



**UNIVERSITI PUTRA MALAYSIA**

***MULTIVIEW FACE EMOTION RECOGNITION USING  
GEOMETRICAL AND TEXTURE FEATURES***

**FARHAD GOODARZI**

**FK 2018 21**



**MULTIVIEW FACE EMOTION RECOGNITION USING  
GEOMETRICAL AND TEXTURE FEATURES**

By

**FARHAD GOODARZI**

**Thesis Submitted to the School of Graduate Studies, Universiti  
Putra Malaysia, in Fulfilment of the Requirements for the Degree of  
Doctor of Philosophy**

**October 2017**

## **COPYRIGHT**

All material contained within the thesis, including without limitation text, logos, icons, photographs and all other artwork, is copyright material of Universiti Putra Malaysia unless otherwise stated. Use may be made of any material contained within the thesis for non-commercial purposes from the copyright holder. Commercial use of material may only be made with the express, prior, written permission of Universiti Putra Malaysia.

Copyright © Universiti Putra Malaysia



## DEDICATIONS

*In the name of God, Most Gracious, Most Merciful  
This thesis is dedicated to:*

*Father & Mother  
Family & Friends*

...



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in  
fulfilment of the requirement for the degree of Doctor of Philosophy

## **MULTIVIEW FACE EMOTION RECOGNITION USING GEOMETRICAL AND TEXTURE FEATURES**

By

**FARHAD GOODARZI**

**October 2017**

**Chairman : M. Iqbal Bin Saripan, PhD**  
**Faculty : Engineering**

In the last decade, facial emotion recognition has attracted more and more interest of researchers in the computer vision community. Facial emotions are a form of nonverbal communication, used to exchange social and emotional information in human-human-interaction. By finding the emotion from the human face automatically and reacting proactively, several applications could benefit. The examples of these are the human-computer-interfaces or security systems, driver safety systems and social science's domain. In order to use facial emotion recognition systems in real time situations, it is essential to recognize emotions not only from frontal face images but also from images containing faces with pose variations. Furthermore, facial landmarks have to be located automatically. The degree of intensity of human facial emotions varies from person to person. Some people may express the seven basic emotions more intense than others or they may use it in different ways. In this thesis, a real time emotion recognition system is presented. The system works on both, frontal and non-frontal faces. A 3D face pose estimation algorithm detects head rotations of Yaw, Roll and Pitch for emotion recognition. UPM3D-FE and BU3D-FE databases are used in this research for training purposes which include rotation and capturing of faces in different angles. After detecting the human face, several features are extracted from human face automatically and the geometrical facial features combined with texture features, are given to a back propagation neural network which is trained with various face images. This enables us to determine the emotion in real-time from the face of a person. Basically, the contributions are that the method is capable of detecting the face and facial landmarks in the live video; the landmark detection on the face is done automatically in each frame using both texture of facial points and relative positions of points on the face. Also, the emotion is detected from frontal and angled face and in the case where half of face is not visible (side view) the other half is reconstructed and emotion is detected. Geometrical and texture features are used for emotion recognition and the texture features are

taken from specific areas of the face in a novel approach. The results show an improvement over existing approaches in determining emotions for various face poses. The effects of gender, ethnicity, color, mixed emotions and intensity of emotion have been analyzed as well. The resulting face emotion recognition system works real time in less than twenty milliseconds per frame. For UPM3DFE, in case of seven emotions, the accuracy is 63.08% for multiview and 62.19% for near frontal faces for emotion recognition, and for the BU3DFE, 80.61% accuracy was found for near frontal faces and 77.48% for multi view in the case of seven basic emotions. The achieved face emotion recognition method has improved emotion recognition accuracy and also it is able to adapt to the yaw and pitch rotation of face. Both databases (UPM3D and BU3D) were tested for the role of gender, ethnicity, color, mixed emotions and intensity of emotions. After cross validation, for the BU3DFE database, the best results were achieved for Indians and Southeast Asian (56.6% and 50.2%) subjects. In the case of UPM3DFE, the best results were achieved for Middle east and southeast Asians subjects (66.6% and 69.1%), and the lowest results were achieved in both databases for black subjects (45% and 54.54%). With regard to mixed emotions, it has been found that BU3DFE is 67.72% accurate in recognizing mixed emotions and UPM3DFE accuracy is 56.09%. In case of different emotion intensities in BU3DFE, the results for multi view faces manifested 71.11% for 1<sup>st</sup> emotion intensity, and 73.21% for 2<sup>nd</sup> emotion intensity, 75.1% for 3<sup>rd</sup> emotion intensity and 79.31% for 4<sup>th</sup> emotion intensity.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia  
sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

## **PENGECAMAN EMOSI WAJAH BERBILANG ARAH MENGUNAKAN CIRI-CIRI GEOMETRI DAN TEKSTUR**

Oleh

**FARHAD GOODARZI**

**Oktober 2017**

**Pengerusi : M. Iqbal Bin Saripan, PhD**  
**Fakulti : Kejuruteraan**

Sejak sedekad yang lalu, penyelidikan tentang pengecaman emosi wajah semakin mendapat perhatian daripada para penyelidik dalam komuniti penglihatan komputer. Ekspresi wajah adalah satu bentuk komunikasi bukan lisan, yang digunakan untuk pertukaran maklumat sosial dan emosi dalam interaksi sesama manusia. Dengan mengenali emosi seseorang individu dan diikuti tindak balas yang proaktif, banyak aplikasi boleh mendapat manfaat daripada sistem pengecaman ekspresi wajah automatik ini, yang mana sebagai contoh, sistem antaramuka manusia-komputer atau sistem keselamatan. Aplikasi pengecaman emosi juga terdapat pada sistem keselamatan pemandu dan sains sosial. Bagi menggunakan sistem pengecaman ekspresi wajah dalam situasi masa nyata, adalah amat penting untuk mengenali ekspresi bukan sahaja dari imej pandangan hadapan wajah, malah perlu merangkumi imej wajah dari pelbagai sudut. Di samping itu, titik-titik penting wajah juga perlu dikenalpasti secara automatik. Tahap keamatan ekspresi wajah setiap individu itu berbeza. Seseorang orang menzahirkan tujuh emosi asas secara lebih jelas berbanding yang lain atau mereka juga boleh menunjukkannya dengan cara yang berbeza. Dalam tesis ini, sistem pengecaman emosi masa nyata telah dibentangkan. Sistem ini berfungsi dengan imej pandangan hadapan muka ataupun dari sudut pandangan yang lain. Algoritma 3D untuk anggaran riak wajah mengesan putaran muka hanyutan (Yaw), olekan (Roll) dan jongketan (Pitch) dalam proses pengecaman emosi. UPM3D-FE dan BU3D-FE merupakan pangkalan data yang digunakan dalam kajian ini untuk tujuan latihan termasuk memutar dan mengambil imej wajah dalam sudut yang berbeza. Selepas mengesan kawasan muka, beberapa ciri telah diekstrak secara automatik daripada wajah tersebut dan ciri-ciri geometri yang digabungkan dengan ciri-ciri tekstur, akan dijadikan input kepada rangkaian neural perambatan balik yang akan dilatih menggunakan pelbagai imej wajah. Ini membolehkan kami menentukan emosi seseorang dalam masa nyata dari imej wajah mereka. Pada asasnya sumbangan utama kajian ini adalah sistem yang

