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Department of Information Engineering and Computer Science

A LiDAR Error Model for Cooperative Driving Simulations

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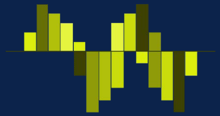
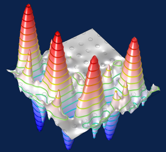
Agenda

Motivation



Dataset description



Trace Analysis

Cooperative driving Simulation

Application development for connected and autonomous vehicles

Simulation

- Unlimited use cases
- Repeatability
- Safety
- Lack of sensor characterization

Field Operation Tests

- Real Vehicle/Hardware
- Negligible approximation of physical processes
- Huge Costs
- Scalability issue
- Repeatability issue

Motivation

SUMO SIMULATION OF URBAN MOBILITY
Veins Vehicles in Network Simulation
VSimRTI V2X Simulation Runtime Infrastructure
ROS
GAZEBO

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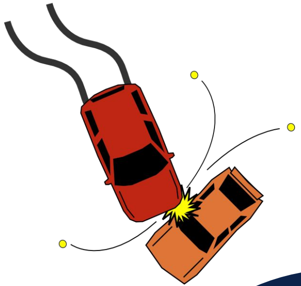
Importance of sensor characterization for cooperative driving

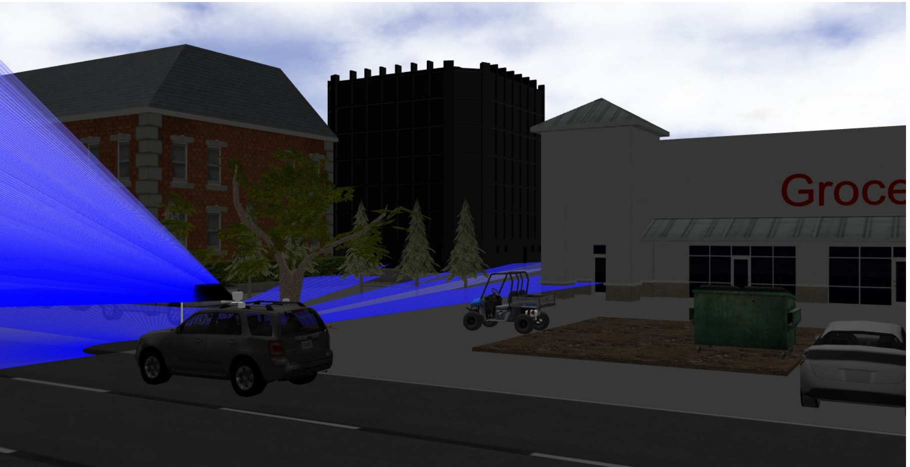
Distance measurement

Lane detection

Emergency braking

FAULTY MEASUREMENT





STOCHASTIC ERROR MODELING

Motivation

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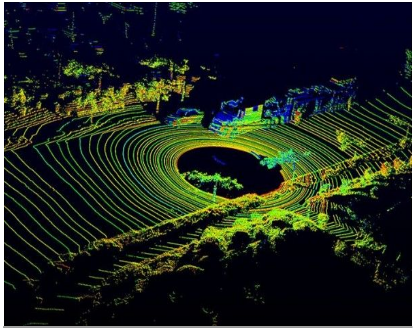
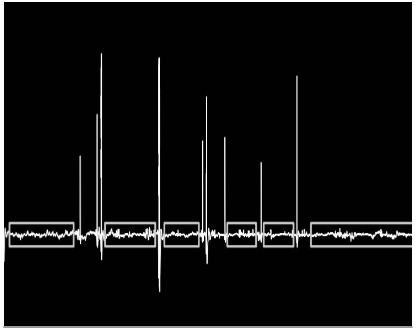
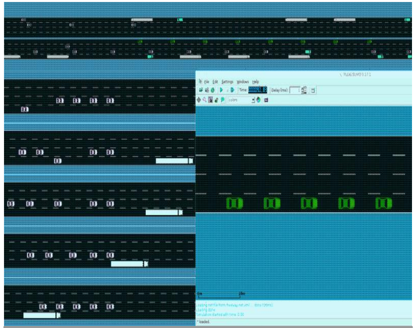
Key contribution of the presented research



Analysis of real-world LiDAR traces to understand the underlying model



Development of a stochastic error model, capable of reproducing measurement errors



