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

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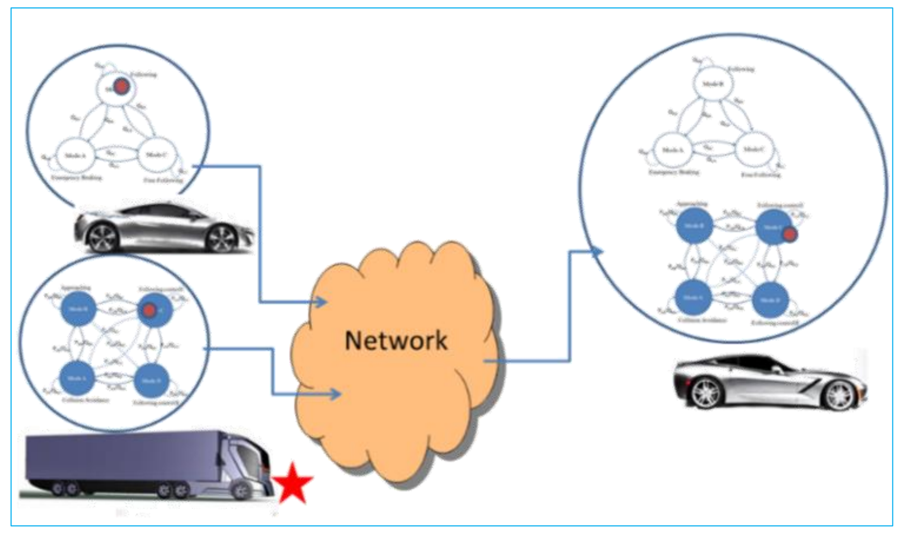
Motivation and Problem Statement

- Enormous network resource demands of ***V2X Communications*** is a serious challenge to make it fully scalable, as required by real-world applications.
- Proposed ***Model-Based Communications and Networking*** methodology makes phenomenal performance improvements in wireless channel utilization compared to the state-of-the-art techniques, i.e. adaptive raw data communication.
- Generating ***precise models*** is the first key task to realize this idea.
- ***Bayesian Non-Parametric Inference*** approaches are evidently appropriate solutions for precise adaptive model construction.
- Sticky-Switching Linear Dynamical Systems-Hierarchical Dirichlet Process-Hidden Markov Model ***(Sticky-SLDS-HDP-HMM)*** is nominated in this work as a non-Parametric Bayesian-Stochastic Hybrid System ***(SHS)*** approach which continuously tracks the joint vehicle-driver behaviors and updates the model by adding/removing necessary/unnecessary states on the fly.



Background Theory of the Modeling Framework

SLDS-HDP-HMM and AR-HDP-HMM (Theoretically Infinite-State HMM Models)

$$\nu_k|\lambda \sim Beta(1,\lambda) \qquad for\ k = 1,2,\ldots$$

$$\varphi_k = \nu_k \prod_{h=1}^{k-1}(1-\nu_h) \qquad for\ k = 1,2,\ldots$$

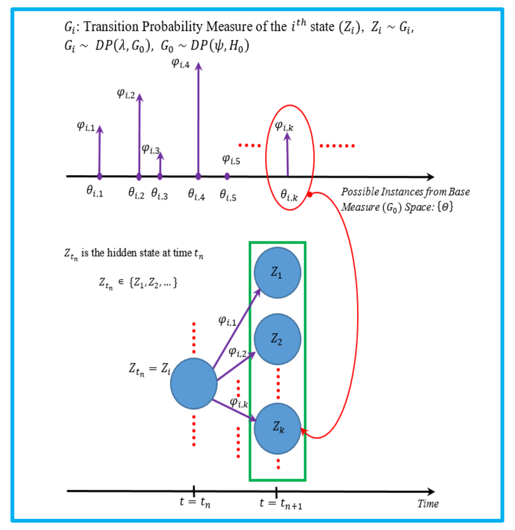
$$\Phi \sim GEM(\lambda) \iff \Phi = \{\varphi_1, \varphi_2, \ldots\}, \varphi_k \in (0,1), \ (\forall k = 1,2,\ldots), \ \textstyle\sum_{k=1}^{\infty} \varphi_k = 1$$

$$G_i \sim DP(\lambda, G_0) \iff G_i = \sum_{k=1}^{\infty} \varphi_{i,k}\delta_{\theta_{i,k}} \qquad \left\{\begin{matrix} \theta_{i,k}|G_0 \sim G_0 \\ \{\varphi_{i,:}\} \sim GEM(\lambda) \end{matrix}\right\} for\ k = 1,2,\ldots$$

