Brain-eNet: Towards an Enabling Technology for BCI-IoT Systems

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Abstract— Brain-Computer Interface (BCI) and Internet of Things (IoT) systems have recently been amalgamated to create BCIoT. Most of the early applications have focused on the healthcare sector, and more recently, in education, virtual reality, smart homes, and smart vehicles, amongst others. While there are many transversal developing stages that can be satisfied by a single system, no common enabling technology or standards exist. These challenges are address in the proposed platform, Brain-eNet. This technology was developed considering the constraints-space defined by BCIoT real-time mobile applications. This is expected to enable the development of BCIoT systems by providing modular hardware and software resources. Two instances of this platform implementation are provided, a motor intent detection for rehabilitation and an emotion recognition system.

I. INTRODUCTION

Since the term Internet of Things (IoT) was first used by Ashton in 2009 [1] defining it as the result of "adding radio-frequency identification and other sensors to everyday objects", this field has been vastly growing and evolving to give shape to a more holistic definition given by Ng and Wakenshaw [2] "as a network of entities that are connected through any form of sensor, enabling these entities, which we term as Internet-connected constituents, to be located, identified, and even operated upon".

In a similar fashion, Brain-Computer Interfaces (BCI) have been evolving since their inception in 1973 through the work of Jacques Vidal [3]. The BCI term can be defined as an additional communication channel of the brain with the world using non-normal output "pathways of peripheral nerves and muscles" [4], [5]. From current BCI technologies, electroencephalography-based BCI (EEG BCI) is the more affordable and simple to implement outside the lab in most environments [5]. Thence, from this point forward, when we refer to BCI it is assumed that we are referring to EEG-BCI.

Early proof-of-concept BCIoT applications have been developed in health care [6], smart homes [7], [8], virtual reality [9], [8], and smart vehicles [10], among others. In these applications, researchers usually collect data using off-the-shelf EEG headsets, which are transmitted to a computing device where it is processed to give commands to the specific end-effector (e.g., a computer, physical or virtual object(s), and even an avatar) [11]. This approach has some difficulties associated with the following:

- Cost: This pertains to the EEG headsets, processing units, and cloud computing services required in BCIoT systems.
- Reliability: The dependence on remote processing units increases latency and increases privacy issues risk. This indicates the need for the development of Edge computing to ensure robustness and reliability [12].
- Usability: To use these systems, a certain level of technical proficiency is typically required, resulting in a barrier for users who are not technologically inclined [13].
- Computational complexity: These systems often involve a substantial number of channels, which results in increased computational demands and complexity [14]. Additionally, an enabling platform necessitates the development of processing pipelines that exhibit computational efficiency. This will be more critical if the application considers wearable BCIs and mobility, as it is necessary their implementation in battery powered-embedded systems [15], [16].
- No real-time denoising: Most of the denoising algorithms employed in BCI systems are for offline use, thereby imposing limitations on the practical implementation of BCIoT systems in real-time [17].
- Context Augmentation: The application context can be leveraged to relax the constraints-space. Problems that are considered intractable can be solved by making the correct assumptions of the context [18], [19], [20].

Because of these challenges, the exponential growth in BCIoT applications has been thwarted. Some companies have tried to counteract the high cost (See Table I) of the BCI component. Nevertheless, none of these systems allow for any preprocessing or processing onboard,

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needing additional computing resources in-situ.

TABLE I: Low cost solutions

Product	Number of Channels	Price
Muse 2 [21]	IMU and 4 EEG	$249.99
Emotiv Insight 2 [22]	IMU and 5 EEG	$499.00
Ultracortex Mark IV [23]	IMU and 16 EEG	$399.99
Neurosky MindWave 2 [24]	1 EEG	$129.99

In this article, we proposed Brain-eNet, a BCIoT platform that addresses the above challenges and it is expected to become an enabling technology for BCIoT applications in medical and non-medical sectors. The article is organized as follows: Section 2 discusses the methodology. Section 3 presents two applications of the proposed system, and section 4 provides a discussion and concluding remarks.

