

Facial Expression Recognition Using Depth Information and Spatiotemporal Features

Md. Zia Uddin

Dept. of Computer Education, Sungkyunkwan University, Seoul, South Korea

ziauddin@skku.edu

Abstract— Facial expression recognition is considered to be one of the very important topics in image processing, pattern recognition, and computer vision due to its broad applications such as human-computer interaction, behavior analysis, and image understanding. In this work, a novel approach is proposed to recognize some facial expressions from time-sequential depth videos. First of all, efficient Local Directional Pattern (LDP) features are obtained from the time-sequential depth faces that are further augmented with the optical flow features. The augmented features are classified by Generalized Discriminant Analysis (GDA) to make the features more robust and finally, the spatiotemporal features are fed into Hidden Markov Models (HMMs) to train and recognize different facial expressions successfully. The depth information-based proposed facial expression recognition approach is compared to the conventional approaches where the proposed one outperforms others.

Keywords—Facial Expression, LDP, Optical Flows, GDA, HMM.

I. INTRODUCTION

Video cameras are nowadays very widely utilized for various surveillance applications such facial expression recognition (FER), which provides computers a way of sensing a peoples' emotion [1]-[10]. In case of extracting expression images through RGB cameras, most of the FER works used Principal Component Analysis (PCA), which is very well known for dimension reduction and used in many earlier works. In [3], PCA was used to recognize Facial Action Units (FAUs) from the facial expression images. In [5] as well as [6], PCA was used for FER with the Facial Action Coding System (FACS). Very recently, Independent Component Analysis (ICA) has been extensively utilized for FER based on local face image features [5], [10], [11]-[21]. In [14], the authors used ICA to extract local features and then classified several facial expressions. In [15], ICA was used to recognize the FAUs. Besides ICA, Local Binary Patterns (LBP) has been used lately for FER [22]-[24]. The main property of LBP features is their tolerance against illumination changes as well as their computational simplicity. Later on, LBP was improved by focusing on face pixel's gradient information and named as Local Directional Pattern (LDP) to represent local face features [25]. As like as LBP, LDP features also have the tolerance against illumination changes but they represent much robust features than LBP due to considering the gradient information for each pixel as aforementioned [25]. Thus, LDP can be a robust approach and hence can be adopted for FER. Although the LBP-based features seem to be useful for expression

recognition, all expressions follow the different motion information and hence should be separated well if one utilizes motion information such as optical flows in the consecutive expression images. Regarding the motion information-based facial expression recognition, several works have been done to describe various expressions [26], [27]. Thus, by augmenting the LBP features with the optical flow features, one should be able to come up with robust facial expression recognition systems. A robust discriminant analysis called General Discriminant Analysis (GDA) has recently been used in different applications where GDA significantly shows the superiority over the traditional feature extraction approaches such as PCA and LDA [28], [29]. Thus, GDA can be a robust tool to be used to obtain better discrimination among the face images from different expressions. However, RGB faces captured through a normal RGB camera cannot provide the depth of the far and near parts of human face in the facial expression video where the depth information can contribute to extract efficient features to describe the expression more efficiently. On the contrary, depth faces obtained through the depth camera can be employed to represent better FER. In depth-based face images, the pixel values are set based on the distance to the camera. Hence, depth images can represent better expression than the normal RGB camera images. Thus, the depth video should allow one to come up with more efficient person independent FER. For modeling time-sequential events such as FER, Hidden Markov Model (HMM), a robust has been very popular [1], [6]. Hence, HMMs can be used on the features of different facial expressions for time-sequential FER.

In this work, a novel approach is proposed for FER in combination of LDP, optical flows, GDA, and HMM using facial expression images obtained through a depth camera. The local LDP features are extracted first from the facial expression depth images and are then augmented with the optical flow motion features. The augmented LBP and motion features are then classified via GDA. Each of these local features are then compared to the codebook vectors generated from the training facial expression depth image features and converted to discrete symbols. Finally, the generated symbol sequences are utilized to train the HMMs of the facial expressions to be applied later for recognition based on the highest likelihood.

II. PROPOSED FER APPROACH

First, a strong feature space is generated via LDP, optical motion flows, and GDA to project all the feature vectors

including training and testing. Then, discrete symbol sequences are generated from the features using vector quantization and applied on the corresponding expression HMM. For testing an expression image sequence, the testing symbol sequence is applied on all the trained HMMs and one is chosen with the highest likelihood. Fig. 1 shows the basic steps of training and testing of expressions through HMMs.

