eyes. Mean of these vertices decide the centre of eyes. Haar cascade use for the detection of nose position. According to author in [1] the experiment for detection of position of these parts is about 98% was correct. If Haar classifier are not use for detection of eyes and nose then the co-ordinate of landmark is detected by anthropometric statistics of face. Positions of eyes always

Ngyun et.al [50] facial topographic are used for the detection of eyebrow corner and lip. The extraction of region of interest of mouth is performed by using the position of nose. The distinct edge always produces by upper lip. The detection of upper lips perform by using Horizontal edge detector. Then Sobel edge detector [51] was used. Number of edges were obtained with different expression. These edges further threshold by using Otsu method [52]. In this technique many connected region are found in binary image. The components having an area less than threshold were removed by connected components analysis. On resulting binary image, morphological dilation operation was perform. Just below the nose, the connected components with larger area was selected as upper lip region.

EYEBROW CORNER DETECTION

The same steps for upper lip detection are follow for the eyebrow detection. The areas of interest near eyebrow are selected. If we apply the adaptive threshold operation before applying horizontal Sobel operation then it will increase the accuracy. The horizontal edge detector help in reducing the false detection of eye brow position due to partial occlusion by hair. The inner eye brow corner can easily be detected accurately.

ACTIVE FACIAL PATCHES EXTRACTION

When expressions changes, depending upon the position of active facial muscles, local patches are extracted from image. In [1] author consider that the facial regions exhibiting considerable variations during one expression.

IV. FEATURE EXTRACTION AND CLASSIFICATIO

LBP was widely used as a robust illumination invariants feature descriptor comparison between neighbour and central pixel value [53] is perform then binary number generation occur. The pattern created by using eight neighbour hoods pixel is given by:

$$LBP(x, y) = n$$

Where i_c is the central pixel value at (x, y) in pixel value of neighbourhood of central value of (x , y) and the function range and domain is defined by:

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x<0 \end{cases}$$

we can use histogram of LBP image as a features descriptor and it is stated as:

$$Hi = \sum xy \; I\left\{ LBP(x, y) = i \right\} \quad i = 0,1,2 \ldots . n-1$$

Where n is the number of labels produced by LBP operator. Using different bin widths, the histograms can be grouped to discover different features. For instance, LBP with eight neighbouring points produces 256 labels. If we collect its histograms in 32 bins, then we are basically grouping the patterns [0, 7], [8, 15], [16, 23]; . . . ; and [248, 255] together. This is same as ignoring the least significant bits of the unsigned integer, i.e., using patterns of one side of local neighbourhood.

V. LEARNING SALIENT FACIAL PATCHES ACROSS EXPRESSIONS

In most of the literatures, all the facial features are concatenated to recognize the expression. However, this generate feature vector of high dimension. In [1] author proclaim that the features from a fewer facial patches can replace the high dimensional features without significant diminution of the recognition accuracy. From human perception, not all facial patches are responsible for recognition of one expression. The facial patches responsible for recognition of each expression can be used separately to recognize that particular expression. Based on this hypothesis, in [1] author evaluated the performance of each facial patch for recognition of different expressions. Facial muscles features of such patches are redundant while classifying the expressions. Therefore, after extracting the active facial patches, we selected the salient facial patches responsible for discrimination between each pair of basic expressions.

MULTICLASS CLASSIFICATION

For classification of extracted features into different expression categories SVM was used. SVM [54] is machine-learning algorithm used for mapping the features vector to a different plane. SVM is binary classifier. In [1] author implemented the one against one technology for multiclass classification [55].

VI. EXPERIMENTS & DISCUSSION

In [1] author proposed two mostly used facial expression database that is JAFEE (Japanese female facial expression) [56] and Cohn-Kanade (CK+). During training stage, a SVM classifier was trained between each point of expression.

EXPERIMENTS ON THE COHN-KANADE DATABASE

Cohn-Kanade having, 6 basic emotions of facial experiments of both female & male. In [1] author in his experiment from sequence, the last image were selected where peak intensity of expression were found .Author uses the 329 images in total: happiness (69), sadness (56), anger (41), disgust (45), surprise (65), Fear (53).

EXPERIMENTS ON THE JAFEE DATABASE

The same testing parameter that are apply on Cohn and JAFEE database. In our experiments on JAFFE database, we used 183 images in total: anger (30), disgust (32), fear (29), happiness (31), sadness (31), and surprise (30). Over all accuracy of 91.8 percent was obtained. From the experiments on JAFFE database, it was observed that the proposed system recognises all expressions with 91.8 percent recall and92.63

percent precision achieving an average F-score of92.22 percent. The system performed worst for sadness expression as it misclassified sadness as anger.

