Brain-computer interface for mental attention

Fatemeh Fahimi

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Brain-Computer Interface for Mental Attention

A thesis submitted to the Nanyang Technological University in partial
fulfilment of the requirement for the degree of Doctor of Philosophy

By

Fatemeh Fahimi

School of Computer Science and Engineering

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Prof Cuntai Guan

Authorship Attribution Statement

This thesis contains material from 5 papers published in the following peer-reviewed journals and conferences in which I am listed as an author.

Chapter 3 is published as:

F. Fahimi, W. B. Goh, T. S. Lee, and C. Guan, “EEG Predicts the Attention Level of Elderly Measured by RBANS”, *International Journal of Crowd Science*, Vol. 2, Issue: 3, pp. 272-282 (2018). DOI: [10.1108/IJCS-09-2018-0022](https://doi.org/10.1108/IJCS-09-2018-0022).

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The contributions of the co-authors are as follows:

- Prof. Guan was technical lead PI and Dr. Lee was clinical lead PI of the project associated with the dataset used in this paper.
- Prof. Guan and I provided the study direction.
- I implemented the methods, analysed the data, and prepared the manuscript drafts.
- The manuscript was revised by Prof. Guan and Assoc. Prof. Goh.

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- Prof. Guan was technical lead PI and Dr. Lee was clinical lead PI of the project associated with the dataset used in this paper.
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The contributions of the co-authors are as follows:

- I implemented the methods, analysed the data, and prepared the manuscript drafts.
- All co-authors advised on the study and revised the manuscript.

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and

to my mother,

Thank you for your unconditional love and support, I love you endlessly.

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Abstract

A brain-computer interface (BCI) records, processes, and translates brain activity into commands for an interactive application. This thesis mainly addresses the attention-related challenges that electroencephalography (EEG)-based BCI systems face, including assessment of subject's attention status using EEG-based BCI, continuous attention detection from EEG, and improving the BCI performance under attention diversion.

Firstly, a correlation analysis between EEG and attentional behaviour is performed to find the EEG attention-representative features. These features are then used to assess the attention status that is measured by a neurophysiological assessment test. Attention status shows how well is the functioning of the attention domain. The results show the effectiveness of EEG in the assessment of attention status and thus verify the feasibility of attention detection using EEG.

Subsequently, deep learning (DL) method is used to learn hidden information in the EEG for attention detection. We propose an end-to-end DL-based framework with subject-to-subject transfer learning strategies. The results show that the proposed methods significantly outperform state-of-the-art methods. Moreover, visualization of the deep neural network's perceived input of attention and non-attention demonstrates that the proposed framework truly learns meaningful information from the EEG data.

Last but not least, an experiment that includes focused and diverted attention conditions is designed and implemented to investigate the effect of attention diversion on the performance of BCI in the detection of movement intention. A significant drop in the BCI performance under the diverted attention condition was observed. To improve the performance, we propose a novel approach based on generative adversarial networks

(GANs) to augment EEG. The results show that the proposed method significantly improves the BCI performance.

The research presented in this thesis firstly shows the effectiveness of EEG-based BCI in the assessment of attention status and thus the feasibility of attention detection using EEG. Subsequently, the thesis proposes a novel method for continuous attention detection from EEG that shows superior results over baseline methods in subject-to-subject classification. The interpretability of the results and the generalizability of the method are other advantages of the proposed method. Lastly, the thesis proposes a data augmentation method that improves the BCI performance under attention diversion which is a challenging condition in real-life applications of BCI. The present study can contribute to the improvement of cognitive BCI systems, especially those developed for attention training/treatment, and can be further extended to other BCI applications.

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List of Abbreviations

ADHD	Attention-Deficit Hyperactivity Disorder
AGR	Alpha-Gamma Ratio
ANT	Attention Network Test
ASR	Artifact Subspace Reconstruction
BCI	Brain-Computer Interface
CNN	Convolutional Neural Networks
CNS	Central Nervous System
CSP	Common Spatial Pattern
DCGANs	Deep Convolutional Generative Adversarial Networks
DCNN	Deep Convolutional Neural Networks
DL	Deep Learning
DR	Data Representation
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
ERP	Event-Related Potentials
FBCSP	Filter Bank Common Spatial Pattern
FFT	Fast Fourier Transform
GANs	Generative Adversarial Networks
ICA	Independent Component Analysis
LDA	Linear Discriminant Analysis
LOO	Leave-One Subject-Out
LSTM	Long Short-Term Memory
MI	Movement Intention

MIBIF	Mutual Information-based Best Individual Feature
NBPW	Naive Bayesian Parzen Window
PSD	Power Spectral Density
QEEG	Quantitative Electroencephalography
RBANS	Repeatable Battery for the Assessment of Neurophysiological Status
RNN	Recurrent Neural Networks
RT	Response Time
SAE	Stacked Auto-Encoders
SCP	Slow Cortical Potentials
SSVEP	Steady-State Visual Evoked Potentials
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
TBR	Theta-Beta Ratio

Chapter 1

Introduction

Brain-computer Interface (BCI) is a system that records, processes, and translates brain signals into output commands for a wide variety of applications [2-4]. BCI was initially targeted at facilitating disabled people's lives [5] by decoding their mental intentions, for example, to control a wheelchair [6-8], to spell the letters/words [9-14], or to move a cursor on the screen [15-17]. BCI had been also applied for rehabilitation purposes such as stroke rehabilitation [5, 18-21]. In recent years, BCI had found other applications such as cognitive training [22-24], mental disorders treatment [25-27], and non-medical applications [28, 29] such as video games [30].

The successful implementation of BCI systems offers several benefits. BCI systems for medical applications serve people with disabilities, people with cognitive impairment, and healthy individuals. For example, in recent years, BCI has shown significant improvement in motor function recovery for stroke survivors [31]. BCI can also be used to convert a passive prosthetics into an active one through the translation of mental intentions into commands [32]. This will reduce the dependency of disabled people on their caregivers. Another recent application of BCI is cognitive training that has several advantages over traditional methods. The traditional methods are expensive, need several time-consuming face-to-face sessions with a trained instructor, and take a long time to make a positive change. On the other hand, BCI-based cognitive training is cheaper, more exciting, and can be implemented anywhere which is important for individuals with mobility problems [24].

Many BCI systems use electroencephalography (EEG) for brain data acquisition. The advantages of this acquisition method are ease of use, portability, lower cost compared to other methods, and most importantly, high temporal resolution and non-invasiveness [33]. The recording modality in this thesis is EEG.

Since its introduction in 1973 [34], research on BCI has rapidly evolved over the past decades. However, BCI is still facing several challenges in different areas such as constructing easy-to-use recording techniques to capture brain signals with a high spatial and temporal resolution, developing effective EEG artifact removal methods ideally integrated with the signal acquisition, and enhancing signal processing techniques to increase accuracy and robustness of BCI systems.

One area that needs significant improvement in signal processing is BCI for cognitive applications. One of these applications is the treatment of attention disorders or attention training [26, 35-38]. EEG-based BCI systems developed for this purpose face several challenges related to attention. This thesis focuses on addressing the attention-related challenges that are described in the following sections.

1.1 Research Motivation

Attention plays a key role in many cognitive BCI systems, for example, in the systems that are designed for the treatment of attention-deficit hyperactivity disorder (ADHD), detection of mild cognitive impairment (MCI), or enhancement of cognitive function. In these types of BCI systems, assessment of subjects' cognitive status including attention is important. Thus, the assessment of attention status using EEG-based BCI is the first challenge to be addressed in this thesis.

The second challenge is continuous attention detection from EEG. In fact, in BCI-based attention training/treatment systems, obtaining accurate attention detection is of high importance because user's attention usually serves as a control signal. Thus, a false attention detection generates a wrong control (or feedback) signal and decreases the BCI performance and reliability.

The third challenge to be addressed is improving the BCI performance under attention diversion. In a typical BCI experiment, users are seated in a quiet place and are instructed to fully focus on the task. However, users' attention might be diverted by several internal and external distractions in reality. This attention diversion may affect the performance of the BCI system [39]. In other words, a previously trained model may no longer be optimal under such circumstances. Improving the performance of the BCI system under attention diversion is a challenging task that solving it will not only benefit cognitive BCI systems, it will also benefit other types of BCIs.

1.2 The objective of the Thesis

A summary of the thesis objective and the related challenges is demonstrated in Figure 1.1. The overall objective of this thesis is to address the attention-related challenges in EEG-based BCI systems that are described in section 1.1 and listed below:

- Assessment of attention status using EEG-based BCI
- Continuous attention detection from EEG
  - within a unified end-to-end framework
  - with subject-to-subject transfer
- Improving performance of EEG-based BCI under attention diversion

Figure 1.1 An overview of the research objective and the challenges to be addressed in the present thesis.

1.3 Organization of the Thesis

This thesis is outlined in 6 chapters. Chapter 2 defines the attention system and presents a review of BCI. The primary goal of chapter 2 is to make the readers familiar with the concepts and the challenges in BCI within the scope of this thesis. Subsequently, chapters 3, 4, and 5 describe the contributions of this thesis in addressing the challenges listed in section 1.2. More specifically, chapter 3 investigates the effectiveness of EEG in the assessment of attention status to verify the feasibility of attention detection using EEG. Chapter 4 proposes an end-to-end deep convolutional neural networks (DCNN)-based framework for attention detection from EEG. It first reviews the related work and then moves on to the description of the proposed methods in details. Chapter 5 first describes the experiment that is done to evaluate the effect of attention diversion on BCI performance and then proposes a method based on generative adversarial networks (GANs) to boost the BCI performance under attention diversion. Lastly, chapter 6 concludes the thesis and introduces potential directions for future work. Chapters 3 and 4 are respectively based on our published work in [40, 41] and [1, 42]. The content presented in chapter 5 is under revision and a part of it is accepted for publication [43].

Chapter 2

Attention and EEG-based Brain-Computer Interface

This chapter reviews the main concepts related to attention and EEG-based BCI to provide a background of the research presented in this thesis. It first describes the attention system of the human brain and the common tests for attention evaluation including the ones used in the present thesis. The chapter then moves on to the review of BCI. Finally, it discusses the role of attention in BCI systems and the related challenges to be addressed in this thesis.

2.1 Neuroscience of Attention

Advanced neuroimaging techniques have enabled researchers to gain a deeper understanding of the brain areas involved in the attentional processes. The most popular model of attention system is the one proposed by Posner and Petersen [44]. They suggested that the attention system has a discrete anatomical basis and is divided into 3 different networks, each associated with different attention functions. These networks are called alerting, orienting, and executive control [44]. Twenty years later, they updated their research on the attention system based on the advances in brain imaging and the important findings brought by researchers during past years [45]. As stated in their updated review, the idea of the discrete anatomical basis of the attention system is still valid and has evolved over time. Briefly, alerting is defined as obtaining and maintaining the alert state, orienting is the selection of information from sensory input, and executive control is defined as resolving conflict among responses.

Table 2.1 summarizes the attention networks along with their associated functions, brain areas, and neuromodulators [46]. The following paragraphs elaborate on each network.

Table 2.1 Attention networks and their associated attentional functions, brain areas, and modulator.

Attention network	Attention functions	Brain areas	Neuromodulator
Alerting	Achieving and maintaining the alert state	Locus Coeruleus Frontal and parietal cortex	Norepinephrine
Orienting	Prioritizing sensory inputs	Superior parietal Temporal parietal junction Frontal eye fields Superior colliculus Pulvinar	Acetylcholine
Executive control	Solving conflicts	Anterior cingulate Anterior Insula Basal ganglia	Dopamine

This table is adapted from [46].

Alerting is the process involved in achieving and maintaining the alert state. One approach to study alertness is associated with tonic alertness which is defined as “intrinsic arousal that fluctuates on the order of minutes to hours” [47]. Another approach is associated with phasic alertness which is defined as “the rapid change in attention due to a brief event” [47]. This brief event usually refers to a warning stimulus [47, 48]. For example, in many experiments, a warning signal is represented before the main target to change the mental state from resting state to the preparation phase. Subsequently, the response readiness to the target will be increased. Phasic alertness is considered as a basis for orienting [47]. Based on the neuroimaging results, alerting is associated with the norepinephrine system of the brain including the locus coeruleus in the pons, frontal, and parietal cortical areas [46].

Orienting involves the functions related to selecting specific information among various sensory inputs [45], e.g., when a person intentionally focuses on a certain area of the visual field [49]. The orienting network is associated with the ventral and dorsal frontal, parietal areas, and subcortical areas of the superior colliculus and pulvinar [46].

Executive control involves more complex functions such as monitoring and solving conflicts, decision making, planning, error detection, etc. [45, 49]. The executive attention network is associated with the anterior cingulate cortex (ACC), anterior insula, and underlying striatum [46].

2.2 Evaluation of Attention

This section describes the commonly used tests for the evaluation of attention. Many neuroimaging studies on attention recorded the brain data during these tests [50-53]. Besides the below-mentioned tests, variations of Flanker task [54], psychomotor vigilance test (PVT) [55], and the Wisconsin card sorting test [56] are other examples.

In BCI studies on attention, these tests are mainly used in 2 ways: 1) as the attention-demanding task during which the participants' brain data are recorded [26, 57], or 2) as ground truth to measure attention status and evaluate the effectiveness of BCI-based training/treatment [23, 24, 58]. In chapter 3 of this thesis, EEG data are recorded during the Stroop colour test and ground truth for attention status is measured by repeatable battery for the assessment of neurophysiological status (RBANS). In chapter 4, EEG data are recorded during the Stroop colour test.

2.2.1 Stroop Colour Test

In the Stroop colour test, participants are asked to name the ink colour of the word. For example, if the word 'Red' is printed in blue, the answer is blue. Reading is an automatic process in the brain and it is even hard to inhibit [59]. This tendency to read the word will thus interfere with the processing of other information about the word, such as its ink colour [59]. This is called the Stroop effect and traces back to 1935 when psychologist John Ridley Stroop first demonstrated it [60].

The Stroop test mainly involves executive control, described in section 2.1, as it is, in fact, solving a conflict. The Stroop effect is usually studied under 3 conditions: baseline or control, congruent, and incongruent [59]. In the control condition, a non-colour word (e.g. book) or a string of letters (e.g. XXX) is printed in colour. In the congruent condition, the meaning of the word is the same as the ink colour (e.g. blue is written in blue). In the incongruent condition, the word is the name of a colour but it is different from the ink colour (e.g. red is written in green). Table 2.2 lists some examples of control, congruent, and incongruent Stroop test. The main performance measure is the response time in the Stroop test. Based on several experiments, the response time increased in the incongruent condition compared to the baseline and decreased in the congruent condition compared to the baseline [59]. Since its introduction in 1935, the Stroop test had been used in numerous studies including EEG processing [50, 61] to evaluate attention.

Table 2.2 Examples of stimuli in the Stroop test.

Control	Congruent	Incongruent
house	green	red
cat	red	yellow
ball	blue	white
tree	black	blue
baby	yellow	black
book	purple	white

This table is adapted from [59].

2.2.2 Repeatable Battery for the Assessment of Neurophysiological Status (RBANS)

The RBANS was introduced in 1998 for the detection of abnormal cognitive decline in older adults and as a cognitive screening test for younger subjects [62]. It was designed particularly for the assessment of 5 cognitive domains including attention, delayed memory, immediate memory, visuospatial/construction, and language.

The RBANS is an individually administrated test, simple, and takes less than 30 minutes. It contains 12 subtests that yield 5 domain scores (i.e. attention score, etc.) and 1 total scale score. Two of 12 subtests are for the assessment of attention and are called digit span and coding. In digit span, a digit is presented and read aloud for 1 s followed by 0.75 s interval before the next digit is presented. The subject is asked to remember the string of these digits and recall it. The length of the string varies from 2 to 9 digits. If the subject fails to recall a string from a certain length, another sting from that length would be presented. In coding, 9 simple symbols are assigned to numbers 1 to 9 in a horizontal table (key table) on top of the page/screen. The subject is presented with a page/screen filled with symbols and is asked to fill in the correct number for each symbol based on the key table. The score is the number of symbols correctly assigned to their corresponding numbers in 90 s [62, 63].

The RBANS has been used to characterize and assess cognitive decline in many studies including BCI studies whereby the RBANS is mainly used as ground truth or as an efficacy measure for the BCI-based treatment [23]. In chapter 3 of this thesis, attention scores obtained from RBANS are used to provide the true labels for the assessment of attention status using EEG.

2.2.3 Attention Network Test (ANT)

The ANT was introduced by Fan, et al. [64] to evaluate the functions of alerting, orienting, and executive control and their independence. The authors suggested that the ANT can be used to assess attention abnormalities in various cases such as attention-deficit disorder and schizophrenia. The ANT may also be used as a phenotype in studies that evaluate the effect of genes on attention networks and as an activation task for neuroimaging [64].

