CONVOLUTIONAL NEURAL NETWORKS FOR CLASSIFICATION
TEEG AND EEG

Thao Nguyen Ngoc Pham
University of Rhode Island, nguyen_pham@uri.edu

Follow this and additional works at: https://digitalcommons.uri.edu/theses

Recommended Citation
https://digitalcommons.uri.edu/theses/2340

This Thesis is brought to you for free and open access by DigitalCommons@URI. It has been accepted for inclusion in Open Access Master's Theses by an authorized administrator of DigitalCommons@URI. For more information, please contact digitalcommons-group@uri.edu.
CONVOLUTIONAL NEURAL NETWORKS FOR CLASSIFICATION TEEG AND EEG

BY

THAO NGUYEN NGOC PHAM

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

ELECTRICAL ENGINEERING

UNIVERSITY OF RHODE ISLAND
ABSTRACT

Electroencephalogram (EEG) is a commonly used non-invasive method that acquires voltage of the brain during neural activities by using conventional disc electrodes. However, there are some fundamental limitations associated with EEG such as poor spatial resolution and signal-to-noise ratio (SNR), inaccurate data due to overlapping information, and artifact contamination. Also, the EEG software filtering solutions had the potential of distorting EEG data making the results unreliable. The tripolar electroencephalogram (tEEG) records brain signals by using the tripolar concentric ring electrodes (TCRE). Based on the surface Laplacian algorithm, signals recorded from TCRE overcome the limitations of EEG. tEEG has better SNR and spatial resolution, the ability of acquiring high frequency activities (up to 425 Hz so far) and can also perform muscle artifact rejection (electromyography (EMG) rejection). This study aimed to determine if the tEEG gives better performance in language mapping with the “language dominant hemisphere classification” and motor cortex mapping with “finger movements classification”. Our analysis shows that tEEG yields higher average classification accuracy when compared to EEG using spectrum data even with simple signal processing procedures.
ACKNOWLEDGMENTS

Firstly, I would like to express my deepest gratitude to my thesis advisor, Dr. Kaushallya Adhikari, for her invaluable guidance and support throughout my pursuit of a degree. Dr. Adhikari’s dedication and expertise are the main reasons why I switched from the non-thesis option to the thesis one. She has always been available to provide me with insightful feedback, which has helped me to refine my research skills and develop a deeper understanding of the subject matter. Secondly, I would like to extend my sincere thanks to Dr. Walter Besio, he is one of my favorite professors since my undergraduate years at URI. He generously provided me with access to his lab facilities and helped with collecting high-quality data for this research project. Special thanks to my parents, Truc Pham and Suong Nguyen, whose unwavering love, care, and support have been a source of strength and motivation during my most challenging times. I would also like to take this opportunity to express my appreciation to my sister, Hieu Pham, who selflessly sacrificed her own dream for me to be here. I owe all my success to my family, and I cannot thank them enough for their unconditional love and support. Additionally, I would like to acknowledge the staff at URI’s International Center and my friends, whose support and assistance have made my transition to a new country and culture much smoother and easier. Lastly, I am thankful to Dr. Kaushallya Adhikari, Dr. Walter Besio, Dr. Vanessa Harwood, and Dr. Alisa Baron for being part of my thesis committee.
PREFACE

The thesis is written in manuscript format and contains 2 manuscripts. The first manuscript was accepted by 2022 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society and is now published in IEEE Xplore. This manuscript focused on proving the feasibility of tEEG in classification of language dominant hemisphere in language mapping experiment. The second manuscript is submitted to IEEE World AI IoT Congress 2023. This manuscript focuses on proving the feasibility of tEEG in classification of finger movement in the motor imagery finger movement experiment.
# TABLE OF CONTENTS

ABSTRACT ...................................................................................................................... ii

ACKNOWLEDGMENTS ................................................................................................... iii

PREFACE ......................................................................................................................... iv

TABLE OF CONTENTS .................................................................................................... v

LIST OF TABLES .............................................................................................................. vii

LIST OF FIGURES .......................................................................................................... viii

MANUSCRIPT 1 ................................................................................................................. 1

Language Mapping using tEEG and EEG Data with Convolutional Neural Networks ...................... 1

1.1 Abstract ...................................................................................................................... 2

1.2 Introduction ................................................................................................................ 2

1.3 Methodology ............................................................................................................. 6

1.3.1 Data Acquisition ................................................................................................... 7

2.3.2 Signal Processing ................................................................................................. 8

Result ............................................................................................................................... 12

1.4 Conclusion ................................................................................................................. 13

ACKNOWLEDGEMENT ................................................................................................. 13

List of references .......................................................................................................... 13

MANUSCRIPT 2 ............................................................................................................... 18
Deep Learning-Based Classification of Finger Movements using tEEG and EEG Signals......18

2.1 Abstract............................................................................................................................................19
2.2 Introduction .......................................................................................................................................19
2.3 Methodology .....................................................................................................................................22
    2.3.1 tEEG Innovation .....................................................................................................................22
    2.3.2 Data Acquisition .....................................................................................................................24
    2.3.3 Signal Processing .....................................................................................................................27
    2.3.4 Deep Learning .........................................................................................................................32
2.4 Result ................................................................................................................................................37
2.5 Conclusion .........................................................................................................................................39
List of Preferences ....................................................................................................................................39
LIST OF TABLES

