Brain Computer Interface using Machine Learning

Cristian-Valeriu Soare
University Politehnica of Bucharest, Faculty of Automatic Control and Computers, Computer Science Department
cristian.soare@cti.pub.ro

ABSTRACT
This paper presents the design and development of a complete hardware and software solution for a brain computer interface (BCI). It consists of a non-intrusive multiple channel data acquisition device which captures the electrical brain wave signals and passes the data to a computer. The computer then uses signal processing and machine learning algorithms to identify patterns in the signals received from the BCI. The goal of the device is to be a highly adaptable BCI, able to be used in a multitude of applications ranging from object recognition to basic control functions. Currently, the system is work in progress.

Author Keywords
Brain-computer interface; Data acquisition; Machine learning; EEG; Feature extraction

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous; I.2.m. Artificial intelligence: Miscellaneous

INTRODUCTION
Brain computer interfaces have been a subject of research for decades. Their primary use has been mind prosthetic control for patients with severed limbs, neurological diseases study and treatment (such as epilepsy) and the study of the brain itself. They are generally composed from an EEG (electroencephalography) system which records brain wave electrical signals by the means of electrodes either placed on the scalp, in a non-intrusive manner, or implanted in the brain, in an intrusive manner. Brain implanted computer interfaces have far greater accuracy when compared with non-intrusive techniques, and thus, they are mainly used in medical research and treatment. Lately, however, non-intrusive solutions have seen a rise in popularity as they can be easily used in various applications: basic mind-controlled devices such as drones, remote controlled (RC) cars as well as computer games. Therefore, nowadays there are commercially available BCI devices such as NeuroSky [2] or Emotiv [3] headsets which provide basic EEG data acquisition and offer programming SDKs for easy software development. This paper focuses on implementing such a device, able to handle a multitude of use cases. From the simple control of a computer, RC car or drone maneuvering to medical use and brain research, this BCI aims at providing the hardware and software necessary for a complete easy to configure and enhance system. One other notable non-invasive BCI system can be achieved by using functional magnetic resonance imaging (fMRI) scans of the brain. Through this technique a 3D representation of the blood pressure distribution within the brain can be obtained. In 2008 scientists at the Advanced Telecommunications Research (ATR) Computational Neuroscience Laboratories in Kyoto, Japan successfully reconstructed 10x10 black and white images from the brain using such a system.

BRAIN WAVES AND REGIONS
Brain waves are caused by neural oscillations within the brain. They have been studied by measuring the cumulative signals of large groups of neurons using EEG devices. Brain waves are classified according to their frequency and amplitude. Each frequency band is shown to correspond to a different mental activity and since each cortex has a distinct function, these signals can be more prominent in some parts of the brain when compared to others. Therefore, a time-frequency analysis of the signal is one of the first steps in decoding their information. The signal frequency bands are as follows [1]:

- Delta (less than 4 Hz) - are high amplitude waves that in the frontal part of the brain. They are present during slow-wave sleep (dreamless NREM stage).
- Theta (4 - 7 Hz) - are the waves most often present during states of drowsiness or idling thoughts.
- Alpha (8 - 15 Hz) - waves are located in the posterior regions of the brain, on both sides. They are present during a relaxed state of the brain.
- Beta (16 - 31 Hz) - are low amplitude waves located most prominently in the front, but also on both sides of the brain and manifest during active thinking.
- Gamma (more than 32 Hz) - are located in the somatosensory cortex and are displayed during the perception of two different senses, such as sound and sight.
- Mu (8 - 12 Hz) - are sensorimotor waves located in the sensorimotor cortex.

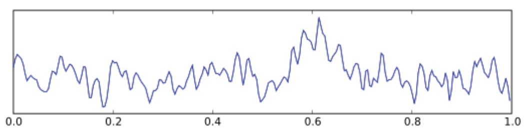

Figure 1: One second of typical EEG signal.

