PATTERN RECOGNITION BASED EMOTIONAL DEFICITS ASSESSMENT IN STROKE PATIENTS USING TIME FREQUENCY ANALYSIS

by

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LIST OF ABBREVIATIONS

<L>	Mean of Diagonal Line Length
ANS	Autonomic Nervous System
APEN	Approximate Entropy
BCI	Brain-computer Interface
BDI	Beck Depression Inventory
CD	Correlation Dimension
CNS	Central Nervous System
coif5	Coiflet 5
CVA	Cerebrovascular Accident
db4	Daubechies 4
db6	Daubechies 6
DEAP	Database for Emotion Analysis using Physiological Signals
DET	Determinism
DFA	Detrended Fluctuation Analysis
DT	Decision Tree
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EEG	Electroencephalogram
EHI	Edinburgh Handedness Inventory
EMG	Electromyogram
ENTR	Entropy of The Diagonal Line Length
FADS	Facial Action Coding System
FFT	Fast Fourier Transform

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HCI	Human-machine Interaction
HE	Hurst Exponent
IADS	International Affective Digital Sounds
IAPS	International Affective Picture System
IIR	Infinite Impulse Response
KNN	K-nearest Neighbour
LAM	Laminarity
LBD	Left-brain Damaged
LDA	Linear Discriminant Analysis
Lmax	Maximum Diagonal Line Length
MMSE	Mini Mental State Examination
MRI	Magnetic Resonance Image
MWT	Multiwavelet
NC	Normal Control
NYEB	New York Emotion Battery
PDF	Probability Density Function
PNN	Probabilistic Neural Network
PPG	Photopletysmography
RBD	Right-brain Damaged
RF	Random Forest
RPDE	Recurrence Probability Density Entropy
RQA	Recurrence Quantification Analysis
RR	Recurrence Rate
SK	Skin Temperature
SVM	Support Vector Machine

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sym8	Symlet 8
T1	Recurrence Time of 1st Type
T2	Recurrence Time of 2nd Type
TQWT	Tuned-Q Wavelet Transform
TT	Trapping Time
WHO	World Health Organization

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LIST OF SYMBOLS

ψ	Mother wavelet function
C	Wavelet coefficients
Hz	Hertz
r	Redundancy parameter in TQWT
m	Mean of the time series
d_e	Euclidean distance
σ	Smoothing parameter
N_{tree}	The number of trees to be built
M_{try}	The number of variables chosen for splitting at each node
f_{RF}	Final prediction result
Ac	Averaged classification accuracy
Sen	Sensitivity
δ	Singular values
α	EEG alpha band
β	EEG beta band
γ	EEG gamma band
$R_{i,j}$	Recurrence matrix
$F(n)$	Root mean square fluctuation
R/S	Rescaled range series in hurst exponent
S_T	Deviation series
R_T	Range of series
z_T	Accumulated time series
y_T	Adjusted time series

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J_{max} Maximum number of levels

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Kemelesetan Penilaian Emosi di Kalangan Pesakit Strok berdasarkan Pengiktirafan Corak dengan menggunakan Analisa Kekerapan-Masa