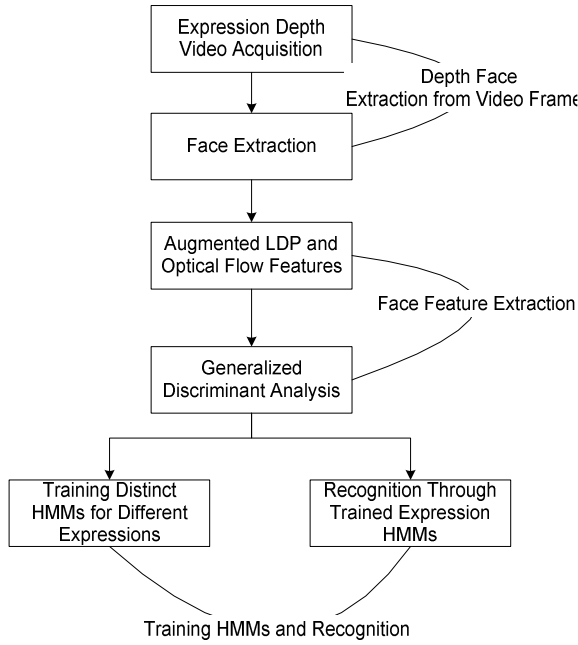


Figure 1. Basic steps involved in the proposed facial expression recognition system.

A. Pre-processing of Depth

The images of different expressions are captured by a depth camera [30] where the camera generates RGB and distance information (i.e., depth) simultaneously for the objects captured by the camera. Fig. 2 shows a depth and pseudo color image of a surprise expression where the pixel differences of different face parts are very much clear in depth and pseudo color images. Figs. 3(a) and (b) show five generalized depth faces from a surprise and anger expressions respectively.

B. LDP Feature Extraction

The Local Directional Pattern (LDP) assigns an eight-bit binary to each pixel of an input depth image. This pattern is then calculated by comparing the relative edge response values of a pixel in eight different directions. Kirsch, Prewitt and Sobel edge detector are some of the different representative edge detectors that can be used. Amongst which, the Kirsch edge detector [26] detects the edges more accurately than the others as it considers all eight neighbors. Given a central pixel in the image, the eight directional edge response values $\{d_i\}$, $i=0,1,\dots,7$ are computed by Kirsch masks D_i in eight different orientations centered on its position and Fig. 4 shows these masks.

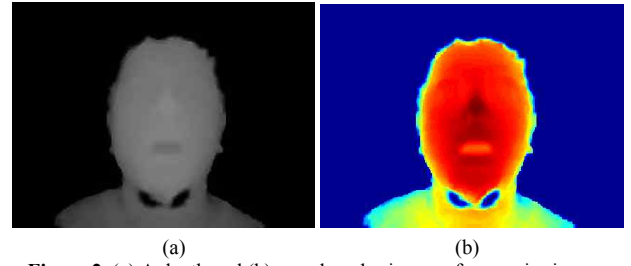


Figure 2. (a) A depth and (b) pseudo color image of a surprise image.

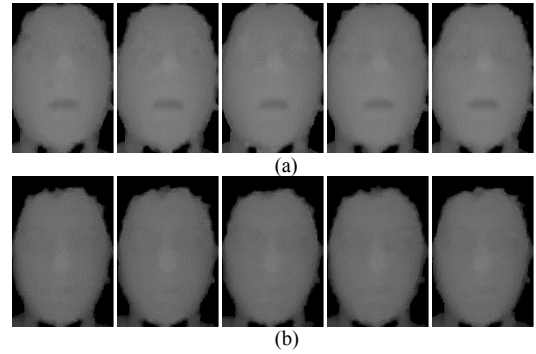


Figure 3. Example sequential depth images of (a) surprised and (b) anger facial expression.

$$LDP_p = \sum_{k=0}^7 Z_k (d_k - d_p) \times 2^k, \quad Z_k(a) = \begin{cases} 1 & a \geq 0 \\ 0 & a < 0 \end{cases} \quad (1)$$

where m_p is the p -th most significant directional response.

