A Multisensory Driven Adaptation to Improve Driver's Comfort

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http://vehical.org

Understanding Driver Behavior for Smart Vehicles

- Empirical Reachability Analysis for Predictions with Safety Guarantees[1]
  - How to capture the variety of human driver behaviors, while providing certificates on safety?
- Applying the Model in Semi- and Fully Autonomous Vehicles[2,3]
  - How can we design a **minimally invasive control** scheme that takes into account the driver state?

[1] V. Govindarajan, et al., "Robustness vs. Utility Trade-off in Reachability Analysis for Human-in-the-Loop Systems"
[2] K. Driggs-Campbell, et al., "Improved Driver Modeling for Human-in-the-Loop Vehicular Control
[3] K. Driggs-Campbell, et al., "Integrating Intuitive Driver Models in Autonomous Planning for Interactive Maneuvers"

Understanding Driver Behavior for Smart Vehicles

- Impressive results using visual data
- An important piece of information to perceive the world around us is being neglected: **Sounds**

Why is sound important?

- The sound is informative
  - danger and the state of the environment can be perceived by humans from the sounds
- Noise in the interior of a vehicle might increase the probability of traffic accidents
  - physiological effects of sounds
- The passengers, the driver, and the vehicle are components of a vibro-acoustical system

Why is sound important?

- There is a complex tradeoff between no disturbing noises and the expectations of the listener
  - The sound quality
  - The brand
  - The model of the car

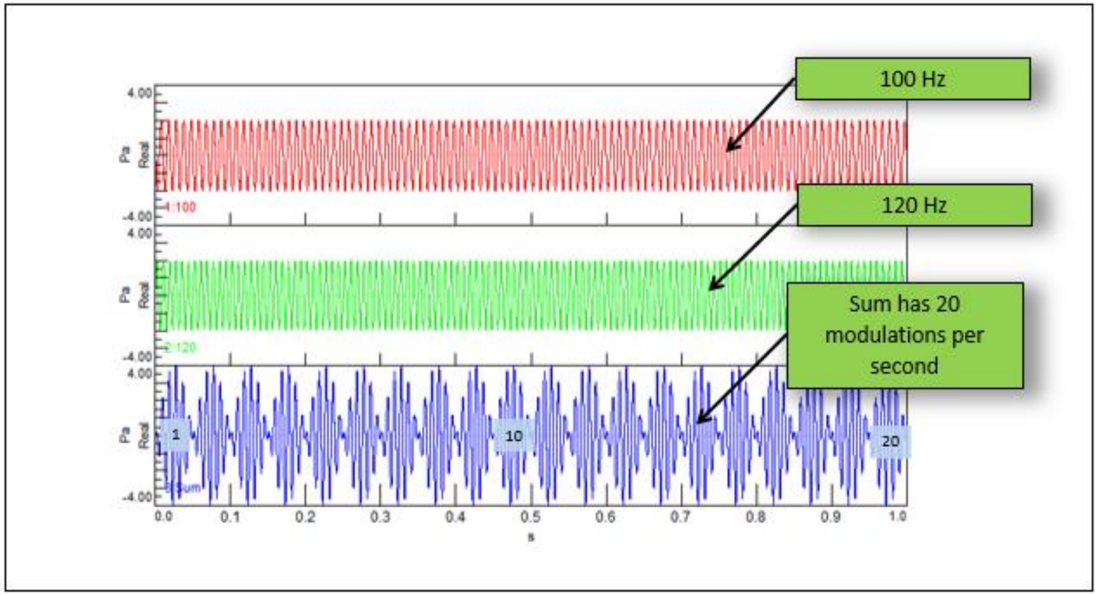
- The goal is to keep the environment inside the vehicle comfortable not a fully silence environment

Psychoacoustic and sound

- Works on noise treatment in the vehicle focus on
  - noise measurement
  - adjustment on designing and manufacturing phases
  - measure the vehicle interior noise to gather data for production and design phases.
- Keeping the environment inside the vehicle comfortable remains a major challenge

The amplitude of the sound might rise and fall over time

- Why do the sounds rise and fall over time?
  - Multiple frequency tones present in the sound constructively and destructively interfere with each other causing the modulation.



Measuring the annoyance

- The sound annoyance are closely related to the psychoacoustic indices:
  - **Fluctuation and Roughness**: A modulated signal has a higher roughness and fluctuation and is considerably more unpleasant
  - **Sharpness**: depends on the spectral composition
  - **Loudness**: takes into account the distributions of critical bands in the human hearing

Psychoacoustic indices

- Fluctuation Strength (**F**) and Roughness (**R**): Sound Modulation Metrics
  - **Fluctuation** Strength : sounds with 20 modulations per second or less
  - **Roughness**: sounds with modulations between 20 and 300 times per second

Sharpness

- The sharpness (**S**) is a sensation value which is caused by high frequency components in a given noise.
    - It is related to the spectral characteristics of the sound
    - Sharpness increases with high-frequency energy
    - Distortion increases sharpness

Loudness

- The loudness (**L**) metric is based of perceived loudness
  - not a physical phenomena but a **psychological phenomena**
  - the metric was developed with a group of people, unlike decibels which is simply a math equation

Psychoacoustic annoyance (PA) metric

- PA is composed of the Fluctuation (**F**), Roughness (**R**), Sharpness (**S**), and Loudness (**N$_5$**)
  - Results of **psychoacoustic experiments** with modulated versus unmodulated narrow- band and broadband sounds of different spectral distribution.
  - N_5 is the 95% percentile Loudness

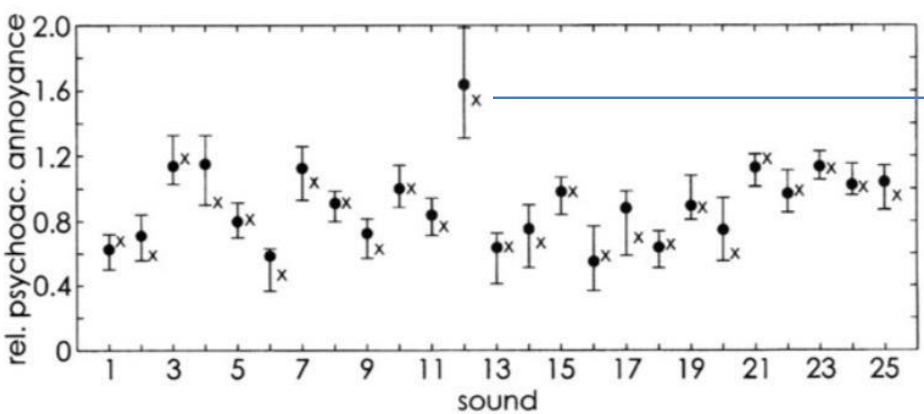


Fig. 16.12. Psychoacoustic annoyance of car sounds listed in Table 16.2. *Dots*: Data from psychoacoustic experiments.

$$\mathrm{PA} = N_5 \left(1 + \sqrt{w_S^2 + w_{FR}^2}\right)$$

$$w_S = \begin{cases} (S - 1.75) \cdot 0.25 \lg(N_5 + 10) & S > 1.75 \\ 0 & S \leqslant 1.75 \end{cases}$$

$$w_{FR} = \frac{2.18}{N_5^{0.4}}(0.4F + 0.6R)$$

Measuring the annoyance

- Annoyance measured by the psychoacoustic annoyance (PA) metric - higher is more annoying
  - car sound only: **10.71** (PA value)

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Measuring the annoyance

- Annoyance measured by the psychoacoustic annoyance (PA) metric - higher is more annoying
    - car sound only: **10.71** (PA value)
    - kid crying: **19.77** (PA value)
    - beells and beeps: **45.2** (PA value)
- Sound captured from the environment: **45.7** (PA)