The original ANT took only 30 minutes and was designed in an easy-to-perform way to be suitable for children, adults, and patients. Figure 2.1 shows the cue types, the stimuli, and one example of ANT. In the original test, there were 4 cue types, namely, no cue, centre

cue, double cue, and spatial cue; and 6 stimuli including 2 neutral, 2 congruent, and 2 incongruent. The participants were asked to determine the direction of the central arrow (left or right) and their performance was assessed by tracking how response time changes by alterations in cue and flanker type. In fact, the efficiency of each attention network was measured through a couple of cognitive subtractions. The alerting efficiency was calculated by deducting the average response time of the double cue conditions from the average response time of the no cue conditions. The orienting measure was obtained by subtracting the average response time of spatial cue conditions from the average response time of centre cue conditions. Finally, the executive control effect was calculated by deducting the average response time of congruent conditions from the average response time of incongruent conditions. The authors reported that although these 3 networks have distinct anatomy, there are some interactions between them [64]. The ANT has been used for attention study in several research areas including BCI [53, 65].

Figure 2.1 The Attention Network Test: (a) cue types, (b) 6 stimuli used in ANT, (c) an example of the test [64].

2.3 EEG-based Brain-Computer Interface

The definition of BCI states that “a BCI is a system that measures central nervous system (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment” [66]. A general framework of a

typical BCI system is shown in Figure 2.2. It has 4 main stages: signal acquisition, pre-processing, feature extraction, and classification (or translation). Users' brain activity will be recorded while they are focusing on a specific stimulus or performing a task. The recorded data will be first pre-processed to remove noise and artifact (i.e., eye blink, muscle movement, etc.). Then, features will be extracted from the pre-processed data to be used as classifier's input. A command signal will be generated based on the classification output for the external device or use in an interactive application. The common methods used in each stage are reviewed in the following subsections.

Figure 2.2 The general framework of an online Brain-computer interface, adapted from [66].

2.3.1 Brain Data Acquisition

There are various techniques for brain data acquisition, each with advantages and disadvantages. These techniques fall into 2 general categories: invasive and non-invasive [67]. Invasive methods need surgical interventions to implant the electrode in the brain. In contrary, non-invasive methods record brain activity from the scalp with no need for

surgery. Although the output of the invasive method is of higher quality and better spatial resolution, this technique is less preferred in BCI than non-invasive methods [68]. The reason is the need for multiple surgeries to insert the electrodes and replace them regularly. Therefore, many BCI researchers prefer non-invasive methods [68].

EEG is by far the most popular non-invasive recording technique in BCI [68]. We have also used EEG in the research presented in this dissertation. EEG records electrical activity caused by ionic currents within neurons [69]. This electrical activity is captured by small metal electrodes which are placed on the scalp, usually based on the international 10-20 system. Figure 2.3 shows the position of the electrodes based on the 10-20 system for 21 electrodes. The qualities that make EEG the preferred recording method in BCI are non-invasiveness and ease of use, high temporal resolution, portability, and low setup cost [68]. Poor spatial resolution and non-stationarity [68, 70] are the main disadvantages of this technique.

EEG can be affected by environmental noise, line noise, cable movement, eye blink, and muscle activity. Pre-processing is therefore essential to enhance the signal-to-noise ratio (SNR). The following section describes the techniques used in BCI for pre-processing.

Figure 2.3 Position of the electrodes based on the 10-20 system for 21 electrodes. This figure is taken from [68].

2.3.2 Pre-processing Methods in EEG-based BCI

Pre-processing increases the signal-to-noise ratio. The choice of the pre-processing method depends on the data recording technique and knowledge of the signal [71]. Artifact detection, spectral, and spatial filtering are common methods [71]. The method of artifact detection searches for the parts of the signal affected by eye blink, muscle artifacts, etc., usually by visual screening or thresholding, and then removes them from the signal. Spectral filtering, such as band-pass filtering, cleans the data from line noise and drifts [72] while spatial filtering incorporates the signals recorded from several electrodes in order to concentrate on the activities in a specific part of the brain. The most well-known spatial filtering methods are Laplacian filter [73], common spatial pattern (CSP) [74-77], and independent component analysis (ICA) [78]. There are also some methods that optimize both spectral and spatial filters, for example, filter bank common spatial pattern (FBCSP) [79]. In a typical BCI system, pre-processing is usually followed by feature extraction.

2.3.3 Feature Extraction and Selection Methods in EEG-based BCI

EEG signals recorded from multiple electrodes over long periods of time can be represented by several features. The most extensively used features are frequency band powers (spectral) and temporal features [80]. The spectral features determine the power or the energy of the EEG in a certain frequency band over a given channel and are notably used in motor imagery-based BCI, steady-state visual evoked potentials (SSVEP)-based BCI, and mental state decoding [80]. There are several ways to compute these values [81]. On the other hand, temporal features are mostly used for event-related potential (ERP) detection [80]. In EEG-based BCI, spectral and temporal features are usually extracted after spatial filtering [80]. Besides these features, there are other kinds of features that have been explored, such as connectivity features including phase-locking values and coherence [82].

Feature extraction is usually accompanied by a feature selection to select the most informative subset of features [80]. The feature selection algorithms lie in 3 main categories: filter, wrapper and embedded methods [80]. Filter methods are based on the relationship between the feature and the class label, mutual information-based feature selection [83], and maximum relevance minimum redundancy [84] are some examples of filter methods. On the other hand, wrapper methods recursively choose a subset of features and send it to the classifier until the stopping criterion, for example, classification accuracy, has met. The genetic algorithm used in [85, 86] and the evolutionary methods [87] are of the wrapper category. Unlike wrapper methods where the evaluation of selected features is done separately, the embedded methods are an integrated process of feature selection and evaluation. Decision trees fall into the embedded category [88]. Overall, the filter methods have been used more than the other 2 methods [80].

Although it is believed that feature extraction and selection are important in BCI as they transform the raw EEG into a representation that is suitable for prediction, the end-to-end learning methods which learn from raw EEG instead of pre-extracted features has recently emerged in BCI and showed to be promising [89]. Nowadays, deep learning (DL) methods by taking raw EEG as input integrates the feature extraction and classification stages [80]. The following section describes the recent classification approaches in EEG-based BCI, including deep learning.

2.3.4 Classification approaches in EEG-based BCI

The latest classification approaches used in EEG-based BCI fall into 4 main categories: matrix-based classifiers, adaptive classifiers, transfer learning, and deep learning [80].

In matrix-based classifiers, input EEG is represented as a matrix, usually covariance matrix, instead of a vector of features [80]. A recent matrix-based approach that is successfully applied in EEG-based BCI is Riemannian geometry-based classifier [90-92]. Basically, the

idea is mapping the data into a geometrical space where the data can be manipulated easily. The Riemannian classifier can be applied either directly on the data or on its projection onto the tangent space. According to the results of several studies, this approach is fairly robust, accurate, simple, and does not need parameter tuning as it is required in typical classifiers [90-94]. Other matrix-based classification approaches are presented in [95-97].

The adaptive classification approach is implemented in 2 main ways: supervised [70, 98] and unsupervised [99, 100]. In the supervised approach, the true labels of new samples are known. In contrary, in the unsupervised approach, the true labels of new samples are not given. In this case, the true labels of new samples will be estimated. In both supervised and unsupervised adaptation, the model can be either updated based on new samples or retrained on the new training set which is augmented by new samples [80].

In BCI systems, especially those for patients, elderly, and children, it is tiring and time-consuming to calibrate the system. In other words, a calibration-free BCI system is always preferred [101-105]. Towards minimizing the calibration, researchers have implemented session-to-session and subject-to-subject transfer learning approaches [106-111], that are challenging owing to EEG non-stationarity. An interesting approach is the combination of transfer learning and adaptive. Chapter 4 of this thesis implements this approach.

Deep learning has recently become popular in EEG-based BCI. There is an increasing number of studies that employ deep learning for classification [89, 112-118]. Deep learning approach learns the features and the classifier model within one unified framework. The proposed frameworks in chapters 4 and 5 of this thesis are based on deep learning. There, a comprehensive review of DL-based classifiers in BCI is presented.

2.3.5 BCI Applications

A very first BCI application was to help disabled people to control artificial limbs or communicate with others. Numerous groups had worked towards this goal [2, 119-121].

However, BCI had recently found meaningful applications in other areas as well, such as stroke rehabilitation [5, 122], treatment of attention deficit hyperactivity disorder [26], treatment of schizophrenia [27], and enhancement of cognitive functions [22, 23]. These studies had reported significant improvement in patients or healthy users' condition after the BCI-based treatment/training. Figure 2.4 shows an example of a BCI-based attention training for ADHD. BCI had been also applied for non-medical purposes such as environment control [123], games, music, and virtual reality [124-126]. Readers can refer to [127] for more details about BCI applications.

Since the present thesis is within the scope of EEG-based BCI for cognitive applications, we review recent studies on cognitive EEG-based BCI in the following section.

Figure 2.4 A BCI-based attention training program, taken from [26].

2.3.6 Cognitive EEG-based BCI

Cognitive BCI studies can be stratified into 2 main categories: cognitive assessment and cognitive training [128].

BCI for cognitive assessment aims at assessing cognitive functions using brain signal [129, 130]. In BCI systems, depending on the task, various cognitive functions such as attention

will be involved. It is therefore essential to reliably assess and measure the involved functions.

BCI for cognitive training aims at introducing a new cognitive training method based on BCI [26, 131]. In a typical BCI-based training system, the patients or healthy subjects' brain signal will be decoded to be used in an interactive application. Through the feedback sessions, the participants will gradually learn how to perform better by self-regulating their brain activity and obtaining, for example, a higher level of attention [26]. In these BCI systems, a wide variety of signal processing and machine learning techniques, as well as clinical assessments, are being applied to investigate the efficacy of the proposed BCI-based training/treatment method.

A summary of the recent EEG-based cognitive BCI studies is presented in Table 2.3.

Table 2.3 A summary of EEG-based BCI for cognitive applications.

Reference	Contribution	Signal/ Paradigm	Subjects	Task/ Experiment	Evaluation Measure
[25]	Developing a BCI system for attention training in ADHD children	Spectral-spatial features	172 ADHD children	A BCI-based 3D game with an avatar, called Cogoland	ADHD rating scale, child behaviour checklist, pediatrics adverse events rating scale
[131]	Introducing a P300-based neurofeedback training to improve attention	P300	28 healthy subjects	P300-based speller task with and without neurofeedback	ERP and Alpha power
[132]	Developing a real-time BCI for emotion recognition with the application for patients with disorder of consciousness (DOC)	Log power spectral density features	10 healthy subjects & 8 DOC patients	Watching positive and negative video clips	SVM classification accuracy
[24]	Developing a BCI system for cognitive training in healthy elderly	Spectral-spatial features	227 healthy elderly	A BCI-based game called BRAINMEM that includes card matching,	RBANS score, Rivermead behavioural memory test (RBMT) score

					shopping list, shopping list recall, and face matching
[133]	Introducing a new method for feature extraction based on a combination of multivariate empirical mode decomposition (MEMD) and phase space reconstruction (PSR)	Phase space features	7 healthy subjects		5 mental tasks: relaxation, arithmetic, letter composing, geometric figure rotation, visual counting Classification accuracy between mental arithmetic and letter composing tasks
[57]	Extraction of cortical connectivity pattern associated with attention components (alerting, orienting and executive control) using PDC and graph theory	Connectivity patterns estimated through Partial Directed Coherence	15 healthy subjects	ANT	The correlation coefficient between the behavioural index and EEG features for each attention component.
[134]	Exploring EEG features for attention detection in ADHD children	Spectral features	120 ADHD children		Stroop test for calibration and BCI-based game for training Classification accuracy
[135]	Development of a BCI-based auditory paradigm for aphasia rehabilitation.	ERP	20 elderly healthy subjects and 1 stroke patient with aphasia	ERP responses to 6 bi-syllabic words in an auditory BCI framework	Classification accuracy between target and non-target words
[136]	Evaluation of BCI-based functional electrical stimulation (FES) training on brain activity in children with spastic cerebral palsy	Sensorimotor rhythm (SMR)	18 children with cerebral palsy	Wrist and hand extension	SMR and EEG mid-beta waves (15-20 Hz)
[137]	Providing a theoretical explanation of why BCI is a beneficial tool for aphasia recovery (pilot study).	P300	5 patients with post-stroke aphasia	Visual P300 speller paradigm, attention test administrated by TAP software	Accuracy (spelling performance) and usability of BCI
[138]	Development of a motor imagery-based BCI tool to decelerate the cognitive impairments due to aging.	SMR	63 healthy elderly	Controlling the cursor presented on a screen through	Change in Luria-AND

				a motor imagery-based BCI.	scores and EEG power spectrum
[129]	Evaluation of P300-based BCI for the administration of a motor-verbal free cognitive battery in amyotrophic lateral sclerosis (ALS) patients.	P300	15 ALS patients and 15 healthy control subjects	4 neurophysiological tests administrated by P300-BCI: token test, d2 test, Raven's coloured progressive matrices, and modified card sorting test	Test scores and execution times
[139]	Detection and assessment of number processing and mental calculation (as residual cognitive functions) in patients with disorders of consciousness	P300+SS VEP	11 patients: 6 vegetative state, 3 minimally conscious, 2 emerged from a minimally conscious state	Number recognition, number comparison and mental calculation (+/-)	Task accuracy
[140]	Providing a new measure of BCI performance and subject's cognitive resources based on the zone of proximal development (ZPD)	Power of Beta over sensorimotor regions (FC3, C3, CP3).	2 healthy subjects	Cued motor imagery	Zone of proximal development
[141]	Development and evaluation of a BCI-based memory/attention training system for elderly	Spatial-spectral patterns	39 healthy elderly	Stroop colour test for calibration, card-pairing game for BCI training	RBANS scores, safety query, acceptability and usability questionnaire
[142]	Developing a P300 based VR attention training system for ADHD (preliminary study)	P300 (from Pz)	6 healthy subjects	Two oddball attention experiments; ANISPELL and T-search	Accuracy in the detection of P300
[143]	1) a comprehensive discussion on the implementation of passive BCI for working memory load (WML) assessment during learning	Spectral EEG waves	16 healthy subjects	n-back task and reading-span task (each with 3 levels of difficulty)	Accuracy of cross-task WML classification

	2) segregation of WML levels based on the cross-task classification				
[144]	Development of a motor imagery-based BCI tool to decelerate the cognitive impairments due to aging.	SMR	40 healthy elderly	Combination of motor imagery exercises, memory, and logical relation tasks	Change in Luria-AND scores
[145]	Definition of EEG-derived indexes of brain networks underlying memory tasks	SMR	2 stroke patients	neurofeedback-based treatment protocol implemented in BCI closed loop, and Sternberg task	Accuracy and reaction time in response to Sternberg task, Corsi Block Tapping Test, and Rey Auditory Verbal Learning Test, and connectivity patterns
[23]	Development and evaluation of a BCI-based memory/attention training system for the elderly (pilot study)	Spectral-spatial features	31 healthy elderly	Stroop colour test for calibration, card-pairing game for BCI training	RBANS scores, safety query, acceptability and usability questionnaire
[130]	Integration of BCI and eye-tracking tools for the cognitive assessment of executive functions	P300	8 healthy subjects and 1 ALS patient	Modified phonemic fluency test, modified semantic fluency test	Fluency indexes, execution time, scores of usability and psychological questionnaire
[146]	Investigation of a neuropsychological battery for cognitive assessment based on the integration of BCI and eye-tracking tools (a pilot study)	P300	8 healthy subjects	Modified phonemic fluency test, modified semantic fluency test	Fluency indexes, execution time, scores of usability and psychological questionnaire
[26]	Investigation of an intensive BCI-based attention training game for ADHD children	Spatial-spectral patterns	20 ADHD children	BCI-based games	ADHD rating scale-IV, the correlation between EEG index and ADHD score

[147]	Assessment of conditional associative learning in one late-stage ALS patient	Slow cortical potentials (SCP)	1 ALS patient	Matching to sample with 3 types of visual stimuli: signs, colourful discs and geometrical shapes	Test accuracy
[148]	Assessment of cognitive abilities in 2 ALS patients using self-regulation of SCP	SCP	2 ALS patients	Simple computations and discrimination of odd/even numbers, consonants/vowels, etc.	Test accuracy

Scoping approach: We searched the Google Scholar database to find the studies conducted over the past 10 years (2008-2019). The keywords for this search were “EEG”, “BCI”, “Cognitive”. Later, the results were narrowed down to the studies that were published in peer-reviewed journals and conferences. This table only includes the most relevant works.