$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}$	$\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}$	$\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$	$\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$
east D_0	north east D_1	north D_2	north west D_3
$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}$	$\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}$	$\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}$	$\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$
west D_4	south west D_5	south D_6	south east D_7

Figure 4. Kirsch edge masks in eight directions.

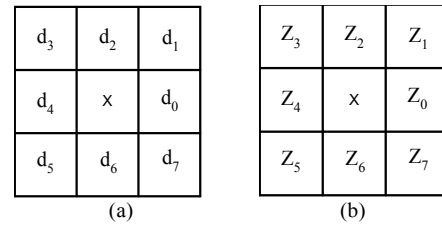
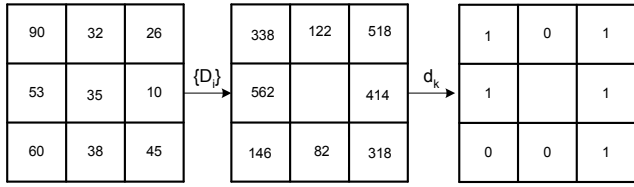


Figure 5. (a) Edge response to eight directions and (b) LDP binary bit positions.



LDP Binary Code=00011011 LDP Decimal Code=155
Figure 6. LDP code.

The presence of a corner or an edge represents high response values in some particular directions and therefore, it is interesting to know the p most prominent directions in order to generate the LDP. Here, the top- p directional bit responses d_k are set to 1. The remaining bits of 8-bit LDP pattern are set to 0. Finally, the LDP code is derived by (1). Fig. 5 shows the mask response as well as LDP bit positions and Fig. 6 an exemplary LDP code with $p=5$. Thus, an image is transformed to the LDP map using LDP code. The image textual feature is presented by the histogram of the LDP map of which the i^{th} bin can be defined as

$$T_i = \sum_{x,y} I\{LDP(x,y) = i\}, i = 0, 1, \dots, q-1 \quad (2)$$

where q is the number of the LDP histogram bins (normally $q = 256$) for an image I . Then, the histogram of the LDP map is presented as

$$H = (T_0, T_1, \dots, T_{q-1}). \quad (3)$$

To describe the LDP features, a depth silhouette image is divided into non-overlapping rectangle regions and the histogram is computed for each region. Furthermore, the whole LDP feature E is expressed as a concatenated sequence of histograms

$$E = (H^1, H^2, \dots, H^s) \quad (4)$$

where s represents the number of non-overlapped regions in the image. However, the LDP features from the depth faces can be represented as E .

C. Optical Flow Features

The optical flows of the facial expression images from the consecutive facial expression frames are obtained using Lucas-Kanade method [22]. Then, the flow region is divided into sub-blocks to compute the average flow vector. Fig. 7 shows two consecutive surprise images and corresponding optical flows. The vectors are then converted to a single row vector as

$$J = [\bar{O}_1, \bar{O}_2, \dots, \bar{O}_t] \quad (5)$$

where t is the number of average vectors and each element consists of two components along x- and y-axis.

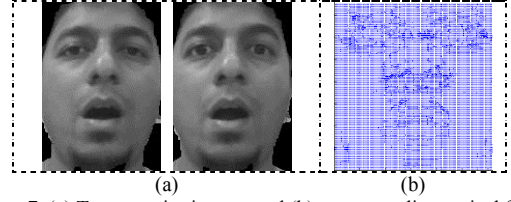


Figure 7. (a) Two surprise images and (b) corresponding optical flows.

D. Augmented LDP and Motion Features

From the above analysis, it can be noticed that both the feature extraction approaches extract robust features for FER. Hence, both the LDP and optical flow features for an expression image can be augmented together to get improved features. Thus, the augmented features a frame can be represented as

$$M = [E_1, E_2, \dots, E_y, J_1, J_2, \dots, J_z] \quad (6)$$

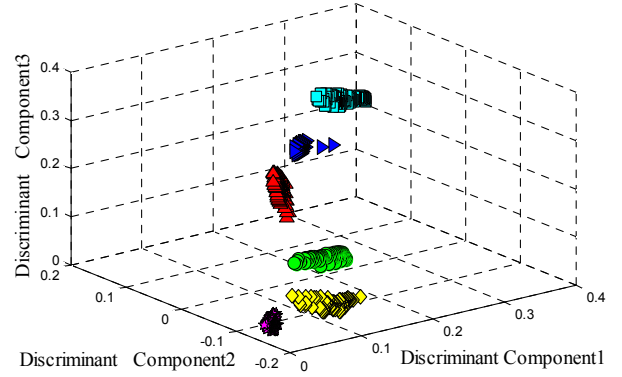


Figure 8. 3-D plot of GDA on augmented features of depth faces from four expressions.

