A Personalized Highway Driving Assistance System

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Outline

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- Types of Autonomy in Vehicles
  - Semi-Autonomous: Cruise Control, Emergency Braking, Lane Departure Warning
  - Fully Autonomous: Google (Waymo), Tesla self driving cars
- Shortcomings
  - Majority of autonomous driving systems are focused on safety
  - Maneuvers generated are pre-defined and conservative

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Motivation

- Drivers' Points of View
  - People have various driving styles
  - Conservative driving does not satisfy everyone
  - Interest and trust in autonomous driving will be decreased

Solution

The autonomous features must be designed according to the drivers' preferences.

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- Drivers' steering input prediction using a transfer function
- Drivers' lane-change intent prediction using Relevance Vector Machine (RVM)
- Disadvantages:
  - Behavior is simplified
  - Environment is simplified
  - Output is given as a recommendation to the driver
  - The model may not perform well in an unseen scenario.

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Related Work

Maneuver Decision Making and Control

- Maneuver that requires both decision making and control: Lane Change
- The lane change decision is made to maximize driving safety and quality
  - Optimization methods are employed
- Mixed integer programming is used for an optimized decision
  - MIP could result in loss of convexity.

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Proposed Highway Driving Assistance System

- **Proposed Approach:** Driver Model + Controller
- **Scenario of Interest:** Highway driving
  - It is very close to autonomous driving.
- **System Modes:** Most maneuvers on a highway:
  - Path Following
  - Car Following
  - Lane Change
- The modes are activated according to:
  - Driver's preference
  - Environment condition
- These modes can be overridden for a mandatory maneuver (exit).

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Proposed Highway Driving Assistance System

- Driver Model
  - Data from an individual driver
  - Random Forest regression is used for modeling driver behavior
- Control System:
  - Model Predictive Control (MPC) system for tracking arbitrary references
- Longitudinal motion is studied in order to maintain safe speed and distance with surrounding vehicles
- Assumptions:
  - Available equipment for autonomous control of vehicle
  - Available data from surrounding vehicles and environment through V2V, V2I and sensors

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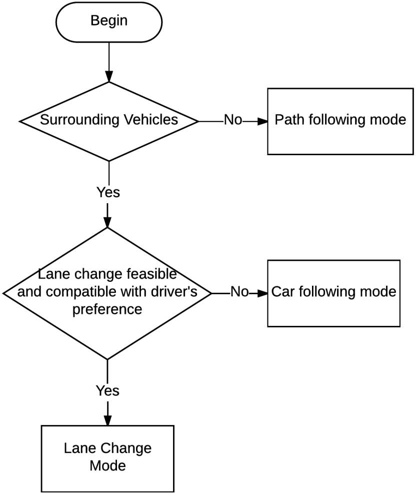
- Factors for Mode Activation:
  - Vehicle Safety
  - Driver's Preference



Driver Model

Pre-processing

- Input Features:
  - Vehicle Position
  - Vehicle Velocity
- Target variable: vehicle acceleration
- All input variables are scaled in the range of [0, 1]
- Target variable transformed into exponential space
- Feature Generator

$$\mathcal{F} = [d \quad d^2 \quad d^3 \quad v \quad v \times d \quad d^2 \times v \quad v^2 \quad d \times v^2 \quad v^3] \tag{1}$$

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Driver Model

Random Forest Regression Algorithm

Random Forest Regression Algorithm

Input: Number of randomly chosen predictors in each split: m_{try},
Number of bootstrap sample: n_{tree}

Output: Average of the output of all tree, P

1: **for** $i = 1$ to n_{tree} **do**
2: randomly select m_{try} number of features
3: grow an un-pruned regression tree with m_{try} randomly selected features/predictors
4: choose the best split among these randomly selected predictors
5: **end for**
6: for a new sample, predict the output of n_{tree} number of trees and average their output. Denote the output as P
7: **return** P

Preliminaries

- Consider a linear discrete system:

$$x_{t+1} = Ax_t + Bu_t \tag{2}$$

- In model predictive control (MPC) a constrained optimization is solved at each time instant
- If the sets X, U are convex, the MPC problem can be solved with Quadratic Programming (QP)

$$\min_{U_t} J = \frac{1}{2} w^T H w + d^T w \tag{3a}$$

$$H_{in} w \leq K_{in} \tag{3b}$$

$$H_{eq} w = K_e q \tag{3c}$$

Where $w = [U_t, x_{t+1}^T, \cdots, x_{t+N}^T]$

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MPC for Tracking Dynamic Reference

- MPC controller for tracking periodic references is used here:

$$V_N(x, r_x, r_u; x^r, u^r, u_N) = V_t(x; x^r, u^r, u_N) + V_p(r_x, r_u; x^r, u^r) \quad (4)$$

