

Hand Gesture Classification

Data Labeling of Gesture Based Biosignals

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PROJECT MOTIVATION

When collecting gesture-related biosignals for researching, developing, and training gesture classification models, one of the most important preprocessing steps is identifying which regions of the signal correspond to the intentional performance of the gesture (known as “onset detection” or “activity detection”). Purely signal-based onset detection methods exist but are often susceptible to noise such as electromagnetic interference (EMI), and they generally perform poorly with low signal-to-noise ratio (SNR) signals. Further, these methods provide no information about which gesture was performed. Thus, we are leveraging computer vision (CV) methods to perform activity detection of biosignals based on recorded videos of the user’s hand while performing the gesture. Onset detection is used to ensure accurate labeling of the samples used to train these models: in particular, it is important to capture as much of the active signal as possible, and even more important to avoid labeling “inactive” or “resting” samples, surrounding the true active region, as “active”. (Fig. 1)

KEY ACCOMPLISHMENTS

Generated Key Points to use for Validation:

In the data collection, the users were given the Pison Device to wear during the collection process which was recording their hand gestures. The task for the keypoint generation was to process every video file collected for the data set and pass it through an already existing algorithm. This program essentially looked through each video frame by frame looking for certain key points, which were previously defined as cases where gestures were done by the user.

DTW Onset detection on all Sessions:

Dynamic Time Warping is an algorithm that was used for onset detection in this project. This algorithm is very dependent on how accurate the thresholds are for the gestures in this project. Since this was a small dataset to work off of, the thresholds should be adjusted in the future. After implementation of this algorithm, it was clear that better thresholding data is needed for this algorithm to be successful in the future.

KWL Onset Detection on all Sessions:

KWL onset detection was used to aid in better defining the true onsets and offsets. After implementing KWL, it was easy to see that the threshold values were hypersensitive. More adjustments will need to be made for a more accurate result from KWL. The KWL algorithm seems the most promising and will be used in the future.

Bio-Signals and Hodges onset detection on all sessions:

This was another algorithm that was solely signal based instead of being a video-based detection. This implementation was extremely accurate and showed impressive results in terms of the onset and offset bounds of accuracy. Fig. 1

Metrics Implementation:

A script was written solely to test the accuracy and ability of the algorithms used to detect onsets and offsets. The onsets and offsets were given from the true onset and offset script and KWL, DTW, and Bio-signals were all tested to see how they did against each other. Overall, bio-signals and KWL performed the best, and some parameters were tweaked to yield even better results. The use of another script was crucial for giving new test values for the thresholds and inputs for the KWL and bio-signals onset detections. The algorithms were then run again and ran through the metrics to see any differences between the different parameters used.

Onset Detection Visualization:

In order to visualize the onset detection algorithms, and how efficient each of them were, a script was generated to plot the square waves from each onset detection algorithm against the initial EMG data. This would then allow a better understanding of how accurate the algorithms were. Fig. 2

Roboflow Implementation:

During the course of this project, Roboflow was integrated into the model to speed up the development process. Roboflow is an outside company, in which Pison is using their software to help aid in labeling images split images from the initial video files. A large amount of images were then uploaded to Roboflow via API call, which were then manually labeled to test and train a model. The more images and more variety that is uploaded the more accurate and robust the model gets. Fig. 3

Split reps Manual Labeling True Onsets:

Through the use of a GUI, each session was split into blocks, which would then show the EMG data in a visual setting. From then on, a true onset and offset was taken for multiple high confidence sessions. These onsets and offsets were stored in an array of 0s and 1s, 0s being nothing is happening and 1s being a gesture is occurring. Fig. 4

ANTICIPATED BEST OUTCOME

The anticipated best outcome of this project has been changed since the initial start of this project. The new ABO consists of having a fully constructed semi-automated pipeline that can accurately label the necessary hand gestures for this project. This project also now consists of a new Roboflow aspect which is now going to be used as an alternate form of processing images against a machine learning model. Note that this project is funded by a grant from the National Science Foundation (NSF). We are aiming to achieve robust accuracy (99+% overall classification accuracy), but in terms of the contractual deliverable, this is not strictly necessary.

