NON-LINEAR HUMAN EMOTION RECOGNITION SYSTEM USING ECG AND EMG

by

Jerritta Selvaraj
(1040610471)

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

School of Mechatronic Engineering
UNIVERSITI MALAYSIA PERLIS

2013

UNIVERSITI MALAYSIA PERLIS

DECLARATION OF THESIS

Author's full name : JERRITTA SELVARAJ

Date of birth : 26-06-1982

Title : NON-LINEAR HUMAN EMOTION RECOGNITION SYSTEM USING ECG AND EMG

Academic Session : 2013-2014

I hereby declare that the thesis becomes the property of Universiti Malaysia Perlis (UniMAP) and to be placed at the library of UniMAP. This thesis is classified as :

☐	**CONFIDENTIAL**	(Contains confidential information under the Official Secret Act 1972)*
☐	**RESTRICTED**	(Contains restricted information as specified by the organization where research was done)*
√	**OPEN ACCESS**	I agree that my thesis is to be made immediately available as hard copy or on-line open access (full text)

I, the author, give permission to the UniMAP to reproduce this thesis in whole or in part for the purpose of research or academic exchange only (except during a period of _____ years, if so requested above).

Certified by:

SIGNATURE

SIGNATURE OF SUPERVISOR

F7006790

(NEW IC NO. / PASSPORT NO.)

DR. M. MURUGAPPAN

NAME OF SUPERVISOR

Date :_________________

Date : _________________

NOTES : * If the thesis is CONFIDENTIAL or RESTRICTED, please attach with the letter from the organization with period and reasons for confidentially or restriction.

ACKNOWLEDGEMENT

The fear of the LORD is the beginning of wisdom; all who follow his precepts have good understanding. First and foremost, I thank God for being with me, guiding me and giving me the opportunity, wisdom, understanding and courage in every phase of this research work.

The successful completion of this thesis work relies on the influence of many people who have generously given their time and energy in specific ways. I take this opportunity to express my gratitude and thanks to each of you who have been a part of this PhD journey.

I am grateful to the support and supervision of Dr. M. Murugappan, who brought in this opportunity, for his suggestions, guidance, encouragement and challenges throughout this work from its beginning. Indeed, his inputs and ideas were of immense help in the making of this thesis.

I extend my thanks to Prof. Sazali Bin Yaacob for the valuable comments, discussions, ideas and suggestions that helped me through this work. I also thank Dr. Wan Khairunizam Bin Wan Ahmad, for his support in the starting and continuing of this research. I am also grateful to Prof. R. Nagarajan for his inputs and comments during the initial stages of this thesis.

I take this time to thank the dean, school of Mechatronic Engineering Professor Dr. Abdul Hamid bin Adom and the program chairman Dr. Cheng Ee Meng for their cooperation and administrative assistance through this course of study.

I would also like to express my gratitude and thanks to the vice chancellor of UniMAP, Yang Berbahagia Brigedier Jeneral Datuk Prof. Dr. Kamarudin Hussin, for providing me an opportunity in this university and the financial support through graduate assistantship.

It is an honor to thank my fellow colleagues, undergraduate students, members of automav cluster and intelligent signal processing cluster who helped me by participating in the pilot study and data collection experiment. I would also like to thank Teacher Mary, parents, neighbors and friends from Kangar locality who helped me in getting

kids and elderly people as subjects for the data collection experiment. Their cooperation and help indeed helped me to develop the diverse database developed through this thesis.

At this junction, I would also like to appreciate my family and friends whose presence and prayers made a difference. Specifically, I would like to thank my parents, and parents in law, siblings and friend Lynda who constantly motivated, enquired and prayed about this research. Special thanks to Pas. Guna, Sis. Dharshini, Shalom, uncle David and aunty Beulah, uncle LT, Robbins annan, Jairish annan, Mylin akka, Nixon annan, Shia akka, Shaun, Shamma and Ben who took the time to meet and encourage us here in Perlis.

I also take this time to thank my husband Arun who stood beside me as a counselor, mentor and friend supporting in every possible way. I thank him for his physical presence in the toughest times, spiritual and mental support and for being the anchor that I could rely on in this world.

