Wearable Ambulatory 2-Channel EEG NeuroMonitor Platform for Real-Life Engagement Monitoring Based on Brain Activities at the Prefrontal Cortex

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Abstract

Real-life engagement monitoring is crucial in many clinical and therapy applications such as classroom activities of children with developmental delays including autism spectrum disorder, attention-deficit hyperactivity disorder (ADHD), Down syndrome, or cerebral palsy. Generally, the prefrontal cortex of the human brain shows increased neuronal activities during attentive tasks, which can be monitored non-invasively with electroencephalogram (EEG) recordings. For real-life engagement monitoring, we have developed a custom hardware-software embedded system, the "NeuroMonitor." The hardware is designed on a small 11.35 cm^2 4-layer PCB containing a programmable system-on-a-chip (PSoC 3) microcontroller, an analog front end for 2-channel bipolar or referential montage EEG data collection, and a dual Bluetooth and microSD card digital back end. The AFE contains a low-power instrumentation amplifier, followed by a notch filter (f_{cn} = 60 Hz), and a band-pass filter composed of a 2nd-order Chebyshev-I active low-pass filter cascaded with a 2nd order low-pass filter (f_{cl} = 125 Hz), followed by a 1st order high-pass filter (f_{ch} = 0.5Hz). PSoC's integrated ADC (16-bit, 256 sps) samples this filtered signal with a mutex dual-buffer.

The system can operate either in offline mode, to store the collected data in the onboard microSD card, or online mode, to wirelessly transmit the data through the Bluetooth module at a baud rate of 115.2 kbps. The hardware weighs only 41.8 gm with an 800 mAh Li-Poly battery and snap leads. The active mode power consumption of the NeuroMonitor device is 32 mA, which can be optimized with dynamic frequency shifting (DFS) technique for over 90 hours of continuous operation on a single charge. A GUI allows initialization of the system through a micro-USB port or Bluetooth, also used to recharge the battery through a

power management chip. NeuroMonitor platform is deployable in real-life settings to monitor brain activities at two sites of the prefrontal cortex during daily activities.

Introduction

The human brain consists of billions of neurons that store and transmit massive amount of information through electrochemical processes [1]. These activities, when converted to electrical signals at cellular level, are known as action potentials. Extracellular matrix records simultaneous neuronal activities as local field potential and neuronal spiking activities. On the dura matter, these signals are recorded as electrocorticography signals. Noninvasively, these electrical signals can be recorded by placing electroencephalography (EEG) sensors at the scalp, using non-contact approach through magnetoencephalography (MEG), or using functional magnetic resonance imaging (fMRI) [2]. These non-contact technologies, however, require setup or equipment that is not suitable for the use of beyond clinical settings due to weight and restriction on subject movements. For instance, fMRI requires equipment to generate extremely high magnetic field strengths (typically 1.5 to 3 Tesla), and MEG requires highly sensitive magnetic sensors (e.g., a superconducting quantum interference device) [3]. MRI is an indirect measure of neuronal activities as it depends on blood oxygen level dependent imaging. Positron emission tomography of brain imaging requires the introduction of a radionuclide tracer on a biologically active molecule inside the body, and 3-dimensional imaging is reconstructed from a pair of emitted gamma rays indirectly by positron emitting.

Non-invasively collected scalp EEG signals are predominantly oscillatory wave activities that relate to mental states, massive synchronous neuro-stimulations and activities of various brain lobes [4]. EEG signals are typically classified as delta (0.1-3.5 Hz), theta (4-7.5 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (>30 Hz) rhythms. A copious amount of research have conclusively related various brain lobes responsible for specific cognitive activities, enabling EEG analysis as an efficacious modality for various types of studies in neuroscience, cognitive science and psychology [2,5]. For instance, the frontal lobe is associated with problem solving, mental flexibility, judgment, creativity, foresightedness, and deficiencies, whereas the temporal lobe is primarily responsible for auditory sensation, perception, language comprehension, long-term memory, and sexual behavior [6]. EEG signals have been analyzed to assess the mental states and neuronal activities of neurological disorder patients [7, 8].

