THE ANDREW & ERNA VITERBI FACULTY OF ELECTRICAL ENGINEERING

SIPL
Signal and Image Processing Lab

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Automobile Driver Fingerprinting

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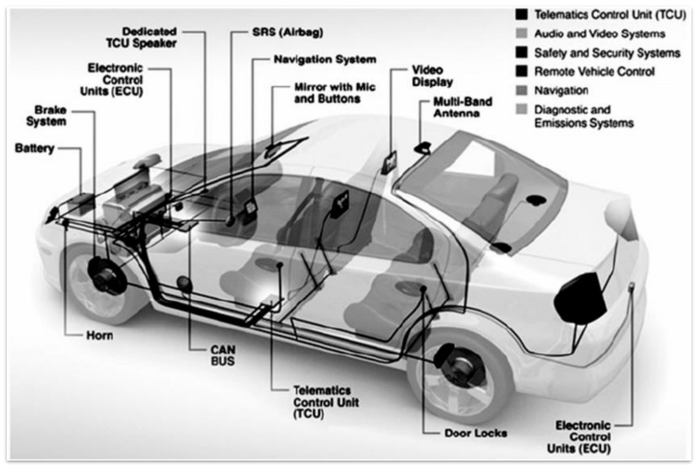
Introduction

- In advanced car systems, information passes through many units (ECUs) using CAN-Bus protocol. It's possible to extract wide range of data from many sensors.
- Using the data to identify the drivers, applying feature extraction with non-linear methods of dimension reduction.



Car units connected to CAN-Bus

Goals

- Classify the drivers
  - dimension reduction utilizes the data
  - Within minimal driving time
  - Computationally efficient algorithm

Challenges

- Drivers with similar style
- Environment influences and dependencies
  - Traffic, car accidents, random pedestrians
- Finding dimension reduction method which utilizes the data
- Processing data according to hyper-parameters

Data Preprocessing

- The data from the CAN-Bus is recorded in packets form
- Transforming the data into time-series form
- Receiving 51 sensors for each recorded driver

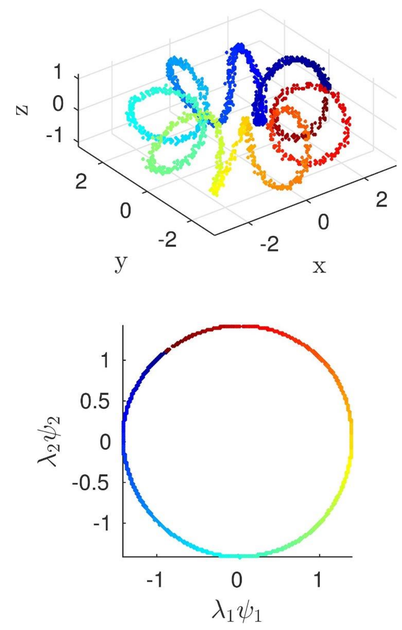
PathOrder	Class	Time(s)	Steering_v	Steering_v	Acceleratic	Calculated	Master_cy	...
1	A	1	-3.4	0	-8.8	0	325.5	
1	A	2	-3.6	0	-0.2	0	0.9	
1	A	3	-3.6	0	-0.2	0	0.9	
1	A	4	-3.6	0	-0.2	0	0.9	
1	A	5	-3.5	0	-0.2	0	0.9	
1	A	6	-3.4	0	-0.2	0	36.7	
1	A	7	-3.6	0	-0.2	0	61.8	
1	A	8	-1.6	0	-0.2	0	38.9	
1	A	9	7.9	8	-0.2	0	12.5	

Time-series data

- Filtering sensors according to their variance
- Dividing the data to windows according to hyper-parameters
  - Window length and overlap
- Getting windows for each driver

Dimension Reduction

- Chosen non-linear method is Diffusion Map
- The goal of the algorithm is to find the structure on which the data lays on and representing it in fewer dimensions space
- The diffusion distance between samples is the Euclidian distance in that space
- The new space composed of multiplication between eigen values and vectors obtained by decomposing the Markov Matrix



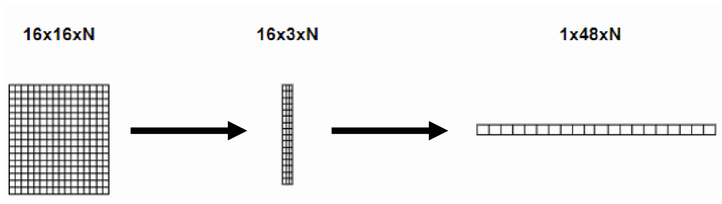
Example for 3-dimensional helix represented in 2-dimensional diffusion map

