CAREER: Multi-Resolution Model and Context Aware Information Networking for Cooperative Vehicle Efficiency and Safety Systems

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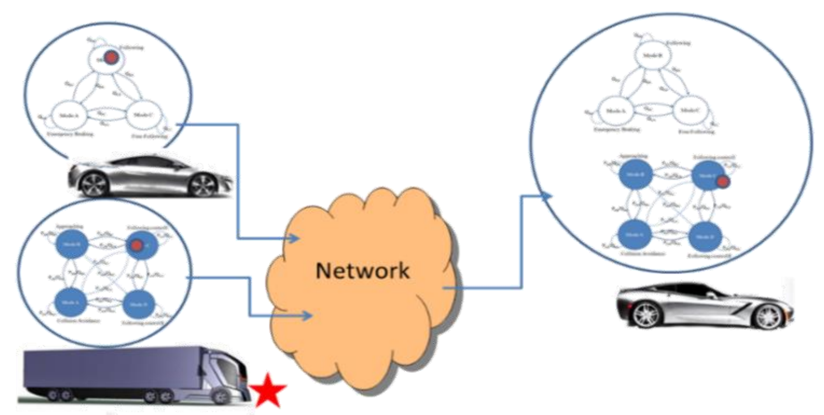
Motivation and Problem Statement

- The performance of cooperative vehicular applications is tightly dependent on the availability of information through Vehicle-to-Everything (V2X) communications.
- Scalability is one of the main challenges, preventing rich collaboration.
- Proposed approach: Replacing raw data dissemination communication with model-based communication (MBC)
- MBC proposes populating the V2X message content in a more intelligent way, by replacing the raw sensory data with models and model parameters of a mathematical stochastic model that describes vehicle behavior.



Modeling Framework and Approach

- Stochastic Hybrid Systems (SHS) framework is appropriate for modeling combined dynamics (movements) of vehicle and driver. Gaussian Mixture Models (GMM) is a powerful tool for clustering and regression in multi-modal problems.

Modeling Using Gaussian Mixture Models: A Data-Driven Approach

- Assuming d-dimensional observations, e.g., sequences of vehicle's Longitudinal Speed (s) or Heading (h) measured at d equidistance time intervals, are independently sampled from K unknown multivariate Gaussian distributions, the observation pdf is:

$$p(x) = \sum_{i=1}^{K} \pi_k N(x|\mu_i, \Sigma_i)$$

- The set of the parameters $\{K, \{\pi_i, \mu_i, \Sigma_i\}_{i=1,\dots,K}\}$ can be inferred from the training data using MCMC algorithms such as Gibs Sampling for Dirichlet Process Gaussian Mixture Model.
- We consider s and h as independent multi variate random variables to be modeled as GMM.
- Having r-dim. partial observations s and h, i.e., sequences measured at r equidistance time intervals (r < d), the current and the most probable mode of speed and heading and their predictive distributions at timestamp $r+1, \dots, d$ can be derived as:

$$k_s^* = \underset{k_s}{\operatorname{argmax}}\, p(s \in \Omega_k|s) \quad \text{and} \quad \tilde{s}|s,k^* \sim N\left(\mu_{k_s^*}^{d-r} + \Sigma_{k_s^*}^{(d-r)\times r}\left(\Sigma_{k_s^*}^{r\times r}\right)^{-1}(s-\mu_{k_s^*}^{r}), \Sigma_{k_s^*}^{(d-r)\times(d-r)} - \Sigma_{k_s^*}^{(d-r)\times r}\left(\Sigma_{k_s^*}^{(r)\times(r)}\right)^{-1}\Sigma_{k_s^*}^{(r)\times(d-r)}\right)$$

$$k_h^* = \underset{h}{\operatorname{argmax}}\, p(h \in \Omega_k|h) \quad \text{and} \quad \tilde{h}|h,k_h^* \sim N\left(\mu_{k_h^*}^{d-r} + \Sigma_{k_h^*}^{(d-r)\times r}\left(\Sigma_{k_h^*}^{r\times r}\right)^{-1}(h-\mu_{k_h^*}^{r}), \Sigma_{k_h^*}^{(d-r)\times(d-r)} - \Sigma_{k_h^*}^{(d-r)\times r}\left(\Sigma_{k_h^*}^{(r)\times(r)}\right)^{-1}\Sigma_{k_h^*}^{(r)\times(d-r)}\right)$$

