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# Analysis of EEG Signals for Non-technical and Non-medical Students

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The interaction between humans and computers is one of the most pressing challenges in contemporary society. Subtleties of this communication require that human-computer interfaces are conceptualized and tested by highly specialized experts. Here we describe a novel academic course for human-oriented designers and project managers, with the emphasis being put on the communication between the human brain and computer. Outcomes of the course were validated on 12 course participants both: qualitatively – educational experience, and quantitatively – outcomes of a project and final exam. T-test comparison revealed that students who participated in the course gained specialized knowledge, as compared to students who did not take part in the course. Moreover, students generally agreed that the course was helpful and interesting, however, about one-third of them considered the course hard. All in all, we find our brain-computer interfaces course useful in instructing specialist oriented on the human-factor of the communication between human and the machine.

Keywords: brain-computer interface, project-based learning, electroencephalography, teaching framework, higher education

## INTRODUCTION

In order to create a brain-computer interface (BCI), one has to incorporate the knowledge from various fields of study: biomedical engineering, advanced signal processing, artificial intelligence algorithms, and neuroscience (Wolpaw & Wolpaw, 2012). By creating a direct communication pathway between the cerebral cortex and external devices (without utilizing muscles and peripheral nervous system) BCI allows for mapping intentions of the person onto directive (control) signals. This kind of technology may be particularly useful for quadriplegic patients or for people suffering

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from the *locked-in-syndrome*, for whom BCI may be the only way to communicate with the surrounding world (Holz et al., 2015, Vansteensel et al., 2016). Although the significance of BCI-focused education for students in engineering (Katona & Kovari, 2016) and medical sciences (Shih et al., 2012) has already been noted, there is still a great demand of people whose role is to integrate these two approaches and coordinate work of teams developing BCI-based solutions.

Cognitive science is a multidisciplinary study of the way people acquire, process, and perceive information in order to create coherent representations of the mental, as well as physical, phenomena. Additionally, this field of science gathers knowledge about the processes underlying behavior of biological and artificial entities (although in the case of the latter the term "behavior" should be used with caution). Cognitive science program attempts to combine the following faculties: psychology, biology, computer science (mainly in terms of artificial intelligence), linguistics, logic, and philosophy, into a coherent methodological framework powerful enough to explain the means by which cognitive systems gather and process the information.

For humans, the primary organ responsible for conducting, transforming, and extracting useful information from the signal (incoming from different modalities, such as visual, auditory, tactile, etc.) is the nervous system. Students undergoing cognitive science courses are acquainted with structural (neuroanatomy) and functional (cognitive neuroscience) organization of the cerebral cortex, subcortical structures, and the more exterior parts of the nervous system: spinal cord and peripheral nervous system. In addition to that, they learn programming (usually relatively high-level technologies such as Python, R, or MATLAB) and human-computer interaction, where they are presented with basics of bioelectrical signal processing (electromyography/ electroencephalography; EMG/EEG). Altogether, it provides an excellent background for cognitive science students to gain a deeper understanding of the theoretical as well as practical grounds of BCI and ways of developing such solutions. Notably, to coordinate the work of a team developing BCIs neither the extensive knowledge of higher mathematics nor medical training is required. However, one has to know the general approach of each of the fields involved to successfully administer this kind of a project.

Considering the fact that cognitive science is not a technical course per se and students are familiarized only with the basics of programming, our major scope while preparing a BCI course for them was to fill the gap that could have emerged in this regard. This article specifies the details of the course. Moreover, there is an evaluation attempt: the range of knowledge about BCI acquired by the students and their satisfaction with the course has been checked. Thus, we prepared simplified scripts to introduce procedures such as filtration or classification of the signal (see below). Ready-to-use Python solutions for EEG signal analysis such as python-MNE (Gramfort et al., 2013; Gramfort et al.,2014) or PyEEG (Bao et al., 2011) are either too complicated to encompass or not suitable for further real-time decoding of particular brain states.

