Communication Evaluation of a Wireless 4-Channel Wearable EEG for Brain-Computer Interface (BCI) and Healthcare Applications

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***Abstract*—This paper evaluates the communication performance of a wearable electroencephalography (EEG) headband for brain-computer interface (BCI) and healthcare applications. Our study is motivated by the application of EEG sensors to epileptic seizure prediction using short duration segments. Using packet delivery ratio (PDR) as the metric, we show that shorter segments suffer from lower PDR which can have catastrophic implications for health/BCI applications based on predictive modeling.**

***Index Terms*—BCI, Wearables, Wireless EEG, Epilepsy, Seizure Prediction, Packet Loss, Performance Evaluation**

I. Introduction

Wearable technology has revolutionized medicine at the point-of-care. Increasingly, machine learning/artificial intelligence (ML/AI) applied to data collected from wearable sensors is enabling continuous monitoring, diagnostics and real-time prediction of irregular events related to human health. Another area of increasing interest is brain-computer interface (BCI) where humans interact with computers in novel ways. Rapid advancement in ML models will further increase BCI and healthcare applications leveraging real-time data from humans.

One area of significant interest is usage of various sensors to detect repeat seizures [1] afflicting people with epilepsy [2]. To facilitate *prediction* of these seizures, a more accurate data modality such as electroencephalography (EEG) is needed which directly measures brain activity. The introduction of consumer-grade wearable EEG devices in the market, with fixed-position dry electrodes eliminates the need for clinical expertise for usage. It also has the potential to revolutionize real-time seizure prediction in ambulatory or home-care settings. Wearable EEG devices equipped with wireless communication capabilities such as Bluetooth or Wi-Fi can facilitate energy-efficient real-time signal collection with high sampling rates [2]. However, challenges such as degradation of data quality due to fading effects of noisy wireless channels, low transmission powers, interference [3] are hurdles to progress - and need a more formal investigation.

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In this paper, we investigate and characterize the communication performance using packet delivery ratio (PDR) between a wearable Bluetooth-enabled EEG headband and portable edge devices. We present preliminary experimental results from two devices, a laptop and a smart phone, tested at two different distances. We also briefly outline next steps for more comprehensive experiments including testing with the predictive model at multiple longer distances with line-of-sight (LOS) and non-LOS communication.

II. Related Work

The form factor of wireless communication-enabled wearable EEG headsets has improved significantly. A recent comparison of consumer-grade EEG in terms of SNR, sampling rate, channels, SDK, etc. reports on their usefulness compared to medical grade EEG [4]. Earlier work shows that the quality of portable gel-free electrodes has improved in terms of contaminated EEG segments, SNR and band power variation [5] , but may still need improvement for clinical usage.

However, recent works evaluating the quality of wearable EEG wireless communication either focus excessively on the sensors or do not consider packet loss. For example, Liu et al. developed a quality assessment model that is based upon the received signal amplitude, alpha band power spectral density (PSD) ratio and power frequency ratio [6]. In contrast, the work of [7] evaluated the EEG signal quality in various environmental settings (offices, homes, and public parks) and proposed a mitigation method by emphasizing sensor re-design rather than the received raw EEG data.

The works of [8], [9] study the impact of wireless communication on data quality in terms of packet loss. The work of [8] demonstrated that the packet loss ratio is higher in shorter transmission durations compared to longer periods. This indicates that most of the packet loss may occur in the initial stages of setup and handshaking. A more recent paper [9] examined packet loss from the wearable EEG to the edge device at different distances. Their results on BCI with varying number of sensors on 11 different human subjects indicated a packet loss of 14% and 27% at distances of 1m and 2m, respectively. However, the above studies do not perform a comprehensive evaluation of packet loss on different platforms and environments.