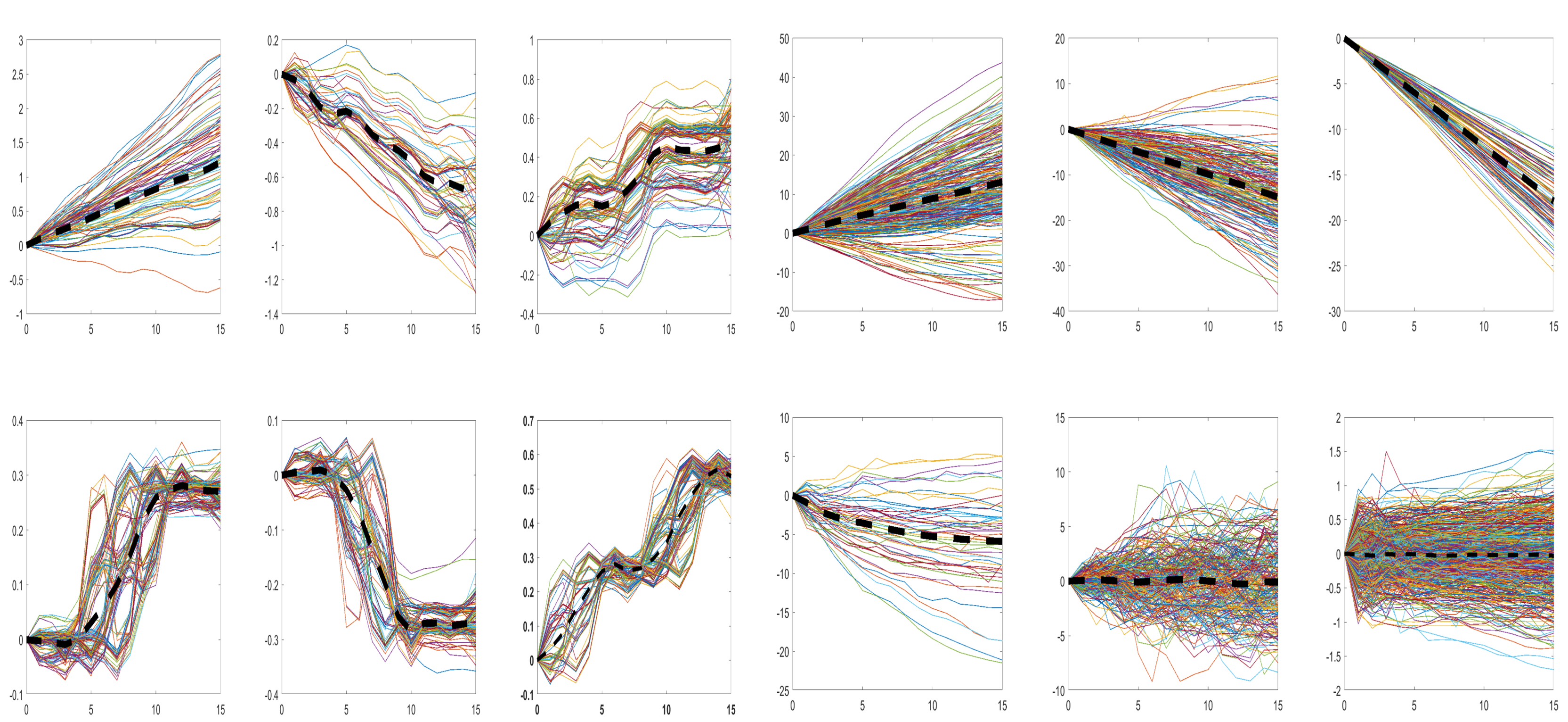
- The forecasted position is derived by integrating over the predictive distributions.