Embedded system (ES) technology consists of hardware, software, and an environment encountering physical constraints and execution constraints that have to be dealt with by hardware-software co-design [9-11]. The device is developed with state-of-the-art ES technology that can be combined with body sensor network (BSN) or body area network (BAN), consisting of other sensors for multimodal physiological signal recording to provide a context-aware perception with increased specificity and reliability [12]. In conjunction with BSN or BAN, the device can be used for long duration unsupervised monitoring of patients with real-time feedback for many neurological episodes. It can also be clinically important for patient welfare and beneficial for their care providers (e.g., neurologists or clinician) by improving diagnosis, prognosis, and treatment efficacy.

Most of the commercially available wireless EEG data capture systems contain a large number of multichannel electrodes [4]. While these are excellent choices to provide the complete brain imaging and activity data of various lobes, these are rarely practical to be deployed for daily activity monitoring in natural settings due to obtrusiveness of the large wired device. Recently, there are devices developed that provide a smaller number of electrodes within a fashionable framework that could lead to data collection from real-life settings. The 14-channel EPOC and Insight neuro-headsets (from Emotiv) connect wirelessly to a computer using USB receivers and can provide access to raw EEG data for ~12 hours [13]. B-Alert X4 has a 4-channel EEG system with BT and SD card storage and is attached to the head with a harness [14]. The first FDA-approved, single-channel EEG recording device, iBrain, is small and portable, attached to an elastic head harness [15]. Other examples of single-channel EEG systems are MindWave, ThinkGear and MindSet from NeuroSky [16].

Other commercial wireless EEG acquisition systems include Biosemi, Enbio, Starstim, g.NAUTIUS, Imec, BioExplorer pendent, Ez-Air Light, FlexComp Infinity, MyoTrac Inifinity, Muse headset from Interaxon Inc, BrainWave, iFocusBand from Green Pty Ltd, Mindflex from Mattel, Neural Impulse Actuator from OCZ Technologies, Mindball rom Interactive Productline, BrainScope headset from BrainScope, and XWave headset and Sonic from PLX Devices [17-19]. Furthermore, many research articles have presented various types of EEG systems and sensors including ModularEEG from OpenEEG project and OpenBCI from OpenBCI project [20-24]. Many wireless EEG-based medical devices have demonstrated effective data collection and analysis [23-26].

None of the available devices would fit the subject group of our study, children with developmental delays between two to three years of age. Our research group was uniquely positioned to develop a hardware-software co-designed ambulatory EEG monitoring platform. The prototype has been developed, evaluated, optimized, and demonstrated over the last two years by the research team [27-32]. The system has been deployed to monitor classroom activities; however, it has the potential to be applied to many other neurological disorder patient monitoring such as autism spectrum disorder, attention-deficit hyperactivity disorder (ADHD), epilepsy, Alzheimer's, and post-traumatic stress disorder patients.

System Description

Embedded Hardware

We have developed a framework using a hardware-software co-design approach. This ambulatory scalp EEG data collection device, named "NeuroMonitor," can record 2-channel bipolar or referential montage EEG data in a real-world setting. EEG signals at the scalp are roughly less than 100 μV and 100 Hz, which necessitate extremely low-noise amplification and high input impedance amplifier. To collect EEG data from the prefrontal cortex (such as Fp1, Fp2 or AF3, AF4 locations of Intl. 10-20 electrode systems) of the subjects, we have used a commercial EEG/EMG sensor (GS26, Bio-Medical Instruments, Warren, MI). This disposable sensor contains a 0.5 percent saline base gel on a 10 mm flat pellet Ag/AgCl electrode surrounded by a paper-thin transparent self-adhesive tape disc of 1-inch diameter.

On the back of the electrode, a snap lead connects to the sensor to the NeuroMonitor device. In a minimalistic configuration, 4-electrode system is used for EEG and 3-electrode system is used for ECG.