Table of contents

DECLARATION OF THESIS	**i**
ACKNOWLEDGEMENT	**ii**
TABLE OF CONTENTS	**iv**
LIST OF TABLES	**x**
LIST OF FIGURES	**xi**
LIST OF ABBREVIATIONS	**xiii**
ABSTRAK (BM)	**xvi**
ABSTRACT (ENGLISH)	**xvii**
CHAPTER 1 INTRODUCTION	Error! Bookmark not defined.
1.1 Research Background	**Error! Bookmark not defined.**
1.2 Problem Statement	**Error! Bookmark not defined.**
1.3 Thesis Objectives	**Error! Bookmark not defined.**
1.4 Organization of the Thesis	**Error! Bookmark not defined.**
CHAPTER 2 REVIEW ON EMOTION RECOGNITION SYSTEM USING ECG AND EMG SIGNALS	Error! Bookmark not defined.
2.1 Introduction	**Error! Bookmark not defined.**
2.2 Emotion Definition	**Error! Bookmark not defined.**
2.2.1 Theories of Emotion	**Error! Bookmark not defined.**
2.2.2 Emotion Models	**Error! Bookmark not defined.**

2.3 Physiological Signal Based Emotion Recognition System **Error! Bookmark not defined.**

2.3.1 Need of Physiological Signals Based Emotion Recognition System **Error! Bookmark not defined.**

2.3.2 Classical Emotion Recognition System Using Physiological Signals **Error! Bookmark not defined.**

2.3.3 Previous Studies on Emotion Recognition **Error! Bookmark not defined.**

2.4 Emotion Elicitation Protocol **Error! Bookmark not defined.**

2.4.1 Factors Influencing Emotion Elicitation **Error! Bookmark not defined.**

2.4.2 Emotion Elicitation Methods **Error! Bookmark not defined.**

2.5 Physiological Signals **Error! Bookmark not defined.**

2.5.1 ECG signals **Error! Bookmark not defined.**

2.5.2 EMG Signals **Error! Bookmark not defined.**

2.6 Non-Linear Analysis of Physiological Signals **Error! Bookmark not defined.**

2.6.1 Previous Works on Non-Linear Analysis of Physiological Signals **Error! Bookmark not defined.**

2.6.2 Need of Non-Linear Analysis in Emotion Recognition **Error! Bookmark not defined.**

2.7 Applications of Emotion Recognition System **Error! Bookmark not defined.**

2.8 Conclusion **Error! Bookmark not defined.**

CHAPTER 3 DATA ACQUISITION AND PRE-PROCESSING Error! Bookmark not defined.

3.1 Introduction **Error! Bookmark not defined.**

3.2 Emotion Elicitation Protocol **Error! Bookmark not defined.**

3.2.1 Pilot Study **Error! Bookmark not defined.**

3.2.2 Design of Emotion Elicitation Protocol **Error! Bookmark not defined.**

3.3 Data Collection Experiment **Error! Bookmark not defined.**

3.3.1 Data Acquisition Device and Electrode placement **Error! Bookmark not defined.**

3.3.2 Subjects **Error! Bookmark not defined.**

3.3.3 Experimental Procedure **Error! Bookmark not defined.**

3.4 Pre-Processing of Emotional ECG Data **Error! Bookmark not defined.**

3.4.1 Sources of Noises and Artifacts in ECG Signals **Error! Bookmark not defined.**

3.4.2 Methods to Remove Noises and Artefacts from ECG Signals **Error! Bookmark not defined.**

3.4.3 Performance Measures **Error! Bookmark not defined.**

3.4.4 Detection of QRS Complex from ECG Signal **Error! Bookmark not defined.**

3.4.5 Frequency of QRS Complex **Error! Bookmark not defined.**

3.4.6 Reliability of ECG Data **Error! Bookmark not defined.**

3.5 Pre-processing of Emotional EMG Data **Error! Bookmark not defined.**

3.5.1 Sources of Noises and Artifacts in EMG signals **Error! Bookmark not defined.**

3.5.2 Methods to Remove Noises and Artifacts from EMG Signals **Error! Bookmark not defined.**

3.5.3 Frequency of EMG signals **Error! Bookmark not defined.**

3.5.4 Reliability of EMG Data **Error! Bookmark not defined.**

3.6 Conclusion **Error! Bookmark not defined.**

CHAPTER 4 EMOTIONAL FEATURE EXTRACTION AND CLASSIFICATION Error! Bookmark not defined.