Recently, more emphasis is being put on usability-related issues while conceptualizing, implementing, and evaluating BCIs (Choi et al., 2017; Kübler et al., 2014; Loup-Escande et al., 2017; Stamps & Hamam, 2010). Various specific aspects of BCI usability are being studied: workload and satisfaction (Riccio et al., 2011; Zander et al., 2010); learnability (Du, 2019; Lorenz et al., 2014); user-friendliness, pleasantness, and fatigue (Jukiewicz & Cysewska-Sobusiak, 2016; Cipresso et al., 2012); etc. Examining how people perceive and operate on designed services is already well recognized and studied in the field of computer software development (Jacko, 2012; Preece et al., 2015). Such problems require a profound knowledge of cognitive psychology, e.g., notions such as Gibson's affordances (Blin, 2016) and principles of Gestalt psychology (Koffka, 2013), as well as a substantial experience in designing and performing studies with participants (to test the prepared application with the users). Thus, cognitive science linking theoretical knowledge with a practical approach perfectly suits the needs of evaluating human performance on the BCI in terms of usability (Linek & Tochtermann, 2011). Our objective in this study was to evaluate the outcomes of a BCI course, for which both medical and technical knowledge is required, on the group of cognitive science students.

**Overview of the Software and Hardware**

In the course proposed by us, we utilized the following technologies and software: (1) OpenBCI (http://openbci.com); (2) custom scripts for EEG signal analysis - asEEG (https://github.com/mjukiewicz/asEEG); (3) python simple EEG package - PySEEG (https://github.com/mikbuch/pyseeg); and (4) blind signal separation for EEG data with ICA - bss_ica_eeg (https://github.com/mikbuch/bss_ica_eeg). Below we describe each of these applications in greater detail.

OpenBCI is a low-cost, open-source platform for measuring and recording electrical activity elicited by the brain (EEG); muscles (EMG), including eye-muscles (electrooculography, EOG); or the heart (electrocardiography, ECG) (Frey, 2016). The manufacturer also provides the basic graphical user interface (implemented in Processing) as well as a control class (in Python). Utilizing the latter, we build a more advanced interface for EEG/EMG data acquisition and analysis - PySEEG. With this package, it is possible to simultaneously present stimuli on a computer screen and acquire the data from the scalp of the participant (for this purpose we used specific triggers, as in the standard EEG software/paradigms). Afterward, students analyzed the signal with a separate, simplified tool for filtering, transforming, and visualizing the data (asEEG). The final, more demanding task was to create a model to classify the data – brain states had to be decoded from either P300 or SSVEP-related brain signals. For this purpose, students were familiarized with a standard Python machine learning tool - Scikit-Learn (http://scikit-learn.org, see: Pedregosa et al., 2011 and Buitinck et al., 2013).

**Course Sequence and Students Background**

EEG signal analysis classes were introduced to the cognitive science program at Adam Mickiewicz University in 2017 as one of three facultative courses to choose (besides "the basic" set of lectures and classes) during the 7th semester of the studies (out of 10). Curriculum preceding EEG analysis comprised: Python Programming, Data Analysis and Visualization, Neuroscience, Human-Computer Interaction, and Methodology of

Psychological Research with Elements of Statistics. Students had also worked on several research projects (including ones on psychometry and perceptual processes).

The main learning outcomes of these past courses that students know are:
- how to use Python modules in the analysis of EEG signals;
- what are the physical and mathematical basis of signal analysis;
- how to filter bioelectrical signals and subsequently use Fourier analysis to create a spectrum of the signal;
- how are EEG devices constructed and how they may be utilized to measure electrical signals generated by the brain;
- how to recognize evoked potentials in a bioelectrical signal;
- how to use synchronization *triggers* in EEG research;
- how to prepare stimuli for an EEG study;
- what are the intuitions behind signal separation algorithms (such as independent component analysis, ICA), and how to use them;
- how to design and conduct an EEG experiment, and how to analyze data acquired during such an experiment;
- what brain-computer interfaces are and how to utilize evoked potentials for sending the control signals to the computer.

The general schedule of the course is presented in Table 1.

**Practical Sequence**

Each of the classes within the course followed the same generic order:
1. theoretical introduction;
2. preparation of stimuli;
3. mounting electrodes on the head of the participant;
4. checking correctness of electrode assembly (by measuring impedance);
5. conducting an experiment;
6. data analysis.

