Development of Predictive Algorithms for Electrical Stimulation Based Major Depressive Disorder Therapy

By
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CERTIFICATE OF ORIGINAL AUTHORSHIP

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as part of the collaborative doctoral degree and/or fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Acronyms

AIM: Alpha inactivity mechanism

ANOVA: One-way analysis of variance

BCI: Brain computer interface

BM: Boltzmann machine

CRBM: Convolutional restricted Boltzmann machine

CDBN: Convolutional deep belief network

CD: Contrastive divergence

CGI: Clinical global impression

CDBNs: Convolutional deep belief networks

CNN: Convolutional neural network

CRBM: Convolutional restricted Boltzmann Machine

DBN: Deep belief network

DBNs: Deep belief networks

DCNs: Deep convex networks

DNN: Deep neural network

DLPFC: Dorsolateral prefrontal cortex

ECG: Electrocardiogram

ECT: Electroconvulsive therapy

EEG: Electroencephalography or Electroencephalogram

ELM: Extreme learning machine

EMG: Electromyography

EOG: Electrooculography

ERPs: Event-related potentials

FIS: Fuzzy inference system

KNN: K-nearest neighbours

ICA: Independent component analysis

LDA: Linear discriminant analysis

LDAA: left-domain alpha asymmetry

MCHDBN: Multichannel deep delief network

MCMC: Markov chains monte carlo

MDD: Major depressive disorder

MDBN: Multimodal deep belief network

MDRS: Montgomery-Åsberg depression rating scale

MLP: Multi-layer perceptron

MLPs: Multi-layer perceptron neural networks

MIMO: Multi-input and multi-output

MPH: Minimum peak hight *(MinPeakHeight)*

MPP: Minimum peak prominence *(MinPeakProminence*

PSD: Power spectral density

PSO: Particle swarm optimisation

QIDS-SR: Quick inventory of depressive symptomatology

RBM: Restricted Boltzmann machine

SD: Standard deviation

SDMT: Symbol digit modalities test

SIFT: Scale-invariant feature transform

sMRI: Structural magnetic resonance imaging

SVM: Suport vector machine

tDCS: Transcranial direct current stimulation

TMS: Transcranial magnetic stimulation

rTMS: repetitive Transcranial magnetic stimulation

TSLOW: Time to onset of slowing

WHO: World health organization

WE: Wavelet entropy

WT: Wavelet transform

Abstract

Major depressive disorder (MDD) is a brain disorder that is characterised by negative thoughts, mood and behaviour. Transcranial direct current stimulation (tDCS) has emerged recently as a promising brain-stimulation treatment for MDD. A standard tDCS treatment involves numerous sessions that are run over a few weeks, however, not all participants respond to this type of treatment. This delay could have negative impact upon patients that do not respond, being an inefficient use of staff time and exposing patients to ineffective treatment. The early identification of patients who respond to this type of treatment is needed. Electroencephalography (EEG) signal is a significant tool that can be used to study the modulatory effects of tDCS treatment. The significant part of this research aims to predict the clinical outcomes of tDCS treatment by analysing the patients' EEG signals.

EEG signal is a complex signal that has high sensitivity to noise. EEG signal records both neural and non-neural activities from a large number of electrodes, therefore, the analysis and classification of EEG signals proved to be quite challenging. Machine learning has attracted the attention of many researches as a powerful approach for analysing various types of signals, including EEG. Algorithms for channel/feature selection, classification, detection, prediction and fusion have been developed. Recently, deep neural networks, particularly deep belief networks (DBNs), have emerged as a new hierarchical technique for modelling high level abstractions of data, and have been successfully applied to a number of classification problems. Similar to most classification algorithms, the existing DBNs have been mainly designed to handle single stream data, and there are hardly any attempts to generalize those to suit multi-channel signals.

Accordingly, the first part of this research investigates the utilisation of DBN to differentiate between tDCS sessions based on classification EEG signals, particularly the implementation of multi-channel DBNs. One of the important attributes that needs to be carefully studied is considering the multi-channel nature of EEG in the design and training of deep networks.

A second part of this research aims to predict which patients improve in mood and cognitive in response to tDCS treatment based on EEG data that were collected at the start of tDCS treatment. Classifying power spectral density (PSD) of resting-state EEG is achieved using support vector machine (SVM), linear discriminate analysis (LDA) and extreme learning machine (ELM). Participants were labelled as improved/not improved based on the change in mood and cognitive scores. The obtained classification results of all channel pair combinations are used to identify the most relevant brain regions. The frontal area is found to be particularly informative for the prediction of the clinical outcome of the tDCS treatment. Subject independent results reveal that our proposed method enables the correct identification of the treatment outcome for seven of the ten participants for mood improvement and nine of ten participants for cognitive improvement. This represents an encouraging sign that EEG-based classification may help to tailor the selection of patients for treatment with tDCS brain stimulation.

The second line treatment of depressive disorder is electroconvulsive therapy (ECT). ECT is an effective and widely used treatment for major depressive disorder, in which a brief electric current is passed through the brain to trigger a brief seizure. The second main aim in this research is to identify seizure quality rating by utilising a set of seizure parameters. Four seizure related parameters, (time to onset of slowing, regularity, stereotypy and post-ictal suppression) are used as inputs to decision tree and fuzzy rule-based classifiers to predict seizure quality ratings. The classification results show that the four seizure parameters provide relevant information about the rating of seizure quality. Automatic scoring of seizure quality could be beneficial to clinicians working in electroconvulsive therapy.