Table 1.1. CNN Results........................................................................................................... 12

Table 2.1 Training Accuracy Result for MI Index Finger................................................. 39
LIST OF FIGURES

Figure 1.1. (Left) disc electrode, (Right) TCRE ................................................. 4

Figure 1.2. tEEG Interface .................................................................................. 5

Figure 1.3. TCRE location (4 sets of 5 arrays) ...................................................... 8

Figure 2.1a. Left: Disc Electrode. Right: TCRE ...................................................... 24

Figure 2.1b. tEEG Interface ................................................................................. 24

Figure 2.2. Electrode Montage ............................................................................. 25

Figure 2.3. Timeline for Trials in MI Experiment .................................................. 27

Figure 2.4. Time-domain Channel 1 Data Corresponding to Physical Movement ................................................................. 29

Figure 2.5. Time-domain Channel 1 Data Corresponding to Imaginary Movement ................................................................. 30

Figure 2.6. Frequency-domain Channel 1 Data Corresponding to Physical Movement .................................................................. 31

Figure 2.7. Frequency-domain Channel 1 Data Corresponding to Imaginary Movement .................................................................. 32

Figure 2.8 CNN Architecture .............................................................................. 33

Figure 2.9. Training Classification Accuracy of Channels C3 and FC2 ........... 38
MANUSCRIPT 1

Language Mapping using tEEG and EEG Data with Convolutional Neural Networks

Kaushallya Adhikari¹, Member, IEEE, Thao Pham¹, Joanne Hall², Alexander Rotenberg² and Walter G. Besio¹, Senior Member, IEEE

*Research supported by Northeast Big Data Innovation Hub 2021

¹ University of Rhode Island, Kingston, RI, USA

² Boston Children’s Hospital, MA, USA

Manuscript is published in IEEE Xplore for 2022 44th Annual International Conference of the IEEE Engineer in Medical and Biology Society (EMBC).
1.1 Abstract

Tripolar electroencephalography (tEEG) has been found to have significantly better signal-to-noise ratio, spatial resolution, mutual information, and high-frequencies compared to EEG. This paper analyzes the tEEG signals acquired simultaneously with the EEG signals and compares their ability to map language to left and right hemispheres using convolutional neural networks (CNNs). The results show that while the time-domain features of tEEG and EEG signals lead to comparable functional mapping, the frequency domain features are significantly different. The left and right hemisphere classification performances using tEEG are equivalent in time and frequency domains. However, frequency domain classification for EEG results are less accurate. Clinical Relevance - This technique could quickly, and noninvasively, guide clinicians about language dominance when preparing for resective surgery.

1.2 Introduction

Many patients, children in particular, cannot tolerate awake craniotomy and intraoperative language mapping, and this need drives the search for optimal preoperative noninvasive functional language mapping. Mapping of eloquent brain areas is critical for preservation of function after resective brain surgery, as is necessary for many patients with epilepsy, brain tumors, brain vascular malformations, and related disorders. Among the essential considerations in
formulating a neurosurgical plan is establishing the language hemispheric
dominance, particularly if the planned resection is in the left hemisphere which
is often, but not universally, dominant for language [1], [2]. We have been
developing tripolar electroencephalography (tEEG) with significantly higher
spatial resolution, muscle artifact rejection, and high-frequency features,
compared to conventional EEG. To prove the feasibility of tEEG for functional
language mapping, our goal is to test: whether correct hemispheric dominance
can be measured by scalp tEEG, noninvasively and passively. To accomplish
this, we developed a high-spatial resolution tEEG system and implemented a
deep learning methodology, convolutional neural networks (CNNs), to
incorporate the expanded signal features provided by tEEG. In the future, after
proving feasibility on healthy participants, we will deploy the full head high
density scalp tEEG mapping technology to localize function within a quadrant,
as would be needed for surgical planning when there is a possibility that the
planned resection overlaps with a functional language area [3].

Noninvasive mapping of cortical especially for the vulnerable patient
population who cannot tolerate awake craniotomy, fMRI or TMS, is an important
unmet need [4]. A quick, high fidelity, and noninvasive mapping technique is
desired to address this need for preoperative functional mapping of cortical
function. An improved EEG maybe a reasonable solution. Also, the signal
processing technique used to decode the measurements needs to be fast,
reliable, capable of handling large datasets, and automated. These
requirements lead us to deep learning techniques. The use of CNNs may make the signal processing more efficient, such as applying raw signals, lessening the time to results [5] [6].

