

ABSTRACT

Typically, the legitimate driver of a vehicle can only gain authorization to access their vehicle through tokens such as ignition keys. However, this system can only authorize at the beginning of a driving session and cannot always prevent vehicle misuse. We propose to use posture data to continuously authenticate the driver of a vehicle by determining which features of posture uniquely characterize an individuals' driving behavior. A simulated driving environment was used to collect data of driver posture including shoulder and wrist position. These features are classified using a Support Vector Machine (SVM) learning algorithm. Our study with 50 users can continuously determine a driver to be authorized or not with over 99.9% certainty.

BACKGROUND

Ignition keys are traditionally how authorized drivers are granted access to their vehicle, however this cannot detect many instances of vehicle misuse



Examples of Undetected Vehicle Misuse

- Someone steals ignition key, hot-wires car, or carjacks during a driving session to gain illegitimate access
- A non-insured driver driving a vehicle that an insurance provider only legally allows insured drivers to access
- Renting a car from a car rental agency that stipulates that only certain people can drive, and allowing other non-authorized people to drive the rented car

PROBLEM & OBJECTIVE

Research problem

- Currently no way to authorize a driver continuously during a driving session
- Current system of authorization can only authenticate a driver either offline or as a session starts
- Many instances of vehicle misuse cannot be detected due to current system
- An authorization system must have high accuracy and low error rate to prevent false alarms and illegitimate access
- Previous studies have not achieved high enough accuracy to reasonably be used for driver authentication

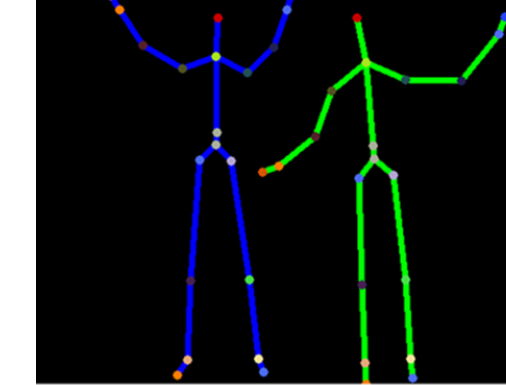
Objective

To be able to accurately and continuously authenticate drivers by determining which features of posture uniquely characterize an individuals' driving behavior, as well as the discovery and analysis of other potential features for driver authentication classification

EXPERIMENTAL ENVIRONMENT

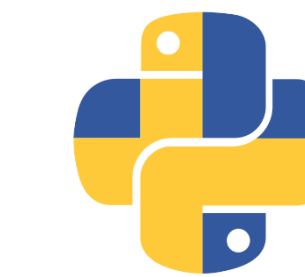
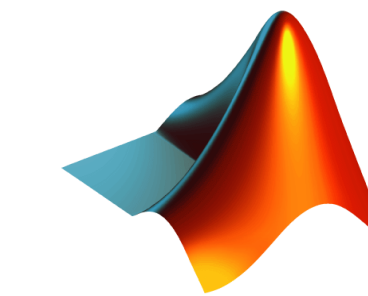
New York Institute of Technology, Manhattan, NY:
Edward Guilianno Global Center (EGGC) Building
On the 6th floor

OpenDS Driving Simulator with Microsoft Kinect and Logitech Steering Wheel G27

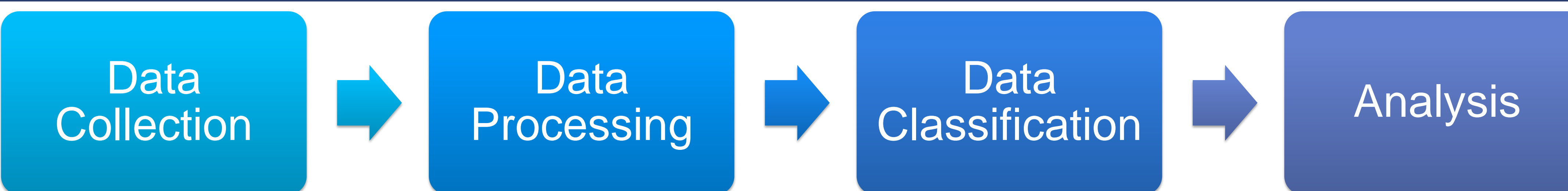


Kinect Skeleton

MATLAB and Python for data processing and analysis.



