



Dwight Look College of

ENGINEERING
TEXAS A&M UNIVERSITY

Team 61: Driver Drowsiness Detection

Bi-Weekly Update 2

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TA: Max Lesser



Project Summary

Problem:

Driving fatigue has been a major cause of accidents on the road. Truck drivers are at a greater risk of driver fatigue because of the long hours spent driving.

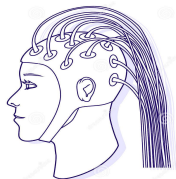
Solution:

Our Driver Drowsiness Detection System will use a machine learning (ML) algorithm and electroencephalogram (EEG) device to determine a driver's level of fatigue and alert the driver to rest.

Project/Subsystem Overview

EEG

- Filter out unwanted frequencies.
- Take in brain waves in microvolts and amplify them to volts.
- Send data to MCU



MCU

- Receive incoming signals from EEG
- Send data to computer running ML algorithm



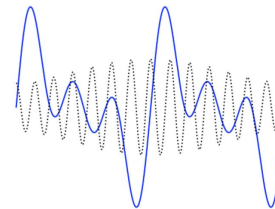
Dakota

Simulator

- Collect data
- Muse 2 EEG device

Signal Processor

- Perform live analysis of signals
- Process raw EEG signals



ML Algorithm

- Input processed EEG signals
- Output fatigue state of user



Team 2: Coady and Ali



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Project Timeline

January	February	March	January
SP/ML Light Integration	SP/ML Live Analysis	System Refinements	System Verifications
EEG/MCU Interfacing	EEG PCB Complete		Integration of SP/ML & EEG (stretch goal)
			Final Presentations/Demo