Figure 1 depicts the NeuroMonitor prototype board with battery and EEG sensors. The analog front end (AFE) was designed with a differential amplifier configuration with ground terminal and reference terminal to bias to body potential as in [33]. EEG signals are subjected to various noise and artifacts including utility line interference (60 Hz), common and differential mode interference, thermal noise and shot noise of components, eye blink related artifacts, muscle artifact, heart beat related artifacts, and so forth. To minimize these noises, the AFE consists of a low noise differential instrument amplifier (ISL28270, Intersil Americas, Palm Bay, FL) and a 3-stage bio-potential scheme with an active notch filter (f_c = 60 Hz), implemented with a MCP6002 op-amp (Microchip Technologies Inc., Chandler, AZ) followed by a band-pass filter (f_{cl} = 0.5 to f_{ch} = 125 Hz) realized by concatenating a 2nd order Chebyshev-I low pass filter, a 2nd order low pass passive filter, and a 1st order high pass passive filter. The signal is biased and passed through a final amplification stage to achieve a total of 72 dB amplification. The AFE can be modified to capture electrocardiogram (ECG) data. To do so, AFE component values are altered to achieve a band pass filter cutoff of 0.5 Hz to 126 Hz, with a gain of 39.45 dB.

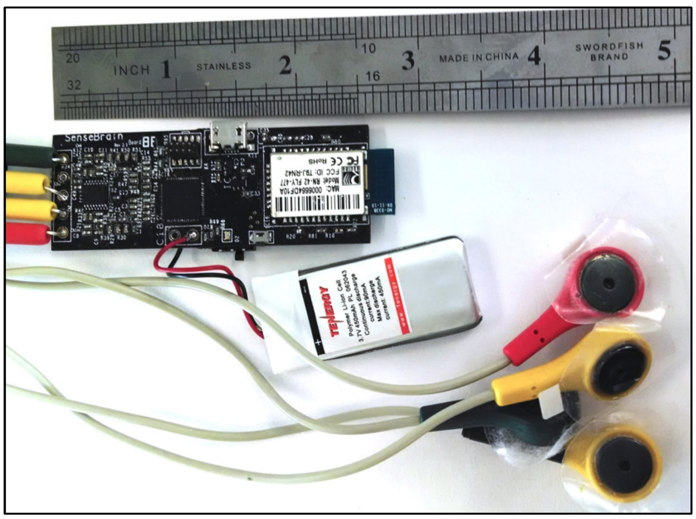

Figure 1. A photograph of the prototype NueroMonitor device (rev. 3) connected to four disposable EEG/EMG sensors and a rechargeable LiPoly battery, beside a ruler. The device is capable of recording 2-channel bipolar or referential montage EEG/ECG data and transmitting the buffered data wirelessly through the onboard BT module.

Two channel signals are then digitized through an analog multiplexer followed by a 16-bit Delta-Sigma ADC sampling the analog data at 256 sps. The ADC and the last 2 op-amps of each channel are housed within a low-power PSoC microcontroller to reduce the required footprint (PSoC 3 is from Cypress Semiconductor Corp., San Jose, CA). The 4-layer PCB contains a VDD and a GND layers as middle layers, where the GND is separated in analog and digital planes are connected at the ADC. The PCB also contains a microSD card socket

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at the bottom layer, and a Class 2 Bluetooth (BT) wireless communication module (RN-42, Roving Networks, Los Gatos, CA) at the top layer. The device is powered by a rechargeable 800 mAh Li-Poly battery with nominal voltage of 3.7 V (All-Battery.com). The battery recharges through a power management controller chip MCP73831 (Microchip Technology, AZ) from a microUSB. The port also allows data communication to a computer for configuration and mode selection. The size of NeuroMonitor is 2.2″×0.8″×0.36″, and it weighs only 41.8 gm. The device can be easily concealed inside a wearable accessory, such as a headband or a baseball cap.

Embedded Firmware

The embedded firmware was written in C using PSOC Creator IDE software (Cypress Semiconductor Corp., San Jose, CA). The microcontroller was programmed with MiniProg 3 through JTAG port. In online mode, the device communicates with a remote computer through the BT module in serial port profile at a baud rate of 115.2 kbps to an external device (e.g., a smartphone or a laptop). In offline mode, data are stored in the onboard microSD card for offline data storage for later analysis.