4.1 Introduction **Error! Bookmark not defined.**

4.2 Emotional Features **Error! Bookmark not defined.**

4.2.1 Statistical Features **Error! Bookmark not defined.**

4.2.2 Higher Order Statistical (HOS) Features **Error! Bookmark not defined.**

4.2.3 Non-Linear Features **Error! Bookmark not defined.**

4.2.4 Emotional Feature Validation **Error! Bookmark not defined.**

4.3 Hilbert Huang Transform (HHT) **Error! Bookmark not defined.**

4.3.1 Empirical Mode Decomposition (EMD) **Error! Bookmark not defined.**

4.3.2 Hilbert Spectral Analysis **Error! Bookmark not defined.**

4.3.3 Proposed Fourier Spectral Analysis **Error! Bookmark not defined.**

4.4 Proposed HOS based Hurst analysis **Error! Bookmark not defined.**

4.4.1 Skewness based Hurst **Error! Bookmark not defined.**

4.4.2 Kurtosis based Hurst **Error! Bookmark not defined.**

4.5 Fusion of ECG and EMG signals **Error! Bookmark not defined.**

4.5.1 Principal Component Analysis **Error! Bookmark not defined.**

4.5.2 Classical multidimensional Scaling (CMDS) **Error! Bookmark not defined.**

4.6 Classification of Emotional states **Error! Bookmark not defined.**

4.6.1 Naïve Bayes Classifier **Error! Bookmark not defined.**

4.6.2 Regression Tree Classifier **Error! Bookmark not defined.**

4.6.3 K-Nearest Neighbor Classifier (KNN) **Error! Bookmark not defined.**

4.6.4 Fuzzy K Nearest Neighbor Classifier **Error! Bookmark not defined.**

4.6.5 Cross-validation **Error! Bookmark not defined.**

4.7 Conclusion **Error! Bookmark not defined.**

CHAPTER 5 RESULTS AND DISCUSSION Error! Bookmark not defined.

5.1 Introduction **Error! Bookmark not defined.**

5.2 Pre-processing of emotional physiological signals **Error! Bookmark not defined.**

5.2.1 Pre-processing of ECG signals **Error! Bookmark not defined.**

5.2.2 Pre-processing of EMG signals **Error! Bookmark not defined.**

5.3 Classification of emotional states using ECG signals **Error! Bookmark not defined.**

5.3.1 Performance of the emotional features **Error! Bookmark not defined.**

5.3.2 Performance of EMD analysis **Error! Bookmark not defined.**

5.3.3 Performance of the proposed HOS based Hurst analysis **Error! Bookmark not defined.**

5.4 Classification of emotional states using EMG signals **Error! Bookmark not defined.**

5.4.1 Performance of emotional features **Error! Bookmark not defined.**

5.4.2 Performance of EMD analysis **Error! Bookmark not defined.**

5.4.3 Performance of the proposed Hurst features **Error! Bookmark not defined.**

5.5 Classification of emotional states using both ECG and EMG signals **Error! Bookmark not defined.**

5.6 Comparison of performance metrics with previous research works **Error! Bookmark not defined.**

5.7 Discussion **Error! Bookmark not defined.**

5.8 Conclusion **Error! Bookmark not defined.**

CHAPTER 6 CONCLUSION AND FUTURE WORK Error! Bookmark not defined.

6.1 Conclusion **Error! Bookmark not defined.**

6.1.1 Data Acquisition **Error! Bookmark not defined.**

6.1.2 Non-linear features and algorithms **Error! Bookmark not defined.**

6.1.3 Proposed methods of computing Hurst exponent **Error! Bookmark not defined.**

6.1.4 Fusion of ECG and EMG signals **Error! Bookmark not defined.**

6.2 Research contributions **Error! Bookmark not defined.**

6.3 Future work **Error! Bookmark not defined.**

REFERENCES Error! Bookmark not defined.

APPENDIX A PREVIOUS STUDIES ON EMOTION RECOGNITION Error! Bookmark not defined.

APPENDIX B PILOT STUDY DETAILS Error! Bookmark not defined.

APPENDIX C DATA COLLECTION DETAILS Error! Bookmark not defined.

APPENDIX D PRE-PROCESSING RESULTS Error! Bookmark not defined.

APPENDIX E CLASSIFICATION OF EMOTIONAL STATES FROM ECG SIGNALS Error! Bookmark not defined.

