Extending wireless wearable EEG device with Single Board Computer for real-time neurofeedback and neuromodulation applications

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Abstract*—Neurofeedback is a self-driven brain training technique by providing real-time feedback of one's own brain activity, and is widely used in clinical treatment and also in other industries such as gaming. Neuromodulation, on the other hand, is an automatic brain training technique where real-time brain activity can better guide the presentation of external stimulations for effective changes. For both the techniques, real-time changes in the brain activity are usually measured as oscillatory patterns from Electroencephalogram (EEG). Conventional setup for neurofeedback and neuromodulation use bulky EEG devices and PCs in wired settings that are intrusive, uncomfortable and limit usability in real-world settings. But, setting up a wearable EEG device (like MUSE) wirelessly to a powerful Single Board Computer (SBC) (like BeagleBone AI, Coral Dev Board) could help overcome this limitation. Though multiple research groups have used such a setup, they are not generic enough for wide scale applications of neurofeedback and neuromodulation. This paper tries to address this lacuna by demonstrating the steps to achieve such a setup and use of open source frameworks like brain flow and signal processing tools like mne and tensorflow for the same. Such a setup and framework would help conduct research in neurofeedback and neuromodulation using low-cost wearable EEG and SBCs.

***Keywords*— Neurofeedback, EEG, Coral Dev Board, BeagleBone AI, Real-time, Signal processing**

I INTRODUCTION

Electroencephalogram (EEG) is one of the non-invasive diagnostic technologies for the brain, which measures the neural electrical activity as micro voltages across time. EEG has been widely used in the diagnosis of neurological conditions like Epilepsy, where it helps in localizing abnormal functional activities. Moreover, EEG signals are often viewed as oscillations with varying frequencies and amplitudes that help determine different arousal states and cognitive activities. These oscillations are classified into five canonical types: Delta (0.5-4 Hz) - occurs during non-REM sleep, sleep without dreams, very low awareness states; Theta (4-8 Hz) - occurs during light sleep, deep meditation and during reduced consciousness states; Alpha (8-12 Hz) - occurs during relaxed state, creative and super-learning state; Beta (13-30Hz) - occurs during the normal waking state, engaging in some tasks and the outside world; Gamma (30-40Hz) - occurs during intense concentration and learning. These brain oscillatory patterns can be used to provide real-time feedback of one's own mental states (Neurofeedback) or to provide stimulations (visual, auditory, electric or magnetic) to alter brain states (Neuromodulation).

An EEG acquisition system typically consists of sensors placed on specified locations of the scalp (usually with conductive gel or paste) connected to differential amplifiers. The amplifier then transmits the amplified and filtered data to a computer as digitized values for further visualization, analysis and storage. Most EEG acquisition systems are wired, but EEG acquisition can also occur wirelessly, via Bluetooth, WiFi, etc., running on battery power - within a small form factor. Thus, wireless wearable EEG devices solve the issue of restricting the mobility of subjects and yet without compromising the signal quality. They achieve this by integrating all the hardware units onto a few dedicated integrated circuits (ICs), thereby reducing the size and weight of the recording apparatus [1]. With recent development, the wireless EEG data acquisition also includes features like active grounding, electromagnetic shielding, dry electrodes, etc., which further improves signal quality, subject comfort, user friendliness, accessibility, and mobility [2]. Some of such low-cost, wireless, wearable EEG acquisition devices are developed by companies like Neurosky, Mindwave, OpenBCI, Emotiv, gtec, Neurosity and MUSE.

Most of the above-mentioned wearable EEG devices seamlessly interface with proprietary mobile phone applications, with limited or no access to raw EEG data. But, to use the mobile EEG data for more research-grade applications, they need further preprocessing and feature extraction methods. This usually requires interfacing with more flexible software tools (like MATLAB or Python) running on high-end Personal Computers (PCs), which makes the whole set-up less mobile. However, the PCs can now be replaced with capable Single-board computers (SBCs) for signal acquisition and further signal processing, thereby offering the flexible use of algorithms and retaining the mobility aspect of a wearable device. SBCs usually include a system-on-chip (SoC) which contains a general-purpose processor, typically based on ARM architecture. Compared to a desktop PC or a laptop that runs on x64 architecture, ARM uses a reduced instruction set, making chips smaller and more energy efficient [3]. Most SBCs run on Linux operating systems and can port open source software packages of PCs like Python or Octave and their toolboxes. SBCs, when integrated with EEG devices, facilitate the development of Brain-Computer Interface (BCI) applications like neurofeedback and neuromodulation. Examples of SBCs used in such applications are Raspberry Pi, Nvidia Jetson, Coral Dev Board, and BeagleBone AI (BBAI).