ABSTRAK

Persepsi emosi pada pesakit strok terjejas kerana terdapat kelainan pada otak. Di sini, tesis ini memberi tumpuan kepada kesan kerosakan otak kiri dan kerosakan otak kanan ke arah pengiktirafan emosi. Disebabkan pengiktirafan emosi terjejas, adalah satu cabaran untuk pesakit strok untuk menyatakan diri mereka dalam komunikasi harian. Oleh itu, ia adalah inspirasi untuk melihat kemungkinan untuk meramalkan keadaan emosi pesakit untuk mengelakkan strok berulang. Dalam kerja ini, electroencephalograph (EEG) daripada 19 pesakit kerosakan otak kiri (LBD), 19 pesakit kerosakan otak kanan (RBD) dan 19 kawalan biasa (NC) dikumpulkan sebagai pangkalan data. Semasa pengumpulan data, enam emosi (sedih, jijik, ketakutan, kemarahan, gembira dan mengejutkan) diinduksi dengan menggunakan rangsangan visual audio. Selepas menormalkan, isyarat EEG ditapis dengan menggunakan penapis band-pass pesanan Butterworth ke-6 pada frekuensi cut-off 0.5 Hz dan 49 Hz. Kemudian, teknik paket wavelet transform (WPT) dilaksanakan untuk melokalkan lima jalur frekuensi: alpha (8 Hz-13 Hz), beta (13 Hz-30 Hz), gamma (30 Hz-49 Hz), alpha-to-gamma 8 Hz-49 Hz), beta-to-gamma (13 Hz-49 Hz). Sebaliknya, transformasi wavelet Q-factor yang ditala (TQWT) juga digunakan pada lima jalur frekuensi untuk mendapatkan 6 sub-band. Dalam WPT, empat keluarga wavelet dipilih: daubechies 4 (db4), daubechies 6 (db6), coiflet 5 (coif5) dan symmlet 8 (sym8). Eksponen Hurst (HE), analisis turun naik yang menjejaskan (DFA), analisis kuantifikasi ulangan (RQA) digunakan untuk mengekstrak eksponen korelasi, eksponen korelasi DFA, dan 11 langkah yang berbeza daripada plot berulang dari setiap kumpulan dan keluarga wavelet dan dikelaskan dengan menggunakan K jiran terdekat (KNN), rangkaian neural kebarangkalian (PNN) dan hutan rawak (RF). Peringkat pengkelasan dilakukan berdasarkan perbandingan antara tiga kumpulan dan juga antara enam emosi. 290 kombinasi ciri-ciri yang dilakukan tetapi ciri yang paling penting dalam pengiktirafan emosi dan pengiktirafan kumpulan adalah masing-masing panjang garis pepenjuru (<L>) dan Peratusan Kemirunan Kemungkinan Entropi (RPDE). Langkah-langkah RQA didapati paling menyumbang dalam memberikan ketepatan klasifikasi yang tinggi. Sementara itu, eksponen korelasi seperti Hurst dan DFA didapati tidak cekap dalam klasifikasi emosi. Ketepatan pengiktirafan emosi meningkat dengan baik selepas ciri-ciri berubah menjadi skor dengan menggunakan algoritma Analisis Komponen Prinsip (PCA). Ketepatan klasifikasi emosi maksimum didapati dalam LBD (85.29%). Dalam klasifikasi kumpulan, RPDE telah memberikan ketepatan tertinggi (99.41%) melalui pengelas RF. Kumpulan LBD didapati mempunyai ketepatan purata yang lebih tinggi berbanding dengan kumpulan RBD yang menyokong 'hipotesis hemisfera kanan'. Hasil menunjukkan bahawa sistem pengiktirafan emosi yang dicadangkan boleh dipercayai dengan ketepatan klasifikasi yang boleh diterima yang membantu pemantauan emosi di kalangan pesakit strok serta orang yang sihat. Sementara itu, pengiktirafan kumpulan (LBD, RBD dan NC) boleh digunakan untuk mengenal pasti kehadiran strok LBD atau RBD.

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Pattern Recognition Based Emotional Deficits Assessment in Stroke Patients using Time Frequency Analysis