The embedded firmware implements a mutex duel buffer for continuous sampling, ensuring data integrity. The analog signal sampling is achieved at the ADC, triggered by a timer-driven interrupt at 3.9 ms interval (256 sps). The sampled 16-bit data from both channels are placed in one of the buffer using the Interrupt Service Routine. When the buffer is full, a flag is set to use the other buffer for subsequent samples. In the meantime, the full buffer data are appended with a header containing information on type and serial number of the packet, and then transmitted wirelessly through the BT via a universal asynchronous receiver/transmitter port (online mode). The sniff mode of BT is set at 100 μs. The firmware can be enhanced by transmitting timestamps, which can be realized by synchronizing the onboard real time clock with the remote computer. Furthermore, power consumption can be improved with direct memory access (DMA) and dynamic clocking for power minimization.

Interfacing Software

The GUI was programmed with Visual Basic (version 2010, Microsoft Corp., WA), then later ported to MATLAB (Mathworks Inc. Natick, MA) that can initialize the NeuroMonitor device and configure online or offline mode. The online mode data are received with the MATLAB interface that allows real time monitoring of sequential reception of all packets; otherwise, it generates an error message. Also, the real-time program arranges the upper and lower bytes of the received data to form the 16-bit integer and saves each channel in a vector. A third vector stores metadata such as packet number. A user clickable marker provision is also implemented that allows insertion of marker points in the third vector to correlate the raw EEG data with the noted events during data collection.

Functional Verification

The NeuroMonitor device is functionally verified by a number of experiments. Raw data using the NeuroMonitor device from representative experiments are included in Figures 2 and 3. The data were collected in online mode through the BT interface. In Figure 2, the raw data from Fp1 location of a subject was collected when the subject was frowning and four sequential eye-blinking. Muscle artifacts from frowning and eye-blinking are readily recognizable in the raw data as these artifacts have more than 1 order of amplitude. These artifacts were later removed by denoising algorithm such as wavelet-enhanced independent component analysis technique. In Figure 3, the raw data with our NeuroMonitor device is compared with a clinically approved 64-channel NeuroScan EEG data collection device (Compumedics Sleep, Charlotte, NC) by simultaneous data collection from the same site (AF4 of Intl. 10-20 electrode systems) with minimal spatial separation from a subject in relaxed state inside a magnetically shielded room. The data show correlation of the NeuroMonitor and NeuroScan raw data, while the NeuroMonitor device shows more sensitivity, higher noise, and higher amplification.

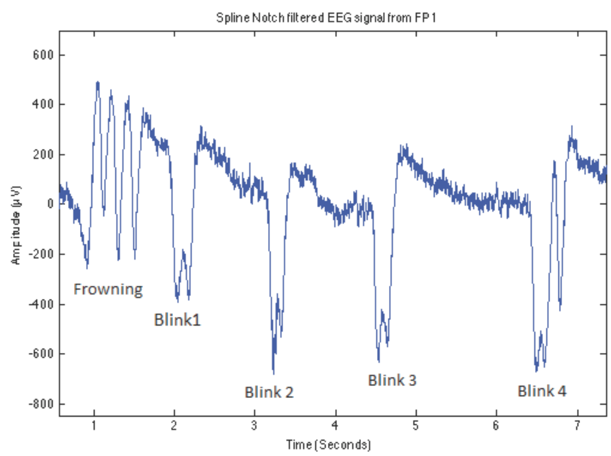

Figure 2. Raw data collected with NeuroMonitor device. The data are superimpositions of brain signals (EEG data) with artifactual components (such as frowning or blinking of eyes). These raw data are analyzed with MATLAB software to remove the artifacts and denoised further to obtain clean EEG data.