Cognitive BCI systems mainly those that are developed for attention assessment or training face several challenges. The next section discusses the attention-related matters in BCI systems and the related challenges to be addressed in this thesis.

2.4 Attention in BCI Systems

Attention is a complex cognitive function that allocates the processing resources to a certain task such as sensory stimuli, memories, or in general any mental task. It may be degenerated due to neurological disorders such as ADHD. People who suffer from ADHD have difficulties in maintaining their focused attention on a specific task. Attention impairment might also happen with aging. The traditional training/treatment methods mostly include psychostimulants or consultation with psychologists. Inevitable side effects and drug-abuse are disadvantages of taking psychostimulants [149-151]. On the other hand, psychology-based methods are safe but they take a long time to make a small improvement in the patient's condition. Moreover, it is expensive and monotonous.

With advances in brain imaging and signal processing techniques, researchers have started to investigate the efficacy of BCI in the treatment of attention disorders and enhancement of cognitive functions including attention [26, 35-38]. The performance of such BCI systems is associated with the improvement in the user's attention status. Therefore, assessment of attention status using EEG-based BCI, as a surrogate for neurophysiological tests, is important. This is the first challenge that this thesis addresses.

In many cognitive BCI systems, the amount of attention that subjects allocate to the task plays a key role in the interface. In other words, attention serves as a control signal. For instance, in [25, 26], the application for attention training was a 3D game with an avatar which was being controlled by subjects' attention. The authors reported that based on the ADHD rating scale, the inattentive symptoms of ADHD children who underwent the BCI-based attention training program decreased by 3.5 ± 3.97 while the change in the control group was 1.9 ± 4.42 (p -value = 0.01) [25]. In such BCI systems, to successfully run the BCI-based program, it is essential to detect the times the BCI user is attentive from EEG. This continuous attention detection from EEG is the second challenge to be addressed in this thesis.

In BCI systems, although subjects are instructed to be focused, their attention is prone to diversion by several external and internal distractions during brain-computer interfacing, especially outside laboratories. These distractions might impair the performance of BCI systems [39]. The problem of attention diversion is not limited to only cognitive BCI systems, rather, it is related to all BCI systems. Hence, finding a solution to improve the performance of BCI under attention diversion is another important task which is the third challenge to be addressed in this thesis.

2.5 Summary

This chapter first described the neuroscience of attention and the well-known tests for attention evaluation including the Stroop test and RBANS that are used in this thesis. It then briefly reviewed the methods of pre-processing, feature extraction, and classification in EEG-based BCI including deep learning, transfer learning, and adaptive classifiers that are applied in this thesis. Finally, it discussed the role of attention in BCI systems and described the attention-related challenges to be addressed in this thesis which are the assessment of attention status using EEG-based BCI, continuous attention detection from EEG, and improving the BCI performance under attention diversion. The next chapters propose solutions to address these challenges and provide a detailed review of the related work.

Chapter 3

Effectiveness of EEG-based BCI in the Classification of Attention Status¹

The review in chapter 2 highlighted that one important challenge in BCI systems developed for attention treatment or training is the assessment of attention status. This chapter proposes a method to address this challenge. The contents of this chapter have been presented in [40, 41].

3.1 Objective

The objective is to evaluate the effectiveness of EEG-based BCI in the assessment of attention status. For this purpose, we perform a correlation analysis between the EEG features extracted from several time windows and the subjects' performance measure in response to the Stroop test to find the EEG attention-representative features and the most informative EEG time window. Then, we use the detected EEG features to evaluate the effectiveness of EEG in the assessment of attention status that is measured by RBANS.

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¹ **F. Fahimi**, et al., "EEG predicts the attention level of elderly measured by RBANS", *International Journal of Crowd Science*, **2** 272-82, 2018.

F. Fahimi, et al., "Neural Indexes of Attention Extracted from EEG Correlate with Elderly Reaction Time in response to an Attentional Task", *Proceedings of the 3rd International Conference on Crowd Science and Engineering*, (ACM), 2018.

3.2 Related Work

In this section, we review the most common quantitative EEG (QEEG) features that are reported to be attention-representative to provide a background for the research presented in this chapter.

A recent study targeted at distinguishing between 2 mental attention states, focused and unfocused, revealed that these attention states are respectively associated with increased and decreased activity at the frequency range of 1-10 Hz in frontal EEG channels including F3, F4, and Fz [152]. In their study, EEG signals were recorded while subjects were controlling a simulated train for 35-55 minutes and the spectrogram of EEG was calculated using short-time Fourier transform (STFT). In another study, by exploring the relationship between pre-cue EEG and subjects' performance in response to the task, Hanslmayr, et al. [153] found out that alpha, beta and gamma oscillations are informative about subjects' attention. They reported that an increase in pre-cue beta and gamma and a decrease in pre-cue alpha indicated a high performance in a single trial [153]. The results of other similar studies confirmed that increased beta activity is an indicator of attention [154, 155].

In addition to beta, the interaction between alpha rhythm and attention had also been widely studied [156]. These studies mostly reported that lower alpha activity reflected higher attention. The comprehensive reviews are presented in [157-159]. In one study, the association between visual reaction time and EEG alpha activity was explored. EEG data were collected from 14 participants (22.1 ± 2.4 years old) using Fz channel [160]. Several parameters from alpha oscillation were extracted including peak alpha frequency and quality factor (peak frequency/bandwidth). Moreover, different types of reaction time including immediate reaction time and movement time were defined. The results of this work revealed a negative correlation between immediate reaction time and quality factor [160]. In a more recent study, frequency-domain features of EEG recorded during mental

tasks (e.g., simple arithmetic tasks) were extracted using fast Fourier transform (FFT), and utilized for the detection of transition in mental state [161]. Based on their result, alpha-band activity extracted from posterior electrodes was optimal for attention detection [161].

In addition to individual frequency bands, theta-beta ratio (TBR) has been also widely reported to be an attention-representative feature [162-164]. For example, in a recent study, the authors analysed the EEG of 74 healthy subjects and reported that smaller frontal EEG TBR is associated with higher attention [162]. TBR has been also used to characterize ADHD [164, 165] and it is mainly reported that people with ADHD showed an elevated TBR compared to control group [165].

In this chapter, we also explore EEG spectral features to find attention-representative features. The following sections first describe the materials and methods used in this chapter and then presents and discusses the results.

3.3 Materials and Methods

The dataset that is used in this chapter was collected prior to this research for a BCI-based cognitive training program registered under NCT02228187 at clinicaltrials.gov. The program was developed for the elderly [23]. Elderly people due to aging are prone to cognitive impairment and thus they are one of the main potential users of cognitive BCI. EEG signals were recorded while subjects were performing the Stroop test. In the Stroop test, the performance measure is response time (RT). Thus, a correlation analysis between EEG features and RT is performed to find the EEG features that are correlated with attention. On the other hand, subjects' attention status was measured using RBANS which is a neurophysiological test for the assessment of cognitive domains including attention. It gives an attention score that indicates the overall attention status of the subject. Therefore, RBANS scores are used as ground truth for label derivation.

3.3.1 Participants

One hundred five healthy elderly subjects (60-80 years old) participated in the experiment. They were Chinese with literacy in English. They met the eligibility criteria including certain scores in clinical dementia rating (CDR), mini-mental state examination (MMSE), and geriatric depression scale (GDS).

3.3.2 Tasks

RBANS, introduced in section 2.2.2, is used to evaluate the subjects' attention status. The obtained RBANS attention scores are used as ground truth of attention status. In general, attention status can be stratified into 3 main categories based on the RBANS attention scores as shown in Table 3.1 [166]. The test was administrated by research assistants who were trained in psychology and had experience in performing neurophysiological tests.

Table 3.1 Subject stratification criteria based on the RBANS attention score [166].

Category	RBANS score range	Number of subjects
Poor Attention Status	≤ 90	14
Average Attention Status	> 90 and < 109	54
Good Attention Status	≥ 109	37

In addition, the subjects performed another attentional task called Stroop colour test during which their EEG data were recorded. The Stroop colour test is a well-known test for attention analysis [167, 168] and is introduced in section 2.2.1. The protocol and an example of the test are shown in Figure 3.1. The subjects performed the Stroop test in 3 sessions, each consisted of 40 repetitions of the Stroop test (attention) and rest phase (non-attention). The sessions were about 10 minutes long.

3.3.3 EEG Acquisition

The participants wore a wireless EEG headband with dry forehead electrodes (ground and sensor) connected to a computer via Bluetooth. The EEG was recorded from a bipolar frontal channel (Fp1-Fp2) at 256 Hz sampling frequency. The efficiency of frontal EEG in studying attention-related tasks has been shown in several studies [23, 26, 134, 169, 170]. Moreover, using the simplified setting for EEG recording assured the comfort of elderly subjects.

(a) Recording protocol: Stroop test followed by a rest period. The duration of each Stroop test is at least 6 seconds; depending on the subject's response time, it might take slightly longer. The consecutive rest period has the same duration as the Stroop test.

(b) An example of a Stroop test question.

Figure 3.1 Stroop Test.

3.3.4 EEG Processing

Data are high-pass filtered at 0.5 Hz using finite impulse response (FIR) filter and then segmented into various time intervals including [0 0.5], [0 1], [0 1.5], and [0 2] s, with time 0 being the cue (question) onset in the Stroop colour test. Figure 3.2 shows the segmentation diagram. The segments are visually screened to detect and discard noisy ones. Furthermore, trials with incorrect answers and those with RT value beyond the span of one standard deviation (SD) away from the average RT are considered as outliers and excluded from the

analysis. The total number of segments for each participant thus depended on their RT and the number of incorrect or outlier attempts that are excluded. In this study, the number of segments across subjects is 264 ± 40 .

After pre-processing, 10 spectral features, as listed in Table 3.2, are extracted from the EEG segments as neural features of attention. These features include relative and normalized ratio powers of delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and low gamma (30-45 Hz) bands. To compute the relative powers, the absolute power of each frequency band is divided by the total power calculated over 0.5-45 Hz. Chebyshev type II band-pass filter is applied for EEG decomposition and band-pass filter at 0.5-45 Hz.

Figure 3.2 Segmentation diagram of EEG.

Table 3.2 Features Definition [40, 41].

Feature	Formulation
Relative Delta Power	$RDP = \delta / T$
Relative Theta Power	$RTP = \theta / T$
Relative Alpha Power	$RAP = \alpha / T$
Relative Beta Power	$RBP = \beta / T$
Relative Gamma Power	$RGP = \gamma / T$
Theta-Beta Ratio	$TBR = \theta / \beta$

Theta-Gamma Ratio	$TGR = \theta / \gamma$
Alpha-Beta Ratio	$ABR = \alpha / \beta$
Alpha-Gamma Ratio	$AGR = \alpha / \gamma$
Theta/(Beta+Alpha)	$TBAR = \theta / (\alpha + \beta)$
T is total power which equals to the sum of five main frequency bands' powers.	

3.3.5 Correlation between EEG and Response Time

The performance measure of the subjects who performed the Stroop test is their RT that shows attentional behaviour [59]. It is defined as the amount of time a subject takes to respond to a question in the Stroop test. Spearman's rank correlation coefficients between RT values and EEG spectral features are computed to find the EEG attention-representative features.

3.3.6 Assessment of Attention Status Using EEG

The objective of this study is to evaluate the effectiveness of EEG in the assessment of attention status. For this purpose, after finding the EEG features that are correlated with RT, we use these features to train a classifier in order to detect the subjects with poor attention status based on their RBANS score as shown in Table 3.1 [166]. In this study, we use linear discriminant analysis (LDA) classifier with a diagonal covariance matrix estimate with 10×5-fold cross-validation. Classification is done in 2 ways:

- Poor vs Good: detection of the subjects with poor attention status from the subjects with good attention status.
- Poor vs Others: detection of the subjects with poor attention status from all other subjects (those with average and good attention status).

3.4 Results

This section first presents the results of the correlation analysis in finding the EEG attention-representative features and the most informative interval. Then, it presents the results of the assessment of attention status using the detected EEG attention-representative features.

3.4.1 EEG Attention-Representative Features

The results of the correlation analysis between RT, as behavioural feature of attention, and EEG during the Stroop test, as neural features of attention show that 1) TBR is positively correlated with RT ($p\text{-value} < 0.0001$), meaning that higher beta and lower theta powers are associated with a faster RT, and 2) there is a significant negative correlation between alpha-gamma ratio (AGR) and RT ($p\text{-value} < 0.0001$).

Figure 3.3 demonstrates the correlation coefficient (r^2 -value) between AGR and RT (blue) and TBR and RT (green) for EEG segment lengths of 0.5, 1, 1.5, and 2 s which are respectively associated with time windows of [0 0.5], [0 1], [0 1.5], and [0 2] s. As can be seen, the strongest correlation is related to [0 0.5] s. Figure 3.4 shows the relationship between AGR and RT (bottom left) and TBR and RT (bottom right) in this time window.

These observations suggest that although EEG frequency bands may not be informative about attention on their own, the interactions between them (alpha and gamma/ theta and beta) are significantly correlated with RT as the performance measure. The r -values have the same range as those reported in similar studies [171].

Figure 3.3 Correlation coefficient between AGR and RT (blue), and TBR and RT (green) for different EEG segment lengths [40, 41].

Figure 3.4 Results of correlation analysis. Top: distribution of RT, AGR, and TBR values, bottom: correlation between AGR and RT (left), and TBR and RT (right) in the time window of [0 0.5] s. Each circle shows one subject [40, 41].

3.4.2 The Most Informative EEG Time Segment

We observed that EEG features extracted from the time window of [0 0.5] s have the highest correlation with RT. To investigate whether this is due to the period under analysis or is simply because of the window length, segmentation is repeated using a sliding window

with a fixed length of 0.5-s and 50% overlapping. Figure 3.5 shows the results. Please note that to avoid any overlap with the next question in the Stroop test, segmentation is done from question (cue) onset until one SD away from the average RT. The average RT and SD are respectively 2.20 s and 0.45 s, thus, the segmentation is done until 1.75 s after each cue ($2.20 - 0.45 = 1.75$). Given the window length of 0.5 s, the start point of the last window will be at the time of 1.25 s with reference to the cue.

As can be seen in Figure 3.5, the value of correlation coefficient is independent of EEG segment length but dependent on the time interval under analysis; the strongest correlation again is associated with the time window of [0 0.5] s.

Figure 3.5 Correlation coefficient between AGR and RT (blue), and TBR and RT (green) against the start point of EEG segment with reference to the cue onset for a fixed segment length of 0.5 s [40, 41].

To gain a better understanding of EEG fluctuations over time and frequency in the period of [0 0.5] s, the grand average spectrogram is illustrated in Figure 3.6. To calculate the grand average spectrogram, EEG, denoted by X , is divided into n segments:

$$X = \{x[1], x[2], \dots, x[n]\} \quad (3.1)$$

The spectrogram of X which is denoted by $\hat{X}$ is computed by taking STFT of X :

$$\hat{X} = F(X) \quad (3.2)$$

Basically, $\hat{X}$ is the frequency-time representation of X in which each element is indexed by frequency and time. The power spectral density (PSD) values of $\hat{X}$ elements are calculated as in (3.3).

$$p(i, j) = P(\hat{X}(i, j)) \quad (3.3)$$

Finally, the grand average of PSD values is taken over corresponding frequency-time points to obtain the grand average spectrogram as shown in Figure 3.6. A higher activity can be seen around time 0, the cue onset, which goes on until 0.5 s and then gradually decreases.

Figure 3.6 Grand average spectrogram of EEG over all subjects and all trials [40, 41].

3.4.3 Effectiveness of EEG in the Assessment of Attention Status

The correlation analysis led to the detection of EEG attention-representative features. Here, we further verify the findings and evaluate the effectiveness of EEG in the assessment of attention status. Particularly, EEG is used to detect the subjects with poor attention status based on their RBANS attention score (see Table 3.1). The technique of 10×5-fold cross-validation with LDA has been applied for classification which is done once using all EEG

spectral features, as listed in Table 3.2, and RT, and once using only correlated features and RT.

Based on Table 3.1, Poor vs Good and Poor vs Others, defined in section 3.3.6, are imbalanced classifications. Unlike balanced classification where the accuracy is a common performance measure, in imbalanced classification, accuracy is misleading. For example, if the non-target class occurrence is 90% and target class occurrence is 10%, a classifier that recognizes all trials as non-target gives an accuracy of 90% which is highly misleading. In the case of imbalanced classifications, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve (AUC) should be reported. Sensitivity is the percentage of the actual positives truly detected as positive (true positive rate), it is also known as recall. Specificity is the percentage of the actual negatives truly detected as negative (true negative rate). Ideally, both sensitivity and specificity should be high for diagnosis purposes, however, high sensitivity is more crucial. The AUC is a good indicator of these metrics and shows the performance of the classifier. Here, the positive or target class is the group of the subjects with poor attention status.

