A SURVEY ON FACIAL EXPRESSION RECOGNITION ROBUST TO PARTIAL OCCLUSION

Sreelakshmi P[1], Sumithra M D[2]

[1]*MTech Student, Dept. Of Computer Science & Engineering, LBS Institute of Technology for Women, Kerala, India*
[2]*Professor, Dept. Of Computer Science & Engineering, LBS Institute of Technology for Women, Kerala, India*

---***---

Abstract - Over the years, many efforts have been done in the progress of automatic Facial Expression Recognition. The development of an automatic emotion recognition system is a challenging task and has many applications in behavior prediction, entertainment, security, health and human-computer interaction. Majority of researches in this field are mainly based on non-occluded facial images collected in a constrained laboratory environment, which do not reflect real-world scenarios. However, facial occlusions are common in real-life situations. In the recent years, it is shown an increase in the studies of Facial Expression Recognition system which is able to handle partial occlusions. This survey presents a review of approaches in Facial Expression Recognition in the presence of partial occlusions.

***Key Words*: Facial Expression Recognition, Partial Occlusion, Emotion Recognition**

1.INTRODUCTION

Emotion indicates the mental condition of human personality and manners of thinking. Facial expressions are non-verbal mode of communication among all human beings. Automatic Expression Recognition has potential applications in online tutoring systems, students stress level assessments, on board Expression detection of drivers, emotionally sensitive robots, personalized service provisions, entertainment and many more. The universally recognized facial expressions of Emotion are anger, disgust, fear, happiness, sadness and surprise. The three main stages in an automatic Facial Expression Recognition system are face detection, facial feature extraction and emotion recognition. Psychologists created a set of facial muscle movements known as Action units for making the facial expression recognition process more standardized. That is termed as Facial Action Coding System(FACS)[24].

A persistent issue on creating Facial Expression Recognition systems is that majority of them are based on images that doesnt consider real-world scenarios. Furthermore, it experiences many challenges which includes occlusions, pose variations, illumination changes and changes in gender, age and skincolor. In addition to, most of the image datasets are made out of non-occluded and frontal-view images. An ideal Facial Emotion Recognition system should have the capacity to deal with every one of these challenges. Eventhough a lot of studies are made to consider the various challenges of emotion recognition, the area of partial occlusions have been touched the least.

In real-world scenarios, faces can be easily occluded either passively or actively which can obstruct the accurate expression recognition. It is quite usual that peoples faces can be obstructed by other people in a crowd, hands, hair, moustache or any facial accessories like scarf, sunglasses, hat, masks etc. The presence of these occlusions can deadly affect the automatic Facial Expression Recognition process due to imprecise facial feature localization, errors in alignment or face registration. The literature studies reveal that Facial Expression recognition systems can attain high accuracy in a restricted environment but they suffer significant degradation in performance with these occlusions.

Works on expression recognition in a constraint conditions has been in scene for past many years but recognition under unconstraint environments is a recent issue. In prior studies on Facial Emotion Recognition, no investigation revealed explicitly structured methods to overcome facial occlusion. In 2001 Bourel et al[1] was the first to propose a machine system for Facial Expression Recognition which can handle partial occlusion by recovering the geometric facial points in upper face, mouth and left/right half of face. With the improvement in deep learning methods, recent studies have concentrated on the application of deep Neural Networks to specifically perform Facial Expression Recognition on occluded face images without going through the ordinary steps. Instead of giving an extensive overview on all previous methodologies on Facial Expression Recognition, this survey concentrates on those that have explained or researched Expression Recognition of facial images with partial occlusion.

2. FACIAL EXPRESSION RECOGNITION APPROACHES

Based on the methodologies used for handling he partial occlusion he Facial Expression Recognition approaches can be classified into feature reconstruction based approach,sparse coding based approach, sub-space based approach,statistical prediction model based approach and deep neural network based approach.

2.1 Feature reconstruction based approach

The impact of partial occlusion in facial images are overcome in feature reconstruction based approach by reconstructing the geometric or texture features of the face image.