dibangunkan dapat mengesan kawasan muka dan beberapa titik penting pada muka di dalam video secara langsung; pengesanan titik penting pada muka dilakukan secara automatik pada setiap bingkai menggunakan tekstur titik-titik penting pada muka dan kedudukan relatifnya. Di samping itu, emosi seseorang dapat dikesan hanya berpandukan pada imej pandangan hadapan atau dari sudut pandangan yang lain, yang mana jika terdapat separuh kawasan muka yang tidak kelihatan, ianya akan dibina semula seterusnya pengecaman emosi dapat dilakukan. Ciri geometri dan tekstur telah digunakan bagi pengecaman emosi dan ciri tekstur diambil dari kawasan tertentu menggunakan pendekatan yang baru. Hasil kajian ini menunjukkan peningkatan berbanding pendekatan sedia ada dalam menentukan emosi bagi pelbagai gaya muka. Kesan jantina, etnik, warna dan emosi bercampur-baur serta keamatan emosi juga telah dianalisis. Kaedah pengecaman emosi wajah ini berfungsi secara masa nyata dan memerlukan kurang daripada setengah saat bagi setiap bingkai. Untuk UPM3DFE, dalam kes tujuh jenis emosi, ketepatan yang dicapai adalah 63.08% untuk paparan pelbagai sudut, dan 62.19% bagi pandangan hadapan dalam pengecaman emosi. Manakala bagi BU3DFE itu, 80.61% ketepatan telah dicapai untuk wajah pandangan hadapan dan 77.48% bagi paparan pelbagai sudut, bagi tujuh emosi asas. Kaedah pengecaman emosi ini telah meningkatkan ketepatan pengecaman dan boleh berfungsi dengan imej muka yang telah berputar secara hanyutan (yaw) dan jongketan (pitch). Kedua-dua pangkalan data (UPM3D dan BU3D) telah diuji untuk kesan jantina, etnik, warna dan emosi yang bercampur-baur dan berkeamatan berbeza. Dengan kaedah pengesanan silang, bagi pangkalan data BU3DFE, keputusan terbaik dicapai dengan subjek dari kaum India dan Asia Tenggara (56.6% dan 50.2%). Bagi UPM3DFE, keputusan terbaik telah dicapai dengan subjek dari Timur Tengah dan Asia Tenggara (66.6% dan 69.1%) dan ketepatan terendah didapati pada subjek dari benua Afrika (45% dan 54.54%). Berhubung dengan emosi yang bercampur-baur, BU3DFE telah berjaya mencapai ketepatan 67.72% dalam mengenali emosi yang pelbagai manakala ketepatan bagi UPM3DFE ialah 56.09% bagi kes yang sama. Untuk kes keamatan yang berbeza-beza bagi BU3DFE, keputusan bagi wajah dari pandangan pelbagai sudut mencapai 71.11% bagi keamatan pertama, 73.21% bagi keamatan kedua, 75.1% bagi keamatan ketiga dan 79.31% bagi keamatan keempat.



## ACKNOWLEDGEMENTS

My thanks to God for all things throughout my journey of knowledge investigation.

First and foremost, I would like to express my sincere appreciation to my supervisor Professor Dr. M. Iqbal Saripan for giving me an opportunity to start off this project. Through the course of my study, I have had the great destiny to get to know and interact with him. His comments and suggestions for further development as well as his assistance during writing this thesis have guided to me to progress in my studies. His talent, diverse background, interest, teaching and research style has provided for me exceptional opportunity to learn and made me become a better student.

I would like to express my truthful thanks and appreciation to the supervisory committee members Professor Dr. Mohd Hamiruce Marhaban and Dr. Fakhrul Zaman Rokhani for their guidance, valuable suggestions and advice throughout this work in making this a success.

Finally, I owe my sincere thanks to my parents for their encouragement and affirmation, which made it possible for me to achieve this work.

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

**M. Iqbal Bin Saripan, PhD**

Professor  
Faculty of Engineering  
Universiti Putra Malaysia  
(Chairman)

**Fakhrul Zaman Rokhani, PhD**

Senior Lecturer  
Faculty of Engineering  
Universiti Putra Malaysia  
(Member)

**Mohammad Hamiruce Marhaban, PhD**

Professor  
Faculty of Engineering  
Universiti Putra Malaysia  
(Member)

---

**ROBIAH BINTI YUNUS, PhD**

Professor and Dean  
School of Graduate Studies  
Universiti Putra Malaysia

Date:

## Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any other institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and Innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software.

Signature: \_\_\_\_\_ Date: \_\_\_\_\_

Name and Matric Number: Farhad Goodarzi, GS33448

## TABLE OF CONTENTS

	Page
<b>ABSTRACT</b>	i
<b><i>ABSTRAK</i></b>	iii
<b>ACKNOWLEDGEMENTS</b>	v
<b>APPROVAL</b>	vi
<b>DECLARATION</b>	viii
<b>LIST OF TABLES</b>	xiii
<b>LIST OF FIGURES</b>	xv
<b>LIST OF ABBREVIATIONS</b>	xx
 <b>CHAPTER</b>	
<b>1 INTRODUCTION</b>	1
1.1 Introduction	1
1.2 Problem statement	2
1.3 Aim and Objectives	4
1.4 Scope of the study	4
1.5 Contributions of Thesis	5
1.6 Outline of Thesis	5
 <b>2 LITERATURE REVIEW</b>	7
2.1 Introduction	7
2.2 Facial feature points detection	7
2.2.1 AAM based methods for Facial feature points detection	9
2.2.2 CLM based methods for facial feature points detection	13
2.2.3 Regression based methods for Facial feature points detection	14
2.2.4 Other methods (graphical model, joint face alignment and independent detectors)	14
2.3 Face detection	19
2.3.1 Integral image in Viola and Jones face detection	20
2.3.2 Adaptive boosting in Viola and Jones face detection	21
2.3.3 Attentional cascade in Viola and Jones face detection	21
2.3.4 Other methods in face detection	22
2.4 Face pose estimation	22
2.4.1 Categories of methods for face pose estimation	23
2.4.2 Hybrid methods in pose estimation	26
2.5 Face emotion recognition	27
2.5.1 Geometrical face emotion recognition	31
2.5.2 Appearance face emotion recognition	37
2.5.3 Multi view facial emotion recognition	39
2.5.4 Real time facial emotion recognition	47
2.6 Mixed emotions, gender, ethnicity and color in emotion recognition	47
2.7 Emotion intensity in face emotion recognition	47
2.8 Backpropagation neural network for emotion recognition	48

2.9	Feature selection for emotion recognition	51
2.10	Summary	53
<b>3</b>	<b>METHODOLOGY</b>	<b>56</b>
3.1	Introduction	56
3.1.1	General flow of the emotion recognition method	57
3.2	Facial points detection and geometrical face pose estimation	58
3.2.1	Calibration of pose estimation	60
3.2.2	Analysis and testing of pose estimation	63
3.3	Real time multi-view face emotion recognition	66
3.3.1	Multi-view face detection	67
3.3.2	Geometrical features extraction	68
3.3.3	Appearance features extraction	72
3.3.4	Neural network structure for emotion recognition	84
3.4	Neural networks setup	86
3.4.1	Composition of BU3DFE and UPM3DFE	87
3.4.2	Multi view subjects preparation in BU3DFE and UPM3DFE	88
3.4.3	Inter database homogeneity of BU3DFE and UPM3DFE	91
3.4.4	Statistical analysis for feature selection on databases	91
3.4.5	Effects of ethnicity, color, gender, and mixed emotions	92
3.4.6	Effects of emotion intensity in face emotion recognition	92
3.5	Summary	93
<b>4</b>	<b>RESULTS AND DISCUSSION</b>	<b>94</b>
4.1	Introduction	94
4.2	Facial feature points detection	94
4.2.1	Results	94
4.2.2	Discussions	99
4.3	Geometrical face pose estimation	99
4.3.1	Results	99
4.3.2	Discussion	100
4.4	Multi-view Face emotion recognition	101
4.5	UPM3DFE database emotion recognition	104
4.5.1	Statistical analysis	104
4.5.2	Results	107
4.5.3	Discussion	107
4.6	BU3DFE database emotion recognition	108
4.6.1	Statistical analysis	108
4.6.2	Results	111
4.7	Emotion intensity effect on face emotion recognition	113
4.8	Mixed database emotion recognition	115
4.8.1	Statistical analysis	115
4.8.2	Results	118
4.9	Ethnicity, color and gender effects on emotion recognition	118
4.10	Effect of mixed emotion on emotion recognition	119
4.11	Comparison with other methods	121
4.12	Real time Analysis	122

4.13 Summary	124
<b>5 CONCLUSIONS AND FUTURE WORKS</b>	<b>126</b>
5.1 Conclusions	126
5.2 Future Works	128
<b>REFERENCES</b>	<b>129</b>
<b>APPENDICES</b>	<b>142</b>
<b>BIODATA OF STUDENT</b>	<b>163</b>
<b>LIST OF PUBLICATIONS</b>	<b>164</b>



## LIST OF TABLES

Table	Page
2.1 Facial points detection methods comparison table	18
2.2 Head pose estimation methods. the star methods are more commonly used and achieving high precision	24
2.3 Facial emotion recognition comparison table	44
2.4 Emotion intensity accuracy results	48
3.1 Part of table for values of division for yaw and roll (division for yaw is Equation 3.2 and division for pitch is Equation 3.4) near (50 to 80 cm), far (100 to 150 cm) distance of person from camera	61
3.2 Attributes of basic emotions	71
3.3 Geometrical features for emotion detection	71
3.4 Comparison of BU3DFE and UPM3DFE databases	87
3.5 Available mixed emotions in BU3DFE and UPM3DFE databases	87
4.1 Average mean normalized deviation and the average maximal normalized deviation for 8 points detection PDM.	96
4.2 Comparison of current method with different methods available for head pose estimation	100
4.3 Confusion matrix with 20 neurons in hidden layer for person independent and seven emotions	103
4.4 Confusion matrix with 28 neurons in hidden layer for person independent and seven emotions	103
4.5 Feature rankings of UPM3DFE multi view according to Mrmr method	106
4.6 Confusion matrix for multi view UPM3DFE seven emotions.	107
4.7 Confusion matrix for near frontal UPM3DFE seven emotions.	107
4.8 Rates of false positive, false negative and true positive, false positive for UPM3DFE database	107
4.9 Feature rankings of BU3DFE multi view according to Mrmr method	110
4.10 Confusion matrix for near frontal BU3DFE seven emotions.	112
4.11 Confusion matrix for multi view BU3DFE seven emotions.	113
4.12 Rates of false positive, false negative and true positive, false positive for near-frontal and multi view subjects in BU3DFE database	113
4.13 Confusion matrix for multi view BU3DFE seven emotions 1 <sup>st</sup> emotion intensity.	114
4.14 Confusion matrix for multi view BU3DFE seven emotions 2 <sup>nd</sup> emotion intensity.	114
4.15 Confusion matrix for multi view BU3DFE seven emotions 3 <sup>rd</sup> emotion intensity.	115
4.16 Confusion matrix for multi view BU3DFE seven emotions 4 <sup>th</sup> emotion intensity.	115