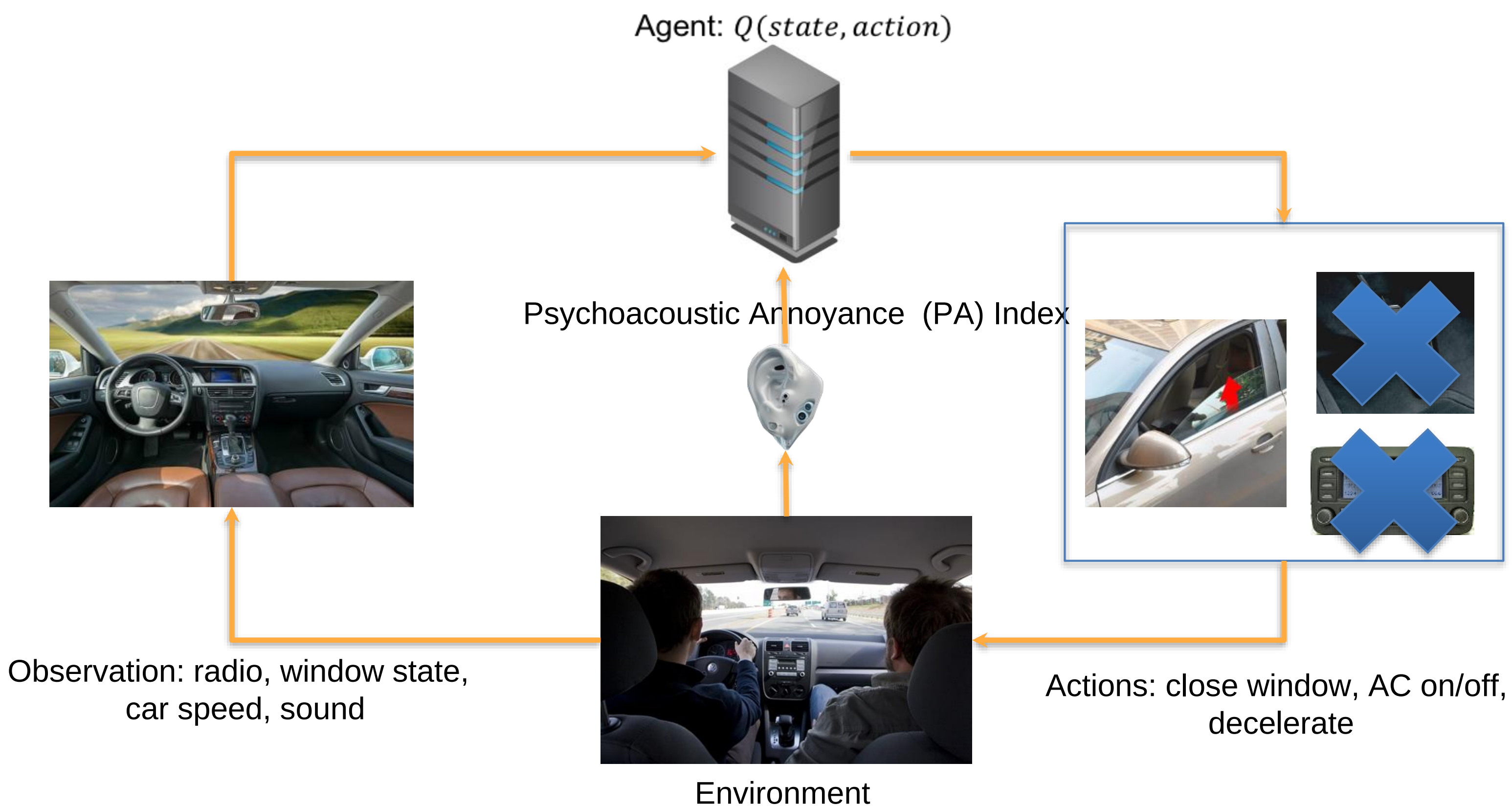
Where does the annoyance come from?

- We can learn from the environment how to change the state inside the car to avoid an unpleasant environment in the interior of the vehicle,
  - turn the radio off
  - closing the car windows
  - slowing the car speed down

- Exploration-Exploitation approach

Reinforcement learning approach

- Deep Q-learning Network
  - The reward is given by the PA metric



Simulation experiments

The RL Agent

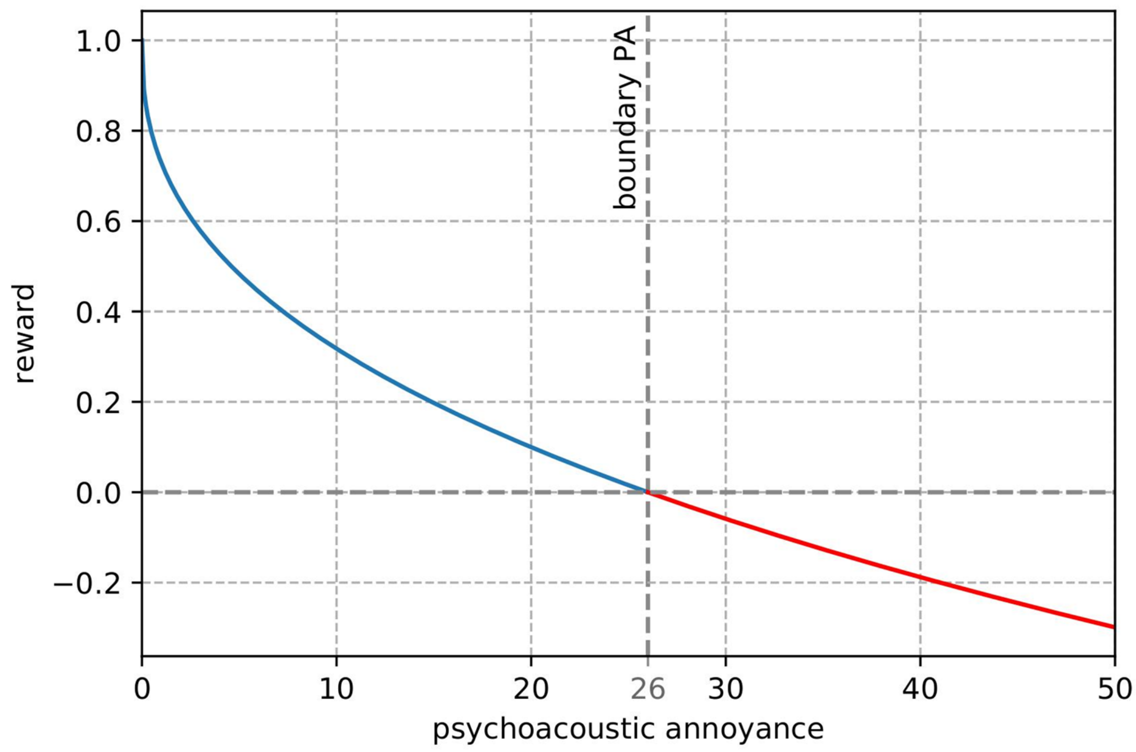
$$r_t = 1 - \sqrt[4]{\frac{PA_t}{PA_{bound}}}$$

The agent is presented with:

- the current speed,
- the state of the windows (open/closed),
- the state of the air-conditioning (on/off),
- several seconds of sound.

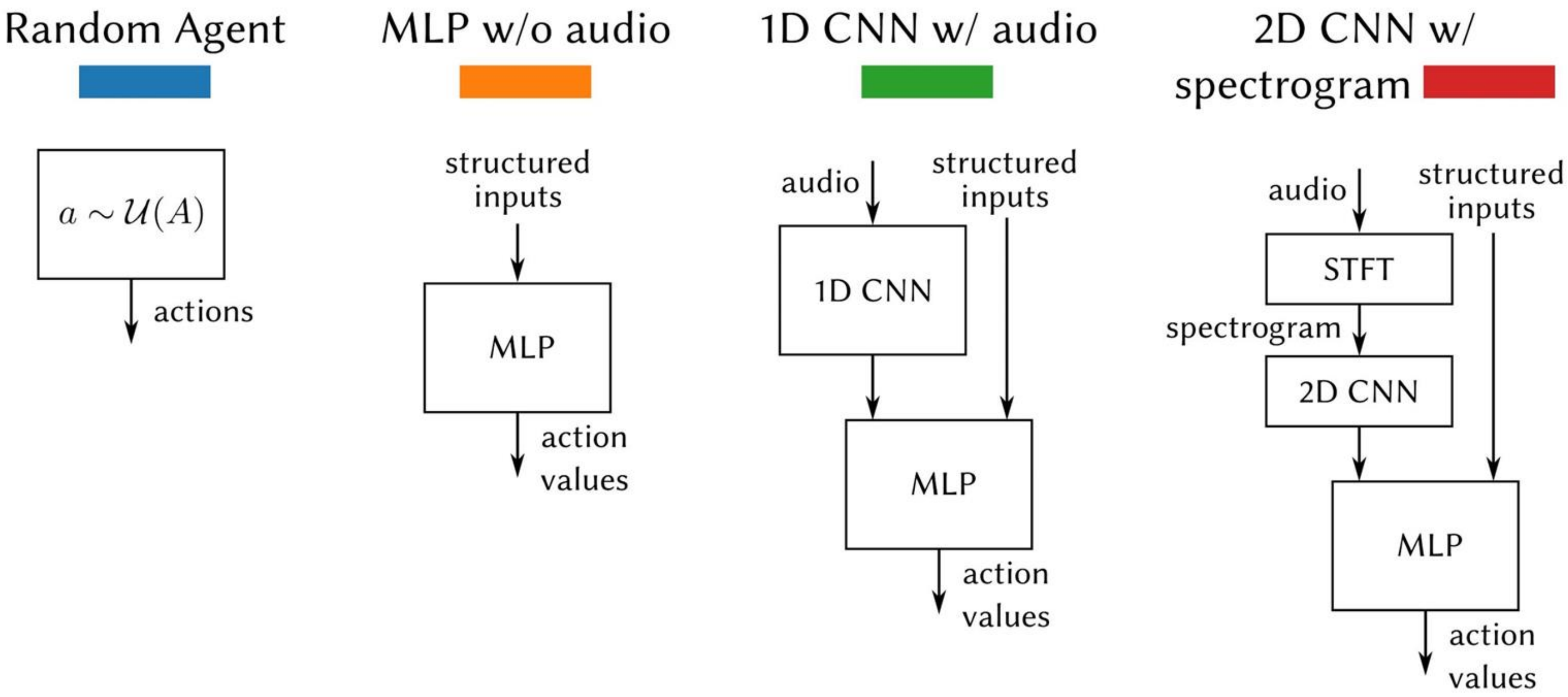
The reward is based directly on the PA.