Towner et al.[2] described three PCA based procedures to reconstruct the regions of upper and lower missing facial feature points. The results demonstrated that more facial expression related informations are concentrated on the lower part of the face. The reconstructed feature points then supply into the Support Vector Machine (SVM) for classifying among six facial emotions.

Zhang et al.[3] proposed a method which is able to detect 54 facial points from face images having occlusions and pose variations by using Iterative Closest Point(ICP) algorithm, Binary Robust Invariant Scalable Keypoints(BRISK), Gabor filtering and Fuzzy C-Means(FCM) clustering. Inorder to deal with facial occlusions, a neutral landmark is generated initially in the occluded regions by applying ICP and then by using FCM, the shape of occluded part in the face region are constructed with the help of previous knowledge of non-occluded facial elements. Further reconstruction of occluded regions are done by the post processing to attain the geometry that fit best. To obtain 18 AUs and to recognize seven emotions plus neutral expression, this geometry of facial points were used and it was achieved with the help of Support Vector Regression(SVR) and Artificial Neural Networks(ANNs). More than 78% accuracy is obtained under facial occlusions of top and bottom facial regions.

The techniques focused on texture appearance reconstruction is mainly based on Robust PCA(RPCA) algorithm. Mao et al.[4] proposed an approach of detecting occlusion using RPCA algorithm and saliency detection for robust emotion recognition. Occluded regions are reconstructed using RPCA projection and classification of emotions is performed using a reweighted AdaBoost algorithm. On conducting experiments on Beihang University Facial Expression (BHUFE) and JAFFE databases this mehod attained an accuracy rates of 59.30%, 84.80% and 68.80% for handling hand, hair and sunglasses occlusions separately.

Cornejo et al.[5] proposed an approach in which initially occluded regions of face are reconstructed using RPCA followed by the CENsus Transform hISTogram (CENTRIST) features were extracted from facial expression representation. K-nearest neighbor (KNN) and Support Vector Machine (SVM) classifiers are used for facial expression recognition.This method achieves an accuracy rate above 90% even for non-occluded images.

2.2 Sparse coding based approach

Training samples are treated as a dictionary by the sparse coding approach and robust object recognition is done using a sparse representation of a test image. A linear combination of training images belonging to the same class is used for its formation. Given a target occluded face image, they can compute the sparse coefficient to classify the subject in the image. If the individuals of the training classes look different and the training samples for each class are sufficiently large, most non-zero values for the coefficient vector fall in one class and the vector is naturally sparse. The sparse coefficients vector are used to generate an non-occluded image of the target using the weighted sum of training images.

The first work in applying the Sparse Representation Classifier (SRC) into Facial Expression recognition is proposed by Cotter[6]. SRC yields good results compared to the Gabor and Eigenfaces features with an ANN or SVM classifier.Using SRC, sparse representation of an unknown test image is found using the known training samples.Each image is represented using the pixel values and l_1 minimization is used to get its sparse representation, which is used directly for the classification purpose. They also identified that the use of black and white color in block occlusions also affect the performance.

Cotter[19] improved his previous work[6] by employing splitting of the facial image into smaller equal sized subim-ages and a separate Sparse Representation Classifier(SRC) classifies expressions at each region.The classification decision obtained from each region is combined to reach a final decision.To get better results for recognition of emo tions under occlusion conditions, a voting method called Weighted Voting SRC method is introduced which assign a vote for each class in the region by taken into account the class representation error.It out performs the previous SRC based method and Gabor based methods for facial occlusions >25%.

To attain more robustness and effectiveness in sparse representation, Liu et al.[7] propose a maximum likelihood estimation sparse representation (MLESR) model.The sparse coding is shown in this paper as a sparsely constrained robust regression problem. So as to reduce the impact of facial occlusion, different weights are assigned to pixels in occluded regions and iteratively updated until a convergence is obtained. For test image, is final sparse representation is obtained by using optimal weight matrix and its emotion class is determined by minimal residual associated with this image.The MLESR obtained better results than SRC and Gabor based SRC (GSRC) under random occlusion.