4.17 Rates of false positive, false negative and true positive, false positive for different emotion intensities, multi view subjects in BU3DFE database	115
4.18 Feature rankings of mixed emotions features according to Mmr method	117
4.19 Rates of false positive, false negative and true positive, false positive for mixed BU-UPM database	118
4.20 Gender in 7 emotion recognition in each database	118
4.21 Color and ethnicity in 7 emotion recognition for each database:	119
4.22 Subjects identified to manifest mixed emotions in BU and UPM databases	120
4.23 Mixed emotions in 7 emotion recognition for each database	120
4.24 Real time analysis of FER system (System dual core 2.4 Ghz , 4Gb Ram).	123
4.25 Real time analysis of FER system (System core i5 3.4 Ghz , 8Gb Ram).	123



## LIST OF FIGURES

Figure	Page
1.1 Basic stages of classification system	1
1.2 Comparison of different smile expressions with different expression intensities. a)mild, b)average, c)intense.	3
2.1 Example of an image containing 68 manually labelled points from Multi-PIE database	8
2.2 Illustration of statistical distribution of facial feature points. There are 600 shapes (smaller dot points in black) normalized by Procrustes analysis. The larger dot points in red indicate the mean shape of all shapes.	10
2.3 Some face images obtained from the feature transformation in the tensor-based AAM. Columns represent specific combination of pose, emotion, and illumination. (a) Input images; (b) model-fitted images; (c) direct transformed images; (d) indirect transformed images; (e) ground-truth images	11
2.4 Two-dimensional shape and appearance variation for view-based 2D + 3D AAM—frontal model (top), right model (middle), and left model (bottom). (a) The linear shape variation modes. (b) The linear appearance variation modes.	11
2.5 Example synthesis for (a) neutral, (b) tender, (c) happy, (d) sad, (e) afraid and (f) angry, (g) same angry frame without teeth modifications or hair, (h) close up of teeth, (top) before modification and (bottom) after.	12
2.6 Shape initialization and comparison of different temporal constraints. (a)–(d) Show the shape initialization process. (e) Is resulting shape of a frame using proposed initialization scheme and temporal matching constraint. (f) Is the result of original AAMs initialized without temporal constraints. (g)–(j) Use similar shape initialization scheme but different temporal constraints.	13
2.7 ASM search space	14
2.8 Diagram showing the flow of the algorithm proposed using gaussian MRF	15
2.9 Joint face alignment results	16
2.10 Outline of independent detector method	17
2.11 Faces in the wild examples, with the differences in the pose, facial expression, lighting conditions, background and etc	19
2.12 Integral image and Haar like rectangle features (a-f)	20
2.13 The first (a) and second (b) features selected by the Adaboost algorithm	21
2.14 The attentional cascade algorithm	22
2.15 Face 3 degrees of freedom in 3D space, yaw (rotation around Z axis), pitch (rotation around X axis) and roll (rotation around Y axis)	23

2.16	Head tracking with matching. After training synthetically spatially shifted heads are generated. If best match is to one of shifted images, the cropping window is adjusted until best match head is one in centered head position	25
2.17	Categories of existing methods in human face emotion recognition	28
2.18	Some upper face AUs and their descriptions	28
2.19	some of the 84 facial points (FPs) used in FAP system	29
2.20	Subject posing fear emotion but the result is combination of fear and happy	30
2.21	Posed displays of Surprise, disgust and anger are exaggerated from CK	30
2.22	Emotion recognition procedure	31
2.23	Facial Points identified on face (a) Mesh imposed on face image (b)	32
2.24	The shape model defined by a set of facial landmarks	32
2.25	(a) Face border detection (b) eye detection from binary image and S images (c) Detected eyes (d) detected and binary Cr mouth.	33
2.26	(a) original mouth image. (b) Median filtered image (c) Image after FCM clustering (d) Measurement of MO from dips in intensity plot	34
2.27	EO determination (a) Dark pixel histogram creation (b) White pixels histogram creation (c) Addition of the dark and white pixel histograms.	35
2.28	Determination of EBC from rectangular patch found after image segmentation	36
2.29	Block diagram of Mamdani type emotion control	37
2.30	35 manually selected facial points	38
2.31	Face AUs recognition from texture	38
2.32	Emotion recognition using optical flow and average movement of facial areas	39
2.33	Feature vectors are built by concatenating feature histograms from each sub-block of the grid	39
2.34	The overview of the proposed three-step approach	40
2.35	The overview of GSRRR based multi-view facial emotion recognition method. (a) The training stage of the method, including the training facial feature extraction, multi-view training facial feature vectors synthesis. (b) The testing stage of the method, including the testing facial feature extraction, head pose estimation, multi-view testing feature vectors synthesis, and emotion classification	41
2.36	Comparison between Pose Specific Classification (PSC) and Pose Specific Linear Mapping (PSLM). I) Splitting data into the subsets based on the viewpoints by means of supervised classification. II) Learn mapping functions by transforming non-frontal subsets to the frontal. III) Map to the frontal view, and IV) Emotion classification. For testing, head pose is estimated of the input, next map it to the frontal and finally classify for emotions	42

2.37	Global and local transformations: (a) Three samples from different view angles and HOG features; their reconstructions using (b) a global mapping and (c) a pairwise mapping	43
2.38	Error function important points. (a) $E(w)$ the error function as surface function. At any point the gradient of error function is given by vector $\nabla E$ (b) Sample error function with four stationary points. A is local minimum, B is local maximum, and D is global minimum	49
2.39	Gradient descent methods. (a) Unmodified Gradient descent progression in case where a surface has low curvature (b) Effect of adding momentum to gradient descent. (c) Use of momentum in case where a surface has low curvature leads to faster progress (d) Use of momentum in High curvature surface does not have much effect	50
2.40	Conjugate gradient method. (a) After a line minimization the new gradient is perpendicular to line search direction (b) Selecting of conjugate directions (c) Application of conjugate gradients, algorithm reaches minimum of error after two steps	51
3.1	Testing phase for the face emotion recognition method.	57
3.2	Facial feature points used for geometric pose estimation, a) 7 basic facial points (8 points with face center), b) The positions of the points on face and their search space.	59
3.3	Facial feature head pose reading in (a) overall yaw and pitch, (b) pitch, and (c) yaw	61
3.4	Graph of equations for determining pitch from Equation 3.4 division	62
3.5	Graph of equations for determining Yaw from Equation 3.2 division	63
3.6	Head pose estimation test. a) Head pose roll angle is $21^\circ$ and the head is bent to the left in picture. b) Head pose yaw angle is $-45^\circ$ and the head moved to the left. roll and pitch are nearly zero. c) Head pose pitch angle is $+45^\circ$ and the head is bent backwards	64
3.7	Head pose in frontal pose. All the angles roll, yaw and pitch are zero (values are written on left). Left picture is same room condition, right picture is after brightness and contrast correction	64
3.8	Face boundary detection using face color for asserting the facial points fall within face boundary otherwise outer eye point is moved back to face boundary (orange color)	65
3.9	Side view face landmarks PDM model.	66
3.10	Camera setup for face emotion recognition	67
3.11	Face detection flowchart for multi view face detection	68
3.12	Added facial feature points for eyebrow centers (s12,s13), upper and lower lip (s14,s15) and upper and lower left eye (s8,s9), and upper and lower right eye (s10,s11)	70
3.13	Forehead texture for Anger, Disgust, Fear, Sad and Happy expressions	72