Features Extraction

- Applying the algorithm on the drivers' windows
  - Getting the new space matrix and choosing 3 vectors with biggest eigen values-

$$L \times 17 \Rightarrow 16 \times 16 \Rightarrow 1 \times 48$$

L represents the window length hyper-parameter



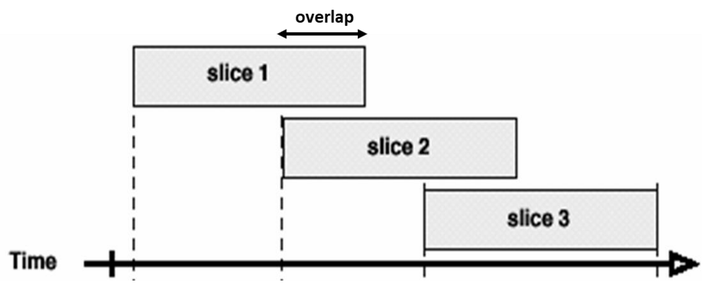
For each driver getting N windows, applying the algorithm resulting in vector for each window

Classification

- Chosen multi-Class classifier is Random Forest
- Training the classifier with feature vectors
- Optimize by cross-validation to determine hyper-parameters

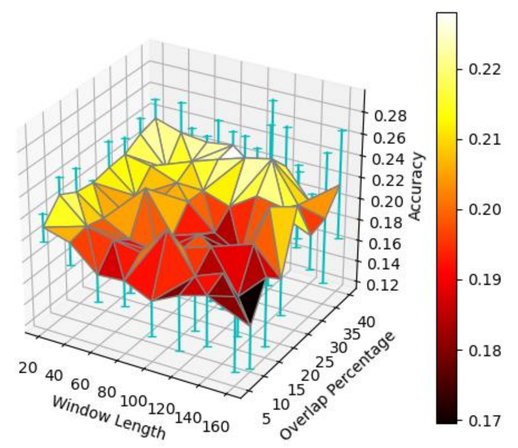
$$Window\ Length = [20,40,60,80,100,120,140,160]$$

$$Window\ Overlap = [5,10,15,20,25,30,35,40]$$



Visualization of the hyper-parameters

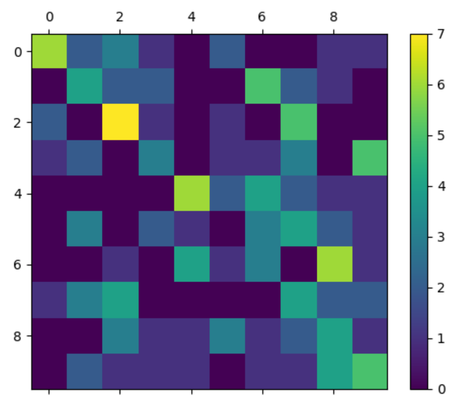
- Optimization results-



Window Length=120 Window Overlap=35%
Resulting 27%±5% accuracy

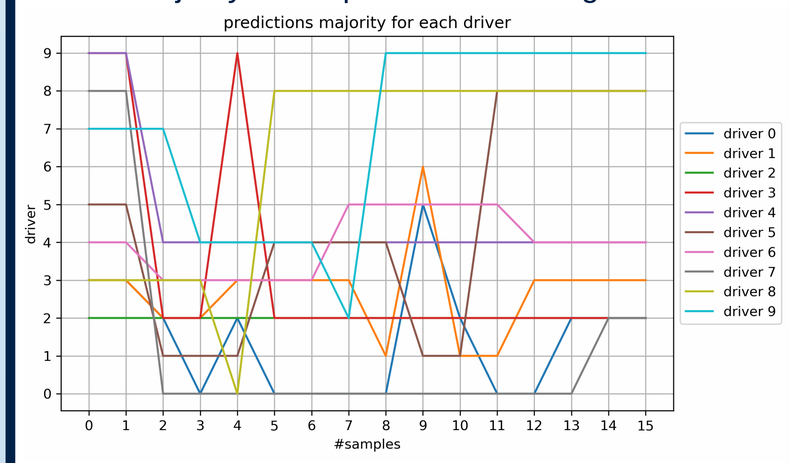
Results

- Using the results of the optimization
- Results on the test set-



Confusion Matrix on test set
Accuracy = 26.25%

- The classifier distinguishes better between drivers 0,2,4 with accuracy of 40%, and worse for others
- Simulation of real event- for each driver, taking the majority of the predictions through time-



- Drivers 4,8,9 converge to the right values

Conclusions

- Classifier results with optimized hyper-parameters with accuracy of 26.25% aren't satisfying
- Simulation of real event results aren't satisfying, reaching only 3 out of 10 drivers prediction right
- The diffusion space isn't allowing distinction between drivers
- Diffusion Map isn't a good fit for this data dimension reduction