Table 1
Time schedule of the course

| Week | Subject | Description |
|---|---|---|
| 1 | Python - Pandas module | Data analysis library, based on NumPy |
| 2 | Python - Matplotlib package | Data visualization package, great integration with Pandas |
| 3 | Introduction to data analysis | Theoretical background, waves as information medium |
| 4 | Electrocardiography (ECG) | Extracting heart rate from acquired signal |
| 5 | Electroencephalography (EEG) | Detecting electrical activity of the brain |
| 6 | Brain waves | Frequency bands observed for different cognitive states |
| 7 | Stimulus | Experimental control of brain responses |
| 8 | Triggers/markers | Synchronizing stimuli with behavior of the subject |
| 9 | P300 | Measuring decision making process |
| 10 | SSVEP | Steady state visually evoked potentials |
| 11 | Brain-computer interfaces | Designing and implementing BCI |
| 12 | Managing datasets | Handling the data off-line and on-line |
| 13 | Project, part 1 | Project proposal and beginning of work |
| 14 | Project, part 2 | Data acquisition and data analysis |
| 15 | Discussion | Projects presentations and future ideas |

**Python**

*Objective*: Familiarizing students with the following modules: Pandas, NumPy, SciPy, Matplotlib, and PySEEG libraries.

Before starting the measurement of EEG signals, students had to be familiarized with some of the most popular Python libraries for data analysis and visualization. In order to achieve this, they were asked to write (on their own) simple scripts introducing them to the issue of signal analysis with Python. They practiced using *DataFrame* and *Series* structures from Pandas library and the *numpy.array* structure from NumPy. The visualization part was utilized with the Matplotlib library.

In this part, students learned the basic signals parameters and concepts such as digital filtration, Fast Fourier Transform, signal spectrum, spectrogram.

All the subsequent tasks were performed in groups of 3 or 4 students.

**Acquiring Electrocardiographic (ECG) Signals**

*Objective*: acquire and interpret bio-electrical heart activity.

Proceeding to the signal acquisition, students had to measure bioelectric signals generated by the heart. As the time-course of the ECG signal is quite recognizable by the general population, it is relatively easy for students to handle the task of acquiring this kind of signal and estimating its quality. Subsequent adjustment of cut-off frequencies of the digital filters should also be quite straightforward, as students were aware of which shape of the function they have to obtain.

**Estimating Alpha Waves From Acquired Brain Signals (EEG)**

*Objective*: learn how to measure brain-originated signals.

Students are instructed how to mount electrodes on the head using the international 10-20 standard.

Alpha waves are brain oscillations measurable in the occipital areas when the subject is relaxed and/or the eyes are closed. Because it is a spontaneous cortical phenomenon, its acquisition is well-suited as the introduction to EEG signal acquisition (Dustman & Beck, 1965).

During these classes, students practice mounting electrodes, inspecting assembly correctness (by measuring impedance), and choosing appropriate parameters of digital filters.

**Evoked Potentials: SSVEP**

*Objective*: get a more advanced understanding of visually evoked potentials.

Brain responses to external or internal stimuli are called evoked potentials (EP). Given long enough time for stimuli exposition, a brain state corresponding to a behavioral setup becomes invariant in time. The measured signal may then be characterized by relatively straightforward functions. An example of such phenomena is steady-state visually evoked potentials (SSVEP). This brain response originates in the occipital cortex when the subject is presented with visual stimulus that changes (e.g., shows up and disappears, or fades in and out) with some constant frequency (Vialatte et al., 2010).

