Published in final edited form as:

Conf Proc IEEE Eng Med Biol Soc. 2011 ; 2011: 1888–1891. doi:10.1109/IEMBS.2011.6090535.

Low Cost Electroencephalographic Acquisition Amplifier to serve as Teaching and Research Tool

Ankit Jain [Student Member, IEEE] [graduate student],

Electrical Engineering Department, The Pennsylvania State University, University Park PA 16802 USA (ajain@psu.edu)

Insoo Kim [Member, IEEE] [research associate], and

Department of Engineering Sciences and Mechanics at the The Pennsylvania State University, University Park PA 16802 USA (insoo@psu.edu)

Bruce J. Gluckman [Member, IEEE] [Associate Director]

Penn State Center for Neural Engineering and Associate Professor with the Department of Engineering Science and Mechanics at the Pennsylvania State University, University Park, PA 16802 USA and also with the Department of Neurosurgery at the Hershey Medical Center, Hershey, PA 17033 USA (BruceGluckman@psu.edu).

Abstract

We describe the development and testing of a low cost, easily constructed electroencephalographic acquisition amplifier for noninvasive Brain Computer Interface (BCI) education and research. The acquisition amplifier is constructed from newly available off-the-shelf integrated circuit components, and readily sends a 24-bit data stream via USB bus to a computer platform. We demonstrate here the hardware's use in the analysis of a visually evoked P300 paradigm for a choose one-of-eight task. This clearly shows the applicability of this system as a low cost teaching and research tool.

I. Introduction

MANY people with severe motor disabilities have disruption in the communication pathway between the brain targeted muscles [1]. Many studies have demonstrated brain computer interfaces (BCIs) utilizing non-invasive scalp electroencephalographic (EEG) recordings as way of developing alternative output communication pathway from brain (e.g. [1]-[5]).

The skills for implementing and improving BCIs range from the basics of electronics and biopotential recordings, to the implementation of off-line and real-time signal processing, to the cognitive and human factors considerations in making a human-machine interface. Indeed, the interdisciplinary nature of this work often leads experts in one field or another to neglect the complexity of the challenges of the others. Therefore, it is of great educational benefit to use BCI as a platform for an integrated introduction to these topics. Additionally, the tools used in BCI overlap heavily with those used for cognitive and brain-state studies in psychology, human factors, transportation safety and neuroeconomics.

To that extent, the need to provide a robust and safe accessible platform for students to acquire high quality EEG and directly and easily access the data stream in real time from a broad range of computational platforms presents itself. We have in the last three years offered at Penn State an introductory course on non-invasive BCIs, and found that one of the significant limitations of the course was that it utilized a highly limited number of commercial, clinical grade EEG amplifiers. The costs limited the number of available recording platforms, which in turn led to significantly limited access by the students of the

hardware. Such limited access contributed to a reluctance by students to fully investigate their use and limits, as well as significantly restricted their ability to creatively develop their own interfaces and projects outside the commercially provided programming environment.

Our objectives were to design an acquisition amplifier for high performance EEG recording that could be readily distributed to each student, would be readily interfaced to a computer through many different computational platforms, and would provide an educational platform for teaching both the hardware design elements as well as be exceedingly easy to use.

We note that there are other EEG and biopotential platforms available, some targeted to engineering education, that typically cost between \$3-\$6k. Others now available targeted to the gaming community and cost between \$200 - \$500 [6], [8], [9].

We have developed a new low cost 8 channel EEG acquisition hardware whose component costs run less than \$100 (USD) with of order 10 components, suitable to be packaged within a kit for each student in a course to own and develop analysis software with on their own computer.

We demonstrate the acquisition system's use with a visually evoked P300 paradigm in a choose-one-of-eight paradigm of the type used to train a classic P300 type speller [4].

II. SYSTEM ARCHITECTURE

The development of this system was enabled by the production of commercially available integrated circuits (i.e. Texas Instruments) that form a complete front end biopotential amplifier and digitization system. In addition to basic switching, differencing, and modest preamplification, these ICs contain up to 8 simultaneous 24 bit continuous sigma-delta analog to digital converters ($\Sigma\Delta$ ADC). The key advantage of the $\Sigma\Delta$ ADC in this architecture is that they effectively preclude the need for anti-alias filtering prior to digitization [7], [12], [15]. The high bit number and dynamic range of these ADC allows for DC coupled recordings with almost all signal processing then relegated to the computer.