3.14	Lower face texture for Anger, Disgust, Fear, Sad, Happy and surprise expressions	73
3.15	Five areas of face skin are used for texture features extraction (left and right lip corners, forehead, between eyebrows and nose)from UPM3DFE database	74
3.16	Feature one (left mouth contrast texture) average, minimum and maximum values in seven emotions from UPM3DFE database	76
3.17	Feature one (left mouth contrast texture) average, minimum and maximum values in seven emotions from BU3DFE database	77
3.18	Feature nine (right mouth contrast texture) average, minimum and maximum values in seven emotions from UPM3DFE database	77
3.19	Feature nine (right mouth contrast texture) average, minimum and maximum values in seven emotions from BU3DFE database	78
3.20	Feature forty six (mouth width) average, minimum and maximum values in seven emotions from UPM3DFE database	79
3.21	Feature forty six (mouth width) average, minimum and maximum values in seven emotions from BU3DFE database	79
3.22	Feature forty seven (Distance of mouth to nose) average, minimum and maximum values in seven emotions from UPM3DFE database	80
3.23	Feature forty seven (Distance of mouth to nose) average, minimum and maximum values in seven emotions from BU3DFE database	80
3.24	Feature forty four (eyebrow distance) average, minimum and maximum values in seven emotions from UPM3DFE database	81
3.25	Feature forty four (eyebrow distance) average, minimum and maximum values in seven emotions from BU3DFE database	82
3.26	Feature forty five (mouth height) average, minimum and maximum values in seven emotions from UPM3DFE database	82
3.27	Feature forty five (mouth height) average, minimum and maximum values in seven emotions from BU3DFE database	83
3.28	Feature thirty three (nose contrast texture) average, minimum and maximum values in seven emotions from UPM3DFE database	83
3.29	Feature thirty three (nose contrast texture) average, minimum and maximum values in seven emotions from BU3DFE database	84
3.30	Activation function types. (a) Antisymmetric activation function. (b) Nonsymmetric activation function	85
3.31	Neural Network architecture for emotion recognition	86
3.32	UPM3DFE database subjects preparation for emotion recognition	88
3.33	Three rotation angles a) rotation about $x_3$ (z) b)rotation about $x_2$ (y) c) rotation about $x_1$ (x).	89
3.34	Training for multi view emotion recognition. Rows are the seven emotions and columns from left are yaw $-90^\circ$ , yaw $90^\circ$ , pitch $+45^\circ$ , yaw $+45^\circ$ , yaw $-45^\circ$ , frontal, and pitch $-45^\circ$	90
3.35	Test of homogeneity in BU3D and UPM3D for emotion recognition	91
3.36	Female BU3DFE subject 1, happy emotions for emotion recognition a) emotion intensity 1, b) emotion intensity 2, c) emotion intensity 3, and d) emotion intensity 4	92

4.1	Two accuracy measures of eight facial points. The green points are ground truth points and red points are detected points.	95
4.2	Two accuracy measures of sixteen facial points. The green points are ground truth points and red points are detected points	96
4.3	Side view facial points detection for emotion recognition (a) 13 points detection on side view face (b) Point correction result of eye brow, nose tip and mouth points	97
4.4	Side view facial points detection for emotion recognition (a) side view face detection (b) skin detection result (c) nose, eye brow and mouth points correction	98
4.5	Side view facial points detection error in surprise emotion expression	99
4.6	Neural Networks architecture for emotion recognition implemented in Matlab	101
4.7	Graph of number of hidden layers with respect to generalization error for emotion recognition neural network for BU3DFE	102
4.8	Graph of number of hidden layers with respect to generalization error for emotion recognition neural network UPM3DFE	102
4.9	Features selection. (a) near frontal, and (b) profile face images	104
4.10	Anova test on UPM3DFE features	105
4.11	Misclassification error with respect to number of features the minimum error occurs at 48 features on UPM3DFE features	106
4.12	UPM3DFE subject posing for (a) anger and (b) disgust. Problems of mixed emotions, and low light condition.	108
4.13	Anova test on BU3DFE features	109
4.14	Misclassification error with respect to number of features, the minimum error occurs at 49 features on BU3DFE features and all features are needed	110
4.15	Emotion recognition chart for seven emotions BU3DFE with GLCM for near frontal	111
4.16	Emotion recognition chart for seven emotions BU3DFE with GLCM for multi view.	112
4.17	Comparison of different approaches on effect of emotion intensity on emotion recognition for BU3DFE database.	114
4.18	Anova test on mixed emotion database features	116
4.19	Misclassification error with respect to number of features, the minimum error occurs at 49 features for mixed database (BU and UPM) features.	117
4.20	Emotion recognition graph comparing different methods for person independent using 2D capturing camera	121
4.21	Shadow appearance in subjects during training (a) (b) female (c) (d) male subjects.	122
4.22	Real time comparison of proposed method with other works in milliseconds	124



## LIST OF ABBREVIATIONS AND SYMBOLS

3DFE	3D facial expression
Adaboost	Adaptive boosting
BP	Back propagation
ASM	active shape model
AAM	active appearance model
AU	action unit
DPM	Deformable parts model
$F_r$	frame rate in frame-per-second (fps)
FAPS	Facial animation parameters
FER	Facial expression recognition
fps	frames per second (unit)
GB	Giga byte(unit)
GHz	Giga hertz(unit)
HSV	hue-saturation-value
LDA	Linear discriminant analysis
LFW	Labeled Faces in the Wild
Logsig	Logarithmic sigmoid
mRMR	minimum Redundancy Maximum Relevance
NN	neural network
PCA	principal components analysis
PDM	point deformation model
SIFT	scale invariant feature transform
SVM	support vector machine
SVR	support vector regression
Tansig	Tangent sigmoid

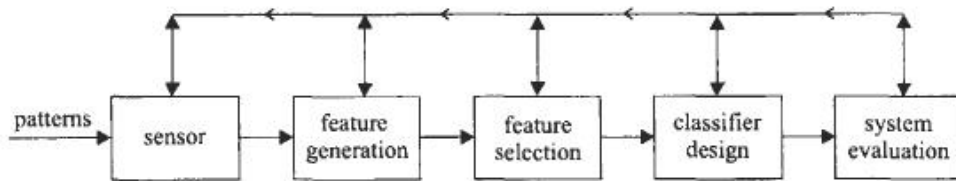
## CHAPTER 1

### INTRODUCTION

#### 1.1 Introduction

Until recently most available data sets of expressive faces were of limited size mainly the prototypical expressions of seven basic emotions (Anger, Disgust, Fear, Happiness, Sadness, Surprise and neutral). Recent efforts focus on recognition of complex and spontaneous emotional phenomena (e.g. boredom, lack of attention, frustration, stress, etc) [1, 2].

The overall view of a classification system [3, 4] is brought in Figure 1.1 which consists of a sensor, which is a camera in this thesis, that generates features (pixels), and next the relative features are selected from these features. After this, these features are classified into some classes and evaluation is done for the results of classification.



**Figure 1.1: Basic stages of classification system [4]**

In case of the proposed classifying system in this thesis, a normal camera or a webcam device can be used to capture the sequence of pictures. After this, some features are selected from the many features existing in the image and the classifier can distinguish between emotional states. In the end, the performance is evaluated.

Facial imaging is one of the current neurometric or biometric methods used to measure emotional response. Most of the other techniques such as bio-sensors, eye tracking, EEG and fMRI require specialized equipment to generate their measurements. Moreover, they require highly trained specialist to interpret and analyze the results. facial imaging, by contrast, is comparatively simple to implement. In other words, facial imaging is easier and has more speed and precision (and it has lower cost) compared to other methods.

The applications of the facial imaging system can be expanded to many different areas, including home, online, store and mobile. The results can be stored as visualized reports that can be analyzed by statistical software. The data can also later be used by market research analyzes.

Other applications of facial imaging emotion recognition are in robotics, health care, monitoring and alarming tasks, and many other areas.

## **1.2 Problem statement**

Due to the complexity in the human face and facial emotions and the many muscles involved in forming the seven basic emotions, recognizing and classifying these emotions is a major issue and an open problem in the computer vision. The problem is more complex when considering non frontal faces since the head can turn in angles yaw, pitch, and roll.

The distinctions between some emotions are confusing [5]. They are namely, anger and disgust, fear and happiness, fear and anger, sadness with anger. Also, some facial expressions represent mixed emotions and the level of the expressed emotion varies.

In general, emotion is often communicated by changes in one or more facial features. In addition, the same facial feature may be involved in more than one emotion. Presence and absence of one or more facial actions can change the emotion meaning. For example, Figure 1.2 shows different smile expressions. All three subjects have AU12 (lip corners pulled sideways).