Ouyang et al. [8] proposed a method which use Local Binary Pattern (LBP) maps. They suggested conjunction of LBP maps and SRC framework which was found to out-perform existing methods of SRC for solving eye occluded and corrupted images. This method attain an average 72.39% recognition rates when 30% of the face is occluded at the eye region.

Haung et al.[23] integrated the component-based feature descriptors, sparse-representation based occlusion detection and a video sequence based weight learning for facial expression to get a Facial Expression Recognition system especially under occlusion. The features were extracted from the eyes, nose and mouth components on the video sequences by using Spatio-Temporal Local Binary Pattern(STLBP) and Edge Map. Sparse Representation is used for occlusion detection and finding the occluded parts in these components. The six feature vectors generated from three components concatenated into one by using the a multiple feature fusion which consist of a fusion module and weight learning via multiple kernel learning. This method achieved a recognition rate of 93%, 79.08% and 73.54% for eyes, mouth and lower-face occlusion respectively in CK+ database images.

2.3 Sub-space based approach

The sub-space based methodologies treat the entire facial region as comprising of a set of local sub-regions and try to diffuse data from its neighborhood non-occluded regions.

Zhang et al. [9] proposed a feature fusion approach robust to occlusions based on Monte Carlo algorithm for extracting a set of Gabor based templates from image data sets.Then, template matching is applied to find the most similar features located within a space around the extracted templates, generating features robust to occlusion. A linear SVM is used to select a set of distance features from whole feature set. Results showed that this method is robust to eyes or mouth occlusions, achieving accuracy rates of 95.1% (eye occlusion) and 90.80% (mouth occlusion) for CK dataset; and 80.30% (eye occlusion) and 78.40% (mouth occlusion) for JAFFE data set.However, this approach obtained 75.00% and 48.80% recognition rates for CK and JAFFE databases respectively, when randomly occluded patches where applied over faces in both training and testing phases.

Shuai-shi Liu et al.[22] suggested using Gabor multi-orientation features fusion and local Gabor binary pattern histogram sequence (LGBPHS) for Facial Expression Recognition under partial occlusion. Initially the image is transformed to get a Gabor Magnitude Pictures using Gabor filters and by using fusion rule the Gabor features of multiple orientations in the same scale were fused. Lastly, each LGBP Map is further divided into non-overlapping rectangle regions with equal size and the histogram of each unit is computed and combined as facial expression features. Support Vector Machine(SVM) is further used for the classification of expressions. LGBPHS based method attained an accuracy rate of 86%, 92%, 90% and 91% for eyes, mouth, left half and right half occlusions respectively.

Rui Li et al.[21] applies a feature extraction method that combines Gabor filters and gray-level co-occurrence matrix(GLCM) for the process of Facial Expression Recognition in the presence of occlusion. The facial features were extracted using these methods and by the linear combination of the image features a group of low dimensional feature vector are formed. Finally, the feature vector is normalized by Gaussian normalization and the Gabor feature statistics is linearly superimposed by the texture features extracted based on GLCM. For the classification process K-Nearest Neighbors (K-NN) method is used. Achieves higher recognition rate compared to traditional Gabor algorithm and F-LGBPHS algorithm.

Guo and Ruan[20] came up with a local feature descriptor named local binary covariance matrices (LBCM) which is based on Region Covariance Matrices(RCM).Using LBCM, for each region of interest a covariance matrix is constructed with location, intensity and local binary pattern of each pixel. The distance between the covariance matrices from gallery and probe sets is considered inorder to improve robustness against partial occlusions and also discard the contributions from regions at maximal distance. LBCM attain an recognition accuracy rate of 93.65% for eye occlusions and 92.86% for mouth occlusion.

Dapogny et al.[18] presented a Weighted Local Sub-space Random Forest (WLS-RF) framework to deal with the problem of Facial Expression Recognition under the presence of partial occlusion. The proposed work trained Randomized trees by utilizing local subspaces in a random facial masks form. A hierarchical autoencoder network is utilized to obtain local face pattern manifolds and local confidence scores were obtained based on the reconstruction error outputted by this network. These confidence weights are given into the feature point alignment framework to improve the robustness of the feature point alignment in images having partial occlusions. WLS-RF attain a accuracy rate of 67.1% under mouth occlusion when the training of classifiers are done on non-occluded faces and testing on occluded faces.

