HHS Public Access
Author manuscript
*Conf Proc IEEE Eng Med Biol Soc*. Author manuscript; available in PMC 2018 January 22.

Published in final edited form as:
*Conf Proc IEEE Eng Med Biol Soc*. 2016 August ; 2016: 3010–3014. doi:10.1109/EMBC.2016.7591363.

# Designing a Hands-On Brain Computer Interface Laboratory Course

**Bahar Khalighinejad**,
Department of Electrical Engineering, Columbia University, New York, NY

**Laura Kathleen Long**, and
Doctoral Program in Neurobiology and Behavior, Columbia University, New York, NY

**Nima Mesgarani**
Department of Electrical Engineering, Columbia University, New York, NY

## Abstract

Devices and systems that interact with the brain have become a growing field of research and development in recent years. Engineering students are well positioned to contribute to both hardware development and signal analysis techniques in this field. However, this area has been left out of most engineering curricula. We developed an electroencephalography (EEG) based brain computer interface (BCI) laboratory course to educate students through hands-on experiments. The course is offered jointly by the Biomedical Engineering, Electrical Engineering, and Computer Science Departments of Columbia University in the City of New York and is open to senior undergraduate and graduate students. The course provides an effective introduction to the experimental design, neuroscience concepts, data analysis techniques, and technical skills required in the field of BCI.

## I. INTRODUCTION

Brain computer interface (BCI), a promising new field of neuroengineering, refers to any system that uses brain signals to control a computer or machine. Electroencephalography (EEG) provides an affordable, noninvasive measure of neural activity using scalp electrodes to measure the electrical activity of the brain [1], [2]. EEG-based BCI systems are growing rapidly; current applications include communication and control for disabled individuals [3], [4], fatigue recognition [5], and mental-state monitoring [6], [7], [8].

The critical role of laboratories in science education has been widely recognized [9], [10], [11]. Laboratory courses provide interactive environments where students are able to learn new concepts through hands-on experiments involving data acquisition, data analysis, and real-time system implementation. Considering the interdisciplinary nature of neuroengineering, it is crucial to educate a new generation of engineers with a deep understanding of how neural signals are recorded and how they encode information about various sensory, behavioral, and cognitive processes. To address this need and bridge the gap left in traditional engineering curricula, we propose a hands-on teaching laboratory.

Our teaching objectives are to expose students to biosignal measurement hardware and neural signal processing methods; teach scientific methodologies and experimental design; introduce students to BCI; and equip them with the skills required for industry and academic positions in neuroengineering. The course has been offered twice, in fall 2014 and fall 2015. It is offered jointly through the Biomedical Engineering, Electrical Engineering, and Computer Science Departments and targeted primarily to senior undergraduate and graduate students in those departments. The course is also open to students in other programs, notably including Psychology and Neurobiology and Behavior.

We created a suite of lectures, lab instructions, projects, homework, and guest lectures to cover major concepts in BCI systems with an emphasis on hands-on projects. In this paper, we describe the course structure, objectives, materials, and evaluate the course based on student feedback.

## II. OBJECTIVES AND COURSE STRUCTURE BCI

Laboratory is a 3-credit course with 35 hours of instruction offered to senior undergraduates and graduate students. The recommended prerequisites of the course are basic familiarity with signal processing and programming in MATLAB. Each experiment requires about two hours of lab work and is preceded by a thirty-minute lecture to provide background and context. Students collect data in groups of three and have open access to the lab if they want to continue working outside of class time.

Coursework consists of nine experiments and two projects. Students submit weekly lab reports and homework designed to teach concrete skills and concepts as well as two project reports designed to encourage more in-depth experiment design and analysis.

