Online learning for comfort functions of the passengers in autonomous driving and the challenges

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GOAL: Autonomous Vehicle SAE level 5
● Efficiency
● Comfort
● Safety
- Efficiency
- Comfort
- Safety
Outline

Introduction and Classification

Approaches: Existing and Implemented

Challenges

Conclusion and Future work
Introduction and Classification

- What are comfort functions?
- What makes them important?
- How are they currently implemented?
Introduction and Classification

- Navigation control
- Velocity and Steering control
- Infotainment systems (speech and gesture recognition)

- Suspension systems
- Seat Ergonomics
- Ambience and Temperature control

Non-Beneficial

Beneficial

Comfort functions

Machine Learning
Comfort functions: no Online ML required

- Suspension system
  - Tasks of the suspension system
  - Main suspension categories
  - What is being done
Comfort functions: no Online ML required
Comfort functions: no Online ML required
Comfort functions: no Online ML required

- Seat geometry control
  - Seat design
  - Stages of influencing the geometry
  - Comfort estimation
Comfort functions: no Online ML required
Comfort functions: no Online ML required

- Other comfort functions of this type
- Why are Online ML methods not being actively implemented
- What attempts have been made in this direction.
Comfort functions: Online ML required

● Trajectory Planning
  ○ moving from point A to point B while avoiding collisions over time
  ○ Path Planning + Motion Planning w.r.t. velocity, time & kinematics

● Why place it as a comfort function
  ○ Mitigates whole body vibration, jerk exposure of occupants
Comfort functions: Online ML required

Standard Modular AV Architecture

Model Predictive Control and learning based AV Architecture
Comfort functions: Online ML required

- **Trajectory Planning - Key Changes**
  - Trajectory controller replaced by Robust Learning based MPC Controller, generator by driver model
  - **Motivation** - Learning from Human Behavior (Driving Style); and their perception of comfort
  - **Methodology** - Inverse Reinforcement Learning (IRL)
    - model the individual style in terms of a cost function
    - use feature-based inverse reinforcement learning to find optimum model parameters
    - efficiently compute trajectories
  - **Currently Used in** - Bosch’s AVs

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Comfort functions: Online ML required

- Velocity and steering control
  - **Motivation** - Comfort via Navigational Ease
  - **Methodology** - Longitudinal Speed control problem formulation
    - Traditional proportional integral derivative (PID) replaced by self-adaptive PID of radial basis function neural network (RBFNN-PID)
    - Maximal deceleration and bounded jerk limits set for comfort
    - Forward simulation model = self-adaptive RBFNN-PID driver model + a vehicle dynamic model.
  - **Currently Used in** - Drive.ai’s “From piecewise to holistic DL approach for AVs”
Comfort functions: our implementation

- End to End Deep Learning
- Longitudinal movement control

Actual Steering Angle = [0.069214]
Predicted Steering Angle = [0.06796788]
L1 Error: [0.00124512]

Actual Steering Angle = [-0.00128867]
Predicted Steering Angle = [0.00138041]
L1 Error: [0.00260907]

Actual Steering Angle = [-0.002977]
Predicted Steering Angle = [-0.09123489]
L1 Error: [0.00174211]
Comfort functions: our implementation

- Trajectory Planning
- IRL Method, with movement control we “learned” previously as the observed driving style (input) for this simulation

At training time step 0

At the end of training
Challenges

- Data
  - Acquisition
  - Transportation

“For the sake of machine learning specifically there’s such a thing as a point of diminishing return.”

- Sacha Arnoud, Head, Waymo’s machine learning and perception division.
Challenges

● Safety Assurance

Learning-based Systems break all the conformity assessment principles and processes

“Safety usually isn’t about how you handle nominal cases. It’s about how well you handle edge cases.”
- Prof. Philip Koopman, Carnegie Mellon University
Conclusion and Future Work

- Summary
- Our experience
- Current state
- Comfort estimation
Conclusion and Future Work

- Future work
- Possible solutions to challenges
  - Humanisation of AV modules
    - Edge-case Research
    - Multimodal Redundancy
    - "Self-Supervised" Neural Networks
Conclusion and Future Work

● Duality in the approaches

● Remember -

“Autonomous Vehicles are likely to fail differently than humans.”

Prof. Philip Koopman, Carnegie Mellon University
Thank you!
Questions?
References:

[7] “Inside Waymo’s strategy to grow the best brains for self-driving cars”, article from The Verge
[8] Videos from Audi, Monroe, Continental and Bose official websites
References:

Appendix
Appendix

Steering Angles for normal_1 and swerve_1 runs

Number of data points per driving strategy

Normal
74.49% (34913)

Swerve
25.51% (11925)

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Normal label distribution

Swerve label distribution

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IRL for Trajectory Control

- Quintic Splines for position -

\[ s_j : [t_j, t_{j+1}] \rightarrow \mathbb{R}^2 \]

- Trajectory defined as -

\[ r(t) = s_j(t), \text{ for } t \in [t_j, t_{j+1}] \]

- IRL MLE Approximation as -

\[ \mathbb{E}_{p(r|\theta)}[f] = \int p(r | \theta) f(r) dr \]
Appendix

RBFNN for Velocity Control

- Research Strategy
  For Longitudinal Speed Problem

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Edge Case Research

What About Edge Cases?

- You should expect the extreme, weird, unusual
  - Unusual road obstacles
  - Extreme weather
  - Strange behaviors

- Edge Case are surprises
  - You won’t see these in testing
    ➔ Edge cases are the stuff you didn’t think of!

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Edge Case Research - One possible solution

What We’re Learning With Hologram

- A scalable way to test & train on Edge Cases

Your fleet and your data lake → Hologram cluster tests your CNN → Hologram cluster trains your CNN → Your CNN becomes more robust

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Self-Supervised Neural Networks

Non-rigid image registration using self-supervised fully convolutional networks without training data
Hongming Li ; Yong Fan. 2018
Appendix

Multimodal Redundancy

Multimodal vehicle detection: fusing 3D-LIDAR and color camera data
Alireza Asvadi, Luis Garrote, Cristiano Premebida, Paulo Peixoto, Urbano J. Nunes
Appendix

Bi-LSTMs for Autonomous driving

3DOF Pedestrian Trajectory Prediction Learned from Long-Term Autonomous Mobile Robot Deployment Data
Li Sun ; Zhi Yan ; Sergi Molina Mellado ; Marc Hanheide ; Tom Duckett. 2018

Parallel planning: a new motion planning framework for autonomous driving
Long Chen ; Xuemin Hu ; Wei Tian ; Hong Wang ; Dongpu Cao ; Fei-Yue Wang 2019