

بسم الله الرحمن الرحيم



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شبكة المعلومات الجامعية التوثيق الالكتروني والميكرو فيلم



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جامعة عين شمس

التوثيق الإلكتروني والميكروفيلم

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AIN SHAMS UNIVERSITY

FACULTY OF ENGINEERING

Computer and Systems Engineering

Deep Learning Approaches for Motor Imagery Brain-Computer Interfaces

A Thesis submitted in partial fulfilment of the requirements of the degree of

Master of Science in Electrical Engineering

(Computer and Systems Engineering)

by

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Bachelor of Science in Electrical Engineering

(Computer and Systems Engineering)

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Abstract

Motor imagery represents one Brain-Computer Interface (BCI) paradigm that has been utilized in developing applications to assist subjects with motor disability. Such paradigm relies on analyzing brain electroencephalography (EEG) activity to identify the intended movement direction. Existing motor imagery feature extraction techniques are focused on utilizing traditional signal processing and machine learning techniques. Recent advances in the deep learning field has inspired the development of few methods for motor imagery classification that achieved further performance improvement. This thesis introduces a deep neural network approach for motor imagery classification using Long Short-Term Memory (LSTM) combined with Autoencoders based on a sequence-to-sequence architecture. The proposed network extracts features from the frequency-domain representation of EEG signals. This network is trained to obtain low-dimensional representation of EEG features that are then fed into a multi-layer perceptron of 3 layers for classification. Systematic and extensive examinations have been carried out by applying the approach to public benchmark EEG datasets. The obtained results outperform classical state-of-the-art methods employing standard frequency-domain features and common spatial patterns, and comparative results to methods such as filter bank common spatial pattern and its variants. Our results indicate the efficacy of the proposed LSTM autoencoder approach in EEG motor imagery classification.

Keywords: Motor imagery, deep learning, long short-term memory, brain computer interface, EEG

Summary

A Brain-Computer Interface (BCI) system aims at processing brain signals to recognize human intention that is subsequently used to control an external device. BCI systems are based on monitoring and analyzing electroencephalography (EEG) brain activity. EEG activity is a non-invasive signal that can include different patterns such as P300 evoked potentials, steady-state visual evoked potentials (SSVEP) and motor imagery (MI) rhythms. MI signals are evoked during the imagination of movement without performing the actual action. In this thesis, a deep learning approach based on Long-Short-Term-Memory and Autoencoder has been developed and introduced to solve Motor imagery classification problem competing with state-of-the-art methods.

The chapters of this thesis are divided into 5 chapters, which are as follows:

Chapter 1 provides an introduction to the thesis outlining the research scope, objectives and contributions.

Chapter 2 gives a literature review of brain computer interface, electroencephalography, motor imagery and machine learning.

Chapter 3 introduces the proposed approach along with a detailed description of the methods developed and the training process.

Chapter 4 demonstrates the achieved results and comparisons of our experiments and proposed approach to other approaches.

Chapter 5 gives the conclusions and future work.

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Table of Contents

1	CHAPTER 1 Introduction	1
1.1	Research Scope	2
1.2	Research Objectives	2
1.3	Research Contributions	3
1.4	Thesis Outline	3
2	CHAPTER 2 Background	5
2.1	Introduction	5
2.2	Brain Structure	6
2.2.1	Cerebrum	6
2.2.2	The Cerebrum lobes	8
2.3	Brain-Computer Interface (BCI)	11
2.4	Neural Interfaces	11
2.4.1	Invasive Methods	11
2.4.2	Non-Invasive Methods	11
2.5	Mental Strategies and Brain Patterns	12
2.5.1	Selective attention	13
2.5.2	P300	13
2.5.3	SSVEP	13
2.5.4	Motor Imagery	14
2.6	Signal Processing	18
2.6.1	Noise Removal: Common Average Rejection (CAR)	18
2.6.2	Filtering	19
2.6.3	Fast Fourier Transform	22
2.7	Preprocessing methods	23
2.7.1	Data Augmentation	23
2.7.2	Data Normalization	26
2.8	Machine Learning	28
2.8.1	Supervised Learning	28

2.8.2	Unsupervised Learning	29
2.8.3	Reinforcement learning.....	29
2.9	Artificial Neural Networks (ANNs)	29
2.9.1	Fully Connected Neural Networks (FCNN)	30
2.9.2	Convolutional Neural Networks (CNNs)	31
2.9.3	Recurrent Neural Networks (RNNs)	33
2.9.4	Long Short-Term Memory (LSTM).....	34
2.9.5	Auto-Encoders Networks (AENs)	36
2.9.6	Deep Belief Network (DBN)	38
2.10	Related Work.....	40
2.10.1	Chin, Gan and Coyle.....	40
2.10.2	Denoising Autoencoder (DAE)	42
2.10.3	Bispectrum-based feature extraction technique for BCI.....	43
2.10.4	Convolutional Neural Networks based on augmented Common Spatial Filter (CSP).....	44
2.10.5	Filter-Bank Common Spatial Filter (FBCSP)	45
2.10.6	Frequential Deep Belief Network (FDBN).....	46
3	CHAPTER 3 The Proposed Deep Learning Approach	48
3.1	Proposed Approach Overview.....	48
3.2	Datasets	48
3.3	Processing Sequence.....	51
3.4	Feature Selection.....	51
3.5	Sequence-to-Sequence Architecture.....	53
3.6	LSTM Autoencoder (LSTM-AE)	54
3.7	Training	56
3.8	Optimizers.....	58
3.8.1	Adam.....	58
3.8.2	Adamax	58
3.8.3	AMSGrad.....	59
4	CHAPTER 4 Comparisons and Results	60