Our course learning objectives are described following:

### Experimental design [12], [13]

- Experiment design and optimization
- Data collection and quality control
- Hypothesis testing

### Neuroscience concepts [2], [14]

- Neural mechanisms of EEG
- Biological artifacts
- Event related potentials (ERP), including mismatch negativity (MMN) and P300
- Neurofeedback
- Auditory steady state response (ASSR)
- Steady state visually evoked potential (SSVEP)
- Imagined movement

### Data analysis [2], [15], [16]

- Preprocessing: epoching and noise reduction
- Finite impulse response (FIR) filtering
- Linear discriminant analysis (LDA) classification
- Fast Fourier transform (FFT) and frequency-domain processing
- Common spatial pattern (CSP) filters

### Technical skills

- Hardware setup and debugging
- MATLAB and Simulink
- EEG recording and analysis software
- Publicly available data analysis software including EEGLab [17]

## III. Hardware Configuration

Our laboratory consists of seven stations, each of which includes all equipment necessary for data collection. Students work in groups of three per station. The four main elements of each station are:

- *g. USBamp:* Biosignal amplifier made by g.tec medical engineering [18].
- *g. Gammabox:* Power supply and driver/interface box for 16 active electrodes [18].
- *EEG Cap:* Elastic cap with eighteen active electrodes, including one reference and one ground.
- *Desktop computer:* Hardware required includes monitor with refresh rate of 60 fps, speakers, and stereo headphones. Software required includes MATLAB, g.BSanalyze, and g.Recorder [19].

In each experiment, one member of the group is chosen as the subject of the experiment and wears the EEG cap; the other two members set up the hardware, apply conductive gel, and ensure a low-impedance connection between the electrodes and the scalp. During data collection, the subject sits in a chair with armrests to minimize movement artifacts. Students rotate roles each week; every student experiences being both subject and experimenter to familiarize them with the challenges involved in collecting high quality neural data and identifying the sources of noise.

## IV. BCI Hands-on Lab

The course components include lectures, lab instructions, lab reports, homework, and projects. Lab and project instructions can be found on our course website: http://naplab.ee.columbia.edu/bcilab

### A. Lectures

We begin each class session with a thirty-minute lecture to familiarize students with the underlying neuroscience and related applications in research and industry. Two lectures are dedicated to introducing students to software used in the course, specifically EEGLab and Simulink. We provide reference books [2], [14] and online resources [16] for students interested in learning more complicated concepts including independent component analysis (ICA) [20], principal component analysis (PCA) [21], and infinite impulse response (IIR) filtering [15].

A series of guest lectures were given by researchers in various related fields to expose students to interdisciplinary perspectives and applications of BCI. Guest lecturers included faculty from the music, neurology, psychiatry, and biobehavioral sciences departments. Topics included the transformation of neural patterns into music [22], applications of non-invasive neural recording to epilepsy, sleep, and schizophrenia [23], and language development in children [24].

### B. Lab Instructions

To ensure sufficient control over experimental procedure [10], we carefully prepared detailed step-by-step lab instructions for each experiment, including information about hardware configuration and software setup; experimental design and data collection; and instructions for homework assignments and lab reports [25]. For example, the neurofeedback lab instructions walked students through setting up bandpass and lowpass filters in a Simulink module to calculate and display the real-time power of the alpha and theta bands, then instructed the EEG subject to practice controlling the signal. We elicited student feedback on each document and made appropriate edits where instructions were unclear. Table 1 describes learning objectives for each experiment.

### C. Projects

We designed two projects to expose students to more in-depth data analysis. We provide detailed instructions for project reports, which follow the format of a formal scientific report consisting of an introduction, method, results, and conclusion.

In project 1, the students' main objective is to calculate event related potentials in response to an auditory oddball paradigm where the subject hears a series of standard and deviant tones. Students design the experiment, then collect, preprocess, and analyze data. They conduct individual and group-level analysis to explain the relationship between ERP components (mismatch negativity and P300), subject attention, and deviant probability. Students may rely on previous instruction to analyze their data, but are also encouraged to use any toolbox or method they find useful in improving their results.

