Bayesian Inference of Automated Vehicle's Car-Following Uncertainties: Enabling Dynamic Monitoring

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1. Research Objective

This paper proposes a methodology to characterize uncertainty in automated vehicle (AV) dynamics in real time via Bayesian inference. Based on the estimated uncertainty, the method aims to continuously monitor the car-following performance of the AV to support strategic actions to maintain a desired performance. The sequential components in our methodology are:

i. Stochastic Gradient Langevin Dynamics (SGLD) for real time estimation of vehicular dynamics uncertainty
ii. Dynamic monitoring of car-following stability
iii. Strategic action for control adjustment if anomaly is detected

2. Background

I. General Longitudinal Vehicle Dynamics (GLVD)

Our estimation technique uses the GLVD general formulation below to capture two key uncertainty parameter relative to vehicle dynamics; T_L which is the actuation lag and K_L the ratio of the demanded acceleration that can be realized. Accordingly, the method would use real time sensor data on jerk ($\dot{a}(t)$), acceleration $a(t)$, and controller demanded acceleration $u(t)$.

$$\dot{a}(t) = -\frac{1}{T_L}a(t) + \frac{K_L}{T_L}u(t)$$

3. Formulation

I. The Bayesian Approach

Given a set of sensor data stream D_i, the goal is to estimate the posterior distribution in real-time of parameters T_L^t and K_L^t, defined as $P(T_L^t, K_L^t \mid D_i)$. This is extremely challenging in real-time setting given the non-linearity, unavailability of a closed formulation, and fast update frequency. Thus, typical probability sampling technique are ineffective.

We then resort to empirical methods for estimating $P(T_L^t, K_L^t \mid D_i)$. As such we use the Maximum a Posterior (MAP) formulation for our setting to achieve a the below stochastic formulation:

$$\min_{K_L^t, T_L^t} \; -\left(\log P(K_L^t, T_L^t) + \sum_{i}^{N_{\tilde{t}}} \log P(\dot{a}_i | a_i, u_i, K_L^t, T_L^t)\right)$$

Solving the above MAP provides a point estimate, yet what we require is estimating the entire posterior distribution, which means collecting multiple samples and then estimating the distribution empirically.

II. The Stochastic Gradient Langevin Dynamics (SGLD)

To estimate the posterior distribution through the MAP, we develop an SGLD approach. The basic idea here is to iterate around the MAP solution, collect samples of the posterior distribution and then empirical estimate this posterior. Specifically, for our real-time estimation scheme at each iteration t, a mini-batch $\{D^{(\tilde{t},i)}\}_{i=1,\dots,N_i}$ of size $N_{\tilde{t}}$ is used to update the SGLD parameters according to:

$$\nabla(K_L^t, T_L^t) = \frac{\eta_t}{2}\left(\nabla \log P(K_L^t, T_L^t) + \frac{N_{\tilde{t}}}{n}\sum_{i=1}^{n} \nabla \log P(\dot{a}_i | a_i, u_i, K_L^t, T_L^t)\right) + \varepsilon_t$$

$$\varepsilon_t \sim \mathcal{N}(0, \eta_t \boldsymbol{I})$$

Algorithm 1: SGLD Parameter Estimation

Input: $\boldsymbol{\theta}^{(0)} = [K_L^0, T_L^0] \in R^2$, initial step size $\eta_1 > 0$.
for $k = 1, 2, \dots, K$ **do**
  Randomly sample a subset of the minibatch $\{D^{(k,i)}_{i=1,\dots,N_k}\}$ of size N_k;
  Compute the stochastic gradient $\nabla(K_L^k, T_L^k)$;
  $\eta_k \leftarrow \frac{\eta_1}{k}$;
  $\boldsymbol{\theta}^{(k)} \leftarrow \boldsymbol{\theta}^{(k-1)} - \eta_k \nabla(K_L^k, T_L^k)$;
end for
for $k > c$ **do**
  Collect output $\boldsymbol{\theta}^{(k)} \sim P(K_L^t, T_L^t | D_{\tilde{t}})$
end for