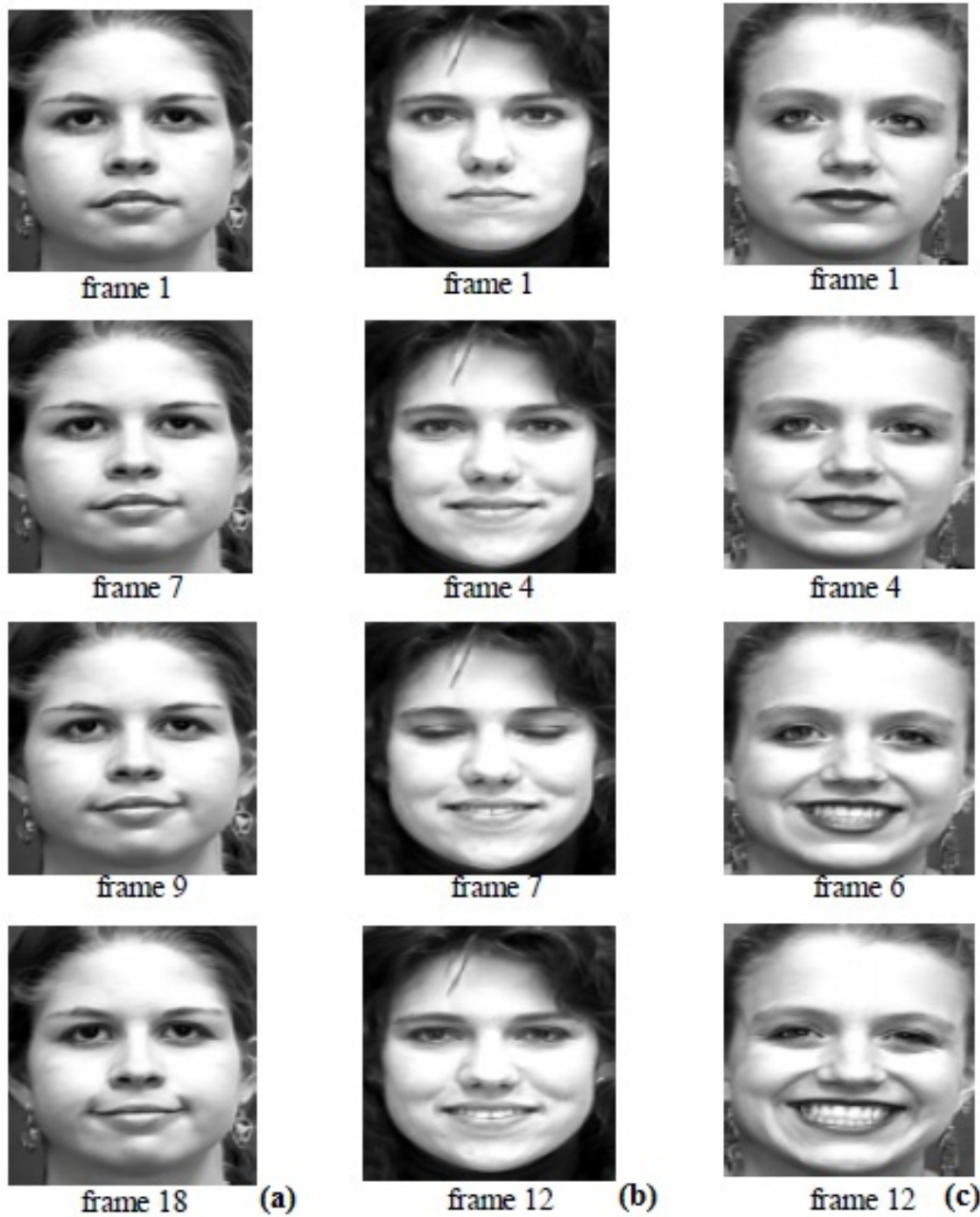


Figure 1.2: Comparison of different smile expressions with different expression intensities [6]. a) mild, b) average, c) intense.

Subjects b and c, are examples of emotional smile in which lip corners pulled sideways (AU12), the cheeks raised (AU6) and lips apart (AU25). Subject c additionally has wrinkles around the corner of the eyes. The degree of smiling or happy is related to the intensity of raising cheeks and lip corners and the existence of wrinkles. Therefore, it is not only important to discover the basic emotions, but also find out the intensity of these emotions. This helps to discriminate different emotions that have similar structure on face, but have different meanings.

Facial Action Coding System (FACS) [7], is a system to describe facial expressions. This system for facial muscles coding is described in Section 2.4 of this thesis. Manually coding all the action units (AU) on the face is a complicated task. It takes up to 10 hours for a trained programmer to code one minute of video of facial expressions [8, 9]. Therefore, it is desirable and necessary to automate the process of extraction of facial parts movements and coding. The system is necessary to work in real time, since the changes of expressions on the face occur in real time. In the case of absence of such a real-time feature, some expressions will be missed from detection or even the emotion may be reported falsely.

The role of gender, ethnicity, and color also need to be analyzed in different databases, and to find how these factors affect the recognition of emotions.

### **1.3 Aim and Objectives**

Basically, the main aim of this thesis is to detect the seven basic emotions automatically in real time on the face of the person at different facial poses.

The objectives of this study are:

1. To recognize the seven basic emotions automatically in frontal, non-frontal and side view faces.
2. To consider the emotion intensity in emotion recognition to find the difference in emotions and recognizing mixed emotions by discriminating the different emotion intensities that are present in the face.
3. To identify and analyze the effects of ethnicity, color, gender in emotion recognition using both BU3DFE and UPM3DFE databases.
4. To analyze the real time delay of the proposed face emotion recognition method.

### **1.4 Scope of the study**

The scope of this study is to recognize the human facial emotions database with high accuracy using UPM-3D database [10] and BU3DFE database [11]. The human facial emotions studied here are mainly the seven basic emotions (anger, disgust, fear, happiness, sadness and surprise and neutral).

During testing of new data, it can either reject the valid emotion (FN) or accept the false emotion or data (FP). For security reasons, the first error is not critical but the second error is critical as should be kept as low as possible. The classification algorithm can be manipulated to minimize critical error which is false positive (FP).

For mixed emotions recognitions the number of mixed emotions for both BU3DFE and UPM3DFE have been identified to be 13. They are namely sad-anger, sad-neutral, fear-sad, fear-neutral, fear-anger, anger-disgust, fear-happy, anger-happy, disgust-happy, sad-happy, fear-surprise, surprise-happy, and sad-disgust emotions.

## **1.5 Contributions of Thesis**

The contributions of the thesis is automatic recognition of facial emotions in case of the seven basic emotions (including neutral) for person independent (unidentified persons) and multi view cases. Current emotion recognition systems as discussed in the literature review chapter suffer from some aspects such as lack of multi view face emotion detection (both yaw and pitch), low accuracy, and not having fully automatic feature extraction for person independent analysis.

The proposed work includes the missing features in existing systems and shows improvement over other methods with respect to emotion recognition accuracy. Moreover, the effects of gender, ethnicity, mixed emotions and degree of emotion were examined for both UPM3DFE and BU3DFE databases, and composition of the database in emotion recognition has been carefully studied.

## **1.6 Outline of Thesis**

Chapter 1 (Introduction): Presents the introduction and background for this research. The problem statement, objectives of research, scope of research, and contributions of the study were covered in this chapter.

Chapter 2 (Literature review): Presents a critical literature review which covers various works and methods of facial points detection, face pose estimation, face emotion recognition and the different databases made for these purposes. This chapter will outline the strengths and weaknesses of the existing methods.

Chapter 3 (Methodology): It explains the methods and strategies for facial points detection, pose estimation, face emotion recognition, and the role of gender, ethnicity, mixed emotions and intensity in emotion recognition which were used in the research to achieve the specified objectives.

Chapter 4 (Results and discussions): It expresses the obtained results in detail. The results include emotion recognition accuracy for both BU3DFE and UPM3DFE, and analysis of the role of gender, ethnicity, color, mixed emotions and different intensities of emotion in face emotion recognition. These results are illustrated in the form of accuracy percentages, comparison graphs, plotted

curves and Figures. The achieved results are discussed in detail in this chapter.

Chapter 5 (Conclusions and future works): Provides a summary of the thesis, and lists the final achievements and verifies them with the drawn objectives in the first chapter to ensure all the objectives have been achieved. Finally, the recommendations for possible future works in the field is also mentioned in this chapter.