II. METHODS

The product specifications considered in the design of an IoT-enabled BCI system included onboard de-noising capabilities to handle artifacts that contaminate the EEG, machine learning model calibration for neural classification, impedance measurement to assess signal quality, WiFi/Bluetooth connectivity for IoT, usability and flexibility for electrode locations to fit a spectrum of applications in the medical and non-medical sectors, including neural engineering research applications. Additional criteria have been summarized in [25], [26] and [27].

A. Hardware Module

The system is composed of a proprietary chip that is interfaced with an embedded platform, the BeagleBone Black - Wireless (BBB-W) [28] chosen due to its low-cost, compatibility, and wireless capabilities (Bluetooth and WiFi).

TABLE II: Amplifier Specifications

Amplifier Specifications	
Number of Channels	8
SNR	121 dB
Input Noise	1.39 μV_{PP}
CMRR	110 dB
ADC Resolution	24 bits
Input Impedance	1000 MΩ
Maximum Sampling Rate	500 Hz
Bandwidth	DC-131 Hz
Input range	$\pm$ 104mV
Resolution	0.012 μV

The amplifier of Brain-eNet is the ADS1299 chip from Texas Instruments, Inc. [29], specifications shown in Table II, which follows the technical specifications defined in [30] and standards considerations highlighted in [11]. In addition to sensing EEG and electrooculography (EOG) signals, the system also measures head motion data using an Inertial Measurement Unit (IMU, ICM-20948) chosen because of its low power consumption, low error, and it is equipped with a 3-axes gyroscope, accelerometer, and magnetometer. Specifications for the IMU are shown in Table III.

TABLE III: Inertial Movement Unit Specifications

Inertial Movement Unit Specifications	
Gyro Full-Scale Range	250-2000 dps
Acc Full-Scale Range	2-16 g
Zero offset error	5 for 250 dps
ADC Resolution	24 bits
Zero-g Offset	$\pm$50 mg
Power Consumption Acc+Mgn	0.580 mW
Power Consumption Gyro	4.43 mW

B. Firmware Module

The firmware was developed using modularity as a core design principle so that the firmware toolkit can be easily used, adapted, and suitable for different BCIoT applications. The current programming language used for the module is C++ for communication with both the amplifier and IMU. The current communication protocol is Serial Peripheral Interface (SPI), a synchronous serial communication commonly used for short-distance communication. The current EEG, EOG, and IMU features include amplifier setup of channel amplification, measurement of impedance values from the electrode system, raw data collection, saving data into memory, or streaming it to the BBB-W for processing. The current sampling frequency of the system is 500 Hz in open-loop. However, the sampling frequency will be limited by the computing resources of the embedded platform and the specific application, for example for the second implementation (see Section III-D.2), where a camera and video processing are needed, the sampling frequency is on average 190 Hz.

Table IV depicts the overall BCIoT specifications of the Brain-eNet, with embedded Bluetooth and WiFi communication modules. It can be programmed in multiple programming languages, it allows for onboard real-time de-noising of the signals and neural decoding. The current implementation is limited to applications with up to eight channels (any combination of dry EEG and EOG electrodes), excluding the reference electrodes.

III. RESULTS

A. Signal Acquisition

The signal acquisition process starts with amplifier setup, gathering data at a sampling rate of 500 Hz (open-loop), converting the received hexadecimal values into voltage values, and subsequently organizing the trial data into files suitable for subsequent analysis or streaming to the BBB-W for processing. Figure 1 illustrates the synchronized collection of 5-EEG, 3-EOG,

