IoT-enabled Multimodal Sensing Headwear System

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***Abstract*—with the proliferation of Internet of Things (IoT) paradigm, wearable devices and solutions aim to resolve unmet needs from military, automotive to healthcare domains. Particularly, there are growing interests in wearable Brain Computer Interface (BCI) from both commercial and research applications. Still uphill challenges lie ahead to bring such BCI technologies to mass market due to lack of technical, usability and application aspects. To fill these gaps, this paper presents design, development and evaluation of an IoT-enabled multimodal headwear system, iMESH. Our solution senses user's neural, physiological and physical states through direct measurements and derives health parameters. We then developed driving fatigue assessment application as exemplar to illustrate applicability and feasibility of the proposed solution. Initial results are promising and with ongoing development on methodologies, we are hoping to further develop and validate iMESH functionalities in different applications.**

Keywords—Internet of Things (IoT), Brain Computer Interface (BCI), Multimodal Sensing Headwear.

I. Introduction

With pervasiveness of smart phone in our daily life and proliferation of IoT technologies, paradigm in health and wellness shifts from centralized to mobile care [1, 2]. In recent years, BCI technology garnered huge interests to bring into mass consumer market beyond clinical and lab settings [3]. There is a potential to integrate BCI technology with existing IoT technologies to create integrated body-mind wellness care [4]. There are some initial works on providing robust communication for such wearable BCI devices interfacing with IoT [5, 6]. Even wearable BCI is applicable in intelligent transport domains for preserving safety and wellness [3, 7].

This paper presents design and implementation of wearable multimodal sensing system connecting to IoT ecosystem [8]. In recent years, there are a few successful crowd funding projects for wearable BCI such as Muse[$], Emotiv Insight[&], OpenBCI[%],. Such EEG devices target application areas ranging from sleep, entertainment, sport, etc. to safety and neuro-marketing [9]. Still there are challenges and limitations in providing as a general purpose BCI wearable device available for application developers. Nevertheless, existing wearable devices do not provide diverse sensing needs to measure motion, physiological and neural states of subject under observation. From our experiments with two EEG headsets for controlling drones, various data quality and usability issues were identified [10]. This motivates us to design and develop an IoT-enabled multimodal headwear system, iMESH. Based on the limitations and issues identified [10], we have evaluated different electrode materials, headwear design concepts and signal quality of iMESH.

The system design, architecture and implementation of the proposed multimodal headwear will be explained in section 2. Section 3 describes experiment design, criteria and evaluation of proposed headwear in design, signal quality and sensed health parameters. Section 4 presents driving simulator scenario with results achieved for real-time mental fatigue assessment application. Finally, limitations and future works relevant to proposed multimodal headwear system can be found in section 5.

II. System Design and Architecture

Existing consumer BCI headsets and research prototypes [3, 9] only provide from one to five EEG channels and motion sensor. But physiological parameters such as HR, HRV, etc. are crucial to quantify various user wellness states. In addition to EEG and motion sensing, iMESH supports 2 PPG sensors as shown in Table 1; thus able to detect different neural, physiological and motion parameters.

TABLE I. Comparison of Different Wearable EEG Solutions

Modality	***Muse***	***Emotiv Insight***	***iMESH***	***OpenBCI Ganglion***	***[3]***	**Mindwave mobile[*]**
EEG	4	5	4	4	5	1
PPG	0	0	2	Add-on*	0	0
IMU	Yes	Yes	Yes	Yes	-	No

A. Hardware Design and Architecture

The following Fig 1(a) describes six hardware sub-modules involved in iMESH's PCB module. EEG Analog Front End (AFE) consists of instrumentation amplifier, bias feedbacks with Programmable Gain Amplifier (PGA) and Delta-Sigma Analog to Digital Controller (ADC) to acquire unipolar brain wave signals. PPG AFE includes Light Emitting Diode (LED) driver,

[$]https://www.indiegogo.com/projects/muse-the-brain-sensing-headband#/
[&]https://www.kickstarter.com/projects/tanttle/emotiv-insight-optimize-your-brain-fitness-and-per
[%]https://www.kickstarter.com/projects/openbci/openbci-biosensing-for-everybody
[*]https://store.neurosky.com/pages/mindwave
[#]https://www.rigado.com/products/modules/bmd-350/

Trans-Impedance Amplifier and ADC connected to both infrared and red LED and photo detectors. IMU DAQ senses physical motion using integrated 3-axis accelerometer and 3-axis gyroscope (six degrees of freedom). MCU and BLE wireless sub-modules are designed with SoC module, BMD350 from Rigado Inc#. Power management supports different regulated voltages required by EEG, PPG and IMU sensors and battery charging. iMESH board size is 24 x 39 x 4 mm^3 fabricated with 4-layered PCB as shown in Fig 1(b).