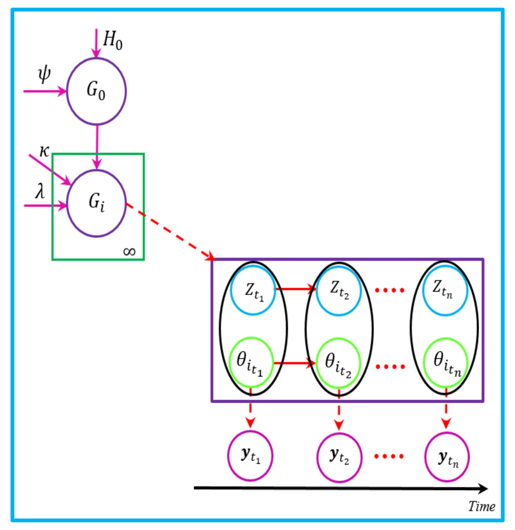
$$G_0 \sim DP(\psi, H_0)$$

$$x_{t_n} = A^{(z_{t_n})}x_{t_{n-1}} + e(z_{t_n})$$

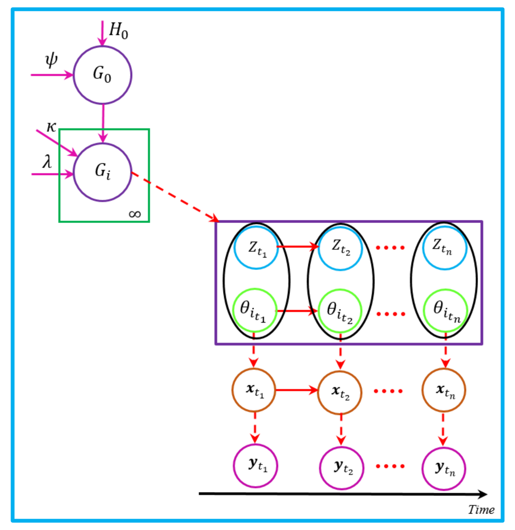
$$y_{t_n} = Cx_{t_n} + g(t_n)$$



HDP-HMM[1]

