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# Board 143: Work in Progress: Mind and Computer: Integration of Brain-Computer Interfaces in Engineering Curricula

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# Mind and Computer: Integration of Brain-Computer Interfaces in Engineering Curricula

## Abstract

Non-invasive Brain-computer Interface (BCI) is a new science that detects patterns in the human brain's signals and leverages these neurological responses for various applications. The first application of BCI was in the medical field to support individuals with disabilities, enable them to communicate, operate computers, and utilize assistive devices like wheelchairs and robotic arms. However, nowadays, the BCI technology and its application have been extended to different fields such as education, entertainment and gaming, and robotics. BCI, an emerging interdisciplinary field, offers many exciting research opportunities and holds the promise of creating numerous job prospects in the future. Therefore, it is necessary to add this topic to the curriculum of universities to educate the next generations of students.

Integrating BCI courses into engineering curricula offers a range of advantages, benefiting both students and the engineering field. BCI courses will provide opportunities for students to explore interdisciplinary avenues, fostering collaboration between fields such as mechanical engineering, computer engineering, psychology, and neuroscience. Due to the nature of the BCI topic, projects with hands-on experiences could be designed to facilitate practical, experiential learning that will engage students and leave a lasting impact. Students will be exposed to cutting-edge technology and research areas through BCI courses which will ignite innovation and encourage them to contribute to the evolving field of neuro-engineering. Moreover, the next generation of technologies will follow the user-centric design as there is more emphasis on human needs interacting with technology, so BCI courses will be aligned with modern engineering practices, which will open doors to diverse career opportunities in gaming, assistive technologies, healthcare, robotics, and human-computer interaction.

To comply with such demand, a new course titled "Brain-Computer Interface" was developed at Lawrence Technological University (LTU) located in the state of Michigan in Spring 2024. This course integrates theory, cutting-edge simulations, hands-on experience, and working with data acquisition systems in real-time to provide students with a comprehensive understanding of BCI technology and its practical applications. The course curriculum covers the fundamentals of neural signal processing, hardware and software components, and real-world case studies. This innovative course also reflects our university's commitment to offering cutting-edge education that prepares students to meet future challenges and contribute to advancing engineering and technology. This paper will report the details of the developed course, implementation steps, and student feedback.

### 1 Introduction

Brain-computer Interface (BCI) in its non-invasive form is a new science that detects patterns in the human brain's signals and uses the result for different applications. The BCI was introduced to the research society by UCLA computer science professor Jacques Vidal in 1973 and he described BCI as "any computer-based system that produces detailed information on brain function" [1]. BCI is also defined as "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 environment" by Jonathan Wolpaw [2]. The primary motivation for BCIs is their potential to restore lost sensory and motor function prosthetic devices, however, there are some other applications for these systems.

BCI systems could be designed using several brain technologies in three forms invasive (i.e., brain signals get collected from electrodes inserted into brain tissue, this requires surgical procedure), semi-invasive (i.e., brain signals get collected from electrodes inserted within the skull but not brain tissue, this requires surgical procedure), and non-invasive (i.e., brain signals get collected from electrodes placed on the scalp without any need to a surgical procedure). One of the well-known examples of invasive BCI is the chip implementation in a patient's brain by Neuralink to restore independence and improve lives [3]. Electrocorticography (ECoG) is considered a semi-invasive technology that is less invasive than fully implanted electrodes used in invasive BCIs [4]. Non-invasive technologies are the most common electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS). EEG-based BCI systems are growing rapidly with various applications, including game interaction, robot control [5], improving the quality of human-robot interaction [6], clinical trials [7], emotion detection [8], fatigue recognition [9], and sleep quality monitoring [10].