In project 2, the students' main objectives are to use common spatial pattern (CSP) filters [16] and linear discriminant analysis (LDA) [26] to separate and classify neural signals during different imagined movements. Students collect, preprocess, and analyze their data. After finding CSP filters, they train an LDA classifier to decode single trial imagined movements and test their classifier using cross-validation. Students receive bonus points if they code their own classifier. In their reports, they are responsible for explaining their method, rationale, and results; they also propose future improvements.

### D. Lab Report

Each student group submits weekly lab reports documenting data collection, describing the experimental procedure, and answering basic conceptual questions. Lab reports require students to take notes during the experiment and carefully document their procedures and results in a written report. Lab reports also allow the instructor to provide feedback.

### E. Homework

Homework requires students to use signal processing techniques and software tools to analyze EEG data in MATLAB. For example, in the neurofeedback homework, students designed their own filters and signal envelope detection to calculate the alpha and theta power from the raw signal, then compared their filters to the Simulink output. Some other examples of homework tasks include removing artifacts, designing FIR filters, analyzing data in time and frequency domains, and plotting neural responses on a scalp map. Homework is individually submitted, and weekly TA appointments are available to provide students with ample feedback.

## V. Student Activities Beyond the Course

Interested students can continue working in BCI related areas and projects in subsequent semesters through various undergraduate and graduate research courses. For example, several undergraduate students have chosen BCI projects as their undergraduate senior capstone projects. In addition, many students in the course have chosen to participate in several outreach activities to showcase their projects with demonstrations. This includes Columbia's Hardware Hackathon MakeCU 2016 [27], Columbia School of Engineering and Sciences 150th Anniversary Design Expo 2014 [28], Electrical Engineering Department Expo (2015), and the annual Science and Engineering Expo at the School at Columbia University's Community and Outreach Program 2016 [29]. These research and outreach activities expand the overall impact of the course.

## VI. Evaluations

### A. Description of Survey Design & Administration

To track student learning and garner feedback about the course, we administered surveys to the 2015 class during the second and final weeks of the course. Students were not required to participate and were allowed to request their data be withheld from analysis. Nineteen of twenty students participated and consented for their data to be included in our analysis. All data were de-identified before analysis.

### B. Technical Skills

At the beginning and end of the semester, we asked students to rate their knowledge of various skills, fields, and software on a scale from 1 to 5, where 1 was "Novice" and 5 was "Expert". We saw improvements in student self-reported proficiency on all items addressed

(Figure 1). Student proficiency improved across all the specific concepts covered in class experiments and projects (1A). Students reported improved familiarity with the main fields and concepts involved in the course: experimental design, brain computer interfaces, neuroscience, neuroengineering, signal processing, and machine learning (1B). Lastly, we asked how familiar students were with the software used in the course (1C). We saw small improvements in familiarity with MATLAB and Simulink and large improvements in EEG recording and analysis software; this result is consistent with the fact that most students already had exposure to MATLAB before the course, but only a few had previously used EEG-specific software.

### C. Student Goals

To track student goals, in the first survey we asked students why they were taking the class and what benefits they hoped to gain. In the final survey, we asked how well the course fulfilled their expectations.

The students' main motivations for enrolling in the course were interests in applying engineering to the human brain, learning new signal processing techniques, and gaining hands-on experience in experiment design. A few students hoped to learn skills to apply to their own research. Student goals included learning more about brain computer interfaces, their applications, and neuroscience; gaining a better fluency with research; and applying signal processing to biological datasets.

In the final survey, we asked students to describe their impressions of the course, including which elements they felt were most effective. Student feedback was overwhelmingly positive, and most students felt the course had fulfilled their stated expectations. Many students agreed that the most effective aspect of the course was the hands-on experience with experimental design and data analysis.

## VII. Challenges and Suggestions

An interdisciplinary course poses unique opportunities, but also unique challenges. As student backgrounds are varied, it is challenging to adequately provide sufficient background for all needs. Of 19 students enrolled in the 2015 course, 13 students belonged to Electrical Engineering, 4 to Biomedical Engineering, one to Neurobiology and Behavior, and one to Computer Engineering.