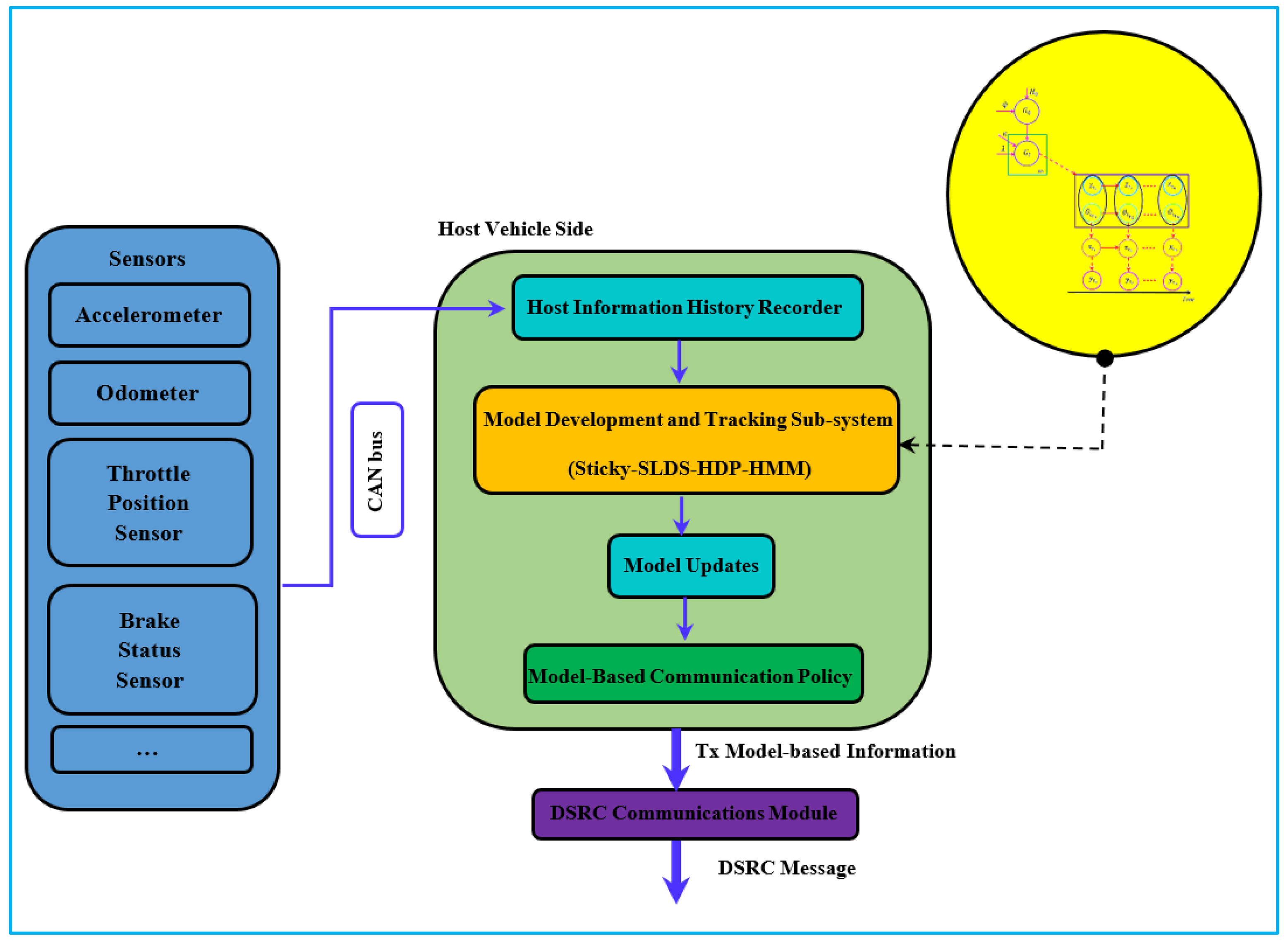


Sticky-AR-HDP-HMM[2]