Our overall system design for this system included the requirements of low cost, low component count, ease of programming and interfacing with standard computers and human compatibility/safety.

The complete EEG recording system architecture is illustrated in Fig. 1A. We utilize standard EEG electrodes common to other systems. For course use, individual students can purchase and use/reuse their own disposable electrodes, or course-purchased and cleaned gold-plated electrodes. Standard electrodes plug into our acquisition hardware either through standard touch-free safety plugs, although a less-costly model is to use standard DB-9 or DB-25 type plugs.

The acquisition hardware, (Fig. 1B) comprises of three main components: the analog front (TI ADS 1298), microcontroller (TI MSP430F5525), and isolation circuitry for USB and power.

Analog front end: ADS 1298

Our hardware setup consists of the new analog front from Texas Instruments ADS1298. It contains 8 simultaneous sampling, 24-bit, $\Sigma\Delta$ ADCs which aid in reduction of size, power and overall cost of the device [7]. It has a built-in programmable gain amplifier (PGA), internal reference, and an onboard oscillator. Additionally it can be configured for various differential input configurations and referencing, as well as both passive and active ground configurations.

Microcontroller MSP430F5525

We use a low-power low-cost microcontroller for programming the ADS1298 and transmitting data from it to a computer. The communication between the ADS1298 front end and the microcontroller is accomplished using a serial peripheral communication interface (SPI). Communication between the microcontroller and the computer is done through standard a USB connection.

Microcontroller Programming

The microcontroller is programmed to interface with the analog front end using SPI communication. For achieving maximum efficiency we set up direct memory access transfers to receive conversion data from the front end to be sent to the PC.

Computer Interface

For interfacing with Windows based computers, we use the Texas Instruments USB to virtual COM port driver. Then all communications to and from the device appear as a data stream on a COM-Port, which is easily accessed from within a variety of software packages including MATLAB/Simulink, LabVIEW and student-written programs in C/C++.

III. DEMONSTRATION OF USE

We demonstrate here the quality and utility of this hardware platform. We compare signals with the commercially available g.USBamp biosignal amplifier available from Guger Technologies [13], [14]. We then demonstrate its use in a visually-evoked P300 training paradigm from our BCI course.

Alpha Waves

One of the first and most readily observed EEG signals is the distinct Alpha wave seen when the subject closes their eyes. Short examples of EEG under eyes open and eyes-closed rest conditions are shown in Fig. 2, recorded from one of the authors (BJG) with our amp from O1 referenced to CPz. This data was acquired with a sampling rate of 250 samples per second. The acquisition hardware is inherently DC coupled, and the CT $\Sigma\Delta$ ADC effects its own low-pass Nyquist filter to prevent aliasing. The only post-processing filtering applied is a 0.5 Hz digital high-pass filter. During the recording period, the subject was asked to spend consecutive one-minute periods in eyes-open then eyes-closed rest conditions.

The spectral power density for these high-pass filtered recordings are shown in Fig. 3a. Here we have averaged over the full 60 s periods of same behavioral condition. Notice that there is very little obvious 60 Hz contamination of these signals neither in the raw traces, nor in the spectra. Because of the high dynamic range, this 60 Hz pickup can be readily removed in post-processing.

Validation

In order to directly compare the signal quality with a commercially available unit, data was recorded from both our amplifier and a Gtec g.USBamp sequentially without removing the electrodes from the subjects scalp – just by unplugging the leads from one amp and connecting them to the other. The recording subject did not move substantially in position between recordings, and the two amplifiers were kept next to each other on the same table behind the subject.

In Fig. 3b we show the comparable averaged spectral power from the g.USBamp, under eyes open and eyes-closed rest conditions, also recorded from O1 referenced to CPz. Three key differences appear between these different recordings. First, the low frequency components

match approximately in distribution and magnitude. In other tests, both systems match in calibration when used with an isolated low-impedance waveform generator.

Second, the Gtec amp has a much higher 60 Hz line noise, along with substantial additional harmonics and shoulder frequencies at $\sim 60 \pm 16$ Hz. Second, the background noise level on the Gtec amp appears to be about an order of magnitude *higher* than that for our amp at the highest frequencies. We stress that neither system utilized any other filtering than their inherent anti-aliasing filters and the post-processing-applied 0.5 Hz filter.