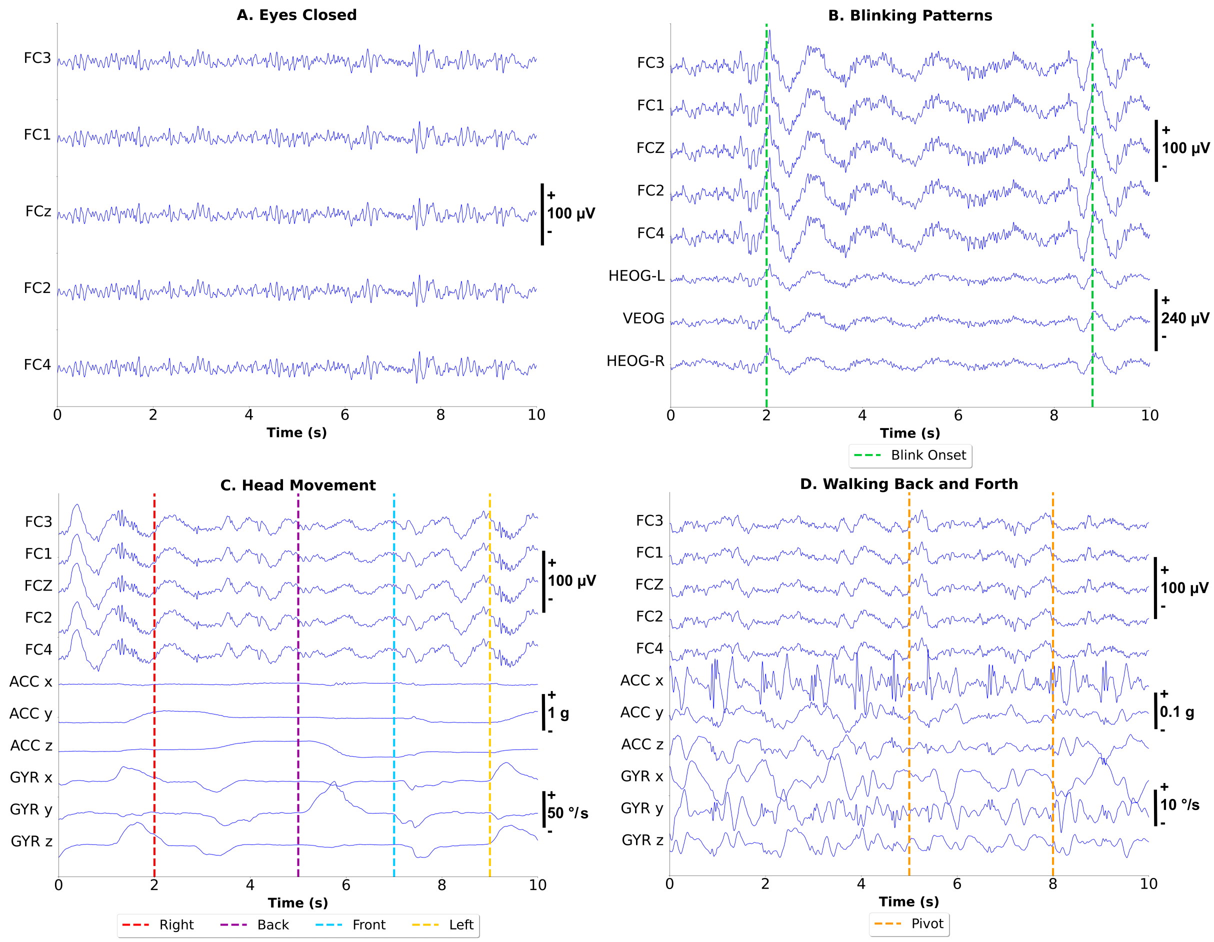


Fig. 1: Raster plot of synchronized EEG, EOG and IMU data from the proposed BCIoT system during eyes closed, head movement with open eyes, and during walking. A. Eyes closed: A participant was instructed to close his eyes during a session. B. Blinking Patterns: A participant was instructed to blink his eyes 2 times, and the blinking artifacts can be observed around 2 sec and 9 sec; identified with green dashed lines. C. Head Movement: The participant was instructed to move his head to the right (shown by a red dashed line), backward (purple dashed line), forward (blue dashed line), and to the left (yellow dashed line). D. Walking Back and Forth: The participant was instructed to walk in one direction back and forth. The plot's orange dashed line shows places where the participant changed direction (forward and backward).