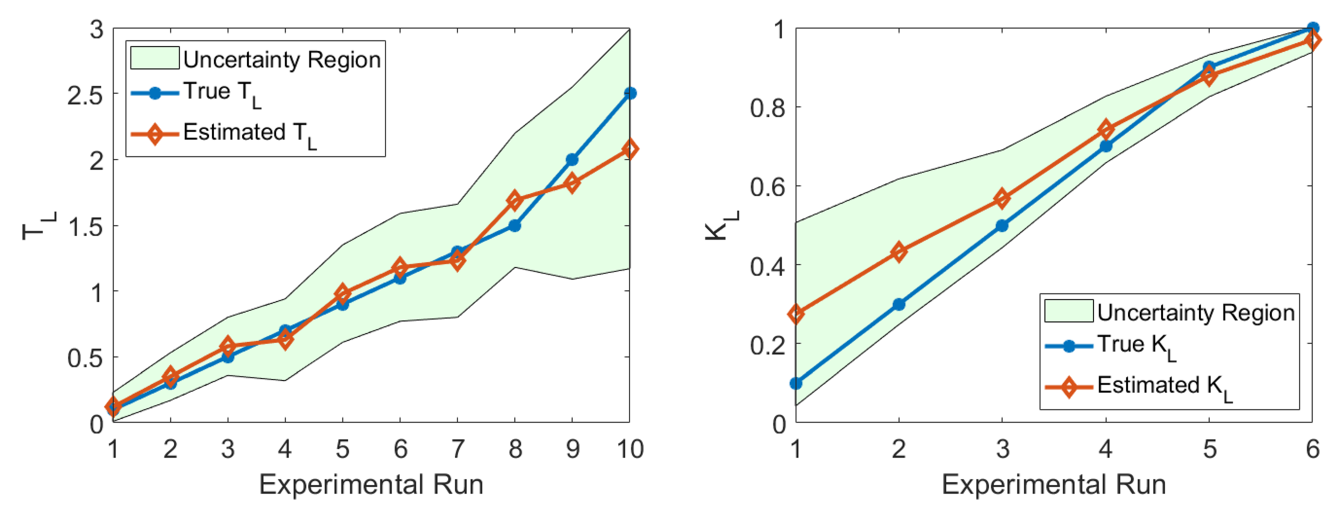
III. Updating with New Data and Performance

Our approach is a dynamic and iterative one. Specifically, we are not just interested in estimating the posterior distribution $P(T_L^t, K_L^t \mid D_i)$ but to continuously update it on the fly when new data is available. The idea is simple, we use the current posterior as a prior but with certain regularization. This regularization serves to penalize large deviations from the previous estimated posterior distribution. With the new prior we adjust our MAP formulation to fit the new setting.

$$\mathbb{P}^{(t)}_{prior} \sim \mathcal{N}\left(\left[\bar{K}_L^{(t-1)}, \bar{T}_L^{(t-1)}\right]^\top, \lambda \boldsymbol{I}\right)$$

$$\min_{K_L^t, T_L^t} \left(\sum_{i=1}^{N_{\tilde{t}}}\left[\dot{a}_i - \dot{a}_i\left(\left[K_L^{(t)}, T_L^{(t)}\right]\right)\right]^2 - \frac{\sigma^2}{\lambda}\left\|\left[\bar{K}_L^{(t)}, \bar{T}_L^{(t)}\right]^\top - \left[\bar{K}_L^{(t-1)}, \bar{T}_L^{(t-1)}\right]^\top\right\|_2^2\right)$$