The EEG-based BCI cycle encompasses multiple stages as shown in Figure 1. A BCI cycle starts with data acquisition, followed by pre-processing, feature extraction, and then the decoding step. This research area is inherently multidisciplinary, uniting experts from various fields such as computer science, electrical engineering, psychology, neuroscience, and human-computer interaction. Therefore, BCI offers many exciting research opportunities and holds the promise of creating numerous job prospects in the future. It is necessary to add this topic to the curriculum of universities to educate the next generations of students. To address this need, a new course titled

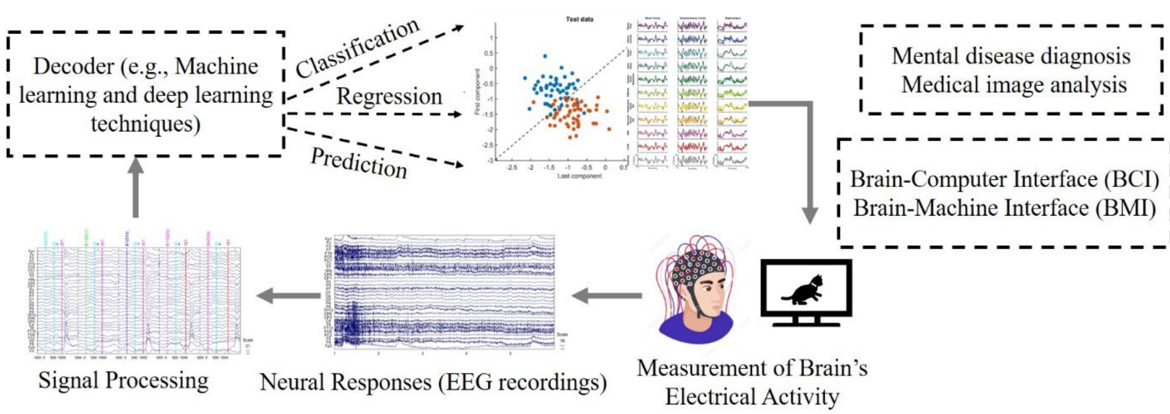


**Figure 1: BCI cycle and neural decoding process.**

“Brain-Computer Interface” was designed and developed for the first time in the Mechanical, Robotics, and Industrial Engineering (MRIE) Department at Lawrence Technological University (LTU) in the state of Michigan. Despite being offered within the MRIE Department, there is also a collaboration with the Humanities, Social Sciences, and Communication Department from the College of Arts and Science to improve the quality of this course and introduce new perspectives of this field to engineering students.

## 2 Course Structure and Organization

This three-credit hour course is designed for students studying robotics engineering or mechanical engineering at the senior or graduate levels. However, there are currently no prerequisites and any senior or graduate student in the College of Engineering is welcome to enroll. It is expected that prerequisite coursework will be added in the future. The first offering of this course is in Spring 2024.

The student population at this university is a mix of traditional, commuter, and international students. Undergraduate demographics differ by program but are mostly traditional domestic students with a few nontraditional domestic students. By senior year, most students are working at least part-time. Graduate students are split between domestic students who are working full-time and international students who may have part-time jobs. Due to the high number of students working at least part-time, graduate-level courses within the MRIE department are offered only in the evenings.

### 2.1 Course Objective

The course content explores the interesting field of BCI, covering its uses, technologies, and practical aspects. The main goal is to help students understand the basics of BCI and how it's applied in different areas. Within the realm of BCI, the course focuses on non-invasive methods and EEG signals, in particular. At the end of this course, students will:

- Understand the concept and significance of BCI in modern science and technology.
- Recognize various brain technologies pivotal in designing BCI systems.
- Grasp the fundamentals and applications of EEG signals.
- Acquire skills in preprocessing EEG signals using MATLAB and EEGLAB.
- Apply machine learning algorithms to analyze preprocessed EEG data.

### 2.2 Learning Outcomes

Upon completing this course, students will be able to:

- Define BCI and articulate its relevance and potential impacts across different fields.
- Identify key technologies and methodologies used in the creation of BCI systems, with a focus on non-invasive approaches.
- Describe EEG signals, including their characteristics and importance in BCI.
- Perform preprocessing tasks on EEG signals utilizing MATLAB and EEGLAB to prepare the data for further analysis.

