33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

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

Ankit Jain, *Student Member, IEEE*, Insoo Kim, *Member, IEEE*, Bruce J. Gluckman, *Member, IEEE*

Abstract— **We described the development and testing of a low cost, easily constructed electroencephalographic (EEG) acquisition amplifier for noninvasive Brain Computer Interface (BCI) education and research. The acquisition amplifier was constructed from newly available off-the-shelf integrated circuit components, and readily sends a 24-bit data stream via USB (Universal Serial 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 BCIs utilizing non-invasive scalp EEG recordings as way of developing an 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 University 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 for the students to the hardware. This limited access contributed to reluctance by students to fully investigate the potential of the hardware. In addition, it significantly restricted the students' 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 \$3000-\$6000 (USD). Others now available targeted to the gaming community and cost \$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 a commercially available biopotential amplifier (ADS1298, Texas Instruments, Inc.) that forms 8 channels of preamplifiers and 24-bit continuous-time sigma-delta analog-to-digital converters (CTΣΔ ADC) with digital communication interfaces and other peripheral circuits. The key advantage of the CTΣΔ 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 ADCs allow for DC coupled recordings with almost all the signal processing then

Manuscript received April 15, 2011. 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.

Ankit Jain is a graduate student in the Electrical Engineering Department, The Pennsylvania State University, University Park PA 16802 USA (e-mail: ajain@ psu.edu).

Insoo Kim is a research associate in Department of Engineering Sciences and Mechanics at the The Pennsylvania State University, University Park PA 16802 USA (e-mail: insoo@ psu.edu).

Bruce J. Gluckman is Associate Director of the 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 (e-mail: BruceGluckman@psu.edu).

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 gold-plated cup EEG electrodes common to other systems. For course use, individual students can purchase and use their own disposable electrodes, or use course-purchased and cleaned gold-plated electrodes. Standard electrodes plug into our proposed 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: an analog front-end (ADS1298, Texas Instruments, Inc.), a microcontroller (MSP430F5525, Texas Instruments, Inc.), and isolation circuitry for USB and power (ADuM4160 & ADuM5000, Analog Devices, Inc.).

Analog front-end (ADS 1298): The use of ADS1298 aids remarkably in reduction of size, power and overall cost of the device [7]. It has a built-in programmable gain amplifier (PGA) with gain of 1-12, CTΣΔ ADC dedicated to each channel, internal reference for ADCs, an on-chip clock oscillator, and a serial peripheral interface (SPI) communication port. Additionally it can be configured for various differential input and referencing configurations, as well as both passive and active ground configurations.

Microcontroller (MSP430F5525): We use a low-power low-cost microcontroller for communicating with the ADS1298 and transmitting data from it to a computer. The communication between the ADS1298 and the microcontroller is accomplished using a SPI. For achieving maximum efficiency, we set up direct memory access transfers to receive conversion data from the front-end to be sent to the computer. Communication between the microcontroller and the computer is done through a standard USB connection. The microcontroller is programmed and configured as a USB CDC device (USB Communication Device Class), that can be recognized as a Virtual COM-port device, which can be easily accessed from within a variety of operating systems, such as Windows, Linux, and Mac OS, and software packages including MATLAB/Simulink, LabVIEW and student-written programs in C/C++.

USB Data & Power Isolation: We use an isolated DC-to-DC converter (ADuM5000) for supplying isolated power to the analog front-end for human safety. Also, we utilize a USB digital isolator (ADuM4160) for data transferring between the microcontroller and a PC with up to 12 Mbps transfer speed. ADuM5000 and ADuM4160 chips support isolation voltages of 2500 V_{rms} and 5000 V_{rms} for 1-minute duration, respectively [16], [17].

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 (Guger Technologies, Inc.) [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 during eyes open and eyes-closed rest conditions are shown in Fig. 2, recorded from one of the authors (BJG) with the proposed amplifier from O1 referenced to CPz. This data was acquired with a sampling rate of 250 samples per second (SPS). The acquisition hardware is inherently DC coupled, and the CTΣΔ ADC effects its own low-pass Nyquist filter to prevent aliasing. The only post-processing filtering (non-hardware 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 densities for these high-pass filtered recordings are shown in Fig. 3a. Here we have averaged over the full 60-second periods of same behavioral condition. One should note that there is very little 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

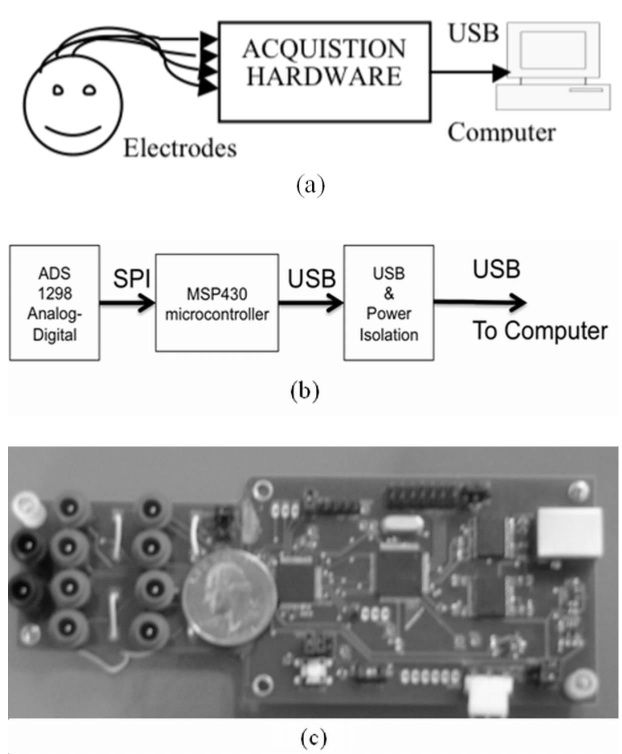

Fig. 1. Low-Cost 8-Channel EEG System for BCI Education. (a) Overview of BCI system. Electrodes on the head connect to our low-cost EEG acquisition hardware, which provides a continuous stream of digital data to the computer. (b) Overall architecture of the acquisition hardware. The main pieces involved 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.

readily removed in post-processing.

