



**NON-LINEAR HUMAN EMOTION RECOGNITION
SYSTEM USING ECG AND EMG**

by

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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	-	Electrodermal 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

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Sistem Pengesanan 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). Pengesanan 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 pengesanan ciri-ciri statistik konvensional yang digunakan untuk aplikasi pengesanan 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 pengelasan (Tree regresi, naif Bayes, jiran K-terdekat (KNN) dan kabur K-paling hampir Neighbor (FKNN)). Statistik Perintah Tinggi (HOS) dan ciri-ciri bukan linear diperolehi 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 diperolehi melalui semua kaedah tersebut didapati signifikan secara statistik ($p < 0.01$). 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-Palacios & 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

user independent approach, respectively (Jonghwa & Ande, 2008). Similarly, 86% and 45% accuracy have been obtained for detecting two (joy and sadness) and six (Amusement, Contentment, Disgust, Fear, Sad, Neutral) emotions respectively in a user independent approach (Choubeila Maaoui & Pruski, 2010; Wan-Hui, Yu-Hui, & Guang-Yuan, 2009). In general, the performance of user dependant system is better than the user independent system. However, the performance of the emotion recognition systems developed so far depends on several factors such as the number of subjects, number of emotions under consideration, the type of emotion inducement stimuli, the number and location of placing the electrodes etc. Hence more analysis is needed in order to develop a robust, reliable and automatic emotion recognition system.

1.2 Problem Statement

A careful study on physiological signals based emotion recognition system shows ambiguity in many crucial areas such as the emotion elicitation stimuli, processing of signals and features that are analyzed, frequency range of physiological signals and dependency on user. Different types of stimuli such as visual, audio, audio-visual etc. have been used by researchers to induce the different emotional states (Gross & W. Levenson, 1995; Jonghwa & Ande, 2008; Lang, M.M. Bradley, & Cuthbert, 2001; Stevenson & James, 2008). There has been no standardized guideline yet on the above factors. Researchers have always worked with an aim to induce the target emotions in the best possible way. The frequency ranges of physiological signals analyzed by the different researchers vary widely. In the case of EMG signals some researchers have used frequencies as low as 0.08 Hz and some other researchers have used higher frequencies greater than 20 Hz and ranging until 500 Hz (Jonghwa & Ande, 2008;