- Implement machine learning techniques on EEG data to extract meaningful insights, demonstrating an understanding of how these algorithms can be applied in BCI contexts.

## 2.3 Course Organization

The course organization is structured around the themes of Neuroscience, Data Analysis, and EEG-based BCI Hardware. The sessions are held two days per week during the 16-week semester. This course is a combination of lectures, working with software, and hardware. The class size is 6 students and as a new course offered as elective credit, enrollment was low. Table 1 summarizes the course schedule for 16 weeks.

**Table 1: Course Schedule**

| Week | Class period 1 | Class period 2 | Major topic |
|---|---|---|---|
| 1 | Class introduction | Introduction to BCI | Introduction and Neuroscience Concept |
| 2 | Intro to different types of BCI | Different types of brain technologies | Introduction and Neuroscience Concept |
| 3 | Guest speaker | Introduction to EEG signals | Introduction and Neuroscience Concept |
| 4 | Introduction to EEG signals | Artifacts in EEG | Introduction and Neuroscience Concept |
| 5 | Analysis techniques for EEG signals | Recording, participants, and task in EEG | Introduction and Neuroscience Concept |
| 6 | Signal processing for EEG | Students' reading assignment presentation | Data Analysis |
| 7 | Feature extraction for EEG | Feature extraction for EEG | Data Analysis |
| 8 | Signal processing in MATLAB | Signal processing in MATLAB | Data Analysis |
| 9 | Signal Processing in EEG Lab | Signal Processing in EEG Lab | Data Analysis |
| 10 | Introduction to the g.tec cap | Setting up the g.tec cap | Hardware |
| 11 | Data collection with the g.tec cap | Data collection with the g.tec cap | Hardware |
| 12 | Data collection and signal processing | Data collection and signal processing | Hardware |
| 13 | Machine learning for EEG-based BCI | Machine learning for EEG-based BCI | Data Analysis |
| 14 | Machine learning for EEG-based BCI | Machine learning for EEG-based BCI | Data Analysis |
| 15 | Ethics in BCI | Ethics in BCI | Summary Sessions |
| 16 | Student's project presentation | Student's project presentation | Presentation |

### 2.3.1 Neuroscience Concept

The first portion of the course focuses on an introduction to BCI and the underlying neuroscience. This includes the definition of BCI, various neurotechnology devices used in implementing BCI systems, different categorizations for BCI systems, and some basic neuroscience principles. Also, to enhance student engagement with the neuroscience aspects of the course, a guest lecturer from the Humanities, Social Sciences, and Communication department was invited to the class. The guest lecturer, whose research focuses on language and cognition, covered the following topics:

- The complexity of cognition

- Cognitive experiments
- Levels of analysis in cognitive science
- Cognitive neuroscience
- Building blocks of the nervous system
- Mechanisms of neuronal communication
- Neuropsychology
- Brain stimulation techniques, including Transcranial Magnetic Stimulation (TMS) and Transcranial Direct Current Stimulation (tDCS)

Students will also have the opportunity to visit the Cognitive Cognition Lab, housed within the Humanities, Social Sciences, and Communication Department's department. During this visit, they will witness a demonstration of a tDCS device and have the opportunity to work with it.