3-axis gyroscope, and 3-axis accelerometer data. The five EEG channels are positioned over the sensorimotor cortex for movement intent detection. The signals shown have been passed through a fourth-order band-pass filter between 0.5 Hz and 20 Hz and plotted prior to the de-noising module.

B. Impedance Measurement

In dry-electrode EEG systems, monitoring good signal quality (high signal-to-noise ratio (SNR)) is critical as it is necessary to have good contact between the electrodes and the scalp or skin. [31]. This requires measuring and displaying impedance values so potential users can adjust electrodes that show high impedance accordingly.

C. Onboard Denoising

As discussed earlier, EEG suffers from low spatial resolution, low SNR, and artifacts such as eye blinks and eye movements, shifts in electrode potentials, and motion artifacts. Because of EEG's signal properties, a BCIoT system should be able to process EEG and denoise the brain signals effectively. However, common signal-denoising methods, such as independent component analysis (ICA) are not generally applicable to mobile or real-time applications. Implemented capabilities of the Brain-eNet system include a high pass filter, H-Infinity Adaptive Noise Cancellation used for real-time eye artifact removal [17], and a low pass filter. Additionally, real-time adaptive motion artifact removal [32] using IMU data is under development.

D. Deployment of Brain-eNet

In this section, two implementations of BCIoT demonstrate the adaptability and flexibility of the proposed hardware across various applications with

TABLE IV: Current Engineering Specifications of Brain-eNet

Brain-Computer Interface Specifications	
Processor Speed	1 GHz
Processor Memory	512 MB
Processor Storage	4 GB
Open-Loop Sampling Frequency	500 Hz
Connectivity	USB client for power & communications. USB host. 802.11 b/g/n WiFi, Bluetooth 4.1 plus BLE. HDMI.
Back-end Programming Language	C++, Python
Front-end Programming Language	JS, CSS, HTML, Swift
Battery	2.96 kWh + charge indicator
De-noising	Low and High Pass Filters, Adaptive Noise Cancellation (H^{∞} based)
Features Extracted	Slope, negative peak amplitude, area, and Mahalanobis distance
Machine Learning Algorithm	Support Vector Machine, Linear Discriminant Analysis
Maximum number of Channels (any combination of EEG/EOG)	8

minimal modifications. Drawing from the initial experience, the software modules were subsequently reconfigured to align with the existing principles of modularity already implemented in the hardware. The second implementation shows some partial results.

Fig. 2: NeuroEXO System: In this instantiation, we have a BCIoT platform for rehabilitation. The system is dedicated to motor imagery in a BCI application with five (EEG) electrodes across the sensorimotor cortex, three EOG electrodes, and two reference electrodes. EOG electrodes are found in the foremost arms and the front band. The deployed hardware and software can be found in the posterior area of the headset inside the white translucent box. [33]

1) NeuroEXO: An IoT-enabled BCI system for upper-limb motor rehabilitation: The first application where the hardware was deployed was the NeuroEXO system, a "Brain-controlled Upper-Limb Robot-Assisted Rehabilitation Device for Stroke Survivors" [33]. The application focuses on using an EEG-controlled robotic device, rebless (H Robotics) [34], for neural rehabilitation of the sensorimotor cortex. The clinical application required the use of five (EEG) comb electrodes located in FC3, FC1, FCz, FC2, and FC4 (according to the international 10–20 system), based on findings from a prior BCI clinical trial for upper-limb rehabilitation after stroke [35], [36]. Additionally, the system used three electrooculography (EOG) electrodes located on the user's face at the right and left temple and above the left eye, to create a reference to remove eye artifacts from EEG signals using Adaptive Noise Cancellation algorithm based on H-infinity [17] [37].