APPENDIX F CLASSIFICATION OF EMOTIONAL STATES FROM EMG SIGNALS Error! Bookmark not defined.

APPENDIX G GRAPHICAL USER INTERFACE Error! Bookmark not defined.

LIST OF PUBLICATION **224**

List of Tables

No		**Page**
2.1	Frequency Ranges of EMG Signals Used in Different Research Works	45
3.1	Order of Emotional Video Clips	58
5.1	Reliability of emotional ECG data	120
5.2	Reliability of emotional EMG data	123
5.3	Sensitivity and Specificity of emotional ECG features	125
5.4	Summary of average accuracy in EMD based analysis of ECG signals	130

5.5	Summary of Hurst analysis (ECG)	133
5.6	Sensitivity and specificity of emotional EMG features	135
5.7	Summary of average accuracy in EMD based analysis of EMG signals	138
5.8	Summary of Hurst analysis (EMG)	141
5.9	Fusion of ECG and EMG features using PCA	143
5.10	Fusion of ECG and EMG features using MDS	143
5.11	Sensitivity and specificity obtained after fusion of ECG and EMG features	144
5.12	Comparison of the performance of ECG based emotion recognition system with previous research works	145
5.13	Comparison of the performance of EMG based emotion recognition system with previous research works	146
5.14	Comparison of the performance of multiple physiological signals based emotion recognition system with previous research works	147
5.15	Performance of the developed algorithm for AuDB database	149

List of Figures

No		Page
2.1	Emotion process	17
2.2	Discrete emotional model	20
2.3	Dimensional model of emotions (a)Two dimensional model of emotions (b) Circumplex model of emotions	21
2.4	Three dimensional model of emotions	21
2.5	Classical emotion recognition system	25
2.6	Morphology of ECG signal	40
3.1	Data Acquisition Methodology	53
3.2	Design of Emotion Elicitation Protocol	56
3.3	Setup of data collection experiment	59
3.4	Placement of ECG electrodes	60
3.5	Placement of EMG electrodes	61
3.6	Experimental methodology	63
3.7	Baseline Wander in ECG Signals	66
4.1	Procedure used to develop an emotion recognition system	81
4.2	Emotional Feature Extraction methods	82
4.3	EMD analysis using Hilbert transform and Discrete Fourier Transform	93
5.1	Effect of level of decomposition on the three performance measures	115
5.2	Removal of baseline wanders from ECG signals	116
5.3	Frequency plots of ECG signals before and after pre-processing	117
5.4	Detection of QRS complex from emotional ECG signals	118

5.5	Pre-processing of emotional EMG signals	122
5.6	Intrinsic Mode functions obtained by applying EMD	126
5.7	Frequency of consecutive IMF's	127
5.8	Instantaneous amplitude and instantaneous frequency of IMF1	129
5.9	EMD analysis of the different emotional states (ECG)	131
5.10	Hurst exponent derived using the different methods (ECG)	132
5.11	EMD analysis of the different emotional states (EMG)	138
5.12	Hurst exponent derived using the different methods (EMG)	140
5.13	Comparison of maximum classification rate before and after fusion	144

List of Abbreviations

AC	-	Alternate Current
AE	-	Approximate Entropy
ANN	-	Artificial Neural Network
ANOVA	-	Analysis of Variance
ANS	-	Autonomic Nervous System
AV	-	Atrioventricular
BVP	-	Blood Volume Pulse
CCA	-	Canonical Correlation Analysis
CD	-	Correlation Dimension
CMDS	-	Classical Multidimensional Scaling
DBI	-	Davies-Bouldin Index
DC	-	Direct Current
DFA	-	Detrended Fluctuation Analysis
ECG	-	Electrocardiogram
EDA	-	Elctrodermal Activity
EEG	-	Electroencephalogram
EMD	-	Empirical Mode Decomposition
EMG	-	Electromyogram
EQ	-	Emotional Quotient
FA	-	Fluctuation Analysis
FKNN	-	Fuzzy K-Nearest Neighbor
FVS	-	Finite Variance Analysis

