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A Stochastic Hybrid Structure for Predicting Disturbances in Mixed Automated and Human-Driven Vehicular Scenarios

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Abstract: In this work, we introduce a stochastic prediction method which can be utilized in applications such as cooperative adaptive cruise control (CACC) to predict interfering vehicles' movements. One of the main criteria in the design of automated vehicle systems is their robustness against the disturbances resulted from the non-homogeneity of the vehicular environment. The non-homogeneity is mainly due to the human-driven and automated/autonomous vehicles co-existence. It is therefore imperative for the automated applications to be designed with the capability of handling the uncertain behaviors of human-driven vehicles in a robust manner. This paper presents a method for vehicle movements time-series forecasting using a powerful non-parametric Bayesian inference method, namely Gaussian Processes. The proposed methodology is evaluated using realistic vehicle trajectory data from NGSIM dataset and is shown to provide more accurate results compared to baseline methods that use constant velocity coasting.

Keywords: **Discrete Hybrid Stochastic Automata, Model Predictive Control, Non-parametric Bayesian Inference, Gaussian Processes, Vehicular Networks, Model-Based Communication**

1. INTRODUCTION and SYSTEM DESCRIPTION

Plausible disturbances from different sources such as manned vehicles or vulnerable road users (VRUs) should be appropriately considered during the design phase of the distributed automated vehicular systems, such as cooperative adaptive cruise control (CACC), platooning management (merging/splitting) systems, etc. Although partially automated and fully autonomous vehicles are expected to have a high penetration rate after being commercialized at an affordable price, they will definitely co-exist with manned (human driven) vehicles for an enduring time horizon. This is a valid fact, even when automated vehicles are deployed at a large scale. In addition to the different autonomy levels, various control strategies utilized by automated vehicles is another factor which might induce behavioral non-homogeneities in the vehicular networks. A possible approach to face this problem and design a robust distributed control scheme for a non-homogenous vehicular scenario is finding the appropriate stochastic models for human interventions in the system and then treating these intervention models in different vehicles (network agents) in a consistent manner. In our proposed framework in this work, these stochastic models are interpreted as stochastic disturbances generated by remote vehicles and considered in the design of the stochastic controllers of the host vehicle. This methodology enables the host vehicle to show a more robust behavior and wiser reactions against the uncertainty imposed by unpredictable human interventions caused by the remote vehicles' drivers. These models could be generated either in the vehicle which is directly controlled (fully or partially) by the human driver itself or also in target agents. The former case is considered here, since it is more effective if the models are derived by the manned vehicle and then be transmitted over the communication network for other vehicles which need these models. This notion has been proposed recently in the vehicular literature as Model-Based Communication (MBC) [1], [2], [3], [4]. The better performance of the MBC against the latter case is due to the availability of more accurate raw information for the host vehicle rather than the imperfect raw information received by remote agents due to the network issues such as delay and packet drops. It is obvious that more precise raw information results in forecasting models with higher fidelity. The behavior modeling block, which is the main focus of this work, could be decomposed into two hierarchical layers which are in charge of modeling the large-scale and small-scale behaviors, respectively. Large-scale behaviors are high-level driving actions and maneuvers such as lane-change, take-over, joining or leaving a platoon, steady cruise, etc. The set of large-scale driving behaviors could be interpreted as the system discrete behavioral modes (states). Small-scale behaviors define the dynamics (patterns) of the set of kinematic states of the targeted agent inside different discrete modes. These kinematic states which are required by the host vehicle controllers are simultaneously affected by inherent remote vehicle physical kinematic characteristics and driving style of the driver (driver behavior). Discrete Hybrid Stochastic Automata (DHSA) [5] is a well-known structure which incorporates all of the above mentioned components in a formal way. DHSA is an extension of Discrete Hybrid Automata (DHA) [6], which handles the transition between different behavioral modes (discrete states in DHSA termino-

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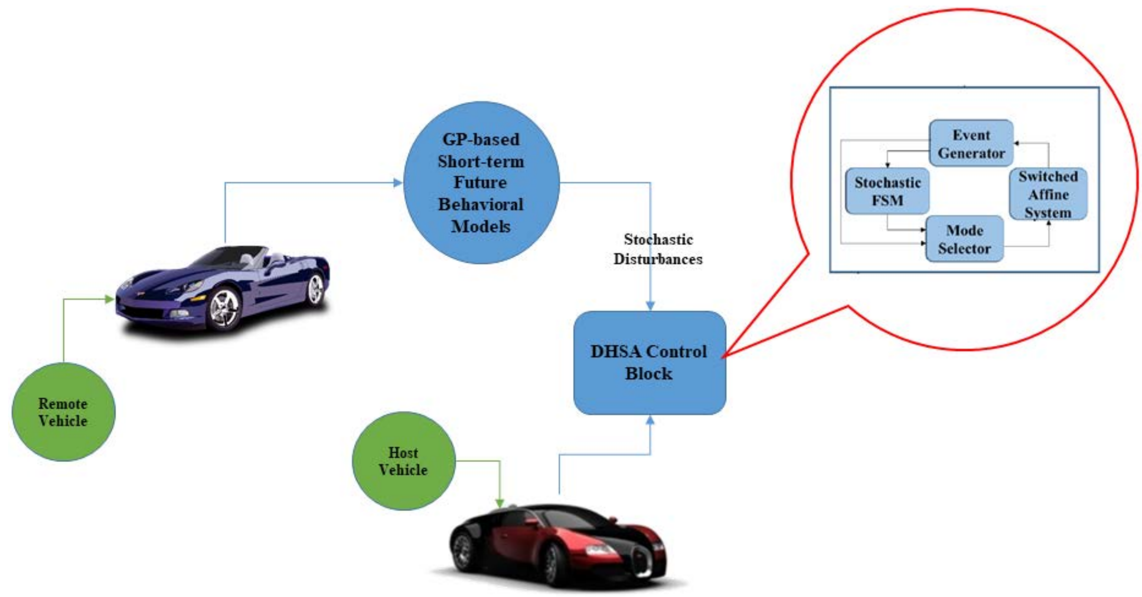