PROJECT OUTCOME

The Anticipated Best Outcome of the project was achieved.

FIGURES

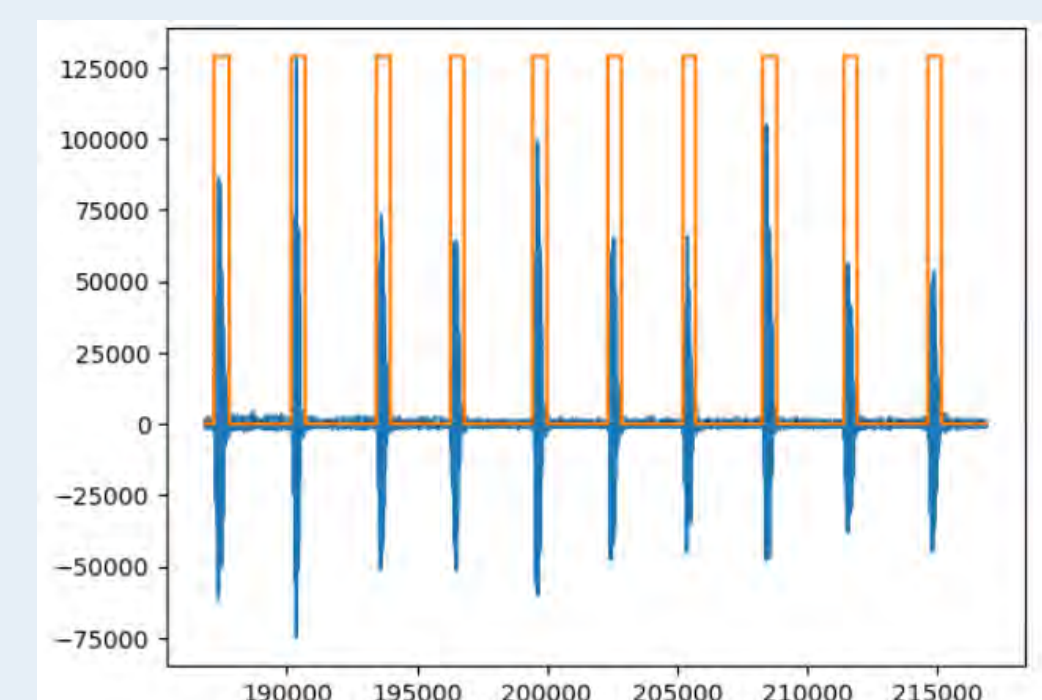


