A perusal on Facial Emotion Recognition System (FERS)

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ABSTRACT
Emotion could be well interpreted using the facial expressions. Several approaches have been proposed for classification of emotion (human affective states). We in this paper steadily examine available approaches for solving the problem of machine understanding of facial emotion and compare important issues like the collection and availability of training and test data. We finally outline the challenges we would work on to advance facial emotion recognition based on the explored latest work of various authors. We conclude this paper with the improvements and further advancement needed in facial expression recognition.

KEY WORDS: Emotions, affective state, facial expression.

1. INTRODUCTION

A saying goes like 'Face is the index of the mind'. Facial emotion is a clear indicator of the emotion notion of a person. Facial expression plays a vital role in understanding the emotional state of a person which was clearly stated by Mehrabian (1968). The emotional state of a person can be cumulated in various ways including face, audio, video, gesture, and bio-embedded signals which would be highly favourable for the popular fields such as cognitive science, medicine, security, education and computer science. Based on previous works of research for over 50 years in this area, the acknowledged six basic emotions are anger, fear, disgust, sadness, happiness and surprise.

Ekman claims that these six emotions have equivalent prototypic facial displays (Ekman, 1978; 2005). Nearly, most of the facial expression analysers established currently tries to identify a set of expressions (i.e.) fear, sadness, disgust, anger, surprise, and happiness. To identify such facial expressions packed with information available, automatic recognition of facial muscle activities is needed. However, the gap of collecting day to day people emotions lay uncovered.

Facial Action Coding System (FACS) proposed by Ekman and Friesen is the frequently used system for the analysis of 44 Action Units (AUs) which is converted to input based on rules for decision making but preparing AUs are literally tedious. An automated system which differentiates AUs in real time in the absence of a human would reduce the effort.

Existing facial expression recognition system identifies only the basic set of emotions with lesser information. More efforts were spent for recognising the facial actions individually or combined by improving the feature extraction and classification method thereby ignoring the semantic relations and dynamics of AU's. An automated system is always challenging due to the abundance, uncertainty and dynamic (Tong, 2007) nature of facial actions during analysis of the facial actions in real time. Latest studies highlight the need to consider the dynamic characteristic of the facial actions for capturing the spontaneous facial expression. Henceforth, the urge for an automatic emotion recognition system for such facial invariants (Pantic and Rothkrantz, 2005) to captures the accurate information.

Yet the appearance of facial action units differs with respect to different culture and they possess dissimilarities nation-wide (Ruttkay, 2009). During which a 3D facial image-based (Zhang, 2011) approach one of the categories of facial emotion recognition methods when 3D images can be used. Usage of this 3D has to be backed with which is the best method as they choose suboptimal will waste time and effort or may be unproductive. In this regard, a detailed survey of the existing works may provide significant answer for the requirements and that is what we are addressing.

Background: Early work exhibit hugely on prototypical expression confronting to the requirement that the facial expression would change spontaneously. The past work provides a gap to address the need to analyse these dynamic expressions for better performance and enriched recognition. A few studies that try to address this is discussed in (Pantic, 2009; Kumano, 2009; Chang, 2005). The proposed framework here emphasis how to address the gap that can handle dynamic or spontaneous expression along with the 3D view using hybrid features.

Analysis of Facial Expression – Overview: Automatic facial expression analysis systems should be designed that can co-exist environment factor, gesture change, voice pitch, cultural differences across races, gender facial structure (Fasel, 2003; Pantic, 2000).Though emotion can be defined or declared by observing the changes on a person's facial expression. There are particular emotions that can be defined or declared by observing the changes the environment. But having the entire environment factor into the system are not feasible. Most of the existing dataset are small which leads to an imperfect representation of facial expression (Fasel, 2003). Facial Action Coding System (FACS) could be employed to overcome this problem.

Facial Action Coding System (FACS): FACS proposed by Ekman and Friesen is used for measuring and describing facial muscular activity (Cohn, 2004). The changes of action muscles are directly associated to the facial appearance.

Automatic recognition of AUs remain difficult as they occur in 7000 combinations causing difficult to detect. Figure 1 shows an example for the brow actions of the AU where AU1 is the inner brow lift, AU2 is the outer brow lift and AU4 is the brow lowering.