![Figure 1.1. (Left) disc electrode, (Right) TCRE](image)

EEG has the advantage of high temporal resolution, but its low spatial resolution and artifact contamination hinder its effectiveness for the purpose of functional cortical localization. Software-based filtering solutions exist for “cleaning” the signal [7], but these require digital transformation and processing of data and may not faithfully model the biological signal. Therefore, researchers and clinicians cannot be certain that the processed data accurately reflect the physiology.

tEEG reduces artifacts and enhances the interpretability of EEG through two inventions: (1) a transformative electrode configuration - the tripolar concentric ring electrode (TCRE); and (2) a proprietary tEEG Interface. Conventional EEG uses the disc electrode which has a single element (Fig. 1, left). The TCRE sensor consists of three concentric rings: outer, middle and center (Fig. 1, right). Each TCRE provides two output signals: (1) a high fidelity,
differential Laplacian signal by combining the differences between outer ring and middle ring; and (2) a conventional EEG signal from the outer ring alone [8].

The distinctive TCRE design enables high-fidelity EEG recording that is an appreciable improvement over conventional disc electrodes. When taking bipolar differences from the closely spaced elements of the TCRE sensors, noise that is common to each element is automatically attenuated.

![TCRE medical interface](image)

Figure 1.2. tEEG Interface

The TCRE is directionally independent to global sources and highly focused on local activity due to its concentric configuration, which attenuates distant radial signals and artifacts by 100 dB one radius from the electrode [9] – thus common artifacts such as muscle and ECG are attenuated in the recording [10]. The tEEG Interface (Fig. 2) configures the electrode elements, routes, and preamplifies the signals. The differentials from the TCRE rings are on the order of a few hundred nanovolts, one-to-two orders of magnitude smaller than EEG. To record nanovolt range signals is technically challenging. A complete tEEG system consists of the TCRE, tEEG Interface, and amplifier-digitizer.
1.3 Methodology

Although the traditional signal processing algorithms have been able to perform functional mapping using ECoG signals, CNNs have been revolutionizing processing and decoding of brain signals. Deep learning techniques are more effective in uncovering hidden patterns and extracting features from large datasets. They have been used with EEG for several lines of study including: cognitive load classification [11], P300 detection with an application to brain-computer interfaces [12], driver's cognitive performance [13], recognition of rhythm stimuli [14], prediction of memory performance (remembered or forgotten) [15], classification of motor imagery signals [16], simultaneous capturing of spectral, temporal, and spatial information for automatic seizure detection [17], automated screening of depression [18], seizure prediction [19], classification of one-trial EEG in a rapid serial visual presentation (RSVP) task [20], and seizure detection in an ambulatory setting [21].

A CNN is a multilayer perceptron that consists of an input layer, an output layer, and many hidden layers between the input and output layers. All weights in all layers are learned through training and a CNN learns to extract its own features automatically [22]. The hidden layers perform three important operations: convolution, activation, and pooling. The three operations are repeated over various layers, where each layer learns to identify distinct
features from the data. After feature learning, a CNN architecture performs classification.

1.3.1 Data Acquisition

We had healthy right-handed and left-handed participants perform overt/covert picture naming for functional cortical mapping, similar to the methods in [4] [23]. First, we recorded 5 min of baseline. Then participants were requested to name, randomly, aloud and silently, a series of line drawings of common inanimate and animate objects displayed on an electronic monitor [4]. The pictures were shown for 3,500 ms each, with 2,500 ms inter stimulus interval, repeatedly for 10 min (100 stimulations, 50 each overt and covert) [4]. Covert naming, without vocalization, was used to delineate between cognitive and motor aspects of expressive language. Four sets of five 10 mm TCRE arrays were placed on the participant's scalp at left anterior, right anterior, left temporoposterior, and right temporoposterior, as illustrated in Fig. 3. The anterior arrays are approximately over Broca’s area associated with verbal expression. The temporoposterior arrays are approximately over the Wernicke’s area associated with verbal understanding. Further, for a comparison study between tEEG and traditional EEG, we recorded from the outer ring of the TCREs concurrently. We randomly performed the tEEG or EEG experiments and analyzed the signals for localization and lateralization using both tEEG and EEG. There were 20 tEEG and 20 eEEG channels and two channels used to acquire eye movement and blink artifact information. The acquired data were
amplified, digitized at 1000 Hz, and hardware band-pass filtered at 1–500 Hz. Data acquisition took approximately 10 minutes. Audio was also recorded for specific onset and offset times of overt speech.

Figure 1.3. TCRE location (4 sets of 5 arrays)

2.3.2 Signal Processing

The primary data analysis technique we employed was CNN. We fed the raw tEEG data into different CNN algorithms. We used maximum pooling layers and ReLU (Rectified Exponential Linear Unity) for activation layers. We used three different input formulations: (a) raw tEEG time-series, where the 2-dimensional (2D) input data array have different channels along one dimension and different time instances along the other dimension; (b) energy in time-series, where the 2-dimensional (2D) input data array have different channels along one dimension and different energy values along the other dimension; and (c)
spectrograms. All input formulations were stored into image format and two-dimensional convolution operation was implemented using the Deep Learning Toolbox in MATLAB.

The first operation performed on the input array (spectrogram or 2D tEEG data) is convolution with K different filters of size $F \times F$ [22]. The number of feature maps or the depth of the resulting convolution and activation layers is equal to K. The second operation is pooling or subsampling, which reduces the width and length of the feature map but retains the depth. The third operation performed is a second convolution, which is then followed by a second activation and a second pooling. With the successive convolution, activation, and pooling, a bipyramidal effect is obtained because at each convolutional or pooling layer, the depth is increased while the length and width are reduced, compared with the corresponding previous layer [22]. There were two possible output classes corresponding to the left and right hemispheres.