BCI HARDWARE DESIGN

Electroencephalography (EEG)

Electroencephalography devices consist in a number of electrodes placed on the scalp; each electrode providing a data channel for further processing. The most important features of such a device are the number of channels, the sampling rate and the sample resolution of each channel. Since data acquisition scenarios are expected to be reproducible to compare subject studies over time, international standards for scalp electrode placement have been defined. One of the most popular ones is the 10-20 system 3.1 which specifies a positioning such that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull. There are also the 10-10 higher resolution system and a proposed 10-5 system.

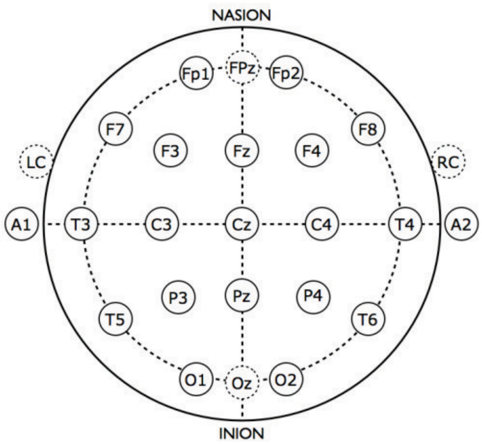

Figure 2. The 10-20 system. The letters F, T, C, O stand for frontal, temporal, central, parietal and occipital.

Commercial solutions

Commercial BCI solutions have risen in popularity due to their ease of use and available SDKs. Such products are:

- NeuroSky [2] - It has one electrode with a sampling rate of 512 Hz. Its frequency range is 3 to 100 Hz. It sends its data through an UART connection.
- Emotiv [3] - a more powerful headset. It has 14 channels of 16 bits resolution and a sampling rate of 128 samples per second. It sends its data through a WiFi connection.
- OpenBCI [4] - available since 2013, this is a DIY open source BCI of high performance. It uses an ADS1299 a 24 bit, 8 channel Analog to Digital Converter (ADC), reaching a maximum of 16 kHz sampling rate (distributed evenly on the number of used channels). The kit also comes with an open source signal monitoring and frequency analyzing software.

IMPLEMENTATION

Hardware Architecture

As EEG signals are of 10 to 100 microvolts in amplitude, they require amplification and filtering before reaching the digital acquisition device. For testing purposes, electrocardiogram (ECG) signals are better suited as they reach 1 to 5 millivolts and are easier to identify. Therefore, each data acquisition board channel has amplification stages with configurable gains. One other issue encountered in bio potential data acquisition is the common mode signal. This parasitic wave forms are typically caused by power line electromagnetic interference. The common mode signal can be rejected using a driven-right-leg[6] circuit designed to feed the amplified and inverted signal back into the subject's leg, effectively cancelling the electric noise.

In this paper, we are using an ADS1258-ep 16-channel ADC with 24 bit of resolution and a maximum of 23.7 kHz sampling rate (distributed evenly on the number of used channels). It is also able to provide 125 ksamples per second in a fixed channel operating mode. The ADC can communicate its data through the standard SPI interface. For acquiring this data a RaspberryPi 2[12] is used, as it is a high performance embedded system capable of an Ethernet connection to send the data to a computer for further processing in real time. Ethernet was the preferred mean of data connection as it is high speed and eliminates the electric noise encountered in UART communication.

Each time a sample is acquired the ADC emits an interrupt on a dedicated pin and 4 bytes of data have to be read by means of SPI (3 bytes of channel data and 1 byte of channel details). If the train of data is not read within the 40 μs window between two sample conversions, the data might be corrupted. Although the RaspberryPi 2 itself is a performant system, the Linux scheduler adds high (milliseconds) interrupt latencies when trying to communicate with the ADC from a user-space written code. To counter this problem, interrupt handling and SPI communication has been achieved within a kernel module which buffers the data to the user-space by a character device interface. The Pi then forwards the data to the computer through an UDP communication. The interrupt response latency has been, therefore, reduced to an average of 4 μs (21 μs worst case scenario), as seen in Figure 3.