A shaping function is applied.

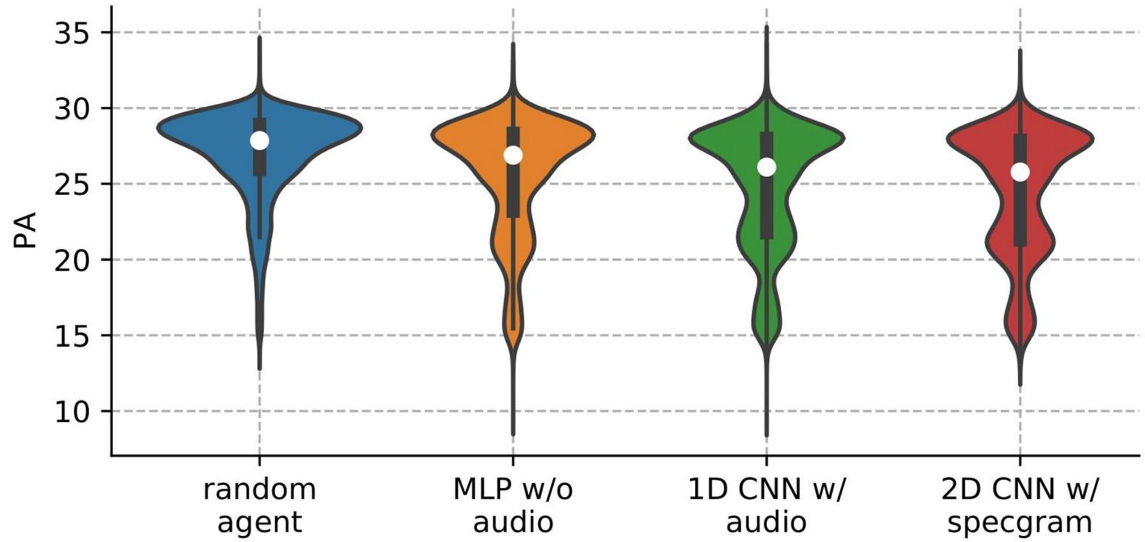


The RL Agents' Architectures

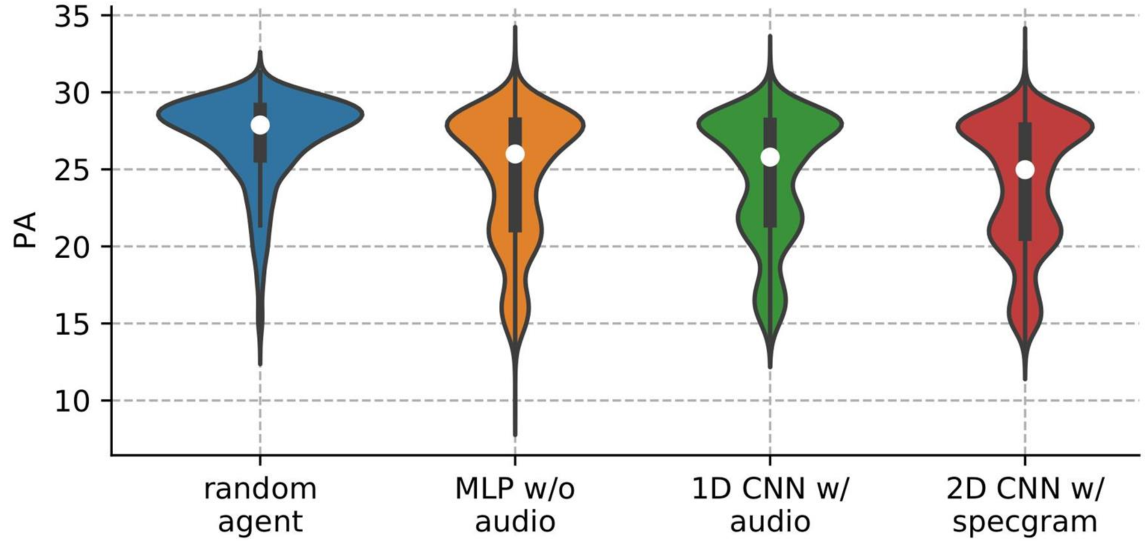
- Several agents and architectures.
- Different ways of preprocessing the audio.