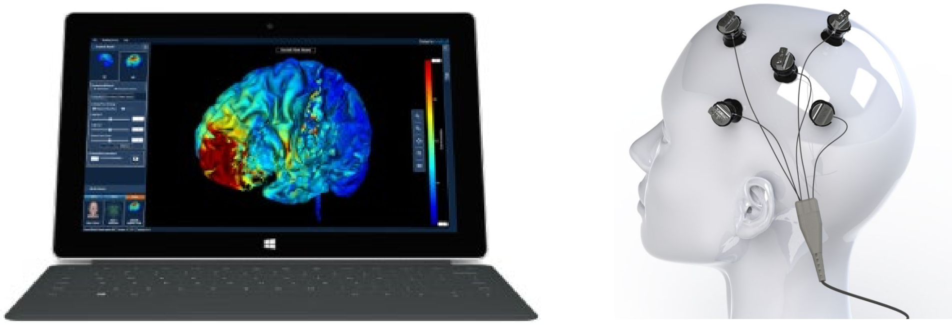

**Figure 2: Transcranial direct current stimulation**

### 2.3.2 Data Analysis

Data analysis plays a pivotal role in BCI systems by extracting meaningful insights from neural signals, enabling accurate interpretation of user intentions or mental states. It aids in improving the performance and reliability of BCI systems through signal processing techniques, feature extraction, and classification algorithms, ultimately enhancing user experience and facilitating the development of diverse applications, from assistive technologies to neurofeedback training.

The second portion of the course concerns data analysis using EEG signals. Data analysis includes preprocessing of EEG data, feature extraction, and application of machine learning to find patterns. Preprocessing EEG data is a crucial step in the process of designing a BCI cycle and experiment. Several sessions in this class are allocated to explain various data preprocessing steps such as importing data, removing bad channels, filtering, down-sampling, re-referencing, artifact detection, artifact rejection/correction, baseline correction, and epoching. Moreover, some feature extraction techniques are elaborated in the class. Two data preprocessing and visualization tools available for EEG analysis, EEGLAB [11] and MNE Python [12], are introduced to the students for hands-on practice of the discussed techniques. However, students practice applying only EEGLAB software tools due to limitations in time using a publicly available EEG dataset. Additional information about MNE Python will be provided for students who are interested in exploring this software more.

The data analysis section is not limited to the data preprocessing and feature extraction. After feature extraction, machine learning and deep learning algorithms are applied to find patterns in data with classification, regression, or prediction [13], [14]. Therefore, students are provided with lectures about the fundamentals of machine learning and how to apply traditional machine learning algorithms to the preprocessed data.

### 2.3.3 Hardware

The last portion of the course deals with the hardware used to capture EEG signals in humans. EEG data acquisition caps are wearable devices designed to capture electrical signals from the brain, featuring strategically placed electrodes on the scalp for non-invasive and painless brain activity collection. Widely used in research, these caps offer insights into cognitive processes like attention and memory. Advancements have made them more affordable and user-friendly, expanding their use in research and clinical settings. Various types, including the traditional 10-20 system cap and high-density EEG cap, cater to different research needs, with electrode numbers and placements varying. Additionally, EEG headbands, with fewer electrodes, are gaining popularity for consumer applications like sleep tracking and meditation, offering a comfortable alternative to traditional caps and expanding the range of EEG technology applications.

This class utilizes the g. Nautilus Research cap, which is specifically designed for research purposes. The cap is equipped with biopotential amplifiers that can transmit data wirelessly and come with active wet or dry electrodes. With a resolution of 24 bits and a sampling rate of either 250 or 500 Hz, the device can acquire EEG data through 32 analog-to-digital converters that operate at 1.024 MHz. The user can choose their desired sampling rate. A sampling rate of 250 Hz results in an oversampling of 4096, which yields a high signal-to-noise ratio. Additionally, the device includes an internal impedance check that determines electrode-skin impedance. The g.Nautilus Research cap is controlled through a C-API and can transmit digitized EEG data to a base station that can be connected to any available USB port on a PC or notebook. Figure 3 shows a picture of the g.tec EEG cap.