Impact of stochastic error on control algorithm using PLEXE simulation

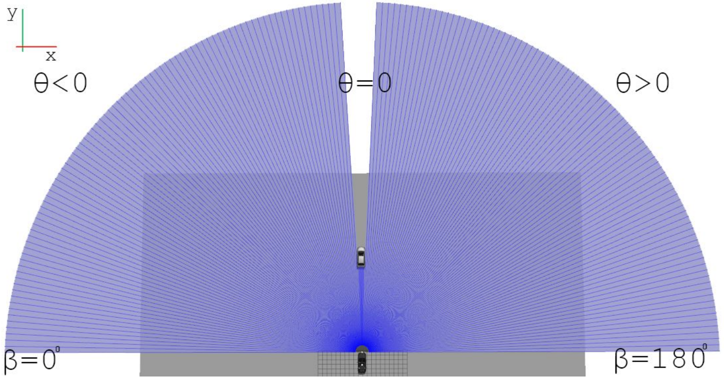
Motivation

Ring road experiment with 22 cars to demonstrate capability of autonomous vehicle to reduce traffic congestions in urban stop-and-go traffic

AV used LiDAR to feed distance to the velocity controller

Relevant publication to the experiment: Stern, R. E., Cui, S., Delle Monache, M. L., Bhadani, R., Bunting, M., Churchill, M., ... & Seibold, B. (2018). **Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments.** *Transportation Research Part C: Emerging Technologies, 89*, 205-221.

A bird's eye-view of ring road experiment



Schematic of LiDAR scanning

Dataset description

Experiment Methodology

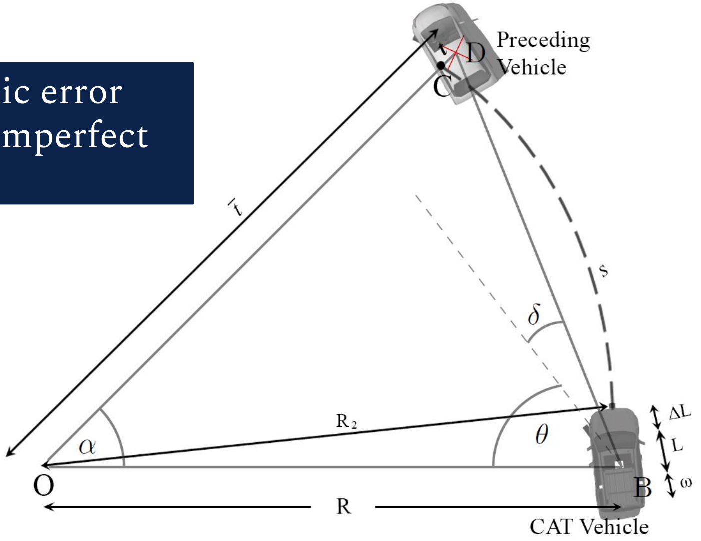
Determine minimum distance point along the trajectory to estimate headway distance

Kalman Filter to remove noise before feeding to the controller

Presented work builds stochastic error model on the top of filtered, yet imperfect sampled data

Dataset description

Used 5th order butterworth low pass filter to clean the trace: used as ground truth after compensating delay