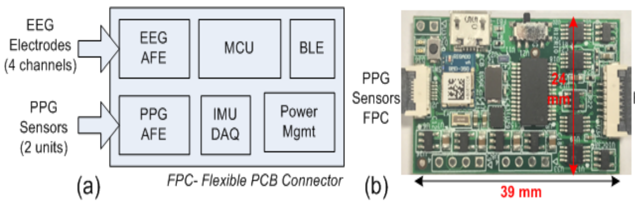

Fig. 1. iMESH Hardware and Prototype module (a) Hardware functional sub-components (b) Actual PCB module with dimensions and sensor connectors

B. Health & Wellness Parameters Measurements

As discussed in previous section, iMESH differentiates itself from other solutions by being able to support three sensing modalities. The following Table II outlines several health and wellness parameters directly measured and derived from acquired EEG, PPG and IMU readings. Below table only lists some basic features and some derived parameters to illustrate capabilities of iMESH (Not exhausted listing). The additional features and advanced parameters can further computed depending on application requirements. Furthermore, multiple features can be extracted with algorithms developed on module, PC or Cloud according to the specific application needs [11, 12, 13].

TABLE II. MEASURED AND DERIVED PARAMETERS OF THREE SENSORS

Sensor	**Health and Wellness Parameters**			
	Direct Measures	***Features***	***Derived Parameters***	
			General	***Specific***
EEG	Brain waves	5 band powers	Attention, Calmness	Fatigue, Emotion
PPG	Pulse Signals	Peaks, IBI #	PR#, PRV#	SpO2, RR#
IMU	Acceleration & Angular raw readings	ms^{-2} & rad/sec	Quaternion, Euler angles	Application specific physical activities

IBI – Inter Beat Interval, PR – Pulse Rate, PRV – Pulse Rate Variability, RR – Respiratory Rate

C. Software Design and Platform

As shown in Fig 2, iMESH software is designed in three layers: module (headwear), gateway (PC/mobile) and cloud. First layer, firmware, at headwear is responsible for sensing, MCU-based processing and wireless transfer using BLE (Bluetooth version 4.2). Middle layer, application and library, is implemented at either PC or mobile platform to wirelessly interface with headwear, perform full-fledged multimodal signal processing, store synchronized data and support further data streaming without geographical range limits. Topmost layer relies on cloud-based Software-as-a-service (SaaS) platform provided by third party IoT platform, Initial State Technologies (https://www.initialstate.com) [14]. The modular integration with existing data platform enables iMESH to be easily accessible anywhere and at any level (local or remote applications at heterogeneous devices) without delving into software architecture implementation details [16]. So this tiered architecture allows iMESH to be easily integrated into any IoT system with multimodal sensing needs.

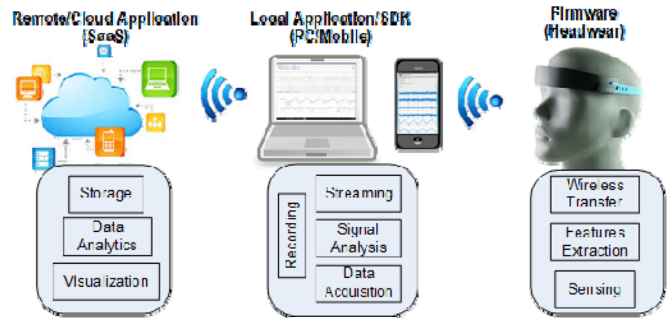

Fig. 2. iMESH Software Design and Components (Right to Left): (a) Headband unit acquiring signals and wireless data transfer (b) Intermediate device (PC or mobile) acquisition and data streaming by direct communication with headband unit (c) Cloud or server remote unit analyzing, visualizing and storing recorded data

III. HARDWARE DESIGN, TESTING AND EVALUATION

As iMESH supports three different sensors, careful hardware design, software interfacing and signal quality evaluation were involved in headwear development [17]. This section explains detailed design, testing results and evaluation of signal quality of iMESH in workbench as well as human subject testing scenarios.

A. Headwear design with Dry Electrodes

In order to ensure convenient and easy usage, dry electrode is commonly used in consumer EEG headsets [18]. Similarly, iMESH uses soft conductive fabric material as dry electrode [19]. EEG electrodes and PPG sensors can easily be fitted into different wearable design, cap (Fig 3-a) or band (Fig 3-c), through flexible PCB substrate (Fig 3-b), connected to the PCB (Fig 1-b). EEG and PPG at forehead are positioned according to EEG 10-20 standard as shown in Fig 3-d. Current dry electrodes can achieve average contact impedance of 200-400 kΩ that is a decent range for data recording with dry electrode.