Figure.1. Eyebrow actions adapted from (Cohn, 2004)

General structure of Facial Expression Analysis System (FEAS): The general design of automatic facial expression analysis consists of three stages as shown in figure 2 as face acquisition, data extraction and expression recognition.

Face acquisition: Face acquisition (Fasel, 2003; Chang, 2005) is the preliminary stage to detect the face frame wise automatically by inspecting the face region for the input image sequences. The quality of the acquired image directly influences the effect of recognition. Some popular face identification methods like Fisher faces, Local Binary Pattern, Viola and Jones face detector records the face in 2D or 3D (Hadid, 2009). In this process, the image to image scale orientation of the face could vary. However, it's difficult to describe the exact location of the face.

Facial data extraction: Geometric feature-based methods or appearance-based methods to extract the facial features from the detected image (Fasel, 2003; Chang, 2005) can be used. The geometric facial methods like deformable template or contour models count on the shape and locations of the facial components. With appearance-based methods, image filters, such as Optical flow or Gabor wavelets are used to capture facial appearance motion. Face normalization is applied before feature vectors are extracted by using expression recognition. Various feature extraction algorithm includes Lucas- Kanade algorithm (Cohn, 2001) for detection of eyes, eyebrows, cheeks; Canny edge detector algorithm for detection of transient features (facial furrow).

Facial Expression Recognition (FER): The final stage as described in FEAS is to identify the facial expression. After this stage, the issue is about expression classification to be categorised as prototypic or non-prototypic expressions. There are list of classifiers defined for performing emotion classification namely neural classifier, fuzzy classifier, Hidden Markov Model Based Classifiers, Naive Bayes Classifier (Mower, 2011; Das, 2009).

Issues on FEAS: There are a number of difficulties in FEAS due to the variation of facial expression across the culture and context of an individual (Ruttkay, 2009). Some of the key issues (Kanade, 2000) with respect to the FEAS are,

- Overlaying of neutral state from transition of AU
- Training data has less spontaneous expression
- Correctness and stability of the training data
- Difference in subject expressiveness
- Orientation of the head and corresponding references
- The quality of image acquisition

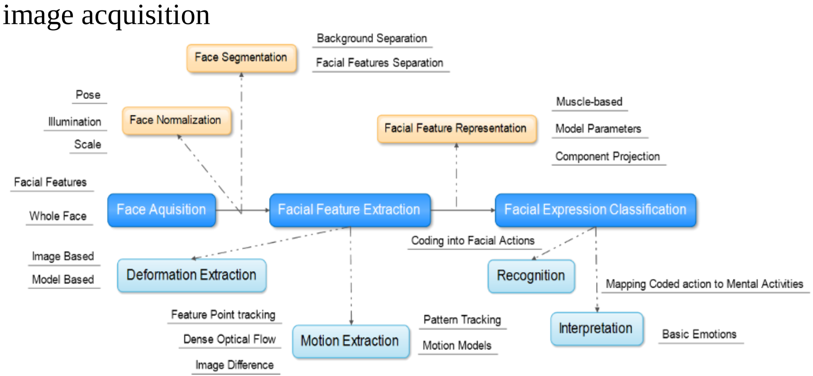

Figure.2. General Framework for Facial Expression Analyzer (Cohn, 2004)

Emotion Recognition Methods: Expression recognition methods can be projected in various angles. Our focus would be on facial expression recognition. To perform facial feature extraction a human face can be projected into three dimensions (Pantic and Maja, 2003) whether the information is temporal / dynamic or whether the features are geometric / appearance based or whether the features are 2D / 3D based. This section would answer the above questions with a relative study.

The frequently used emotion recognition methods (Pantic & Maja, 2003) can be categorized as,

- Static or Dynamic Image based Approach
- 2D or 3D Facial Image based Approach
- Geometric or Appearance Feature Based

Approach

Static vs. Dynamic based Approach: Image being the primary source of a facial recognition system can be in the form of static and dynamic. People mostly rely on static information because facial dynamics provide less accurate information than static facial method. Few of the early listed image-based methods (Maja Pantic, 2004) are Local Binary Pattern (LBP), Principle Component Analysis (PCA) and (Linear Discriminant Analysis) LDA. Studies shows (Zhang, 2005) dynamic data usage is still challenging.

