Algorithms for Complete Physiological Monitoring During Spaceflight

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Motivation

In the environment of a spacecraft, continuous passive monitoring of astronaut physiology is of critical importance. Current approaches to comprehensive health monitoring require a cumbersome array of various sensors which limit the mobility and comfort of astronauts and are collectively prone to malfunction. Together, these factors motivate the development of physiological monitoring algorithms that can accurately reconstruct a missing sensor's data, using the values of the other measurements available.

Previous Research

A great deal of research is being done on the topic of health monitoring, especially when it comes to methods that are invasive or time consuming. Much of this research focuses of on the extrapolation of bio-signals from different measurements. For example, PPG readings can be used to reconstruct ECG data[1]. Similarly, ECG and PTT data can be used to predict blood pressure readings[2]. Consequently, it is possible to extrapolate blood pressure from PPG and PPT data, and it has been done with up to 95% accuracy using machine learning models[3]. Clearly, This technology is extremely beneficial in monitoring bio-signals and diagnosing health risks, especially in the context of spaceflight[4].

Objectives

Given the importance of physiological monitoring, the idiosyncratic nature of physiological waveforms, and the practical constraints of moving equipment into orbit, our objectives are to (1) develop algorithms that enable reliable, real-time reconstruction of missing physiological waveforms using one or more other available waveforms and to (2) discover the minimal subset of monitoring systems needed to obtain the best overall picture of physiological status.

Methods

Data is collected from three sources, also shown in the figures to the right. The Pi Sense Hat streams temperature, humidity, pressure, and gyroscopic data, the Picam streams a live video feed, and the OpenBCI EEG headset stream EEG data to its corresponding dongle on the Raspberry Pi. These data streams are organized and packaged by the Pi, then streamed to our data-ingestion server for analysis. The data can then be viewed in a browser window after processing.