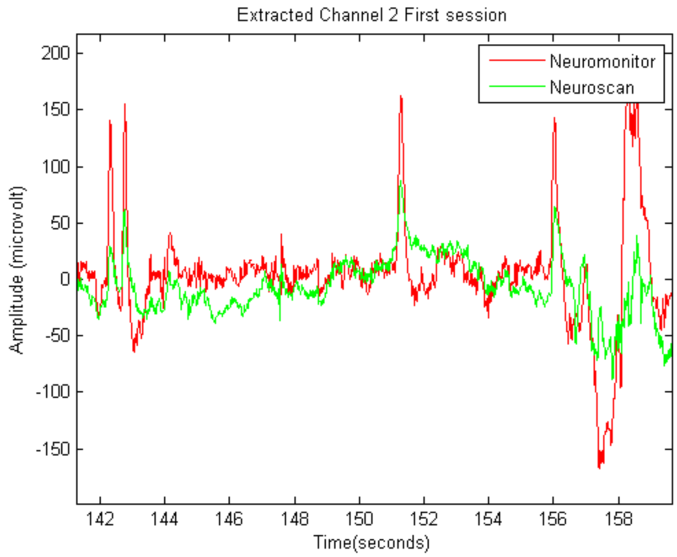

Figure 3. Comparison data of the NeuroMonitor device with a clinically approved EEG system (NeuroScan) for the same channel of data (minimal spatial gap). The plot shows the sensitivity of the NeuroMonitor device is higher compared to that of the NeuroScan system.

As wearable embedded devices, such as the ambulatory NeuroMonitor EEG device, operate with a small rechargeable battery, portability and power consumptions are critical constraints. For power optimization, various approaches can be used such as dynamic voltage scaling, and dynamic frequency scaling (DFS). A DFS approach involves the microcontroller operating at a low-power mode of nominal clock frequency (NF) when idle, then dynamically stepping up to a higher clock frequency (SUF) when tasks arrive for processing. After the task is complete, the CPU falls back to the low-power mode. Figure 4 shows a plot demonstrating power saving with various SUF and NF. The device consumes 32 mA while active in online mode. Without the BT power consumption, the power consumption was optimized to 5.24 mA using the DFS technique. On-going power optimization testing indicates that by using DMA and a revised firmware architecture, the power consumption can even be lowered (3.5 mA). With optimized power consumption, the device could operate continuously for over 90 hours with an 800 mAh battery in a single charge.

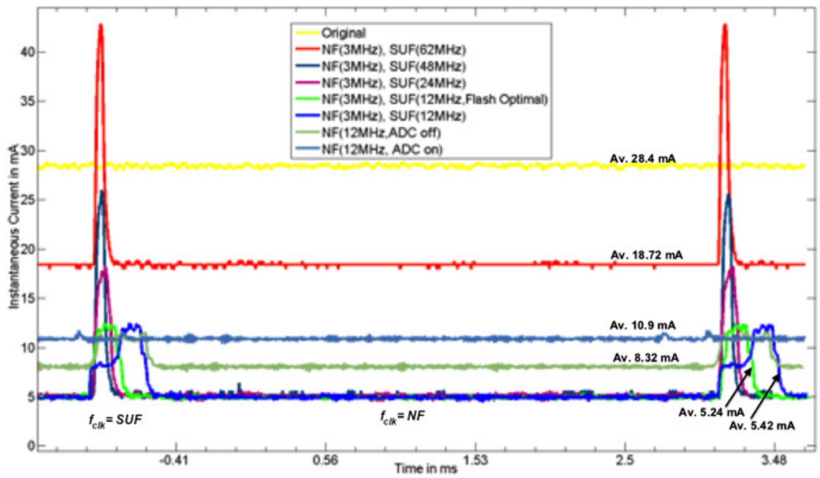

Figure 4. Power optimization with the DFS approach. The spikes of current consumption relate to when the CPU switches to a SUF for performing some task (e.g., fetching data from ADC to buffer), and the flat regions relate to current consumptions for NF.