**Figure 3: g. Nautilus EEG cap**

### 2.3.4 Ethics in BCI

The integration of new technologies into society inevitably introduces risks related to privacy, public health and safety, and ethical considerations. Thus, it is crucial to acknowledge and address these challenges and limitations during the development and deployment phases of new technologies. Given the dual nature of BCI technology, encompassing both invasive and non-invasive approaches across various applications, it is essential to carefully consider the myriad ethical concerns that arise. According to the literature review, various ethical issues associated with BCI technologies, are categorized under three main headings: Physical Factors, Psychological Factors, and Social Factors. Under Physical Factors, 'User Safety' is a primary concern, emphasizing the need to protect users from potential harm. Psychological Factors include 'Humanity and Personhood', reflecting concerns about how BCIs might affect an individual's sense of self, and 'Autonomy', focusing on the user's ability to make independent choices. 'Stigma and Normality' also fall under Psychological Factors, addressing societal perceptions and potential biases towards BCI users. In the realm of Social Factors, 'Privacy and Security' are highlighted, pointing to issues surrounding the protection of personal neural data. 'Research Ethics and Informed Consent' are essential considerations, ensuring that participants are fully aware of the implications of BCI research they are involved in. 'Responsibility and Regulation' pertains to determining accountability for the effects of BCI and establishing appropriate frameworks to govern its use. Lastly, 'Justice' concerns the equitable distribution and access to BCI technologies, ensuring that benefits and burdens are shared fairly among different groups in society [15]- [16].

Since the beginning of the course, there have been initial discussions with students about ethical concerns in BCI technologies. To explore these issues further, two lectures will be allocated specifically to discuss the ethics of BCI in greater detail and to review relevant research studies.

## 3 Student Activities

Three types of activities, including homework assignments, reading assignments, and term projects are designed in this class to provide enough exercise for the three categories of student's activities in this class.

### 3.1 HomeWorks Assignments

This course consists of different types of homework assignments which are in line with the objective of the course and the topics that are covered.

#### 3.1.1 Mini Research on Public Perception of BCI

BCI is a new technology and research has shown that the introduction of new technologies to societies could have some challenges and the public perception may not be positive towards that technology. Therefore, to familiarize students with some of the challenges of BCI technology, the public's perception of new technologies such as BCI (i.e. sci-fi movies) was discussed in the class. They were introduced to the research work of "Hollywood syndrome" which analyzes and discusses the role of the media in influencing various population's perceptions about robots. Then students were asked to do their mini-research on public perception of BCI and present it to the class. In this assignment, students were asked to:

1. Create a 10-question survey.
2. Send the survey to at least ten people that can be family or friends.
3. After data collection, organize it and provide interpretations for the data they have obtained.
4. Include the mean, median, and standard deviations (for each question) along with charts representing the gathered data.
5. Have seven Likert scale questions and three open-ended questions.

As a deliverable, they needed to submit a report in SIGCHI paper format with the following sections: 1) An abstract summarizing their mini-research that answers questions such as What did you do, how did you do it, why did you do it? 2) results section to provide graphs for each multiple-choice question's response along with a paragraph of at least 3 sentences explaining the results for each graph. 3) The conclusion section summarizing the report and their statement on how to improve society's perception of BCI and discussion on how their findings relate (or not relate) to observations mentioned in the "The Hollywood Robot Syndrome" article, and 4) appendix section to list their survey questions.

Students conducted a survey that targeted individuals aged between 18 and 50, receiving responses from 10 to 20 people on average. The survey aimed to gauge public perceptions and understanding of BCI technology through the following questions:

- "Please describe your current understanding of BCI and what you believe to be its main benefits or uses."
- "On a scale from 1 to 5, how strongly do you agree with the statement that BCI can improve the quality of life for individuals with conditions such as quadriplegia, dementia, and Parkinson's disease?"
- "What are your greatest concerns regarding BCI, based on what you know?"
- "Considering your current knowledge, how likely are you, now or in the future, to consider having a BCI device, such as Neuralink, implanted in yourself?"
- "Recent studies suggest that BCI could enhance productivity and efficiency in the workplace. Do you concur with this potential application?"