## REFERENCES

- [1] Maja Pantic. Affective computing. *Encyclopedia of multimedia technology and networking*, 1:8–14, 2005.
- [2] Shaohua Wan and JK Aggarwal. Spontaneous facial expression recognition: A robust metric learning approach. *Pattern Recognition*, 47(5):1859–1868, 2014.
- [3] Richard O Duda, Peter E Hart, and David G Stork. *Pattern Classification*. John Wiley & Sons, 2012.
- [4] Sergios Theodoridis, Aggelos Pikrakis, Konstantinos Koutroumbas, and Dionisis Cavouras. *Introduction to Pattern Recognition: A Matlab Approach*. Academic Press, 2010.
- [5] Irene Kotsia, Ioan Buciuc, and Ioannis Pitas. An Analysis of Facial Expression Recognition under Partial Facial Image Occlusion. *Image and Vision Computing*, 26(7):1052–1067, 2008.
- [6] Jenn-Jier James Lien. *Automatic Recognition of Facial Expressions using Hidden Markov Models and Estimation of Expression Intensity*. PhD thesis, Washington University, St. Louis, 1998.
- [7] Paul Ekman and Wallace Friesen. Facial Action Coding System: A technique for the Measurement of Facial Movements. *Consulting Psychologist*, 2, 1978.
- [8] Jeffrey F Cohn, Adena J Zlochower, James Lien, and Takeo Kanade. Automated Face Analysis by Feature Point Tracking has High Concurrent Validity with Manual FACS Coding. *Psychophysiology*, 36(01):35–43, 1999.
- [9] Marian Stewart Bartlett, Paul A Viola, Terrence J Sejnowski, Beatrice A Golomb, Jan Larsen, Joseph C Hager, and Paul Ekman. Classifying Facial Action. *Advances in Neural Information Processing Systems*, pages 823–829, 1996.
- [10] Habibu Rabiuc, Syamsiah Mashohor, Mohammad Hamiruce Marhaban, and M. Iqbal Saripan. UPM 3D Facial Expression Recognition Database (UPM3DFE). In *PRICAI 2012: Trends in Artificial Intelligence*, pages 470–479. Springer, Berlin Heidelberg, 2012.

- [11] Lijun Yin, Xiaozhou Wei, Yi Sun, Jun Wang, and Matthew J Rosato. A 3D Facial Expression Database for Facial Behavior Research. In *7th international conference on automatic face and gesture recognition, 2006. FGR 2006.*, pages 211–216. IEEE, 2006.
- [12] Paul Viola and Michael Jones. Rapid object detection using a boosted cascade of simple features. In *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2001. CVPR 2001.*, volume 1, pages I–I. IEEE, 2001.
- [13] Hanchuan Peng, Fulmi Long, and Chris Ding. Feature Selection based on Mutual Information Criteria of Max-dependency, Max-relevance, and Min-redundancy. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(8):1226–1238, 2005.
- [14] Ralph Gross, Iain Matthews, Jeffrey Cohn, Takeo Kanade, and Simon Baker. Multi-pie. *Image and Vision Computing*, 28(5):807–813, 2010.
- [15] Paul Viola and Michael J Jones. Robust real-time Face Detection. *International journal of computer vision*, 57(2):137–154, 2004.
- [16] Timothy F Cootes and Christopher J Taylor. Active shape models, smart snakes. In *Proceedings of the British Machine Vision Conference, BMVC92*, pages 266–275. Springer, 1992.
- [17] Xinbo Gao, Ya Su, Xuelong Li, and Dacheng Tao. A Review of Active Appearance Models. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 40(2):145–158, 2010.
- [18] Hyung-Soo Lee and Daijin Kim. Tensor-based AAM with Continuous Variation Estimation: Application to Variation-robust Face Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(6):1102–1116, 2009.
- [19] Timothy F Cootes, Gareth J Edwards, and Christopher J Taylor. Active Appearance Models. In *5th European Conference on Computer Vision, ECCV’98*, pages 484–498. Springer, 1998.
- [20] Jaewon Sung and Daijin Kim. Pose-Robust Facial Expression Recognition Using View-Based 2D 3D AAM. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 38(4):852–866, 2008.



- [21] Robert Anderson, Björn Stenger, Vincent Wan, and Roberto Cipolla. Expressive Visual Text-to-speech using Active Appearance Models. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3382–3389. IEEE, 2013.
- [22] Timothy F Cootes, Gavin V Wheeler, Kevin N Walker, and Christopher J Taylor. View-based Active Appearance Models. *Image and vision computing*, 20(9):657–664, 2002.
- [23] Chen Huang, Xiaoqing Ding, and Chi Fang. Pose Robust Face Tracking by combining View-based AAMs and Temporal filters. *Computer Vision and Image Understanding*, 116(7):777–792, 2012.
- [24] Jason M Saragih, Simon Lucey, and Jeffrey F Cohn. Deformable Model Fitting by Regularized Landmark Mean-shift. *International Journal of Computer Vision*, 91(2):200–215, 2011.
- [25] Timothy F Cootes, Christopher J Taylor, David H Cooper, and Jim Graham. Active Shape Models-their Training and Application. *Computer vision and image understanding*, 61(1):38–59, 1995.
- [26] David G Lowe. Distinctive Image Features from Scale-Invariant Keypoints. *International journal of computer vision*, 60(2):91–110, 2004.
- [27] Timo Ojala, Matti Pietikäinen, and David Harwood. A Comparative Study of Texture Measures with Classification based on Featured Distributions. *Pattern recognition*, 29(1):51–59, 1996.
- [28] Brais Martinez, Michel François Valstar, Xavier Binefa, and Maja Pantic. Local Evidence Aggregation for Regression-based Facial Point Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(5):1149–1163, 2013.
- [29] Michal Uříčář, Vojtěch Franc, and Václav Hlaváč. Detector of Facial Landmarks Learned by the Structured Output SVM. In *International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, VISAPP 2012*, pages 547–556. Springer, 2012.
- [30] Michal Uříčář, Vojtěch Franc, Diego Thomas, Sugimoto Akihiro, and Václav Hlaváč. Real-time Multi-view Facial Landmark Detector Learned by the Structured Output SVM. In *BWILD 2015: Proceedings of the 11th IEEE International Conference on Automatic Face and Gesture Recognition*

*Conference and Workshops*. IEEE, 2015.

- [31] Cong Zhao, Wai-Kuen Cham, and Xiaogang Wang. Joint Face Alignment with a Generic Deformable Face Model. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 561–568. IEEE, 2011.
- [32] Danijela Vukadinovic and Maja Pantic. Fully Automatic Facial Feature Point Detection using Gabor Feature based Boosted Classifiers. In *IEEE International Conference on Systems, Man and Cybernetics*, volume 2, pages 1692–1698. IEEE, 2005.
- [33] Takeo Kanade, Jeffrey F Cohn, and Yingli Tian. Comprehensive Database for Facial Expression Analysis. In *Fourth IEEE International Conference on Automatic Face and Gesture Recognition Proceedings*, pages 46–53. IEEE, 2000.
- [34] Michael M Nordstrøm, Mads Larsen, Janusz Sierakowski, and Mikkel Bille Stegmann. The IMM Face Database-an Annotated Dataset of 240 Face Images. Technical report, Technical University of Denmark, DTU Informatics, Building 321, 2004.
- [35] Gary B. Huang, Manu Ramesh, Tamara Berg, and Erik Learned-Miller. Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments. Technical Report 07-49, University of Massachusetts, Amherst, October 2007.
- [36] Marco La Cascia, Stan Sclaroff, and Vassilis Athitsos. Fast, reliable head tracking under varying illumination: An approach based on registration of texture-mapped 3D models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(4):322–336, 2000.
- [37] Maja Pantic, Michel Valstar, Ron Rademaker, and Ludo Maat. Web-based Database for Facial Expression Analysis. In *IEEE International Conference on Multimedia and Expo, 2005. ICME 2005*, pages 5–10. IEEE, 2005.
- [38] Maja Pantic and Leon J. M. Rothkrantz. Automatic Analysis of Facial Expressions: The state of the art. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(12):1424–1445, 2000.
- [39] Toshiyuki Sakai, Makoto Nagao, and Takeo Kanade. *Computer analysis and classification of photographs of human faces*. Kyoto University, 1972.