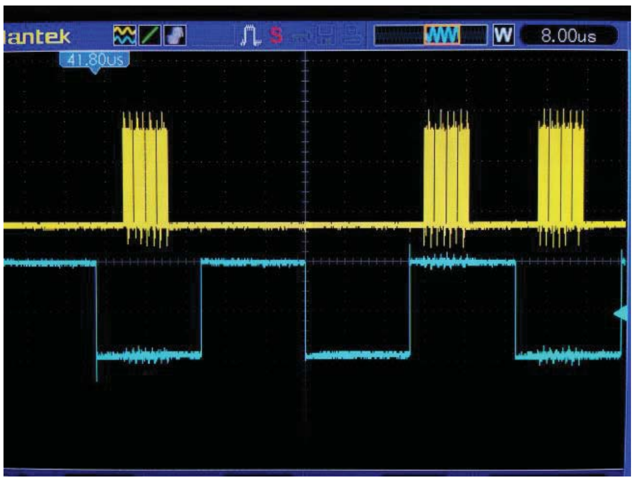

Figure 3. Interrupt response latency test - oscilloscope plots. Yellow plot represents the SPI SCLK signal and the blue plot represents the falling edge interrupt test signal. The second SPI data train is a captured worst case scenario interrupt response latency.

Even though it is not complete yet, the analog hardware component is aimed at obtaining microvolt level accuracy, while the digital one outclasses most of the available EEG sets. Compared with OpenBCI, which uses the ADS1299 (24 bit, 8 channels, 16 ksps), the used ADS1258-ep has 8 more channels, with a sampling rate of 23.7 kHz.

Software Architecture

Data acquisition

The data acquisition and analysis software provides basic plotting functionality (time, frequency and bar plots) as well as plugin interfaces for custom data source and data altering plugins. It is fully written in C++ and uses the Qt Gui toolkit [13] and the QCustomPlot [14] library for graphs. This highly modular framework handles all data transfers and thread management allowing the user to focus on the actual signal processing algorithms as one only needs to implement a few callbacks for passing data through the plugin system. As a simple proof of concept, the framework has been coupled with an audio streaming plugin and a Fast Fourier Transform (FFT) plugin which returns the frequency plot of the signal.

For the BCI application, the source plugin gets the data from the RaspberryPi through the UDP Ethernet communication protocol. The data is then passed through the FFT plugin and through the data interpretation plugins which are used for classifying the signals. Compared to other BCI software solutions, the configurable signal processing pipeline makes this framework more flexible and professional use ready. Its functionality is similar to the OpenVibe [5] software.

Algorithms

Once the data has been recorded, the signals have to be classified. For this task machine learning offers promising techniques for pattern matching and identification.

Convolutional Neural Network

Neural networks are mathematical models inspired by biological neural networks which are used to estimate or approximate functions that can depend on a large number of inputs. Their architecture is a system of interconnected neurons which exchange values between each other. These models are suitable for pattern matching since they can be trained to fit non-linear and arbitrary functions. Convolutional neural networks [7] use kernels mapped on the input to create feature maps on higher order layers. The weights between the kernel and every linked neuron in the upper layer are shared. This architecture allows identifying features in patterns in an offset-independent manner, a property of great use in signal and image classification. It is very popular for hand writing recognition tasks.

As seen in Figure 4, the first algorithm prototype consists in a convolutional neural network with 3 layers: the convolutional, subsampling and fully connected layer. Its input is formed by n spectrograms, where n is the number of signal channels. Although the architecture is in theory promising, because of the high dimensionality of the problem, the network may fail to converge if not provided enough training samples. Since the order of the input is around 105, it is hard to provide a similar number of training examples.