Visually Evoked P300 Demo

One of the most successful and useful of the non-invasive EEG-based BCI modalities utilizes the oddball evoked responses typically from visual stimuli. Farewell and Donchin [4] are credited with demonstrating the first use of such responses to create a direct brain-activity to computer spelling system. Within such a paradigm, an array of targets – for example letters for a speller – are serially highlighted in random order. Each time a target is highlighted, it evokes a measurable brain signal or potential – a visually evoked potential. If the subject concentrates on a particular target, the shape and time-course of the evoked potential is different, and has a marked peak at approximately 300 ms after the stimulus, denoted the P300.

Within an educational course, for a BCI choice system, students learn to detect in real time the visually evoked potential and discriminate from the presence or absence of the P300 which target the subject chose. In order to learn how to do so, and to determine the difference between the choice and not-choice evoked potentials for a particular subject, we typically first have the subject focus on a prescribed (and known to the analyzer) ordering of targets.

For this demonstration, we present the results of recordings and analysis from such a training period for a user not already well trained in the use of a P300 choice BCI.

We present a pick 1 out of 8 targets (illustrated in Fig. 4). The targets are flashed in random order, while the indicator in the center instructs the subject which target to choose. It has been shown that to achieve a better classification on trial to trial basis one must average over at least 2 presentations of each target [4] in order to reduce variance and ensure the user didn't momentarily lose concentration during the presentation of the stimuli.

Visual presentation as well as data acquisition was performed within the Simulink coding environment through the virtual com port. Care was taken to track and minimize phase delays between when samples were taken vs. when they are analyzed in the code.

We recorded data from one subject with almost no BCI training using from channels CPz, P3, P4, Pz, PO7, PO8, O1 and O2, with Cz as both reference and ground. The incoming signal was sampled at 250 Hz using our amp. The paradigm presented stimuli on for 80 ms and off time of 120 ms, 40 trials per session and 3 runs for one trial to improve the classification accuracy.

Data analysis included the following steps. First, all data was filtered using 5th order butterworth filter with pass-band of 1-30 Hz. We then applied common spatial pattern (CSP) filter to the data [10], [11]. The CSP aims to create spatial mixtures of the channels under the assumption that the data comes from different sources that have different activations. Here we assume these are represented by times of choice (having both visual evoked potential and P300), and time of not choice (having just visual evoked potential).

The evoked responses average for all Choice and all Not Choice stimuli are shown in Fig. 5. Notice the large difference near 300 ms post-stimulus time for those stimuli associated with Choice targets. In order to create a BCI discrete choice system, one needs to discriminate on a trial-by-trial basis which target was chosen. To do this, we next down-sample the data by a factor of 10, and use a Fisher's linear-discrimination analysis (LDA) to separate the Choice from Not Choice evoked potentials.

To further test the performance of this discrimination, we separate the trials in to training and testing trials. This prevents our mistaking over fitting of the data for good predictive discrimination.

Shown in Fig. 6 are the histograms of LDA values for the out-of-sample evoked potentials for Choice and Not Choice targets. Notice the groups are well separated. We get approximately an 80% correct identification of the choice target. This reflects good performance for a first training set from an un-trained user.

IV. DISCUSSION

We have demonstrated here a low cost eight channel electroencephalographic acquisition hardware which can record human scalp EEG data with high fidelity. Low cost here is low enough that such devices could be purchased by each student in a BCI or other EEG-related lab course. We have demonstrated the applicability of our system using the well known P300 paradigm for a Brain Computer Interface application. The above results prove that our system can serve as low cost teaching tool for undergraduate or graduate students in engineering and science majors.

Acknowledgments

We thank Steven J. Schiff for helpful discussions in the design of this hardware.

This work was supported in part by the National Institutes of Health grant R01NS065096; The One Laptop Per ICU Patient Grant by Penn State's Institute for Computational Science, Social Science Research Institute, and Huck Institutes for Life Sciences, the Pennsylvania Keystone Innovation Program, and the Pennsylvania Tobacco Settlement.

