UNIVERSITI PUTRA MALAYSIA

MULTIVIEW FACE EMOTION RECOGNITION USING GEOMETRICAL AND TEXTURE FEATURES

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By

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

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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

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Chairman : M. Iqbal Bin Saripan, PhD
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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 1st emotion intensity, and 73.21% for 2nd emotion intensity, 75.1% for 3rd emotion intensity and 79.31% for 4th emotion intensity.

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

PENGECAMAN EMOSI WAJAH BERBILANG ARAH MENGGUNAKAN CIRI-CIRI GEOMETRI DAN TEKSTUR

Oleh

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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 mengecam 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 mengecam 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. Sesetengah 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 megambil 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 pengesahan 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 mengecam 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.

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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:

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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.

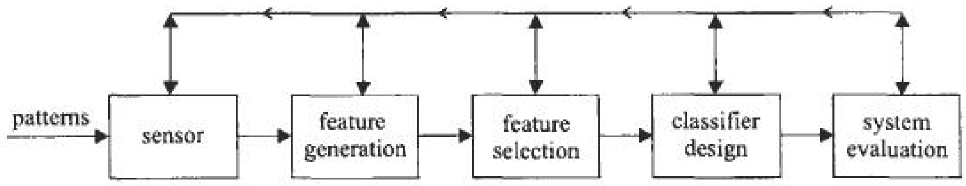

Figure 1.1: Basic stages of classification system [4]

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).

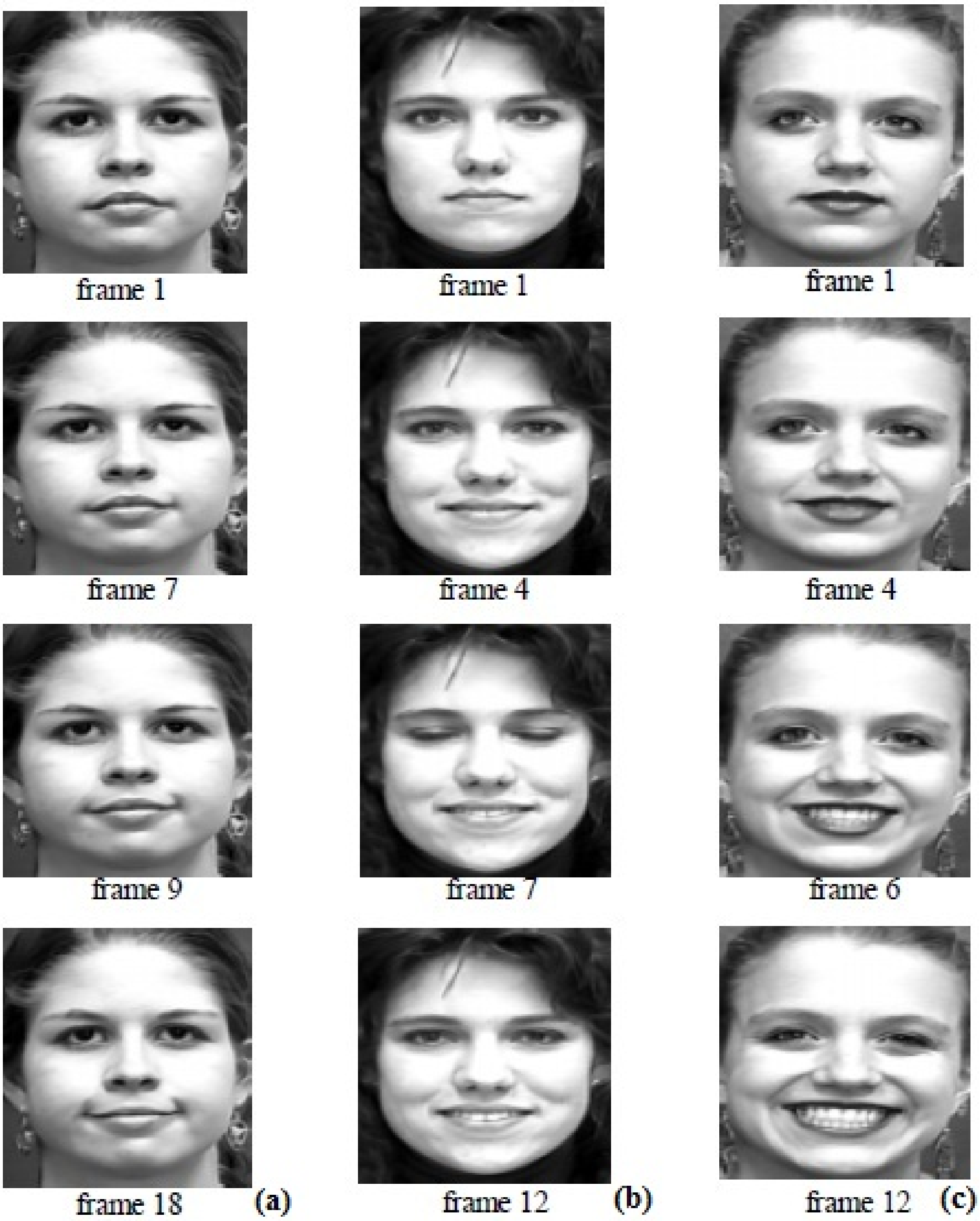

Figure 1.2: Comparison of different smile expressions with different expression intensities [6]. a) mild, b) average, c) intense.

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.

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