Applications

We have deployed the NeuroMonitor device for real-life data collection of children with developmental delays at Special Kids and Families (SKF), a non-profit organization in Memphis. A representative plot is shown in Figure 5, where the subject was responding to classroom activities with the device worn inside a baseball cap and data collected with online mode. The data can be subjected to various classification approaches to identify events of interest. In this example, cognitive load index (CLI) is determined from the power of different rhythms. It has been shown that beta rhythm power intensifies (i.e., power spectral density, PSD) with attention, while that of alpha and theta decreases. Hence, the CLI is defined as,

$$CLI = \frac{PSD_\beta}{PSD_\alpha + PSD_\theta}$$

where, PSD_β, PSD_α and PSD_θ are the PSDs of beta, alpha, and theta rhythms, respectively.

Prolonged duration and personalized monitoring of patients with neurological disorders (such as symptomatic or cryptogenic epilepsy) will significantly enhance efficacy of patient care and aligns well with the national priorities. A product with such capabilities and usability will, in addition to epilepsy patient monitoring outside clinical settings, also find applications to other neurological disorder patients. Similar monitoring can be beneficial to Alzheimer's, PTSD, autism spectrum disorder, and ADHD patients, as well as for assessment of working memory load and cognitive stress by detecting corresponding events of interest (noteworthy episodes).

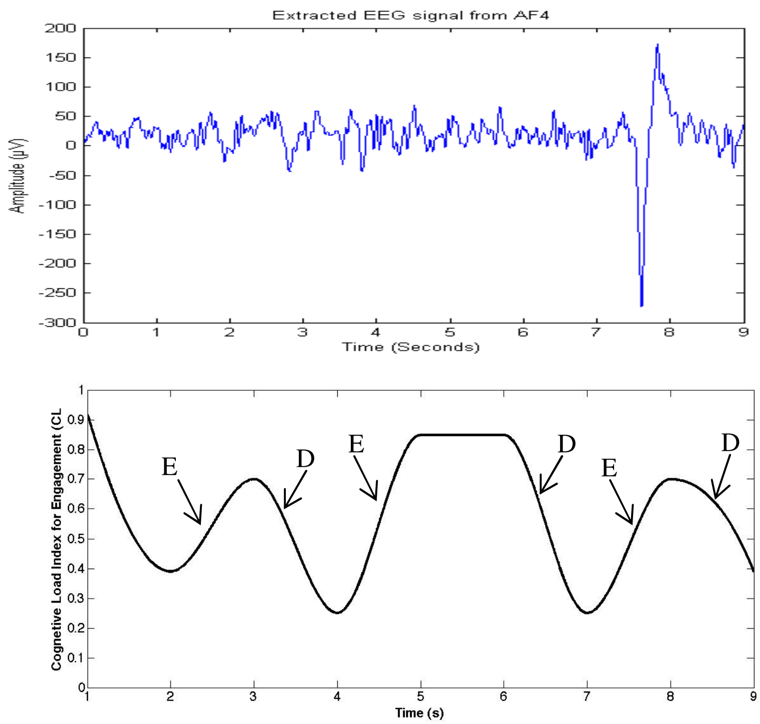

Figure 5. Data collected form a subject at SKF in classroom settings (left) and corresponding engagement metric computed through the analysis software for engagement study (right). The CLI indicates engagement (E) and disengagement (D) during classroom instruction.

Conclusions

Neuronal activity monitoring in real-life settings over long periods is of significant medical need and technological challenge to improve diagnosis, prognosis, and efficacy of treatment, as well as reduce healthcare cost with a transformative patient-centric care paradigm. As a practical framework, we have developed NeuroMonitor device with key features including small size and weight, concealable within a baseball cap or a headband, 2-channel bipolar or referential montage EEG or ECG data collection at real-life settings, two modes of operation (online and offline), and a low power consumption of 32 mA in active online mode, which was optimized to 5.24 mA using DFS (without the BT power consumption). It is estimated that an 800 mAh battery should be able to operate it continuously for over 90 hours. The NeuroMonitor EEG device is readily deployable in real-life settings to allow the subject to perform routine activities without distractions while monitoring cognitive activities or episodes of interest for patients with neurological disorders.

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