Validation: In order to directly compare the signal quality with a commercially available unit, data was recorded from both the proposed amplifier and a g.USBamp sequentially by unplugging the leads from one amplifier and connecting them to the other without removing the electrodes from the subjects' scalp. The 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 and acquired at 256 SPS.

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 g.USBamp has a much higher 60 Hz line noise, along with substantial additional harmonics and shoulder frequencies at ~ 60 ± 16 Hz. Second, the background noise level on the g.USBamp appears to be about an order of magnitude *higher* than that for

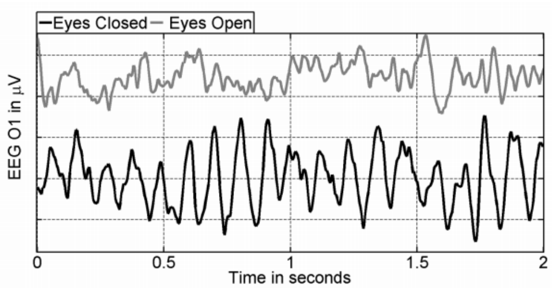

Fig. 2. EEG Quality from the Proposed Amplifier. Example signals recorded from O1, referenced to CPz, under eyes open and eyes closed conditions. Signals were acquired at 250 samples per second, and were later digitally high pass filtered at 0.5 Hz and offset for display purposes. Vertical Grid spacing is 20 μV.

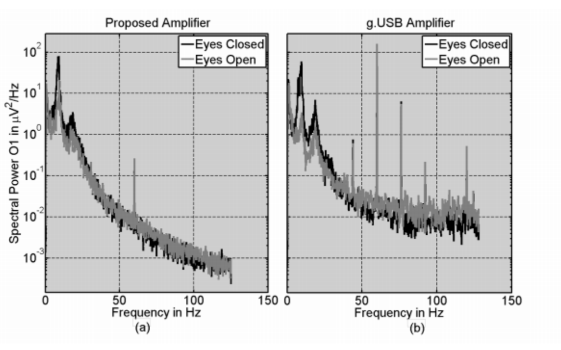

Fig. 3. EEG Spectral Densities under Eyes-Open and Eyes-Closed conditions. Signals recorded from O1, referenced to CPz. Behavioral conditions were held for consecutive 60-second periods. Recordings were first high-pass filtered at 0.5 Hz, the average spectra computed using a Welch averaging scheme with half overlapping 8-second 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 proposed amplifier, recorded at 250 SPS and (b) a g.USBamp, recorded at 256 SPS.

the proposed amplifier 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 corresponding to that target 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 absense 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 for a period of 80ms each and an inter-stimulus interval of 120ms, while the indicator in the center instructs the subject which target to choose. It has been shown that to achieve a better classification on a 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. In one trial, we averaged over 3 presentations for each target, with a total of 40 trials in one recording session.

Visual presentation as well as data acquisition was performed within the Simulink coding environment through a 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.

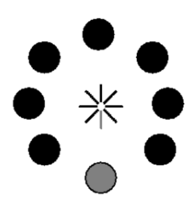

Fig. 4. Visual Display for our Visually Evoked P300 Paradigm. We use a pick-1-of-8 in which the user focuses on or chooses one of the eight targets. The targets are then highlighted serially in a random order by changing their color. For training purposes, to create a series for which the analysis knows what the user chose, the central pointer instructs the user which target to choose.

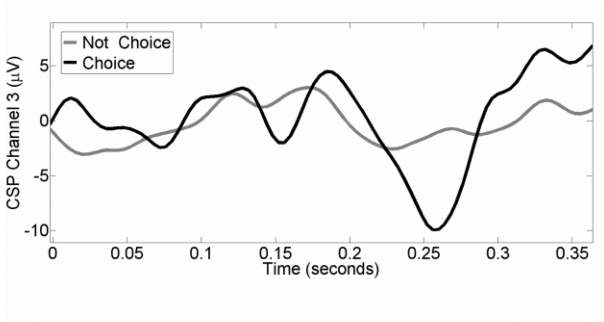

Fig. 5. Visually Evoked Potential for Choice and Not-Choice targets averaged over 40 trials. Notice the large peak approximately 260 ms after the stimulus for Choice target stimuli.

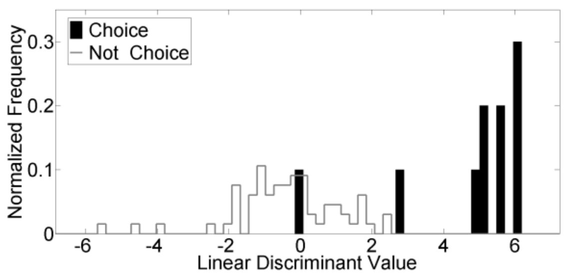

Fig. 6. Classification of Out-of-sample Trials. Shown is the histogram of LDA values for Choice and Not-Choice evoked potentials for out of sample data (25%). The groups are well separated, and yield ~80% correct identification of the chosen target.

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 SPS using the proposed amplifier.

Data analysis included the following steps. First, all data was filtered using 5^{th} order butter-worth 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. One should note that 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 (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 EEG 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 proposed system using the well-known P300 paradigm for a BCI application. The above results prove that our proposed system can serve as a low cost teaching tool for undergraduate or graduate students in engineering and science majors.

Acknowledgment

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

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