PA Violin Plots



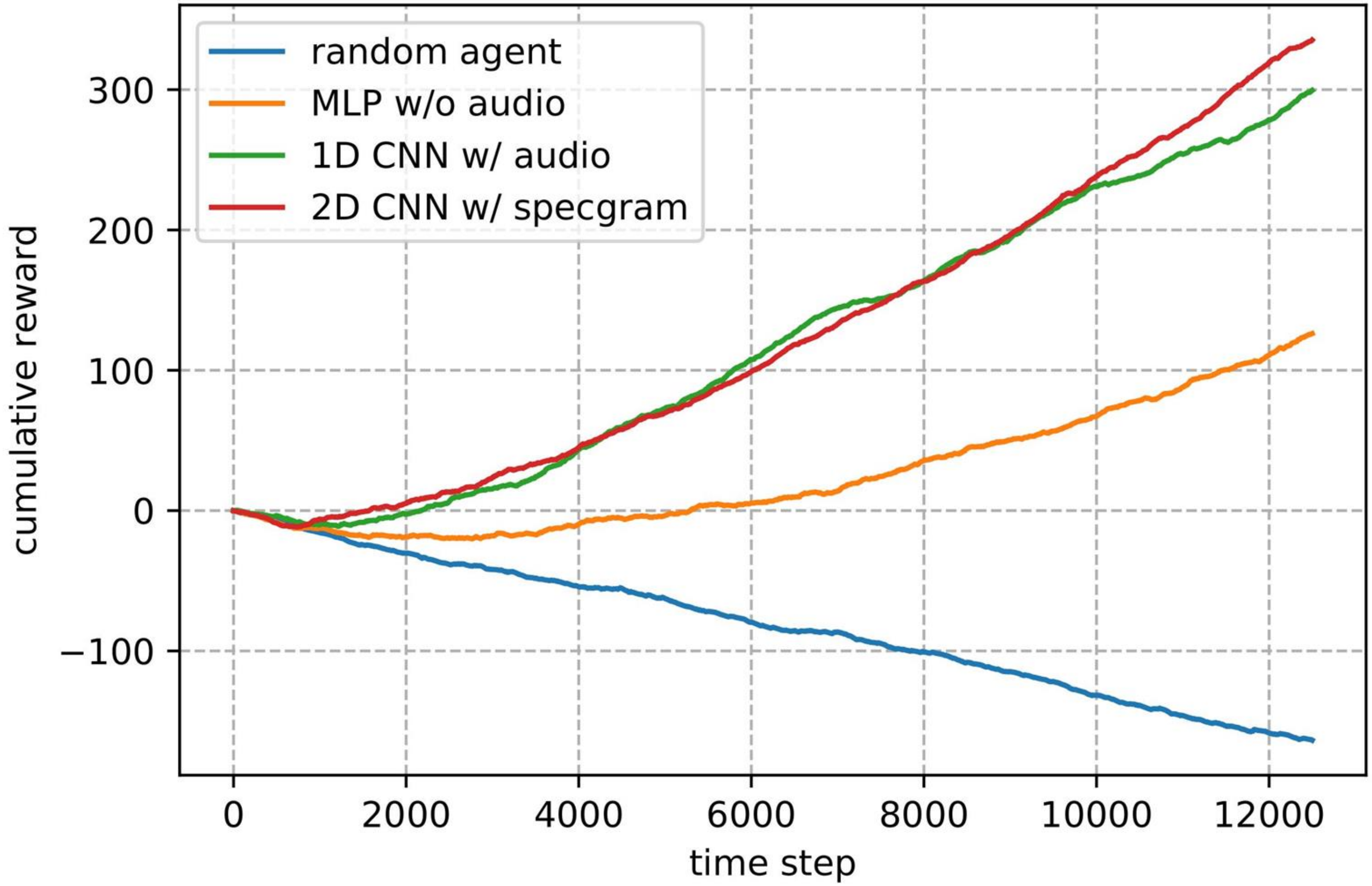
across all steps



after 11 000 steps

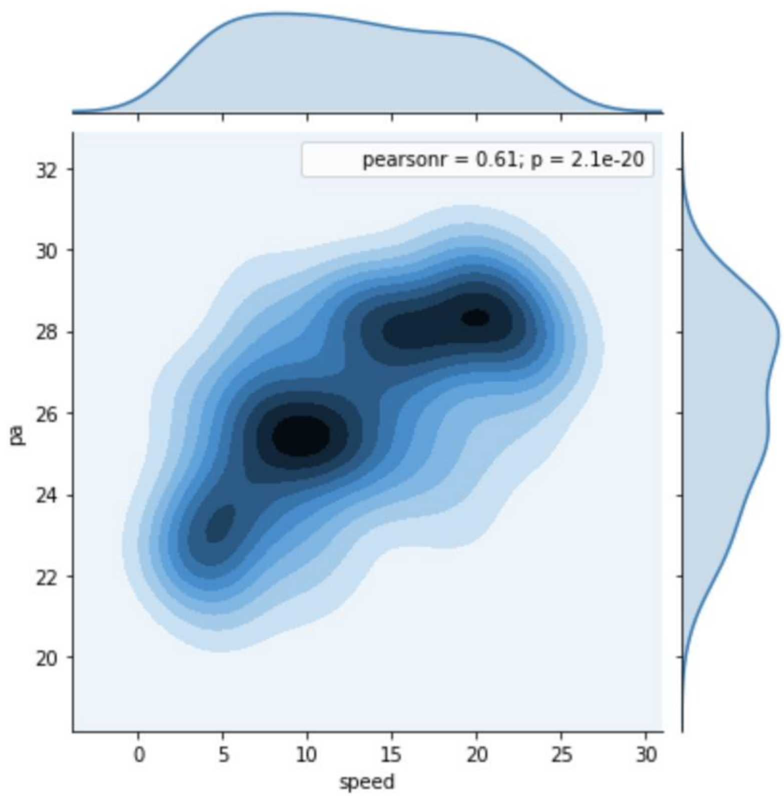
Cumulative Reward

- The cumulative reward increases for all but the random agent.
- Architectures that factor in the sound have an edge.



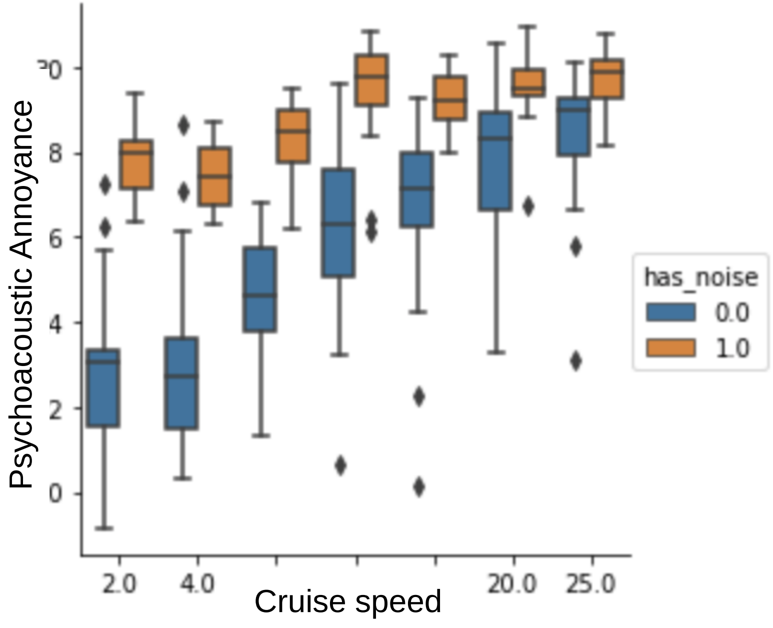
Annoyance vs Speed

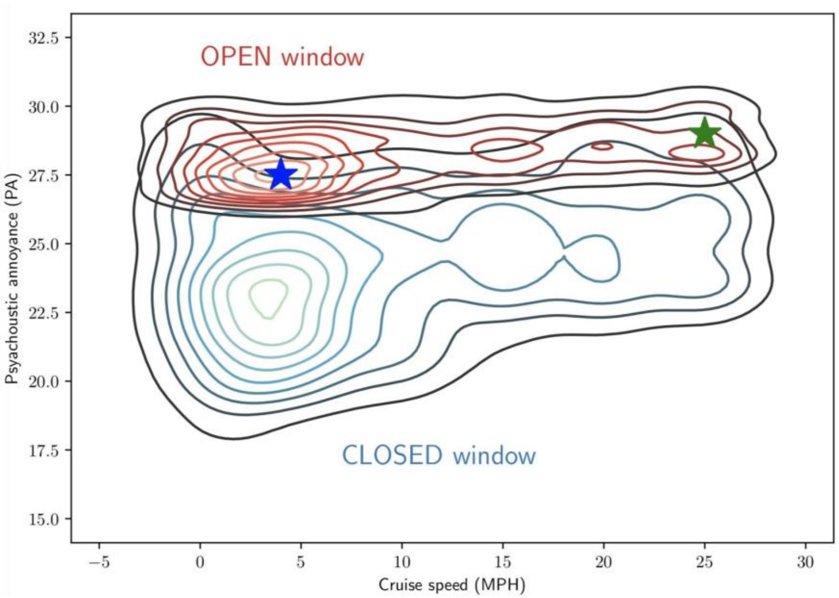
- Varying the cruise speed from 1 to 30 MPH
- Radio and AC off
- Only traffic, cars and pedestrians



Adding annoying sound from outside

- Noise from streets was simulated merging bells and beeps sounds:
  - When we have annoying sound from outside, what should we do? Close the window or slow the car speed down?