E. GDA on Augmented Features

Generalized Discriminant Analysis (GDA) is a discriminant analysis approach that produces an optimal discriminant function that maps the input samples into the classification feature space on which the class identification of the samples is determined. Thus, the goal of GDA is to maximize following equation as

$$G_{GDA} = \frac{|V^T \theta_b V|}{|V^T \theta_t V|} \quad (7)$$

where θ_b and θ_t are the between-class and total scatter matrices of the depth face features after mapping them into a Gaussian kernel function. Thus, the depth face features of different expressions can be extended by GDA as

$$U = G_{GDA}^T M. \quad (8)$$

Fig. 8 shows an exemplar plot of 3-D GDA representation of the LDP features of all the facial expression depth images that shows a good separation among the representation of the depth faces of different classes.

F. HMMs for FER

To decode the depth information-based facial expression features, discrete HMM is employed. Since discrete HMMs are usually trained and tested with discrete symbol sequences, the features are to be symbolized by comparing with the codebook vectors. The codebook is developed by Linde, Buzo and Gray (LBG)'s algorithm on the depth face feature vectors from the training datasets [21]. HMMs have been used extensively to solve a huge number of complex problems in various applications [21]. A basic HMM can be denoted as

$$L = \{\lambda, \pi, A, B\}. \quad (9)$$

where the parameters of HMM λ , π , A , and B represent the possible states, initial probability of the states, state transition probability matrix, and observation symbols' probability matrix respectively.

Fig. 9 shows a trained Neutral expression. Details information regarding HMMs can be obtained from [21]. For testing a facial expression video for recognition, the obtained discrete observation symbol sequence W from the corresponding time-sequential depth images is used to determine the proper model by means of highest likelihood computation of all N trained expression HMMs as follows.

$$Expression = \arg \max_{k=1}^N (P(W | L_k)) \quad (10)$$

$$W = \{W_1, W_2, \dots, W_T\} \quad (11)$$

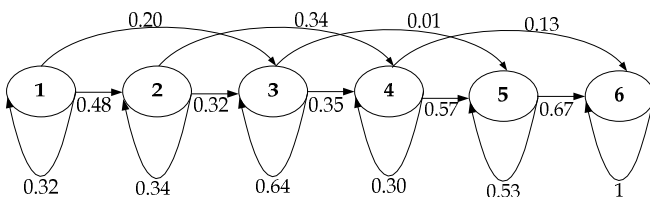


Figure 9. A HMM transition probabilities for anger expression after training.

III. EXPERIMENTAL RESULTS

A FER database was built for six different expressions which are Surprise, Sad, Happy, Disgust, Anger, and Neutral. For training and testing facial expression model, 20 and 40 image sequences were applied. To compare the proposed features with the other feature extraction methods, all methods were implemented with the HMMs to recognize aforementioned six different facial expressions. First of all, RGB camera-based experiments were tried and then they were

followed by the depth videos with the same experimental setups.

Regarding RGB video-based experiments, all the face images were converted to the gray scale first. For the PCA feature case, the eigenvectors were computed from all the dataset and selected 100 eigenvectors to train the HMMs. As shown in Table 1, the average recognition rate obtained using PCA is 58%, the lowest recognition rate in the experiments. Then, ICA features were employed. Table 2 shows the improved average recognition rate (i.e., 76.25%) using ICA. Then, LBP is applied for FER as presented in Table 3, the average recognition rate utilizing LBP representation of facial expression images is 80.42%, which is higher than the PCA and ICA recognition rates. Furthermore, optical flow was performed on the database and it achieved the recognition rate of 81.25% as shown in Table 4. Then, LDP was performed on the database and it achieved the recognition rate of 82.08% as shown in Table 5. To obtain more robust features, GDA was employed on the augmented features achieved the total average recognition rate of 84.17% as shown in Table 6. Thus, LDP-GDA showed its superiority over the other feature extraction methods by achieving the highest recognition rate.