Liu et al. [10] employed a maximum decision fusion of equally sized facial sub-regions. From each sub-region, Weber Local Descriptor Histogram (WLDH) features were extracted and fed into an SVM classifier. The SVM outputs from all sub-regions were combined using a maximum function. The approach achieved more than 87% accuracy for the mouth, eyes, left and right side occlusions in the face using JAFFE images.

2.4 Statistical prediction Model based Approach

The statistical prediction model based approaches use the temporal correlations between the neighboring video frames or spatial dependent information in non-occluded parts in static images to infer the features of occluded regions.

Tan Dat et.al [11] employed a corrective feedback mechanism using a Bayesian framework to the Kanade Lucas Tomasi (KLT) tracker to reliably track facial expressions of people under different head movements and obstructions by hand.The Bayesian feedback mechanism includes a Probabilistic Principal Component Analysis(PPCA) and an online update scheme which helps to adapt people with different face shape.The tracked inputs where fed into the recognition system comprising of seven Hidden Markov Model(HMM) and a Neural Network(NN) to identify four common facial expressions.The proposed tracker had a accuracy rate reduction from 69% to 62% compared to KLT while considering hand occlusions but, if it is trained and tested using the same tracker it will give better outcomes.

Hamma et al.[12] proposed a method to recognize facial expression from images having partial occlusion by considering facial point deformations and a modified Transferable Belief Model(TBM).In order to simulate the different facial occlusions bubble masks are added to the face and the classification task is handled by TBM. TBM is capable of managing a number of imprecise informations and also provide tools for integrating them.

Miyakoshi et al.[13] came up with a Bayesian network based emotion detection system by using facial feature. The characteristics of Bayesian Network classifier to understand the dependencies between target facial expression and explanatory variables make it possible to detect facial emotions without filling the gaps of occlusion. The Bayesian network structure is learned in two phases such as internal phase where K2 algorithm is used to derive the structure of facial features and an external phase to learn the causal relationships among facial features and emotions.This method attained more than 50% recognition rates for facial emotions considering occlusions.

2.5 Deep Neural Networks based approaches

Deep learning techniques is attaining increased acceptance in the Facial emotion recognition field.With the assistance of Deep Neural Networks (DNNs), more promising outcomes are accounted in the emotion recognition areas. It has the advantage of learning more abstract patterns automatically and progressively from raw image pixels in a multiple layer architecture. While traditional approaches use hand-engineered features to train classifiers, DNN can extract more critical facial features which yield better interpretation of the texture of human face.

Ranzato et al.[14] put forward a method which used a gated Markov Random Field(MRF),an efficient generative model, as the lowest layer of Deep Belief Network (DBN).To learn the statistical structure within the hidden activities of the gated MRF the DBN utilizes many layers of Bernouilli hidden variables.In order to fill the occluded region the occluded image is propagated through the four layers using the sequence of posterior distributions. The reconstruction process will occur in the generative direction starting from the top layer representation using the sequence of conditional distributions and the last step comprise of reconstructing the missing pixels with the use of both known pixels and first-layer hidden variables which provide the missing pixels Gaussian distribution.The features where extracted from reconstructed face regions and fed to a linear classifier for emotion recognition. However, training such a model is computationally expensive.

Cheng et al. [15] proposed a deep structure for expression recognition build on Gabor features. The deep learning structure used is a Deep Belief Networks (DBN) that consists of a group of Restricted Boltzmann Machines (RBM). After normalizing the facial images they transformed into Gabor magnitude images by multi-scales and multi-orientations Gabor filters and given as input into a three-layer RBN for the emotion classification process. The deep structure training process is divided into pre-training and fine-tuning steps for generating the best weight for encoding the face structure which contain occlusions.This method obtain 82.86% of performance accuracy rate on the face images with occlusion of eyes, mouth and lower face.