In our survey, many students expressed interest in learning more details of signal processing or neuroscience than we were able to cover within the boundaries of the course. While we provided extra reading material to these students, in the future it may be beneficial to expand the course prerequisites to cover basic neuroscience and signal processing, and offer specialized TA sessions on relevant topics (e.g. neuroscience, signal processing, filtering, MATLAB) at the beginning of the semester.

The hands-on nature of the lab also limited the amount of in-class feedback and discussion of results. Going forward, we plan to dedicate the first ten minutes of each class to reviewing the best results from the previous experiment and discussing the main concepts learned.

## VIII. CONCLUSIONS

This paper describes the first brain computer interface laboratory course offered at Columbia University. The course familiarizes students with new and emerging areas in neuroengineering and biosignal measurement and analysis. The laboratory nature of the course allows students to implement state-of-the-art BCI methods using EEG, conduct hands-on experiments, and learn signal processing and data analysis methodologies. The course has successfully created enthusiasm among engineering students about the traditionally underrepresented field of neuroscience, and informed them about ways they can contribute to the advancement of neural signal processing. Our surveys show that the course successfully met student goals. We also provided students with mechanisms to continue learning and teaching beyond the course; a number of students disseminated knowledge gained in the class to high school and college students by participating in various science and engineering outreach events at Columbia University.

## Acknowledgments

We would like to thank Prof. Keren Bergman, the chair of the Electrical Engineering Department at Columbia University for her strong support of the new BCI Lab course. We would like to thank Dr. Christoph Guger for his help in developing the course materials. Finally, we would like to thank all of our students for their feedback and their participation in the course. This material is based upon work supported by the National Science Foundation Career Award.

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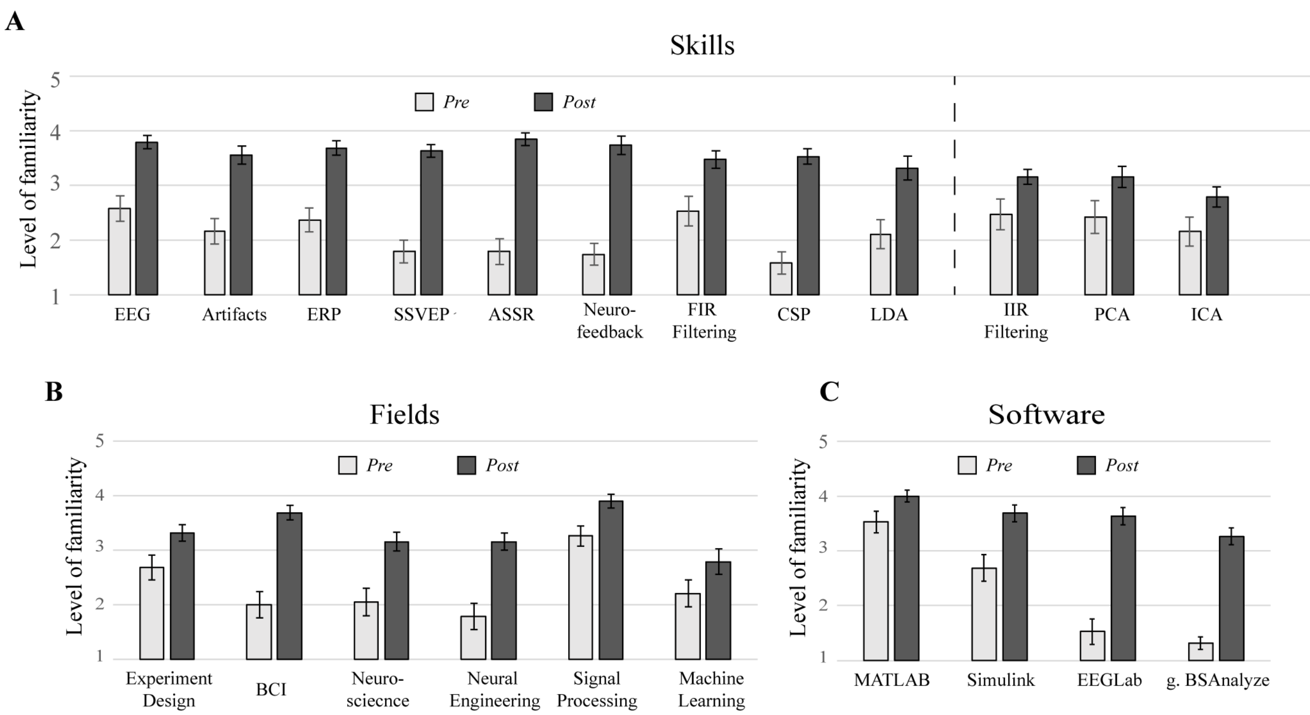