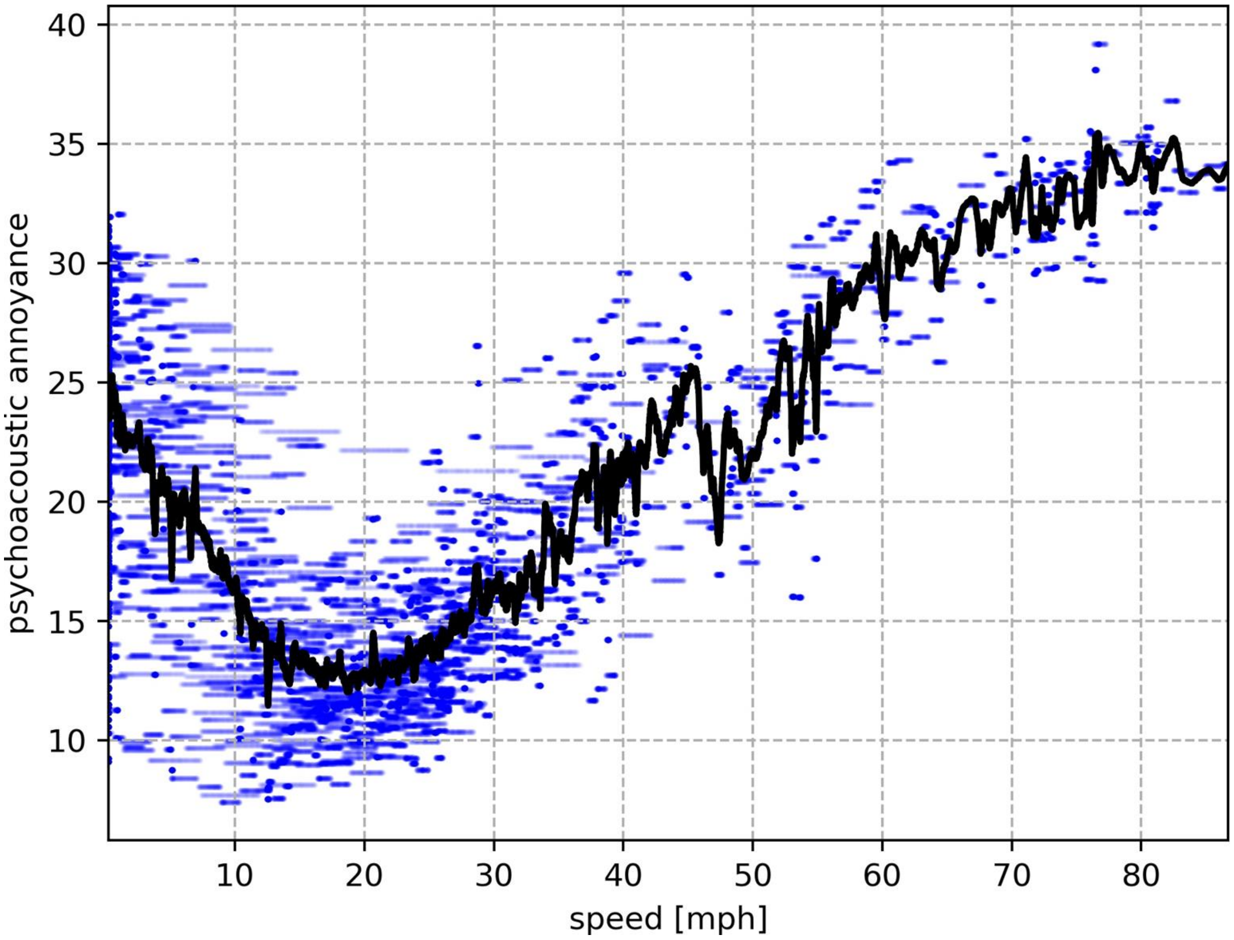
Collecting Data

- Real-life data
  - Lincoln MKS

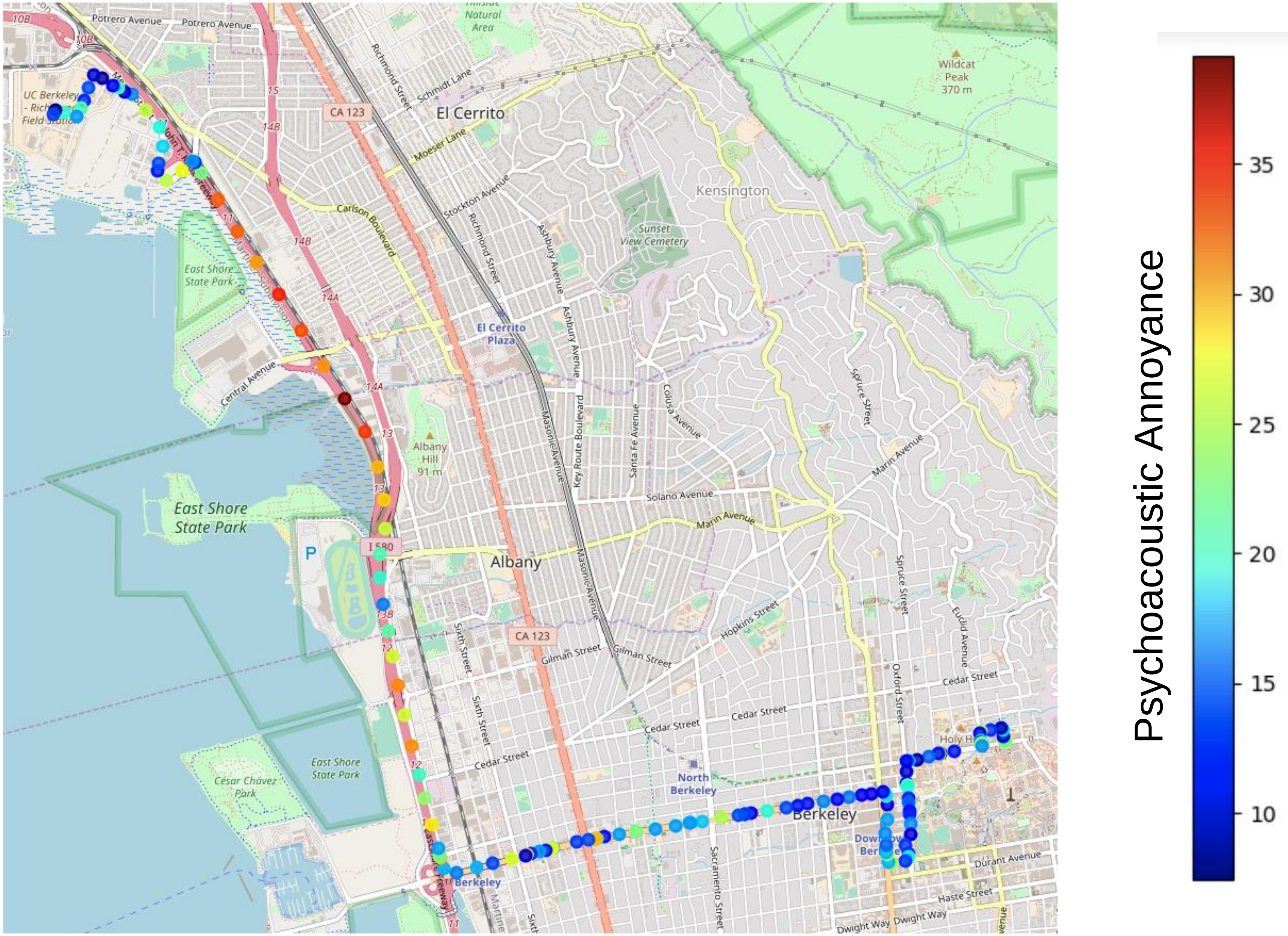
Collecting Data

- Using the BDD Lincoln MKS, we gathered data from:
  - Sensors on the vehicle (e.g., LiDAR, IMU, cameras)
  - Other vehicle data (e.g., vehicle speed, throttle, steering turn signal, etc.)
  - Outside audio captured with a mic
- In total, we gathered over 1TB of data