VII. CONCLUSION

In [2] author proves that the patch based Gabor features show the better result than the point based Gabor features. Different emotions have different salient areas. Majority of these areas are found around the mouth and eyes. JAFFE and CK database, show best performs among four distances. Among six basic emotions anger creates most misrecognitions factor. Largest size of patches are requires by the JAFFE database as compare to CK data base to retrieve useful information. In [1] All major active regions on face are extracted which are responsible for the face deformation during an expression.
These active regions have their predefine positions and size.
Active patches are analysed by the system and salient areas on face are determines where are discriminative features for different expressions. By using the appearance features from the salient patches, one against one classification task are performs by the system and based on majority vote expressions are determine. By using the proposed landmark detection method and also by using recently proposed CLM model based on DRME method expression recognition is carried out recognition accuracy are similar in both cases.
But by using block based LBP histogram features processing results has been obtained. In [1] the local features at the salient patches provide consistent performance at different resolutions. By assessing the few patches, the proposed method in [1] can easily classifies the emotions instead of assessing the whole face. By using different appearance features, there is a possibility for improvement. Recognition via dynamics expression is still a challenging task.
There is a need of further analysis and efforts so that better improvement can be achieve.

REFERENCES

[1] S L Happy and Aurobinda Routray , "*Automatic Facial Expression Recognition Using Features of Salient Facial Patches*," Trans.Affective Comput.vol. 6, no. 4, jan-march 2015

[2] L. Zhang and D. Tjondronegoro, "*Facial expression recognition using facial movement features*," IEEE Trans.Affective Comput.vol. 2, no. 4, pp. 219–229, Oct. 2011.

[3] P. Ekman, W. V. Friesen, and J. C. Hager, "*FACS Manual*," Salt Lake City, UT, USA: A Human Face, May 2002.

[4] J. Whitehill, M. S. Bartlett, and J. Movellan, "*Automatic Facial expression recognition*," in Social Emotions in Nature and Artifact. London, U.K.: Oxford Univ. Press, 2013.

[5] Y. Chang, C. Hu, and M. Turk, "*Manifold of facial Expression*," in Proc. IEEE Int. Workshop Anal. Modeling Faces Gestures, 2003, pp. 28–35.

[6] M. Pantic and I. Patras, "*Dynamics of facial expression: Recognition of facial actions and their temporalsegments From face profile image sequences*," IEEE Trans. Syst., Man, Cybern, vol. 36, no. 2, pp. 433–449, Apr. 2006.

[7] M. Pantic and L. Rothkrantz, "*Facial action recognition For facial expression analysis from static face images*," IEEE Trans. Syst., Man, Cybern, vol. 34, no. 3, pp. 1449–1461, Jun. 2004.

[8] I. Cohen, N. Sebe, A. Garg, L. Chen, and T. Huang, "*Facial expression recognition from video sequences: Temporal and static modeling*,"Compute. Vis. Image Understanding, vol. 91, pp. 160–187, 2003.

[9] S. M. Lajevardi and Z. M. Hussain, "*Automatic facial Expression recognition: Feature extraction and Selection*," Signal, Image Video Process, vol. 6, no. 1, pp. 159–169, 2012.

[10] G. Zhao and M. Pietikainen, "*Dynamic texture Recognition using local binary patterns with an Application to facial expressions*," IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 6, pp. 915–928, Jun. 2007.

[11] T. Jabid, M. Kabir, and O. Chae, "*Robust facial Expression recognition based on local directional Pattern*," ETRI J., vol. 32, pp. 784–794, 2010.

[12]M. H. Kabir, T. Jabid, and O. Chae, "*A local directional Pattern variance (LDPv) based face descriptor for Human facial expression recognition*," in Proc. 7th IEEE Int. Conf. Adv. Video Signal Based Surveillance, 2010, pp. 526–532.

[13] C. Shan and R. Braspenning, "*Recognizing facial Expressions automatically from video*," in Handbook of Ambient Intelligence and Smart Environments, New York, NY, USA: Springer-Verlag, 2010, pp. 479–509.

[14] C. Shan, S. Gong, and P. W. McOwan, "*Robust facial expression recognition using local binary patterns*," in Proc. IEEE Int. Conf.Image Process., 2005, pp. II–370.

[15] C. Shan and T. Gritti, "*Learning discriminative LBP-Histogram bins for facial expression recognition*," in Proc. Brit. Mach. Vis.Conf., 2008, pp. 1–10.

[16] M. Song, D. Tao, Z. Liu, X. Li, and M. Zhou, "*Image ratio features for facial expression recognition Application*," IEEE Trans. Syst.,Man, Cybern., Part B: Cybern., vol. 40, no. 3, pp. 779–788, Jun. 2010.