Xu et a.[16] introduced a facial expression recognition model that rely on transfer features from trained deep convolutional networks (ConvNets) which shows robustness to occlusion. The deep ConvNets consist of four convolutional layers which include max-pooling to extract features level by level, the fully-connected high-level features layer and softmax output layer for predicting the identity classes. The model merge high-level features of two trained deep ConvNets with the same structure and fed into the seven class SVM classifier to classify expressions to one of the six basic emotions plus neutral emotion states. The deep ConvNets model achieved average 81.50% accuracy on the self-built expression database for classifying emotions considering occlusions.

Yong Li et al.[17] proposed a Patch-Gated Convolution Neural Network(PG-CNN) that can detect the occluded facial regions automatically.To decide the regions of interest on the face an intermediate feature map is divided into several patches and each local patch is encoded as a weighted vector by a Patch-Gated Unit. Finally, a representation of occluded face is made by concatenating the weighted local features.The face image is classified among one of the emotional states which is employed using three fully connected layers.

3. ANALYSIS OF DIFFERENT FACIAL EXPRESSION RECOGNITION METHODS IN THE PRESENCE OF PARTIAL OCCLUSION

- Feature reconstruction based approaches provide robustness to occlusions by reconstructing the features based on face configuration from occluded regions. But, they require reliable face detection and facial feature tracking.For reconstructing texture factors precise face alignment, occlusion detection and normalization are needed.
- Sparse coding based approaches are not only robust to small occlusion but can used for estimating occluded or corrupted parts in face region.But their performance dependent on the assumption that the test and training data are linearly correlated. This method also require precise face alignment,location and normalization for feature extraction.
- Subspace based approaches are based on the assumption that occlusions are present only in small part of the face regions, thus their effects can be minimized by feature selection method or by a decision voting strategy. Its performance depend on the subdivision of face image into local regions and this approaches are very sensitive to noise due to imprecise face alignment, face location and normalization.
- Statistical prediction model utilizes spatial relationships or temporal informations inorder to infer the features in occlude regions and they are closer to the real-life situations. The problem lies in the complexity of creating the ground data and requirement for suitable face tracker.
- Deep Neural Networks based approaches doesn't require separate occlusion detection of feature recovery,instead they automatically do the feature extraction process. They have some constrains which include the requirement of large training data, fine-tuning large system parameters and heavy computation.

Table-1: Analysis of Facial Expression Recognition method in the presence of partial occlusion

Author /Year	**Feature Extraction**	**Classifier**	**Occlusion**	**Acc. (%)**
Towner et al. 2007[2]	PCA	Support Vector Machine [SVM]	upper and lower face	70, 82
Zhang et al. 2015[3]	Gabor filtering, BRISK, ICP algorithm, FCM clustering	SVR+ANN	top and bottom face region	>78
Mao et al. 2009[4]	Robust PCA(RPCA) and saliency detection	Reweight-ed Adaboost	hand, hair and sunglasses	59, 85 and 69
Cornejo et al. 2010[5]	CENsus Transform hISTogram (CENTRIST)	SVM or KNN	left/right face and bottom face	92(JAFFE) and 90 (CK+)
Cotter. S. F 2010a[6]	raw pixels	Sparse Representation Classifier (SRC)	noise, block	>91
Cotter.S.F 2010b [19]	raw pixels	Weighted Voting Sparse Representation Classifier (WVSRC)	upper/lower face, block	64, 77, 68
Liu et al. 2014d[7]	raw pixels	Maximum Likelihood Estimation Sparse Representation (MLESR)	random block	87 (JAFFE) and 85 (CK)
Ouyang et al. 2013[8]	LBP Map	SRC	eyes, corruption	72, 87
Zhang et al. 2014b[9]	Gabor-based template	SVM	eyes, mouth, blocks	80,78, 49,80, 75(JAFFE) 95,90, 75,95, 92(CK)