First and foremost, when any rapidly flashing stimulus comes into play with studies on human participants (e.g., in SSVEP or P300 paradigms), the primary concern of the experimenter is the possibility of the epileptic attack. That is why the course comes into the research program, which was approved by the local ethical committee (Ethical Committee of the Faculty of Psychology and Cognitive Science of the Adam Mickiewicz University in Poznań). Secondly, each student participating in the course is instructed about the ethical and percussion procedures when introducing possibly harmful stimuli into the experimental design. Finally, each and every student taking part in the course is himself/herself screened for the slightest possibility of a history of epilepsy in the family and provides written consent for participation in the studies in which rapidly flashing stimuli were to be presented. Besides the ethical procedures, during SSVEP classes, students learned about the theoretical basics of this phenomenon and they acquired the technical skills required to observe this particular brain activity. Students utilize the PySEEG package to create blinking stimuli, set up triggers that mark the moment when the stimulus first appeared on the screen, and to prepare the acquired signal for the analysis (filtration). Observing SSVEP comes down to transform the signal into its frequency domain and interpret the output (see Fig. 1).

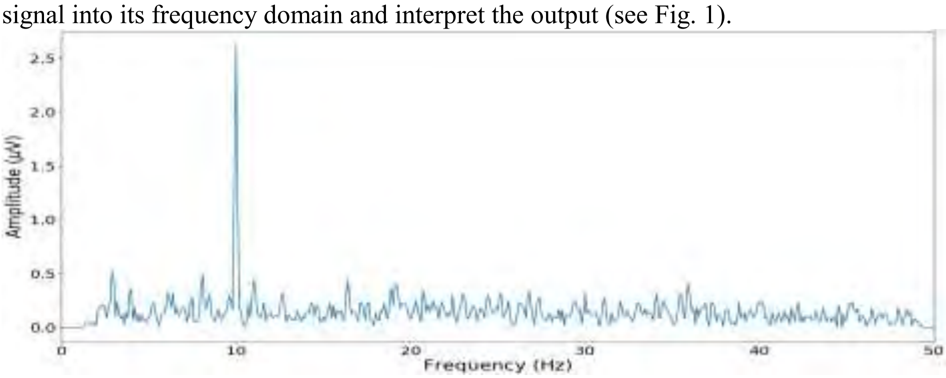


Figure 1
Example of SSVEP response obtained during classes. It presents the signal in frequency domain (after fast Fourier transformation).

**Evoked Potentials: P300**

*Objective*: trace brain signals elicited by decision making and processes related to consciously choosing an option.

The experiment that students were acquainted with this time exploited flashing visual stimuli, in the form of letters or symbols. P300 is an electrical response of the brain - a positive deflection in voltage with a latency (delay between stimulus and response) of roughly 250 to 500 ms. When the “expected” box (where the attention of the user is focused) is being highlighted, P300 potential may be measured from the parietal cortex.

It requires roughly from couple to dozens of the occurrences (highlights) of each of the available options on the screen (e.g., letters) for this phenomenon to be observed in the time domain after filtering out the artifacts (Townsend et al., 2010; McFarland & Wolpaw, 2011), for example, work of the student see Fig. 2.

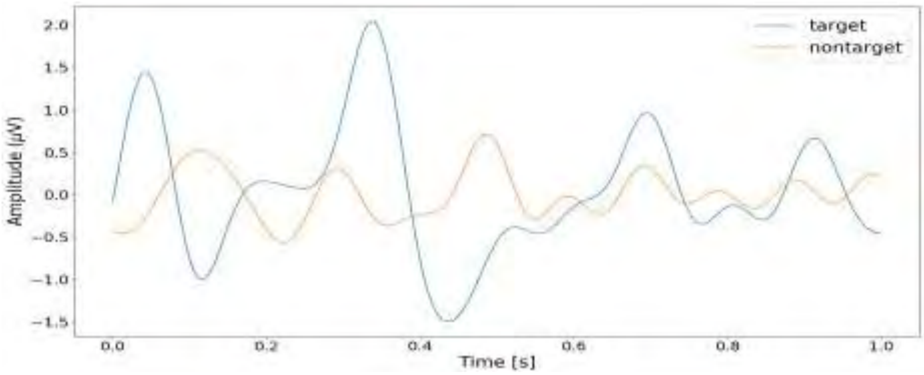


Figure 2
Example of P300 response obtained during classes (after using pre-prepared Python scripts with appropriate filters).