$$\bar{X}(t_1) = \bar{X}(t_0) + \iiint_{t_0}^{t_1} \tilde{s}\cos(\tilde{h})\Pr(\tilde{s})\Pr(\tilde{h})\,dt\,d\tilde{s}\,d\tilde{h}$$

$$\bar{Y}(t_1) = \bar{Y}(t_0) + \iiint_{t_0}^{t_1} \tilde{s}\sin(\tilde{h})\Pr(\tilde{s})\Pr(\tilde{h})\,dt\,d\tilde{s}\,d\tilde{h}$$

Gaussian Mixture Model Inference Results

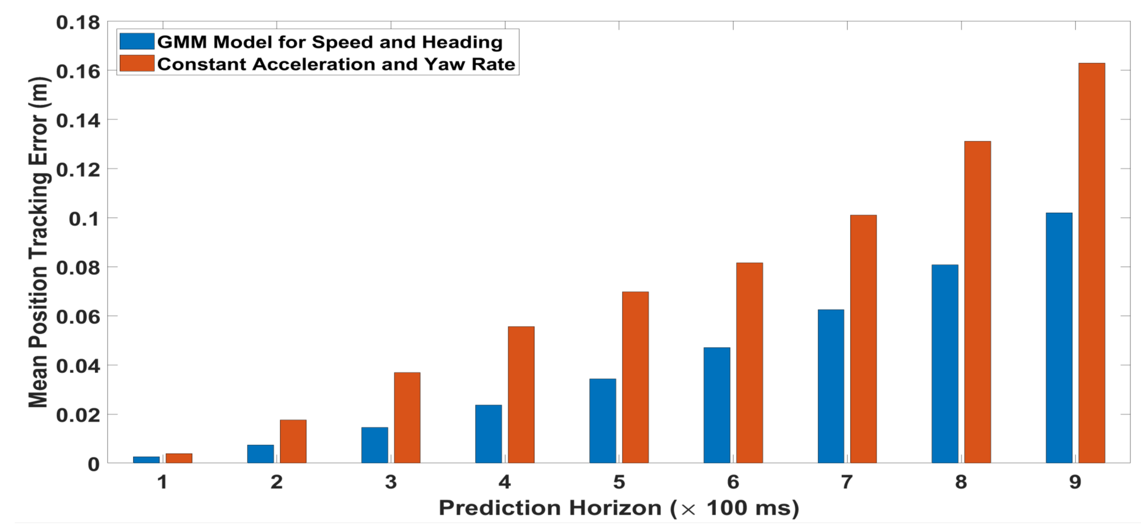
Illustration of 6 distinct modes of deviation of speed and heading and their members (s and h in 1600ms intervals). The black line shows the Gaussian component mean vector. The Gibs Sampler Dirichlet Process GMM has inferred 43 and 31 modes for s and h from training data.