Therefore, if the available wireless wearable EEG devices can be easily interfaced with appropriate SBCs, the translation of current advances in EEG research into real-time neurofeedback and neuromodulation applications will be more effective. Though many solutions exist to achieve this, to the best of our knowledge, we couldn't find a research study that demonstrated a practical application demonstrating all the above (see Table 1). In this paper, we try to address this lacuna

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by describing how the existing framework can be used to interface a commercially available wearable EEG device with two different SBCs optimized for higher signal processing and machine learning (ML) applications. We demonstrate the applicability of this setup for EEG data streaming and basic signal processing, EEG and ECG based neurofeedback and neuromodulation and real-time ML algorithm.

Table I: Summary of the components in existing research in comparison to our proposed work

Ref	**SBC**	**Wireless EEG**	**Real-time**	**Open source**	**Comments**
[3]	✓	✓	✓		Studied on animal model
[2]	✓	✓	✓	✓	Data acquired on SBC, but streaming on PC
[4]	✓	✓			Used Matlab
[5]	✓			✓	Acquisition using microcontroller (Arduino MEGA)
[6]	✓			✓	Used stored dataset. But, processing done on SBC
Our paper	✓	✓	✓	✓	Real-time acquisition and processing done using the open-source platform

II PROPOSED METHODOLOGY

The proposed methodology talks about the setup of the EEG streaming device with two different SBCs.

A. Single Board Computers

Out of the several SBCs available, we have chosen Coral Dev Board and BeagleBone AI as they are optimized for higher processing required for EEG signal processing and machine learning.

1) Coral Dev Board: The Coral Dev board is an SBC used in prototyping. The presence of an on-board Edge TPU coprocessor makes it capable of performing 4 trillion operations per second, using 0.5 watts for each TOPS (tera-operations per second), which is useful for signal processing and machine learning applications. It has good wireless connectivity and runs a lightweight derivative of Debian Linux which is called Mendel Linux. It's not recommended to be used as a standalone system (desktop environment), but it can be interfaced via Serial Console or SSH terminals. Mendel Development tool (MDT) is a command-line tool that helps to interact with the Dev Board, and is installed on the host computer. The run time system is downloaded, and Mendel Linux is flashed onto the Coral Dev board using the micro SD card. Coral Dev has 8 GB of onboard eMMC, which makes the device faster. The OS image is flashed onto the eMMC. As it can boot only from the eMMC, the SD card can be used as expandable memory.

2) Beaglebone AI: The BeagleBone AI (BBAI) is a small, powerful industrial SBC based on the Texas Instruments AM5729 SoC. It is incorporated to develop edge computing-AI interference using pre-trained Neural Networks which can be of further use in the embedded devices. It consists of the TI C66x digital signal processor cores and embedded-vision-engine cores supported through an optimized TIDL machine learning OpenCL API with pre-installed tools. BBAI can also act as a standalone system with keyboard and mouse support and can be interfaced with a monitor via HDMI.

BBAI consists of 16 GB of eMMC which helps in the flashing of the memory. It runs on Linux debian OS installed on eMMC. The BBAI can boot from either the eMMC or the SD card.

B. EEG acquisition Device

The wireless wearable EEG streaming device chosen for this paper is the MUSE S as it is a commercially available device that allows capturing of EEG signals that are of research-grade [7] to have less setup time and maintain the subject's convenience by having fewer electrodes. Moreover, the use of all channels may lead to an overfitting effect.

1) MUSE S: MUSE-S is a wireless, wearable headband EEG which consists of four silver coated fabric electrodes corresponding to antero-frontal and temporo-parietal brain regions on left (AF7, TP9) and right (AF8, TP10) side as per the international 10-20 System. MUSE-S is also equipped with other sensors like gyroscope, accelerometer and photoplethysmography. The headset uses a PIC24 microcontroller and Bluetooth chip for BLE-based communication to stream the EEG data, however it has no onboard storage. It uses a non-standard Open Sound Control (OSC) streaming protocol, and hence needs decoders to be read in regular software tools.

C. Software

1) EEG acquisition tools: Brainflow is an open source software framework primarily written in Python that allows seamless integration of EEG devices including MUSE-S. BrainFlow is a library to parse and obtain biosensory data from devices and it provides protocols for bluetooth connections with or without dedicated dongles as well. The strengths of this library over others are its easy implementation, its board versatility (e.g., a few lines of code can easily adapt the program to receive signals from OpenBCI Cython, g.tec Unicorn, Muse, Neurocity etc). It consists of a powerful API with many features to simplify data acquisition, filtering, denoising, downsampling, and detrending. Though brainflow does not provide compiled versions for most SBCs, they provide the source files and steps to compile for our required SBC architecture using cmake. The brainflow compiled for BBAI was not compatible with the Coral Dev Board as the former has 32-bit architecture while the Coral is of 64bit architecture.