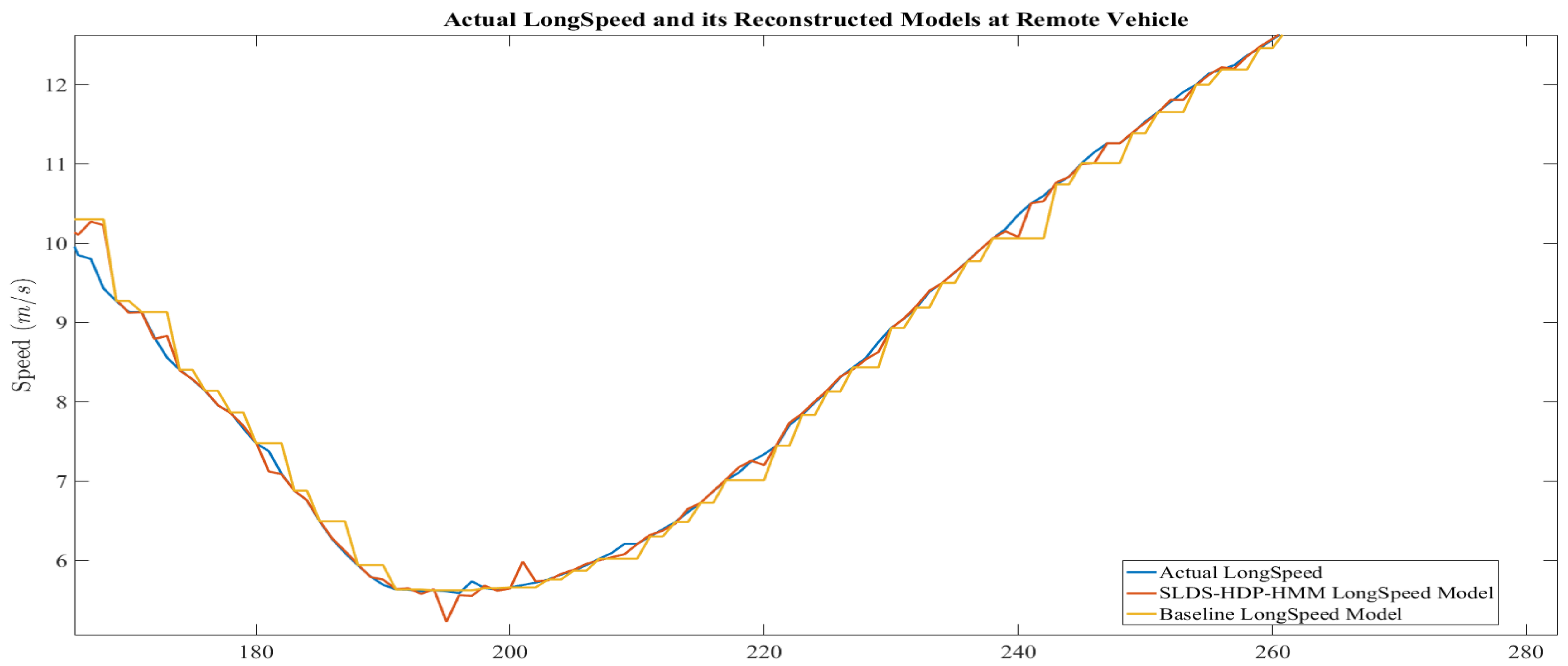


Sticky-SLDS-HDP-HMM [2]