METHODOLOGY



RESULTS

The top 16 features based on fisher scores (Table I) were used in the SVM model for classification. This number of features was chosen based on Figure I, where after 16 features are added, there is negligible change in the Equal Error Rate (EER). Figures II, III, and IV represent the results of classification looking at determining whether a driver was authorized or not authorized. We were able to obtain an average EER of 0.391%, with Figure IV showing that we could even obtain 0% error for some drivers. Figure III shows that the area under the Receiver Operator Characteristic (ROC) curve were all above 0.995. Figure V is the results of classification looking at absolute amount of sleep. We were able to classify the absolute amount of sleep someone had the night before participating in the driving simulation with an average EER of 4.84%, demonstrating that amount of sleep causes distinguishable changes in one's posture.

Feature	Fisher Score
Leading Distance	0.0014
Following Distance	39.0034
Lane Position	0.0015
ZShoulderRight	704.5279
ZShoulderLeft	691.4038
ZElbowLeft	673.7743
ZelbowRight	657.1147
ZshoulderCenter	650.9864
Zhead	637.8091
yPosWorldCoord	552.4931
zPosWorldCoord	535.3134
ZwristRight	453.3136
ZwristLeft	452.5418
yPosImageIndices	416.6947
XelbowRight	403.0092
yPosDepthIndices	344.4244
XwristRight	292.8017
ZhandLeft	286.5853
XshoulderRight	280.1284

Table I. Results of fisher score analysis of features. Higher fisher scores indicates higher classification contribution.