[17] Z. Zeng, M. Pantic, G.I. Roisman, and T.S. Huang, "*A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions*," IEEE Trans. Pattern Analysis and Machine Intelligence,vol. 31, no. 1, pp. 39-58, Jan. 2009.

[18] Y. Zhang and Q. Ji, "*Active and dynamic information Fusion for facial expression understanding from image Sequences*," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 5, pp. 699–714, May 2005.

[19] Y. Tian, T. Kanade, and J. F. Cohn, "*Recognizing lower Face action units for facial expression analysis*," in Proc.IEEE Int. Conf. Autom.Face Gesture Recog., 2000, pp.484–490.

[20] M. Z. Uddin, J. J. Lee, and T.-S. Kim, "*An enhanced Independent component-based human facial expression Recognition from video,*" IEEE Trans. Consum. Electron. vol. 55, no. 4, pp. 2216–2224, Nov. 2009.

[21] M. F. Valstar and M. Pantic, "*Combined support vector machines and hidden Markov models for modelling Facial action temporal dynamics,*" in Proc. IEEE Int. Conf. Human–Comput. Interaction, 2007, pp. 118–127.

[22] T. Cootes, G. Edwards, and C. Taylor, "*Active appearance models*,"IEEE Trans. Pattern Anal. Mach. Intell., vol. 23, no. 6, pp. 681–685, Jun. 2001.

[23] S. Lucey, I. Matthews, C. Hu, Z. Ambadar, F. D. L. Torre, and J.Cohn, "*AAM derived face representations for robust facial action recognition*," in Proc. 7th Int. Conf. Autom. Face Gesture Recog.,2006, pp. 155–160.

[24] A. B. Ashraf, S. Lucey, T. C. Jeffrey F. Cohn, Z. Ambadar, K. M.Prkachin, and P. E. Solomon, "*The painful face–pain expression recognition using active appearance models*," Image Vis. Comput.,vol. 27, no. 12, pp. 1788–1796, 2009.

[25] B. Abboud, F. Davoine, and M. Dang, "*Facial expression recognition and synthesis based on an appearance model*," Signal Process.: Image Commun., vol. 19, no. 8, pp. 723–740, 2004.

[26] A. Asthana, J. Saragih, M. Wagner, and R. Goecke, "*Evaluating aam fitting methods for facial expression recognition*," in Proc. 3rd Int. Conf. Affective Comput. Intell. Interaction Workshops, 2009,pp. 1–8.

[27] C. Martin, U. Werner, and H.-M. Gross, "*A real-time facial expression recognition system based on active appearance models using gray images and edge images*,"in Proc. 8th IEEE Int. Conf. Autom.Face Gesture Recog, 2008, pp. 1–6.

[28] D. Cristinacce and T. F. Cootes, "*Feature detection and tracking with constrained local models*," in Proc. Brit. Mach. Vis. Conf.,2006, pp. 929–938.

[29] J. M. Saragih, S. Lucey, and J. F. Cohn, "*Deformable model fitting by regularized landmark mean-shift*," Int. J. Comput. Vis., vol. 91,no. 2, pp. 200–215, 2011.

[30] A. Asthana, S. Zafeiriou, S. Cheng, and M. Pantic, "*Robust discriminative response map fitting with constrained local models*,"in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2013, pp. 3444–3451.

[31] S. W. Chew, P. Lucey, S. Lucey, J. Saragih, J. F. Cohn, I. Matthews,and S. Sridharan, "*In the pursuit of effective affective computing:The relationship between features and registration,*" IEEE Trans.Syst., Man, Cybernet.,Part B: Cybern, vol. 42, no. 4, pp. 1006–1016,Aug. 2012.

[32] M. Bartlett, G. Littlewort, M. Frank, C. Lainscsek, I. Fasel, and J.Movellan, "*Recognizing facial expression: Machine learning and application to spontaneous behavior,*" in Proc. IEEE Comput. Soc.Conf. Comput. Vis. Pattern Recog., 2005, pp. 568–573.

[33] M. Lyons, J. Budynek, and S. Akamatsu, "*Automatic classification of single facial images*," IEEE Trans. Pattern Anal. Mach. Intell.,vol. 21, no. 12, pp. 1357–1362, Dec. 1999.

[34] A. Hadid, M. Pietikainen, and T. Ahonen, "*A discriminative feature space for detecting and recognizing faces*," in Proc. IEEE Comput.Soc. Conf. Comput. Vis. Pattern Recog., 2004, pp. 797–804.

[35] S. L. Happy, A. George, and A. Routray, "*A real time facial expression classification system using local binary patterns*," in Proc. 4th Int. Conf. Intell. Human Comput. Interaction, 2012, pp. 1–5.