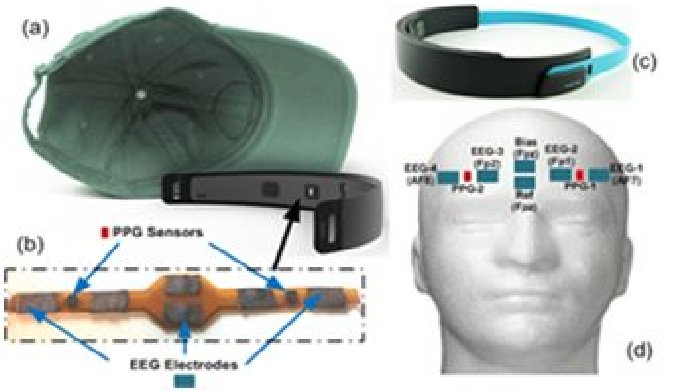

Fig. 3. iMESH Wearable Design and Form Factor (a) Attached sensing strip to cap as accessory (b) Internal of sensor strip in (a) where showing positions of EEG fabric electrodes and PPG sensors (c) Wearable elastic band connected to sensing strip as standalone headband strap (d) Positions of six EEG electrodes and 2 PPG sensors at forehead area

B. Hardware Performance Evaluation

The amplitudes of EEG signals range from 10 to 100 µV [9, 17]. Self-noise or noise floor of EEG AFE is important to ensure such tiny EEG signals can be captured and amplified correctly. Noise floor can be measured by connecting all EEG electrodes except bias to analog ground of the module. iMESH module exhibits average RMS amplitude of 2.5 µV that is lower than nominal EEG amplitude range. This basically explains why iMESH can detect signals and signal changes across EEG signal range.

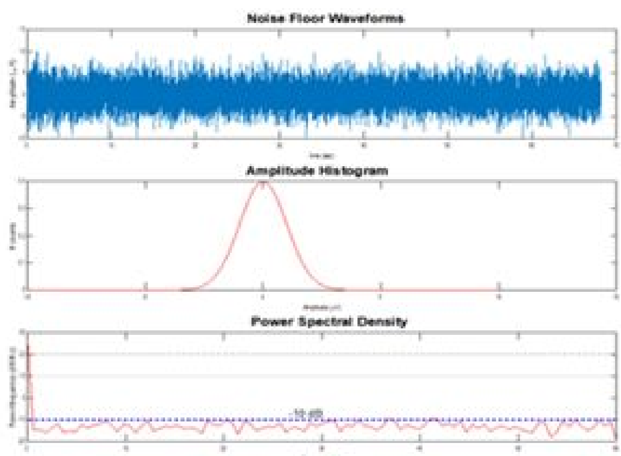

Fig. 4. Noise floor test results with iMESH hardware module (Top) EEG waveforms (Middle) Amplitude Histogram, 2.53µV in time-domain (Bottom) Noise Power Spectral Density (<-10dB) in frequency-domain

Another bench test includes injecting sine waves with varying amplitude and frequency through EEG simulator to test EEG AFE response. The results show no distortion in waveform with amplified signals according to PGA's gain settings set in iMESH's firmware as shown in Fig 5.

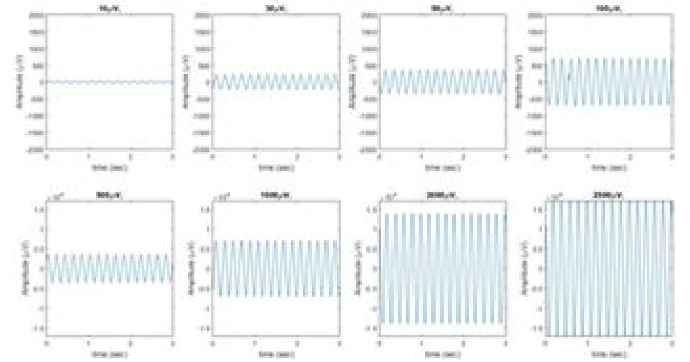

Fig. 5. iMESH EEG amplifier outputs in response to simulated sine wave inputs: Showing eight waveform output plots with input sine wave of 5Hz frequency with eight amplitudes ranging from 10 µV to 2.5 mV (Top-Left graph: 10 µV, Bottom-Righ grapht: 2.5 mV, In-between graphs: outputs with input amplitudes of 20, 50, 100, 200, 500, 1000 µV sequentially)

Subsequent tests involve wireless performance and battery life time evaluation. The operating distance is more than 5 m range from testing inside the lab while subject is wearing the module under blocking and non-blocking conditions. iMESH module lasts more than 7.5 hours with non-optimized firmware for continuous data streaming with 250 Hz sampling using 150 mAh rechargeable LiPo battery. This illustrates that reliable wireless data streaming with long-term usage can be achieved with iMESH for different wearable application needs [2].