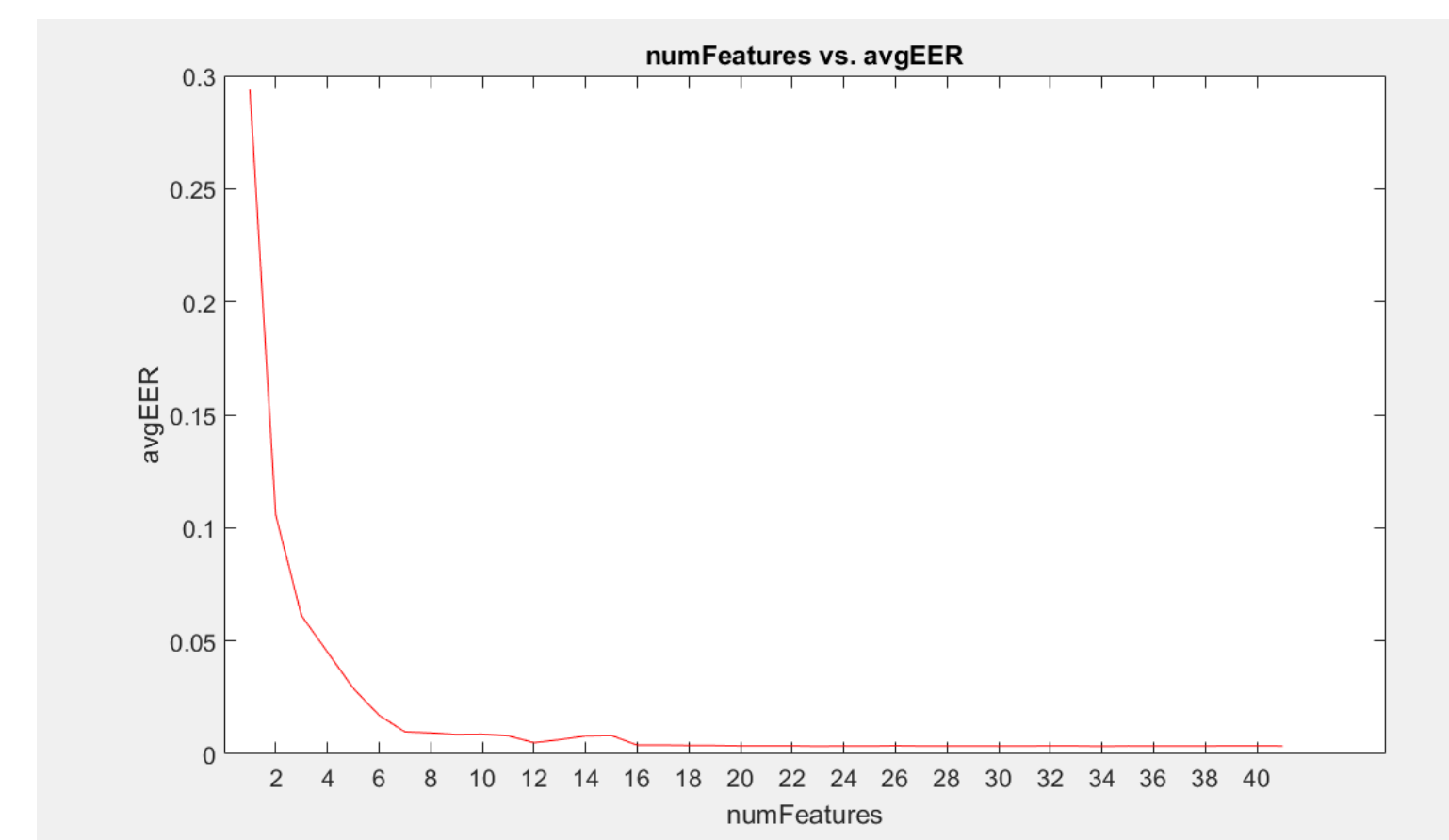


FIGURE I. Comparison of average EER versus number of features.

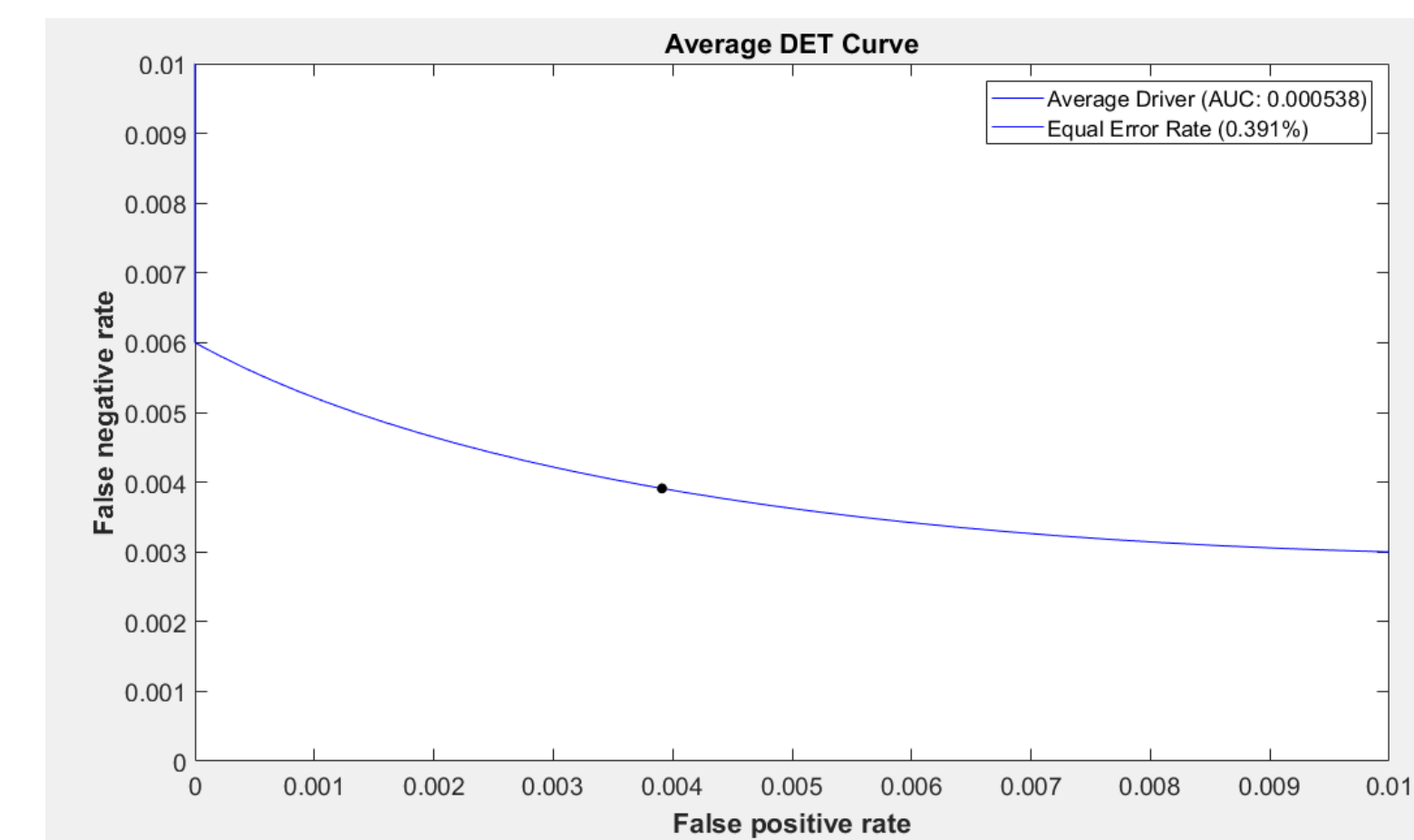


FIGURE II. Average Detection Error Tradeoff (DET) curve for One-Class SVM Classification of all study participants