Dapogny et al. 2016[18]	point distance + Histogram of oriented gradients (HOG)	Weighted Local Subspace Random Forest (WLSRF)	eyes, mouth	72,67 (CK+)
Liu.S.et al. 2014c [10]	Weber Local Descriptor Histogram (WLDH)	SVM + Decision Fusion	eyes, mouth, left/right face	87,90, 90,91
Tan Dat et al. 2008[11]	point distance	Hidden Markov Model(HMM) + ANN	hand	62
Hammal et al. 2009[12]	point distance	Modified TBM	bubble	N/A
Miyakoshi et al. 2011[13]	point displacement	Bayesian Network	eyes, brow, mouth	67,56, 50
Ranzato et al. 2011[14]	raw pixel + Markov Random Field(MRF) + deep belief network(DBN)	linear classifier	eyes, mouth, nose, 70\%, random, right/bottom/top face	N/A
Cheng et al. 2014[15]	Gabor	Deep Belief Networks (DBN)	eyes, mouth, lower/upper face	83, 83, 83, 77
Xu et al. 2015[16]	transfer features from deep convolutional networks (ConvNets)	SVM	block	81.50
Li et al. 2018[17]	feature maps	Patch-Gated Convolution Neutral Network (PG-CNN)	synthetic occlusion	86.27(CK+), 86.27 (MMI)
Song Guo et al. 2011[20]	Local Binary Covariance Matrices (LBCM)	nearest neighbor	eyes, mouth	94, 93
Rui Li et al. 2015[21]	Gabor filters and gray-level co-occurrence matrix (GLCM)	K-Nearest Neighbor (KNN)	Eyes, Mouth, Upper, Lower Left, Right	91,87, 91,84, 87,90, 89(JAFFE) and 85,82, 81,75, 88,82 (RAFD)
Shuai-Shi et al. 2013[22]	Local Gabor Binary Pattern Histogram Sequence (LGBPHS)	SVM	eyes, mouth, left/right face, scarf, sunglass	86, 92, 90, 91, 88, 83
Huang et al. 2012[23]	Spatio-Temporal Local Binary Pattern(STLBP) /edge map	Weight Learning based Feature Fusion (WLFF)	eyes, mouth, lower-face, block	93, 79, 74, 80

4. CONCLUSIONS

This paper reviewed various Facial Expression Recognition approaches for handling partial occlusions. Eventhough, a lot of studies were made in the domain of handling facial occlusions not many researches have been introduced to completely overcome the problem of partial occlusions in Facial Expression Recognition. Many authors have worked on Facial Expression Recognition systems under controlled environments but with uncontrolled conditions less work has been focused. Most researchers have considered artificially generated occlusion and frontal faces, but number of studies considering real-world occlusions and number of prototypical emotion categories are still very limited. The sparse coding based approach and sub-space based approach are mainly used for Facial Expression recognition from static images while statistical prediction model is focused on temporal video based emotion recognition. Feature reconstruction based approach and Deep Neural Networks based approaches can be used for both cases. From the approaches reviewed, Sparse coding based approaches and Deep Neural Networks based approaches give more effective results in the presence of partial occlusions.

REFERENCES

[1] F. Bourel, C. C. Chibelushi, and A. A. Low. Recognition of facial expressions in the presence of occlusion, 2001.

[2] Towner. H. and Slater. M. 2007. Reconstruction and Recognition of Occluded Facial Expressions Using PCA. Affective Computing and Intelligent Interaction, 36-47.

[3] Li Zhang, Kamlesh Mistry, Ming Jiang, Siew Chin Neoh and Mohammed Alamgir Hossain. 2015. Adaptive facial point detection and emotion recognition for a humanoid robot. Computer Vision and Image Understanding. 140, 93-114.

[4] X. Mao, Y. Xue, Z. Li, K. Huang, and S. Lv. Robust Facial Expression Recognition based on RPCA and AdaBoost. In 10th Workshop on Image Analysis for Multimedia Interactive Services, pages 113–116, May 2009.

[5] Cornejo. J. Y. R. and Pedrini. H. 2016. Recognition of occluded facial expressions based on CENTRIST features. IEEE International Conference on Acoustics, Speech and Signal Processing, 1298-1302.