ABSTRACT

Emotion perception in stroke patients is affected since there is abnormality in the brain. Here, this thesis focused on the impact of left brain damage and right brain damage towards emotion recognition. Due to the impaired emotion recognition, it is a challenge for stroke patients to express themselves in daily communication. Hence, it is inspiring to see the possibility to predict patient's emotional state so as to prevent recurrent stroke. In this work, electroencephalograph (EEG) of 19 left brain damage patients (LBD), 19 right brain damage patients (RBD) and 19 normal control (NC) are collected as database. During data collection, six emotions (sad, disgust, fear, anger, happy and surprise) are induced by using audio visual stimuli. After normalization, EEG signals are filtered by using Butterworth 6th order band-pass filter at the cut-off frequencies of 0.5 Hz and 49 Hz. Then, wavelet packet transform (WPT) technique is implemented to localize five frequency bands: alpha (8 Hz–13 Hz), beta (13 Hz–30 Hz), gamma (30 Hz–49 Hz), alpha-to-gamma (8 Hz–49 Hz), beta-to-gamma (13 Hz–49 Hz). On the other hand, tuned Q-factor wavelet transform (TQWT) is also applied on five frequency bands to obtain 6 sub-bands. In WPT, four wavelet families are chosen: daubechies 4 (db4), daubechies 6 (db6), coiflet 5 (coif5) and symmlet 8 (sym8). Hurst exponents (HE), detrended fluctuation analysis (DFA), recurrence quantification analysis (RQA) are used to extract hurst correlation exponent, DFA correlation exponent, and 11 different measures out of recurrence plot from each band and wavelet family and are classified by using K-nearest Neighbour (KNN), Probabilistic Neural Network (PNN) and random forest (RF). Classification stage is done on comparison between three groups and also between six emotions. 290 combinations of feature are done but the most significant feature in emotion recognition and group recognition is mean of diagonal line length (<L>) and Recurrence Probability Density Entropy (RPDE) respectively. RQA measures are found to be most contributing in giving high classification accuracy. Meanwhile, correlation exponents such as Hurst and DFA are found inefficient in emotion classification. Emotion recognition accuracy is improved tremendously after the features are transformed into score by using Principle Component Analysis (PCA) algorithm. The maximum emotion classification accuracy is found in LBD (85.29 %). In group classification, RPDE has given the highest accuracy (99.41 %) through RF classifier. LBD group is found to have the higher average accuracy compared to RBD group which supports the 'right hemisphere hypothesis'. The result shows that the proposed emotional recognition system is reliable with an acceptable classification accuracy which is helpful in emotion monitoring among stroke patients as well as healthy person. Meanwhile, group recognition (LBD, RBD and NC) can be used to identify the presence of LBD or RBD stroke.

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CHAPTER 1

INTRODUCTION

1.1 Stroke and Its Impact on Emotion Recognition

Previously, stroke is known medically as a cerebrovascular accident (CVA). It is a medical emergency where the blood supply to our brain is interrupted which causes sudden death of brain cell. These brain damages will cause slurring speech, memory loss and as well as paralysis depending on the area of damage. When the damage happened to be facial paralysis, emotion expression is almost impossible. This disability often become a challenge in daily communication with friends and family. According to the latest WHO data published in May 2014, stroke deaths in Malaysia reached 15, 497 or 12.19 % of total deaths. The age adjusted death rate is 80.59 per 100, 000 of population ranks Malaysia number 97 in the world (W.H.O., 2014). In a study, a total of 7668 stroke patients were recruited for analysis. On average, patients were aged 62.7 years (standard deviation of 12.5). Ischemic stroke accounts for 79.4% of the cohort with a slightly higher proportion of male patients (55%). Ischemic stroke incidence is estimated to increase annually by 29.5% and hemorrhagic stroke by 18.7% (Aziz, Lee, Ngah, Sidek, et al., 2015).

There are studies explaining about the emotional changes of post-stroke patients which cause psychological illnesses in certain cases (Visser & Annemarie, 2004). Due to the region of brain damage, patients are not able to perceive either positive or negative

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emotions (Reilly, Stiles, Larsen, & Trauner, 1995). Right brain damaged patients are likely to be good at perceiving positive emotions (Joan et al., 1990). Whereas, some stated that right brain is responsible in recognizing emotions, thus left brain damage does not cause impairment in emotion perception (Ehlers & Dalby, 1987; Heilman, Scholes, & Watson, 1975). In summary, although impairment for emotion perception was more frequently observed in individuals with RBD than with LBD, there were a very fair number of studies that found no differences between the two patients group (Rajamanickam, Murugappan, Norlinah, & Sundaraj et al., 2013).

