

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

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CERTIFICATE OF ORIGINAL AUTHORSHIP

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Contents

List of Figures	ix
List of Tables	xii
Acronyms	xiii
Abstract	xvi
1 Introduction	1
1.1 Research Motivation	2
1.2 Research Problem	4
1.3 Research Objectives	6
1.4 Principal Contributions of the Dissertation	6
1.5 Publications	9
1.6 Structure of the Dissertation	10
2 Background and Literature Review	12
2.1 Introduction	12
2.2 Depression	13
2.3 Neurophysiology of Human Brain	13
2.4 Electroencephalogram	15

CONTENTS

2.5	Pre-processing EEG Signal	18
2.5.1	Spectral Analysis of EEG Signal	18
2.5.2	Time-Frequency Distribution of EEG Signal	19
2.5.3	Coherence Analysis of EEG Signal	19
2.6	Diagnosing Depressive Disorder Based on EEG Signals	20
2.7	Transcranial Direct Current Stimulation Treatment	22
2.8	Electroconvulsive Therapy	24
2.9	Seizure Prediction	25
2.10	Machine Learning Classification Techniques	25
2.10.1	Support Vector Machine	26
2.10.2	Extreme Learning Machine	26
2.10.3	Linear Discriminant Analysis	27
2.11	Rule-Based Systems Methods	27
2.11.1	Decision Tree	28
2.11.2	Fuzzy Rule-Based Systems	28
2.12	Deep Learning Techniques	30
2.12.1	Deep Belief Networks	31
2.12.2	General Boltzmann Machine	32
2.12.3	Restricted Boltzmann Machine	33
2.12.4	Convolutional Neural Networks	33
2.13	Classification of EEG Signals Using Machine Learning Techniques	35
2.14	Classification using Deep Learning Techniques	37
2.15	Summary	39
3	Multichannel Deep Belief Networks for the Classification of EEG Data	40
3.1	Introduction	40

CONTENTS

3.2	Deep Belief Networks	41
3.2.1	Training Deep Belief Networks	41
3.2.2	Contrastive Divergence	43
3.2.3	Bernoulli-Bernoulli RBM	44
3.2.4	Gaussian-Bernoulli RBM	44
3.3	Related Work	45
3.4	Proposed Method: A Multichannel Deep Belief Network for the Classification of EEG Data	46
3.4.1	Data Set	47
3.4.2	Experiments and Results	47
3.4.3	Evaluating the Performance of the EEG Channels	49
3.5	Summary	53
4	Predicting Transcranial Direct Current Stimulation Treatment Outcomes of Depression Patients Using Automated EEG Classification	54
4.1	Introduction	54
4.2	Related Work	55
4.3	Methods	56
4.3.1	Participants	56
4.3.2	Protocol	57
4.3.3	EEG Acquisition	58
4.3.4	Transcranial Direct Current Stimulation Treatment	58
4.3.5	EEG Data Analysis	60
4.3.6	Experiment	60
4.4	Initial Investigation: Results and Discussion	64
4.5	Advanced Investigation	66

CONTENTS

4.5.1	Experimental Setting and Evaluation	66
4.5.2	Experimental Results	66
4.5.3	Discussion	70
4.6	Summary	73
5	Estimating the Quality of Electroconvulsive Therapy Induced Seizures	75
5.1	Introduction	75
5.2	Rating of Seizure Parameters and Quality	76
5.3	Related Work	78
5.4	Estimation of ECT-Induced Seizure Quality	79
5.4.1	Participants	79
5.4.2	Electroconvulsive Therapy Procedures	79
5.5	Experiment 1: Classification of Seizure Parameters to Estimate Seizure Quality	80
5.5.1	Decision Tree Classification	80
5.5.2	Fuzzy Rule-Based System	81
5.5.3	Experimental Results and Discussion	82
5.6	Experiment 2: Identification of Seizure Quality Rating Based on EEG Data	86
5.6.1	Pre-processing EEG Signal	86
5.6.2	Feature Extraction Based on Deep Belief Network and EEG Bands	87
5.7	Construction of Seizure Quality Estimation System Based on EEG Data	89
5.7.1	The Proposed EEG-Based Seizure Quality Estimation Method .	92
5.7.2	Results and Discussion	98
5.8	Summary	100
6	Conclusions and Future Directions	103