**Fig. 1.**

Student survey results from Fall 2015. Students rated their proficiency on each concept on a scale from 1 (“Novice”) to 5 (“Expert”); average ratings of 19 students are displayed during the second (Pre) and last (Post) weeks of the course (Error bars are standard error of the mean). We saw improved self-reported proficiency on all concepts, including A) Skills, B) Fields, and C) Software. In 1A, the dashed line separates skills used in class assignments (left) and skills that were touched upon in lecture but not directly used in class assignments (right).

**TABLE I**

Weekly plan and assigned lab instructions

| Experiment Title | Experiment Learning Objectives | Week |
|---|---|---|
| Introduction to EEG | **a.** Set up EEG hardware and experiment<br>**b.** Record from the first subject; recognize good electrode impedance and noisy vs. high-quality data<br>**c.** Learn the basics of Simulink | 2 |
| Biological Artifacts in EEG | **a.** Begin analyzing data in MATLAB<br>**b.** Implement FIR filtering to reduce the effects of biological and nonbiological artifacts on the data<br>**c.** Learn about different neural oscillations and associated cognitive processes | 3 |
| Neurofeedback | **a.** Create a real-time measure of alpha and theta powers in Simulink<br>**b.** Understand mechanisms of neurofeedback | 4 |
| P300 Speller | **a.** Introduce the concept of event related potentials and describe various ERP components<br>**b.** Apply a preprogrammed module to record data and to control a brain-controlled on-line speller<br>**c.** Find ERPs to target vs. non-target letters and mark the significant P300 responses | 5 |
| Auditory ERP | **a.** Introduce auditory ERP components and the auditory oddball paradigm<br>**b.** Design an event marker to track experimental events<br>**c.** Plot neural response on a scalp map; find spatial location of ERP components | 6 |
| ***Project 1***<br>Auditory Oddball Paradigm | **a.** Design and program an auditory oddball experiment<br>**b.** Investigate the effect of subject attention and deviant probability on different ERP components<br>**c.** Implement group analysis using shared dataset between groups | 7,8 |
| Auditory Steady State Response | **a.** Introduce ASSR and frequency-modulated neural components<br>**b.** Design and program an ASSR experiment<br>**c.** Analyze data in the frequency domain using the fast Fourier transform (FFT) | 9 |
| Attentional Modulation of ASSR | **a.** Investigate the effect of attention on ASSR paradigm<br>**b.** Implement online analysis in real-time using Simulink | 10 |
| Steady State Visually Evoked Potentials | **a.** Introduce SSVEP and its applications<br>**b.** Analyze data in frequency domain in a visual paradigm | 11 |
| Imagined Movement | **a.** Understand the basics of human motor cortex<br>**b.** Apply a preprogrammed module to record data for further processes | 12 |
| ***Project 2***<br>Decoding Imagined Movement | **a.** Calculate common spatial pattern (CSP) filters and project data into CSP space<br>**b.** Train an LDA classifier to decode imagined movement of single trials using CSP<br>**c.** Test classifier with cross-validation | 13,14 |