After passing basic work-bench testing successfully, the acquired EEG and PPG signals are evaluated using basic signal fidelity testing procedure using eye blinks, eye closed and eye open events. As show in Fig 6-a, blinks (EOG) can easily be detected using electrodes positioned at Fp1 and Fp2 with Fpz reference montage. The strong EEG alpha power can be seen in Figure 6-b while closing eyes compared with eye open conditions as highlighted in green color box.

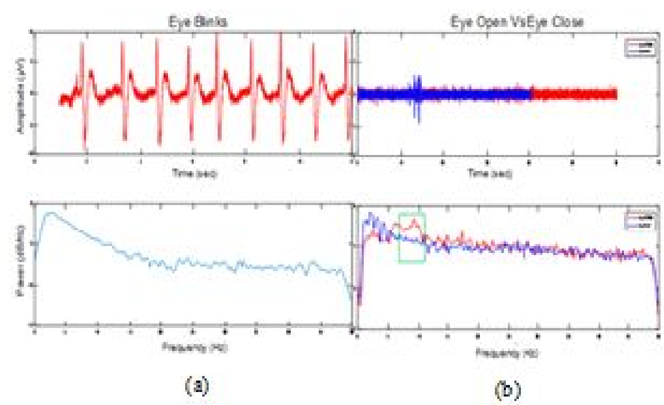

Fig. 6. iMESH EEG Amplifier's Basic EEG signal fidelity testing outcomes with time-domain waveforms (Top) and frequency-domain spectrum plots (Bottom) [Only showing single EEG signal for clarity] (a) Eye blinks for plots at left side (b) eye open and eye close for plots at right side.

The derived physiological parameters such as PR (HR) and PRV (HRV) can be detected from PPG signals applying appropriate signal processing approaches [12, 13]. Fig 7 shows steps involved in derivation of PR and PRV from raw PPG signals. HR and HRV parameters can be detected by processing raw PPG signals through filtering, peak detections and finally, extracting IBI features and applying first order derivatives.

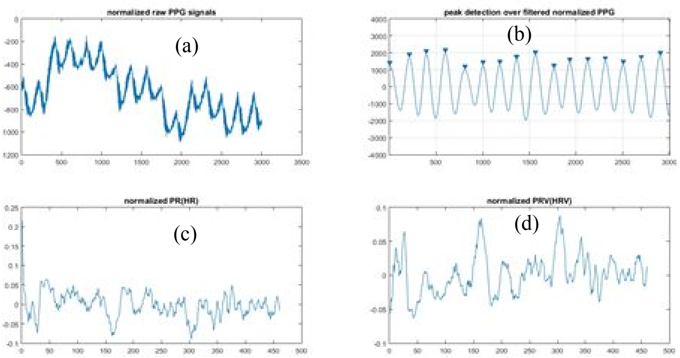

Fig. 7. PPG outputs from iMEHS module (a) Raw PPG signals (b) peaks detection after performing filtered and normalized PPG signals (c) normalized Pulse Rate (PR) (d) normalized Pulse Rate Variability (PRV)

C. Real-time data streaming and visualization

Besides visualizing sensors' readings at local device (PC or mobile), iMESH extends availability of its data to anywhere anytime real-time streaming and analytics using cloud SaaS. The picture in Fig 8 shows a snapshot of visualizing EEG and PPG signals at web browser by streaming from headwear through cloud leveraging library provided by Initial State Technologies. This paves way for BCI data availability beyond local (PC or mobile) processing; and group based analysis of user's neural and physiological states through cloud-based data analytics. This showcases how iMESH can leverage and integrate with existing IoT software and hardware technologies for sensing neural, physical and physiological parameters.

Fig. 8. Real-time streaming and visualization of EEG + PPG signals from iMESH headwer over cloud using library from Initial State Technologies

IV. Experimental Evaluation: Fatigue Assessment

Several solutions applying different sensing and intelligent approaches to mitigate accidents due to fatigue were proposed to improve safety on the road [7, 16]. These research works highlight the necessity of assessing in and off vehicle as well as subject's parameters to reliably determine fatigue states [17]. As many parameters influence driver's fatigue states especially in real-world usage, research and development works are ongoing to prevent road accidents due to driver's fatigue regardless of recent advances in autonomous driving [7].