Available dataset

https://doi.org/10.15695/vudata.cee.1

Dataset description

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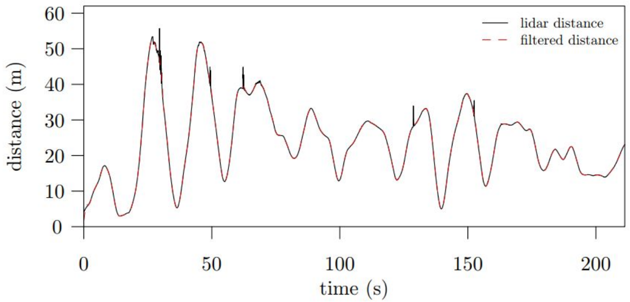
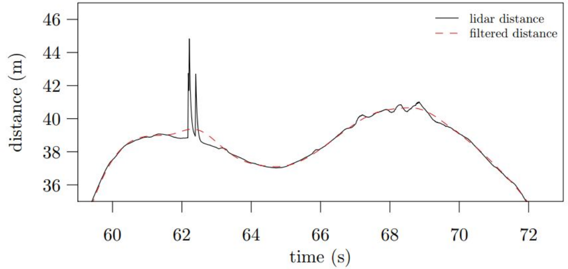
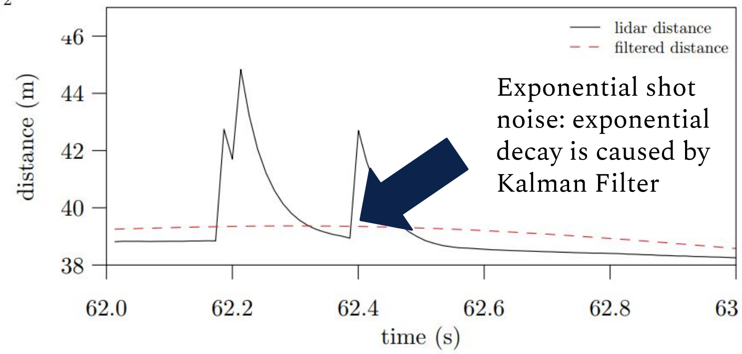
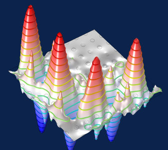
Analysis of LiDAR data







Exponential shot noise: exponential decay is caused by Kalman Filter



Trace Analysis

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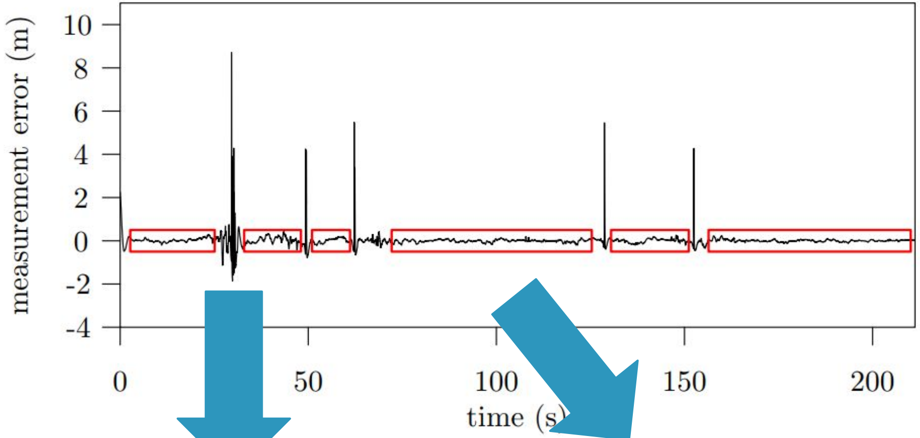
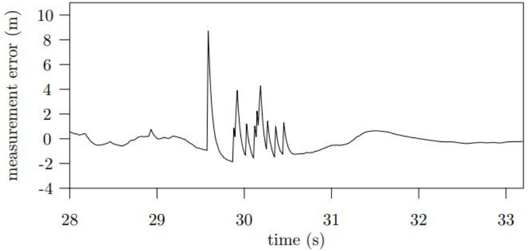
A closer look at traces for shot-errors

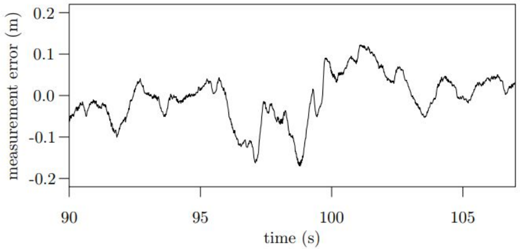


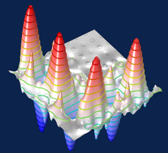
Error in shot-free portion: due to correlated stochastic process

Shot-noise error: random, modeled by Poisson process

$$\epsilon[k] = \epsilon_c[k] + \epsilon_s[k]$$







Trace Analysis

Estimation of correlated noise $\epsilon_c[k]$

Assumption: correlated error to be of the first order autoregressive form:

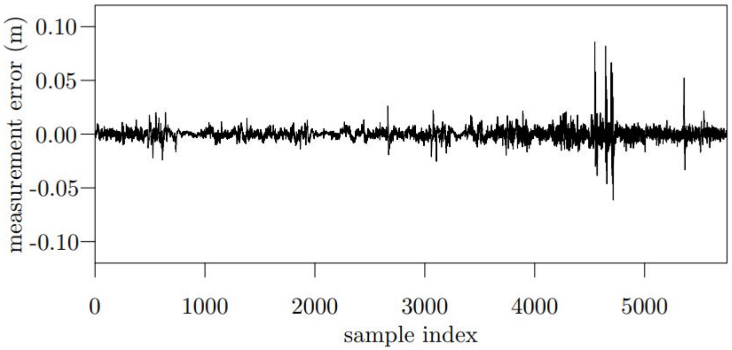
$\epsilon_c[k] = \rho \epsilon_c[k-1] + N_c[k]$

N_c: the innovation process of error of zero mean

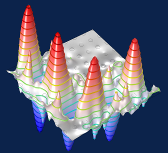
ρ = Correlation coefficient by computing autocorrelation with a lag of 1 sample on shot-free portions of the error

$$\rho_i = \frac{\frac{1}{|\epsilon_i|-1}\sum_{k=1}^{|\epsilon_i|-1} \epsilon_i[k]\cdot\epsilon_i[k-1]}{\frac{1}{|\epsilon_i|}\sum_{k=0}^{|\epsilon_i|-1} \epsilon_i[k]^2}$$

$$N_c[k] = \epsilon_c[k+1] - \bar{\rho}\epsilon_c[k], \quad k = 0, \ldots, |\epsilon_c|-1$$



Residual in innovation process



Trace Analysis

Estimation of correlated noise $\epsilon_c[k]$

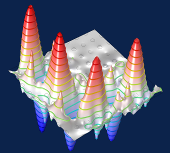
For parameter estimation of the model, we used maximum likelihood estimation

N_c process: generated by multiplying samples drawn from fitted distribution by **B**•2 - 1, **B** is bernoulli distribution with p =0.5

Distribution with highest likelihood was found to be pareto distribution with μ= 0 and σ = 0.0036

Hence, Autoregressive process N_c is:

$$N_c[k+1] = 0.9936 N_c[k] + \mathbf{GP}(\mu = 0, \sigma = 0.0036, \xi = 0.0913) \cdot (\mathbf{B}(p = 0.5) \cdot 2 - 1)$$



Trace Analysis

Estimation of shot noise $\epsilon_s[k]$

Limited number of shots in the dataset: no proper fitting
We focus on estimating nature of shot noise instead.

From the dataset, we have 52 samples of shot noise over 686s, which gives λ = 0.0758.

LiDAR has sampling rate of 75 Hz, hence:

$$\Lambda = \nu\lambda = \frac{0.0758}{75} \simeq 0.001$$

We estimate:

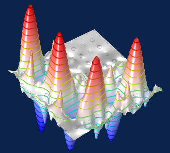
- Interarrival time of homogeneous Poisson process
- Exponential decay parameter
- Amplitude of shots

$$\mathbf{P}(N = n, \Lambda) = \frac{\Lambda^n}{n!}e^{-\Lambda}$$

$$\Lambda = \nu\lambda$$

λ = Average number of occurrences
ν = sampling time

On an average, we have one shots per 1000 samples.



Trace Analysis

Estimation of shot noise $\epsilon_s[k]$

Let's look exponential decay:

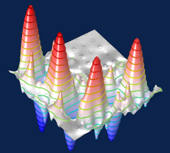
- 3-points strategy for estimation of shot noise: s_{k-1}, s_k, s_{s+1} to compute decay parameter τ.

$$\begin{cases} s_k = s_{k-1} + N_0 \\ s_{k+1} = N_0 e^{-\frac{\tau}{75}} + s_{k-1} \end{cases}$$

No is the amplitude of the shot noise.
Solving for *No:*

$$\tau = -\ln\left(\frac{s_{k+1} - s_{k-1}}{s_k - s_{k-1}}\right) \cdot 75$$

We take the average of τ, which is 23.576.