Most of the previous work discarded facial dynamics and instead considered only the facial structure. Facial expression extraction is primarily carried out on static image. However when considering facial feature actions extraction, usage of single still images could fail. Also when observation is complex or collection of data set are weak then static methods may fail.

Early theories prove that static images are not detail enough to provide the original emotion (Hadid, 2007).This is absolutely true when considering spontaneous affective behaviours. The temporal dynamics can be used to evaluate expression with the factors of intensity and facial expression or muscle activities are considered. The duration of the muscle activity of a dynamic image (Valstar, 2006) varies from 250 ms to 5 s. Most of the works in FER used video as input (Bartlett, 2005; Maja Pantic, 2004; Valstar, 2006).

The dynamic properties of AUs are desirable to exploit the dynamic dependencies (Valstar, 2006) among AUs for spontaneous facial action analysis. A Dynamic Bayesian Network (DBN) could be employed which characterizes the dynamic nature of facial action by directed temporal links among the AUs across consecutive frames. Previously, Hidden Markov Models (Cohn, 2001; Das, 2009; Kanade, 2000) which have been used to recognize the facial expressions was unsuccessful since they were capable of considering only a single AU. Merits and demerits of static and dynamic approaches are shown in table.1.

Table.1. Comparison of Static with Dynamic Approach

Methods	Merits	Demerits
Static (Maja Pantic, 2004; Kumano, 2009; Chang, 2005)	Easier to train and implement.	Cannot reveal subtle changes.
Dynamic (Bartlett, 2005; Cohn, 2004; Zeng, 2009; Zhang, 2005)	Different expression captured as temporal expression.	Complex and required more training, data set and new implementation technique for better result.
	Ability to capture dependencies and temporal behaviours.	
	Classification uncertainty reduced to a minimum.	
	Robustness in handling facial expression.	Facial expressions Intensity measurement is difficult
	Flexibility	

Using DBN and FACS technology, almost all facial expression approaches recognize basic emotion only. But when a dynamic approach is considered there is a need for complex parameterized training samples. Therefore static and dynamic can combined to form a hybrid classifier for future exploration (Woznia, 2014).

2D/3D based method: A face model (Matthews, 2007) is built based on trained data. Then the model should fit to the parameters used. Commonly used face models (Savran, 2008) can be categorized as Active Appearance Models (AAM) or Morphable Models. The practises of 2D image are depicted using AAM and that of a 3D image is through Morphable Models.

Table.2. Comparison of 2D with 3D

Methods	Merits	Demerits
2D (Ashraf, 2009; Jing,2004 Matthews, 2007; Kanade,2000)	Easy availability for dataset and less complex computation	Limited dataset and complex computation
		Subjective to lighting condition
3D (Savran, 2008; Yin, 2006; Hu, Changbo, 2004; Fang,2011)	Lighting condition does not affect the process.	Time consuming initialization process
	3D vector can be used to support 2D distorted vectors.	
	Can be used develop fully independent system.	New fitting techniques are required to converge.

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2D Active Appearance Models: Active Appearance Model (AAM) is defined in eq. 1] (Matthews, 2007). Arithmetically, the shape is as below:

$$\mathbf{s} = \begin{pmatrix} u_1 & u_2 & \dots & u_n \\ v_1 & v_2 & \dots & v_n \end{pmatrix} \quad \text{----------------} \ (1)$$

AAMs construction requires Principal Component Analysis (PCA) which is generally applied to calculate the shape of the model. The major benefit of constructing the AAM is to avoid the trace of noise.

3D Morphable Models: The shape of a 3D Morphable Model (3DMM) is defined in eq. 2. Arithmetically, the shape š is defined as 3D coordinates:

$$\bar{\mathbf{s}} = \begin{pmatrix} x_1 & x_2 & \dots & x_{\overline{n}} \\ y_1 & y_2 & \dots & y_{\overline{n}} \\ z_1 & z_2 & \dots & z_{\overline{n}} \end{pmatrix} \quad \text{--------------} \ (2)$$

3DMMs constructions are usually deeper and denser. Additional benefit includes a natural and less confused face motion. Head posture (Boulay, 2006) plays a vital role in facial action that replicate a person's actual emotion. Most likely emotions are not expressed without head movement. But 2D images may not be precise in identifying the head posture. Hence, the need for 3D space as well.The well-known appearance feature based methods: Gabor-wavelet and the Topographic Context (TC) approach was tested in (Yin, 2006) with both 2D and 3D databases where 2D performed better than 3D.This is because 3D facial shape is enriched with expected information about facial expressions and is stronger than 2D shapes. Recently in paper (Soyel, 2010), 3D facial expression recognition was conducted on BU-3DFE database. Neural network was employed for facial feature distances.