4.1	Performance of the LSTM-AE Approach	61
4.1.1	Performance of the LSTM-AE model	61
4.1.2	Results of Data Normalization Methods	63
4.1.3	Results of Data Augmentation Methods	64
4.1.4	Results of Different Activation Functions.....	64
4.1.5	Results of Different Optimizers.....	65
4.1.6	Results of Different Number of Layers.....	66
4.1.7	Results of Different Number of Nodes	68
4.1.8	Performance of the LSTM-AE Approach for Different Dropout Ratios	69
4.2	Comparison of LSTM-AE with State-of-the-art Methods	71
4.2.1	Across Subjects Performance of LSTM-AE.....	74
5	CHAPTER 5 Conclusions and Future Work.....	77
5.1	Conclusions.....	77
5.2	Future Work	78
	References	80

List of Figures

Figure 2-1 Brain Structure showing 4 major areas: Cerebrum, Cerebellum, Diencephalon and Brain Stem. Adapted from [6]	6
Figure 2-2 Left and Right brain functions show the brain lateralization of two brain hemispheres. Adapted from [8].	7
Figure 2-3 Cerebrum lobes. Adapted from [11]: a. Blue: the frontal lobe b. Yellow: the partial lobes c. Green: The temporal lobes d. Red: the occipital lobes ..	9
Figure 2-4 Motor and sensory regions of cerebral cortex. Adapted from [9].	10
Figure 2-5 Brain Homunculus. Adapted from [10].	10
Figure 2-6 Different recording methods used to control BMIs. Invasive methods include: ECoG electrodes placed on the dura, SEEG electrodes placed through the skull into the cortex and intracortical electrodes implanted in the cortex. Non-invasive methods include: EEG electrodes placed on the scalp and MEG squids placed around the head. Adapted from [14].	12
Figure 2-7 EEG Headset electrodes mapping	15
Figure 2-8 Temporal evolution of (A) movement-related potentials (MRCP), (8) ERD and ERS of beta rhythm, (C) ERD of mu rhythm and (D) rectified EMG for one subject (electrode position C3, right thumb movement). Time is expressed on the horizontal axis from 2 s before to 2 s after movement offset. Adapted from. Adapted from [20].	16
Figure 2-9 Time course of ERD/ERS. For each movement (right hand, left hand or both feet movement), the EEG power of C3, Cz and C4 within 8–12 Hz frequency band :(a) shows the ERD/ERS patterns happening in the right hand movement; (b) shows the ERD/ERS patterns happening in the left hand movement; and (c) shows the ERD/ERS patterns happening in both feet movement. Adapted from [19].	17
Figure 2-10 Common Average Rejection (CAR)	19
Figure 2-11 Filter types (a) Low-pass, (b) High-pass, (c) Band-pass, (d) Band-stop (notch)	20
Figure 2-12 Filter order effect	21
Figure 2-13 IIR Filter	22
Figure 2-14 Time series shifting effect	24
Figure 2-15 Time series rotation effect, (a) Raw data, (b) Rotated data	25
Figure 2-16 Time series noising effect	26
Figure 2-17 Fully Connected Neural Network structure	30
Figure 2-18 Example of Convolutional Neural Network with input image. Adapted from [43]	31
Figure 2-19 ReLU, Sigmoid and Tanh activation function graphs	33
Figure 2-20 LSTM cell structure. Adapted from [47]	35
Figure 2-21 Auto-Encoders Network structure	37

Figure 2-22 Restricted Boltzmann Machines (RBM).....	39
Figure 2-23 DAE for incomplete EEG signals on spectral power features to classify EEG signals structure.....	43
Figure 2-24 Convolutional Neural Networks (CNNs) based on augmented Common Spatial Filter (CSP) structure	45
Figure 2-25 Filter-Bank Common Spatial Filter (FBCSP) sequence of processing	46
Figure 2-26 Frequential Deep Belief Network sequence of processing	47
Figure 3-1 LSTM autoencoder scheme for motor imagery classification	48
Figure 3-2 competition IV dataset 2b recording sessions description (a) Screening, (b) Smiley feedback.....	50
Figure 3-3 Motor imagery electrodes position on the scalp.....	50
Figure 3-4 Sequence of data pre-processing	51
Figure 3-5 . Proposed LSTM autoencoder approach for motor imagery classification with 3 LSTM autoencoder layers followed by three fully connected layers. Layers 1, 2 and 3 in the figure correspond to the hidden layers of the trained autoencoders	56
Figure 3-6 EEG trial structure in seconds	57
Figure 3-7 Structure of Encoder-Decoder part of our approach.....	58
Figure 4-1 EEG time-domain signals recorded on channels 3 and 4 for (a) left and (b) right motor imagery tasks	60