TABLE 1. CONFUSION MATRIX USING NON-DEPTH FACES WITH PCA.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	40%	0	0	10	10	40
Happy	5	45	10	10	20	10
Sad	0	17.50	70	12.50	0	0
Surprise	0	0	0	75	15	10
Neutral	0	5	25	10	60	0
Disgust	0	7.50	27.50	0	0	65
Average	58					

TABLE 2. CONFUSION MATRIX USING NON-DEPTH FACES WITH ICA

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	77.50%	0	0	0	0	22.50
Happy	5	75	10	10	10	0
Sad	0	12.50	77.50	10	0	0
Surprise	0	0	0	80	0	20
Neutral	0	0	20	5	75	0
Disgust	0	7.50	20	0	0	72.50
Average	76.25					

TABLE 3. CONFUSION MATRIX USING NON-DEPTH FACES WITH LBP.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	77.50%	0	10	0	5	7.50
Happy	5	80	10	5	5	0
Sad	0	7.5	82.50	10	0	0
Surprise	0	0	0	80	12.50	7.50
Neutral	0	0	7.50	10	82.50	0
Disgust	0	0	20	0	0	80
Average	80.42					

TABLE 4. CONFUSION MATRIX USING NON-DEPTH FACES WITH OPTICAL FLOWS.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	80	0	10	0	0	10
Happy	5	80	10	10	0	
Sad	0	7.5	82.50	10	0	0
Surprise	0	0	0	82.50	12.50	5
Neutral	0	5	7.50	5	82.50	0
Disgust	0	0	10	10	0	80
Average	81.25					

TABLE 5. CONFUSION MATRIX USING NON-DEPTH FACES WITH LDP.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	80	0	10	0	0	10
Happy	5	80	10	10	0	
Sad	0	7.5	82.50	10	0	0
Surprise	0	0	0	85	10	5
Neutral	0	5	5	5	85	0
Disgust	0	0	10	10	0	80
Average	82.08					

TABLE 6. CONFUSION MATRIX USING NON-DEPTH FACES WITH GDA ON AUGMENTED LDP AND OPTICAL FLOWS.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	85	0	5	0	0	10
Happy	5	85	0	10	0	
Sad	0	7.5	82.50	10	0	0
Surprise	0	0	0	82.50	12.50	5
Neutral	0	5	5	5	85	0
Disgust	0	0	5	10	0	85
Average	84.17					

TABLE 7. CONFUSION MATRIX USING DEPTH FACES WITH PCA.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	50%	0	20	0	15	15
Happy	5	50	10	10	20	10
Sad	0	17.5	70	12.50	0	0
Surprise	0	0	0	80	15	5
Neutral	0	5	25	10	60	0
Disgust	0	5	30	0	0	65
Average	62					

TABLE 8. CONFUSION MATRIX USING DEPTH FACES WITH ICA.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	77.50%	0	22.50	0	0	0
Happy	10	80	10	0	0	0
Sad	0	7.50	82.50	10	0	0
Surprise	0	0	0	80	10	10
Neutral	0	10	7.50	0	82.50	0
Disgust	0	0	10	10	0	80
Average	80.41					

TABLE 9. CONFUSION MATRIX USING DEPTH FACES WITH LBP.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	80%	0	10	0	0	10
Happy	0	82.50	10	7.25	0	0
Sad	0	0	85	15	0	0
Surprise	0	0	0	85	15	0
Neutral	0	5	15	0	85	0
Disgust	0	0	15	2.50	0	82.50
Average	83.50					

TABLE 10. CONFUSION MATRIX USING DEPTH FACES WITH OPTICAL FLOWS.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	87.50%	0	12.50	0	0	0
Happy	10	90	0	0	0	0
Sad	0	0	87.50	0	12.50	0
Surprise	10	0	0	90	0	0
Neutral	0	0	10	0	90	0
Disgust	0	0	10	0	0	90
Average	89.16					

TABLE 11. CONFUSION MATRIX USING DEPTH FACES WITH LDP.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	87.50%	0	12.50	0	0	0
Happy	10	90	0	0	0	0
Sad	0	0	90	0	10	0
Surprise	7.50	0	0	92.50	0	0
Neutral	0	0	7.50	0	92.50	0
Disgust	0	0	10	0	0	90
Average	90.41					

TABLE 12. CONFUSION MATRIX USING DEPTH FACES WITH GDA ON AUGMENTED LDP AND OPTICAL FLOWS.