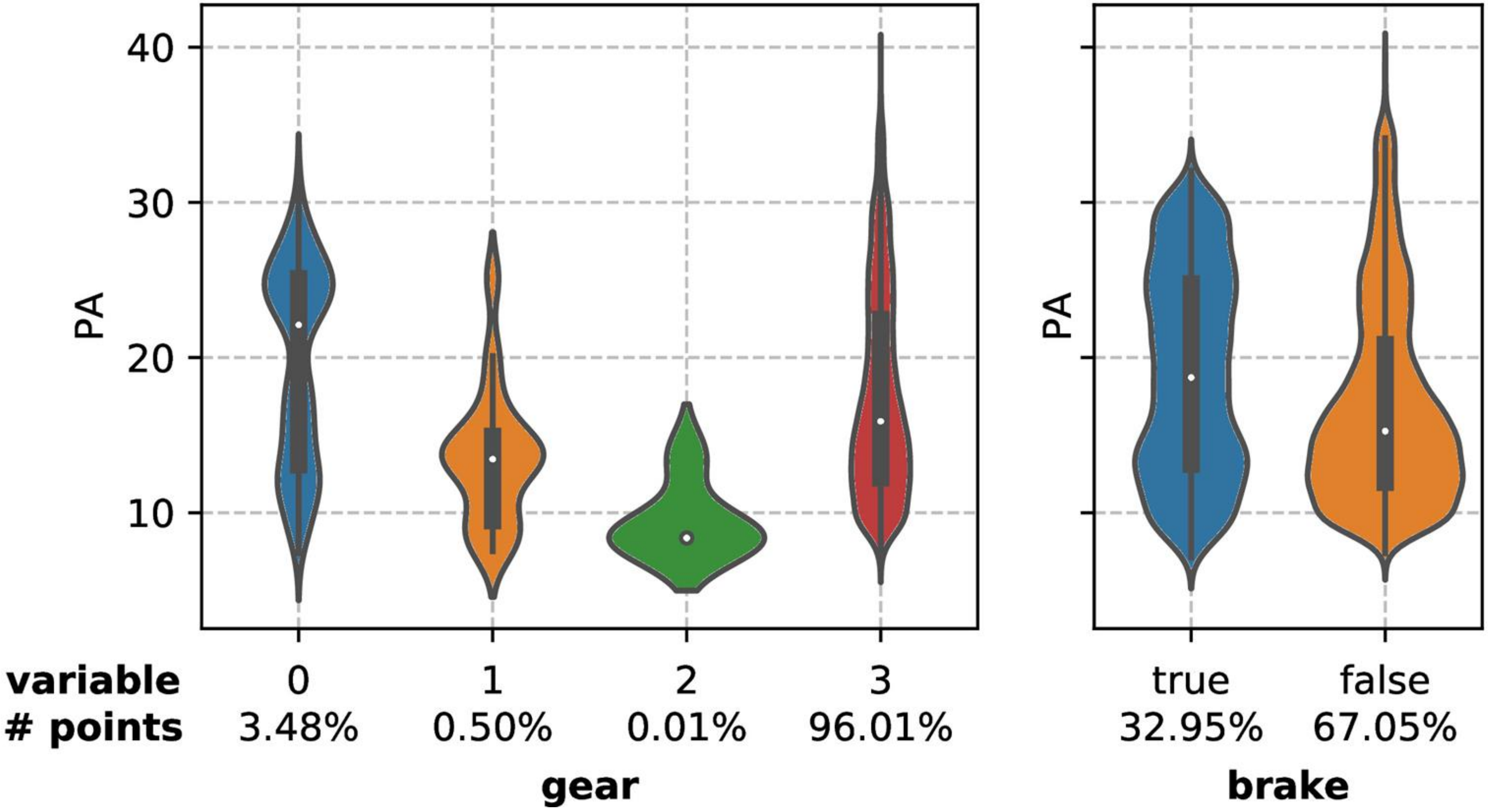
Real data – PA vs Speed



Real data – PA and GPS position



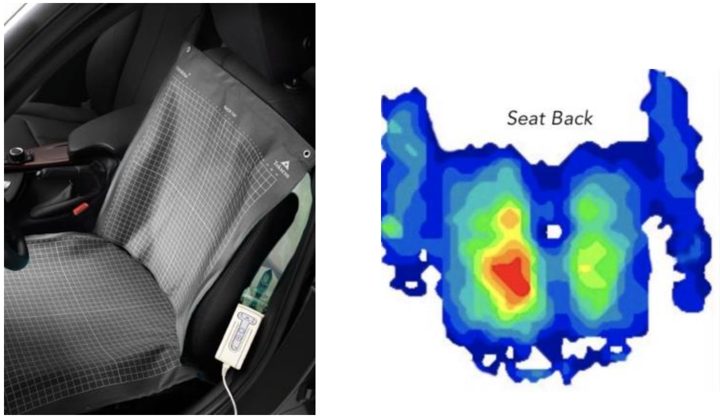
Real data – PA vs Gear and Braking



Acoustic Stimuli Effects on Driving Styles

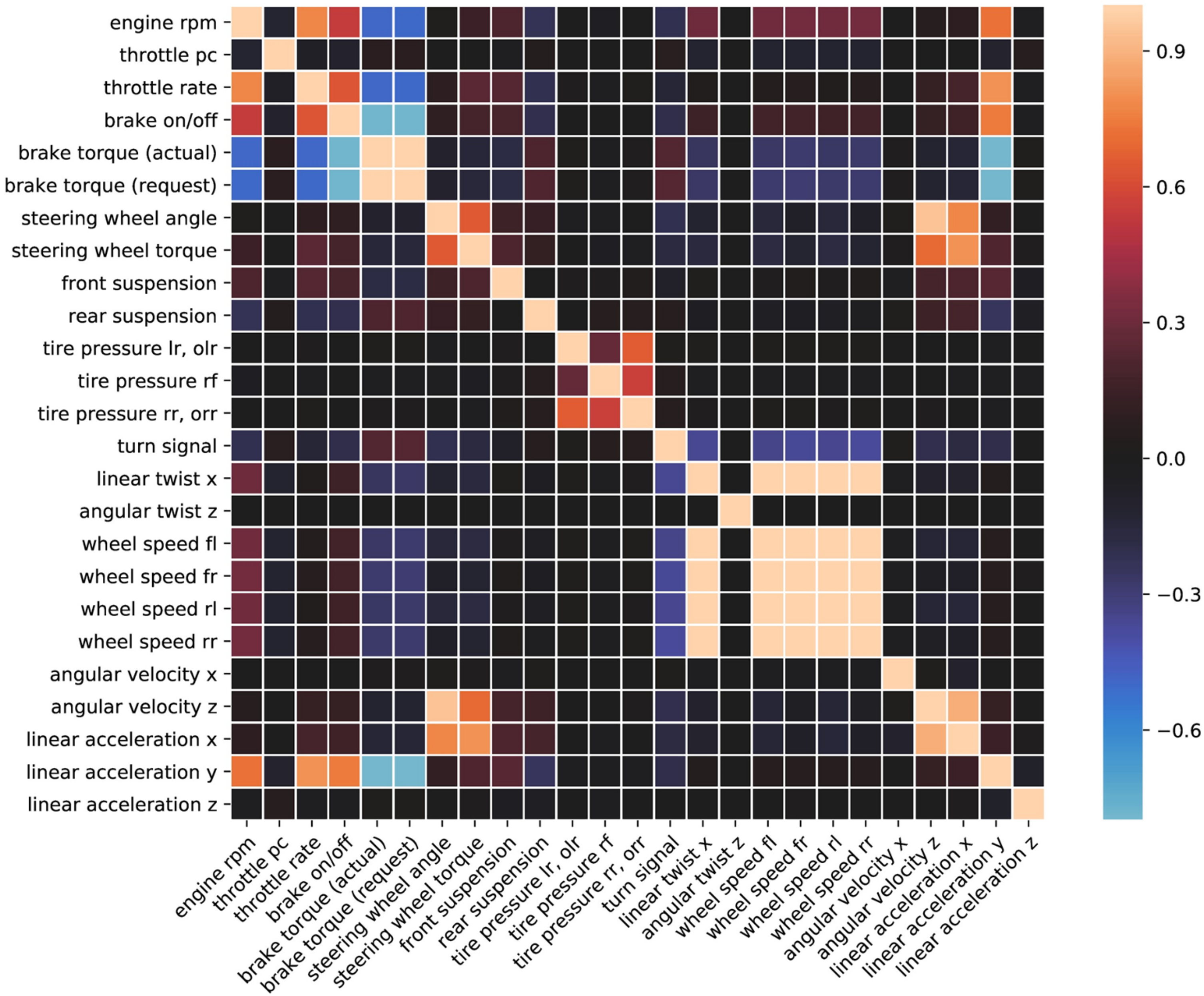
- We conducted a real-world driving experiment (n=9) to investigate the effect of driver **annoyance** states, elicited by acoustic stimuli, on driving style.
- Acoustic modes were induced by two soundtracks
    - Calm instrumentals for sleeping
    - Baby crying sound
- On-board sensors captured the driving data for these two modes
- Pressure mat data was collected on the passenger to build a **passenger dynamics model** and to subsequently infer **passenger comfort**

Participants drove along this route for both acoustic modes



TekScan pressure mat images the passenger seat forces

Feature Correlations (1)