H	-	Hurst exponent
HCI	-	Human Computer Interaction
HHT	-	Hilbert Huang Transform
HOS	-	Higher Order Statistics
HRV	-	Heart Rate Variability
IADS	-	International Affective Digitized Sounds
IAPS	-	International Affective Picture System
ICC	-	Intra Class Correlation Coefficient
IMF	-	Intrinsic Mode Function
KNN	-	K-Nearest Neighbour
LDA	-	Linear Discriminant Analysis
LLE	-	Largest Lyapunov Exponent
MBP	-	Marquardt Back Propagation
MDS	-	Multi Dimensional Scaling
MUAP	-	Motor Unit Action Potential
NLPCA	-	Non-linear Principal Component Analysis
NN	-	Normal to Normal
PCA	-	Principal Component Analysis
RRS	-	Rescaled Range Statistics
RSST	-	Robust Singular Spectrum Transform
SAM	-	Self Assessment Manikin
SBS	-	Sequential Backward Selection
SC	-	Skin Conductance
SD	-	Standard Deviation
SFS	-	Sequential Forward Selection

SFSS	-	Sequential Forward Selection Search
SNR	-	Signal to Noise Ratio
ST	-	Skin Temperature
SVM	-	Support Vector Machine
WT	-	Wavelet Transform

Sistem Pengecaman Emosi Bukan Linear Bagi ECG Dan EMG

Abstrak

Tesis ini memberi tumpuan dalam analisis algoritma linear yang berbeza untuk mendapatkan maklumat emosi yang hadir dalam dua isyarat hayat iaitu Elektrokardiogram (ECG) dan Electromyogram (EMG). Pengecaman emosi adalah salah satu bidang penyelidikan yang muncul dalam interaksi manusia komputer (HCI) dan telah digunakan secara meluas dalam aplikasi seperti e-pembelajaran, bilik darjah pintar, aplikasi perubatan untuk pesakit dengan autisme, penyakit Parkinson dan lain-lain. Enam status emosi asas (bahagia, sedih, takut, kejut jijik dan neutral) didorong dalam enam puluh orang subjek melalui rangsangan dengar-lihat. Emosi kemarahan diabaikan sebagai hasil daripada kajian yang dijalankan untuk mengenal pasti klip video emosi yang boleh menimbulkan emosi sasaran dengan cara yang lebih baik. Isyarat ECG dan EMG telah dipra-proses untuk menghapuskan bunyi yang berlaku akibat gangguan talian kuasa dan kekerapan yang tinggi. Kompleks QRS kemudian diterbitkan dari isyarat ECG dengan menggunakan algoritma berasaskan derivatif. Isyarat EMG telah dilicinkan dan trend itu disingkirkan. Kekerapan emosi telah dikenal pasti dengan pengesahan ciri-ciri statistik konvensional yang digunakan untuk aplikasi pengecaman emosi menggunakan analisis varians (ANOVA) pada tahap kekerapan berbeza. Ciri-ciri emosi yang diekstrak daripada QRS kompleks dan isyarat EMG yang dikenalpasti julat frekuensi emosinya telah diklasifikasikan menggunakan empat pengelas (Tree regresi, naif Bayes, jiran K-terdekat (KNN) dan kabur K-paling hampir Neighbor (FKNN)). Statistik Perintah Tinggi (HOS) dan ciri-ciri bukan linear diperoleh daripada isyarat yang ditapis dan isyarat yang diproses oleh Hilbert Huang Transform (HHT). Satu sistem hibrid yang menggantikan HHT oleh Fourier Transform diskret (DFT) kepada isyarat yang terurai dan dibina semula oleh penguraian Mode Empirical (EMD) telah dicadangkan. Kaedah berasaskan DFT memberi prestasi yang lebih baik dalam kes ECG manakala prestasi HHT lebih baik dalam kes isyarat EMG. Ciri-ciri bukan linear, Hurst telah diekstrak daripada isyarat tertapis menggunakan dua kaedah iaitu Statistik Julat Skala Berulang (RRS) dan Analisis Varian Terhingga (FVA). Kaedah baru seperti RRS berasaskan kepencongan, RRS berasaskan kurtosis, FVA berasaskan kepencongan dan berasaskan FVA kurtosis telah dicadangkan untuk pengkomputeran Hurst dengan menggabungkan HOS dengan kaedah tradisional. Ciri-ciri yang diperoleh melalui semua kaedah tersebut didapati signifikan secara statistic ($p < 0.01$). Kaedah FVA berasaskan kurtosis memberi prestasi yang lebih baik bagi kedua-dua ECG dan isyarat EMG dengan ketepatan, masing-masing 78% dan 62%. Satu sistem yang menggabungkan kedua-dua ECG dan isyarat EMG diperolehi dengan menggabungkan ciri-ciri yang menggunakan analisis komponen utama (PCA) dan skala pelbagai dimensi (MDS). Analisis komponen utama (PCA) digunakan pada semua ciri-ciri Hurst yang diperolehi menggunakan FVA untuk kedua-dua isyarat dan ini menyebabkan ketepatan yang lebih baik daripada 82.54%.