Trace Analysis

Estimation of shot noise $\epsilon_s[k]$

Estimating amplitude of the shot noise

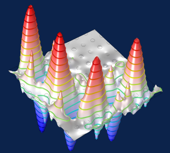
- Computing s_k - s_{k-1} for amplitude, but not this straightforward during burst of shot noise.
- Burst has time-varying correlated noise, but we don't have enough information to calculate value of correlated noise during bursts.
- Hence, we are limited to isolated shot noise and at the beginning of the burst noise.
- *More details in the paper, page 5*

- From dataset, average amplitude of shot noise is 4.364
- Not enough to draw conclusion on distribution of amplitude of shot noise: we make strong assumption that amplitude has exponential distribution with mean of 4.364.
- Putting together:

$$\epsilon_s[k+1] = \mathbf{E}(n = \mathbf{Pois}(\Lambda = 0.001), \mu = 4.364) + \epsilon_s[k] e^{-\frac{23.576}{75}}$$

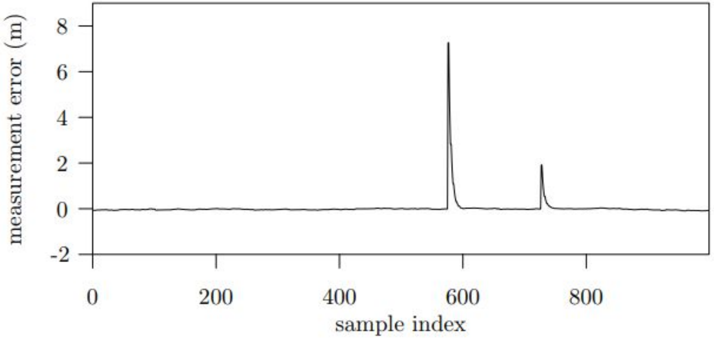
E is random number generator for Erlang-distribution based shot characteristic from dataset.

Detailed discussion in the paper

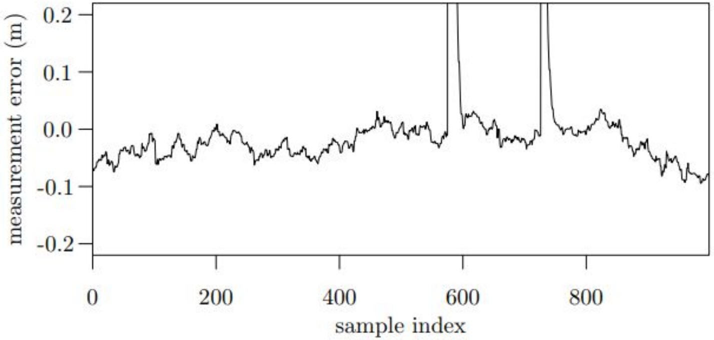


Trace Analysis

Final words on empirical distribution of noise



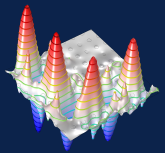
(a) full y-scale



(b) detailed view on correlated error

- Estimation is based on sampling rate of 75 Hz, which is operating frequency of LiDAR
- Synthetically generated data obtained from empirical distribution has smaller error, most probably because of low order of autoregressive process.

Synthetically generated trace from empirical distribution



Trace Analysis

Impact of sensor noise on cooperative driving: a simulation study

PLEXE: A cooperative driving simulator

- Realistic vehicular networking models ✔
- Realistic vehicle dynamics ✔
- Platoon control algorithms ✔

No Error models: assumes error-free measurement ✘

Cooperative driving Simulation

We used error modeled developed in the presented work to study cooperative driving via simulation under noisy conditions.

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Simulation setup

Setup 1: 8 cars with the leader following a constant velocity profile

Setup 2: 8 cars with the leader following a sinusoidal velocity profile

3 control algorithm considered: standard adaptive cruise control, PATH's cooperative ACC, Ploeg's ACC

Cooperative driving Simulation

Implemented as acceleration control:

$$\frac{\mathrm{d}a_i(t)}{\mathrm{d}t} = \frac{1}{\tau}\left(u_i(t) - a_i(t)\right)$$

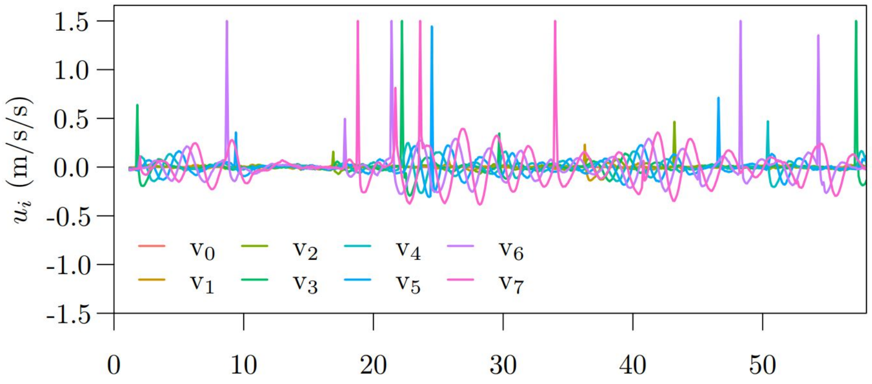
Steady state distance:

$$d = T \cdot v + d_{\text{st}}$$

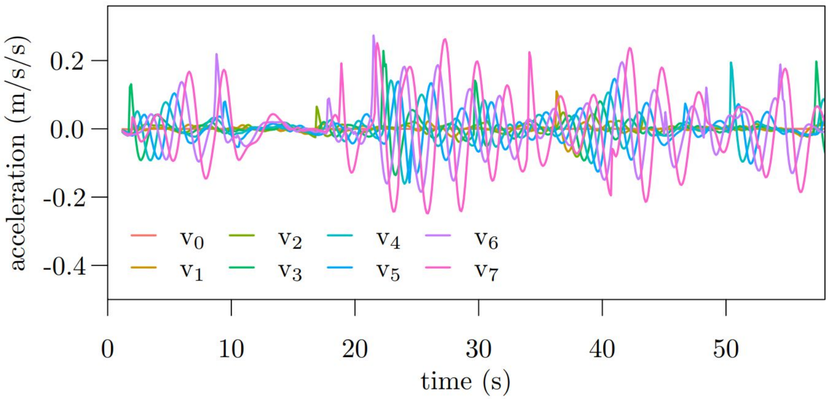
ACC: constant time-headway spacing policy
PATH's ACC: constant distance spacing policy
Ploeg's ACC: constant time-headway spacing policy with string stability at small headway

Rate:
Control system at 100Hz, LiDAR at 75Hz

Simulation with constant velocity profile: ACC



(a) control input u_i



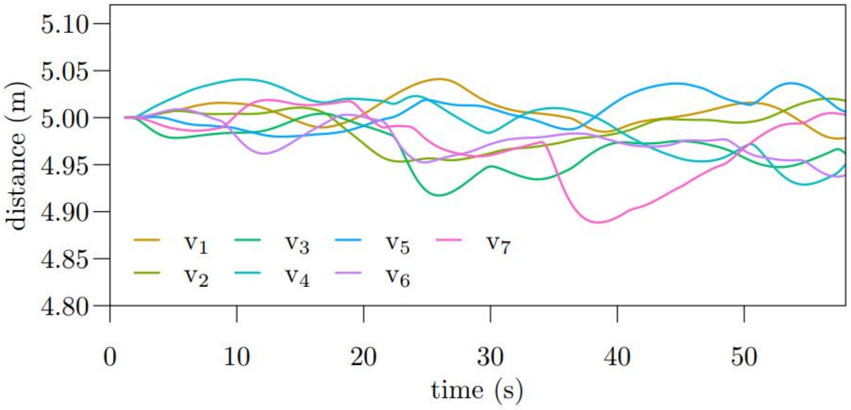
(b) acceleration

Impact of incorporating error model on control dynamics of non-cooperative ACC

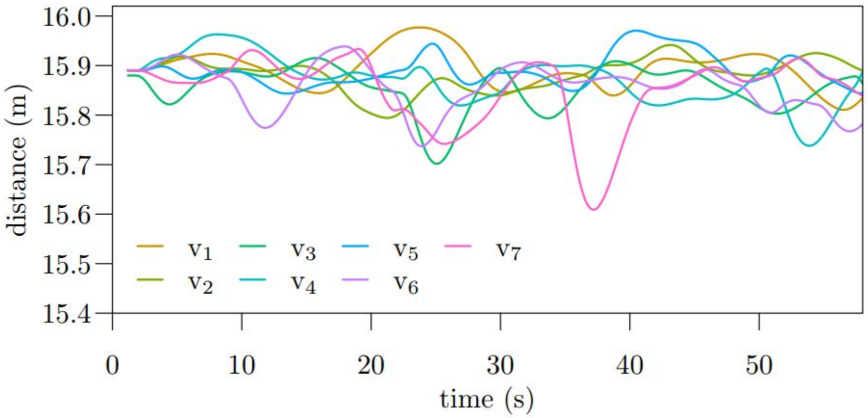
- Notice positive acceleration spikes which may have been caused by LiDAR shot-errors

LiDAR error introduces perturbation in the system which is amplified by following vehicles. Sinusoidal amplification near shot errors.