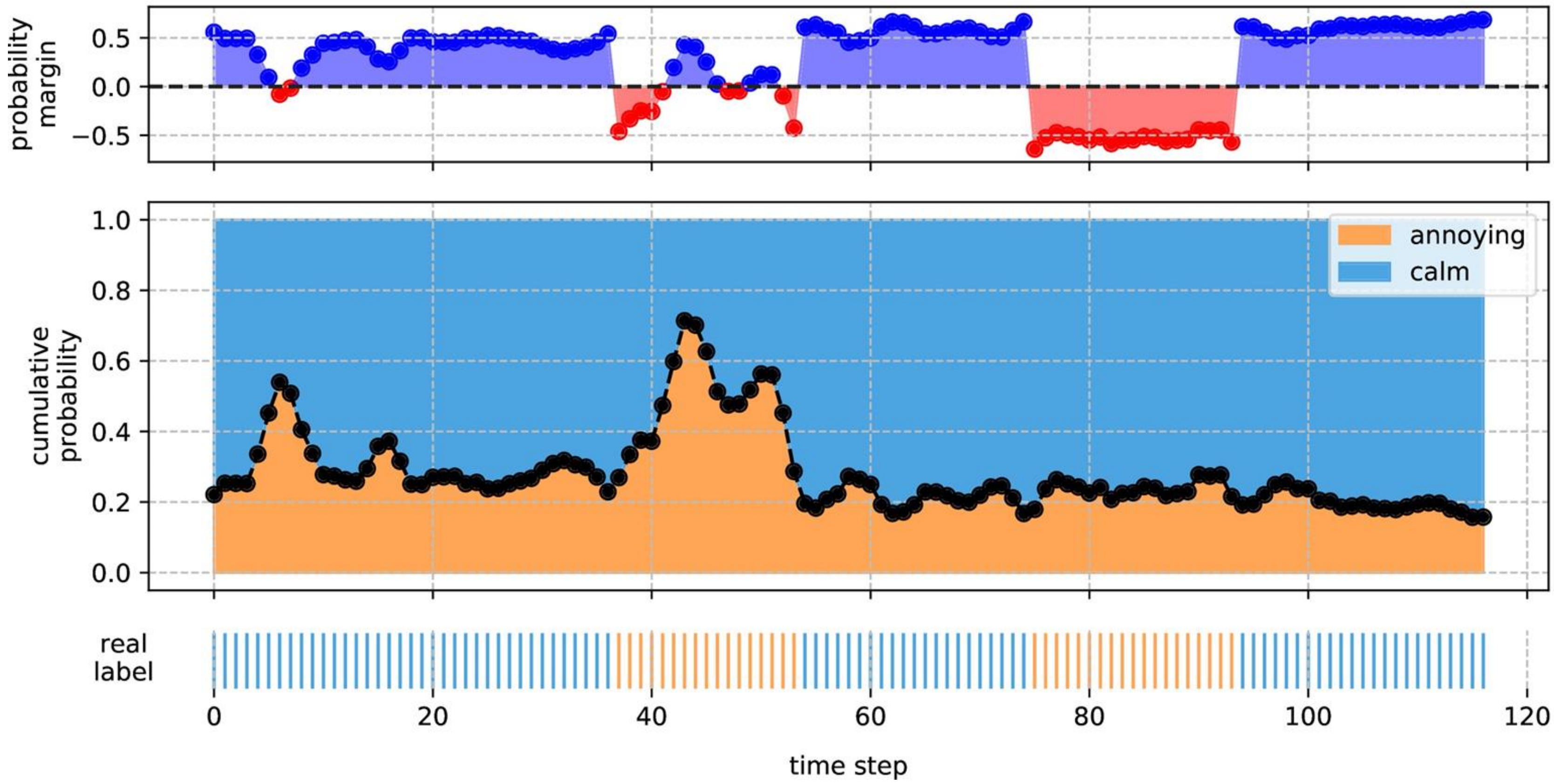


Recognizing the Acoustic Mode (1)

- Telling apart different acoustic modes:
  - Driving with **calm** vs. **annoying** soundscape.
  - Regulated using audio tracks.
- Featurization:
  - Using linear acceleration, angular velocity, linear twist, brake torque (requested), throttle rate, linear jerk.
  - Split into windows of size 2000 (the sampling rate is 50Hz) with the step of 500 samples (windows overlap).
  - Each window preprocessed by computing histograms with 7 bins.
- Validation:
  - Split validation. 75% of experimental runs used for training, 25% for testing.
- Classifier:
  - The light GBM (Gradient Boosting Machine) classifier;
  - 250 estimators; hyperparameters optimized using hyperopt.

Recognizing the Acoustic Mode (2)

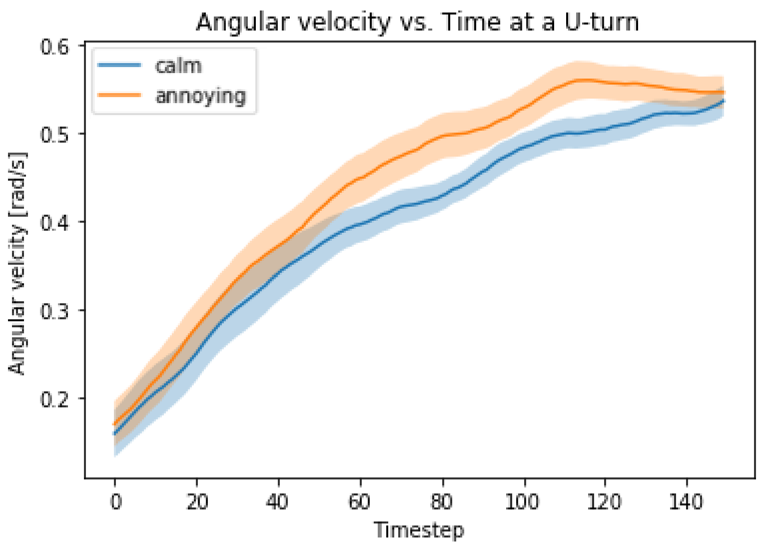
- Classifying window by window; across all test runs (accuracy 74%):



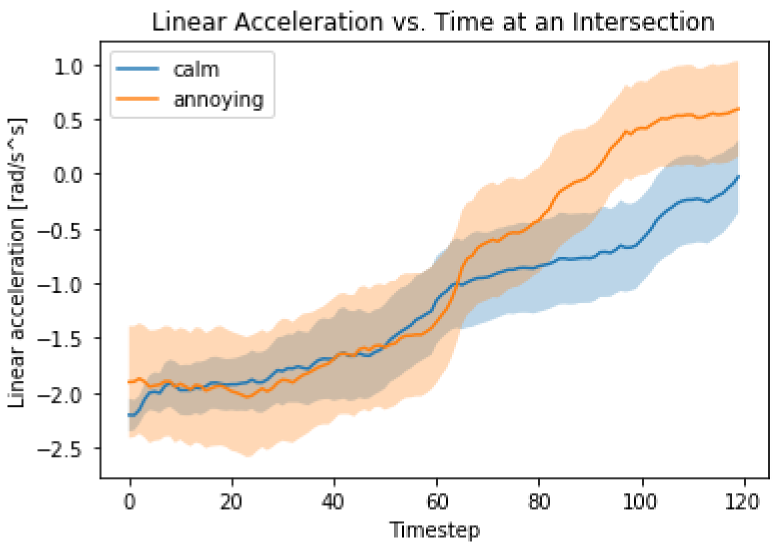
- Probability margin: difference between the score of the correct label and the maximum score among the other labels. Red indicates misclassification.

Recognizing the Acoustic Mode (3)

- Qualitatively, clear driving differences arise between acoustic modes for different maneuvers

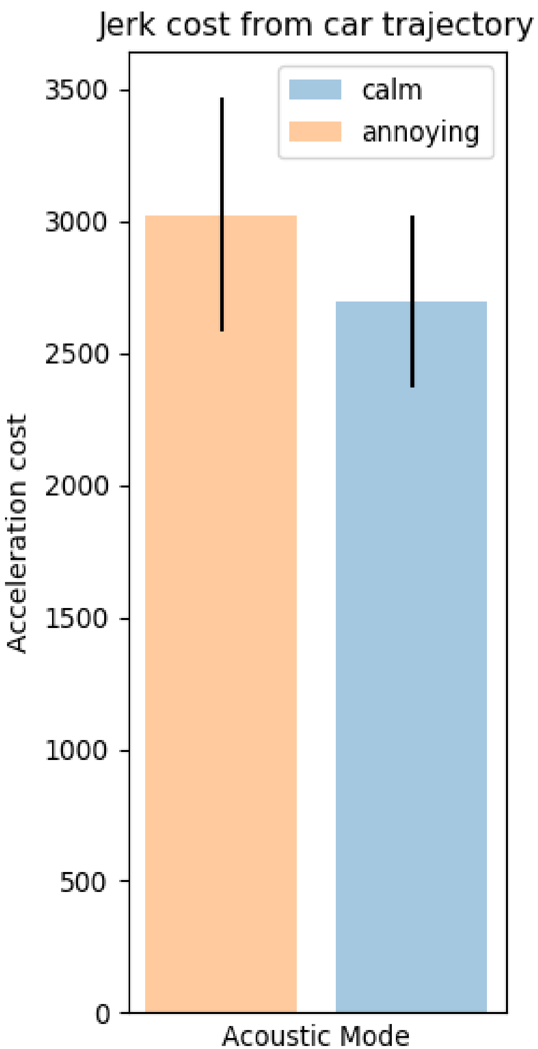


a) U-turn

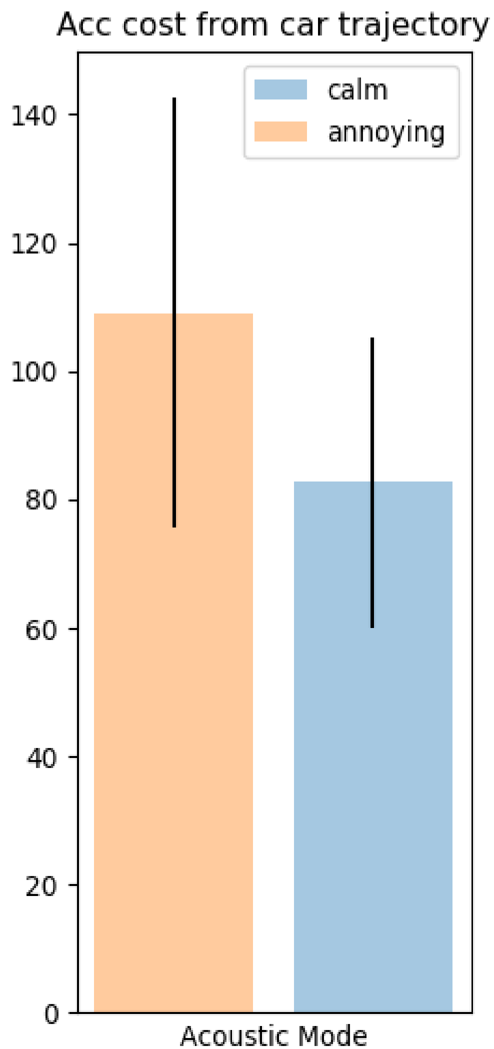


b) Intersection

Recognizing the Acoustic Mode (4)