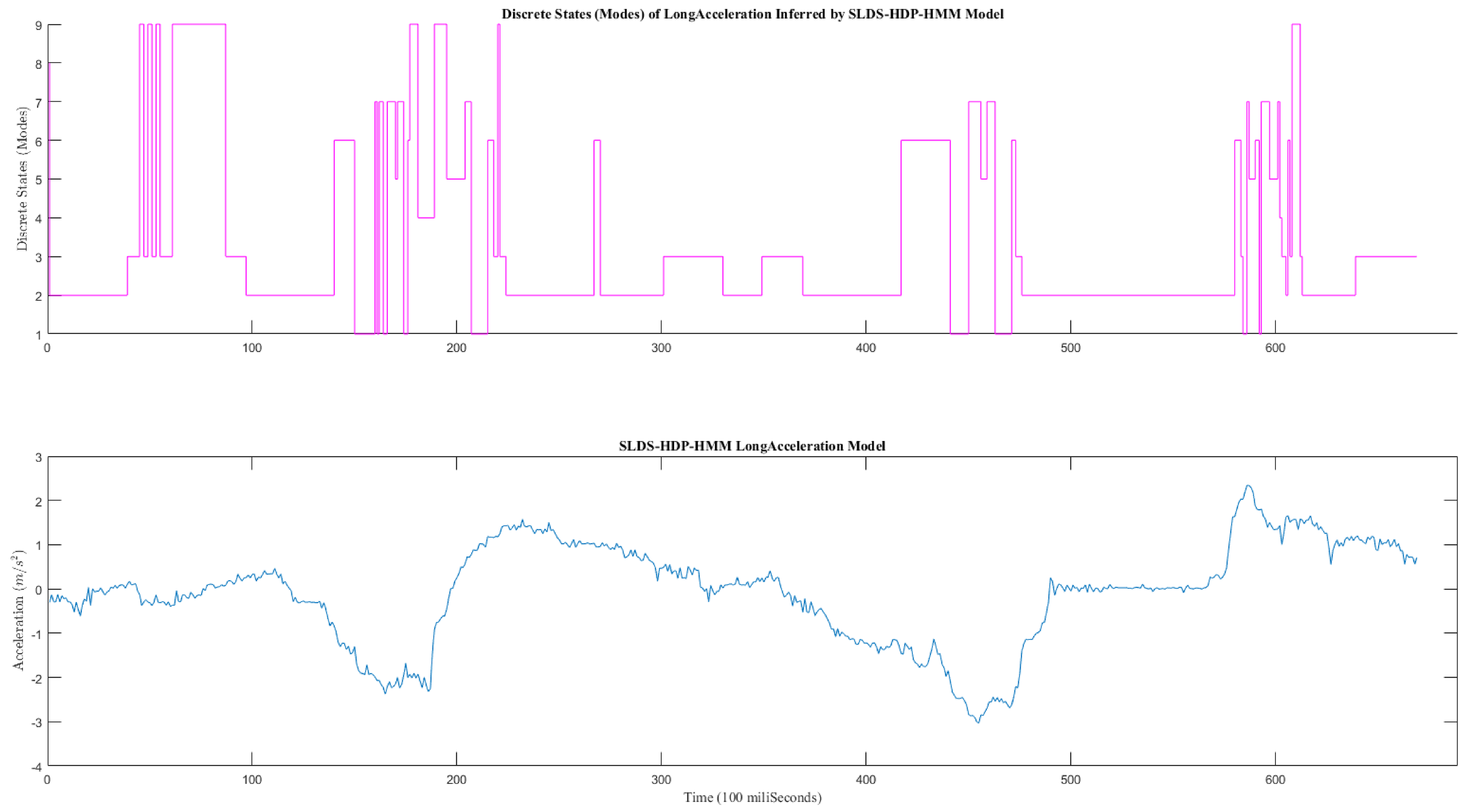
System-Level Architecture



Inference Results

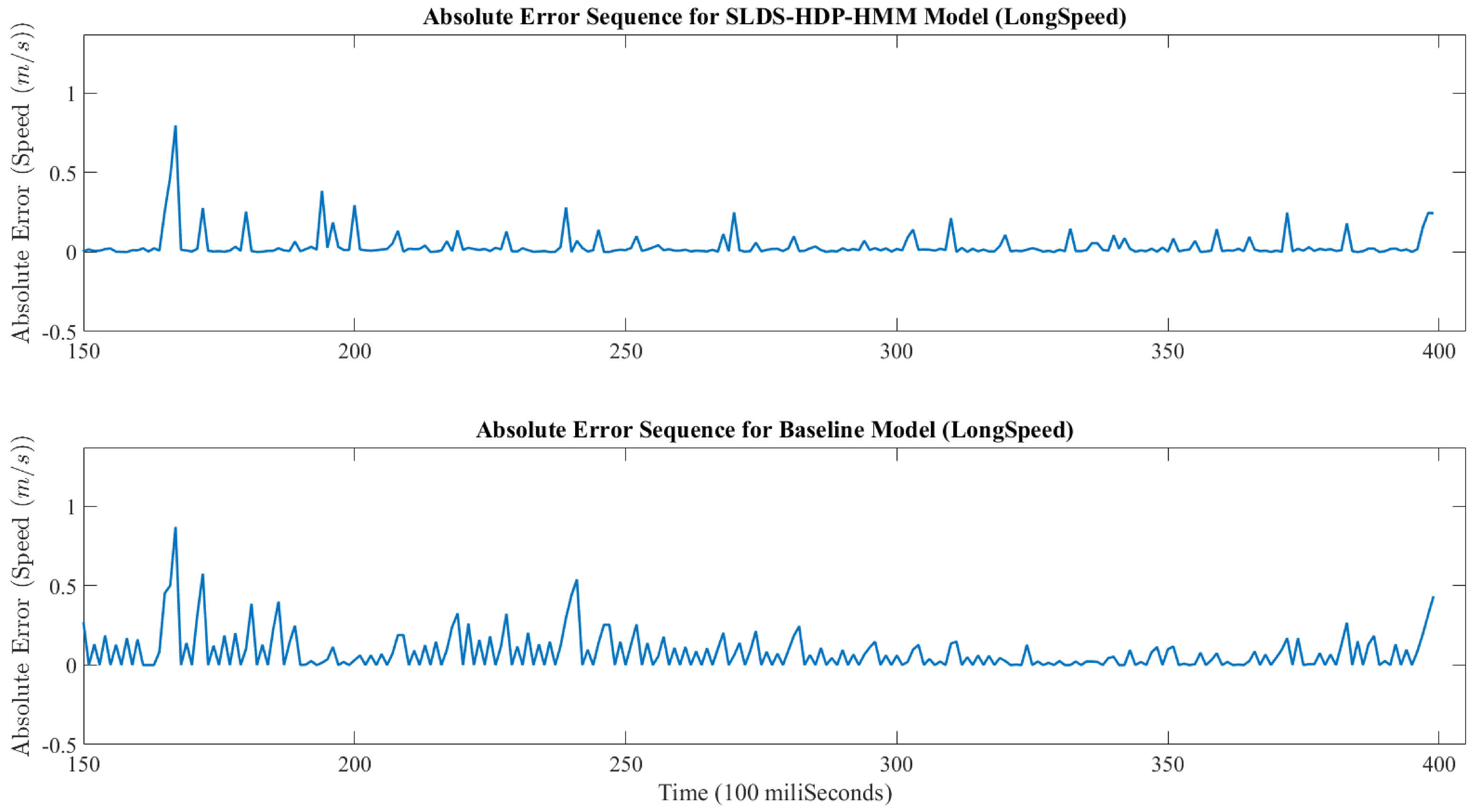


Actual Longitudinal Speed along with its Baseline and Sticky-HDP-HMM Models with 60% Loss