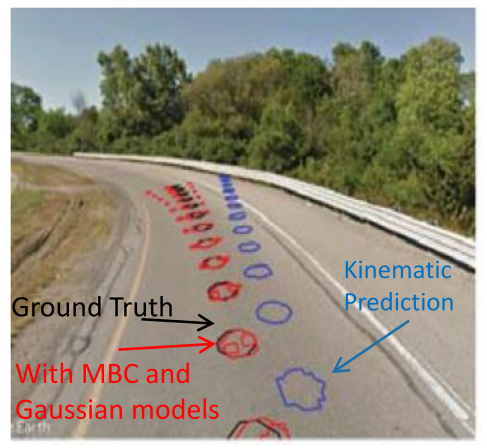


Deviation of Longitudinal Speed

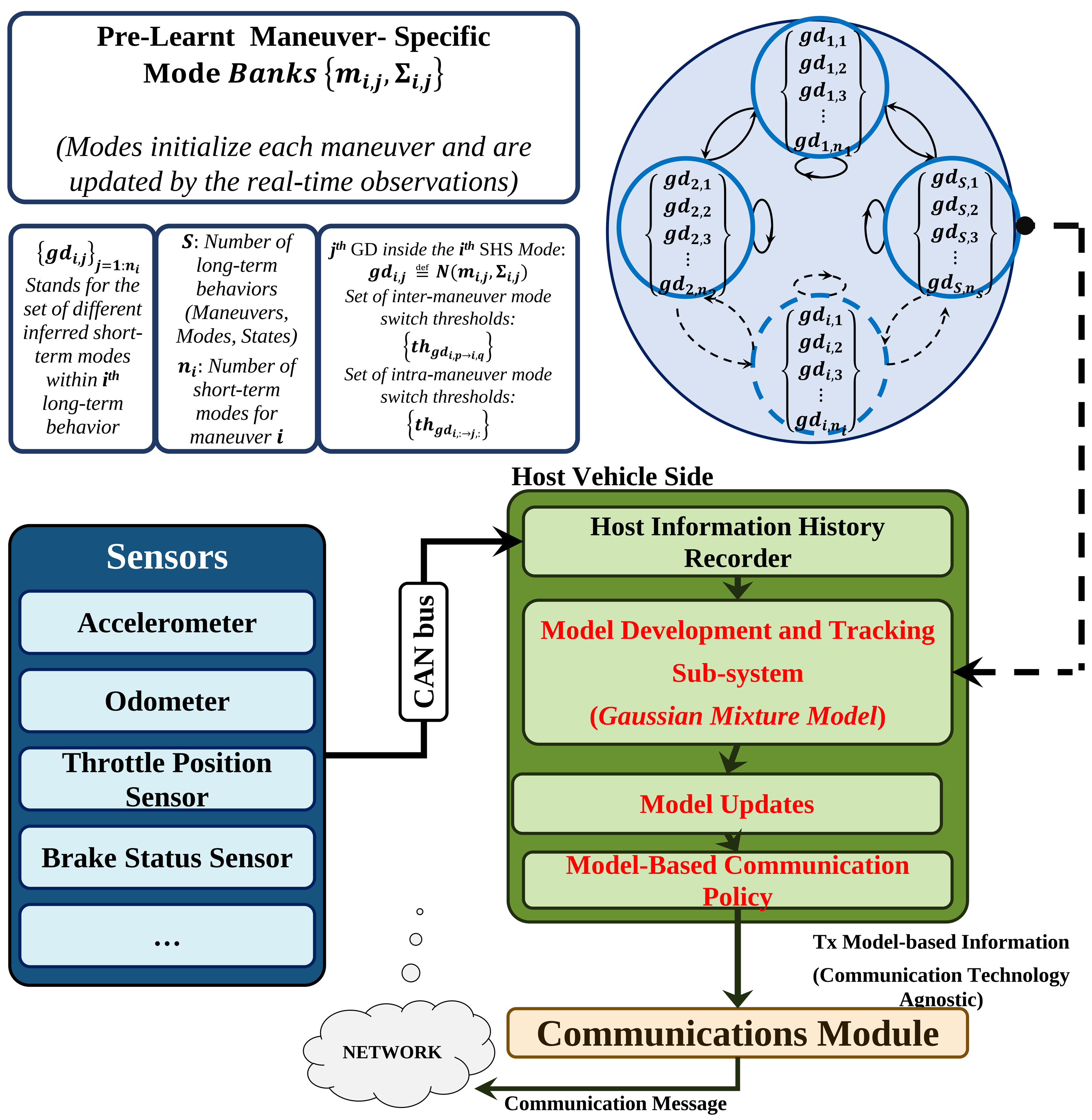
Deviation of Heading

Probabilistic models vs constant acceleration and yaw rate performance in forecasting of position. Two Separate GMMs are trained to model deviation of vehicle's longitudinal Speed and Heading