The spectrogram input to a CNN was of dimensions $W \times W = 128 \times 128$ [22]. For CNNs with raw tEEG data input, the input had size $W \times L = 20 \times 128$ corresponding to 20 tEEG channels and 128 data samples. The same configuration was implemented for the EEG. The filter dimensions for the first convolutional layers was $F \times F$ [22]. We considered different values of F: 3, 10, 15, 20. The stride with which we slide the filter was set to $S = 1$. The width and height of the output of the convolutional layer was $\frac{W-F+2P}{S} + 1$, where
P is the number of zero-padding row or column on one side of the data matrix. For a stride of 1, the convolutional layer output always has dimensions equal to $W - F + 2P + 1$. In order to have the input and output of the convolution layer to have an equal width, $W$, and an equal height, $W$, we set zero-padding parameter to $P = (F - 1)/2$. This obviated the need to compute the height and width of the output of the convolutional layer and ensured that the dimensions are valid for the next layer. The task of downsampling was delegated completely to pooling layers. The output of the first convolutional layer was of size $W \times W \times K$. This output was sent through the activation function, which added non-linearities to the architecture. The activation function output was the input to the first pooling layer. Its purpose was to reduce the spatial size. It worked independently on each depth slice of dimensions $W \times W$. We use the pooling layer filter of size $2 \times 2$ with a stride of 2 along both width and height dimensions in all pooling layers. This pooling operation effectively discarded 75% of its input for every depth slice. The pooling layer did not change the depth dimension.

For all architectures that we considered, after the final pooling layer, we applied flattening as this is a necessary step before classification [22]. The flattened neurons were sent to a fully connected layer. Every neuron of the fully connected layer was connected to all other neurons at its input. The fully connected layer performed the first part of classification and yielded an output with $C$ elements, where $C$ represents the number of classes. This vector was fed to a softmax layer. The softmax function processed the input vector and mapped
the vector into a probability distribution. Each element of the output of the softmax layer was in the range \((0,1)\) and corresponded to the probability of a class. If the \(i^{th}\) input of the input vector is given by \(y_i\), then the output of the softmax layer for that element is \(\text{softmax}(y_i) = e^{y_i} / \sum_{i=1}^{C} e^{y_i}\). Hence, the \(i^{th}\) element of the output of the softmax layer is the probability of the \(i^{th}\) class. The class with the highest probability is the overall output of the network.

We labeled the right-handed patients data as left-hemisphere dominant and the left-handed patients data as right-hemisphere dominant. During the training phase with \(N\) labeled datasets \((x_n, v_n)\), \(n = 1, 2, \ldots, N\), we estimated the values of the free parameters, which are filter weights and biases and are collectively represented by the variable \(\theta\). We initialized all free parameters with random values, computed the output of each layer, and found the output probabilities for each class. We trained the network using stochastic gradient descent with momentum (SGDM) [25]. Due to the compositional form of the neural network model, the gradient descent was easily evaluated using the chain rule of differentiation. The back propagation algorithm had the locality constraint, which meant that the computation performed by each neuron in the network was influenced only by the neurons that were physically connected to it. Such a locality constraint is preferred because it allows a graceful degradation in performance due to hardware errors and forms the foundation for a fault-tolerant network. Also, the locality constraint permits the use of parallel architectures, leading to efficient and fast computations [22].
Result

Table I summarizes the CNN results for a network with 5 layers and $20 \times 20$ filters. We grouped right-handed and left-handed patients' data into two separate categories. We used randomly selected 80% of the data for training and the remaining data for validation. We repeated the process 1000 times and computed the average of the results. Using raw time-series data, tEEG was able to classify the data into left and right hemispheres correctly 81% of the time and the variance over 1000 trials was found to be 0.01. When data energy and spectrograms were used as the inputs, the classification accuracy improved to 93.8% and 96.5%, respectively. A similar analysis for EEG showed an accuracy of 90.2%, 89.3%, and 57.9%, respectively, for raw signal values, energy values, and spectrograms. While classification using raw signal and energy yielded high accuracy for both tEEG and EEG, the spectrograms input resulted worse accuracy in EEG. Our results indicate that while tEEG all input formulations are approximately equivalent for EEG raw signal and energy are more favorable.

Table 1.1. CNN Results

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Accuracy, Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw signal</td>
</tr>
<tr>
<td>tEEG</td>
<td>81, 0.01</td>
</tr>
<tr>
<td>EEG</td>
<td>90.2, 0.01</td>
</tr>
</tbody>
</table>
1.4 Conclusion

Both tEEG and EEG were able to classify the language dominant hemisphere. The tEEG had the highest classification. We are not certain which hemisphere is dominant in these participants. In general, the right-handed people exhibit left hemisphere language dominance and vice versa for left-handed people.

ACKNOWLEDGEMENT

The data collection involving human subjects was approved by the Institutional Review Board with assistance from Boston Children's Hospital.