Expression	Anger	Happy	Sad	Surprise	Neutral	Disgust
Anger	97.50%	0	2.50	0	0	0
Happy	2.50	97.50	0	0	0	0
Sad	0	0	95	5	0	0
Surprise	0	0	0	97.50	0	2.50
Neutral	0	0	0	0	100	0
Disgust	0	0	0	2.50	0	97.50
Average	97.50					

For depth image-based experiments, the setups were kept same as RGB-based work. The average recognition rate using PCA on depth faces is 62% as shown in Table 7. Table 8 shows the average recognition rate ICA feature which is 80.41%. As shown in Table 9, the average recognition rate utilizing LBP is 83.50%, which is higher than that of depth face-based FER applying PCA and ICA. Then, optical flow was tried on the depth faces that achieved the average recognition rate of 89.16% as shown in Table 10. Furthermore, LDP was tried on the same database that achieved the average recognition rate of 90.41% as shown in Table 11. Finally,

GDA was employed on augmented LDP and optical flow motion features and achieved the highest average recognition rate of 97.50% as shown in Table 12. Thus, GDA on augmented LDP and optical flow features for depth face-based FER showed its superiority over all other feature extraction methods including RGB camera-based approaches.

IV. CONCLUSION

Facial expression is considered to be a visible manifestation of cognitive activity, intention, personality, and psychopathology of a person. Besides, it really plays a vital communicative role in interpersonal relations. In this work, a depth video-based robust FER system has been proposed using LDP, optical flows, and GDA features for facial expression feature extraction and HMM for recognition. The proposed method has been compared with other traditional approaches including RGB video-based ones and the recognition results show its superiority over others. In future, the system can be analyzed further with various parameter changes in different environments such as real-time FER.

ACKNOWLEDGMENT

This work was supported by the Samsung Research Fund, Sungkyunkwan University, 2015.