Fig 1: Biosignals Onset Detection

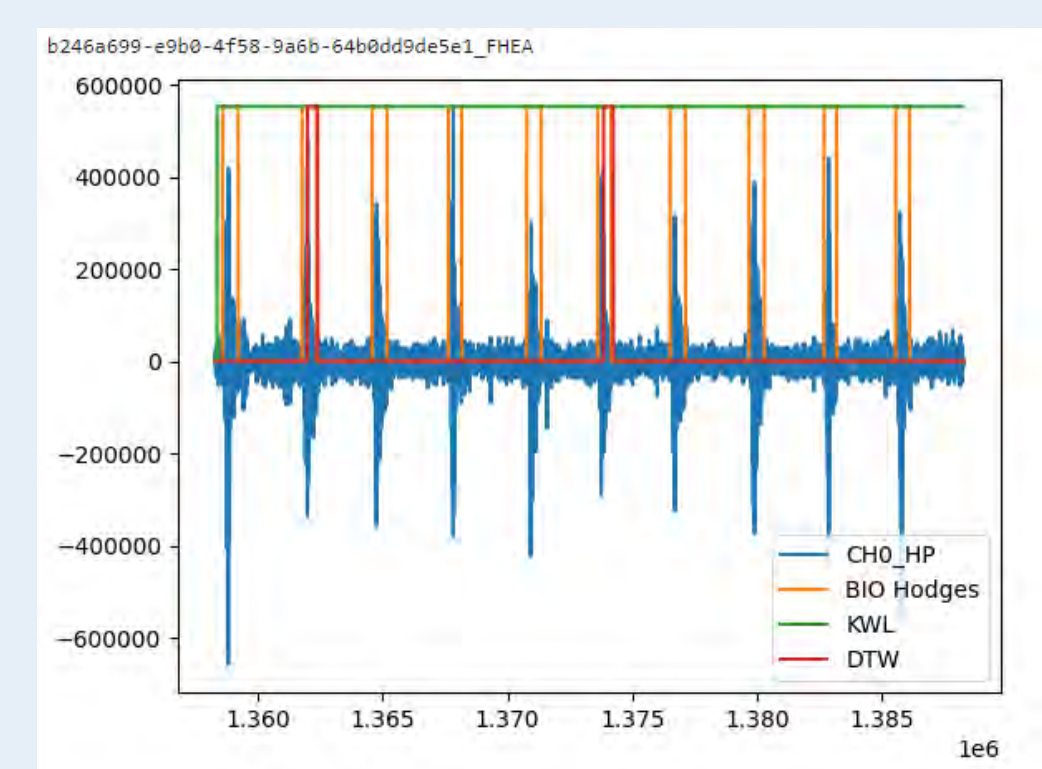


Fig 2: Onset Detection Visualization

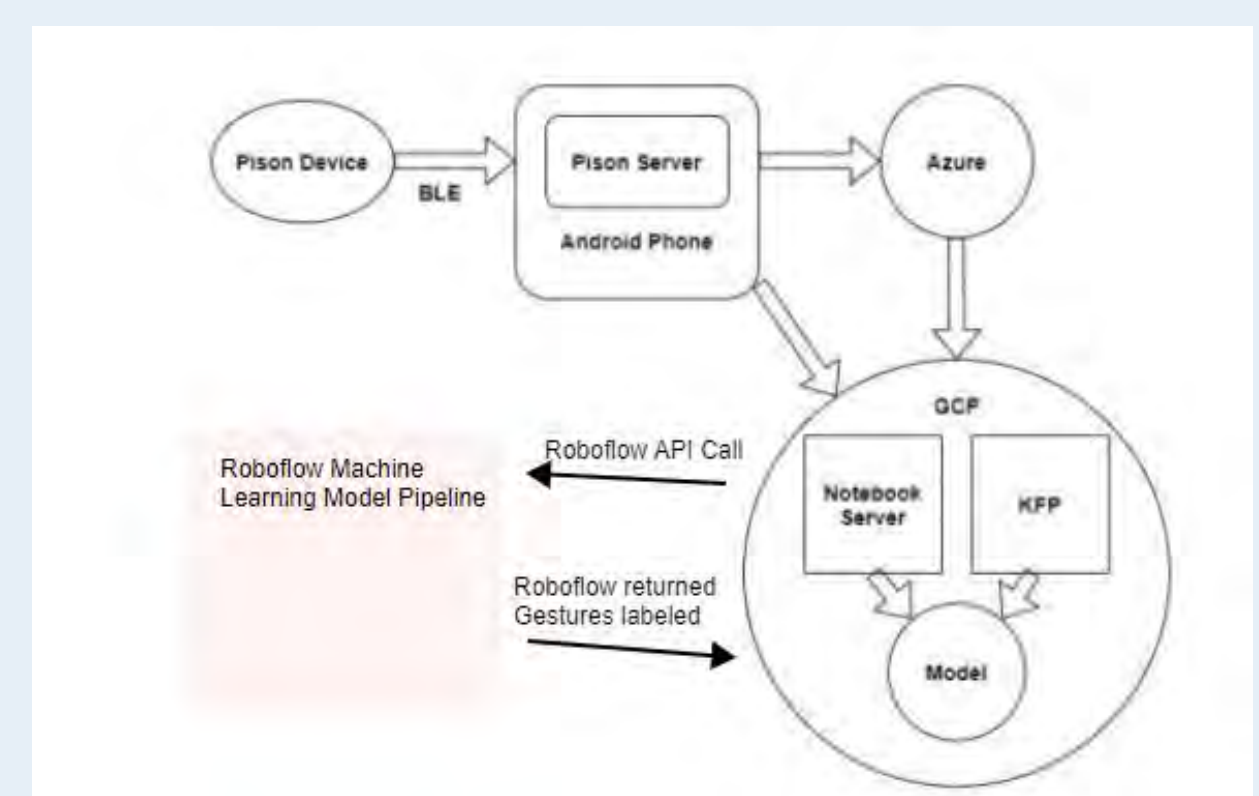