CONTENTS

6.1	Summary	103
6.2	Conclusions	105
6.3	Directions for Future Research	110
Appendix A Independent Component Analysis		112
A.1	Decomposing Data Using Independent Component Analysis	112
A.1.1	Independent Component Analysis of EEG Data	112
A.1.2	Independent Component Analysis Decomposition	112
A.2	Studying and Removing ICA Components	113
A.2.1	Rejecting Data Epochs by Inspection Using ICA	113
A.2.2	Scrolling Through Component Activation	113
A.2.3	Plotting Component Spectra and Maps	116
Bibliography		120

List of Figures

2.1	Structure of a neuron.	13
2.2	Brain regions.	14
2.3	The locations of EEG channels	16
2.4	Discrimination maps of brain between depressive disorder patients and healthy controls.	21
2.5	Restricted Boltzmann Machines.	32
2.6	The structure of convolutional neural network	34
3.1	DBN architectures: (a) Single-stream DBN, (b) Individual DBN for each channel and a top DBN to combine the channels' classification results, and (c) Multi-stream (or multichannel) DBN.	48
3.2	Testing and training divisions.	49
3.3	(a) EEG electrodes montage. (b) Classification accuracy for individual channels (The color bar represents the rank order).	50
3.4	Classification error of the six classification methods.	53
4.1	EEG cap.	59
4.2	Processing of transcranial direct current stimulation treatment.	59
4.3	Flowchart of the classification framework.	61
4.4	Brain regions and electrode placements.	63
4.5	Error rates of the channel pair combinations	64

LIST OF FIGURES

4.6	Best two channel pairs for each brain region.	65
4.7	Classification accuracy of individual channels based on: (a) mood labels (left) and, (b) cognition labels (right).	67
4.8	Classification results for pairs of EEG channels. A) Channel pair FC4-AF8 has the highest classification accuracy for the mood labels (left panel) and the best channel pair CPz-CP2 for the cognition labels (right panel). B) Average classification accuracy for each of the three brain regions (frontal, central/parietal and parietal/occipital).	68
4.9	Classification accuracy of individual classifiers (SVM, LDA and ELM) and their average for the different brain regions. Top panel shows classification accuracy for mood labels and lower panel for cognition labels.	69
4.10	Alpha asymmetry in frontal (F4-F3), central (C4-C3) and parietal (P4-P3) regions for responders (n=5) and non-responders (n=5), as based on the mood labels. [Negative values indicate higher alpha power in the left hemisphere and hence greater right-lateralised activity].	70
5.1	Regularity scoring.	77
5.2	Predicting model.	81
5.3	Membership functions: (a) fuzzy inputs, (b) fuzzy output (seizure quality).	83
5.4	Seizure quality based on: (a) Stereotypy-Regularity (b) Suppression-Regularity, (c) Suppression-Stereotypy.	84
5.5	Tree pruning.	85
5.6	The prediction rate of seizure quality.	85
5.7	T-F distribution: (a) recording 1, (b) recording 46.	88
5.8	Seizure quality score based on DBN features and clinician recordings: (a) before round, (b) after round.	90
5.9	Seizure quality score based on EEG rhythm and clinician recordings: (a) before rounding to integers, (b) after rounding to integers.	91
5.10	Prediction seizure quality rating model.	92

LIST OF FIGURES

5.11	Histogram of peak amplitude: (a) EEG recording 1, (b) EEG recording 22, (c) EEG recording 52.	93
5.12	Peak identification for recording 22: (a) prominence peaks at 1, (b) height peaks at least 1.	94
5.13	Prediction accuracy of seizure quality rating.	98
5.14	Prediction scores of global seizure quality rating based on: (a) clinical seizure rating, (b) estimation seizure indices.	99
5.15	Seizure quality based on (a) Stereotypy-Regularity (b) Suppression-Regularity, (c) Suppression-Stereotypy.	101
A.1	Independent component analysis decomposition	113
A.2	2–D Component Scalp Maps	114
A.3	3–D Component Head Plots	115
A.4	Reject data using ICA	116
A.5	Component properties	117
A.6	Rejecting Data Epochs by Inspection Using ICA	118
A.7	Scrolling	119
A.8	Component Spectra and Maps	119

List of Tables

3.1	Classification error rates of the six classification methods for each of the selected channel subsets	52
4.1	Demographic and clinical information	57
4.2	Scores and labels for individual participants	62
4.3	Description of Mood and Cognitive Improvement Scores	63
4.4	Pairwise ANOVA of the obtained classification results	65
4.5	Average Error rates of the best two channel pairs for the different brain regions.	65
4.6	The average classification error for the three best channel combinations per brain regions	69
5.1	Seizure quality score	78
5.2	Confusion matrix	83
5.3	Algorithm of the proposed EEG-based seizure quality estimation	95

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.