System-Level Architecture With the Proposed GMM-SHS Framework



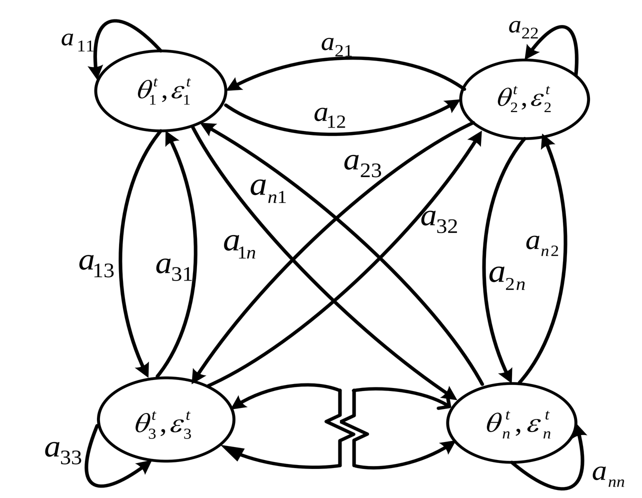
Education and Outreach

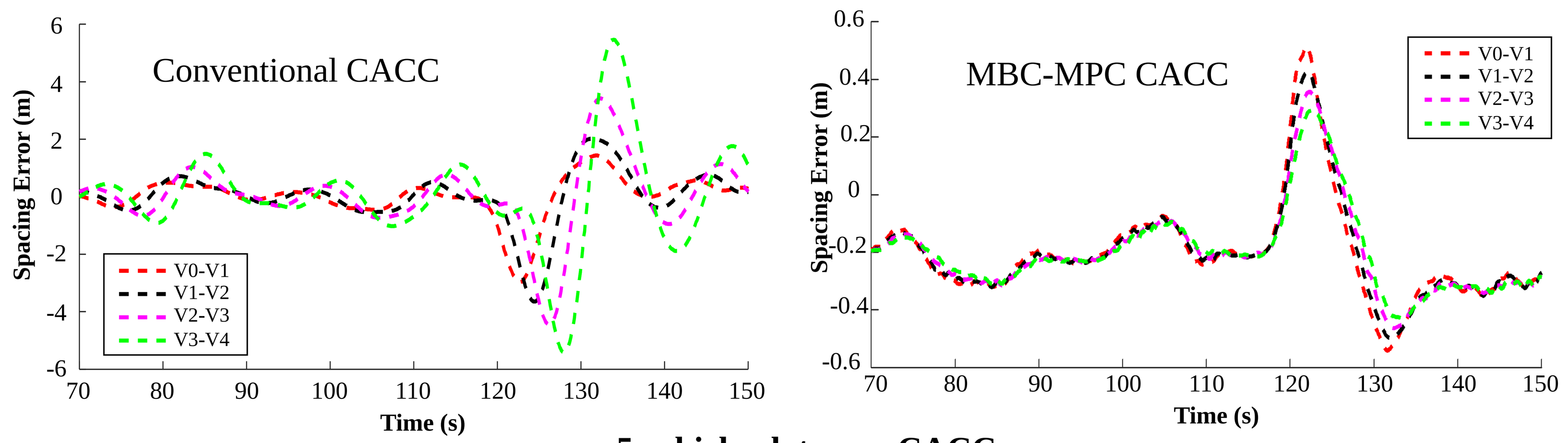
- Two graduate courses designed : 6712 Modeling and Analysis of Networked CPS, 5781 Cyber Physical Technologies for Smart Communities
- >8 undergraduate students (4 from minority groups) involved in this research and building this test vehicle
- Spawned a new research project on cooperative perception and cooperative cognition, as well as a
- Collaborative project on Mass Platooning of automated vehicles

Other Examples and Applications

Cooperative Adaptive Cruise Control

Learn and update model : Use a HMM + ARX hybrid system.
Control: Use exchanged models in model-predictive CACC controllers.
Result is an order of magnitude improvement in spacing error in CACC[6].