Non-linear Human Emotion Recognition using ECG and EMG

Abstract

This thesis focuses on analyzing different nonlinear algorithms to capture the emotional information present in two bio-signals namely Electrocardiogram (ECG) and Electromyogram (EMG). Emotion recognition is one of the emerging research areas in human computer interaction (HCI) and has been widely used in applications such as e-learning, smart classrooms, medical applications for patients with autism, Parkinson's disease etc., Five basic emotional states (happiness, sadness, fear, surprise and disgust) and neutral signal was induced in sixty subjects by means of audio-visual stimuli. The emotion anger was omitted as a result of the pilot study conducted to identify the emotional video clips that could elicit the target emotions in a better way. ECG and EMG signals were pre-processed to eliminate noises that occur due to power line interference and high frequency.QRS complex was then derived from the ECG signals by using a derivative based algorithm. The EMG signals were smoothed and the trend was removed. The emotional frequency was identified by validating the conventional statistical features used for emotion recognition applications using analysis of variance (ANOVA) at different frequency levels. The emotional features extracted from QRS complex and EMG signals at the identified emotional frequency range was classified using four classifiers (Regression Tree, Naïve Bayes, K-nearest neighbor (KNN) and Fuzzy K-Nearest Neighbor (FKNN)). Statistical, Higher Order Statistical (HOS) and non-linear features were obtained from the filtered signals and the signals processed by Hilbert Huang Transform (HHT). A hybrid system replacing Hilbert Transform by Discrete Fourier Transform (DFT) to the signal decomposed and reconstructed by Empirical Mode Decomposition (EMD) was proposed. DFT based method performed better in case of ECG whereas HHT performed better in case of EMG signals. The non-linear feature Hurst was extracted from the filtered signals using two methods namely Rescaled Range Statistics (RRS) and Finite Variance Analysis (FVA). New methods such as Skewness based RRS, Kurtosis based RRS, Skewness based FVA and Kurtosis based FVA were proposed for computing Hurst by combining HOS with the traditional methods. The features achieved in all the methods were found to be statistically significant ($p<0.01$). Kurtosis based FVA method performed better for both ECG and EMG signals with an accuracy of 78% and 62% respectively. A system that combines both ECG and EMG signals was obtained by combining the features using principal component analysis (PCA) and multi dimensional scaling (MDS). Principal component analysis (PCA) applied on all the Hurst features derived using FVA for both the signals resulted in an improved accuracy of 82.54%.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Emotional intelligence consists of the ability to recognize and express emotions, coupled with the ability to regulate these emotions and harness them for useful purposes. Emotions are considered as a basic component of intelligence and have been argued to be a better predictor for measuring the aspects of success in life. It is important for intelligent functioning and it interacts with thinking in ways that are not easily noticeable (Picard, Vyzas, & Healey, 2001). The increase in deployment of adaptive computer systems makes it important for machines to understand human emotions. Equipping machines with a little amount of emotional intelligence creates mutual empathy and improves the relationship between human and machines. It also provides meaningful and easy verbal and non-verbal communication (Jonghwa & Ande, 2008). Emotional ability is found to be an essential factor for the next generation robots and in applications such as intelligent rooms and affective tutoring (Rigas, Katsis, Ganiatsas, & Fotiadis, 2007). Hence, equipping the machines with selective emotional skills will make them appear as intelligent when they respond and adapt to the user's affective response (Picard, et al., 2001). This human machine interaction through affective computing might be useful in several medical applications such as assisting elderly people, new born children and patients with intellectual disabilities, autism or Parkinson's disease who will not be able to express their emotions explicitly (Bal et al.; Martínez et al., 2010).