List of references


Deep Learning-Based Classification of Finger Movements using tEEG and EEG Signals

Thao Pham¹, Kaushallya Adhikari¹, and Walter G. Besio¹

¹ Electrical, Computer and Biomedical Engineering. University of Rhode Island, Kingston, RI, USA

Manuscript is currently submitted to IEEE World AI IoT Congress 2023
2.1 Abstract

Mapping electroencephalography (EEG) signals obtained during hand and finger movements to left or right hands has applications in many fields including motor imagery brain-computer interface (MI-BCI) systems. MI-BCI systems are innovative technology to assist patients with severe motor impairments, however, novice users can face the “BCI-illiteracy” issue and fail to control the system. A step towards assisting such patients is to correctly classify their EEG signals collected while the patients imagine or perform hand/finger movements. This work considers using the tripolar electroencephalography (tEEG) instead of the traditional EEG due to higher signal-to-noise (SNR), better spatial resolution, better artifact noise rejection feature, and ability to capture high-frequency features of tEEG, compared to conventional EEG. In this paper, we compare the performance of tEEG and EEG signals in classifying motor imagery (MI) of right and left index fingers by using a deep learning algorithm: convolutional neural network (CNN). The results show that in 5 out of 7 subjects, CNN is able to perform classification with high accuracy, with the highest accuracy being 96.4% for tEEG data. Keywords—EEG, t-EEG, Deep Learning, CNN

2.2 Introduction

Motor imagery brain-computer interface (MI-BCI) is a promising communication and control system to replace the interconnected feature
between the brain and external environment. The system captures the brain activity patterns associated with imaginary movement and converts them into commands to control assistive devices. The technology brings new prospects which allow individuals with severe motor impairments (stroke, ALS, SCI, etc.) to control the external devices by their brain signals. Researchers and scientists have been extensively investigating to improve the performance of such systems. With MI-BCI systems, scientists have successfully detected different hand movements [1]–[3], different fingers movement of the same hand [4], [5], wrist movements of different hands [6], and upper limb movements [7], [8]. Different bio-signals have been used as the input to control the MI-BCI systems such as electrocorticogram (ECoG) [5], functional near-infrared spectroscopy (fNIRS) [2], electromyography (EMG) [8], but the most commonly used input type is EEG signals. EEG signals are prevalent as the input for the MI-BCI systems because of EEG signals have high temporal resolution and relatively low cost. However, the EEG signals have some drawbacks. Recorded EEG signals are non-stationary and suffer from low SNR and poor spatial resolution [9]. Also, EEG signals often suffer from artifact contamination which affects functional cortical localization. There are software filtering solutions [10] that are designed to improve the signal quality, but the outputs of these filters can include distortion. Therefore, we propose using tripolar EEG (tEEG). tEEG signals are known to have high SNR and spatial resolution. They are also able to capture high frequency activities that are not observed in traditional EEG.
Also, tEEG signals have significantly higher ability to reject muscle artifact effect [11]–[13].

MI-BCI systems traditionally use common spatial patterns (CSP) as primary signal processing method to extract features and linear discriminant analysis (LDA) or support vector machine (SVM) as primary machine learning algorithm for classification [3], [14], [15]. However, it has been shown that fifteen to thirty percent of MI-BCI users have the “BCI-illiteracy” issue, which means that they cannot reach the acceptable threshold accuracy of 70%, even after extensive training [1]. Thus, it is necessary to improve the accuracy to ensure that the MI-BCI users can perform assigned tasks precisely. Artificial neural network based algorithms and especially, convolutional neural networks (CNNs) have shown tremendous ability to perform classification in biomedical fields such as breast cancer diagnoses, tissue extraction, tumor detection and classification [16]. In neuroscience, EEG and CNNs have been used to detect P300 with BCI [17], detect abnormalities such as arrhythmia [18] and seizure [19]. In our previous work [20], we demonstrated the ability of CNN in determining language dominant hemisphere by using tEEG signal. Specifically with MI-BCI, researchers have shown CNN’s ability in significantly increasing classification accuracy by 15.32% to 18.38% compared with traditional machine learning approaches and helping BCI-illiteracy users improve their performance [3], [21].

In this paper, we propose promising solutions to improve the training accuracy with a focus on improving the input signal quality in the MI cognitive
tasks. To prove the feasibility of the tEEG in MI, this study aims to exploit the advantages of tEEG signals in classifying MI of index fingers. To accomplish this, we developed a high-spatial resolution tEEG system to recorded both EEG and tEEG data, we implemented CNN, to incorporate and process the expanded signal features provide by tEEG. In the future, after proving feasibility, we would like to expand the system to full MI-BCI model, in which participants can first train the BCI system and then perform the assistive applications.

The rest of the paper is organized as follows. Section II describes the methodology, including tEEG innovation, data acquisition, and signal processing. Section III presents our results, and Section IV provides conclusions.

2.3 Methodology

To compare the performance between tEEG and EEG in MI classification, data signals were collected from healthy subjects while they were performing MI tasks. Thereon, both signal type recorded data went through the same signal processing and fed into the CNN algorithm. This section described tEEG innovation, data acquisition, signal processing procedures, and deep learning CNN.