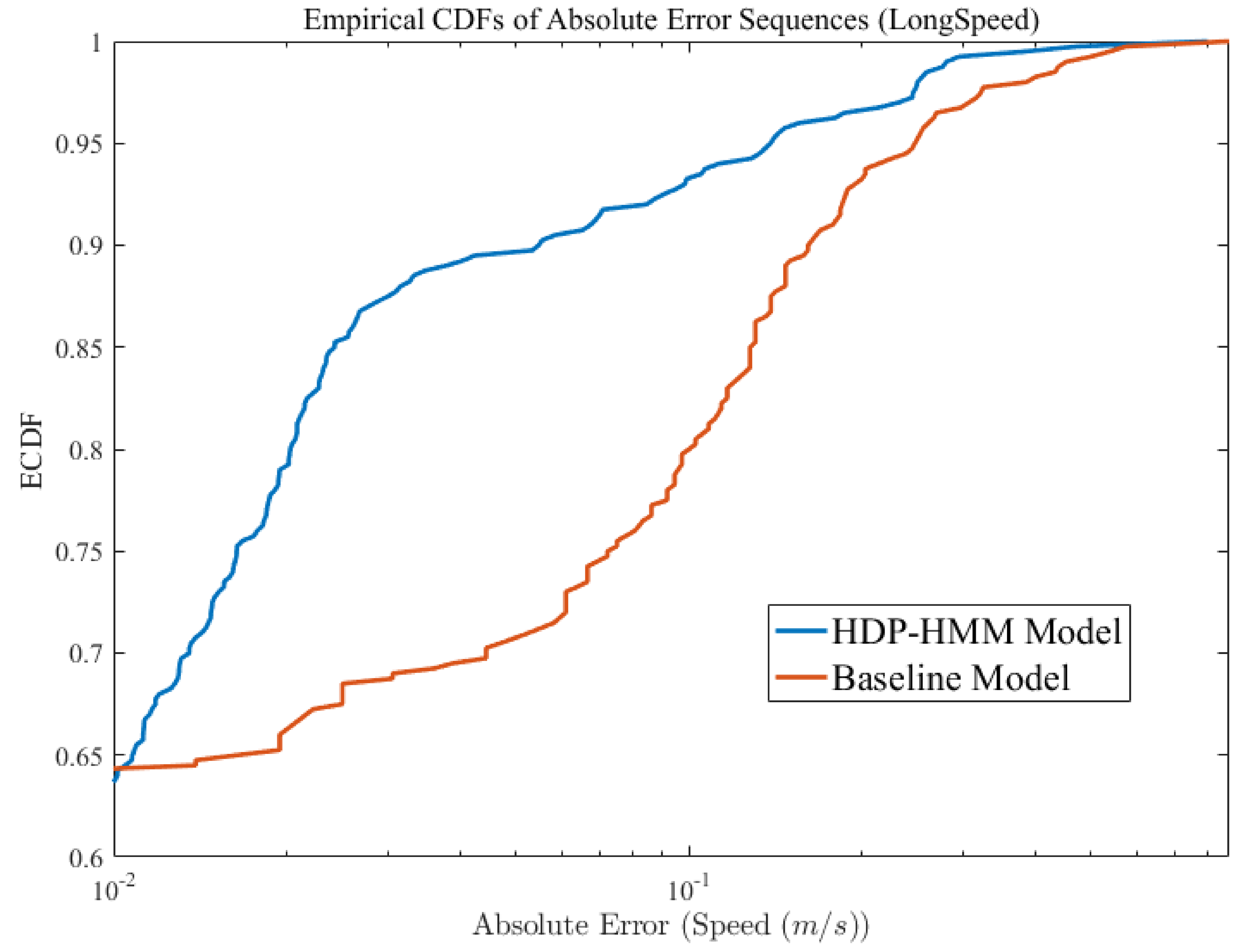


Discrete States of Acceleration inferred by Sticky-HDP-HMM Model

Error Comparison



Absolute Error Sequences of Sticky-SLDS-HDP-HMM and Baseline Methods



Empirical CDFs of Absolute Error for Sticky-SLDS-HDP-HMM and Baseline Methods

References

[1] Teh, Y., Jordan, M., Beal, M., & Blei, D. (2006). Hierarchical Dirichlet Processes. Journal of the American Statistical Association, 101(476), 1566-1581.

[2] E. Fox, "Bayesian nonparametric learning of complex dynamical phenomena," Ph.D. dissertation, Massachusetts Inst. Technol., Cambridge, MA, July 2009.

[3] E. Fox, E. Sudderth, M. Jordan, and A. Willsky, "Nonparametric Bayesian learning of switching dynamical systems," in Proc. Advances in Neural Information Processing Systems, 2009, vol. 21, pp. 457–464.

Other sponsors and collaborators: General Motors, Toyota ITC