An emotionally intelligent system should have a two-fold capability to understand the user's emotion and appropriately respond to it (Rani & Sarkar, 2006). In this thesis, primary emphasis is given on improving the ability of computers and machines to understand human emotions. Most of the intelligent machine interfaces developed till now are based on the audio-visual channels of emotion expression such as facial action, speech or gestures (Ang et al., 2004; Kessous, Castellano, & Caridakis, 2009; S. Koelstra et al., 2012; Morishima, 2000). Though numerous engineering based research studies have been published on these behavior-based models, they rely on the explicit expression of emotions by the subject. While facial actions tend to be the most visible form of emotion expression, they are the most easily controlled with large dependence on social situations (Picard, et al., 2001). Similarly, voice and other external modes of expression can be easily controlled or suppressed depending on the external circumstances. Such unexpressed emotions, socially masked emotions and emotions expressed differently (e.g. an angry person may smile) cannot be tracked by these behaviour-based modalities. The true emotional changes remain internal and are not detected by the audio-visual recording system (Jonghwa & Ande, 2008). Furthermore, recognition of emotions using these modalities are influenced by a number of external factors such as lighting conditions, auditory noise and accessories like glasses (Apolloni et al., 2007).

The expression of an emotion occurs as a result of physiological changes in the Autonomic Nervous System (ANS). For e.g. the muscle tension in the face give rise to facial actions (Picard, et al., 2001). Researchers have showed significant differences between the emotional states using different physiological signals such as electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), skin conductance (SC), skin temperature (ST) and blood volume pulse (BVP). These physiological signals, being an activity of the ANS reflects the inherent state of the person which makes the suppression of emotions or social masking impossible. It is also a natural means of emotion recognition providing an opportunity to track minute emotional changes that are unseen by the natural eye (Rani & Sarkar, 2006).

Physiological signal based emotion recognition is challenging because of the complex nature of physiological signals and subjective nature of emotional states. Some of the challenges in physiological signals based emotion recognition are,

- Physiological sensing is invasive as it involves physical contact with the person. However with the advancement in technology such as conductive rubber electrodes, fabric electrodes and wearable computers, physiological sensing can be made easier without any visible or awkward sensing systems (André et al., 2004; Li & Chen, 2006; Picard, et al., 2001).
- Physiological signals cannot be manipulated. Hence the different emotional states have to be elicited internally in the subject for proper data acquisition. Furthermore, emotions are subjective. All the subjects may not have the same emotional experience for the given emotional stimulus. Also, the same subject might experience a different emotion for the same emotional stimulus at a different instant of time. Hence, estimating the human emotional states is purely a subjective factor and finding a generalized solution for assessing the emotional states is challenging.
- Annotation of physiological signals in emotion research is difficult. Modalities such as speech or image (facial actions and gestures) signals can be heard or seen respectively to understand the underlying emotional states by any person. However, the one dimensional waveform of physiological

signals (changes of signal of amplitude over time) does not convey any information to the user. Hence, data labeling should be done with great care (Jonghwa & Ande, 2008; Picard, et al., 2001).

- Though this research is being active over the past two decades, so far there hasn't been any standardization in key areas such as emotional model, stimulus, physiological measures, features, pattern recognition and classification. An agreement on some of the conventions and guided principles would facilitate the integration of knowledge and expertise in the research community (Arroyo-Palacious & Romano, 2008).

Despite the challenges involved, the ability to capture the underlying and true emotional state of the subject makes this method more important. Researchers have worked either on only one physiological signal (Unimodal) or on a combination of physiological signals (Multimodal) to capture the emotional information (Agrafioti, Hatzinakos, & Anderson, 2012; Jonghwa & Ande, 2008; C. Maaoui, Pruski, & Abdat, 2008; Picard, et al., 2001; Rattanyu, Mizukawa, & Jacko, 2011). Most of the earlier works have focused on analyzing heart (ECG) and muscle (EMG) activities to assess the underlying emotional state of the person. These signals are worked independently or in combination with other physiological signals like BVP, GSR, SC and Respiration. It should also be noted that some of the works on psychophysiology are user dependent and some others are user independent. The Unimodal system developed using ECG signals has achieved a maximum accuracy of 78% for classifying two arousal stages (positive and negative arousal) (Agrafioti, et al., 2012). In multimodal analysis, the researchers managed to obtain a maximum mean classification rate of 95% and 70% on recognizing four emotions (joy, anger, sadness, pleasure) in an user dependant and