**Evoked Potentials: Final project**

As of last, students were asked to come up with their own experiment, based on the literature study, that could expand and consolidate their knowledge on EEG signal acquisition and analysis. Working in the groups of 3, they conducted the designed an experiment, performed the statistical analysis, drew conclusions, and presented their outcomes to the rest of the students attending the course. Some of the topics they chose were: brain response to different stimulus frequencies, how the class of a control signal influences the quality of the measurements (stimulus color, shape, size, etc).

Some examples of the final projects are:

- Influence of Stimulus Color on Steady-State Visual Evoked Potentials
- Influence of Stimulus Frequency on Steady-State Visual Evoked Potentials
- Influence of Stimulus Size on Steady-State Visual Evoked Potentials
- Influence of Reference Electrode Placement on Steady-State Visual Evoked Potentials
- The Readiness Potential
- Physiological benefits of exposure to natural stimuli

**Program Evaluation**

As stated above, the course was concluded with the final project. This provided students with an opportunity to come up with their own experiment, which was part of the grade they were given from the course. Additionally, a qualitative questionnaire (open-ended questions) was conducted before and after the course in order to quantitatively evaluate if participation in the classes provided a noteworthy increase in knowledge on the subject. The test has been completed by a total of 12 students before they attended the course. Out of this group, 7 students concluded the course and filled the questionnaire again. The outcomes of this knowledge test had no impact on the final grade the students obtained and it was performed purely for the purpose of the study described in this paper. The final grade was based on the reports from particular subjects and from the final project.

The questionnaire consisted of single-choice questions that covered knowledge on such subjects as the theory of signal analysis, evoked potentials, or algorithms used in EEG signal processing. The correct answer in each test position was scored for 1 point, while there were no points for the wrong answer. Hence 9 points were the maximal score that each of the participants could have achieved. Average results in both groups are presented in Fig. 3 (error bars present standard deviation). The numeric values of the scores in each group, the standard deviation of these scores, and the results of the *t*-test are shown in Table 2.

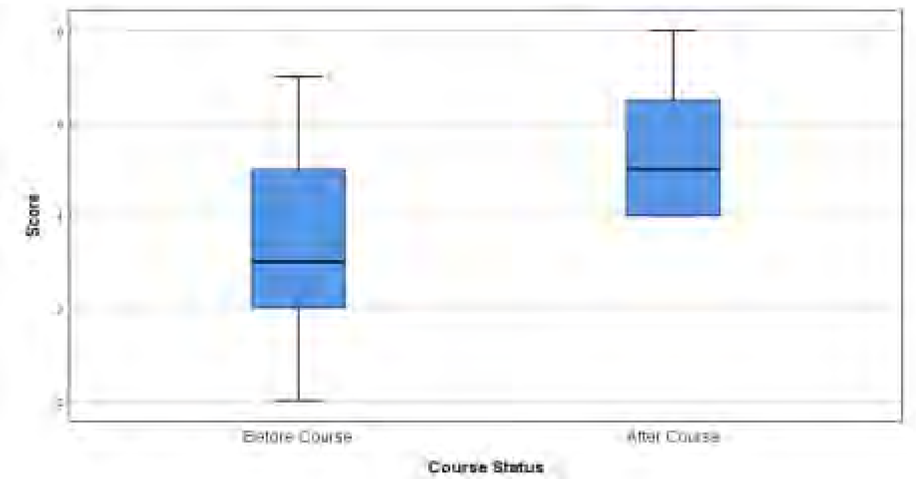


Figure 3
Results of the questionnaire – the difference comparison between participants and non-participants of the course. The non-participants were students matched for stage of education (year of the program) to these who actually participated in the course.

Students were given an opportunity to express their opinion on the course and/or suggest some changes in a questionnaire attached to the test after the course (see Fig. 4).