Table 3.3 presents the results in the detection of the subjects with poor attention status using EEG. According to the results, EEG is capable to predict the poor attention status and using only correlated features for classification improves the performance. The Poor vs Good classification with correlated features achieves an AUC of 82.43%, a sensitivity of 75.00%, and a specificity of 85.68%. Including the group of the subjects with average attention status in classification makes the detection more challenging so that the Poor vs Others classification with correlated features yields an AUC of 70.80%, a sensitivity of 67.14%, and a specificity of 75.27%.

Table 3.3 Classification results for detection of the subjects with poor RBANS attention score.

		AUC	Sensitivity	Specificity
Poor vs Good	correlated features	82.43 (1.38)	75.00 (3.76)	85.68 (2.56)
	all features	81.31 (2.49)	72.86 (3.01)	76.22 (4.73)
Poor vs Others	correlated features	70.80 (1.23)	67.14 (3.69)	75.27 (1.30)
	all features	68.46 (3.25)	60.00 (6.90)	68.57 (4.46)

Numbers in parentheses are standard deviations (SD).

All numbers are in %.

3.5 Discussion

Overall, the results have shown the effectiveness of EEG in the assessment of attention status which in turn verifies the feasibility of attention detection using EEG. In the following sections, we further discuss the results.

3.5.1 EEG Attention-Representative Features

The results of the correlation analysis have shown that TBR is correlated with RT as attentional behaviour. In fact, smaller TBR is associated with better performance (faster RT) in response to the Stroop test. This observation supports the notion that TBR is an attention-representative feature [162-164]. In addition to TBR, the results have revealed a negative correlation between AGR and RT which suggests that the engagement of alpha and gamma might be a carrier of attentional information.

3.5.2 The Most Informative EEG Time Segment

It has been also observed that the EEG over 500 ms after the cue onset has the highest correlation with RT than the other time intervals. The spectrogram of the EEG has verified that there is higher spectral activity around the cue onset approximately until 500 ms which gradually diminishes afterwards. This result is consistent with the results of many previous studies on the analysis of executive control during the Stroop test; they observed the

existence of ERPs only in this time window [172-174] which in turn shows the informative period for feature extraction.

3.5.3 Effectiveness of EEG in the Assessment of Attention Status

We used TBR and AGR extracted from EEG over the most informative interval, [0 0.5] s, to train an LDA classifier in order to detect the subjects with poor attention status. The sensitivity of 75.00%, specificity of 85.68%, and AUC of 82.43% have been achieved which reflect the effectiveness of EEG in the assessment of attention status. Using EEG for the assessment of cognitive function, MCI detection or early diagnosis of cognitive decline had been previously targeted by many research groups [175-177]. In one study, synchrony measures of EEG including Granger causality and stochastic event synchrony were used for early diagnosis of Alzheimer's disease and achieved 83% accuracy [178]. In another work, researchers probed the effectiveness of a P300-based battery for cognitive assessment. By testing their proposed program on healthy subjects, they showed that their proposed battery is reliable [179]. In the present study, we have evaluated the assessment of attention status using EEG which has applications in early prediction of attention impairment using EEG as a replacement or a supplementary tool for traditional clinical batteries such as RBANS. The existing clinical practice relies on detailed batteries which need trained instructors and a long time for administration [175]. Thus, a brief yet reliable EEG-based screening tool will be beneficial.

3.6 Summary

In this chapter, the effectiveness of EEG in the assessment of attention status was evaluated. First, a correlation analysis between EEG features and RT, as a behavioural feature of attention, was performed and the results revealed that TBR and AGR are EEG attention-representative features. Subsequently, an LDA classifier was trained on these features to

detect the subjects with poor attention status based on their RBANS attention score and achieved an AUC of 82.43%, sensitivity of 75.00%, and specificity of 85.68%. To the best of our knowledge, this is the first study on the classification of RBANS score using EEG signals. The significance of this study is in evaluating the potential application of EEG-based BCI in replacing or supplementing the neurophysiological tests such as RBANS. Based on the results, EEG can potentially be used to assess attention status and therefore replace or supplement time-consuming clinical tests that are prone to human error.

Chapter 4

End-to-End Deep Convolutional Neural Network for Attention Detection¹

The review in chapter 2 highlighted that in cognitive BCI systems for attention training, attention serves as a control signal and thus continuous attention detection from EEG is needed. Following chapter 3 that showed the feasibility of attention detection using EEG signals, this chapter proposes a method for attention detection. The contents of this chapter have been presented in [1, 42].

4.1 Objective

The objective is to propose a method for attention detection using deep learning to extract the higher-order features from EEG. The main challenges of current methods are poor performance in subject-to-subject transfer [70], lack of a unified end-to-end framework [112], interpretability of deep neural networks [180, 181], and generalizability of the method [182]. Hence, the objective of this chapter is to develop a classification framework for attention detection that addresses these challenges.

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¹ **F. Fahimi**, et al., “Inter-subject Transfer Learning with End-to-end Deep Convolutional Neural Networks for EEG-based BCI”, *Journal of Neural Engineering (JNE)*, **16** 026007, 2018.

F. Fahimi, et al., “Deep Convolutional Neural Network for the Detection of Attentive Mental State in Elderly”, *7th International BCI Meeting*, California, USA, 2018.

4.2 Related Work

With the advent of deep learning, state-of-the-art classification strategies and many other artificial intelligence tasks have been vastly improved [183]. The emergence of deep learning can be associated with the advancement of the neural network, which itself dates back to the time that researchers had a desire to model the human brain [184]. The most popular types of deep neural networks include deep belief nets [185], recurrent neural networks [186], and convolutional neural networks (CNN). However, CNN by winning the ImageNet challenge [187] in 2012 [188], became more popular. In this thesis, we have also used CNN.

Deep learning first found successful applications in the fields of speech recognition and computer vision [183] and then became popular in other research areas such as BCI [89, 116]. The scope of this chapter is EEG-based cognitive BCI where the aim is to assess and enhance cognitive functions such as attention [22, 23, 26, 189]. In these kinds of BCI systems, user's attention serves as a control signal and thus precise attention detection is crucial.

4.2.1 Methods for Attention Detection from EEG Signals

The traditional methods for attention detection were mainly based on EEG frequency bands oscillations. Numerous studies investigated attention-induced fluctuations in beta [154, 155], alpha [157-159], and engagement between different frequency bands [164, 169]. They reported that increased activity in high-frequency bands such as beta, decreased activity in alpha, theta, and theta-beta ratio indicate attention. In these studies, attentional information stored in the spatial domain was underestimated. Taking the importance of spatial information into account, Hamadicharef, et al. [190] introduced a novel approach for attention level measurement from EEG. They extracted spectral-spatial features using filter bank (FB) and CSP from EEG which was recorded by multiple electrodes from

various brain regions. Then, they used the extracted features to train a Fisher linear discriminant (FLD) classifier for classification [190]. Their approach outperformed the methods based on using only spectral features. In the case of single-channel EEG where spatial information is missing, we previously introduced a framework to discriminate between attention and non-attention in a subjective approach [134]. Several relative and ratio frequency band powers were extracted and then a mutual information-based feature selection was used to find the most informative features for each subject [134].

Overall, in current methods of feature extraction, reduction of the signal into a few features neglects the dynamics of the signal and its temporal information. By directly learning from raw data which is called end-to-end learning, this problem can be avoided. Moreover, feature extraction and classification are separately optimized in the traditional methods while the end-to-end learning integrates these stages and jointly optimizes them. In addition to this problem, building a classification framework which is able to deal with the subject-to-subject non-stationarity and high-dimensionality of EEG has been always a big challenge [70]. DCNN with their ability in handling high-volume datasets, better learning algorithms, and faster computational resources are becoming a superior alternative for conventional EEG classification methods.

4.2.2 Deep Learning for EEG-based BCI

To the best of our knowledge, DL has not yet been applied for attention detection from EEG. Nevertheless, there have been several attempts to use DL for other purposes in EEG-based BCI. In the following paragraphs, we review the main studies.

Tabar and Halici [114] proposed a deep network composed of CNN and stacked auto-encoders (SAE) to boost the classification accuracy of motor imagery BCI. They converted the EEG into images using STFT and then fed the images into a 1D CNN that performed convolution across time samples to extract features. The extracted features were then fed

into an SAE network for classification [114]. They investigated the performance of their proposed network on BCI competition IV-2b dataset and reported that their methodology achieved a higher classification accuracy than the winner of the competition. In a more recent study, Sakhavi, et al. [112] developed a new CNN-based classification framework by introducing envelop representation of EEG using Hilbert transformation and passing it through CNN. Using this data representation, inspired by FBCSP, their method outperformed the best classification accuracy reported on BCI competition IV-2a dataset. In another work, Lu, et al. [116] introduced a deep learning network based on restricted Boltzmann machine (RBM) and named it frequential deep belief network (FDBN). In FDBN, frequency representations of EEG, generated using FFT and wavelet decomposition techniques, were fed through 3 RBMs and 1 output layer for classification. In another study, using a combination of multi-level compressed sensing and RBM, Molina-Cantero, et al. [170] targeted at learning discriminative motion-onset visual evoked potentials (mVEP) features. They reported that deep features extracted by this method performed better than conventional amplitude-based features when using a support vector machine (SVM) classifier.

Deep learning had been also used for mental workload (MWL) classification [191, 192]. Zhang and Li [191] used RBM with EEG channels that had relatively higher importance simply based on the network weights between the input layer and the first hidden layer. Another study used recurrent-convolutional neural network for MWL classification [192]. They transformed EEG signals into spectral images and then sent them into the deep recurrent-convolutional network. They suggested that such representation of data preserves temporal, spectral and spatial information [192]. In another study, Jirayucharoensak, et al. [193] used SAE to build a deep learning network in order to classify different levels of emotion. They extracted the principal components of power spectral densities from 32 EEG

channels to form the input to their proposed DL network which was comprised of 3 auto-encoders and 2 softmax layers.

In a different study with the purpose of providing an insight into the neurophysiological phenomena affect the decision of deep neural networks, Sturm, et al. [117] presented the idea of using layer-wise relevance propagation (LRP). In their methodology, LRP in a backward way decomposed the network decision into some values which were defined as the relevance of each input component with the decision. In terms of classification accuracy, their methodology did not outperform CSP with LDA classifier [117].

4.3 Materials and Methods

The deep learning methods are implemented in Python on an Ubuntu system powered by NVIDIA GeForce GPU, and the baseline methods are implemented in Matlab R2013b on an Intel Xeon CPU @3.5 GHz with 16 GB RAM (except the classification stage of baseline 1 that is done in Python).

4.3.1 Dataset

The EEG data were collected from healthy participants during the Stroop colour test which is a well-known task to study attention [167, 168]. Readers are referred to section 2.2.1 to find a detailed description of the Stroop test. During the test, the participants faced a conflict of information in response to the questions whereby they needed to maintain attention [194].

In total, 120 healthy elderly subjects (60-80 years old) performed 3 sessions of the Stroop test. There were 40 repetitions of the Stroop test (attention) followed by a rest period (non-attention) in each session. Therefore, subjects underwent a change of mental state from attention to non-attention during the task. Each session took approximately 10 minutes. The recording protocol and an example used in the test can be seen in Figure 3.1, chapter 3.

For the convenience of elderly participants, their EEG was recorded using a dry EEG headband with a single bipolar channel which was positioned over the frontal area (Fp1-Fp2), sampled at 256 Hz. The efficiency of frontal EEG in studying attention-related tasks has been shown in several studies [23, 26, 134, 169, 170].

4.3.2 Pre-processing

The average response time in the Stroop test was about 2 s, so a 2-s sliding window with a 1-s shift is applied to segment the EEG data (see Figure 4.1). The EEG data are visually screened to discard noisy segments. Moreover, given that the maximum amplitude of EEG is usually 100 μV [195], a threshold is set at $\pm 100 \mu\text{V}$ to discard the segments affected by ocular artifacts or other noises. The EEG data are also filtered above 0.5 Hz to eliminate any low-frequency artifacts that remained. Segmentation using 2-s window and 1-s shift over 6-s Stroop test and its consecutive 6-s rest produces 5 segments of EEG for attention and 5 segments for rest. Therefore, 3 sessions each comprised of 40 repetitions of the Stroop test and rest produces 600 segments per class per subject (3 sessions $\times$ 40 repeats $\times$ 5 segments). Discarding noisy segments slightly reduces this number for some subjects.

Figure 4.1 Segmentation diagram of EEG.

4.3.3 Subject-to-Subject Transfer Methods

Many studies reported the results of BCI classifier based on cross-validation (CV) which usually over-estimates the performance. This is while in a practical BCI, the desire is subject-to-subject transfer learning to minimize the calibration and decrease the training

load from user side. In this study, we perform the classification with subject-to-subject transfer learning methodologies including leave-one subject-out (LOO) and subject adaptation (adaptive). In the LOO approach, a generalized network will be learned using the data from a pool of other subjects excluding the target subject and then the learned knowledge will be transferred to the target subject. Since retraining is not required, this method will be relatively less computationally demanding.

The LOO method evades long time training for the target subject's data. Nevertheless, this approach might encounter the problem of inter-subject variability when transferring the knowledge from the pool of other subjects (source subjects) to the target subject. An adaptive approach resolves this issue by retraining or updating the model based on a small sample size of the target subject's data. In this way, the problems of excessive retraining time and inter-subject variability can be both addressed.

These subject-to-subject transfer approaches are beneficial in the implementation of real-time BCI systems where the intention is to minimize or even eliminate the calibration [101, 102].

4.3.4 End-to-End DCNN for Attention Detection from EEG

In this section, we propose a method based on CNN for attention detection, and we call it the end-to-end DCNN. In the following subsections, we first describe the input data preparation and then the design of the DCNN.

4.3.4.1 Input Preparation

We use the pre-processed EEG, described in section 4.3.2, as input to DCNN. To preserve the information and minimize the computational load, we avoid feature extraction and transformation of the EEG signal into image (such as spectrogram, as it is done in some studies [192]). We instead define 3 data representation (DR) of EEG with different amounts

of processing to evaluate the impact of processing on the performance of DCNN. These DRs are listed below. Band-pass filtering in DR2 and DR3 is done by Chebyshev type II. In all DRs, EEG segments are down-sampled by a factor of 3 from 256 Hz. Thus, 2-sec segments will produce the input of size 171 time points ($2 \times 256 / 3$).

- 1) DR1: Raw EEG.
- 2) DR2: Band-pass filtered EEG (0.5-40 Hz).
- 3) DR3: Decomposed EEG into 5 typical bands; δ (0.5-4 Hz), θ (4-8Hz), α (8-12 Hz), β (12-30 Hz), and low γ (30-40 Hz).

4.3.4.2 DCNN Architecture

The early CNN, LeNet-5, introduced by Lecun, et al. [196], was composed of a sequence of convolution and pooling layers. Since then, numerous attempts have been made to enhance the performance of CNN through some extensions such as dropout [197] and batch normalization [198] in order to accelerate training, avoid over-fitting, and better preserve the information.

In convolutional layers, the filter, also called kernel, convolves over input and produces element-wise multiplications that will be summed up and produce a single value for that receptive field. Repeating this procedure by sliding the filter all over the input generates a single value for each receptive field. It will eventually produce the activation map or feature map as the output of a convolutional layer. Inserting a pooling layer after a convolution layer reduces the dimension of the feature map by replacing each patch with a single value based on the operation of interest (e.g., maximum for max-pooling). As the input passes through the layers, the high-level feature maps will be generated. For classification tasks, the last layer of CNN is a fully-connected layer which takes the output of the previous layer and produces an n-dimensional vector where n is the number of classes. Using softmax activation function, each element of this vector will represent the probability that the

original input belongs to the corresponding class. In this training procedure, the network's parameters are learned through back-propagation.

Figure 4.2 depicts the schematic diagram of the proposed end-to-end DCNN method. The EEG data representations (DR1, 2, 3) are fed into the network. Since the input data are single-channel time series, 1D filter across time has been used for convolution. The effectiveness of using 1D filter across time even for 2D EEG inputs has been shown in the literature [112, 114].

We insert 3 convolutional layers with 1D filter to generate high-level features. The first convolution layer with 60 filters and a kernel size of 1×4 is followed by a max-pooling layer with a pool size of 1×2 . The output of max-pooling is fed to the second convolution layer with 40 filters and a kernel size of 1×3 . The output of the second convolution layer is then fed to the third convolution layer with 20 filters and a kernel size of 1×2 . Note that by decreasing the dimension over layers, a smaller kernel size is used. After the third convolution layer, the generated feature maps are flattened into a vector which is fed into a fully-connected layer of size 100. Finally, these 100 features are fed into the second fully-connected layer with softmax activation function for classification.