Many researchers have found 3D face models performing better than 2D when geometric features where extracted from 3D models (Fang, 2011) to define the facial emotion changes. As an extract from existing recent works, the Merits and demerits of 2D and 3D based approaches are shown in table 2.

Geometric vs. Appearance based Features: Most of the existing FER approaches extract facial features based on either Geometric Features (GF) or Appearance Features (AF) where GF considers the facial components and AF considers the location of facial point corners that includes wrinkles, bulges, and furrows.

Table.3. Comparison of GF with AF

Methods	Merits	Demerits
GF (Cohn, 2001; Zhang, 2011; Youssif, 2011)	Fast and simple	High precision is still a long reach
	Sensitive to noise	
	Reliable facial detection	
	An optimal head position correctness with few inputs	
AF (Cohn, 2001; Hadid, 2009; Youssif, 2011)	Less reliant on initialization	Manual assistance for shape models required
	Tracking error are null down or almost eliminated	Missing feature in frame has to be handled separately
	Can handle texture and texture changes	
	optimal head in localization error	Could not effectively handle low-resolution images and requires new fitting algorithm
	Precise head position	

There are different ways for AU recognition. Method one is to fix a landmark on AU regions and another method is to landmark based on the FAPs which contain 68 parameters to describe the expression. The final method is to locate based on shape.The below figure 3 depicts some feature points of FAPs in ISO MPEG-4 standard. We use FAP especially for 3D expression recognition (Tekalp, 2000; Raouzaiou, 2002).

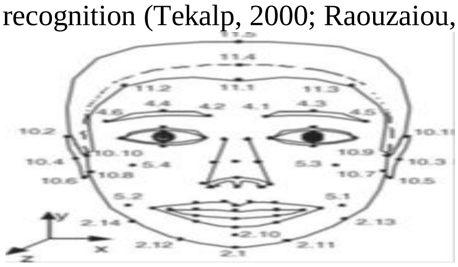

Figure.3. Feature points of a face [34]

To obtain appearance based features the easiest way is to use grey scale facial images. Usually appearance features (Koelstra, 2010) are sensitive to variations of illumination and head pose views. Some of the frequently used appearance features are Gabor wavelet features, Scale Invariant Feature Transform (SIFT) features and Local Binary Pattern (LBP).The geometry of facial components is a good indication for recognizing most of the AUs/expressions. The importance of appearance-based features for expression recognition is emphasized since it contains more information about facial expression. The appearance feature method becomes more difficult than geometric approach when larger amount of data is used (Cohn, 2001).

Hybrid approaches which is a combination of both geometric and appearance extraction (Pande, 2012) resulted with higher accuracies. There should not be any compromise in performance in real time systems. It infers that using both geometric and appearance features might be the optimal choice in the case of stable facial expressions (Koelstra, 2010). Merits and demerits of GF and AF based approaches are listed in table.2.

Datasets for Emotion Recognition: Normally, two traits are considered for building a face database depending on the data modality: 2D vs. 3D and static vs. dynamic. Recently, there are a number of standard face databases available to public (Yin, 2006). The database is intended to illustrate the different facial behaviours at various levels of intensities. It contains different subjects that are mixed across different ethnic. There are four popular facial expression databases (Tang, 2010; Hu, 2008) which are as follows,

Binghamton University - 3D Facial Expression (BU-3DFE) Database: The BU-3DFE database established by Binghamton University was designed to model 3D facial behaviours with varied emotional states at different levels of intensities. It consists of topics related to people with mixed culture across the world.

BinghamtonUniversity-4D Facial Expression (BU-4DFE) Database: The BU-3DFE database created by Binghamton University was modelled only for static facial expression database. To overcome this problem BU-4DFE was developed for dynamic facial expression database.