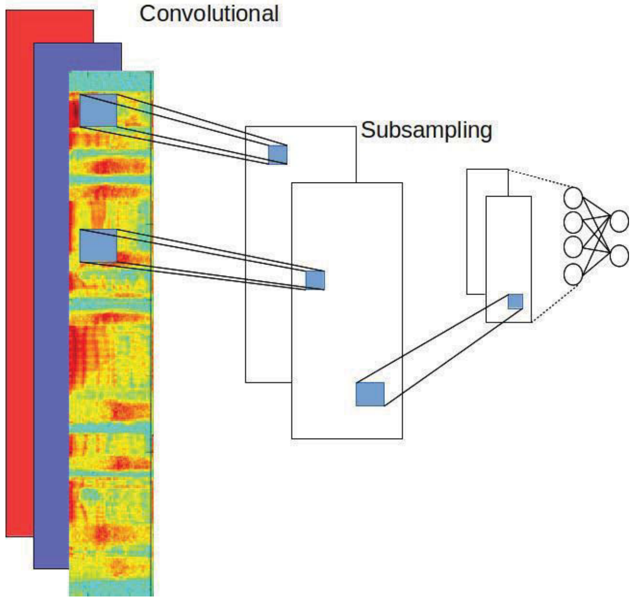

Figure 4. Convolutional neural network.

Feature extraction

Spatial filtering

To counter this problem, one can use a spatial filter to extract features from the signals and reduce the number of inputs in the classifier. The role of this filter is to output signals of high and low variances signals, according to the class of the original signal. Spatial filters can only be applied on binary classification problems.

To train the parameters of such a filter, the Common Spatial Pattern (CSP) algorithm is used.

Other features that may prove of use for the classifier are:

Power Spectral Intensity and Relative Intensity Ratio [8]. For a time series $[x_1, x_2, \ldots x_N]$, and its Fast Fourier Transform result $[X_1, X_2, \ldots X_N]$, a continuous frequency band from f_{low} to f_{high} is sliced into K bins. Boundaries of bins are specified by a vector $[f_1, f_2, \ldots, f_K]$ such that the lower and upper frequencies of the i^{th} bin are f_i and f_{i+1}. The Power Spectral Intensity (PSI) of the k^{th} bin is:

$$PSI_k = \sum_{i=\lfloor N(f_k/f_s)\rfloor}^{\lfloor N(f_{k+1}/f_s)\rfloor} |X_i|, \qquad k = 1, 2, \ldots, K-1$$

where f_s is the sampling rate and N is the number of samples. Commonly used bins for EEG are δ (0.5 − 4Hz), θ (4 − 7Hz), α (8 − 12Hz), β (12 − 30Hz), γ (30 − 100Hz).

Relative Intensity Ratio (RIR) is defined as:

$$RIR_j = \frac{PSI_j}{\sum_{k=1}^{K-1} PSI_k}, \qquad j = 1, 2, \ldots, K-1$$

Spectral entropy [8]. The spectral entropy is defined as:

$$H = -\frac{1}{\log(K)} \sum_{i=1}^{K} RIR_i \log RIR_i$$

EXPERIMENTS

Open datasets

In order to test the algorithms, openly available data sets can be used. PhysioNet [10] offers a bank of EEG and ECG signals in the standard European Data Format (EDF). It has a multitude of signal types from epilepsy seizure recordings to usual brain activity patterns. A particularly interesting dataset is the EEG motor-imagery set [11]. It contains data from 109 subjects who have been instructed to perform several tasks. Each subject opens and closes each of his fists or moves his feet when being signaled by visual cues on a screen. They also perform the same tasks but only imagining them.