2.3.1 tEEG Innovation

Similar to the conventional EEG, tEEG measures and records the electrical brain activity. However, a conventional EEG consists of a disc electrode as
depicted in Fig. 1a whereas tEEG consists of a tripolar concentric ring electrode (TCRE) instead of the conventional disc electrode. The TCRE has three concentric rings: center, middle, and outer. The TCRE technology is based on the application of surface Laplacian algorithm. It includes three concentric rings in a bullseye configuration as illustrated in Fig. 1a. Each ring in the TCRE configuration operates as a single EEG electrode. One difference signal is obtained by subtracting the center disc signal from the middle ring signal. A second difference signal is obtained by subtracting the center disc signal from the outer ring signal. The final tEEG signal is the differential Laplacian signal that combines the two differences [22]. Because of the concentric structure, the amplitudes of distant radial signals and artifacts are approximately equal. Consequently, the amplitudes of radial signals and artifacts in tEEG can be attenuated by 100 dB [23]. Therefore, artifacts result from sources such as muscle artifacts and ECG are diminished in tEEG.

Another reason that tEEG outperforms EEG is the tEEG interface, which is illustrated in Fig. 1b. The purpose of the tEEG interface is to configure the TCRE rings, then direct and amplify the measured signals. The differential signals that are received from the TCRE rings are less than 1 microVolt. Therefore, the ability to record from the TCRE is a technical innovation. A complete tEEG system includes both the TCRE leads and the tEEG interfaces.

In this work, we place EEG electrodes near tEEG electrodes so as to obtain both EEG and tEEG signals for comparison.
2.3.2 Data Acquisition

We recruited 7 healthy subjects for tEEG and EEG data acquisition. There were 4 female and 3 male participants. All participants were novices in BCI and MI tasks. Two of the participants were left-handed and five participants were right-handed. The signals were recorded at the Neural Rehabilitation Engineering Laboratory at University of Rhode Island. Brain signals were recorded using a Brain Amp amplifier (Brain Products, Germany), a tInterf20 (CREmedical, USA), 8 TCRE leads (CREmedical) and 8 traditional EEG electrodes. Electrodes were placed according to the 10-20 system, focusing on primary motor cortex and medial premotor cortex as illustrated in Fig. 2. The primary motor cortex includes the labels C3, C1, Cz, C2, and C4 in Fig. 2 while the medial premotor cortex includes FC2, FCz, and FC1 in the figure. Before placing electrodes on participants’ scalp, conductive paste was applied to
ensure that the impedance of the electrodes was under 10 kOhm for all subjects.
The sampling frequency was 2500 samples/second.

Figure 2.2. Electrode Montage
(Primary motor cortex in red and medial premotor cortex in blue)

During each recording session, subjects were shown a finger on a screen at a specified time. They were requested to either physically move their corresponding finger or imagine moving their corresponding finger. The subjects were shown a total of 500 fingers on the screen. Each of the 10 fingers was shown exactly 50 times. There were 250 physical movements and 250 imaginary movements. The order of the physical and imaginary movements was randomized using the function randi in MATLAB. In the first phase of data acquisition, 1 minute of subject’s baseline data were recorded while the subject had both eyes closed. Then, 1 minute of baseline data were collected while the subject had both eyes open. After baseline data recording, subjects were
directed to follow the instructions on a monitor. Four types of instructions were shown to the subjects:

1) Physical/imaginary: This instruction indicated whether the subjects were to make physical or imaginary movements for the following 10 finger movements.

2) Get ready: This instruction showed a picture of all 10 fingers with a red arrow pointing to only one of the 10 fingers. The subjects were instructed to get ready to move their corresponding finger. The finger order was decided by randomly shuffling a pool of 10 fingers using the `randperm` function in MATLAB.

3) Action: This instruction consisted of green screen. After noticing this instruction, the subjects were expected to move the finger that was determined during the “Get ready” instruction. The subjects either physically moved the finger or imagined moving the finger after instruction.

4) Rest: This instruction consisted of black screen. The subjects were expected to relax their fingers after noticing this instruction.

The total recording session was split into 50 cycles or trials. In each trial, the first 5 seconds were used for physical/imaginary instruction. Each “Get ready”, “Action”, and “Rest” instructions were 2 seconds longs, as illustrated in Fig. 3. During each session, 6 breaks were included to maintain participants’ concentration.
2.3.3 Signal Processing

All signals were passed through a digital notch filter with a stop band of 58-62 Hz to remove the 60 Hz noise from power lines. All signals were also passed through a digital 0.5-110 Hz bandpass filter to remove DC noise and high frequency noise [11].