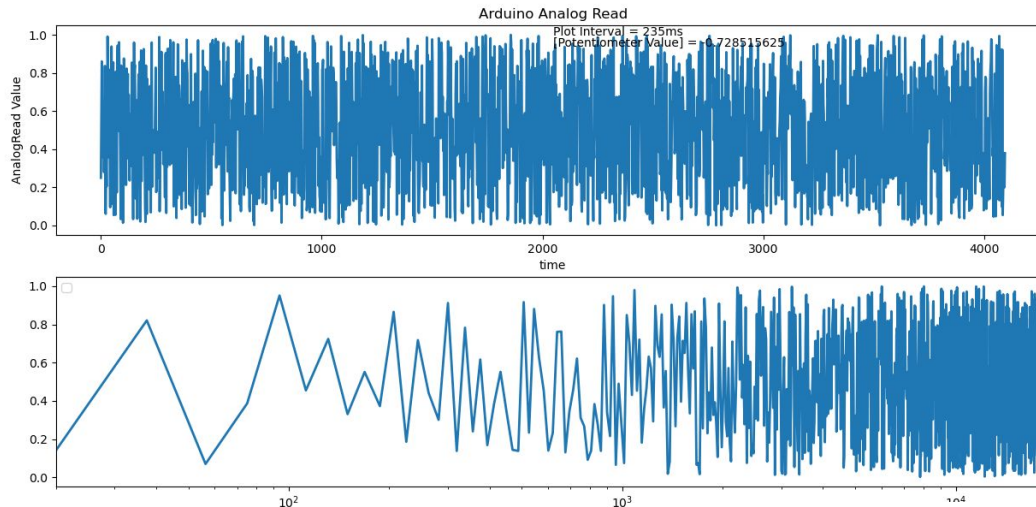
EEG Device

Dakota Mouton

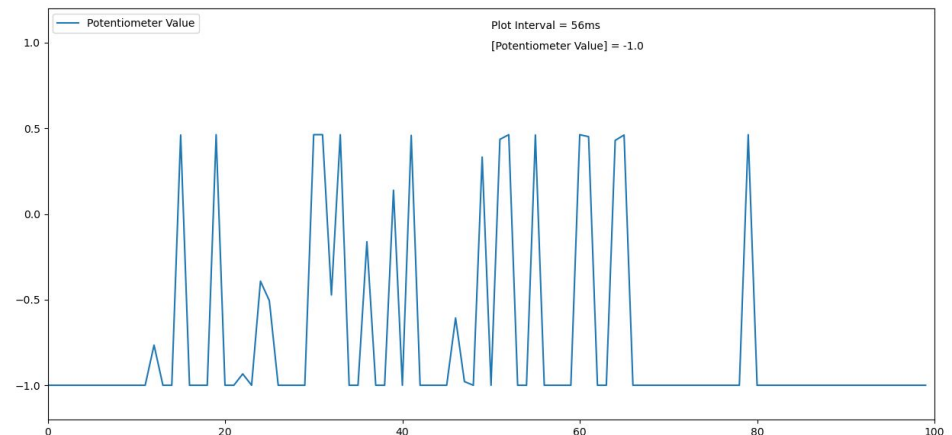
Accomplishments since 403 24 hrs of effort	Ongoing progress/problems and plans until the next presentation
<ul style="list-style-type: none">• Reading live signals from electrodes through arduino board.• Switched to python for more robust live graphing of signal.	<ul style="list-style-type: none">• Verify the live signals are actually as expected by analyzing signals using FFT.• Finish PCB design, order boards, solder components.• Connect to raspberry pi board for ML model to run with new hardware.

EEG Device

Dakota Mouton



- Have FFT graph now showing with live waveform, but only shows one snippet of the signal and is not updating with the live signal.





Signal Processing

Coady Lewis

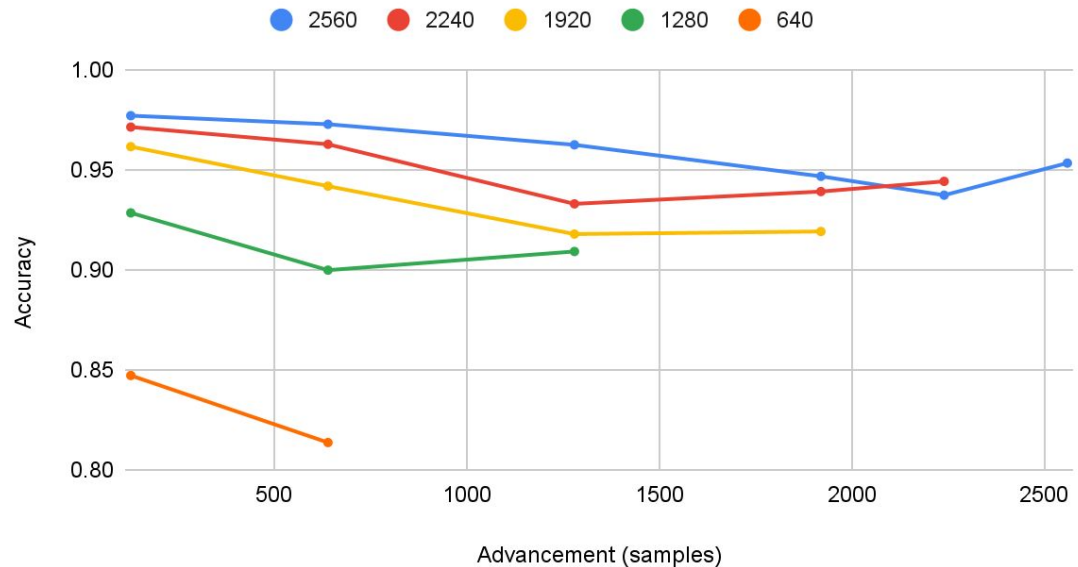
Accomplishments since 403 12 hrs of effort	Ongoing progress/problems and plans until the next presentation
<ul style="list-style-type: none">-Integrated live analysis with ML code to get real-time classification-Partially automated testing process for window size and overlap-Tested 20 different configurations on 4 hour dataset	<ul style="list-style-type: none">-Will collect more data-Will rigorously test live output at the extremes of classification

Signal Processing

Coady Lewis

- Consistent dip in performance as advancement decreases from its max, but performance then increased in all cases
- In all cases, the best results came with very low advancement parameters.