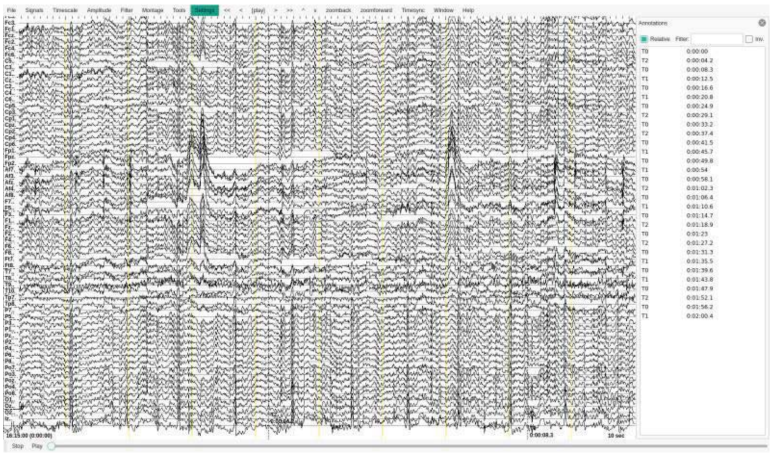

Figure 5. Channel data.

The recordings have 64 channels of data with the electrodes positioned according to the 10-10 system, each with a sample rate of 180 Hz. They have been successfully classified using the MNE [15] Python library. After frequency and spatial (CSP) filtering, the signals have been classified using an SVM algorithm. The classification was 94% accurate. It was tested using cross-validation with 20% of the data used for the test set.

Future experiment

Once the equipment is complete, the following experiment will be performed. A microcontroller will be programmed to blink several LEDs at distinct frequencies (16-30 Hz). The subject will look at each of the LEDs while having his EEG activity monitored. After several sessions, the subject will picture the blinking LEDs in his mind while still being monitored. The goal of the experiment is to see if the visual LED frequencies can be easily found embedded in the signals picked up by the BCI. The pattern identification could prove to be a viable way for physically impaired people to control a computer. Although it is slow to control, the technique allows quick algorithm training thanks to the few features needed for the classification.

CONCLUSION

Although it is still a work in progress, the high precision of the hardware and modularity of the software already form the shape of a successful brain computer interface solution. The software framework is complete and the CSP based classification algorithm has proven reliable. The final goal of the project is to provide the tools a user needs for a ready to use BCI system and the freedom and configurability that would empower one to add new functionality. As for the improvements in the near future, once the system is completed, small computer or RC-car mind driven applications can be achieved.

ACKNOWLEDGMENTS

This project has been developed under the supervision of Prof. Adina Magda Florea and Dr. Traian Rebedea whom I thank for all their support and guidance. Special thanks to Eng. Ion Ciobanu for providing great assistance on the hardware component.

REFERENCES

1. Teplan, M. Fundamentals of EEG measurement. Measurement science review 2.2 (2002), 1-11.
2. NeuroSky headset official specifications http://neurosky. com/biosensors/eeg-sensor/
3. Emotiv Epoc headset official specifications http://emotiv.com/epoc-plus/
4. OpenBCI website http://openbci.com/
5. OpenVibe websie http://openvibe.inria.fr/
6. Winter, B.B. and Webster, J. G. Driven-right-leg circuit design. IEEE Transactions on Biomedical Engineering, 1, (1983), 62–66.
7. LeCun, Y. and Bengio, Y. Convolutional networks for images, speech, and time series. The handbook of brain theory and neural networks, 3361(10), (1995).
8. Forrest Sheng, B., Liu, X. and Zhang, C. PyEEG: an open source python module for EEG/MEG feature extraction. Computational intelligence and neuroscience 2011, (2011).
9. Xiaoou, L. et al. Classification of EEG signals using a multiple kernel learning support vector machine. Sensors 14.7, (2014), 12784-12802.
10. Physio Toolkit Physio Bank. Physionet: Components of a new research resource for complex physiologic signals. Circulation, 101(23), (2000), 215–220.
11. Schalk, G., McFarland, G. J., Hinterberger, T., Birbaumer, N. and Wolpaw, J. R. Bci2000: a general-purpose brain-computer interface (bci) system. IEEE Transactions on biomedical engineering, 51(6), (2004), 1034–1043.
12. Raspberry Pi 2: https://www.raspberrypi.org/products/raspberry-pi-2-model-b/
13. Qt http://www.qt.io/developers/
14. QCustomPlot http://qcustomplot.com
15. MNE library http://martinos.org/mne/stable/index.htm