Stroke study concerning emotions and psychological aspect has been done clinically since decades ago. Recently, people are interested in emotion investigation and the effect of brain hemisphere region in emotion perception. Different methods and database has been carried out and collected in order to test their hypotheses (Rajamanickam et al., 2013). However, none has focused on using physiological data such as EEG and machine learning techniques to recognize emotions and investigate emotion deficits in stroke patients. For instance, in one paper (Karow, Marquardt, & Marshall, 2001), early detection of brain ischemia using EEG is done. However, emotion processing was not covered in this study. Meanwhile, in another paper (Foreman & Claassen, 2012), even though affective processing ability in left and right hemisphere brain-damaged patients was measured in isolated identification tasks, it was done without using EEG signal.

Moreover, development of an intelligent emotional assessment system is very advantageous in Human-Computer Interaction (HCI) applications. HCI enables the human to interact with computer especially through human responses and behavior. Being inspired by the possibilities of human emotion recognition using physiological signals as the input, an emotional asssessment system for stroke patients using physiological signals

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is the main purpose of this research. This system would be remarkably useful for a wide range of application especially in the area of psychology and socio-psychology. Communities like the workers in industries, students, as well as the patients in hospitals can make use of this application to predict their emotional states and also to maintain mental health from time to time. This is important to sustain the quality of human life in the society well-being.

1.2 Research Problem Statement

There are several challenges occurred in previous works regarding emotional stress assessment. Several modalities (visual, audio, audio-visual, recall paradigm and dyadic modalities) have been used to induce the desired emotional response in human but the limitation is that there are ethics in doing experiment on human being. Researchers are not allowed to put any participant into any hazardous situation or experiment that would give negative impact towards their health condition (Research Ethics Committee, 2012). In this research case, the audio-visual stimuli used should not be too extreme in order to avoid emotional breakdown. There is no international standard database exists on this work and hence the efficient database for this work is highly inevitable for developing intelligent emotional stress assessment system. However, researchers believe that the physiological signals which response involuntarily in human body could be the most suitable measure to categorize the emotional states (Ekman & Friesen, 1987). This research work is aim to address the problems in the development of an intelligent emotional assessment system in stroke patients:

i. Emotional EEG database is very important in signal processing. There is no vivid ground truth or any standard is proposed yet to determine the emotional stress state of an individual through different modalities. This forced the researchers to design their own emotion elicitation methods and data acquisition protocol. Most

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of the researchers have considered and applied the universal emotional circumflex model for affective state assessment in psychological study (Russell, 1980). It is difficult to induce emotion among human and expect the same outcome from them. Indeed, human emotion is subjective; every human being would response differently for different emotional situations.

ii. EEG feature extraction plays a major part in attributes selection. In signal processing, previously, most researchers have done their analysis by using statistical time domain methods. Later, frequency domain techniques such as fast-fourier transform and spectral analysis has become very popular. However, these techniques are not sufficient enough to extract good quality attributes from EEG signal which has characteristics of non-stationary and non-linearity. It is also important to exclude unnecessary features because they cannot contribute to good accuracy in classification stage later.

iii. According to literature, 'right hemisphere hypothesis' proposes that right brain is playing the major role in emotional processing regardless of valence. This statement suggests that there will be difference in emotion perception between LBD and RBD patients. However, it is difficult to classify these two groups and find out whether there is significant difference between them.

iv. For emotion recognition among normal healthy human, according to the literature, emotional recognition rate is mostly between 40 % - 70 %. Only a few researchers can produce six-class emotion classification accuracy at 90 % and above.

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