[36] A. Dhall, A. Asthana, R. Goecke, and T. Gedeon, "*Emotion recognition using PHOG and LPQ features*," in Proc. IEEE Int. Conf.Autom. Face Gesture Recog. Workshops, 2011, pp. 878–883.

[37] C. Shan, S. Gong, and P. W. McOwan, "*Facial expression recognition based on local binary patterns: A comprehensive study*,"Image Vis. Comput., vol. 27, no. 6, pp. 803–816, 2009.

[38] K. I. Kim, K. Jung, and H. J. Kim, "*Face recognition using kernel principal component analysis*," IEEE Signal Process. Lett., vol. 9,no. 2, pp. 40–42, Feb. 2002.

[39] A. J. Calder, A. M. Burton, P. Miller, A. W. Young, and S. Akamatsu, "*A principal component analysis of facial expressions*," Vis. Res., vol. 41, no. 9, pp. 1179–1208, 2001.

[40] H.-B. Deng, L.-W. Jin, L.-X. Zhen, and J.-C. Huang, "*A new facial expression recognition method based on local Gabor filter bank and PCA plus LDA*," Int. J. Inform.

Technol., vol. 11, no. 11, pp. 86–96, 2005.

[41] Z. Zhang, Y. Yan, and H. Wang, "*Discriminative filter based regression learning for facial expression recognition,*" in Proc. 20th IEEE Int. Conf. Image Process., 2013, pp. 1192–1196.

[42] C. Shan, S. Gong, and P. W. McOwan, "*A comprehensive empirical study on linear subspace methods for facial expression analysis*,"in Proc. IEEE Conf. Comput. Vis. Pattern Recog. Workshop, 2006,pp. 153–153.

[43] S.-K. Oh, S.-H. Yoo, and W. Pedrycz, "*Design of face recognition algorithm using PCA-LDA combined for hybrid data pre-processing and polynomial-based RBF neural networks: Design and its application*," Expert Syst. Appl., vol. 40, no. 5, pp. 1451–1466, 2013.

[44] Y. Rahulamathavan, R.-W. Phan, J. A. Chambers, and D. J. Parish,"*Facial expression recognition in the encrypted domain based on local fisher discriminant analysis*," IEEE Trans. Affective Comput.,vol. 4, no. 1, pp. 83–92, Jan.-Mar. 2013.

[45] H. Mohammadzade and D. Hatzinakos, "*Projection into expression subspaces for face recognition from single sample per person,*"IEEE Trans. Affective Comput., vol. 4, no. 1, pp. 69–82, Jan.-Mar. 2013.

[46] S. Moore and R. Bowden, "Local binary patterns for multi-view facial expression recognition," Comput. Vis. Image Understanding, vol. 115, no. 4, pp. 541–558, 2011.

[47] L. Zhong, Q. Liu, P. Yang, B. Liu, J. Huang, and D. N. Metaxas, "Learning active facial patches for expression Analysis," in Proc.IEEE Conf. Comput. Vis. Pattern Recog. 2012, pp. 2562–2569.

[48] L. Unzueta, W. Pimenta, J. Goenetxea, L. P. Santos, and F. Dornaika, "Efficient generic face model fitting to Images and videos," Image Vis. Comput., vol. 32, no. 5, pp. 321–334, 2014.

[49] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., 2001, pp. 511–518.

[50] D. Nguyen, D. Halupka, P. Aarabi, and A. Sheikholeslami, "Realtime face detection and lip feature extraction using field-programmable gate arrays," IEEE Trans. Syst., Man, Cybern., Part B: Cybern.,vol. 36, no. 4, pp. 902–912, Aug. 2006.

[51] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 3rd ed.Pearson Education, New Jersey, US, 2008.

[52] N. Otsu, "A threshold selection method from gray-level histograms,"IEEE Trans. Syst., Man Cybern., vol. 9, no. 1, pp. 62–66,Jan. 1979.

[53] T. Ojala, M. Pietikainen, and T. Maenpaa, "*Multiresolution grayscale and rotation invariant Texture classification with local binary patterns*," IEEE Trans.Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987,Jul. 2002.support vector machines," IEEE Trans. Neural Netw, vol. 13, no. 2,pp. 415–425, Mar. 2002.

[54] C.-W. Hsu and C.-J. Lin, "*A comparison of methods for multiclass support vector machines*," IEEE Trans. Neural Netw., vol. 13, no. 2,pp. 415–425, Mar. 2002

[55] M. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba, "*Coding facialexpressions with gabor wavelets*," In Proc. Third IEEE Int. Conf.Automat. Face Gesture Recog., 1998, pp. 200–205.