Simulation with constant velocity profile: Cooperative ACC



(a) PATH's CACC



(b) Ploeg's CACC

Incorporating LiDAR error model introduces some disturbance and causes inter-vehicle distance to float around steady-state value. As result these errors do not control system to stabilize distance value.

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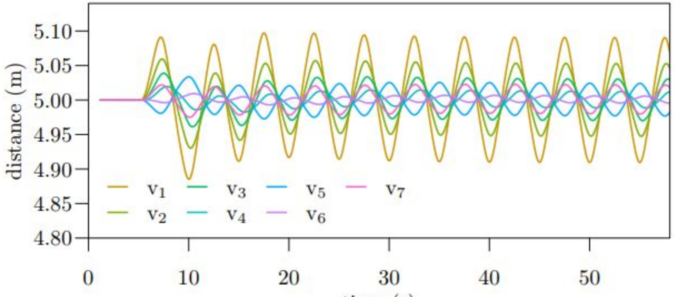
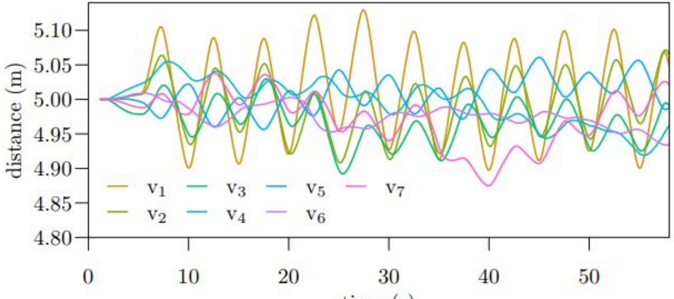
Simulation with sinusoidal velocity profile: Cooperative ACC

PATH's CACC

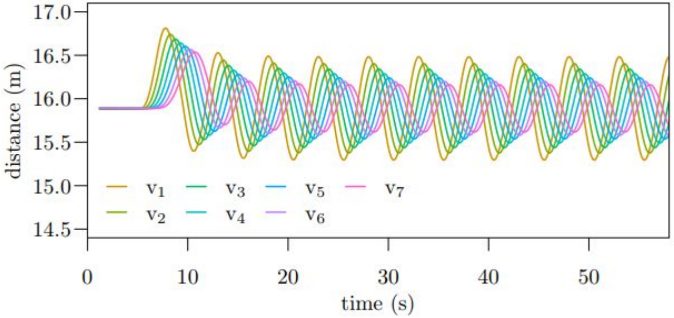


(a) w/o error model

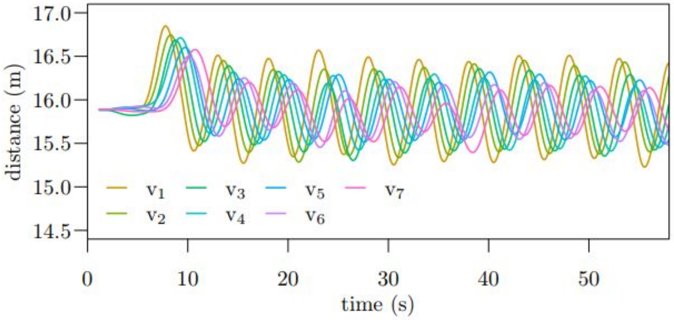


(b) w/ error model

Ploeg's CACC



(a) w/o error model



(b) w/ error model

Discussion about future work

- Empirical model of error derived from LiDAR traces helped spotting instabilities in control systems for cooperative vehicular network.
- Although, we made some strong assumptions about nature of error.
- Lack of ground truth data was a major problem.
- Analysis was based on Kalman filtered trace which have additional delay due to filtering.
- Due to assumption of first order autoregressive model, dataset still shows some residual correlation.
- Relative speed is assumed to be perfectly known which is not true in reality and may exhibit high frequency noise.
- Shot-noise were assumed to be independent which may lead to overestimation of actual distance.

In upcoming work, we are going to relax our assumptions to come up with generalized error model.

COMPOSITIONAL ∞SYSTEMS LAB

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