(1)



(2)

- Smoothness from a system's trajectory can be characterized by its **jerk** and **acceleration** costs [1]:

$$\int_{t=t_i}^{t_f} \dddot{x}_1(t)^2\,dt \qquad (1)$$

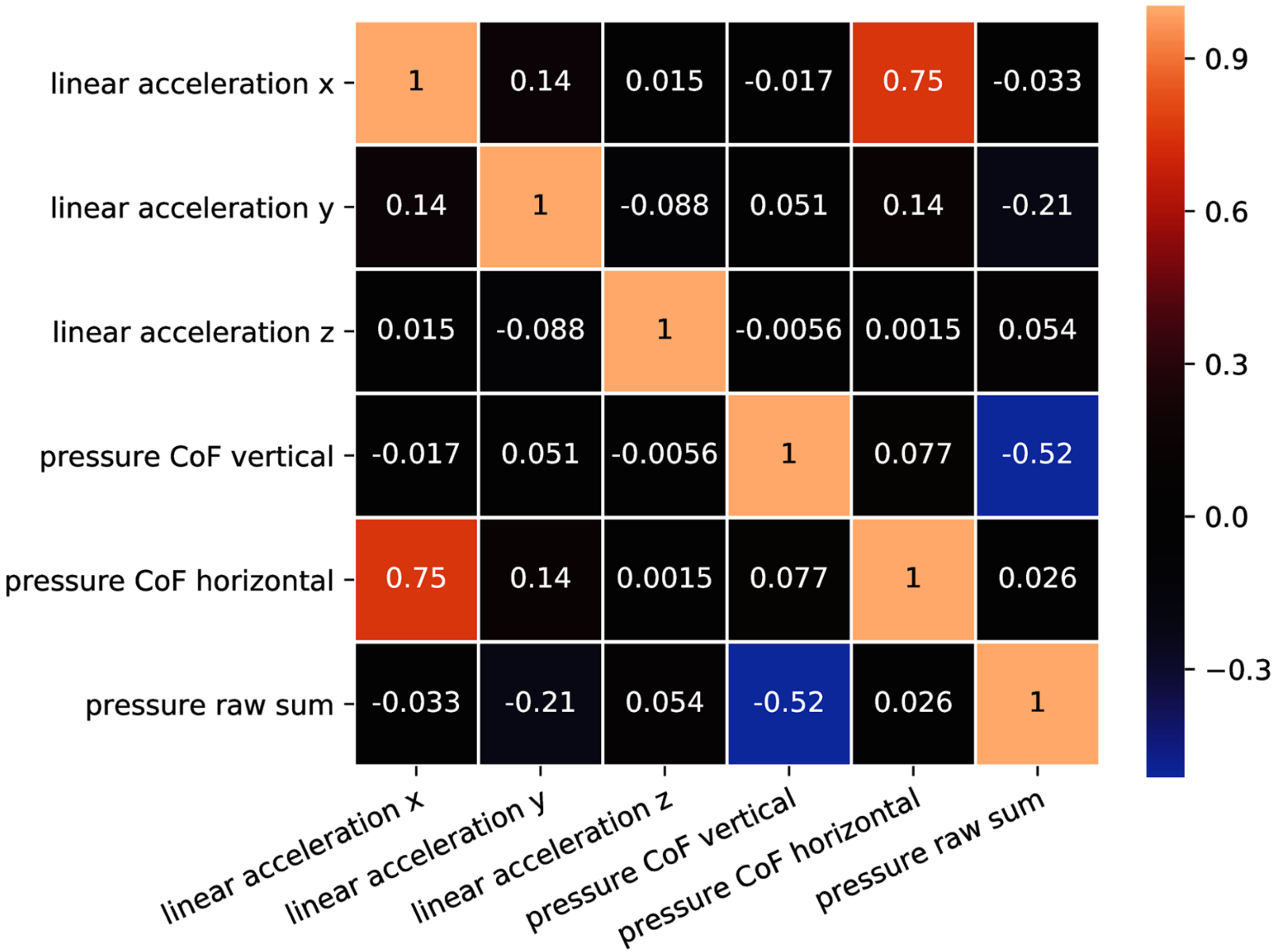
$$\int_{t=t_i}^{t_f} \ddot{x}_1(t)^2\,dt \qquad (2)$$

- Across the multiple riders, the annoying mode showed higher jerk and acceleration costs than the calm mode

[1] R. Shadmehr, et al., "A MINIMUM-JERK TRAJECTORY "

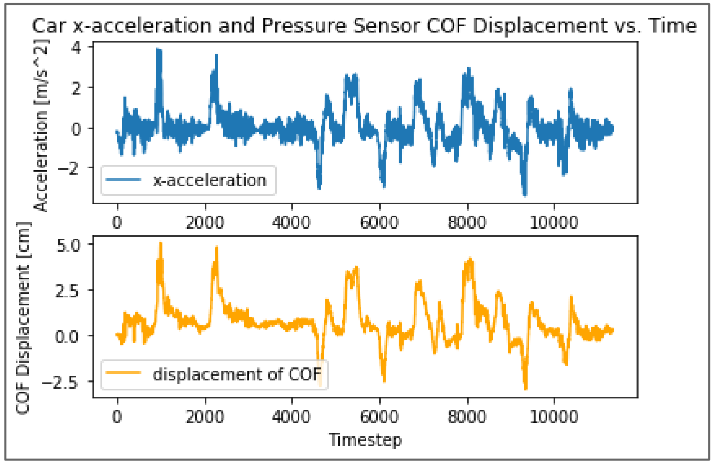
Feature Correlations (2)

- Pressure sensor is correlated with inertial measurements.

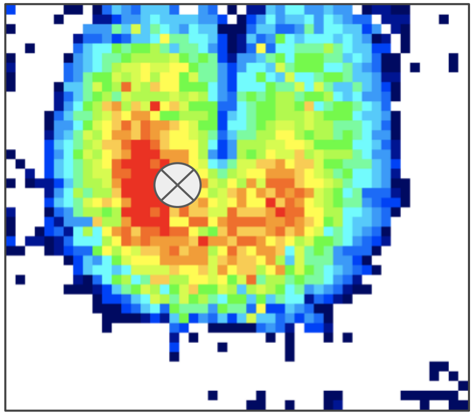


Interaction Forces between Passenger and Vehicle

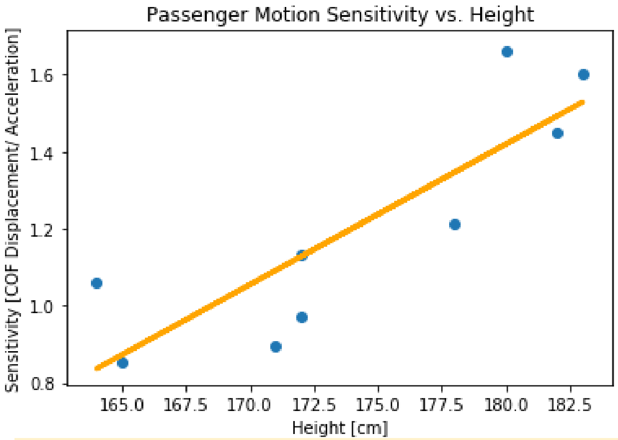
- We quantify how the human body shifts with the car using the pressure data
- There is a clear correlation between linear accelerations and shifting of mass
- Passenger height affects motion sensitivity



Linear acceleration correlates with displacement of the COF



The pressure mat allows us to track the center of force (COF) of the human



Passenger body height impacts COF dynamics

Next steps and future work

- Implement and test real-time identification of driving mode
- Investigate effects of different types of annoyance
  - Eg. Maneuver-based, annoyance with other drivers, etc
- Produce a more complete model of human interactive forces with sensor mats at the back and the feet
- Record biometric data to create and ground a cognitive model

Thank you

Questions?

HART Lab

Human-Assistive Robotic Technologies