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III. Methods and Implementation Details

Our proposed experiments characterize the packet loss of Bluetooth communication between a wearable EEG headband and two different types of edge devices and operating systems. The device considered was a commercially available cloth (textile fabric) based flexible headband with fixed-position electrodes covering the temporal lobe and occipital lobe regions (O1, O2, T3, and T4 according to the standard 10-20 international system) and a gilded flat reference sensor positioned on the forehead. The device is battery operated and can operate up to 12 hours at 10mA and wireless enabled with Bluetooth low energy (BLE). The sampling rate (F_s) is 250 Hz with a voltage amplitude range of ± 0.4V. The software development kit (SDK) is available as part of the device and can integrate with multiple platforms.

We developed software to extract the raw EEG data on two platforms: a laptop with Windows operating system (OS) using Python and an Android smartphone using the JavaScript-based React-Native framework. A companion app was also developed for the phone to search for and connect to the device via BLE. The goal was to characterize the packet loss for consecutive short-term duration frames. This is significant because real-time ML/AI-based tasks such as seizure prediction are accomplished by decisions based on short segments rather than long-term recordings. Larger packet loss or a lower PDR will negatively impact the predictive performance.

Let us say that the segment duration is given by T_s seconds and each packet transmits one set of readings for all channels. Then, the ideal number of packets received is $P_I = T_s \times F_s$. IF P_R packets are received in one segment, the PDR can be calculated as P_R/P_I. For both devices, we characterized the packet loss for T_S = 5, 10, 20 and 40 seconds with each experiment being repeated 10 times for the case when the device was at a distance of 12 inches from the laptop/phone, and at a distance of 10 feet. All of these experiments were conducted by placing it on a table or a flat surface.

IV. Results and Discussion

Given that the sampling rate is 250Hz, the ideal number of received packets for 5, 10, 20 and 40 seconds would be 1250, 2500, 5000 and 10000, respectively. For the case of the EEG headband next to the Windows laptop, the average packet delivery ratio (PDR) across 10 runs is 87.71%, 94.02%, 97.09% and 98.61%, respectively, for segment durations of 5, 10, 20 and 40 seconds. When placed at a distance of 10 feet, the PDR remained nearly the same with values of 87.86%, 93.97%, 97.07% and 98.63%, respectively.

For the Android device, the PDR achieved was slightly lower compared to a Windows laptop. With the EEG headband placed in close proximity (1 feet), the PDR values achieved were 85.76%, 92.75%, 96.43% and 98.27%, respectively, for segments of duration 5, 10, 20 and 40 seconds, respectively. And long distance (10 feet), the PDR achieved was 85.58%, 92.82%, 96.38% and 98.23%. This indicates that in each iteration for each interval there is a consistent loss of 170 – 198 packets with an overall mean packet loss of 146.95 and 146.65, respectively. Table I shows these results in details. Our experiments demonstrate that shorter segments suffer from a lower PDR which visibly lower by up-to 11% compared to longer segment durations. Moreover, the smart phone has a higher packet loss and consequently, a lower PDR compared to the laptop. This may either be caused by more resources being used up in rendering the user interface in a phone or due to a lower communication capability compared to a laptop.

TABLE I
PRELIMINARY PDR RESULTS FOR MULTIPLE CONFIGURATIONS.

Device	T_s	P_I	1 ft distance		10 ft distance	
			P_R	PDR	P_R	PDR
Windows	5	1250	1096.4	87.71%	1098.2	87.86%
	10	2500	2350.4	94.02%	2349.2	93.97%
	20	5000	4854.6	97.09%	4853.4	97.07%
	40	10000	9860.8	98.61%	9862.6	98.63%
Android	5	1250	1072.0	85.76%	1069.8	85.58%
	10	2500	2318.8	92.75%	2320.4	92.82%
	20	5000	4821.6	96.43%	4819.2	96.38%
	40	10000	9827.4	98.27%	9823.2	98.23%

These results warrant further investigation and in the future, we plan to map out the PDR over longer distances including both LOS and NLOS environments in indoor (e.g. long hallways or multi-story homes) and outdoor (e.g. parks or urban streets) settings. Further, we will quantify the delay, battery and machine-learning inference performance with different segment durations, sampling rates and channel configurations. We will quantify the performance for various real-world scenarios and this is an active area of research in our lab.

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