Fig 3: Development Block Diagram Including Roboflow

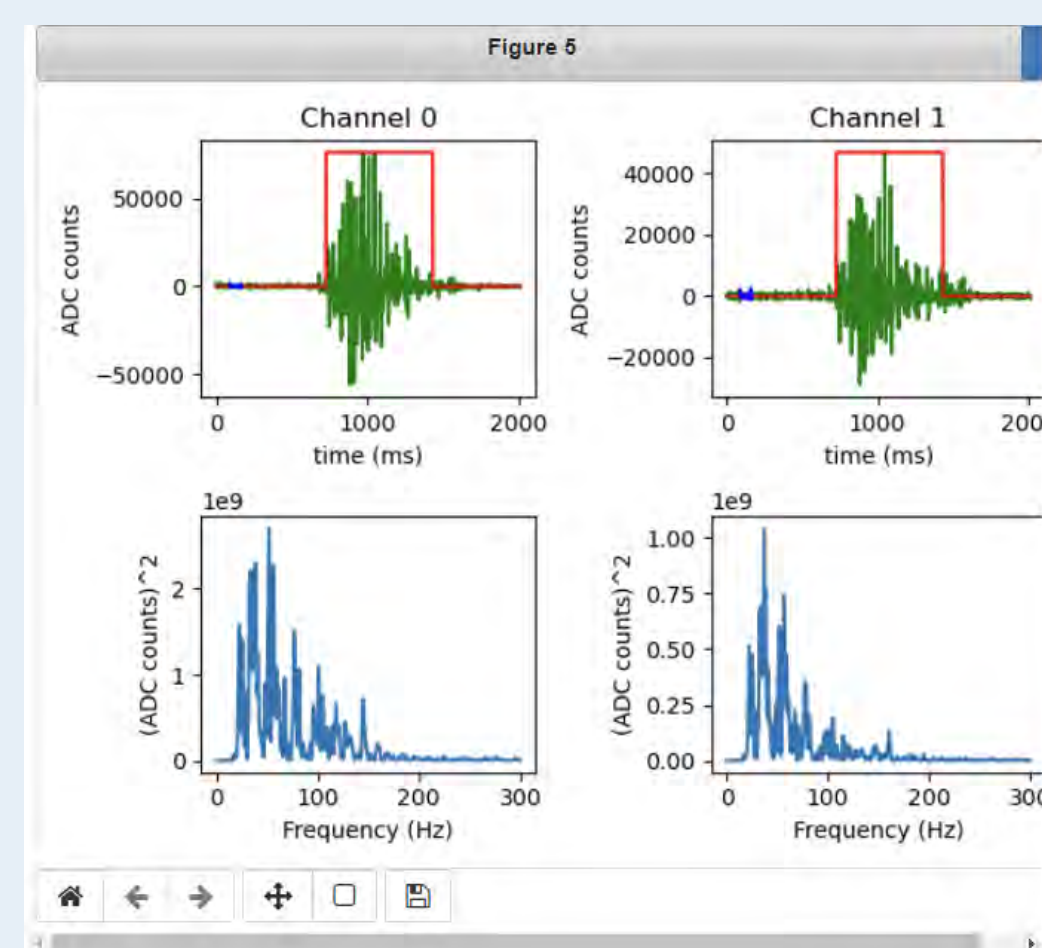


Fig 4: Split Reps Manual Data Labeling