- Planned Trajectory: Steady state behavior

$$V_p(r_x, r_u; x^r, u^r) = \sum_{i=0}^{T-1} \|x^r(i) - r(i)\|_S^2 + \|u^r(i) - r_u(i)\|_V^2 \quad (5)$$

- Tracking Error: Transient behavior

$$V_t(x; x^r, u^r, u_N) = \sum_{i=0}^{N-1} \|x(i) - x^r(i)\|_Q^2 + \|u(i) - u^r(i)\|_R^2 \quad (6)$$

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MPC Formulation

- MPC for tracking a changing reference

$$\min_{x^r, u^r, u_N} \quad V_N(x, r_x, r_u; x^r, u^r, u_N) \tag{7a}$$

$$x(0) = x_0 \tag{7b}$$

$$x(i+1) = Ax(i) + Bu(i) \quad i \in \mathbb{I}_{[0,N-1]} \tag{7c}$$

$$y(i) = Cx(i) + Du(i) \quad i \in \mathbb{I}_{[0,N-1]} \tag{7d}$$

$$(x(i), u(i)) \in \mathcal{Z} \quad i \in \mathbb{I}_{[0,N-1]} \tag{7e}$$

$$x^r(0) = x^r \tag{7f}$$

$$x^r(i+1) = Ax^r(i) + Bu^r(i) \quad i \in \mathbb{I}_{[0,T-1]} \tag{7g}$$

$$y^r(i) = Cx^r(i) + Du^r(i) \quad i \in \mathbb{I}_{[0,T-1]} \tag{7h}$$

$$(x^r(i), u^r(i)) \in \mathcal{Z}^c \quad i \in \mathbb{I}_{[0,N-1]} \tag{7i}$$

$$x(N) = x^r(N) \tag{7j}$$

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Basic constraints are valid at all of the scenarios.

- **Velocity**: Never be less than zero , and not exceeding the road speed limit:

$$v_{min} \leq v_k \leq v_{max} \quad k = 0..N \tag{8}$$

- **Acceleration**: Determined from the vehicle's physical condition:

$$a_{min} \leq a_k \leq a_{max} \quad k = 0..N \tag{9}$$

- **Acceleration Rate**: Variations of acceleration (jerking) should remain in a small range to ensure passengers comfort

$$\Delta a_{min} \leq \Delta a_k \leq \Delta a_{max} \quad k = 0..N \tag{10}$$

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- Position constraints are added to the basic constraints

$$d_{max_k} = min(d_{front_i} - gap) \quad t = 0..N \tag{11a}$$
$$d_{min_k} = max(d_{rear_i} - gap) \quad t = 0..N \tag{11b}$$

- Position Reference

$$d_{ref\,k} = \frac{d_{min_k} + d_{max_k}}{2} \tag{12}$$

  - Weight distribution in the cost function

$$R = \frac{1}{(N_v + 1)^2} \tag{13a}$$
$$Q = 1 - R \tag{13b}$$

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Optimization Constraints

Lane-change Scenarios

- Position constraints in lane change depend on vehicles in both current and target lanes.

$$d_{max_k} = min(d^{cl}_{front_i} - gap, d^{tl}_{front_i} - gap) \quad t = 0..t_{trans} \tag{14a}$$

$$d_{max_k} = min(d^{tl}_{front_i} - gap) \quad t = t_{trans}..N \tag{14b}$$

$$d_{min_k} = max(d^{cl}_{rear_i} - gap, d^{tl}_{rear_i} - gap) \quad t = 0..t_{trans} \tag{14c}$$

$$d_{max_k} = min(d^{tl}_{rear_i} - gap) \quad t = t_{trans}..N \tag{14d}$$

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SHRP2 Naturalistic driving data

- Study was conducted with 3,000 volunteer drivers aged 16 – 98 over 3 years in several locations across the United States.
- Vehicles used had an unprecedented scale of sensors installed on them.