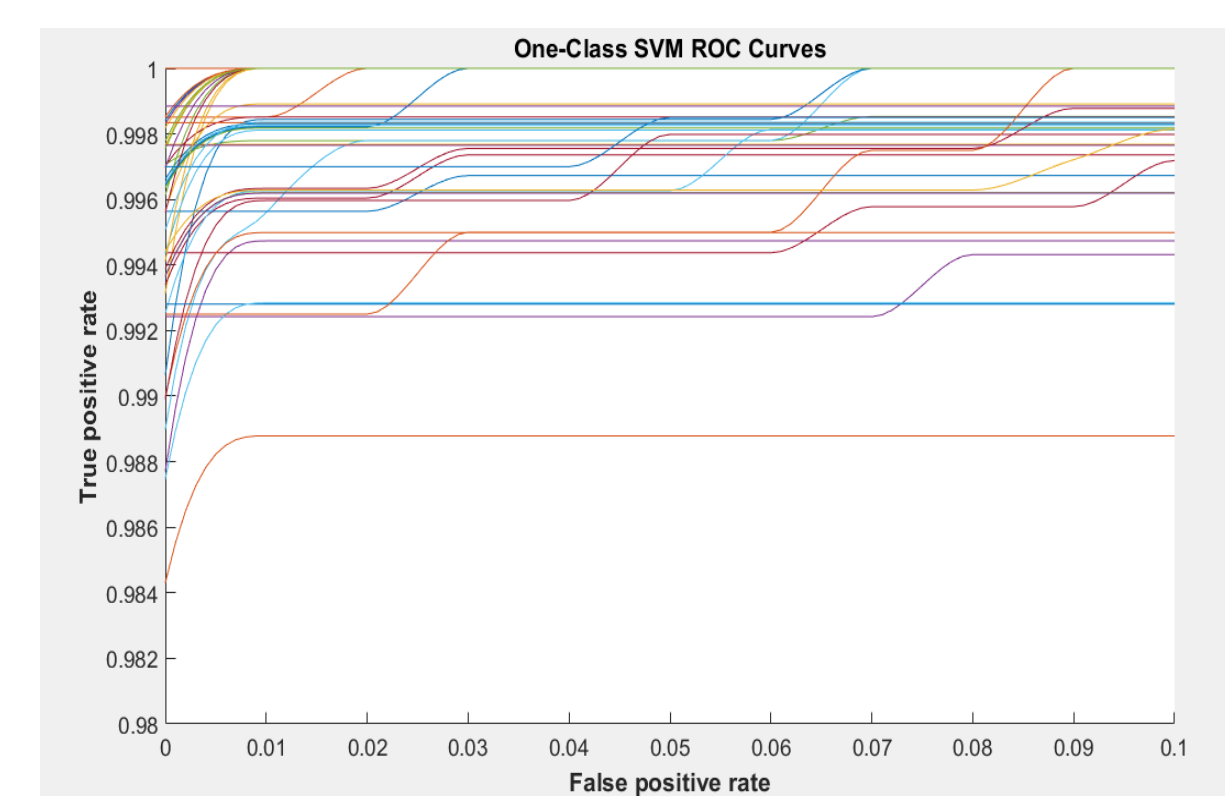


FIGURE III. Area Under Curve (AUC) of ROC for each study participant

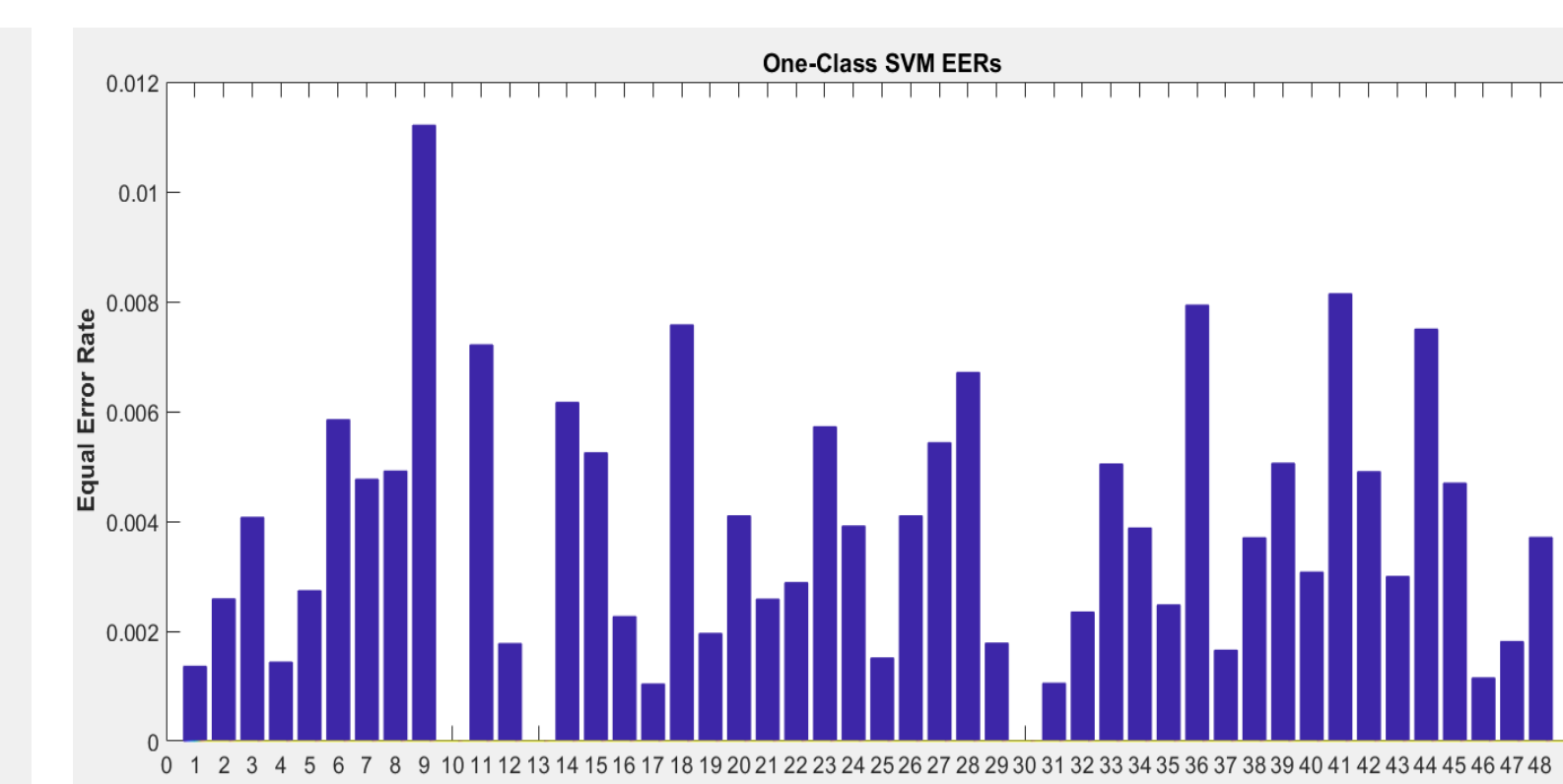


FIGURE IV. EER values for One-Class SVM Classification of all study participants

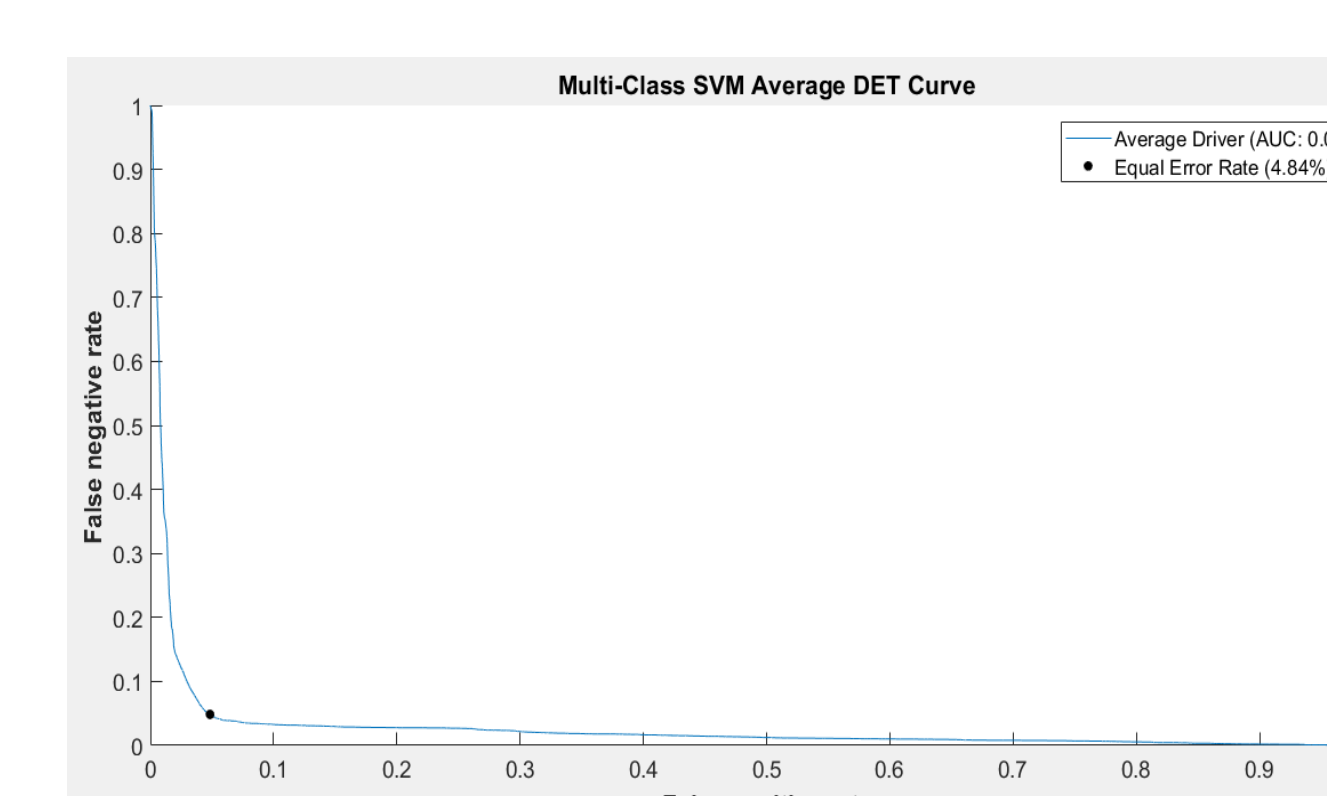


FIGURE V. Average DET curve for One-Class SVM Classification looking to classify the amount of sleep participants had

DISCUSSIONS

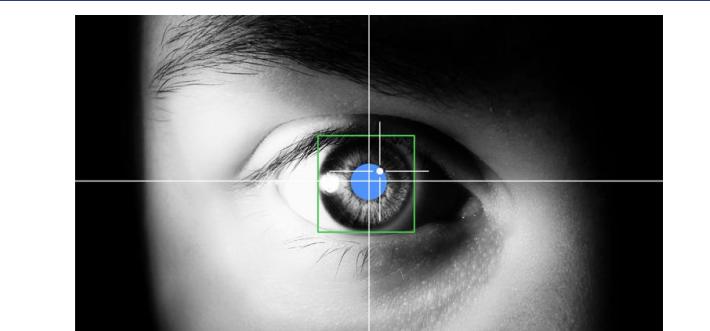
- The very high accuracy of our classification with the Kinect features is due to how consistent features were within drivers rather than how different they were between drivers
- While the classification performs very well utilizing the Kinect data, this method of driver authentication is more intrusive than the sensory driving features used in the previous study
- Following distance would be a good addition to the features tested in the previous study (standard deviation of steering wheel, average pressure on accelerator/brake pedal)
- Our classification was able to identify the amount of sleep participants were getting, demonstrating that there may be common posture attributes between those with less sleep and those with more sleep
- Posture was very consistent in drivers during driving sessions, does this hold true over the course of multiple driving sessions?

CONCLUSIONS

Through our research and experimentation we were able to efficiently determine whether a driver was authorized or not with an error rate of 0.391%. This result shows that posture while driving is unique between drivers and can be used to quickly and accurately authenticate drivers through a driving session. Analyzing other features has also shown that while lane position and leading distance are not very powerful discriminative features, following distance shows potential as a unique identifier of driving behavior.

FUTURE WORK

- Looking into new features such as eye tracking/gaze tracking for driver authorization
- Testing accuracy of other classifier types compared to SVM such as Hidden Markov Model and Gaussian Mixture Model
- Looking further into following distance as a potentially useful feature for driver authorization
- Continue to experiment with Kinect features and expand to include more driving sessions to see if posture changes between sessions
- Look to collect data from participants in a real car and classify
- Perform a study to see if it is possible to mimic another drivers posture and bypass authorization system



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