A 1.2 s epoch of data corresponding to MI of the index fingers was extracted from each trial starting from t=2 s and ending at t=3.2 s to avoid the vision cue visual response. Figures 4, 5, 6, and 7 illustrate the recorded tEEG signals in time and frequency domain. Although there were 8 tEEG channels, we only illustrate channel 1 data which correspond to C3 region in Fig. 2. The left columns in Fig. 4, 5, 6, and 7 correspond to the tEEG data collected during left finger movements while the right columns correspond to the tEEG data collected during the right finger movements. The first, second, third, fourth, and fifth rows correspond to little finger, ring finger, middle finger, index finger, and
thumb, respectively. Fig. 4 and Fig. 5 plot the signals in time domain while Fig. 6 and Fig. 7 plot the signals in frequency domain. The solid black lines in Fig. 4, 5, 6, and 7 are average values in each case. Fig. 4 and Fig. 6 correspond to the physical movement data while Fig. 5 and Fig. 7 correspond to the imaginary movement data. There are 22 epochs in the imaginary case and 27 epochs in the physical case. Manual classification of signals into left hand movement and right hand movement by observing the signals in either time domain or frequency domain is challenging. We resort to using an artificial neural network for this classification.

CNNs have been widely implemented in classifying images into different classes. To analyze the tEEG and EEG data using a CNN, we converted our data to images. We applied the CNN classification algorithm to only imaginary data. In this work, we only used C3 (channel 1, C3 tEEG and channel 2, C3 EEG) and FC2 (channel 15, FC2 tEEG and channel 16, FC2 EEG) signals. To prepare each channel data for CNN, we evaluated the spectrograms of all extracted data epochs. These imaginary action spectrograms were denoted as $P_{i\text{-spec}}$, where $i$ ranged from 1 to 22. We also computed the spectrograms of the rest periods which corresponded to the time segment from $t=0$ s to $t=1.2$ s. The rest period periodograms were averaged and the average was denoted as $P_{\text{rest-avg}}$. The action and average rest periodograms were evaluated for both right and left index fingers for each of 16 channels. We then computed the final data matrix as
\[ R_i = P_{i-spec} - P_{rest-avg} \]  

(1)

which is the modified imaginary action periodogram. These periodograms were converted into images and fed into a CNN.

Figure 2.4. Time-domain Channel 1 Data Corresponding to Physical Movement. 
(The left and right columns represent the data associated with left and right fingers, respectively. The rows from top to bottom correspond to little finger, ring finger, middle finger, index finger, and thumb)
Figure 2.5. Time-domain Channel 1 Data Corresponding to Imaginary Movement. (The left and right columns represent the data associated with left and right fingers, respectively. The rows from top to bottom correspond to little finger, ring finger, middle finger, index finger, and thumb)
Figure 2.6. Frequency-domain Channel 1 Data Corresponding to Physical Movement. (The left and right columns represent the data associated with left and right fingers, respectively. The rows from top to bottom correspond to little finger, ring finger, middle finger, index finger, and thumb)
Figure 2.7. Frequency-domain Channel 1 Data Corresponding to Imaginary Movement. (The left and right columns represent the data associated with left and right fingers, respectively. The rows from top to bottom correspond to little finger, ring finger, middle finger, index finger, and thumb)

2.3.4 Deep Learning

CNN is an artificial neural network which can have many layers for deep learning from data. It has the ability of detecting the hidden patterns in input data such as medical images, audio signals, etc. A CNN has one input layer,
customizable hidden layers, and one output layer. The hidden K layers in a CNN can be further categorized into two types:

1. feature learning layers
2. classification layers.

These layers are shown in Fig. 8. This CNN architecture was previously used in [20], [24]. When the number of hidden layers is more than 2, a CNN is called a deep network. The feature learning layers in our CNN have three types of layers. They are:

1. convolutional layer
2. activation layer
3. pooling layer.

![Figure 2.8 CNN Architecture](image)

The convolutional layers in a CNN consist of weights and biases. The weights and biases are assigned initial values. These values are then learned
and updated during the training phase using labeled data. The prime operation involved in a CNN algorithm is convolution which is given as

\[ (i, j) = (K \ast I)(i, j) = \sum \sum I(i - m, j - n)K(m, n) \]  

where \( I(i, j) \) is the input to a convolution function, \( K(i, j) \) is the filter impulse response, and \( S(i, j) \) is the convolution output. The operation is performed by a multidimensional filter which is a linear time-invariant system. The elements of the matrix \( K \) are also called filter weights. These filter weights are the values learned during the training phase. The matrix \( K \) is also referred to as the filter kernel. In this work, CNN was implemented using Deep Learning Toolbox in MATLAB. All input data matrices, i.e. spectrogram matrices \( S(i, j) \), were stored in the \( 129 \times 7 \) grayscale image format and fed into CNN. For feature learning layers, our network architecture used and repeated the three types of layers. The layers in sequence were:

1. Convolutional Layer 1
2. Activation Layer 1
3. Pooling Layer 1
4. Convolutional Layer 2
5. Activation Layer 2
6. Pooling Layer 2
7. Convolutional Layer 3
Convolution layers characterized by the filters’ sizes and numbers, were used to highlight different data features with the corresponding filter kernels. The network first performed the convolution between the input layer $I$ and the first kernel $K$ with size $m \times n$ with Convolutional Layer 1. We used 32 filters of size $50 \times 2$ in the first layer. Convolutional Layer 1 converted the size of the neurons from $129 \times 7$ to $129 \times 7 \times 50$.

