AUTOMATIC DETECTION OF ALERTNESS LEVEL FROM ELECTROENCEPHALOGRAM SIGNALS AND CORTICAL AUDITORY EVOKED POTENTIAL RESPONSES

by

Alaleh Rabie

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Certificate

I, Alaleh Rabie, hereby declare that this thesis titled, automatic detection of alertness level from EEG signals and its application to the assessment of hearing using the CAEP response, and the work presented is the product of my own work. I certify that:

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Dedication

I would like to dedicate this thesis to all broken heart parents who have children with hearing loss. God bless you all for your patience.

ABSTRACT

This research aims to identify the degree of alertness of subjects that undergo the Cortical Auditory Evoked Potential (CAEP) based hearing test. One of the important factors that influence this is the alertness state of subjects. Research has shown that for this test to be useful, subjects need to stay at a constant state of engagement. Accordingly, this thesis focuses on developing a system that will be able to classify each portion of the recorded signal into one of four states; engaged, calm, drowsy and asleep. In order to achieve this, we studied the relationship between CAEP responses and the alertness states, and we validated the existence of this relationship. We have also developed a method to search for the best channel/rhythm combination for each alertness state.

In the first study, two sets of features were considered to represent the recorded data. The first set was based on the wavelet transform of the background EEG, while the second set was obtained from the peaks of the CAEP responses. Obtained results suggest that the CAEP-based features were very comparable, in terms of classification accuracy, to the well-established wavelet-based features of EEG signals (79% compared to 80%). In the second study, the EEG rhythms of subjects were analysed. Investigation of the importance of the different EEG rhythms in terms of their capabilities in differentiating between the different alertness states was conducted. This is followed by considering subsets that contain 2, 3, 4 as well as all 5 EEG rhythms. Finally, a feature subset selection method based on differential evolution (DE) that has been proposed particularly to deal with multichannel signals is used to search for the best subset of EEG rhythms for the various channels. It was shown that higher frequency EEG rhythms (γ, β) are better classifiers for the subject's alertness state than α , θ , and δ (lower frequency EEG rhythms). Optimal combinations of different EEG rhythms have been described. The proposed differential evolution feature selection algorithm is shown to produce better results than the ranking and sequential forward selection approaches. Obtained results suggest that the best subsets are formed using combinations of channels and features that are influenced by high frequency rhythms.

ABBREVIATIONS

ABR: Auditory Brainstem Response

ANN: A Nearest Neighbour

ANOVA: Analysis of Variance

AP: Action Potential

AR: Autoregressive

BERA: Brainstem Evoked Response Audiometry

BSS: Blind Source Separation

CAEP: Cortical Auditory Evoked Potential

CAP: Compound Action Potentials

CM: Cochlear Microphonic

CN: Cochlear Nucleus

CNS: Central Nervous System

CWT: Continuous Wavelet Transform

DE: Differential Evolution

DEFS: Differential Evolution Feature Selection

DWT: Discrete Wavelet Transform

EEG: Electroencephalogram

EP: Evoked Potential

FFT: Fast Fourier Transform

GA: Genetic Algorithm

ICA: Independent Component Analysis

KNN: K-nearest Neighbour

KSOM: Kohonen's Self-organizing Map

LDA: Linear Discriminant Analysis

LSD: Least Significant Difference

MLR: Middle Latency Response

MP: Matching Pursuit

OAE: Otoacoustic Emissions

PCA: Principal Component Analysis

PNS: Peripheral Nervous System

PP: Projection Pursuit

PS: Physiological Signals

PSA: Particle Swarm Optimisation

REM: Rapid Eye Movement

SEP: Sound Evoked Potentials

SFS: Sequential Forward Search

SP: Summating Potential

SPL: Sound Pressure Level

SVM: Support Vector Machine

SWS: Slow Wave Sleep

TEC: Total Error of Classification

TM: Tympanic Membrane

TRN: Thalamic Reticular Nucleus

uLDA: uncorrelated Linear Discriminant Analysis

VEO: Vertical Electro-Oculogram

VCN: Ventral Cochlear Nucleus

WT: Wavelet Transform

WPT: Wavelet Packet Transform

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