- [40] Martin A Fischler and Robert A Elschlager. The representation and matching of pictorial structures. *IEEE Transactions on computers*, 100(1):67–92, 1973.
- [41] Gary B Huang, Marwan Mattar, Tamara Berg, and Eric Learned-Miller. Labeled Faces in the Wild: A Database for studying Face Recognition in Unconstrained Environments. In *Workshop on Faces in 'Real-Life' Images: Detection, Alignment, and Recognition*, 2008.
- [42] Yoav Freund and Robert E Schapire. A desicion-theoretic generalization of on-line learning and an application to boosting. In *European conference on computational learning theory*, pages 23–37. Springer, 1995.
- [43] Rainer Lienhart and Jochen Maydt. An extended set of haar-like features for rapid object detection. In *Proceedings of International Conference on Image Processing.*, volume 1, pages I–I. IEEE, 2002.
- [44] Jayanti Das and Hiranmoy Roy. Human face detection in color images using hsv color histogram and wld. In *International Conference on Computational Intelligence and Communication Networks (CICN)*, pages 198–202. IEEE, 2014.
- [45] Erik Murphy-Chutorian and Mohan M Trivedi. Head Pose estimation in Computer Vision: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(4):607–626, 2009.
- [46] Sourabh Niyogi and William T Freeman. Example-based Head Tracking. In *Proceedings of the Second International Conference on Automatic Face and Gesture Recognition*, pages 374–378. IEEE, 1996.
- [47] Jamie Sherrah, Shaogang Gong, and Eng-Jon Ong. Face distributions in Similarity Space under Varying Head Pose. *Image and Vision Computing*, 19(12):807–819, 2001.
- [48] Michael Jones and Paul Viola. Fast Multi-view Face Detection. *Mitsubishi Electric Research Lab TR-20003-96*, 3:14, 2003.
- [49] Henry A Rowley, Shumeet Baluja, and Takeo Kanade. Rotation Invariant Neural Network-based Face Detection. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Proceedings*, pages 38–44. IEEE, 1998.
- [50] Hankyu Moon and Matt L Miller. Estimating Facial Pose from a Sparse

- Representation [Face Recognition Applications]. In *International Conference on Image Processing, ICIP'04*, volume 1, pages 75–78. IEEE, 2004.
- [51] Norbert Krüger, Michael Pöttsch, and Christoph von der Malsburg. Determination of Face Position and Pose with a Learned Representation based on Labeled Graphs. *Image and vision computing*, 15(8):665–673, 1997.
- [52] Andreas Lanitis, Camillo Jose Taylor, Tim Cootes, and Tariq Ahmed. Automatic Interpretation of Human Faces and Hand Gestures using Flexible Models. In *International Workshop on Automatic Face-and Gesture-Recognition*. Citeseer, 1995.
- [53] Andrew Gee and Roberto Cipolla. Determining the Gaze of Faces in Images. *Image and Vision Computing*, 12(10):639–647, 1994.
- [54] Gangqiang Zhao, Ling Chen, Jie Song, and Gencai Chen. Large Head Movement Tracking using Sift-based Registration. In *Proceedings of the 15th international conference on Multimedia*, pages 807–810. ACM, 2007.
- [55] Ravikanth Pappu and Paul A Beardsley. A Qualitative Approach to Classifying Gaze Direction. In *Third IEEE International Conference on Automatic Face and Gesture Recognition Proceedings.*, pages 160–165. IEEE, 1998.
- [56] Tony S Jebara and Alex Pentland. Parametrized Structure from Motion for 3D Adaptive Feedback Tracking of Faces. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Proceedings*, pages 144–150. IEEE, 1997.
- [57] Jeffrey Huang, Xuhui Shao, and Harry Wechsler. Face Pose Discrimination using Support Vector Machines (SVM). In *Fourteenth International Conference on Pattern Recognition, 1998. Proceedings.*, volume 1, pages 154–156. IEEE, 1998.
- [58] Charles Darwin. *The Expression of the Emotions in Man and Animals*. Oxford University Press, 1998.
- [59] Daniel L Swets and John Juyang Weng. Using Discriminant Eigenfeatures for Image Retrieval. *IEEE Transactions on pattern analysis and machine intelligence*, 18(8):831–836, 1996.
- [60] Igor S Pandzic and Robert Forchheimer. *MPEG-4 Facial Animation, the*

*Standard, Implementation and Applications.* John Wiley&Sons, 2002.

- [61] W Gerrod Parrott. *Emotions in Social Psychology: Essential Readings.* Psychology Press, 2001.
- [62] Ting Wu, Siyao Fu, and Guosheng Yang. Survey of the Facial Expression Recognition Research. In *Advances in Brain Inspired Cognitive Systems*, pages 392–402. Springer, Berlin Heidelberg, 2012.
- [63] A. Punitha and M. Kalaiselvi Geetha. Texture based Emotion Recognition from Facial Expressions using Support Vector Machine. *International Journal of Computer Applications*, 80(5):1–5, October 2013.
- [64] Salih Burak Gokturk, J-Y Bouguet, Carlo Tomasi, and Bernd Girod. Model-based Face Tracking for View-independent Facial Expression Recognition. In *Fifth IEEE International Conference on Automatic Face and Gesture Recognition Proceedings.*, pages 287–293. IEEE, 2002.
- [65] Ya Chang, Changbo Hu, Rogerio Feris, and Matthew Turk. Manifold based Analysis of Facial Expression. *Image and Vision Computing*, 24(6):605–614, 2006.
- [66] Fatemeh Shahrabi Farahani, Mansour Sheikhan, and Ali Farrokhi. A Fuzzy Approach for Facial Emotion Recognition. In *13th Iranian Conference on Fuzzy Systems (IFSC), 2013*, pages 1–4. IEEE, 2013.
- [67] EH Mamdani. Applications of Fuzzy set Theory to Control Systems: A Survey. *Fuzzy automata and decision processes*, pages 77–88, 1977.
- [68] Aruna Chakraborty, Amit Konar, Uday Kumar Chakraborty, and Amita Chatterjee. Emotion Recognition from Facial Expressions and its Control using Fuzzy Logic. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 39(4):726–743, 2009.
- [69] Guodong Guo and Charles R Dyer. Learning from Examples in the Small Sample Case: Face Expression Recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics.*, 35(3):477–488, 2005.
- [70] Michael J Lyons, Shigeru Akamatsu, Miyuki Kamachi, Jiro Gyoba, and Julien Budynek. The Japanese Female Facial Expression Database (JAFFE) , 1998.

- [71] Marian Stewart Bartlett, Gwen Littlewort, Mark Frank, Claudia Lainscsek, Ian Fasel, and Javier Movellan. Fully Automatic Facial Action Recognition in Spontaneous Behavior. In *7th International Conference on automatic face and gesture recognition, FGR 2006.*, pages 223–230. IEEE, 2006.
- [72] Keith Anderson and Peter W McOwan. A real-time Automated System for the Recognition of Human Facial Expressions. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 36(1):96–105, 2006.
- [73] S Moore and R Bowden. Local Binary Patterns for Multi-view Facial Expression Recognition. *Computer Vision and Image Understanding*, 115(4):541–558, 2011.
- [74] Ognjen Rudovic, Maja Pantic, and Ioannis Patras. Coupled Gaussian Processes for Pose-invariant Facial Expression Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(6):1357–1369, 2013.
- [75] Wenming Zheng. Multi-View Facial Expression Recognition Based on Group Sparse Reduced-Rank Regression. *IEEE Transactions on Affective Computing*, 5(1):71–85, 2014.
- [76] Mahdi Jampour, Vincent Lepetit, Thomas Mauthner, and Horst Bischof. Pose-specific non-linear mappings in feature space towards multiview facial expression recognition. *Image and Vision Computing*, 58:38–46, 2017.
- [77] Mahdi Jampour, Thomas Mauthner, and Horst Bischof. Pairwise linear regression: An efficient and fast multi-view facial expression recognition. In *11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, volume 1, pages 1–8. IEEE, 2015.
- [78] Chih-Chung Chang and Chih-Jen Lin. Libsvm: a library for support vector machines. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 2(3):27–28, 2011.
- [79] Michael Lyons, Shigeru Akamatsu, Miyuki Kamachi, and Jiro Gyoba. Coding Facial Expressions with Gabor Wavelets. In *Third IEEE International Conference on Automatic Face and Gesture Recognition, Proceedings.*, pages 200–205. IEEE, 1998.
- [80] Irene Kotsia and Ioannis Pitas. Facial Expression Recognition in Image Sequences using Geometric Deformation Features and Support Vector

- Machines. *IEEE Transactions on Image Processing*, 16(1):172–187, 2007.
- [81] Yuxiao Hu, Zhihong Zeng, Lijun Yin, Xiaozhou Wei, Jilin Tu, and Thomas S Huang. A Study of Non-frontal-view Facial Expressions Recognition. In *19th International Conference on Pattern Recognition, ICPR 2008.*, pages 1–4. IEEE, 2008.
  - [82] Yuxiao Hu, Zhihong Zeng, Lijun Yin, Xiaozhou Wei, Xi Zhou, and Thomas S Huang. Multi-view facial expression recognition. In *8th IEEE International conference on Automatic face & gesture recognition, 2008. FG'08. on*, pages 1–6. IEEE, 2008.
  - [83] Nikolas Hesse, Tobias Gehrig, Hua Gao, and Hazim Kemal Ekenel. Multi-view Facial Expression Recognition using Local Appearance Features. In *21st International Conference on Pattern Recognition (ICPR)*, pages 3533–3536. IEEE, 2012.
  - [84] Usman Tariq, Jianchao Yang, and Thomas S Huang. Multi-view facial expression recognition analysis with generic sparse coding feature. In *European Conference on Computer Vision*, pages 578–588. Springer, 2012.
  - [85] Anwar Saeed, Ayoub Al-Hamadi, Robert Niese, and Moftah Elzobi. Frame-Based Facial Expression Recognition Using Geometrical Features. *Advances in Human-Computer Interaction*, 2014.
  - [86] Claudio Loconsole, Domenico Chiaradia, Vitoantonio Bevilacqua, and Antonio Frisoli. Real-Time Emotion Recognition: An Improved Hybrid Approach for Classification Performance. In *Intelligent Computing Theory*, pages 320–331. Springer, 2014.
  - [87] Marian Stewart Bartlett, Gwen Littlewort, Ian Fasel, and Javier R Movellan. Real Time Face Detection and Facial Expression Recognition: Development and Applications to Human Computer Interaction . In *Conference on Computer Vision and Pattern Recognition Workshop, CVPRW'03.*, volume 5, pages 53–53. IEEE, 2003.
  - [88] Myunghoon Suk and Balakrishnan Prabhakaran. Real-Time Mobile Facial Expression Recognition System—A Case Study. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 132–137. IEEE, 2014.
  - [89] Anh Vo and Ngoc Quoc Ly. Facial Expression Recognition Using



Pyramid Local Phase Quantization Descriptor. In *Knowledge and Systems Engineering*, pages 105–115. Springer, 2015.