To evaluate how iMESH works well on detecting fatigue states, we conducted pilot in-house trials using EEG and PPG sensors with simulated driving scenarios. The experiment design and protocols are explained details in [21]. A total of ten healthy subjects who have no sleep disorders or deprivation participated in 1.5 hours long driving experiment as shown in Fig 5. Besides EEG and PPG recording from iMESH, camera and eye tracker data are recorded for data labeling and validation. Subject has to complete driving game that emulates monotonous driving scenarios. In this driving test, deviations of car are programmed at random [2-10s] interval from center lane to either left or right lane for evaluating user's sleepiness through reaction time. During the experiment, subject was instructed to look at the game screen and turn steering wheel at correct direction immediately whenever simulator deviates car from center lane to left or right lane in random intervals. Reaction time (RT) for each lane-departure event was calculated as the time latency between deviation (at the start of lane deviation event in driving game) and response onset (when user turning steering wheel). Current fatigue assessment uses RT as surrogate measures to classify between fatigue and non-fatigue events during driving scenarios.

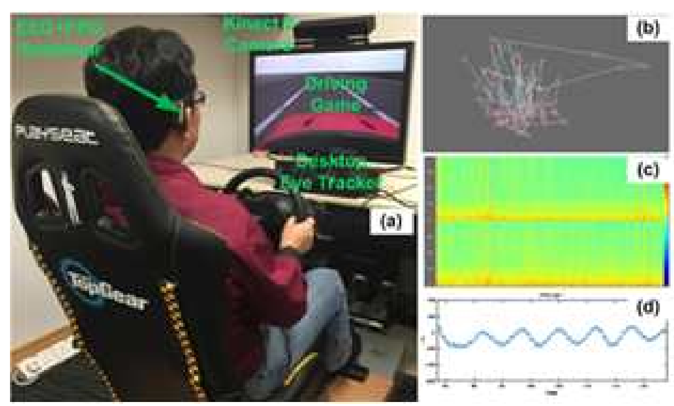

Fig. 9. Fatigue Driving Experiment Setup (a) Driving Simulator with headwear and additional sensors such as desktop eye trackers and kinect camera for ground-truth evaluation (b) eye tracker plots (c) EEG spectrogram (d) PPG signals [snapshots taken from one session of driving experiment]

With the labeled fatigue and non-fatigue datasets according to RT ranges, mean classification has accuracy of 86.4% using features extracted from EEG modality alone. Eye tracker modality using gaze positions and gaze velocity has only 77.6% accuracy. By combining EEG with PPG modalities, fatigue detection accuracy improves 4 to 5 % compared with EEG modality alone. This initial outcome is encouraging to include multimodal sensors in detecting fatigue. Though motion data is not used currently, its inclusion will be useful for head movement based fatigue states detection as well as for reducing or removing motion artifacts from EEG and PPG readings [22, 23].

V. Discussion and Conclusion

There will be unprecedented benefits by integrating wearable BCI with existing IoT paradigm in various applications [1, 3, 20]. With integrated motion sensors, motion artifacts to EEG and PPG signals caused due to body and head movements can be alleviated [22, 23]. In our fatigue states recognition, data labeling is solely based on time responds to lane deviation events. There might be potentially biased datasets, imprecise labeling and over fitting of data considered in fatigue states classification [3]. Also, comparison of iMESH with clinical grade EEG amplifier for signal fidelity and performance is yet to be carried out.

Though feasible, there are several challenges in deriving reliable health parameters from sensors used in iMESH [12, 13, 20]. iMESH is the first step in realizing a wearable BCI that goes beyond conventional wearable by exploiting Low-power wireless and IoT technologies [1, 20]. Driving fatigue assessment is complex due to several intrinsic influences and extrinsic factors in both technical and usability aspects. The next step involves validation in real-world scenarios with development of efficient counter-measures to reduce fatigue states for safe driving [24].

This paper presents the design and evaluation of a wireless low-power headwear system. iMESH leverages on low-power SoC, IoT and SaaS platform for multimodal sensing, real-time streaming, cloud storage and data analytics. We presented hardware, software and design with evaluation of iMESH functionalities and performance. Further evaluation with fatigue assessment using driving simulator is developed and validated. With integrated neural, physiological and physical sensing, iMESH can be used in diverse applications by taking advantages of integrated modular hardware and software eco system.

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