Table 2
Questionnaire results

| Course Status | Mean | Std. Deviation | Statistic |
|---|---|---|---|
| After Course | 5,43 | 1.618 | |
| Before Course | 3,33 | 1.969 | |
| | | | t = -2,377 |
| | | | $p$ = 0.029 |

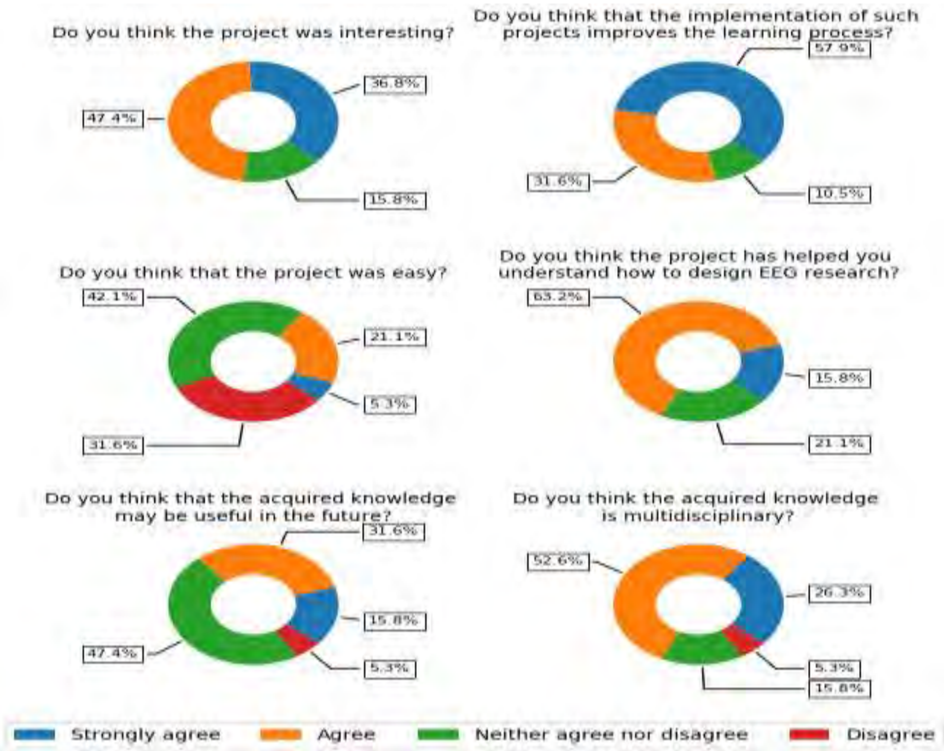


Figure 4
Survey results – student's opinion on the course

Although the difference between the results in both groups was not statistically significant at α=0.05, a clear trend was observed ($p < 0.062$). The outcome may be due to too sophisticated questions, as even average for students after the course has not reached 50% in the test (best score was 66%; for averaged results refer to Fig. 3). Given the fact that the course was focused on the practical tasks, the completion of (or question about) some specific procedures should have been evaluated instead of theory, which other students may have gained elsewhere (e.g., lectures on similar, neuroscientific subjects).

**DISCUSSION**

The objective of our study was to evaluate the outcomes of a BCI course for cognitive science students. Similarly to the work by Katona and Kovari (2016) we wanted to show that not only technical (computer engineering) students can excel at brain-computer technologies. The evaluation we performed shows that the course allows students acquiring both practical and theoretical knowledge on BCI. With still-growing interest in information and communication technologies (ICT), aspects of educating future specialists in the field of application functionality and usability plays a pivotal role

(Punie & Ala-Mutka, 2007; van Laar et. al, 2019). Potential applications of brain-computer interfaces as control interfaces and in rehabilitation place this method among the most promising future technologies (McFarland & Wolpaw, 2017; Chaudhary et al., 2016). Hence, highly specialized individuals, who understand engineering, medical, but also psychological and ethical aspects will be needed to create operational brain-computer interface systems. This article describes an educational scenario that we created and validated on a group of social sciences students who can eventually become experts in the field of BCI.

## CONCLUSIONS

In this article, we presented a coherent course for BCI-oriented EEG signal analysis. These materials were prepared for social sciences students with no strong background in neither engineering nor medicine. However, cognitive science is a field of study that combines both of these two disciplines and we believe that the course we created is a valuable experience for students participating in it. We hope that our course can support future scientists, usability specialists, UX researchers/designers, testers, developers, and project managers in their interdisciplinary endeavors to define new, innovative means of communication utilizing some of the most advanced technologies.

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