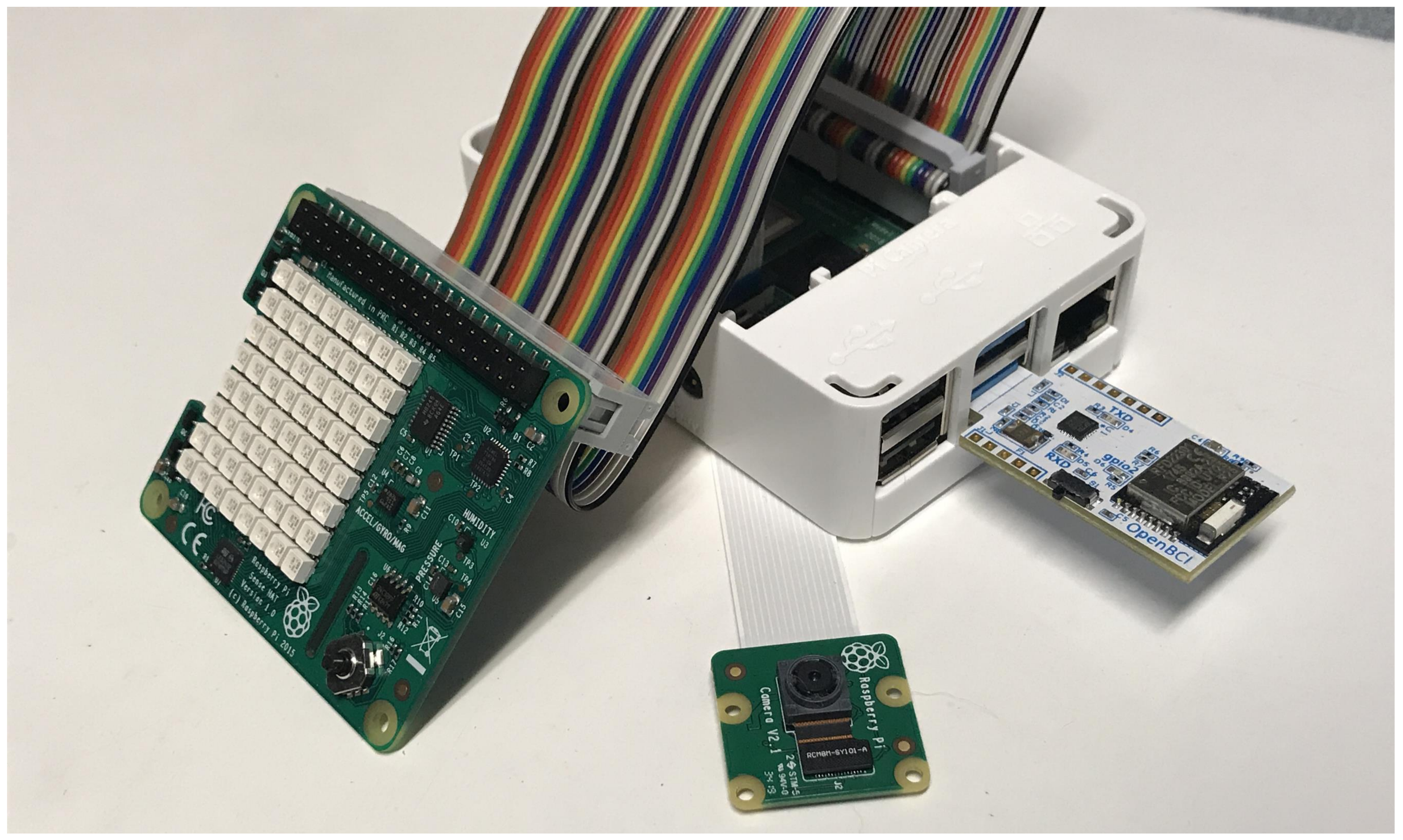

Fig. 1: Raspberry Pi sensor hub. From left to right: Sense Hat, Picam, and the OpenBCI dongle.

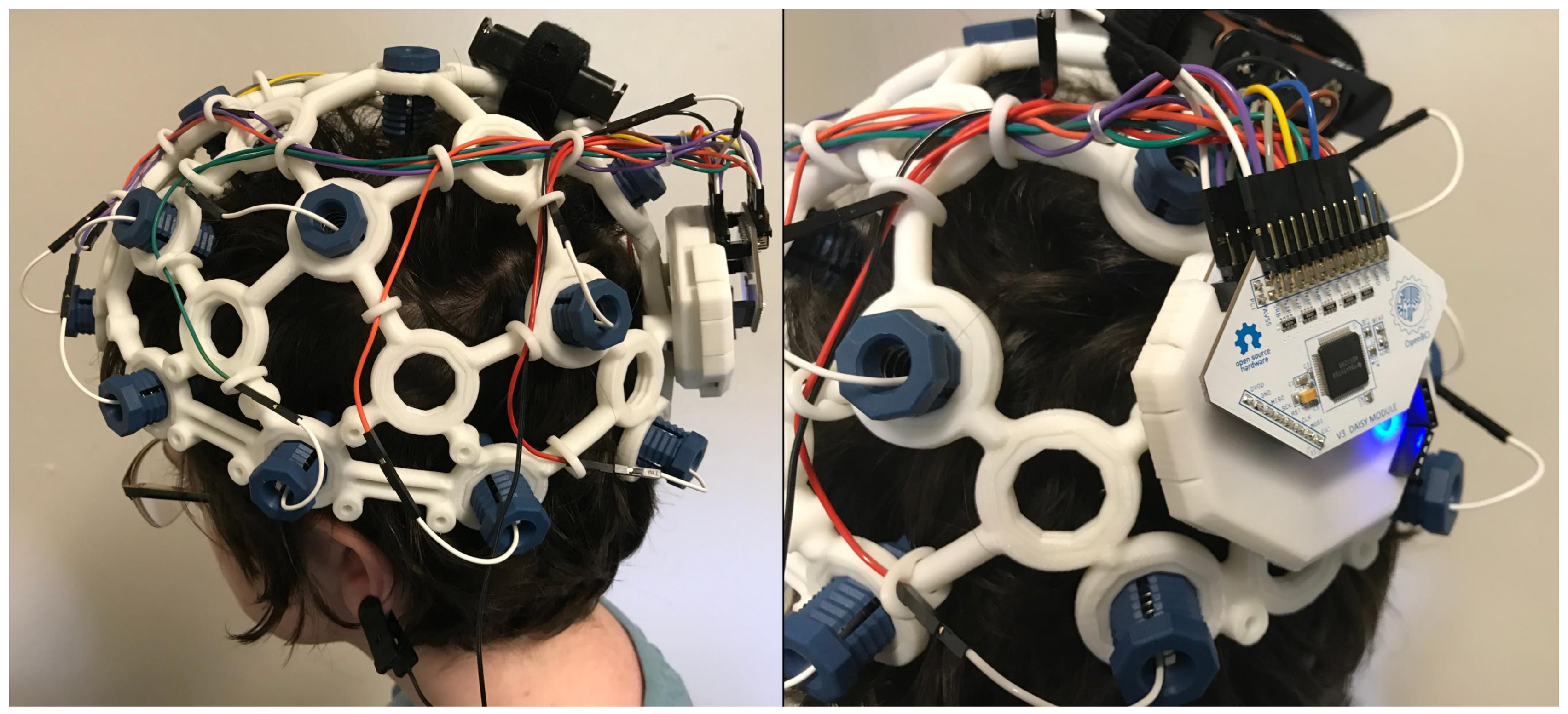

Fig. 2: Wireless EEG setup.