The survey revealed that many participants were not well-informed about BCI technologies and exhibited a general reluctance towards adopting BCI-based services or technologies. Notably, despite this lack of familiarity, respondents demonstrated a keen ability to recognize the application of BCI in assisting individuals with disabilities. This observation suggests a potential avenue for further research to explore the correlation between a person's disability status and their willingness to embrace BCI technologies.

### 3.1.2 Programming Assignments

Students were re assigned two homework assignments which consisted of working with the EEG lab software and programming parts [11]. In these assignments, students practiced how to:

- Inspect channel locations
- Plot channel data
- Change sampling frequency
- Detect artifacts
- Remove artifacts
- Filter data
- Epoch data
- Implement time-frequency analysis

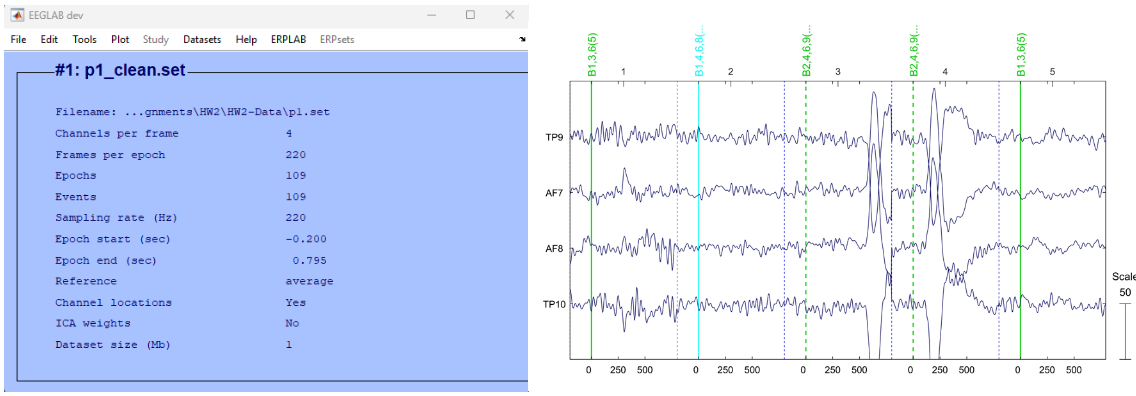


**Figure 4: EEGLAB GUI**

The first assignment required students to engage directly with the EEGLAB graphical user interface (GUI) shown in Figure 4. This task served to familiarize them with various techniques available within the software and allowed them to use the toolbox to derive necessary commands for subsequent programming tasks. The second assignment challenged students to craft their own functions using EEGLAB's built-in features. This exercise was designed to deepen their understanding of data analysis processes by requiring them to apply these functions in the analysis of EEG data.

### 3.2 Reading Assignments

The purpose of this assignment was to deepen students' understanding of BCIs by critically analyzing and presenting a research paper on a topic related to this field. Through this assignment, students had the opportunity to explore a specific aspect of BCIs in depth and develop their presentation and critical thinking skills.

Students were asked to choose one research paper from reputable journals or conference proceedings that address different aspects of BCI. The papers should have been published within the last ten years and should focus on significant developments, innovations, or challenges in the field of BCIs. They needed to 1) read the paper thoroughly, understand the research problem, methodology, results, and conclusions, and 2) prepare a presentation summarizing the paper's key points.

Students chose research papers spanning a variety of topics within BCI technology, including innovative approaches to restoring upper limb function after spinal cord injuries, compact deep learning models for silent speech interpretation, EEG data classification for mental state analysis, BCI-based soft robotic glove rehabilitation for stroke patients, BCI-generated speech for controlling home automation devices, and the use of BCI in overcoming paralysis. This selection underscored the students' fascination with the diverse applications of BCI technology, serving as evidence of BCI's multidisciplinary nature.