Carnegie Mellon University Multi-PIE Database: The Multi-PIE facial expression database, of Carnegie Mellon University (CMU), consists of large number of facial images from different continents.

Bosphorus 3D Database: The Bosphorus database consists of heterogeneous combination of 107 subjects with multiple features. Several limitations such as image capturing, processing, non-existence of 3D and natural spontaneous expression exist in the current system (Toole, 2005; Yin, 2006).

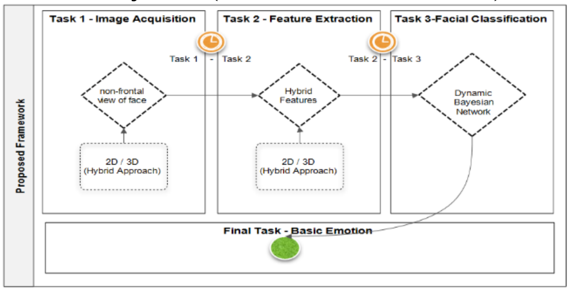

Figure.4. Proposed framework for IFEA

Latest Research in Automatic Facial Expression Analysis: The latest inquiries in automatic facial expression analysis (Lee, 2011; Konar, 2014; Mower, 2011; Tian, 2005; Zeng, 2009; Youssif, 2011) guidelines are as follows:

- An acquisition system that can extract data with external noise reduction
- A system that should have multiple recognition mode
- A system which should have automatic capabilities to adapt to real time scenario

Future Work: Our aim is to design an Ideal Facial Expression Analyzer (IFEA) (shown in figure.4) which would solve the early researchers problem namely face detection and varied illumination, modality of 3D input during rigid head motions, illumination invariant by nature and also extract geometrically invariant features problem of pose estimation. Usage of 3D as input eliminates the need for dealing with variation in illumination. When there is an occurrence of more than one modality, a system to choose a well-defined schema is required in a FER system.

The new emotion recognition can consequently transform any 2D facial image into a 3D model. That model will have the capacity to express an extensive variety of feelings. When this 3D image database is included for cross cultural variations, the possibility of emotion recognition along with different facial actions shows better improvement. To extract features geometric based approach is chosen.Various data source ascends the need for multiple modality, schema and common evaluation protocol. These can be either been automatically chosen or can be left to be chosen based on the user needs.

Modelling of dynamic and semantic relationship of AU could be optimally modelled using DBN where the facial actions are illustrated as links among directed temporal and the semantics are illustrated as links to static AU's. Based on the theory modelling, the dependencies among AU could improve the recognition over the earlier methods.

Hybrid approaches can be emphasised for designing an ideal system for expression recognition. The combined approaches include both static and dynamic images along with hybrid features namely geometric and appearance features.

Working flow of the proposed framework happen as four abstracted modular task to help system resilience during optimization and upgrades to the system. Each module has specific task to perform such as image acquisition, feature extraction, facial classification and the final emotion detection.

4. CONCLUSION

Our work on the review was to narrow down to the best and optimal existing work that can be used and reinvent the required missing links for our future work. The next step would be to the development our proposed system for real applications. The accuracy of automated facial expression measurement in spontaneous behaviour may be considerably improved by 3D alignment of faces compared with the existing models. None of the earlier research addresses the challenges spontaneous expressions. Latest addition of affective data set shows potential shift in future research. One of the future directions might be to rely more on generic facial geometry information for analysis, which would not limit us to a particular face database. The second challenge would be to develop a high resolution 3D database with the naturally occurring facial behaviour. Next to the 3D challenge, we would record 4D face databases with more quality features.

Apart from the above, the hardware setup for 3D and 4D data are even greater. Finally, there would also be demand on 360 degree view. The current imaging systems could limit handling large variation issue.

REFERENCES

Bartlett, Marian Stewart, Recognizing facial expression, machine learning and application to spontaneous behavior, Computer Vision and Pattern Recognition, CVPR, IEEE Computer Society Conference on, 2, 2005.

Boulay, Bernard, Francois Brémond and Monique Thonnat, Applying 3d human model in a posture recognition system, Pattern Recognition Letters, 27 (15), 2006, 1788-1796.