- [90] Swapna Agarwal and Dipti Prasad Mukherjee. Facial expression recognition through adaptive learning of local motion descriptor. *Multimedia Tools and Applications*, pages 1–27, 2015.
- [91] Swapna Agarwal and Dipti Prasad Mukherjee. Decoding mixed emotions from expression map of face images. In *10th IEEE International Conference Automatic Face and Gesture Recognition (FG)*, pages 1–6. IEEE, 2013.
- [92] M Nabil Hewahi and AbdulRahman M Baraka. Emotion recognition model based on facial expressions, ethnicity and gender using backpropagation neural network. *International Journal of Technology Diffusion (IJTD)*, 3(1):33–43, 2012.
- [93] Christopher M. Bishop. *Neural Networks for Pattern Recognition*. Oxford university press, 1995.
- [94] Anil K Jain, Robert P. W. Duin, and Jianchang Mao. Statistical pattern recognition: A review. *IEEE Transactions on pattern analysis and machine intelligence*, 22(1):4–37, 2000.
- [95] Juha Reunanen. Overfitting in making comparisons between variable selection methods. *Journal of Machine Learning Research*, 3(Mar):1371–1382, 2003.
- [96] M Karthigayan, M Rizon, R Nagarajan, and Sazali Yaacob. *Genetic Algorithm and Neural Network for Face Emotion Recognition*. INTECH Open Access Publisher, 2008.
- [97] Govind U Kharat and Sanjay V Dudul. Emotion Recognition from Facial Expression using Neural Networks. In *Human-Computer Systems Interaction*, pages 207–219. Springer, 2009.
- [98] Robert E Schapire. The Boosting Approach to Machine Learning: An overview. In *Nonlinear estimation and classification*, pages 149–171. Springer, Berlin Heidelberg, 2003.
- [99] David Crandall, Pedro Felzenszwalb, and Daniel Huttenlocher. Spatial priors for Part-based Recognition using Statistical Models. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2005.*, volume 1, pages 10–17. IEEE, 2005.

- [100] Thanarat Horprasert, Yaser Yacoob, and Larry S Davis. Computing 3-d head orientation from a monocular image sequence. In *Proceedings of the Second International Conference on Automatic Face and Gesture Recognition*, pages 242–247. IEEE, 1996.
- [101] Hamit Soyel and Hasan Demirel. Facial Expression Recognition using 3D Facial Feature Distances. In *Image Analysis and Recognition*, pages 831–838. Springer, Berlin Heidelberg, 2007.
- [102] Hamimah Ujir. *3D Facial Expression Classification using a Statistical Model of Surface Normals and a Modular Approach*. PhD thesis, University of Birmingham, 2013.
- [103] Robert M Haralick, Karthikeyan Shanmugam, and Its' Hak Dinstein. Textural Features for Image Classification. *IEEE Transactions on Systems Man and Cybernetics*, (6):610–621, 1973.
- [104] Fritz Albrechtsen. Statistical Texture Measures Computed from Gray Level Cooccurrence Matrices. *Image Processing Laboratory, Department of Informatics, University of Oslo*, pages 1–14, 1995.
- [105] Fernando Roberti de Siqueira, William Robson Schwartz, and Helio Pedrini. Multi-scale gray level co-occurrence matrices for texture description. *Neurocomputing*, 120:336–345, 2013.
- [106] Martin Fodsslette Møller. A Scaled Conjugate Galgorithm for Fast Supervised Learning. *Neural networks*, 6(4):525–533, 1993.
- [107] Yann Le Cun Ido Kanter Sara and A Solla. Second Order Properties of Error Surfaces Learning Time and Generalization. In *Advances in Neural Information Processing Systems*, volume 3, pages 918–924, 1991.
- [108] Yann A LeCun, Léon Bottou, Genevieve B Orr, and Klaus-Robert Müller. Efficient backprop. In *Neural networks: Tricks of the trade*, pages 9–48. Springer, 2012.
- [109] Simon Haykin. *Neural Networks: A Comprehensive Foundation*. Prentice Hall PTR, Upper Saddle River, NJ, USA, 2nd edition, 1998.
- [110] Paolo Cignoni, Massimiliano Corsini, and Guido Ranzuglia. MeshLab: an Open-Source 3D Mesh Processing System. *European Research Consortium for Informatics and Mathematics (ERCIM) News*, 2008(73), 2008.

- [111] Zhengyou Zhang. Feature-based Facial Expression Recognition: Sensitivity Analysis and Experiments with a Multilayer Perceptron. *International Journal of Pattern Recognition and Artificial Intelligence*, 13(06):893–911, 1999.
- [112] George B Arfken and Hans J Weber. *Mathematical methods for physicists international student edition*. Academic press, 2005.
- [113] Timothy F. Cootes, Gareth J. Edwards, and Christopher J. Taylor. Active appearance models. *IEEE Transactions on pattern analysis and machine intelligence*, 23(6):681–685, 2001.
- [114] Vojtěch Franc and Soeren Sonnenburg. Optimized cutting plane algorithm for support vector machines. In *Proceedings of the 25th international conference on Machine learning*, pages 320–327. ACM, 2008.
- [115] Mark Everingham, Josef Sivic, and Andrew Zisserman. Taking the bite out of automated naming of characters in tv video. *Image and Vision Computing*, 27(5):545–559, 2009.
- [116] Rainer Stiefelhagen. Estimating Head Pose with Neural Networks-results on the Pointing04 ICPR Workshop Evaluation Data. In *Pointing’04 ICPR Workshop of the Int. Conf. on Pattern Recognition*, pages 344–348, 2004.
- [117] Marcos Luzardo, Matti Karppa, Jorma Laaksonen, and Tommi Jantunen. Head Pose Estimation for Sign Language Video. In *Image Analysis*, pages 349–360. Springer, 2013.
- [118] Nicolas Gourier, Jérôme Maisonnasse, Daniela Hall, and James L Crowley. Head Pose Estimation on Low Resolution Images. In *Multimodal Technologies for Perception of Humans*, pages 270–280. Springer, 2007.
- [119] Jilin Tu, Yun Fu, Yuxiao Hu, and Thomas Huang. Evaluation of Head Pose Estimation for Studio Data. In *Multimodal Technologies for Perception of Humans*, pages 281–290. Springer, 2007.
- [120] Willem A Arrindell and Jan Van der Ende. An empirical test of the utility of the observations-to-variables ratio in factor and components analysis. *Applied Psychological Measurement*, 9(2):165–178, 1985.
- [121] Xiangxin Zhu and Deva Ramanan. Face detection, Pose estimation, and Landmark Localization in the Wild. In *IEEE Conference on Computer Vision*



and *Pattern Recognition (CVPR)*, pages 2879–2886. IEEE, 2012.

- [122] Yu Wei, Xiong Bing, and Charayaphan Chareonsak. FPGA Implementation of AdaBoost Algorithm for Detection of Face Biometrics. In *IEEE International Workshop on Biomedical Circuits and Systems*, pages 1–6. IEEE, 2004.
- [123] Sachin Sudhakar Farfade, Mohammad J Saberian, and Li-Jia Li. Multi-view face detection using deep convolutional neural networks. pages 643–650, 2015.
- [124] Alessandra Bandrabur, Laura Florea, Cornel Florea, and Matei Mancas. Late fusion of facial dynamics for automatic expression recognition. *Turkish Journal of Electrical Engineering & Computer Sciences*, 25(4):2696–2707, 2017.
- [125] Patrick Lucey, Jeffrey F Cohn, Takeo Kanade, Jason Saragih, Zara Ambadar, and Iain Matthews. The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 94–101. IEEE, 2010.