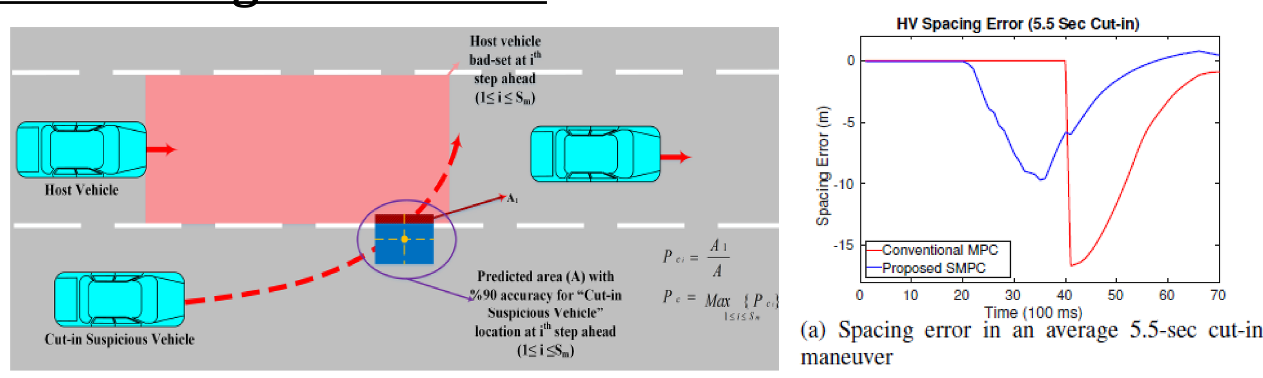




5 vehicle platoon – CACC

Handling Vehicles Interfering in a Platoon

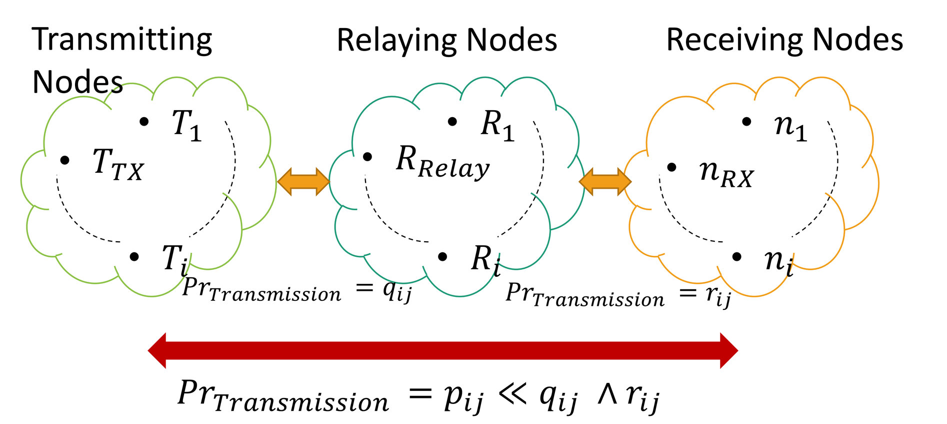
Probability of a vehicle cutting in can be derived from our models, then stochastic model predictive control is used to handle the interfering vehicle



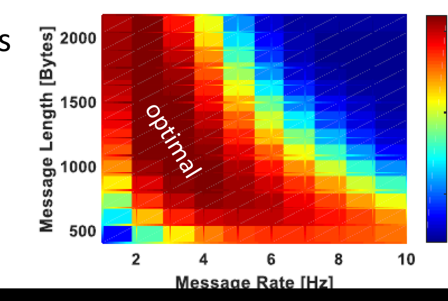
(a) Spacing error in an average 5.5-sec cut-in maneuver

Model Aware Relaying

Using Error-Driven MBC, the relaying nodes can sort the transmitting nodes based on the accuracy of their latest probabilistic models shared with receiving nodes. This leads to efficiently using the limited communication resources and consequently less channel congestion while maintaining the tracking accuracy at the desirable level.



Map accuracy for choices of rate and message length, for a distance-based map relaying strategy in DSRC V2X



Future Work

- Investigating the existence of natural driving patterns corresponding to the sequences of the short-term Gaussian modes
- Investigating more sophisticated rules to rank the transmitting nodes by each relaying node to balance between communication load and safety requirements.

References

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[6] E. Moradi-Pari, H. N. Mahjoub, H. Kazemi, Y. P. Fallah and A. Tahmasbi-Sarvestani, "Utilizing Model-Based Communication and Control for Cooperative Automated Vehicle Applications," in *IEEE Transactions on Intelligent Vehicles*, vol. 2, no. 1, pp. 38-51, March 2017.