Chang Y, Vieira M, Turk M and Velho L, Automatic 3D Facial Expression Analysis in Videos, Proc. IEEE Int'l Workshop Analysis and Modeling of Faces and Gestures (AMFG '05), 3723, 2005, 293-307, 2005

Cohn J and Ekman P, Measuring facial action by manual coding, facial EMG, and automatic facial image analysis, in Handbook of Nonverbal Behavior Research Methods in the Affective Sciences (eds Harrigan J.A, Rosenthal R and Scherer K), Oxford University Press, New York, 2005, 9–64.

Cohn J.F, Reed L.I, Ambadar Z, Xiao J and Moriyama T, Automatic analysis and recognition of brow actions and head motion in spontaneous facial behavior, in Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, 1, 2004, 610–616.

Cohn, Ying-liTian TakeoKanade Jeffrey F, Recognizing Facial Actions by Combining Geometric Features and Regional Appearance Patterns, 2001.

Das S, Halder A, Bhowmik P, Chakraborty A, Konar A and Nagar A.K, Voice and facial expression based classification of emotion using linear support vector machine, in International Conference on Developments in eSystems Engineering (DESE), AbuDhabi, UAE, 2009.

Ekman P and Friesen W.V, Facial Action Coding System, A Technique for the Measurement of Facial Movement.-Consulting Psychologists Press, 1978.

Fang T, Zhao X, Ocegueda O, Shah S.K and Kakadiaris I.A, 3D facial expression recognition, a perspective on promises and challenges, in 2011 IEEE International Conference on Automatic Face & Gesture Recognition and Workshops (FG 2011), 2011, 603–610.

Fasel B and Luettin J, Automatic facial expression analysis, a survey, *Pattern Recognition*, 36, 2003, 259–275.

Hadid, Abdenour and Matti Pietikäinen, Combining appearance and motion for face and gender recognition from videos, Pattern Recognition 42 (11), 2009, 2818-2827.

Hadid, Abdenour, Matti Pietikäinen, and Stan Li Z, Learning personal specific facial dynamics for face recognition from videos, Analysis and Modeling of Faces and Gestures. Springer Berlin Heidelberg, 2007, 1-15.

Hu Y, Zeng Z, Yin L, Wei X, Tu J and Huang T.S, A study of non-frontal-view facial expressions recognition, in Proceedings of ICPR, 2008, 1–4.

Hu, Changbo, Fitting a Single Active Appearance Model Simultaneously to Multiple Images, BMVC, 2004.

Kanade T, Cohn J.F and Tian Y, Comprehensive database for facial expression analysis, in Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition, 2000, 46–53

Koelstra, Sander, Maja Pantic, and Ioannis Yiannis Patras, A dynamic texture-based approach to recognition of facial actions and their temporal models, Pattern Analysis and Machine Intelligence, IEEE Transactions on, 32 (11), 2010, 1940-1954.

Konar, Amit, and Aruna Chakraborty. Emotion Recognition, A Pattern Analysis Approach. John Wiley & Sons, 2014.

Kumano S, Otsuka K, Yamato J, Maeda E and Sato Y, Pose-invariant facial expression recognition using variable-intensity templates, Int. J. Comput. Vis, 83 (2), 2009, 178–194, 2009.

Lee, Chi-Chun, Emotion recognition using a hierarchical binary decision tree approach, Speech Communication, 53 (9), 2011, 1162-1171.

Matthews, Iain, Jing Xiao, and Simon Baker, 2D vs. 3D deformable face models, Representational power, construction, and real-time fitting, International journal of computer vision 75 (1), 2007, 93-113.

Mehrabian A, Communication without words, Psych. Today, 2 (4), 1968, 53–56, 1968

Mower E, Mataric M.J and Narayanan S, A framework for automatic human emotion classification using emotion profiles, IEEE Transactions on Speech and Audio Processing, 19 (5), 2011, 1057–1070.

Mower, Emily and Shrikanth Narayanan, A hierarchical static-dynamic framework for emotion classification, Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on, IEEE, 2011.

O'Toole A.J, A Video Database of Moving Faces and People, IEEE Trans. Pattern Analysis and Machine Intelligence, 27 (5), 2005, 812-816.

Pande, Sachin, and Spurti Shinde, A Survey on, Emotion Recognition with respect to Database and Various Recognition Techniques, International Journal of Computer Applications, 58 (3), 2012.