REFERENCES

- [1] M. T. Rahman and N. Kehtarnavaz, "Real-Time Face-Priority Auto Focus for Digital and Cell-Phone Cameras," *IEEE Transactions on Consumer Electronics*, vol. 54, no. 4, pp. 1506–1513, 2008.
- [2] M. Z. Uddin and A.M. Jehad Sarkar, "A Facial Expression Recognition System from Depth Video," in *Proceedings of The 2014 International Conference on Image Processing, Computer Vision, & Pattern Recognition*, pp. 151–120, 2014.
- [3] C. Padgett and G. Cottrell, "Representation face images for emotion classification," *Advances in Neural Information Processing Systems*, vol. 9, Cambridge, MA, MIT Press, 1997.
- [4] S. Mitra and T. Acharya, "Gesture Recognition: A survey," *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews*, vol. 37, no. 3, pp. 311–324, 2007.
- [5] G. Donato, M. S. Bartlett, J. C. Hager, P. Ekman, and T. J. Sejnowski, "Classifying Facial Actions," *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 21, no. 10, pp. 974–989, 1999.
- [6] P. Ekman and W. V. Priesen, "Facial Action Coding System: A technique for the Measurement of Facial Movement," *Consulting Psychologists Press*, Palo Alto, CA, 1978.
- [7] M. Meulders, P. D. Boeck, I. V. Mechelen, and A. Gelman, "Probabilistic feature analysis of facial perception of emotions," *Applied Statistics*, vol. 54, no. 4, pp. 781–793, 2005.
- [8] A. J. Calder, A. M. Burton, P. Miller, A. W. Young, and S. Akamatsu, "A principal component analysis of facial expressions," *Vision Research*, vol. 41, pp. 1179–1208, 2001.
- [9] S. Dubuisson, F. Davoine, and M. Masson, "A solution for facial expression representation and recognition," *Signal Processing: Image Communication*, vol. 17, pp. 657–673, 2002.
- [10] I. Buciu, C. Kotropoulos, and I. Pitas, "ICA and Gabor Representation for Facial Expression Recognition," in *Proceedings of the IEEE*, pp. 855–858, 2003.
- [11] F. chen and K. Kotani, "Facial Expression Recognition by Supervised Independent Component Analysis Using MAP Estimation," *IEICE Transactions on Information and Systems*, vol. E91-D, no. 2, pp. 341–350, 2008.
- [12] A. Hyvarinen, J. Karhunen, and E. Oja, "Independent Component Analysis," *John Wiley & Sons*, 2001.
- [13] Y. Karklin and M.S Lewicki, "Learning higher-order structures in natural images," *Network: Computation in Neural Systems*, vol. 14, pp. 483–499, 2003.
- [14] M. S. Bartlett, G. Donato, J. R. Movellan, J. C. Hager, P. Ekman, and T. J. Sejnowski, "Face Image Analysis for Expression Measurement and Detection of Deceit," in *Proceedings of the Sixth Joint Symposium on Neural Computation*, pp. 8–15, 1999.
- [15] C. Chao-Fa and F. Y. Shin, "Recognizing Facial Action Units Using Independent Component Analysis and Support Vector Machine," *Pattern Recognition*, vol. 39, pp. 1795–1798, 2006.
- [16] A. J. Calder, A. W. Young, and J. Keane, "Contour information in facial expression perception," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 26, no. 2, pp. 527–551, 2000.
- [17] M. J. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba, "Coding facial expressions with Gabor wavelets," in *Proceedings of the Third IEEE International Conference on Automatic Face and Gesture Recognition*, pp.200–205, 1998.
- [18] M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski, "Face Recognition by Independent Component Analysis," *IEEE Transaction on Neural Networks*, vol. 13, no. 6, pp. 1450–1464, 2002.
- [19] C. Liu, "Enhanced independent component analysis and its application to content based face image retrieval," *IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics*, vol. 34, no. 2, pp. 1117–1127, 2004.
- [20] P. J. Phillips, H. Wechsler, J. Huang, and P. Rauss, "The FERET database and evaluation procedure for face-recognition algorithms," *Image and Vision Computing*, vol. 16, pp. 295–306, 1998.
- [21] M. Z. Uddin, J. J. Lee, and T.-S. Kim, "An Enhanced Independent Component-Based Human Facial Expression Recognition from Video," *IEEE Transactions on Consumer Electronics*, vol. 55, no. 4, pp. 2216–2224, 2009.
- [22] T. Ojala, M. Pietikäinen, T. Mäenpää, "Multiresolution gray scale and rotation invariant texture analysis with local binary patterns," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, pp. 971–987, 2002.
- [23] C. Shan, S. Gong, P. McOwan, "Robust facial expression recognition using local binary patterns," in *Proceedings of IEEE International Conference on Image Processing (ICIP)*, pp. 370–373, 2005.
- [24] C. Shan, S. Gong, and P. McOwan, "Facial expression recognition based on local binary patterns: A comprehensive study," *Image Vis. Comput.*, vol. 27, pp. 803–816, 2009.
- [25] T. Jabit, M. H. Kabir, O. Chae, "Local Directional Pattern (LDP) A Robust Image Descriptor for Object Recognition", in *Proceedings of the IEEE Advanced Video and Signal Based Surveillance (AVSS)*, pp. 482–487, 2010.
- [26] J. J. Lien, A. Zlochow, J.F. Cohn, and T. Kanade, "Automated Facial Expression Recognition", in *Proceedings of the Third IEEE International Conference on Automatic Face and Gesture Recognition*, pp. 390–395, 1998.
- [27] Y. Yacoob and L.S. Davis, "Recognizing Human Facial Expressions From Long Image Sequences Using Optical Flow", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 18, no. 6, pp. 632–646, 1996.
- [28] L. Shen, L. Bai, and M. Fairhurst, "Gabor wavelets and General Discriminant Analysis for face identification and verification," *Image and Vision Computing*, Vol. 25, pp. 553–563, 2007.
- [29] P. Yu, D. Xu, and P. Yu, "Comparison of PCA, LDA and GDA for Palm print Verification," in *Proceedings of the International Conference on Information, Networking and Automation*, pp.148–152, 2010.
- [30] G. J. Iddan and G. Yahav, "3D imaging in the studio (and elsewhere...)," in *Proceedings of SPIE*, vol. 4298, pp 48–55, 2001.



Md. Zia Uddin is working as an Assistant Professor in Computer Education Department of Sungkyunkwan University (SKKU) of South Korea. SKKU is one of the leading universities in South Korea with good world ranking as well. He received his Ph.D. degree from Biomedical Engineering department of Kyung Hee University of South Korea in February 2011. His research interest includes smart home healthcare, computer vision, image processing, video surveillance, human computer interaction, human activity recognition, and facial expression recognition.