2) Additional signal processing tools: Some of the additional signal processing which can be used are MNE [8] and YASA [9], MNE can be used in pre-processing of the data such as Filtering, scaling, decimation, Partitioning and augmentation of the data set. YASA can be used in event detection, spectral analysis and artifact rejection.

3) Tools for Stimulus Interfaces: Pygame [10] is a multimedia library for python for making games and multimedia applications and it is open source. It is a wrapper around the Simple DirectMedia Layer (SDL) library. From the Pygame package, the pygame mixer module is used for loading sound files and controlling them. By using the pygame mixer module, we have the basic functionalities to increase and decrease the volume of a sound file, which we have used in our audio-visual based real time neurofeedback framework.

4) Machine learning tools: Tensorflow [11] is one of the machine learning tools which offers a powerful library, resources and tools for numerical computation, it helps us to train and build our own modules.

D. Experimental setup of Single board computer with MUSE

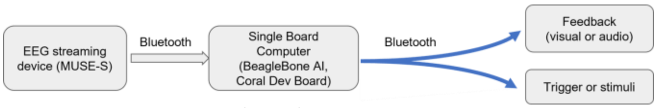

Fig.1. Workflow of the proposed system

Fig. 1. shows how we have set up the connection between the eeg streaming device and SBC. The wireless EEG streaming device (MUSE-S) was connected to an SBC (BBAI or Coral Dev Board) via bluetooth for real-time streaming of EEG data. We conducted this setup separately for BBAI and the Coral Dev Board. Brainflow library was installed in both the SBCs, and the standard codes were used to achieve stable connection. Connection between MUSE-S and BBAI required an external bluetooth dongle, as the onboard bluetooth was not accessible. However, the Coral dev Board could be directly connected to the Muse-S without an external dongle.

1) Pilot demonstrations: Using the above experimental setup few pilot studies were conducted. We first tried streaming real-time EEG data from MUSE-S to either of the SBCs and explored basic signal processing capability of the Brainflow library. To test the feasibility of this setup for closed-loop auditory presentation, we detected R-wave peaks of real-time ECG data as well as the instantaneous theta phase 0 of EEG data as events and produced external auditory stimuli at the event. We also explored the workability of TensorFlow models on both Coral and BBAI

III EXPERIMENTAL RESULTS & DISCUSSION

A. Basic Signal processing

Filtering is one of the most basic pre-processing steps required when receiving a raw EEG stream from a device. A wrong filter can introduce artifacts like ripple, phase delay and other distortion within the passband. We used an IIR butterworth filter, as these are usually preferred for real-time data analysis as required in this work. The Butterworth bandpass filter is implemented during the pre-processing stage. The butterworth filter provides a response that generates no/minimal ripple and maximally flat in the passband and stopband [12]. It provides good average transient characteristics and an expansive transition region from band pass to band stop thus enabling a good compromise between amplitude response selectivity [3]. Real-time filtering is performed on short chunks of data, unlike offline filtering which can be done on a large set of data (both past and future segments). Besides pre-processing, filtered can also be used to extract different frequency bands such as Delta (0.3-4 Hz), theta (4-8Hz), Alpha (8-13Hz), beta (13-30Hz) and gamma (>30Hz), for real-time evaluation.

B. Closed-loop auditory presentation

1) Heart rate timed auditory stimuli:

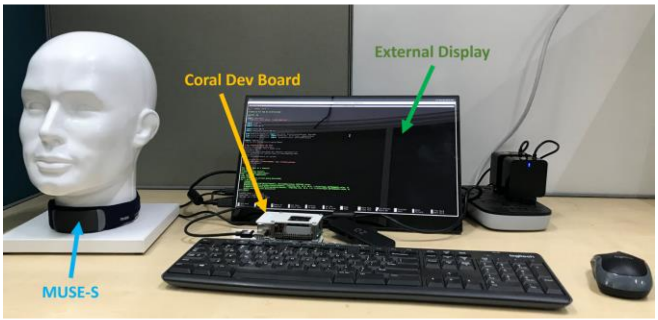

Fig. 2. Setup to acquire Heart rate timed auditory stimuli

The MUSE-S headband is used for the EEG acquisition, but it also can be worn around the neck to get the electrocardiography (ECG) data (Fig. 2). Real-time ECG is streamed onto the SBC, and the acquired signal is filtered. In ECG data, R wave peaks of the QRS complex were detected in real-time, using the peak detection function of the scipy library. To present an auditory stimulus with each R wave detection, we could play a sound file (using the subprocess library) within the detection loop. A more elegant approach would be to use a Pygame mixer which will run on a parallel thread than that of the peak detection, and therefore allow us to modulate an ongoing sound (like increase the volume) with each detection. An audio file is used to play along with the ECG data, frequency is increased with every R-peak detection.