We use 2 dropout layers to avoid overfitting, one with the probability of 20% after flattening, and one with the probability of 30% after the first fully-connected layer. The rectified linear unit (ReLU) [199] has been used as activation function except in the last layer where softmax is used for classification. We apply the Adam method [200] for optimization, and trial and error method for hyper-parameter selection [201]. The proposed architecture is aligned with those that are successfully applied for EEG classification [202].

Figure 4.2 Schematic diagram of the end-to-end DCNN-based classification method. The first and second tuples written under ‘ Convolution ’ respectively refer to the kernel size and stride. The left boxes are respectively associated with DR1, DR2, and DR3 [1].

4.3.5 Baseline Methods for Attention Detection from Single-channel EEG

In order to provide a fair baseline, we implement the method introduced by Liu, et al. [169] for attention detection from single-channel EEG. Additionally, to be consistent with the input representations, we perform the traditional feature extraction and classification method using the typical frequency bands, as in DR3, and LDA classifier.

According to the method by Liu, et al. [169], we extract the frequency band energies including delta (0.5-3Hz), theta (4-7Hz), alpha (8-13Hz), beta (14-30Hz), and alpha-beta ratio using FFT and send them into SVM with polynomial kernel function for classification. We denote this baseline method as FFT-SVM.

As the second baseline, we decompose the EEG data into 5 subsequent frequency bands, same as DR3, including δ (0.5-4 Hz), θ (4-8Hz), α (8-12 Hz), β (12-30 Hz), and low γ (30-40 Hz) using Chebyshev type II filter. Then, we compute the mean of the squared values as band powers and send them into LDA for classification. We denote this baseline method as DR3-LDA.

We also found another study which had attempted to detect attention from frontal single-channel EEG data [170]. In their study, the Neurosky device was used for EEG recording. This device generated the attention indicator and other information such as frequency band powers. The authors simply used the attention indicator obtained from the device to detect attention using LDA classifier. Since the attention indicator used for the classification was generated by the recording device and no details of the algorithm were provided, it was not feasible to implement their methodology as a baseline.

4.3.6 Evaluating the Interpretability of the End-to-End DCNN

Besides the quantitative evaluation of the performance, it is important to obtain an understanding of what the network learns from the input EEG data and whether the learned

information is meaningful. For this purpose, we perform activation maximization technique to visualize the deep neural network's perceived input of attention and non-attention [203]. In this method, we look for an input pattern that maximizes the activation of a certain class denoted by c . In other words, the objective is to solve (4.1) through back-propagation.

$$x^* = \arg \max_x (a_c(x, \varphi) - R_\theta(x)) \quad (4.1)$$

In (4.1), a_c is the activation of the input signal x with the network parameters φ , $R_\theta(x)$ is the regularization term with parameters θ , and x^* is the input pattern that maximizes the activation of class c , meaning that x^* is an input that when is fed to the network, the output is class c . In fact, this perceived input is what the network recognizes as class c . We use LP-norm (with $P = 6$) as the regularization function.

4.3.7 Evaluating the Generalizability of the End-to-End DCNN

To evaluate the generalizability of the proposed end-to-end DCNN method, we implement it on a multi-channel public dataset on attention which was collected for a study on covert attention [204]. Eight healthy subjects (18–27 years old) participated in the experiment and their EEG was recorded using a 64-channel cap with the electrodes placed based on the international 10–10 system. The sampling frequency during recording was set at 1000 Hz, which was later down-sampled to 200 Hz. The experiment included the sequences of attention, response, and rest. In the present study, since the classification task is attention detection from rest, the EEG data is segmented during attention and rest phases. According to the original work on this dataset [204], the optimal channels to study attention were PO3, 4, 7–10, Oz, O1, and O2. Thus, we use these 9 recommended channels.

As the first baseline for the multi-channel dataset, we implement the popular method of FBCSP [74] with mutual information-based best individual feature (MIBIF) for feature selection and naive Bayesian Parzen window (NBPW) for classification as proposed in

[74]. In addition to classification with LOO which provides the results for a fair comparison, we perform intra-subject classification with 10-fold cross-validation.

As the second baseline for the multi-channel dataset, we implement the shallow ConvNet method which is introduced by Schirrmeister, et al. [89], inspired by the FBCSP method. Briefly, it has two hidden layers that perform temporal convolution and spatial filtering for band power feature decoding. Unlike the FBCSP method, the shallow ConvNet jointly optimizes all the computational steps through a single network [89].

4.4 Results

The results of this study are presented in 4 subsections, each associated with one of the challenges that has been mentioned in section 4.1, namely, subject-to-subject transfer, end-to-end framework, interpretability of deep learning, and generalizability of the method. The terms ‘adaptive’ and ‘subject adaptation’ are used interchangeably. The reported p -values are calculated using the Wilcoxon test.

4.4.1 Subject-to-Subject Transfer

In this section, the results of the subject-to-subject classification using the baseline and proposed methods are presented.

4.4.1.1 Baseline

The baseline methods are described in section 4.3.5. The classification approach used by the authors of the first baseline, FFT-SVM, was k-fold cross-validation within-subject within-session [169]. But, we performed LOO for both baseline methods to provide a fair comparison with the results of the end-to-end DCNN. Table 4.1 (top) shows the results of the baseline methods.

Implementing the method of FFT-SVM as it is described in the original work by Liu, et al. [169] yielded an average accuracy of only 50.70%. Additionally, to improve accuracy, we

normalized the features that improved the average accuracy to 67.90%. The method of DR3-LDA yielded an average accuracy of 68.23% with no statistically significant difference compared to the FFT-SVM (p -value = 0.87). These values are lower than the generally accepted threshold for BCI which is 70% [205, 206]. In fact, more than half of the subjects have accuracy below 70% at baseline.

4.4.1.2 End-to-end DCNN with LOO

In this method, the network is trained on the data from all the subjects excluding the target subject and the model is transferred to the target subject. Table 4.1 (bottom) shows the results of the proposed methods.

The average accuracies of the end-to-end DCNN-LOO with DR1, DR2, and DR3 are respectively 76.20%, 75.07%, and 76.68% which are significantly better than the baseline methods with 7.92% improvement on average (p -value < 0.0001). However, there is no statistically significant difference between the results of DR1, DR2, and DR3. This method also yielded a considerable drop in the percentage of the subjects with accuracy < 70%, so that only 26.67%, 24.17%, and 23.34% of total 120 subjects have accuracy < 70% with DR1, DR2, and DR3 respectively.

4.4.1.3 End-to-end DCNN with Subject Adaptation

In this method, a previously trained model on other subjects' data is updated based on half of the target subject's data. This adaptation is performed in 2 folds; once the model is updated based on the first half of the target subject's data and once based on the second half of the target subject's data. The reported accuracies for the end-to-end DCNN-adaptive are the average of these 2 folds. Table 4.1 (bottom) shows the results of the proposed methods.

The average accuracies of the end-to-end DCNN-adaptive with DR1, DR2, and DR3 are respectively 79.26%, 78.12% and 79.86% which are significantly better than the baseline methods with 11.02% improvement on average (p -value < 0.0001) and better than the LOO with 3.10% improvement on average (p -value < 0.01). However, there is no statistically significant difference between the results of DR1, DR2, and DR3. This method also yielded a considerable drop in the percentage of the subjects with accuracy $< 70\%$, so that only 15.83%, 17.50%, and 15.83% of total 120 subjects have accuracy $< 70\%$ with DR1, DR2, and DR3 respectively.

Figure 4.3 and Figure 4.4 visually compare the discussed methods. Overall, the end-to-end DCNN with subject adaptation achieves the best performance. There is a statistically significant difference between LOO and subject adaptation but there is no significant difference between data representations within each method.

Table 4.1 Classification accuracy of the baseline and the end-to-end DCNN methods.

Baseline methods						
	FFT-SVM			DR3-LDA		
Accuracy (SD)	67.90 (11.02)			68.23 (10.89)		
Range (min-max)	64.56 (22.06-86.62)			62.06 (26.31-88.37)		
#subjects with accuracy $< 70\%$	54.17%			50.84%		

End-to-end DCNN with subject-to-subject transfer learning						
	End-to-end DCNN-LOO			End-to-end DCNN-Adaptive		
	DR1	DR2	DR3	DR1	DR2	DR3
Accuracy (SD)	76.20 (8.98)	75.07 (8.50)	76.68 (8.80)	79.26 (7.67)	78.12 (7.75)	79.86 (7.69)
Range (min-max)	44.06 (48.24-92.30)	44.45 (46.84-91.29)	40.46 (51.92-92.38)	35.24 (58.45-93.69)	38.67 (53.15-91.82)	36.02 (58.78-94.80)
#subjects with accuracy $< 70\%$	26.67%	24.17%	23.34%	15.83%	17.50%	15.83%

SD refers to standard deviation.

Figure 4.3 Comparing the performance of the baseline and end-to-end DCNN methods for attention detection. The end-to-end DCNN methods, adaptive and LOO, significantly outperform the baseline methods and the adaptive outperforms the LOO. There is no statistically significant difference between the methods within each group (e.g., between DR1, DR2, and DR3 in LOO) [1].

(a)

(b)

(c)

Figure 4.4 Distribution of classification accuracies: (a) baseline methods, (b) end-to-end DCNN-LOO, and (c) end-to-end DCNN-adaptive.

4.4.2 End-to-End Framework

Using deep learning methods, it is possible to integrate the feature extraction and classification stages by learning directly from the raw EEG instead of the pre-extracted features. This end-to-end framework is implemented in this study by using 3 different data representations with minimal pre-processing as input to the DCNN.

The first representation, DR1, is raw EEG with the least amount of pre-processing only implemented to remove artifacts. DCNN with DR1 as input outperforms the best baseline, DR3-LDA, in which the input features were pre-extracted. In fact, compared to the DR3-LDA, the end-to-end DCNN-LOO achieves 7.97% improvement and the end-to-end DCNN-adaptive achieves 11.03% improvement ($p\text{-value} < 0.0001$).

Going one step further in data preparation, the data are band-pass filtered at 0.5-40 Hz and is called DR2. Interestingly, by using DR2 as input to the DCNN, the average classification accuracy drops by 1.13% in LOO and 1.14% in adaptive. However, these differences are not statistically significant ($p\text{-value} > 0.1$).

To form the third data representation, DR3, the EEG data are decomposed into the conventional EEG frequency bands including δ , θ , α , β and low γ . Using DR3 as input to the DCNN produces slightly better results than DR1 by 0.48% improvement in LOO and 0.60% improvement in adaptive. However, these differences are not statistically significant ($p\text{-value} > 0.1$).

It can be seen that there is no statistically significant difference between the results of DCNN trained on DR1, DR2, and DR3. It suggests that DCNN does not benefit from the processed EEG (DR2 and DR3) and except artifact removal, any further processing is redundant. Thus, for the rest of the analyses, we use DR1 which needs the least preparation, and in the rest of this chapter, the end-to-end DCNN refers to the end-to-end DCNN with DR1 unless stated otherwise.

4.4.3 Interpretability of the End-to-End DCNN

The visualization method is described in section 4.3.6 and the results are plotted in Figure 4.5. Interestingly, as can be seen in Figure 4.5 (a) and (b), the patterns that the network has learned from the raw EEG for attention and non-attention are easy to distinguish. The perceived pattern for attention class encompasses the high-frequency oscillations while the perceived pattern for non-attention class shows low-frequency oscillations. For further investigation, we compute the PSD of these perceived inputs using the Burg algorithm. Figure 4.5 (c) and (d) demonstrate the PSD over the most common frequency bands namely theta (4-8Hz), alpha (8-12Hz), beta1 (12-16Hz), beta2 (16-20Hz), high beta (20-30Hz), and low gamma (30-40Hz). It can be observed that with a change in mental state from non-attentive to attentive:

- 1) Beta activity increases.
- 2) This increase in beta is more prominent in beta2.
- 3) Theta activity diminishes.
- 4) Theta-beta ratio decreases. This can be inferred from observations 1 to 3.

These observations are consistent with the results of the studies on attention-induced frequency oscillations [154, 164] and suggest that the proposed network can successfully learn meaningful information from the raw EEG.

Figure 4.5 Visualization results: (a) the network perception of the attention class, (b) the network perception of the non-attention class, (c) PSD of the network perception of the attention class, and (d) PSD of the network perception of the non-attention class. As can be seen in (a) and (b), attention class shows high-frequency oscillations while these components are disappeared in non-attention class. As can be seen in (c) and (d), beta, especially beta 2, has higher activity while theta has lower activity in attention class than non-attention class. These observations show that the network has learned meaningful attentional information from raw EEG [1].

4.4.4 Generalizability of the End-to-End DCNN

As described in section 4.3.7, the end-to-end DCNN, as well as 2 baseline methods, are implemented on a public multi-channel dataset to evaluate the generalizability of the method. Table 4.2 presents the results.

In LOO classification, the shallow ConvNet outperforms the FBCSP, and the end-to-end DCNN outperforms both the shallow ConvNet and the FBCSP (p -value < 0.001). The proposed end-to-end DCNN achieves an average accuracy of 79.10% which is significantly better than the FBCSP (+18.31%, p -value < 0.001) and the shallow ConvNet (+6.28%, p -value < 0.001). In fact, the end-to-end DCNN with LOO classification achieves the accuracy as high as the FBCSP with intra-subject classification.

The end-to-end DCNN with subject adaptation further improves the classification and achieves an average accuracy of 89.32%. Moreover, with the proposed method the accuracy of all subjects increases to above 70%.

Table 4.2 Results of attention detection from multi-channel EEG using end-to-end DCNN.

	FBCSP		Shallow ConvNet	End-to-end DCNN	
	Intra-subject	LOO	LOO	LOO	Adaptive
Accuracy (SD)	80.01 (6.43)	60.79 (6.74)	72.82 (6.54)	79.10 (7.60)	89.32 (4.47)
Range (min-max)	18.83 (72.83-91.67)	19.42 (55.25-74.67)	16.27 (65.33-81.60)	18.30 (72.67-90.97)	11.69 (82.66-94.35)
#subjects with accuracy < 70%	0%	7 out of 8	4 out of 8	0%	0%

SD refers to standard deviation.

4.5 Discussion

The emergence of deep learning techniques has highly enhanced the classification tasks in several areas such as speech and vision. In recent years, these networks have been successfully applied in BCI systems as well. The huge amount of EEG time series can be fed into deep neural networks for classification. The classification methods for EEG-based BCI face 4 main challenges: 1) poor performance in subject-to-subject transfer [70], 2) lack of a unified end-to-end framework [112], 3) interpretability of deep neural networks [180, 181], and 4) generalizability of the method [182]. To address these 4 challenges, we proposed an end-to-end DCNN framework for attention detection from EEG with the potential applications in cognitive BCI, game-based BCI, and neuro-rehabilitation.

4.5.1 Subject-to-Subject Transfer

Owing to subject-to-subject EEG non-stationarity, majority of BCI studies perform intra-subject classification. For example, Molina-Cantero, et al. [170] had performed attention detection for each subject in each session separately and reported an average accuracy of 79.50%. This simplified way of within-subject within-session classification will certainly

deteriorate when subject-to-subject and session-to-session variations exist. Moreover, calibration and retraining for every new subject and new session is time-consuming and therefore the desire in BCI is to transfer a previously trained model to the new target subject. In this study, the proposed framework showed to be effective for subject-to-subject classification. Based on Table 4.1, the proposed method with subject adaptation achieved an accuracy above 70% for 84.17% of the subjects. This is while the baseline methods could hardly reach 70%.

Figure 4.6 shows how the subjects with accuracy lower than 70% at the baseline benefit from the end-to-end DCNN method. Sixty-one subjects out of 120 that is 50.84%, had an accuracy below 70% at DR3-LDA (the better baseline). With the proposed end-to-end framework, the size of this group decreased from 50.84% to only 26.67% with LOO and 15.83% with adaptive. The average accuracy of these 61 subjects increased by 10.84% with LOO and 15.09% with adaptive (p -value < 0.001). As can be seen in Figure 4.6, the proposed end-to-end DCNN with LOO has boosted the classification accuracy for 58 subjects out of 61, that is 95.08% of the subjects.

Figure 4.6 Classification accuracy for the subjects with poor performance ($< 70\%$) at the baseline. For simplicity in comparison, only DR3-LDA (the better baseline) and the end-to-end DCNN-LOO are compared. The end-to-end DCNN significantly improves the results by 10.84% increase in the average accuracy of these 61 subjects. The proposed method increases the accuracy for 95.08% of these subjects that is 58 subjects out of 61 [1].