REFERENCES

- [1]. Schalk, G.; Mellinger, J. "A Practical Guide to Brain-Computer Interfacing with BCI2000," Springer-Verlag; London: 2010.
- [2]. Wolpaw JR, Birbaume N, McFarland DJ, Pfurtscheller G, Vaughan TM. "Brain-computer interfaces for communication and control,". Clin. Neurophysiol. 2002; 113:767-91. [PubMed: 12048038]
- [3]. Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. "BCI2000: a general-purpose brain-computer interface (BCI) system,". IEEE Trans. Biomed. Eng. 2004; 51:1034-1043. [PubMed: 15188875]
- [4]. Farwell LA, Donchin E. "Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials,". Electroenceph. Clin. Neurophysiol. Dec; 1988 70(6):510-523. [PubMed: 2461285]
- [5]. Wolpaw, JR. "Brain-computer interfaces (BCIs) for communication and control: a mini-review,". Supplements to Clinical Neurophysiology, Elsevier; Advances in Clinical Neurophysiology, Proceedings of the 27th International Congress of Clinical Neurophysiology, AAEM 50th Anniversary and 57th Annual Meeting of the ACNS Joint Meeting; 2004. p. 607-613.
- [6]. Stamps, K.; Hamam, Y. "Towards inexpensive BCI control for wheelchair navigation in the enabled environment - a hardware survey,"; Proceedings of the 2010 international conference on Brain informatics; Berlin, Heidelberg: Springer-Verlag; p. 336-345.(BI'10)

- [7]. ADS1298 datasheet. Available: <http://focus.ti.com/lit/ds/symlink/ads1298.pdf>
- [8]. Neurosky website. Available: <http://www.neurosky.com/>
- [9]. Emotiv website. Available: www.emotiv.com/
- [10]. Koles ZJ. "The quantitative extraction and topographic mapping of the abnormal components in the clinical EEG". *Electroencephalography and Clinical Neurophysiology*. Dec 1; 1991 79(6): 440–447. [PubMed: 1721571]
- [11]. Ramoser H, Müller-Gerking J, Pfurtscheller G. "Optimal spatial filtering of single trial EEG during imagined hand movement,". *IEEE Trans. Rehab. Eng.* Dec.2000 8:441–446.
- [12]. Aziz PM, Sorensen HV, Spiegel J. "An Overview of Sigma – Delta Converters, ". *IEEE Signal Processing Magazine*. 1996; 13(1):61–84.
- [13]. Guger Technologies website. Available: <http://www.gtec.at/Products/Hardware-and-Accessories/g.USBamp-Specs-Features>
- [14]. Brunner P, Bianchi L, Guger C, Cincotti F, Schalk G. "Current trends in hardware and software for brain–computer interfaces (BCIs)," *Journal of Neural Engineering*. 2011; 8(2):025001. [PubMed: 21436536]
- [15]. Kulchycki SD. "Continuous-Time Sigma-Delta ADCs". National Semiconductors, White Paper. 2008:1–8.

Fig. 1.

Low-Cost 8-Channel EEG System for BCI Education. (A) Overview of BCI system. Electrodes on the head connect to our low-cost EEG acquisition hardware, which provides a continuous stream of digital data to the computer. (B) Overall architecture of the acquisition hardware. The main pieces involved are the TI-ADS1298 biopotential front-end digitizer, a low-cost microcontroller to program the front-end and transmit the data to computer, and a USB and Power isolation stage. (C) Photo of an 8-channel prototype.

Fig. 2.

EEG Quality from Our Amp. Example signals recorded from O1, referenced to CPz, under eyes open and eyes closed conditions. Signals were acquired at 250 samples per second, and were later digitally high pass filtered at 0.5 Hz and offset for display purposes. Vertical Grid spacing 20 μ V.

Fig. 3.

EEG Spectral Density under Eyes-Open and Eyes-Closed conditions. Signals recorded from O1, referenced to CPz. Behavioral conditions were held for consecutive 60 s periods. Recordings were first high-pass filtered at 0.5 Hz, the average spectra computed using a Welch averaging scheme with half overlapping 8 s periods. Signals were collected during the same sitting from the same subject with the same electrodes without removing the leads from the scalp from both (A) our amplifier, recorded at 250 SPS and (B) a Gtec g.USBamp, recorded at 256 SPS.

Fig. 4.

Visual display for our visually evoked P300 paradigm. We use a pick-1-of-8 in which the user focuses on or chooses one of the eight targets. The targets are then highlighted serially in a random order by changing their color. For training purposes, to create a series for which the analysis knows what the user chose, the central pointer instructs the user which target to choose.

Fig. 5.

Visually Evoked Potential for Choice and Not-Choice targets averaged over 40 trials. Notice the large peak approximately 260 ms after the stimulus for Choice target stimuli.

Fig. 6. Classification of out-of-sample trials. Shown is the histogram of LDA values for Choice and Not-Choice evoked potentials for out of sample data (25%). The groups are well separated, and yield ~80% correct identification of the chosen target.