Pantic M and Rothkrantz L.J.M, Automatic analysis of facial expressions, the state of the art, IEEE Transactions on Pattern Analysis and Machine Intelligence, 22 (12), 2000, 1424–1445.

Pantic M and Rothkrantz L.J.M, Toward an affect-sensitive multimodal human-computer interaction, Proc. IEEE, 91 (9), 2003, 1370–1390.

Pantic, Maja and Leon JM Rothkrantz, Facial action recognition for facial expression analysis from static face images, Systems, Man, and Cybernetics, Part B, Cybernetics, IEEE Transactions on, 34 (3), 2004, 1449-1461.

Pantic, Maja and Leon JM Rothkrantz, Toward an affect-sensitive multimodal human-computer interaction, Proceedings of the IEEE, 91 (9), 2003, 1370-1390.

Raouzaiou A, Tsapatsoulis N, Karpouzis K and Kollias S, Parameterized facial expression synthesis based on MPEG-4, EURASIP J. Appl. Signal Process, 2002 (1), 2002, 1021–1038.

Ruttkay Z, Cultural dialects of real and synthetic emotional facial expressions, AI Soc, 24 (3), 2009, 307–315.

Savran A, Aly¨uz N, Dibeklioglu H, eliktutan O.C, okberk B.G, Sankur B and Akarun L, Bosphorus database for 3D face analysis, in Biometrics and Identity Management, 2008, 47–56.

Soyel, Hamit and Hasan Demirel, Optimal feature selection for 3D facial expression recognition using coarse-to-fine classification, Turkish Journal of Electrical Engineering and Computer Sciences, 18 (6), 2010, 1031-1040.

Tang H, Hasegawa-Johnson M and Huang T.S, Non-frontal view facial expression recognition based on ergodic hidden Markov model supervectors, in IEEE Conference on Multimedia & Expo (ICME), 2010, 1202–1207.

Tekalp A.M and Ostermann J, Face and 2-D mesh animation in MPEG-4, Signal Process, Image Commun, 15 (4–5), 2000, 387–421.

Tian, Ying-Li, Takeo Kanade, and Jeffrey Cohn F, Facial expression analysis, Handbook of face recognition. Springer New York, 2005, 247-275.

Tong Y, Liao W and Ji Q, Facial action unit recognition by exploiting their dynamic and semantic relationships, IEEE Transactions on Pattern Analysis and Machine Intelligence, 29 (10), 2007, 1683–1699.

Valstar M.F, Pantic M, Ambadar Z and Cohn J.F, Spontaneous vs. posed facial behavior, automatic analysis of brow actions, in Proceedings of the Eighth International Conference on Multimodal Interfaces, 2006, 162–170.

Wozniak, Michał, Manuel Grana, and Emilio Corchado, A survey of multiple classifier systems as hybrid systems, Information Fusion, 16, 2014, 3-17.

Yin L, Wei X, Sun Y, Wang J and Rosato M.J, A 3D facial expression database for facial behavior research, in Proceedings of Seventh International Conference on Automatic Face and Gesture Recognition, 2006, 211–216.

Youssif, Aliaa AA, and Wesam AA Asker, Automatic facial expression recognition system based on geometric and appearance features, Computer and Information Science 4 (2), 2011, 115.

Zeng Z, Pantic M, Roisman G.I and Huang T.S, A survey of affect recognition methods, audio, visual, and spontaneous expressions, IEEE Transactions on Pattern Analysis and Machine Intelligence, 31 (1), 2009, 39–58.

Zhang L, Tjondronegoro D.W and Chandran V, Evaluation of texture and geometry for dimensional facial expression recognition, in 2011 International Conference on Digital Image Computing, Techniques and Applications (DICTA2011), 2011.

Zhang, Yongmian, and Qiang Ji, Active and dynamic information fusion for facial expression understanding from image sequences, Pattern Analysis and Machine Intelligence, IEEE Transactions on 27 (5), 2005, 699-714.

Zheng, Wenming, Hao Tang, and Thomas S. Huang., Emotion Recognition from Non-Frontal Facial Images, Emotion Recognition, A Pattern Analysis Approach, 2014, 183-213.