4.5.2 End-to-End Framework

The proposed framework integrates feature extraction and classification stages by learning from raw EEG and builds an end-to-end framework. This is while in the traditional classification frameworks these tasks are done in separate stages [207]. The combination of convolutional, max-pooling, and dropout layers built a network that by learning directly from raw EEG performed significantly better than the conventional feature extraction and classification techniques. The end-to-end DCNN with subject adaptation achieved an accuracy of 79.26% that is 11.03% higher than the best baseline (p -value < 0.0001). Furthermore, this method lessened the percentage of the subjects with accuracy $< 70\%$ from 50.84% at baseline to only 15.83%.

The performance of the network was investigated by importing two other EEG representations into the DCNN and comparing the results with the ones from raw EEG (DR1). No statistically significant improvement was found in the average accuracies. This shows that the proposed classification framework does not benefit from the processed EEG and, except artifact removal, any further processing is redundant. Moreover, reduction of the signal into a few features usually neglects the dynamics of the signal and its temporal information and causes loss of information. Learning from the raw EEG can potentially avoid such problem.

4.5.3 Interpretability of the End-to-End DCNN

The visualization verified that the learned attentive/non-attentive patterns from the raw EEG were discriminative and meaningful; high-frequency oscillations were found in the attention class but not in the non-attention class. When the brain was involved in the attentional task, EEG showed higher activity in beta, especially in beta 2, and lower activity in theta. These results are in agreement with the findings brought forward by the line of research on attention-induced frequency oscillations [154, 164]. In one study, we applied a

mutual information-based feature selection to discover the most discriminative attention-representative features [134]. Eventually, we found that beta power and theta-beta ratio are the most informative features for attention detection [134]. Here, as a result of visualization, we ended up with similar observations but without any effort for feature extraction and selection. These observations suggest that by learning directly from raw EEG, the end-to-end DCNN is capable to automatically detect important frequency bands for attention detection. In other words, the network, without being directly trained on these features, can recognize that the decreased theta power, increased beta power, and decreased theta-beta ratio are attention indicators.

4.5.4 Generalizability of the End-to-End DCNN

The end-to-end DCNN was proposed for single-channel EEG and achieved promising results. Further, we implemented the proposed method on a public multi-channel EEG dataset to evaluate its generalizability. We also implemented 2 baseline methods, FBCSP [74] and shallow ConveNet [89].

The highest accuracy, 89.32%, was achieved by the end-to-end DCNN with subject adaptation which was 16.50% (p -value < 0.0001) higher than the best baseline (shallow ConvNet). The second highest accuracy, 79.10%, was achieved by the end-to-end DCNN with LOO which was as good as the FBCSP with intra-subject classification. This showed that although the FBCSP had a good performance in intra-subject classification, it failed to produce acceptable results for subject-to-subject classification and its accuracy decreased by 19.21%. This is while the proposed end-to-end DCNN achieved an average accuracy of 79.10% with LOO and 89.32% with subject adaptation.

The results showed that learning from raw EEG instead of pre-extracted features reduced the reliance on a priori assumptions about the data and increased the generalizability of the method.

4.6 Summary

The study presented in this chapter showed that the proposed end-to-end DCNN is a promising method for attention detection from EEG. The proposed method outperformed the baseline methods including LDA, SVM, FBCSP, and Shallow ConvNet. Compared to the best baseline, the end-to-end DCNN with subject adaptation achieved 11.03% improvement in attention detection from single-channel EEG and 16.50% improvement from multi-channel EEG. The visualization of the deep neural network's perceived input of attention and non-attention showed that the learned patterns were meaningful and in agreement with the notion that attention is associated with increased beta power and decreased TBR. These results suggest that by employing DCNN, it is possible to learn from raw EEG and successfully transfer the learned knowledge to a new target subject. The present work can be applied for BCI systems developed for attention training/treatment and may be extended to other types of EEG-based BCIs.

Chapter 5

GANs-based Data Augmentation to Improve BCI Performance under Attention Diversion¹

Majority of BCI algorithms are developed under a controlled condition in the laboratory whereby distractions are minimized. This chapter aims to address the issue that users' attention may be diverted in real-life BCI applications, which may result in a decrease in the BCI classifier's performance. The content of this chapter is under revision and a part of it is accepted for publication [43].

5.1 Objective

The first objective is to evaluate how the BCI performance is affected by attention diversion from an experiment designed with two conditions: focused attention and diverted attention. Subsequently, the second objective is to present a data augmentation technique using GANs to improve the performance of BCI classifier under diverted attention condition.

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¹ **F. Fahimi**, et al., "Generative Adversarial Networks-based Data Augmentation for Brain-Computer Interface", *IEEE Transactions on Neural Networks and Learning Systems (TNNLS)*, 2019, under revision.

F. Fahimi, et al., "Towards EEG Generation Using GANs for BCI Applications". *IEEE-EMBS International Conference on Biomedical and Health Informatics*, Chicago, IL, USA, 2019, in press.

5.2 Related Work

Brain signal is non-stationary and varies from subject to subject and session to session [70]. For example, unlike recording in the laboratories whereby the users perform tasks in a quiet and controlled environment, users' attention may be diverted in real-life BCI applications. As we discussed in section 2.4, this diversion may decrease the performance of the classifier [39]. To improve the robustness of the classifier, additional data can be acquired in such conditions, but it is not practical to record EEG over several long calibration sessions [101] especially when the BCI users are patients, children, or elderly. Moreover, the collected data are not always fully utilizable since data acquisition is usually prone to technical errors such as noise and/or human muscle artifacts like blinking. A potential time- and cost-efficient solution is artificial data generation to augment the real data. Generative methods, with the emphasis on data generation rather than distribution estimation, are the potential answer to this need.

5.2.1 Data Augmentation Using GANs

A recent generative method with successful implementation in image generation is GANs, introduced by Ian Goodfellow, et al. [208]. GANs comprise two competing networks including the generator and the discriminator whose competition eventually leads to the generation of the artificial data of high quality [208]. After its emerge, the method of GANs with promising results in image generation and the potential for further improvement soon became the center of attention. Several researchers have contributed to solving the issues of the first version of GANs. Mirza and Osindero [209] introduced conditional GANs, the idea was to feed some conditioning data into both networks. They conditioned the generator and the discriminator on class labels and reported that conditional GANs trained on the MNIST dataset generated the images of superior quality than the regular GANs. Later, Salimans, et al. [210] proposed techniques to enhance GANs training by investigating a

range of training procedures and architectures. They suggested that the inception score (IS) is a proper metric for models comparison [210]. In other studies, a new version of GANs was presented [211-213]. A very first modification to the original GANs was deep convolutional GANs (DCGANs) that uses DCNN for both the generator and the discriminator for better training [211]. Mao, et al. [212] introduced the method of least square generative adversarial networks (LSGANs) which replaces the sigmoid loss function in the discriminator with a least-squares loss function. Based on their experiments, LSGANs performed better than the regular GANs in terms of learning stability and the quality of the image [212]. The method of Wasserstein GANs is another version which is proposed by Arjovsky, et al. [214] and is gaining attention. The authors' concern was the problem of vanishing gradients caused by minimizing the Jensen-Shannon divergence between the real and the generated data distributions in the original GANs. They showed that Wasserstein distance is a better choice than Jensen-Shannon divergence [213, 214]. Other attempts to improve the networks architecture, training stability, and images quality are presented in [215-218].

5.2.2 EEG Augmentation Using GANs

Although GANs method was originally introduced for image generation, it can be extended to other types of data. For example, GANs have been used for synthesizing audio effectively [219]. In the present study, we use GANs on EEG signals.

There are a few studies on the use of GANs for EEG signals [43, 220-224]. In one study, GANs were conditioned on EEG features in order to improve the image generation [224]. EEG data were recorded while the person was looking at target images. Then, EEG features were extracted using a recurrent neural network (RNN)-based encoder and were fed as conditioning data to the generator and the discriminator networks [224]. A similar study [220] used long short-term memory (LSTM) network followed by a fully-connected layer

with a non-linear activation function, ReLU, as an encoder for EEG feature extraction [220]. In both studies, GANs and variational auto-encoders (VAE) were conditioned on EEG features and the observations suggested that GANs outperformed the VAE [220]. However, the quality of the generated images needed to be improved. The scope of these studies was image generation and EEG was merely used as auxiliary data.

In another study, Wasserstein GANs were used to augment EEG differential entropy (DE) features in order to boost the classification of emotion [222]. The networks were conditioned on class labels and DE features were imported to the discriminator as real data. A few metrics including the discriminator loss and maximum mean discrepancy (MMD) were used for the evaluation of the generated DE features. The classification was done by SVM. The results showed that the classification benefited from the inclusion of the generated DE features in the training set [222].

Although only a handful of studies have applied GANs on EEG data so far, their results suggest that GANs-based methods are a promising approach to cope with the issues associated with EEG.

5.3 Evaluating the Effect of Attention Diversion on the BCI Performance

To evaluate the effect of attention diversion on the performance of BCI systems, we design an experiment in which subjects perform a motor task under two conditions: 1) focused or non-diverted attention condition, and 2) diverted attention condition. The first condition is commonly used in many of the previous BCI studies, however, the performance of BCI under the second condition is not studied well. This is a more realistic scenario, as the subject is likely to be exposed to many distractions, and therefore, it poses bigger challenges for BCI decoders.

5.3.1 Participants

Fourteen individuals with the age range between 21 and 29 years (24.71 ± 2.49 , 6 males and 8 females) participated in the experiment. All participants were healthy, right-handed, and without any hearing or vision abnormalities. The experiment was approved by the local ethical committee and the participants signed an informed consent form. They all could fluently speak English and understand the instructions. The experiment was performed at the Brain-Computer Interface Laboratory of the Department of Health Science and Technology, Aalborg University, Denmark.

5.3.2 Protocol

The main task was opening and closing the right hand. In both conditions, the subjects were seated in a comfortable chair that was placed 1 meter away from the screen, with their right hand on the desk, as can be seen in Figure 5.1(a). In each condition, the subjects performed 40 trials; 10 hand openings, 10 hand closings, 15 s of rest, and again 10 hand openings, and 10 hand closings (Figure 5.1 (b)). Every trial consisted of 5 phases including focus, preparation, execution, hold, and rest. Figure 5.1(c) shows the experiment flow. In the focus phase, the subjects were instructed to focus on the screen and avoid blinking or moving. In the preparation phase, the type of movement to perform was indicated to the subjects. After movement execution, the subjects maintained the movement (hand opened/closed) during the hold phase. In the rest phase, the subjects relaxed. This was a cue-based, non-randomized paradigm in which the subjects were told when and what type of movement to execute.

In the focused condition, there was no distraction, while during the diverted condition a random sequence of beeps was played. The beeps were of different frequencies with a duration of 0.5 s and a random inter-stimulus interval of 1-2 s. In this way, the subjects' attention was diverted by the external noise. More importantly, we wanted to assure that

the subjects could not simply ignore the auditory stimulus while fully focusing on the task as in the focused condition. Therefore, we asked them to count the number of times each tone (beep of a certain frequency) was repeated over 10 consecutive trials. After every block of 10 trials, the subjects were asked to report how many tones of each frequency they heard (see Figure 5.1(b)). The task difficulty was gradually increased over the blocks by starting from only 2 tones (500 and 1000 Hz) played over block 1, 3 tones (500, 750, and 1000 Hz) over block 2, and 4 tones (250, 500, 750, and 1000 Hz) over blocks 3 and 4. Based on the feedback we received from the subjects, their attention was indeed diverted with this oddball paradigm.

5.3.3 EEG Acquisition

The EEG signals were recorded using a g.HIamp-research amplifier and 62 gel-based active electrodes placed in a g.Gamma cap. The recorded EEG channels were Fp1, Fp2, Fpz, AF3, AF4, AF7, AF8, F1-8, Fz, FC1-6, FCz, FT7, FT8, C1-6, Cz, T7, T8, CP1-6, CPz, TP7-10, P1-8, Pz, PO3, PO4, PO7, PO8, POz, O1, O2, and Oz. They were referenced to the right earlobe. AFz channel was used as the ground. Moreover, 2 bipolar electromyography (EMG) channels (4 EMG electrodes) were used to detect the movement onset. They were placed on the hand flexor and extensor muscles that were located using palpation (see Figure 5.1(a)). Before placing the electrodes, the skin was cleaned using an alcohol swab. Data were continuously recorded at 1200 Hz by g.Recorder that is gtec bio-signal recording software.

(a)

Condition 1: Focused

10 Opening	10 Closing	15s rest	10 Opening	10 Closing

Condition 2: Diverted

10 Opening Counting 2 tones	Recall	10 Closing Counting 3 tones	Recall	15s rest	10 Opening Counting 4 tones	Recall	10 Closing Counting 4 tones	Recall

(b)

(c)

Figure 5.1 The experiment for evaluating the effect of attention diversion on BCI performance: (a) a demonstration of the experimental settings including EEG and EMG electrodes, (b) protocol, (c) experiment flow.

5.3.4 Data Preparation

Raw EEG data can be contaminated by several artifacts including eye movements and muscle activity [225]. Therefore, the data are band-pass filtered at 0.01-100 Hz by g.Recorder during acquisition and a notch filter is applied to remove the line frequency of 50 Hz. Further, we apply ICA and artifact subspace reconstruction (ASR) and a high-pass filter with the cut-off at 0.5 Hz to remove electrooculogram (EOG) and EMG artifacts. The spectrum of the data under analysis is thus 0.5-100 Hz. These methods are implemented using EEGLab [226] in Matlab R2013b.

After pre-processing, the EEG signals are segmented into movement intention (MI) and rest epochs for classification. Figure 5.2 shows the segmentation diagram and marks the time intervals under analysis. The exact movement onset is determined from the EMG signals by thresholding. The MI epochs are 2-s segments before the movement onset and the rest epochs are 2-s segments starting 1 s after the rest onset. The reason is that subjects were asked to hold their hand open (or close) during the hold phase and then release it when the rest cue is shown. Thus, we take the rest segments starting from 1 s after the rest onset to make sure that no movement exists. Moreover, we check the EMG signals to assure the lack of the movements in the samples of both classes, MI and rest.

After segmentation, the data are down-sampled to 250 Hz. In total, each subject performed 40 trials in each condition. Therefore, there are 40 samples per class per condition for each subject. The EEG data for each subject in each condition is thus of size $80 \times 500 \times 62$, i.e., 80 samples (40 MI and 40 rest), 500 time points per sample ($2 \text{ s} \times 250 \text{ Hz}$), and 62 EEG channels. Please note that MI epochs prior to hand opening and hand closing are combined into one class, thus, this is a binary classification between MI and rest.

Figure 5.2 Segmentation diagram of EEG.

5.3.5 Baseline Methods for Classification

The classification task is MI detection. The general hypothesis is that with attention diversion the classification performance decreases [39]. To test this hypothesis, we use 2 baseline methods including the FBSCP [74, 79] and the end-to-end DCNN [1].

The method of LOO as described in 4.3.3, is used for classification. With a total of 14 subjects, the training set will have 1040 samples (13 subjects $\times$ 80 samples) and the test set will have 80 samples. In addition to LOO, we perform subject adaptation, hereafter called adaptive, with the end-to-end DCNN. In the adaptive method, the LOO models are updated based on the first half of the target subject's samples and the model is tested on the second half.

5.3.5.1 FBCSP

The method of FBSCP is implemented for benchmarking. We follow the methodology that is described in the original work [74, 79] by applying mutual information-based best individual feature [83] to select discriminative CSP features and naive Bayesian Parzen window for classification.

5.3.5.2 End-to-End DCNN

We use the end-to-end DCNN, described in chapter 4, as another baseline method. The schematic diagram of this framework is depicted in Figure 4.2. The end-to-end DCNN takes the EEG segments as input and passes them through 3 convolution layers. In these layers,

convolution is done with a 1D kernel across time [1, 112, 114] with 60, 40, and 20 filters, kernel sizes of 4, 3, and 2 with stride sizes of 2, 1, and 1 respectively. After the last convolution layer, the features are flattened and then sent to a fully-connected layer of 100 nodes. The output is then sent to the last fully-connected layer with softmax activation function for the classification. In all other layers, ReLU is used as the activation function. Two dropout layers with the probability of 0.2 and 0.3 are inserted respectively before and after the first fully-connected layer to avoid over-fitting (see Figure 4.2). The method of Adam [200] with a learning rate of 0.001 and beta1 of 0.9 is used as the optimizer. The hyper-parameters are selected by trial and error [201]. The modifications applied to this framework are adding batch-normalization [198] after each layer, and replacing softmax activation function with sigmoid in the last layer. Training is done with a batch size of 20.