The output of Convolutional Layer 1 was applied to Activation Layer 1. We used rectified exponential linear unity (ReLU) as the activation function in this work. The purpose of the activation function is to add non-linearity in the algorithm. For any variable $x$, the ReLU function is computed as $R(x) = \max(0, x)$. Activation Layer 1 does not change the size of the neurons. The first ReLU activation layer was followed by Pooling Layer 1. Max, sum, and average pooling functions are commonly employed in a CNN. We used max pooling functions in this work. Max pooling layers reduce the number of neurons by the maximum operation. We used the pooling function to reduce each $2 \times 2$ matrix of neurons to 1 neuron. As shown in Fig. 8, the pooling layer works independently on each depth slice. Thus, the output of Pooling Layer 1 was of size $64 \times 4 \times 50$. The pooling layer was followed by Convolutional Layer 2, which consisted of 64 filters. The output neurons were of size $64 \times 4 \times 64$. The second
convolutional layer was then followed by Activation Layer 2 and Pooling Layer 2. The output neurons of Pooling Layer were of size $32 \times 2 \times 64$. The second max pooling layer was followed by Convolutional Layer 3 consisting of 128 filters, which converted the size of the neurons to $32 \times 2 \times 128$. Convolutional Layer 3 was followed by Activation Layer 3, and Pooling Layer 3. The outputs of the third pooling layer were of size $16 \times 1 \times 128$. These neurons were fed to the classification layers. Since as the neurons passed through the hidden layers, their length and width were reduced while the depth was increased, the neurons progressively acquired a bipyramidal structure.

The classification layer consisted of a flattening layer, a fully connected layer, and a softmax layer as illustrated in Fig. 8. The flattening layer converted the output of the final pooling layer to a vector. The vector was then sent to the fully connected layer to combine all the extracted features that were learned from the preceding layers to identify the larger patterns. We classified the data into 2 classes, which were right index and left index MI. Softmax normalized the output from fully connected layer and evaluated the probabilities of the two classes for each input data set. Each output element of the softmax layer corresponds to probability of a class, which is computed as

$$softmax(y_i) = e^{y_i} / \sum_{i=1}^{C} e^{y_i}$$  \hspace{1cm} (3)
where $y_i$ is the $i$th element at the input of the softmax layer and $C$ is the number of classes. The class with the highest probability in the output of the softmax layer is deemed the correct class [26].

### 2.4 Result

Fig. 9 shows the average training accuracies of finger classification by employing the CNN algorithm. We labeled 2 classification classes as the right and left index finger MI. For each training trials, we used randomly selected 50% of the data for training and the remaining data for validation. The CNN algorithm was able to classify right and left index movements in 5 out of 7 novice subjects. Two subjects failed to reach the 70% of accuracy, which can be attributed to having corrupted data. The classification was performed using signals captured by electrodes located at C3 and FC2. For each set of data, the training process was repeated 50 times and the average of the training accuracies was computed. For all valid subjects, the training accuracies from tEEG is higher than EEG. The highest accuracy achieved with tEEG and EEG signals were 96.94% and 94.94%, respectively.
Figure 2.9. Training Classification Accuracy of Channels C3 and FC2. (*Solid line represents tEEG data and dot line represents EEG data and red line indicates C3 electrode while purple line indicates FC2 electrode.*)

TABLE I shows the mean training accuracies of all 5 validation subjects using tEEG and EEG signal as an input. The classifying accuracies reached an average of 86.69% with standard deviation SD=7.3 with tEEG signals and 81.77% with SD=6.89 for EEG signals. A paired sample t-test with a significant level alpha=0.05 was also used to compare the mean accuracies of tEEG and EEG. The purpose of the test was to determine whether there was statistical evidence that the average tEEG accuracy and the average EEG accuracy were different [27]. The test resulted in the p-value of 0.004046. Since the p-value is less than 0.05, we can conclude that the training accuracy from using tEEG signals was statistically greater than the accuracy of EEG signals.
Table 2.1 Training Accuracy Result for MI Index Finger

<table>
<thead>
<tr>
<th>Signal type</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>tEEG</td>
<td>10</td>
<td>86.69</td>
<td>7.30</td>
</tr>
<tr>
<td>EEG</td>
<td>10</td>
<td>81.77</td>
<td>6.90</td>
</tr>
</tbody>
</table>

2.5 Conclusion

tEEG and EEG data were acquired from healthy participants. The spectrograms of the data epochs corresponding to imaginary index finger movements were computed. The spectrograms for the data epochs acquired during the rest phase were also computed and averaged across many trials. The average rest phase spectrograms were subtracted from the imaginary movement spectrograms and used as CNN inputs. The CNN with 3 convolutional layers, 3 ReLU activation layers, and 3 max pooling layers were able to classify the tEEG and EEG signals into left and right fingers. The average accuracy obtained with tEEG was significantly higher than the average accuracy with EEG.

List of Preferences


BIBLIOGRAPHY


S. Haykin, Neural Networks and Learning Machines, Pearson.


N. Robinson, K. P. Thomas, and A. P. Vinod, “Neurophysiological predictors and spectro-spatial discriminative features for enhancing SMR-BCI,” J


52