[6] Cotter. S. F. 2010a. Sparse Representation for accurate classification of corrupted and occluded facial expressions. IEEE International Conference on Acoustics Speech and Signal Processing, 838-841.

[7] Liu. S. S., et al. 2014d. Facial expression recognition under random block occlusion based on maximum likelihood estimation sparse representation. International Joint Conference on Neural Networks, 1285-1290.

[8] Ouyang. Y., et al. 2013. Robust automatic facial expression detection method based on sparse representation plus LBP map. Optik - International Journal for Light and Electron Optics 124, 24, 6827-6833.

[9] Zhang. L., et al. 2014b. Random Gabor based templates for facial expression recognition in images with facial occlusion. Neurocomputing 145, 0, 451-464.

[10] Liu. S., et al. 2014c. Facial expression recognition under partial occlusion based on Weber Local Descriptor histogram and decision fusion. 33rd Chinese Control Conference, 4664-4668.

[11] Tan Dat. N. and Ranganath. S. 2008. Tracking facial features under occlusions and recognizing facial expressions in sign language. 8th IEEE International Conference on Automatic Face & Gesture Recognition, 1-7.

[12] Hammal. Z., et al. 2009. Comparing a novel model based on the transferable belief model with humans during the recognition of partially occluded facial expressions. Journal of Vision 9, 2, 1-19.

[13] Miyakoshi. Y. and KATO, S. 2011. Facial emotion detection considering partial occlusion of face using Bayesian network. IEEE Symposium on Computers & Informatics, 96-101.

[14] Marc'Aurelio Ranzato, Joshua Susski,Volodymyr Mnih and Geoffrey Hinton. 2011. On deep generative models with applications to recognition. IEEE Conference on Computer Vision and Pattern Recognition, 2857-2864.

[15] Yue Cheng, Bin Jiang and Kebin Jia. 2014. A Deep Structure for Facial Expression Recognition under Partial Occlusion. Tenth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, 211-214.

[16] M. Xu, W. Cheng, Q. Zhao, L. Ma, and F. Xu, "Facial expression recognition based on transfer learning from deep convolutional networks," in Natural Computation (ICNC), 2015 11th International Conference on.IEEE, 2015, pp. 702–708.

[17] Yong Li, Jiabei Zeng, Shiguang Shan and Xilin Chen. 2018. Patch-Gated CNN for Occlusion-aware Facial Expression Recognition.24th International Conference on Pattern Recognition (ICPR).

[18] Arnaud Dapogny, Kévin Bailly, Séverine Dubuisson. 2016. Confidence-Weighted Local Expression Predictions for Occlusion Handling in Expression Recognition and Action Unit detection. arXiv preprint arXiv:1607.06290.

[19] Cotter. S. F. 2010b. Weighted Voting Of Sparse Representation Classifiers For Facial Expression Recognition. 18th European Signal Processing Conference, 1164-1168.

[20] Song Guo, Qiuqi Ruan. 2011. Facial expression recognition using local binary covariance matrices. 4th IET International Conference on Wireless, Mobile & Multimedia Networks, 237-242.

[21] Rui Li, Pengyu Liu, Kebin Jia, Qiang Wu.2015.Facial (xpression Recognition under Partial Occlusion Based on Gabor Filter and Gray-level Co-occurrence Matrix. IEEE 2015 International Conference on Computational Intelligence and Communication Networks

[22] Shuai-shi Liu, Yan Zhang, Ke-ping Liu and Yan Li.2013.Facial Expression Recognition under Partial Occlusion Based on Gabor Multi-orientation Features Fusion and Local Gabor Binary Pattern Histogram Sequence. IEEE Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing.

[23] Xiaohua Huang, Guoying Zhao, Wenming Zheng and Matti Pietikäinen.2012.Towards a dynamic expression recognition system under facial occlusion. Pattern Recognition Letters 33, 16, 2181-2191.

[24] EKMAN, P., FRIESEN, W. 1978. The Facial Action Coding System: A technique for the measurement of facial movement.Consulting Psychologists Press, Palo Alto, CA, USA, 274-280.