2) Neural oscillation timed auditory stimuli:

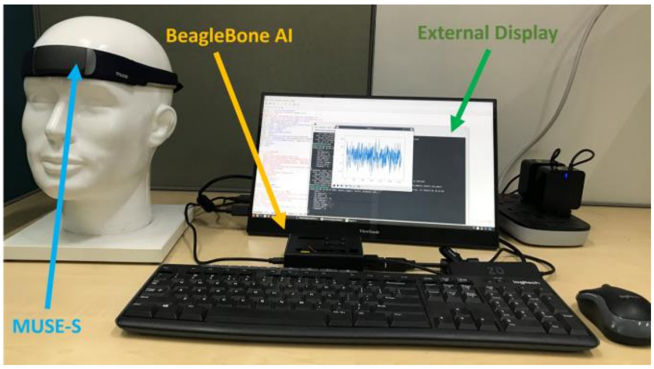

Fig. 3. Set up to acquire Neural oscillation timed auditory stimuli

Here, we estimated the instantaneous phase of theta rhythm from the real-time EEG signal (Fig. 3). To get the instantaneous phase information we used two methods, one is Hilbert Transform and the other is Morlet Wavelet. Hilbert transform was marginally faster than Morlet Wavelet. Whenever the instantaneous phase was 0°, we would present a short auditory tone (using the subprocess library) within the detection loop. However, this feedback was discomforting (4-7 loud beeps per second). This also caused a delay in real-time processing. Instead, the real-time modulation of ongoing sound (using Pygame mixer), made the auditory feedback tolerable and had minimal impact on real-time processing.

C. Machine learning

The standard TensorFlow library for machine learning cannot be directly installed on the SBCs. Tensorflow lite is a lightweight version of Tensorflow designed for inference on embedded devices. So, the Tensorflow model should be trained on a PC or a remote server and then the model should be converted to a Flatbuffer file (.tflite) using TensorFlow Lite converter. This file can now be used on the SBC for classification or regression applications. Coral Dev Board has tensorFlow Lite pre-installed, but BBAI requires the source code to be compiled using CMake. To test this on the SBC setup, we used MNIST data set of digit classification using a multi-layer perceptron model. We ran the algorithm on the SBCs and were successful in achieving the expected results. We also tried out a deep-neural network based autoencoder model that can do real-time EEG state detection. The autoencoder model was trained on eyes open resting EEG data, converted into tflite model using the tensorflow lite converter and were successful in using the tflite interpreter on the SBC. This showed that we can run the machine learning algorithms on the SBCs that can be used for future applications such as real-time BCI applications, including neurofeedback and neuromodulation.

From the above pilot works, we demonstrate the feasibility of extending MUSE-S using SBCs like BBAI and Coral Dev Board, for neurofeedback and neuromodulation applications without restricting the mobility of the subjects.

We also observed several differences between the SBCs that need to be considered preparing the proposed set up which are summarized in Table II.

Table II: Selected differences between the SBC set ups

Coral	**BBAI**
arm64 / aarch64 and it has 8 GB of eMMC. It has quad-core processing unit	armhf -32 bit and it has 16 GB of eMMC. It has a dual-core processing unit.
Coral is Bootable only from eMMC, after flashing from SD card. Further, SD cards can be used as expandable memory	BBAI Bootable from SD card or eMMC. Cannot access eMMC and SD cards simultaneously.
Tensorflow Lite already installed	Tensorflow Lite had to be compiled from source
Inbuilt Bluetooth was easily accessible	Inbuilt Bluetooth was not accessible, external Bluetooth dongle was connected
A stand-alone system is not recommended, only the terminal is accessible.	Can be used as a standalone system. It can be used a mini-computer
MDT when on the same network as of host computer using data cable - MDT can be used to copy files from the host computer, but has a bad text editor Serial console can be accessed using a serial cable	Cloud9 using Power(data) cable. Cloud 9 acts as a terminal for accessing the BBAI board on the PC.

IV CONCLUSIONS & FUTURE WORK

The study shows the integration of the wireless wearable EEG devices with the SBCs, which contribute to the various real time applications. We demonstrated real time data streaming, preprocessing and auditory neurofeedback/neuromodulation and preliminary configuration for running machine learning based algorithms on SBC.

The proposed BCI setup is not limited to the particular application demonstrated here, but can also be used alongwith other measurements such as ambient temperature, accelerometer and gyroscope. The proposed system is portable, low power and low cost, and allows utilising Machine learning based approaches for conducting neuromodulation and neurofeedback protocols. Such a setup can be used to provide more precise neurofeedback as well as smarter closed-loop control for electrical neuromodulations (like tVNS, tDCS). The setup can be used in large scale clinical studies, remote monitoring, home-based studies, etc., even in low resource setting with minimal technical expertise.

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