Regarding signal processing, the system incorporates onboard capabilities for denoising and decoding to identify motor intent effectively. Onboard denoising encompasses the removal of EOG artifacts and bandpass filtering. To detect motor intent, the system utilizes a Support Vector Machine (SVM) model, which undergoes training and testing directly onboard. Furthermore, the system includes other requirements, such as the control of the robotic device and a web application. This web application, developed using Labview and LINX toolkit, facilitates the display of impedance, EEG, and EOG signals. Additionally, it provides a protocol for subjects to follow. The web application is hosted on the same BBB-W used for signal processing onboard, and the visualizations generated can be accessed from a tablet (Amazon Fire 8) or an iPhone (7 and onward). Notably, all the necessary processing for this application is executed locally onboard, eliminating the reliance on external computing resources. Figure 2 illustrates the headset developed.

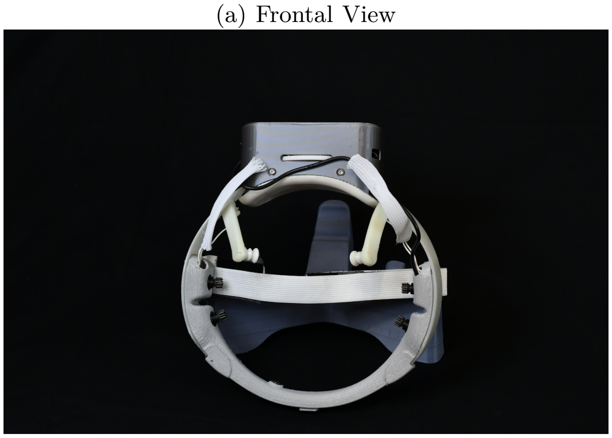
This system is currently undergoing clinical trials at the clinic and at home based on [35], [36]. In the current trials, each participant has one week of training at the clinic and 6 weeks at home training. Up to this point, 5 stroke survivors have been enrolled in this study. The system is currently being validated in a longitudinal study with healthy participants for potential use in non-medical applications. These studies' results and details of implementation are beyond this paper's scope and are partially reported in [33], [38].

2) Remote Health Monitoring: The system was adapted for an emotion recognition application requiring four EEG channels, FT7, T7, FT8, and T8, located over the temporal areas as suggested by [39], one EOG channel, and synchronized video recording for context awareness capabilities. Additional requirements included WiFi communication with an iOS mobile application developed in Swift, a Firebase database to save mobile app information and video context awareness data, and

machine learning.

The system required minimal changes to be implemented and integrated into the emotion recognition application, suggesting that the current hardware and software implementation can be easily adapted to other systems for research in IoT-BCI applications. Figure 3 shows the version of the system for emotion recognition where four EEG electrodes are positioned on the inner lateral areas of the headset, the reference electrodes are located on the posterior arms of the headset, and the deployed system located in the box located in the back of the headset.

(a) Frontal View



(b) Top View

Fig. 3: Remote Health Monitoring: Version of the system dedicated to emotion recognition with 4 EEG electrodes in temporal areas, 1 EOG electrode, 2 reference electrodes, and a camera for context-awareness. The deployed hardware and software can be found in the posterior area of the headset inside the gray box.

IV. DISCUSSION AND CONCLUSIONS

The development of a customized BCI system capable of measuring EEG signals with real-time onboard processing capabilities presents a complex design challenge that necessitates careful consideration of various factors, including portability, usability, interoperability, and reliability. The proposed platform, Brain-eNet, aims to serve as an open test bed for creating cost-effective and portable yet highly efficient and reliable custom IoT-BCI systems. Brain-eNet has been successfully implemented in two real-time fully onboard processing applications, namely motor intent and emotion recognition, and it is anticipated to be applicable in other IoT-BCI implementations. The combination of all these discussed features renders Brain-eNet a self-contained system, which is currently absent from the existing commercial landscape.

Future work is needed to address various areas common to IoT systems, including energy harvesting techniques [40], cloud computing integration [41], Deep Learning algorithms [42], and cybersecurity measures [43]. Cybersecurity is of particular concern, wherein attacks on IoT systems have been observed, targeting specific aspects such as device vulnerabilities, location-based exploits, access level breaches, information damage potential, host reliability, protocol-related and layer-based vulnerabilities, among others [43]. Current implementations do not consider the aspect as it is out of scope. However, the authors are aware of their needs and expect to implement some of the available approaches in the near future.

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