5.4 Improving the BCI Performance under Attention Diversion Using Conditional DCGANs

The idea of the proposed approach is to exploit the recorded EEG to generate synthetic EEG and augment the training set. In order to generate synthetic EEG samples for a target subject, GANs learn from a pool of other subjects' EEG data (inter-subject transfer). This learning procedure is conditioned by auxiliary information about the target subject's EEG data. The samples generated in this way resemble the target subject's EEG data and at the same time, they are different enough to be considered as new samples and contribute to the training set. The following sections describe the proposed method with details.

5.4.1 Conditional DCGANs

GANs include 2 neural networks, a generator G and a discriminator D . In an analogy, these networks can respectively be considered as counterfeiter and police, where the counterfeiter tries to deceive the police with fake money. In GANs, the task of G is to generate the

artificial samples and the task of D is to identify which samples are real and which are generated. The training target for G is to eventually generate samples that are no longer distinguishable from the real samples by the discriminator D . At this point, the generated samples closely resemble the real samples.

Two opposing networks are simultaneously being trained to maximize $\log(D(x))$ and minimize $\log(1 - D(G(z)))$. This adversarial training procedure is formulated as a minimax problem:

$$\min_G \max_D V(G, D) = E_{x \sim p_x} [\log(D(x))] + E_{z \sim p_z} [\log(1 - D(G(z)))] \quad (5.1)$$

where E denotes the expectation operator, $D(x)$ is the probability of x belonging to the real data and $G(z)$ is the generated sample produced by G from a random noise input z as in (5.2).

$$x_g = G(z) \quad (5.2)$$

The cross-entropy loss is used to calculate the discriminator loss (L_D) and the generator loss (L_G) as formulated in (5.3) and (5.4) respectively.

$$L_D = -\log D(x_r) - \log(1 - D(x_g)) \quad (5.3)$$

$$L_G = -\log D(x_g) \quad (5.4)$$

In the present study, since the objective is to generate samples for a target subject, we use conditional GANs [209] in order to condition the networks on a subset of the target subject's data. In this way, the generated samples not only resemble the training samples in general (other subjects' data) but also inherit the specific characteristics of the target subject's data. Please note that the subset used to extract the conditioning vector is then excluded from the test set to avoid any biased results. Given the conditioning vector y , the above equations change as below:

$$\min_G \max_D V(G, D) = E_{x \sim p_x} [\log(D(x, y))] + E_{z \sim p_z} [\log(1 - D(G(z, y)))] \quad (5.5)$$

$$x_g = G(z, y) \quad (5.6)$$

$$L_D = -\log D(x_r, y) - \log(1 - D(x_g, y)) \quad (5.7)$$

$$L_G = -\log D(x_g, y). \quad (5.8)$$

To improve the performance of GANs, we use one-sided label smoothing. Thus, the discriminator loss formulation is modified as:

$$L_D = -0.9 \log D(x_r, y) - 0.1 \log(1 - D(x_r, y)) - \log(1 - D(x_g, y)) \quad (5.9)$$

Considering recent successful implementations of CNN in GANs [211, 220] and EEG applications [1, 42, 89, 112-114, 227], we use CNN architecture for discriminator and generator.

The generator network starts with 2 fully-connected layers followed by a batch-normalization layer. Then, the output is first reshaped to (1, 100, 62) and then up-sampled with the size of 5. The output is then passed through 2 convolution layers with a kernel size of 5 and 62 filters. As suggested by the original DCGANs work [211], we use convolution layer for the generator, not deconvolution layer which is used by some studies [220, 224]. Eventually, the output of the generator (synthetic EEG) has the same shape as the real EEG (500 time points, 62 channel). The hyperbolic tangent is used as activation function.

The discriminator consists of a convolution layer with kernel size of 5 and 62 filters followed by a max-pooling of size 2, another convolution layer with kernel size of 5 and 128 filters followed by a max-pooling of size 2, a flattening layer, a fully-connected layer of size 400, and finally a fully-connected layer of size 1. The hyperbolic tangent activation function is used except in the last layer where a sigmoid activation function is used for classification. The Adam method [200] is used for optimization with learning rate and beta1 parameters initialized at 0.0001 and 0.2, respectively.

5.4.2 EEG Generation with Conditional DCGANs

The overall framework of EEG generation with conditional DCGANs is shown in Figure 5.3. The GANs are trained to learn from other subject's EEG as the training set (or real EEG) while conditioned on the auxiliary information about the target subject's EEG, to transform the random noise input into naturalistic EEG samples that resemble the target subject's EEG samples. Thus, the inputs to the generator are noise and the conditioning vector which are concatenated, and the inputs to the discriminator are the real EEG, the conditioning vector, and the generated EEG. The output of the first fully-connected layer in the discriminator which is a vector of 400 features (section 5.4.1) is concatenated with the conditioning vector and the result is passed to the final fully-connected layer with sigmoid activation function for discrimination. Noise is sampled from a normal distribution with mean 0 and standard deviation 1.

The training or real samples include the EEG samples from all subjects excluding the target subject, thus, the training set for each class is of size (520, 500, 62) where 520 is the number of samples per class (13×40), 500 is the number of time points, and 62 is the number of EEG channels. After training, the generator of the conditional DCGANs can generate any number of synthetic EEG with the same shape as the real EEG.

5.4.2.1 Learning Subjective EEG features as Conditioning Vector

We use the end-to-end DCNN to learn the subjective EEG features as conditioning vector. As shown in Figure 5.4, the output of the first fully-connected layer in the end-to-end DCNN, based on which the classification is done, is extracted to be used as the conditioning vector.

The first half of the target subject's samples are imported into the end-to-end DCNN as input and those 100 features are extracted for each sample. Given 40 samples per class per subject, taking the first half of the samples produces a 20×100 feature matrix per class per

subject. The features are then averaged over samples to obtain a 1×100 feature vector per class per subject. This feature vector is used to define the conditioning vector for the conditional DCGANs. A separate conditional DCGANs is trained for each condition (focused and diverted) using features extracted from that condition. Please note that the subset of samples used for learning the conditioning vector is excluded from the test set to avoid any biased results.

Figure 5.3 Augmented classification with conditional DCGANs-DCNN. In conditional DCGANs, the generator takes random noise and auxiliary information as inputs and generates artificial samples. Through back-propagation, GANs learn to generate (fake) samples that highly resemble the real data. The auxiliary information is a feature vector extracted from a subset of the target subject's data. By importing this feature vector, GANs are conditioned to generate samples that resemble the target subject's samples. After training DCGANs, the generated samples are appended to the real samples to augment the train set. This augmented train set is then imported to DCNN for classification.

Figure 5.4 Learning subjective EEG features as conditioning vector. The first half of the target subject's samples are imported into the end-to-end DCNN as input and the output of the first fully-connected layer (100 features) based on which the classification is done, is extracted as the conditioning vector to be used in the conditional DCGANs.

5.4.3 Evaluating the Quality of the Synthetic EEG

It is important to ensure that the generated samples are of high quality, in other words, they are realistic and diverse. Lack of diversity among the generated samples is an indicator of mode collapse [213], meaning that the generator has collapsed into generating only limited modes of the real data. Here, we use several qualitative and quantitative measures to evaluate the quality of the samples generated by the conditional DCGANs in terms of diversity and similarity with the real samples.

5.4.3.1 GAN-test

We train the classifier on the real samples and test the trained model on the generated samples. The obtained classification accuracy is named GAN-test. A high value of the GAN-test denotes that the test set (synthetic EEG) is similar to the train set (real EEG). The end-to-end DCNN is used for classification.

5.4.3.2 KL divergence

We also calculate the Kullback-Leibler (KL) divergence to investigate the mode collapse. In successful GANs training, the KL divergence between the generated samples should be close to the KL divergence between the real samples.

5.4.3.3 Visualization

Furthermore, we visually inspect the quality of the artificial samples by mapping the generated and real samples into 2 dimensions using t-SNE and temporal distribution.

5.4.4 Augmented Adaptive Classification with Conditional DCGANs-DCNN

The proposed augmented method is a combination of the conditional DCGANs and the end-to-end DCNN. We briefly call it the conditional DCGANs-DCNN. The conditional DCGANs are trained for each subject by learning from the other subjects' data and including the conditioning vector about the target subject as described in section 5.4.2.1 (see Figure 5.3 and Figure 5.4). After reaching training stability, the synthetic EEG samples are generated by the generator.

The hypothesis is that the generated samples resemble the target subject's samples and thus the inclusion of them into the training set will improve the classification. We test this hypothesis by repeating the adaptive classification with the end-to-end DCNN on the augmented data. In other words, this time instead of adapting the LOO models based on the first half of the target subject's samples, we adapt the LOO models based on the augmented set which includes the generated samples and the first half of the target subject's samples. Therefore, we refer to this classification as augmented adaptive with conditional DCGANs-DCNN.

Comparing to the adaptive method, the test set is the same while the training set, based on which the LOO models are adapted, is larger. In this study, the synthetic EEG data with the same number of samples as in the LOO training set are generated ($13 \times 40 = 520$ samples per class per condition) and appended to the training set of the adaptive method. Since the training set of the augmented adaptive is larger, we increase the training batch size from 20 to 40.

5.5 Results

This section presents the results of the experiments. Input data preparation including artifact removal and segmentation, and the implementation of FBCSP are done in Matlab R2013b. The end-to-end DCNN and conditional DCGANs are conducted in Python 3.6 with Keras 2.1.2 and Tensorflow 1.2.1. The reported p -values are calculated using paired, two-sided Wilcoxon test.

5.5.1 The Effect of Attention Diversion on the BCI Performance

We have used the FBCSP and End-to-end DCNN as baseline methods for MI detection from the focused and diverted conditions to evaluate how attention diversion affects the performance of BCI. The results of the classification are given in Table 5.2.

5.5.1.1 Baseline 1: FBCSP

The method of FBCSP is described in section 5.3.5.1 and the results are presented in Table 5.2. According to the results, the performance of the BCI classifier decreases under attention diversion. In fact, the classification accuracy in the focused condition is 77.68% while in the diverted condition is 70.45% that is 7.23% lower than the focused condition (p -value < 0.01). A generally accepted threshold for BCI performance is 70% [205, 206]. The number of subjects with accuracy $< 70\%$ in the focused condition is 2 while in the diverted condition is 5.

5.5.1.2 Baseline 2: End-to-end DCNN

The method of end-to-end DCNN is described in section 5.3.5.2 and the results are presented in Table 5.2. According to the results, the performance of the BCI classifier decreases under attention diversion. In fact, LOO classification accuracy in the focused condition is 80.09% while in the diverted condition is 73.04% that is 7.05% lower than the focused condition (p -value < 0.01). Similarly, the adaptive classification accuracy in the

focused condition is 82.32% while in the diverted condition is 76.43% that is 5.89% lower than the focused condition (p -value < 0.01). Performing LOO, the number of subjects with accuracy $< 70\%$ in the focused condition is 1 while in the diverted condition is 4. Performing adaptive, the number of subjects with accuracy $< 70\%$ in the focused condition is 0 while in the diverted condition is 3. The difference between LOO and adaptive in the focused condition is statistically significant (p -value < 0.02) while in the diverted condition is not significant.

5.5.2 Improving the BCI Performance under Attention Diversion Using Conditional DCGANs

In this section, we first present the training loss of the conditional DCGANs and visualize the generated samples to show the performance of conditional DCGANs in EEG generation. Then, we present the results of the augmented adaptive classification with the conditional DCGANs-DCNN and a comparison between adaptive and augmented adaptive classification.

5.5.2.1 Adversarial Training

In training GANs, achieving training stability is important [217]. The networks' losses over iterations are a good indicator of how the training proceeds. Figure 5.5 plots the generator and the discriminator losses for a random subject over 1000 iterations. In a successful training, it is expected to see a gradual drop in the generator loss and convergence to some constant values for both networks. These criteria can be seen in Figure 5.5; the generator loss gradually decreases and both losses converge to some constant values after approximately 300 iterations. The same trend exists in other subjects' results. A careful choice for parameters initialization (learning rate in the optimizer, etc.), type and order of the layers, the input preparation, single-side label smoothing for the discriminator loss, etc. yielded a stable training.

Figure 5.5 The generator and discriminator losses. Both converge after approximately 300 iterations.

5.5.2.2 Quality of the Synthetic EEG

Here, the results of the quantitative and qualitative evaluation measures defined in section 5.4.3 are presented.

1) GAN-test

The results are reported in Table 5.1. The GAN-test was 99.16% in the focused condition and 97.87% in the diverted condition which indicates that the generated samples are similar to the real samples.

2) KL divergence

The results are presented in Table 5.1. In both conditions, the KL divergence between the generated samples is close to the KL divergence between the real samples which indicates that the generated samples are as diverse as the real samples.

Table 5.1 Quantitative Measures for Quality Evaluation.

		Condition 1: Focused	Condition 2: Diverted
GAN-test		99.16%	97.87%
KL divergence	real	2.01	2.25
	generated	2.53	2.12

3) Visualization

T-SNE is applied to map the high dimensional real (train) and generated EEG samples into 2D space. Figure 5.6 shows the results. The t-SNE embedding of real MI and generated MI are very similar. Similarly, real and generated rest have similar distributions. In this figure, different colors are used to discriminate between the real and generated samples while different markers are used to discriminate between the samples from MI and rest classes.

Besides comparing the generated samples with the train samples, it is interesting to compare them with the test samples. This comparison will show whether the generated samples are similar to the test samples that are not seen before, and therefore they add new and valid information into the training set. Please note that the test set does not include the subset of data used for feature learning in the conditional DCGANs, meaning that the results are not biased. Figure 5.7 shows the test samples in green and the generated samples in red from channel Cz for 3 randomly selected subjects. The horizontal axis shows time points (2 s with the sampling frequency of 250 Hz) and the vertical axis shows the amplitude. As can be seen, the conditional DCGANs method generates artificial EEG similar to the real EEG. The Euclidean distance (ED) between real test samples and synthetic samples is reported next to each plot.

Figure 5.6 T-SNE embedding of real and generated samples. Abbreviation ‘gen’ in the legend stands for ‘generated’. Red color shows generated samples and green color shows real samples. Filled diamonds show MI class and ‘x’s show rest class.

Figure 5.7 Temporal distribution of real test EEG samples and EEG samples generated by conditional DCGANs over channel Cz for the diverted attention condition. Solid lines are mean and faded colours show standard deviation from the mean.

5.5.2.3 Augmented Adaptive Classification with Conditional DCGANs-DCNN

The method of conditional DCGANs-DCNN is described in section 5.4.3 and the results are presented in Table 5.2. According to the results, augmented adaptive with the conditional DCGANs-DCNN improves the classification. The main comparison is between the end-to-end DCNN, mainly adaptive, and the conditional DCGANs-DCNN. Besides accuracy, we have also reported the confusion matrix, presented in Table 5.3.

The augmented adaptive with conditional DCGANs-DCNN yields several improvements in the focused condition: classification accuracy increases to 85.54% that is 5.45% higher than the LOO (p -value < 0.01) and 3.22% higher than the adaptive (p -value < 0.02). In

addition, the accuracy of all subjects is above 70%. Moreover, TPR is as high as 83.21% and FPR is as low as 12.14% (see Table 5.3).

The augmented adaptive with conditional DCGANs-DCNN also enhances the classification in the diverted condition which was the main concern of the study. The accuracy increases to 80.36% that is 7.32% higher than the LOO (p -value < 0.01) and 3.93% higher than the adaptive (p -value < 0.03). In addition, the accuracy of all subjects is above 70%. Moreover, TPR increases to 76.43% and FPR decreases to 15.71% (see Table 5.3).

Figure 5.8 highlights the important methods for comparison by drawing the box-plots, and Table 5.4 represents a summary of the results and statistical comparison between the conditional DCGANs-DCNN and the baseline methods using a paired two-sided Wilcoxon test.

Table 5.2 Classification results of the baseline methods and the proposed DCGANs-DCNN method.

Condition 1: Focused				
	Baseline Methods			Proposed Method
	FBCSP (LOO)	DCNN (LOO)	DCNN (Adaptive)	DCGANs-DCNN (AgAdaptive)
Average (SD)	77.68 (9.99)	80.09 (6.13)	82.32 (3.60)	85.54(5.02)
Range (min-max)	35.00 (57.50-92.50)	25.00 (62.50-87.50)	12.50 (75.00-87.50)	15.00 (77.50-92.50)
#subjects with accuracy < 70%	2 of 14	1 of 14	0	0
Condition 2: Diverted				
	Baseline Methods			Proposed Method
	FBCSP (LOO)	DCNN (LOO)	DCNN (Adaptive)	DCGANs-DCNN (AgAdaptive)
Average (SD)	70.45 (9.50)	73.04 (7.38)	76.43 (7.83)	80.36 (7.46)
Range (min-max)	35.00 (46.25-81.25)	25.00 (60.00-85.00)	22.50 (65.00-87.50)	20.00 (70.00-90.00)
#subjects with accuracy < 70%	5 of 14	4 of 14	3 of 14	0

SD – Standard Deviation

AgAdaptive – Augmented Adaptive

Table 5.3 Confusion matrix.