Accuracy vs. Advancement (5 Window Sizes)



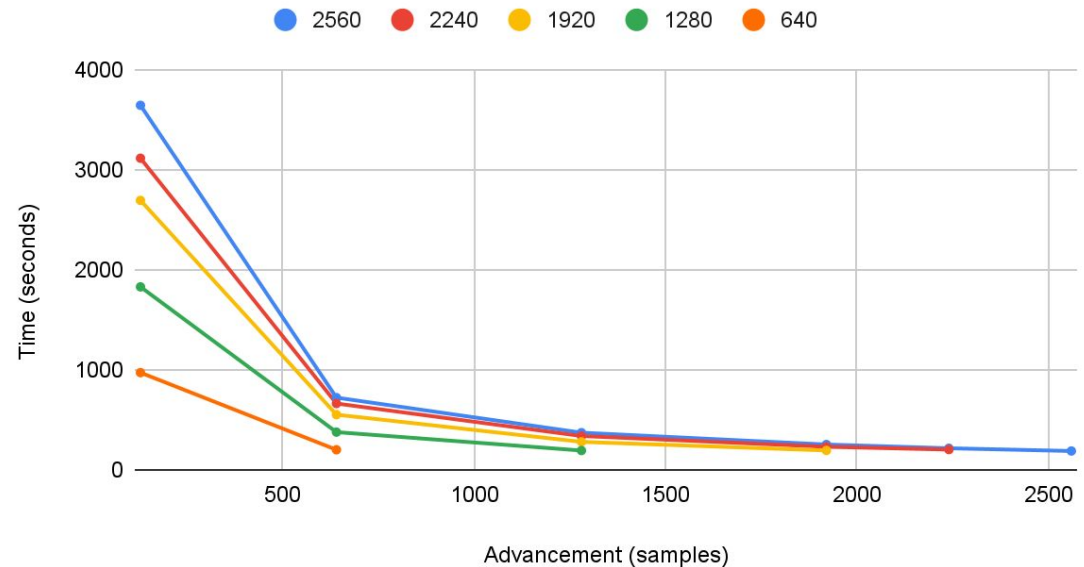
Signal Processing

Coady Lewis

-The total processing, training, and testing time drastically increases as advancement falls below 640 samples. It's up to 1 hour per run so far.

-Lower advancement yields the best results, but there is a cost and a limit this method.

Time Delay vs. Advancement (5 Window Sizes)





Machine Learning

Ali Imran

Accomplishments since 403 12 hrs of effort	Ongoing progress/problems and plans until the next presentation
<ul style="list-style-type: none">- Completed program which takes in raw signal .csv files, runs signal processor through each file, and sends entire processed dataset to train/test ML models- Completed functions for loading trained model and using it to predict new values	<ul style="list-style-type: none">- Collect more training data- Test current models with live analysis



Machine Learning

Ali Imran

<u>Signal Processor (W = 1280)</u>	<u>ML Model</u>	
	Kernel SVM	Neural Network
New: A = 1280 (0% overlap)	90.9	90.6
New: A = 640 (50% overlap)	90	89.1
New: A = 100 (92% overlap)	94.1	91.8
Original (403): A = 100	85	83.5

W = window size

A = advancement parameter (determines amount of overlap)

Live Analysis:

- Testing model on new person
- Longer sessions with approaching drowsiness



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Parts Ordering Status

- EEG Device: PCB

Execution Timeline

[illegible]



Execution & Validation Plan

Driver Drowsiness Detection Validation Plan:

ML/SP - Machine Learning/Signal Processing

Task	Specification	Result	Owner
ML/SP Integrated System Accuracy	> 90% success rate	Exceeded on existing datasets (up to 97%)	Ali, Coady
ML/SP Integrated System Performance	For 30 second chunk of data, output drowsiness state in < 30 seconds	Exceeded, smallest accurate classification interval at 2.5 seconds	Ali, Coady
EEG Filters below 8 Hz	$f \geq 8$ Hz		Dakota
EEG Filters Above 30 Hz	$f \leq 30$ Hz		Dakota
Gain from Instrumentation Amplifier close to 100	$G = 80+$		Dakota
Final voltage readings have amplified from microvolts to volts	$0.148 < V < 0.81172$ But $V < 1$ Input 15 Hz, 30uV		Dakota
Final voltage readings have amplified from microvolts to volts (Max and Min Readings)	Max Input: 10 Hz, 30uV Min Input: 1000 Hz, 20 uV		Dakota
System voltage input	6 V	Regulated to $\pm 5V$	All
Peak Power Consumption	2 W		All



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Thanks for listening!