### 3.3 Working with Hardware

An g.tec EEG cap will be provided for students to work in groups to complete the following activities in the class:

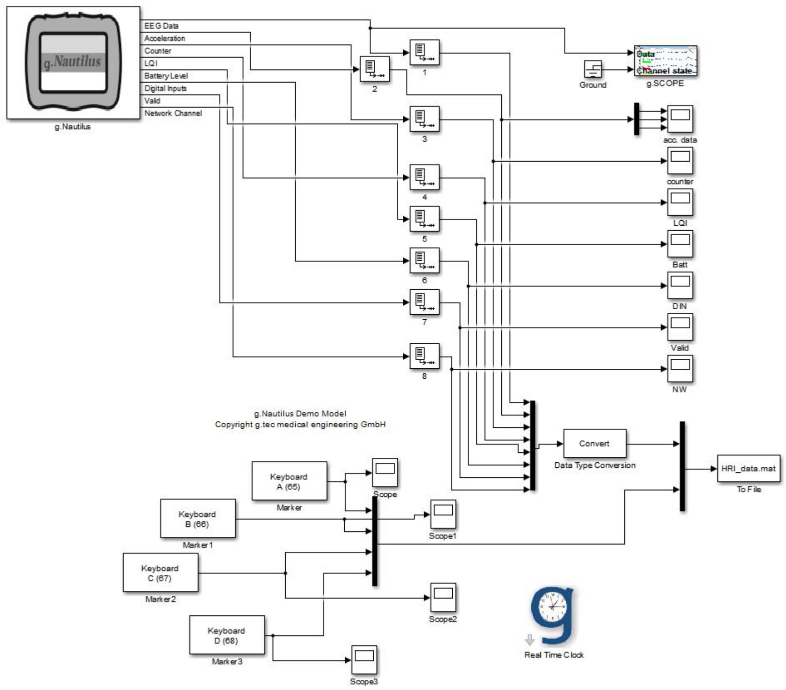


**Figure 5: Simulink file to collect EEG data and preprocess it in real-time.**

1. Set up the EEG cap
2. Establish communication between the EEG cap and desktop computer
3. Create their file in SIMULINK to stream EEG data
4. Use available tools from the g.BSanalyze, and g.Recorder software to preprocess data in real-time
5. Collect EEG data from their group members

Figure 5 depicts a sample Simulink file that students will be tasked with creating as part of their data collection and real-time data preprocessing activities, utilizing the provided cap.

### 3.4 Project

As part of this course, students were assigned a term project to provide them with an opportunity to engage in all stages of the BCI cycle for specific data and applications. Additionally, students had the option to utilize an EEG cap for data collection if they prefer to gather their data.

## 4 Course Evaluation

During the midterm evaluation, students rated the course at 4.42 out of 5, while the instructor received a score of 4.9 out of 5. These high ratings reflect the course's success and effectiveness. However, to evaluate the efficiency of the class, a survey could be administered to students at the end of class to get students' feedback for each component of the class (i.e., introduction and neuroscience, data analysis, and hardware).

## 5 Conclusion

This paper introduces the inaugural Brain-Computer Interface (BCI) course offered at Lawrence Technological University in Michigan. Tailored for both undergraduate and graduate students within the College of Engineering, the course integrates lectures, hands-on hardware experimentation, and software exploration in the realms of mechanical, robotics, and industrial engineering. Its primary aim is to offer students a fresh perspective on brain technologies while furnishing them with a diverse skill set. Through a blend of activities including mini research projects, programming tasks, software manipulation, and project work, students are guided through the various stages of BCI system design, providing them with comprehensive knowledge. The midterm evaluation demonstrated the course's effectiveness and the students' enthusiasm for it.

## References


[1] J. J. Vidal, "Toward Direct Brain-Computer Communication," *Annual Review of Biophysics and Bioengineering*, vol. 2, no. 1, pp. 157–180, 1973, doi: 10.1146/annurev.bb.02.060173.001105.

