A Personalized Highway Driving Assistance System

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Introduction

Background

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
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.
Related Work
Personalized Driver Models

- 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.
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.
**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).
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
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

\[ \mathcal{F} = [d \ d^2 \ d^3 \ v \ v \times d \ d^2 \times v \ v^2 \ d \times v^2 \ v^3] \quad (1) \]
Driver Model
Random Forest Regression Algorithm

Random Forest Regression Algorithm

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

**Output:** Average of the output of all tree, $P$

1. for $i = 1$ to $n_{\text{tree}}$ do
2. randomly select $m_{\text{try}}$ number of features
3. grow an un-pruned regression tree with $m_{\text{try}}$ 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 $n_{\text{tree}}$ number of trees and average their output. Denote the output as $P$
7. return $P$
Preliminaries

- Consider a linear discrete system:
  \[ x_{t+1} = Ax_t + Bu_t \]  \hspace{1cm} (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)

\[
\begin{align*}
\min_{U_t} J &= \frac{1}{2} w^T H w + d^T w \hspace{1cm} (3a) \\
H_{in} w &\leq K_{in} \hspace{1cm} (3b) \\
H_{eq} w &= K_{e} q \hspace{1cm} (3c)
\end{align*}
\]

Where \( w = [U_t, x_{t+1}^T, \cdots, x_{t+N}^T] \)
MPC for Tracking Dynamic Reference

- MPC controller for tracking periodic references is used here:

\[ V_N(x, r_x, r_u; x^r, u^r, u_N) = V_t(x; x^r, u^r, u_N) + V_p(r_x, r_u; x^r, u^r) \]  \hspace{1cm} (4)

- Planned Trajectory: Steady state behavior

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

- Tracking Error: Transient behavior

\[ V_t(x; x^r, u^r, u_N) = \sum_{i=0}^{N-1} \|x(i) - x^r(i)\|_Q^2 + \|u(i) - u^r(i)\|_R^2 \] \hspace{1cm} (6)
MPC Formulation

- MPC for tracking a changing reference

\[
\begin{align*}
\min_{x^{r}, u^{r}, u_{N}} & \quad V_{N}(x, r_{x}, r_{u}; x^{r}, u^{r}, u_{N}) \quad (7a) \\
x(0) &= x_{0} \quad (7b) \\
x(i + 1) &= Ax(i) + Bu(i) \quad i \in \mathbb{I}[0, N-1] \quad (7c) \\
y(i) &= Cx(i) + Du(i) \quad i \in \mathbb{I}[0, N-1] \quad (7d) \\
(x(i), u(i)) &\in \mathcal{Z} \quad i \in \mathbb{I}[0, N-1] \quad (7e) \\
x^{r}(0) &= x^{r} \quad (7f) \\
x^{r}(i + 1) &= Ax^{r}(i) + Bu^{r}(i) \quad i \in \mathbb{I}[0, T-1] \quad (7g) \\
y^{r}(i) &= Cx^{r}(i) + Du^{r}(i) \quad i \in \mathbb{I}[0, T-1] \quad (7h) \\
(x^{r}(i), u^{r}(i)) &\in \mathcal{Z}^{c} \quad i \in \mathbb{I}[0, N-1] \quad (7i) \\
x(N) &= x^{r}(N) \quad (7j)
\end{align*}
\]
Basic constraints are valid at all of the scenarios.

- **Velocity**: Never be less than zero, and not exceeding the road speed limit:
  \[ v_{\text{min}} \leq v_k \leq v_{\text{max}} \quad k = 0..N \]  
  \[ (8) \]

- **Acceleration**: Determined from the vehicle’s physical condition:
  \[ a_{\text{min}} \leq a_k \leq a_{\text{max}} \quad k = 0..N \]  
  \[ (9) \]

- **Acceleration Rate**: Variations of acceleration (jerking) should remain in a small range to ensure passengers comfort
  \[ \Delta a_{\text{min}} \leq \Delta a_k \leq \Delta a_{\text{max}} \quad k = 0..N \]  
  \[ (10) \]
Optimization Constraints

Car Following Scenarios

- Position constraints are added to the basic constraints

\[ d_{\text{max}}_k = \min(d_{\text{front}}_i - \text{gap}) \quad t = 0..N \]  
\[ d_{\text{min}}_k = \max(d_{\text{rear}}_i - \text{gap}) \quad t = 0..N \]  

- Position Reference

\[ d_{\text{ref}}_k = \frac{d_{\text{min}}_k + d_{\text{max}}_k}{2} \]  

- Weight distribution in the cost function

\[ R = \frac{1}{(N_v + 1)^2} \]  
\[ Q = 1 - R \]
Optimization Constraints

Lane-change Scenarios

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

\[
\begin{align*}
    d_{\text{max}_k} &= \min(d_{\text{front}_i}^{c\ell} - \text{gap}, d_{\text{front}_i}^{t\ell} - \text{gap}) & t = 0..t_{\text{trans}} \\
    d_{\text{max}_k} &= \min(d_{\text{front}_i}^{t\ell} - \text{gap}) & t = t_{\text{trans}}..N \\
    d_{\text{min}_k} &= \max(d_{\text{rear}_i}^{c\ell} - \text{gap}, d_{\text{rear}_i}^{t\ell} - \text{gap}) & t = 0..t_{\text{trans}} \\
    d_{\text{max}_k} &= \min(d_{\text{rear}_i}^{t\ell} - \text{gap}) & t = t_{\text{trans}}..N
\end{align*}
\]
Driver Model
Model Training

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.
Driving Scenarios

- **Light Traffic**

  ![Light Traffic Diagram](image)

- **Dense Traffic**

  ![Dense Traffic Diagram](image)
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.
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. ($\text{RMSE} = 4.8613$)
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. \( (\text{RMSE} = 6 \times 10^{-11}) \)
  - 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
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