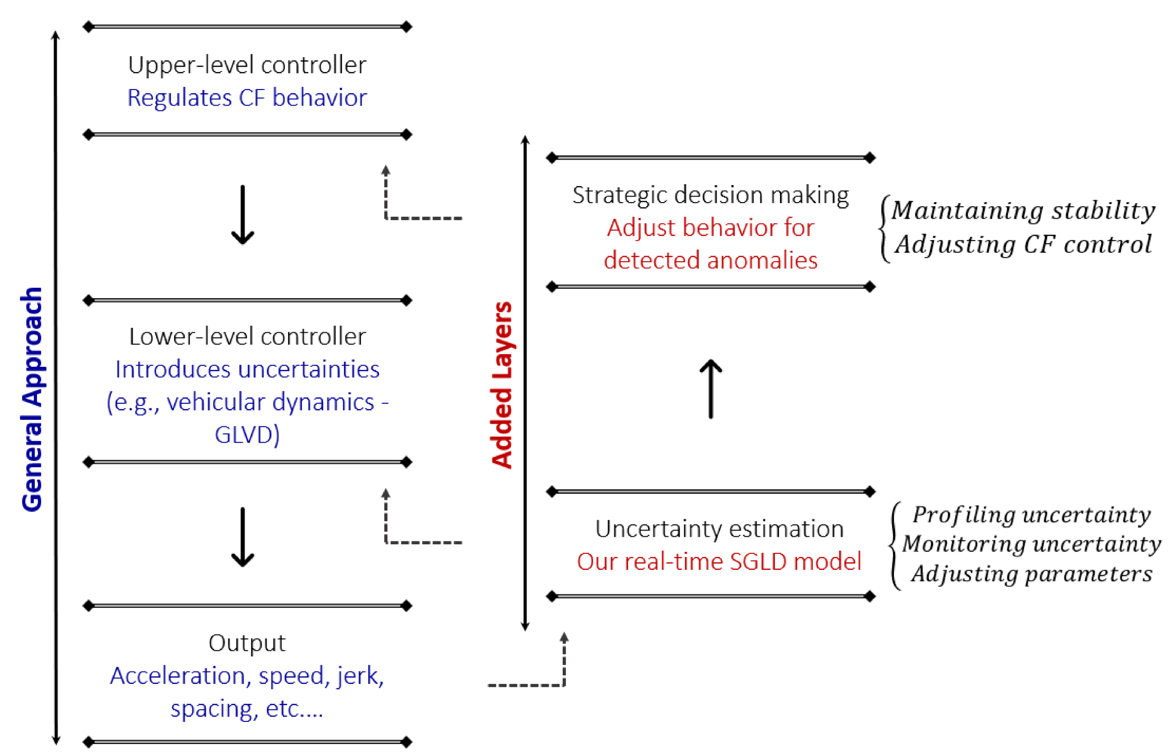
Thus, the output of our dynamic approach is an estimate of T_L and K_L along with uncertainty quantification around each prediction. The model performs well for both parameters. Error increases with large values of T_L and K_L which is expected as the controller is not performing well under there conditions.



4. Strategic Approach

I. Strategic Approach and its Integration into the Control Design

The main idea here is to add a real-time data driven uncertainty estimation layer into the CF controller. This can be adopted for whatever control structure the vehicle is using. Such approach allows us to gauge the performance of the controller in real-time and adjust its behavior to recover desired performance.



II. Online Algorithm

We build an online algorithm that encompasses the envisioned strategic approach. In here we focus to three main intervening strategies depending on severity of the issue: (i) adjust the parameters T_L and K_L inside the controller, (ii) update control gains, (iii) update time gap setting. Note that here we are showing a strategy for a typical linear controller, adjustments are needed for different control structure.

Algorithm 2: Online Strategy: Pseudo Code

Input: Parameter estimates $\theta^{(t)} = \left[K_L^{(t)}, T_L^{(t)}\right]$
if $\theta^{(t)} \neq [K_L, T_L]$ **then**
  Check stability (local and string)
  if *Stable* **then**
    Update lower-level controller: $[K_L, T_L] \leftarrow \left[K_L^{(t)}, T_L^{(t)}\right]$
  end if
  if *Unstable* **then**
    Update upper-level controller:
      1. Update Control gains: $\left[|k_s'| > |k_s|, |k_v'| > |k_v|, |k_a'| < |k_a|\right]^\top \leftarrow [k_s, k_v, k_a]^\top$
      2. Update time gap: $\tau^{*'} < \tau^* \leftarrow \tau^*$
  end if
end if

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