[2] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, no. 6, pp. 767–791, Jun. 2002, doi: 10.1016/S1388-2457(02)00057-3.

[3] P. Studio, "Neuralink," Neuralink. Accessed: Feb. 02, 2024. [Online]. Available: https://neuralink.com/?202308049001

[4] S. K. Mudgal, S. K. Sharma, J. Chaturvedi, and A. Sharma, "Brain computer interface advancement in neurosciences: Applications and issues," *Interdisciplinary Neurosurgery*, vol. 20, p. 100694, Jun. 2020, doi: 10.1016/j.inat.2020.100694.

[5] M. Xiong *et al.*, "A Low-Cost, Semi-Autonomous Wheelchair Controlled by Motor Imagery and Jaw Muscle Activation," in *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Oct. 2019, pp. 2180–2185. doi: 10.1109/SMC.2019.8914544.

[6] "BCI Exploration of User Responses to Vulnerable and Expressive Robot Behaviors | Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction." Accessed: Mar. 26, 2024. [Online]. Available: https://dl.acm.org/doi/abs/10.1145/3610978.3640574

[7] S. Dutta, T. Banerjee, N. D. Roy, and B. Chowdhury, "Development of a BCI-Based Application Using EEG to Assess Attentional Control," in *Proceedings of the Global AI Congress 2019*, J. K. Mandal and S. Mukhopadhyay, Eds., in Advances in Intelligent Systems and Computing. Singapore: Springer, 2020, pp. 659–670. doi: 10.1007/978-981-15-2188-1_52.

[8] E. H. Houssein, A. Hammad, and A. A. Ali, "Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review," *Neural Comput & Applic*, vol. 34, no. 15, pp. 12527–12557, Aug. 2022, doi: 10.1007/s00521-022-07292-4.

[9] P. Li *et al.*, "An EEG-based Brain Cognitive Dynamic Recognition Network for representations of brain fatigue," *Applied Soft Computing*, vol. 146, p. 110613, Oct. 2023, doi: 10.1016/j.asoc.2023.110613.

[10] X. Gu *et al.*, "EEG-Based Brain-Computer Interfaces (BCIs): A Survey of Recent Studies on Signal Sensing Technologies and Computational Intelligence Approaches and Their Applications," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 18, no. 5, pp. 1645–1666, Sep. 2021, doi: 10.1109/TCBB.2021.3052811.

[11] A. Delorme and S. Makeig, “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis,” *Journal of Neuroscience Methods*, vol. 134, no. 1, pp. 9–21, Mar. 2004, doi: 10.1016/j.jneumeth.2003.10.009.

[12] A. Gramfort *et al.*, “MEG and EEG data analysis with MNE-Python,” *Frontiers in Neuroscience*, vol. 7, 2013, Accessed: Jan. 26, 2024. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2013.00267

[13] R. Salehzadeh, B. Rivera, K. Man, N. Jalili, and F. Soylu, “EEG Decoding of Finger Numeral Configurations With Machine Learning,” *Journal of Numerical Cognition*, vol. 9, no. 1, pp. 206–221, 2023.

[14] R. Salehzadeh, F. Soylu, and N. Jalili, “A comparative study of machine learning methods for classifying ERP scalp distribution,” *Biomedical Physics & Engineering Express*, 2023, Accessed: Jan. 26, 2024. [Online]. Available: https://iopscience.iop.org/article/10.1088/2057-1976/acdbd0/meta

[15] S. Burwell, M. Sample, and E. Racine, “Ethical aspects of brain computer interfaces: a scoping review,” *BMC Med Ethics*, vol. 18, no. 1, p. 60, Nov. 2017, doi: 10.1186/s12910-017-0220-y.

[16] A. Coin, M. Mulder, and V. Dubljević, “Ethical Aspects of BCI Technology: What Is the State of the Art?,” *Philosophies*, vol. 5, no. 4, Art. no. 4, Dec. 2020, doi: 10.3390/philosophies5040031.