Model Training

- Imputation is used to increase observations
- All available values of acceleration are used to create a model for the position, to predict the missing values of position.
- The newly imputed values for position and acceleration are used to predict the missing values of velocity following the same procedure.
- As a result, the number of observations increased from 397 to 4231.
- %75 of data for training, %25 of data for testing

Driver Model
Evaluation

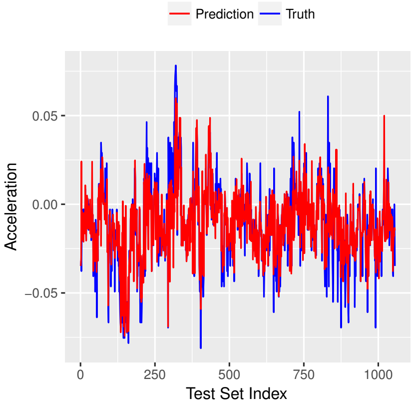

Figure: Raw acceleration predictions, tested on OOB samples

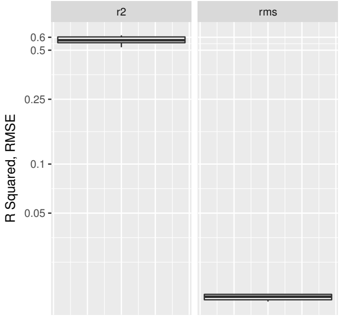

Figure: Performance of model as tested on OOB samples in 10-fold CV from 10 iterations.

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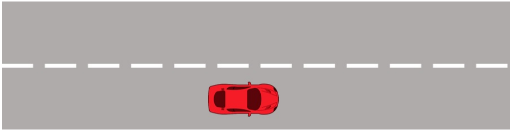
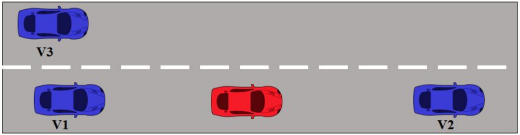
Driving Scenarios

- **Light Traffic**



- **Dense Traffic**



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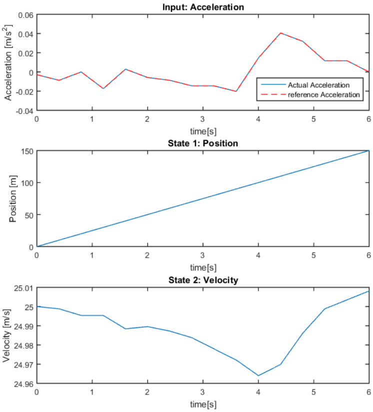
Driving Scenarios

Light Traffic

- Planned trajectory for subject vehicle in current lane
  - The reference acceleration is tracked accurately
  - The speed, acceleration and jerk constraints are satisfied.
  - There are no requirements for position constraint and position reference.
  - No lane change is required.



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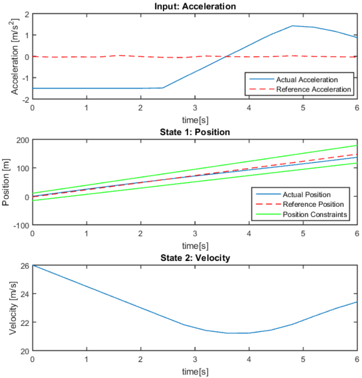
Driving Scenarios

Dense Traffic

- Planned trajectory for subject vehicle in current lane
  - Due to the presence of surrounding vehicles, reference position is introduced.
  - The weight on position tracking is higher than acceleration tracking.
  - Reference position is tracked accurately.
  - Reference acceleration is not tracked well. (RMSE = 4.8613)



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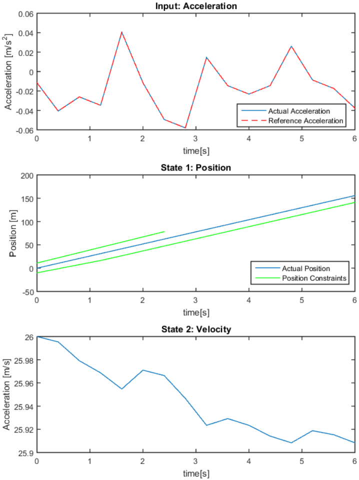
Driving Scenarios

Dense Traffic

- Planned trajectory for subject vehicle in adjacent lane
  - Less surrounding vehicles results in higher weight for acceleration tracking
  - Reference acceleration is tracked accurately. (RMSE $= 6 \times 10^{-11}$)
  - Position constraints are satisfied before and after the lane change.
- **Decision: Vehicle moves to the adjacent lane**



Conclusion

- Proposed Highway driving assistance system
  - Data driven driver model
    - Trained with driver's naturalistic driving data
    - Can emulate different driving styles
  - Model predictive control
    - Capable of tracking dynamic references
    - Ensures driving safety and comfort
- Proposed system able to detect and handle various traffic scenarios
  - Prioritize safety of the vehicle in presence of traffic
  - Alternate between different modes to ensure driver's satisfaction

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Future Work

- Additional filtering component to ensure lane change compatibility with driver's preference
- System is extended to include different models, so detect and adapt to a new driver's style ASAP
- Ensuring driving safety in case of inaccurate or incorrect V2X communication

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Thank You For Your Attention

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