		LOO with end-to-end DCNN			
		Condition1: Focused		Condition2: Diverted	
		<i>MI</i>	<i>Rest</i>	<i>MI</i>	<i>Rest</i>
actual	MI	78.39%	21.61%	71.96%	28.04%
	Rest	18.21%	81.79%	25.89%	74.11%
		Adaptive with end-to-end DCNN			
		Condition1: Focused		Condition2: Diverted	
		<i>MI</i>	<i>Rest</i>	<i>MI</i>	<i>Rest</i>
actual	MI	85.36%	14.64%	71.79%	28.21%
	Rest	20.71%	79.29%	18.93%	81.07%
		Augmented Adaptive with conditional DCGANs-DCNN			
		Condition1: Focused		Condition2: Diverted	
		<i>MI</i>	<i>Rest</i>	<i>MI</i>	<i>Rest</i>
actual	MI	83.21%	16.79%	76.43%	23.57%
	Rest	12.14%	87.86%	15.71%	84.29%

MI – Movement Intention

Rows and columns are respectively associated with actual and predicted classes.

Table 5.4 Comparing the performance of the proposed DCGANs-DCNN method with the baseline methods.

	Method	Average accuracy% (SD)	<i>p</i> -value
Condition 1: Focused	FBCSP	77.68 (9.99)	< 0.01
	DCNN (LOO)	80.09 (6.13)	< 0.01
	DCNN (Adaptive)	82.32 (3.60)	< 0.02
	DCGANs-DCNN	85.54 (5.02)	-
Condition 2: Diverted	FBCSP	70.45 (9.50)	< 0.01
	DCNN (LOO)	73.04 (7.38)	< 0.01
	DCNN (Adaptive)	76.43 (7.83)	< 0.03
	DCGANs-DCNN	80.36 (7.46)	-

Figure 5.8 Comparing the end-to-end DCNN and conditional DCGANs-DCNN. The abbreviation ‘AgAdaptive’ refers to augmented adaptive with conditioned DCGANs-DCNN.

5.5.2.4 Adaptive versus Augmented Adaptive

As mentioned earlier, the main comparison is between adaptive with end-to-end DCNN and augmented adaptive with conditional DCGANs-DCNN. Hence, it is interesting to investigate how each subject’s classification accuracy changes by using augmented adaptive over adaptive which was the best baseline method.

Figure 5.9 shows the scatter plot of adaptive and augmented adaptive accuracies. Each circle represents one subject. The vertical axis is the accuracy of augmented adaptive with conditional DCGANs-DCNN and the horizontal axis is the accuracy of adaptive with end-to-end DCNN. The right plot which is associated with the diverted condition shows that with the augmented adaptive, the accuracy for 12 subjects out of 14 increases. The left plot which is associated with the focused condition shows that with the augmented adaptive, the accuracy for 8 subjects increases and for 4 subjects does not change. Overall, the augmented adaptive method outperforms the adaptive method for the majority of the subjects.

Figure 5.9 The augmented adaptive with conditional DCGANs-DCNN versus adaptive with end-to-end DCNN. The abbreviation ‘acc’ stands for accuracy. Each circle represents one subject. Note that the number of circles in the left plot is 12 and in the right plot is 13 instead of 14. This is because some subjects have the same pair of accuracies and thus their circles fully overlap (subject pairs of (1, 5) and (6, 13) in condition 1 and (8, 14) in condition 2). As can be seen, conditional DCGANs-DCNN increases the classification accuracy for most of the subjects.

5.6 Discussion

In this study, we have investigated the BCI performance under attention diversion and proposed a data augmentation method based on DCGANs to improve BCI performance.

5.6.1 Attention Diversion Decreases the BCI Performance

We designed and implemented an experiment to investigate how the BCI performance is affected by attention diversion. Previously, Brandl, et al. [39] evaluated the performance of motor imagery BCI under distractions. There, they classified CSP features by LDA and reported that the classification performance decreased under distractions. In the present study, we implemented the FBCSP and end-to-end DCNN methods for classification in the focused and diverted attention conditions. The results showed that the performance significantly decreased under the attention diversion.

In the work by Brandl, et al. [39], the training set was EEG recorded under no distraction while the test set was EEG recorded under distractions. Therefore, it is not clear that the decrease in the performance is because of the feature shifts between the train and test samples or is because of the distractions. In this study, we trained a separate classifier for

each condition, meaning that the train and test samples are recorded from the same condition and thus the lower performance in the diverted condition is less likely to be due to a huge feature or distribution shift between the train and test samples, rather, it is likely to be due to the attention diversion that makes the decoding more challenging.

5.6.2 EEG Augmentation with Conditional DCGANs Improves the BCI

Performance under Attention Diversion

We developed a framework based on DCGANs to generate synthetic EEG data from the recorded examples. We used the generated data to supplement the training set of the BCI classifier, and indeed, we have demonstrated that the enhanced training significantly improved the performance. In the diverted condition, the proposed augmented adaptive method yielded significant improvements with a 7.32% increase compared to LOO and 3.93% increase compared to adaptive. Previously, Lotte [101] generated synthetic EEG by recombination of the EEG segments in time and time-frequency domains and showed that the artificially generated samples boosted the classification when the training samples were limited [101]. In another study, the use of synthetic data with EMG signals has been tested for pattern classification and regression control of myoelectric prostheses, and the results were promising [228]. There, the EMG data recorded for the single degree of freedom movements were linearly combined to simulate the movements around multiple degrees of freedom, and the classifier was trained using such linearly enhanced training set. Intrinsically, the EEG signals are more complex compared to EMG; nevertheless, we have shown that the conditional DCGANs is able to successfully capture and mimic the dynamics of the recorded EEG.

Each training iteration on a CPU (Intel(R) Xeon(R) CPU E5-1650 v2 @ 3.5GHz) took approximately 0.58 s. Once the networks were trained, DCGANs were easily used to generate hundreds of samples within a few seconds. To be specific, the generation of 520

samples took about 1.24 s. This is while collecting the same amount of data experimentally would take over an hour. In addition, the experimental data collection would put additional work and cognitive burden on the subject.

A common problem associated with GANs is training instability [216, 217]. However, the proposed method with careful choices for networks' structure, the optimization technique, activation functions, and parameter initialization, did not suffer from this problem and the networks' losses gradually converged. Another challenge that GANs usually face is the low quality of the generated samples [216]. In this work, by conditioning GANs on subjective EEG features, the quality of the generated samples improved.

The artificial samples generated by conditional DCGANs improved the detection performance because they were generated specifically to contribute new information about unseen samples into the train set. To this aim, the GANs were conditioned on a feature vector learned through DCNN from a subset of samples. We used several quantitative and qualitative measures including GAN-test, KL divergence, 2D visualization using t-SNE and temporal distribution to evaluate the quality of the generated samples. The results verified that the generated samples are realistic and diverse.

5.7 Summary

The study in this chapter demonstrated that the proposed GANs-based approach is able to generate naturalistic EEG samples for a target subject by learning from a pool of other subjects. Augmenting the training set with these synthetic EEG samples significantly improved the classification under attention diversion which is known to be challenging in BCI systems. In fact, the proposed conditional DCGANs-DCNN significantly improved the classification accuracy with a 7.32% increase compared to DCNN-LOO and 3.93% increase compared to DCNN-adaptive. The proposed framework can be further extended

to other applications such as minimizing the calibration session or restoration of the corrupted EEG.

Chapter 6

Contributions, Limitations, and Future Work

In this chapter, the contributions of the thesis are summarized and the limitations are explained. Further, the potential directions for future work are mentioned.

6.1 Contributions

This thesis proposed solutions for the attention-related challenges in BCI systems, namely:

- 1) Assessment of attention status using EEG-based BCI.
- 2) Continuous attention detection from EEG.
- 3) Improving EEG-based BCI performance under attention diversion.

These contributions are respectively summarized in sections 6.1.1, 6.1.2, and 6.1.3. A consolidated presentation of the contributions of this thesis is shown in Figure 6.1. Although data augmentation is mainly proposed to improve the BCI performance under attention diversion, it is also a potential solution to address data insufficiency in BCI systems.

Figure 6.1 A summary of the objective, challenges to address, and the proposed solutions.

6.1.1 Assessment of Attention Status Using EEG-based BCI

In chapter 3, the objective was to assess attention status and show the feasibility of attention detection using EEG. The proposed solution is described in section 3.3. Briefly, a correlation analysis between EEG and response time, as a behavioural feature of attention, was conducted to detect EEG attention-representative features. Subsequently, an LDA classifier was trained on the detected features to detect the subjects with poor attention status based on their attention score in RBANS.

The results showed the effectiveness of EEG in the assessment of attention status [40] which verifies the feasibility of attention detection using EEG. Based on the results that are presented in 3.4, the interactions between frequency bands, defined as TBR and AGR, are correlated with response time in the Stroop test which is an attention-demanding task. The observations also suggested that the most informative period of EEG during executive function is a 500 ms duration starting right after the cue onset. These observations are in line with the literature [22, 164, 172, 173]. Using TBR, and AGR extracted from this time

window yielded an AUC of 82.43% in the detection of poor attention status based on RBANS score. This study sheds light on the use of EEG as a potential alternative for time-consuming neurophysiological tests with subjective scoring criteria. This can also benefit the early prediction of attention decline [40].

6.1.2 Continuous Attention Detection from EEG

In chapter 4, the objective was to propose a method for attention detection from EEG that addresses the challenges of subject-to-subject transfer learning, end-to-end framework, interpretability of deep learning, and generalizability. The proposed solution is described in section 4.3. Briefly, a CNN-based classification method, called end-to-end DCNN, was proposed for attention detection. In this method, DCNN was trained on the other subjects' raw EEG to detect attention from the target subject's raw EEG. The DCNN perceived inputs of attention and non-attention were visualized in time and frequency domain to interpret the results.

The results showed the effectiveness of the proposed end-to-end DCNN method in attention detection [1, 42]. Based on the results that are presented in 4.4, the proposed method outperformed the state-of-the-art classification methods including LDA, SVM, FBCSP, and shallow ConvNet by achieving 79.26% accuracy in attention detection from single-channel EEG and 89.32% accuracy in attention detection from multi-channel EEG. The key advantages of the proposed method are: 1) high performance in subject-to-subject classification, 2) end-to-end framework that integrates feature extraction and classification stages by learning from raw EEG, 3) the interpretability of the method that shows the learned patterns for attention and non-attention are meaningful and discriminative, and 4) the generalizability of the method that shows the proposed method is effective for both single- and multi-channel EEG.

6.1.3 Improving EEG-based BCI Performance under Attention Diversion

In chapter 5, the objective was to first evaluate how attention diversion affects the BCI performance and then to propose a method for improving the performance of the BCI classifier under attention diversion. The proposed solution is described in sections 5.3 and 5.4. Briefly, we designed an experiment in which 14 healthy subjects performed a motor task under focused and diverted attention conditions. Implementing the baseline methods including FBCSP and end-to-end DCNN for classification showed that the performance of BCI under attention diversion decreased. To improve the performance drop, we proposed a conditional DCGANs method to generate synthetic EEG with the motivation of augmenting the training set. The conditional DCGANs were trained on the other subject's EEG while were conditioned on the auxiliary information about the target subject to generate synthetic EEG for the target subject. After data augmentation, the classification was done with the end-to-end DCNN. This framework was called conditional DCGANs-DCNN.

The results showed the effectiveness of the conditional DCGANs in improving the BCI performance, especially under attention diversion. Based on the results that are presented in section 5.5, the proposed conditional DCGANs-DCNN method significantly improved the classification accuracy by 5.45% in the focused condition and 7.32% in the diverted condition. This study sheds light on the application of the generative methods in BCI systems. The proposed data augmentation method showed to be effective in improving the classification, however, it might be useful for other purposes as well, for example, in minimizing the calibration sessions in BCI systems or restoration of the corrupted EEG data.

6.2 Limitations

Below, the main limitations of the methods presented in this thesis are listed.

- In the study presented in chapter 3, the data were recorded from a single channel to provide the elderly subjects with comfort. Therefore, only limited features could be extracted from EEG signals for correlation analysis. By recording EEG from more channels, it will be possible to have a more comprehensive analysis of the relationships between EEG and behavioural features of attention.
- The hyper-parameters of deep learning entail the model-specific hyper-parameters such as the number of filters, and the optimizer hyper-parameters such as learning rate. Tuning these parameters is a challenging task so that several studies are dedicated to developing optimization techniques for this purpose [229]. In the study presented in chapters 4 and 5, the hyper-parameters of deep learning were chosen by trial and error. Therefore, a proper hyper-parameter optimization method was missing.
- In image generation, the images generated by the generator can be easily visualized and thus it is easy to see how realistic the generated images are. However, in the case of time-series signals, it is challenging to evaluate how similar the generated signal is to the real signal. In the study presented in chapter 5, we used several measures to show the quality of the generated samples in terms of their diversity and similarity to the real samples. Moreover, data augmentation with the generated EEG led to an increase in the classification accuracy and further validated the quality of the synthetic EEG. Nevertheless, the quality and usefulness of the synthetic samples can be investigated in more depth.

6.3 Directions for Future Work

The work presented in this thesis can be further improved. Future research directions are listed below.

To address limitations:

- Improving QEEG analysis: Although it is practical to use single or few lead EEG for large scale clinical trial, as well as for real applications, it is also interesting to explore the spatial-temporal EEG signals with regard to the manifestation of attention. We could design an experiment with a small group but high-density EEG to study the brain networks and connectivities with regard to the attention process. This may reveal new EEG features representing attentional behaviour and yield a higher performance in the assessment of attention status.
- Hyper-parameter optimization for deep learning: The hyper-parameters of deep neural networks in chapters 4 and 5 were selected by trial and error because finding the best configuration of the hyper-parameters through automatic hyper-parameter optimization methods is a non-trivial task that is constrained by computational resources, cost, and time. Besides trial and error, other approaches to choose the hyper-parameters are grid search, random search, and Bayesian optimization [201, 230, 231]. These approaches are iterative processes that are time-consuming and computationally demanding. One way to improve these techniques is to define early stopping criteria [232] to be applied when the training is not going in the right direction. Overall, hyper-parameter optimization for deep learning is a vital topic and needs an extensive amount of research; one can dedicate an entire thesis to this matter, but if successfully implemented, the performance of deep learning will be increased.
- Quality evaluation of the synthetic EEG: Besides evaluation measures that are presented in chapter 5, other quantitative measures can further verify the similarity

between the real and the synthetic EEG, for example, inception score [210] or maximum mean discrepancy [233].

Other Future Directions:

- In line with the study presented in chapter 3, further research can be done to investigate whether the resting state EEG can be used to predict the subjects' response to the cued task.
- The recent successful applications of CNN for EEG [89, 112, 114] motivated us to use CNN for deep learning methods in chapters 4 and 5. Another method that can be used is LSTM, however, it might be very time-consuming [192]. Furthermore, residual neural networks [234, 235] that have an additional identity mapping compared to CNN should be investigated. The residual neural networks have shown to be promising in computer vision. With a proper design to take signals as input, they may yield a high performance for EEG as well. Another architecture that can be considered is Riemannian networks [236]. This network is introduced particularly to process symmetric positive definite (SPD) matrixes. Given that covariance matrixes are SPD and are commonly used to form the EEG input representations, for instance, in CSP and FBCSP, it may be effective to use Riemannian networks for covariance-based EEG representations.
- In the conditional DCGANs proposed in chapter 5, we used the features learned by DCNN to form the conditioning vector. The performance of the DCGANs conditioned on other feature vectors can be also explored. Depending on the classifier and its input, different types of features such as temporal, spectral, spatial, and their combinations should be assessed.

- In line with the research presented in chapter 5, further research can be done to investigate how the inclusion of the artificial samples changes the features that DCNN classifier learns and whether these changes are meaningful.
- The extension of the deep learning frameworks presented in chapters 4 and 5 to online BCI systems is a long-term goal. To apply the proposed deep learning methods in real-time BCIs, the networks must be trained in advance on the available data. The trained models then can be updated based on every few shots of new incoming data in real-time.

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¹ This paper received the **PREMIA Best Student Paper Award** (Honourable Mention), Aug 2019.

² This paper received **Student Award** at the 7th International BCI Meeting, California, USA, May 2018.

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Awards

- **PREMIA Best Student Paper Award (honourable mention)**

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- **BCI Student Award**

Brain-Computer Interface Society, 2018.

- **Research Presentation Award**

Graduate Research Symposium, School of Computer Science and Engineering (SCSE),
NTU, 2018.