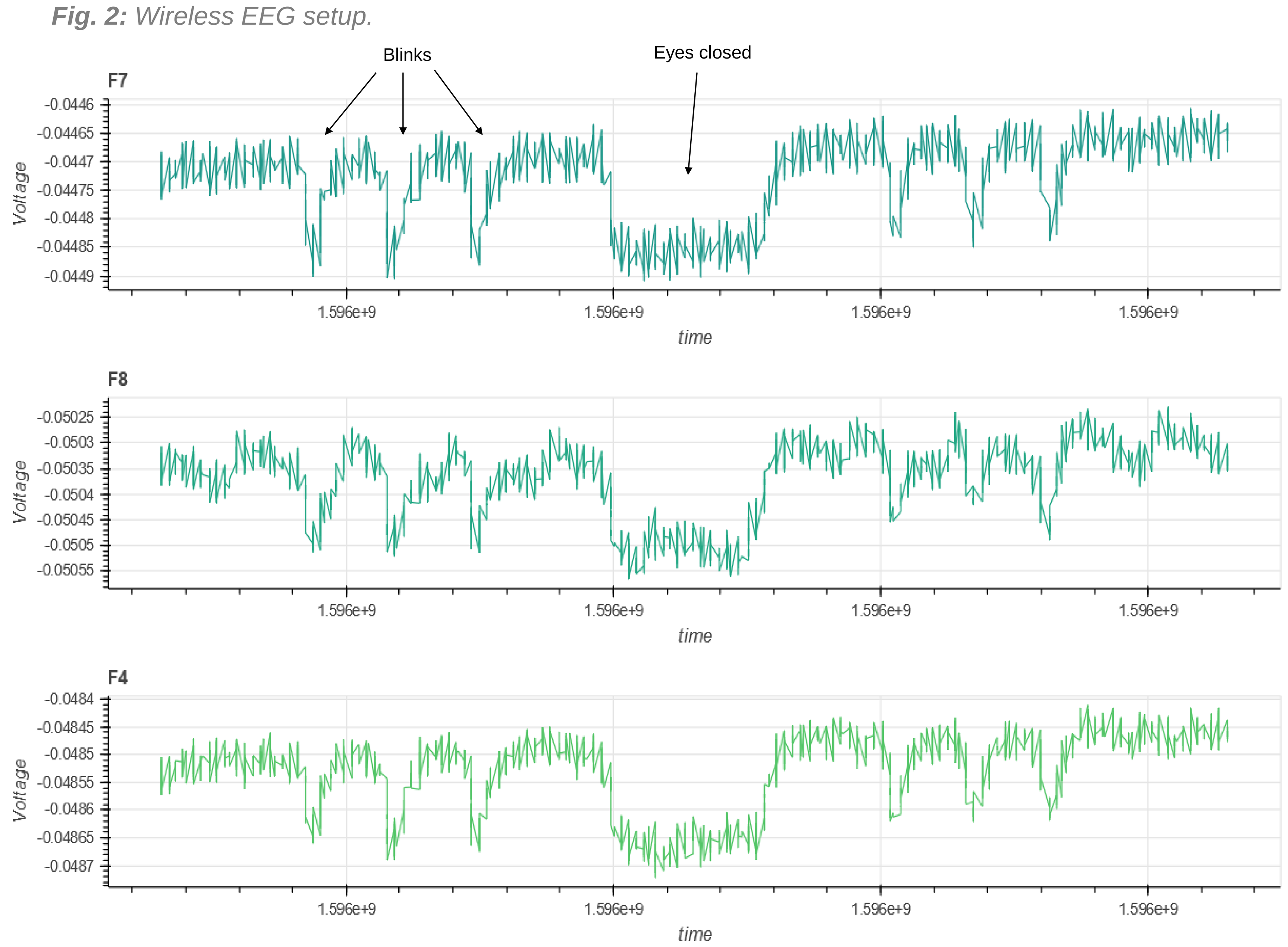

Fig. 3: Three EEG channels (F7, F8, and F4) viewed through a browser window. The decreases in voltages correspond to the subject's eyes being closed.

Next Steps

Continuing this project, we will use publicly available bio-signal datasets to train a deep encoder-decoder network that can reconstruct the values of a missing waveform, using all other available waveforms. We expect to see robust correlations between physiological waveforms that will allow us to identify potentially redundant health monitoring hardware for a spaceflight environment.

After this initial demonstration of efficacy, we will collect physiological and behavioral data of subjects performing multiple tasks in a laboratory environment. Following model development, we will test the ability of models trained on earth to be effectively tuned to new subjects and new tasks using transfer learning. This last point is of particularly importance as it will enable our methods to be tuned to individual astronauts after they've arrived on a spacecraft.

Ultimately, we will endeavor to build a system that is able to accommodate for signal loss, unavailability, or device malfunction via reconstruction of any missing information. This software would be used aboard a spacecraft to continually monitor astronaut health while they remain mobile and enable real-time prediction of health issues or concerns before they could normally be detected.

References

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