Fig. 1. DHSA control framework in host vehicle, which considers the GP models of the remote vehicles as its stochastic input disturbances

logy) of the system in a probabilistic manner via defining the stochastic Finite State Machine (sFSM) rather than deterministic FSM of DHA. The other elements of DHSA are the mode selector (MS), which defines the patterns of continuous dynamics within each discrete state, event generator (EG) which defines the set of possible events which could be generated according to different linear constrains on the continuous state values, and the switched affine system (SAS) which defines a standard linear state space model (discrete difference equation) for the continuous states, continuous inputs, and system disturbances. The events generated by the event generator are affecting the functionalities of both sFSM and mode selector components.

In our configuration, any vehicle sets up a DHSA for itself, including its own continuous dynamics (mainly its position, velocity, and acceleration) as the continuous SAS states in addition to the received models of the remote vehicles' continuous dynamics as the SAS stochastic disturbances. DHSA discrete states (behavioral modes) and their evolution over time are defined by our large-scale behavior modeling block. In fact, this block plays the role of sFSM in DHSA framework. Appropriate SAS dynamic selection (MS functionality) at each moment is handled according to the current discrete state of the system, in addition to the current set of generated events by EG. These events depend on the constraints have been defined on the continuous states, such as the instantaneous distance with the preceding vehicle, current speed offset from the speed limit or from the driver-specified speed through cruise control system, etc.

The overall schematic of the described system architecture is presented in Figure 1.

2. NON-PARAMETRIC BAYESIAN MODELING

2.1 Time-Series Forecasting with Gaussian Processes

In this section, the details of the method used inside the previously mentioned small-scale behavior modeling block is presented. Different continuous state variables of the vehicle are considered as separate time series here. Our goal in this section is deriving the appropriate forecasting models which give accurate estimates for future values of these time series. In order to propose an analytically tractable procedure for modeling the joint vehicle-driver behavior, which at the same time is not limited to some certain criteria, non-parametric Bayesian inference techniques, and particularly Gaussian Processes (GPs) [7], are among the most promising methods in the literature.

In the GP formulation, sequence of observed samples from a signal are treated as one instant of an N-dimensional multivariate Gaussian random vector. N here denotes the number of available observations.

$$\{Y_1, Y_2, \dots Y_N\} \sim Normal(\bar{\mu}, \Sigma_{N\times N}) \quad (1)$$

This N-dimensional multivariate Gaussian is considered as the joint marginalized distribution of the original function at the observation points. This is based on the assumption that all other function values, other than values at observation moments, have been integrated out. The main component of the GP formulation is its N by N correlation matrix, denoted by Σ in (1). This matrix, which is called the kernel function in the GP context, defines the trend of sample functions (sample paths) from the posterior distribution, after Bayesian inference, based on the similarity pattern among the observed values. By choosing an appropriate combination of different kernel types, different patterns could be captured within the available observations.

In this work, we used a realistic vehicular dataset provided by US-DOT, known as NG-SIM (I-80) dataset [8]. We tried to derive a predictive model for the next position of a vehicle based on a history of its previous states (i.e., position, and speeds). We tried a powerful kernel type, i.e., spectral mixture kernel [9], and observed its prediction results versus the constant speed model as the baseline. We have focused on those fractions of the trajectories in which vehicles are making special lateral maneuvers such as lane-change. It has been observed from this analysis that during these special maneuver moments, GP prediction outperforms the baseline model. This is very important, since during a normal driving scenario along the longitudinal direction in a normal traffic situation, constant speed model works well enough and makes predictions with enough precision. In fact, the main bottle neck of this model is at deviation moments from this normal trend, such as lane-change maneuvers.

Figure 2 is an example of the lateral position forecast error comparison at the next sample time for the baseline and SM kernel GP models, assuming we have the last two samples of the speed for each prediction. The forecast moment has been swept during the complete lane change maneuver for each model. It is clear that almost during the whole lateral action, GP generates better predictions for the next moment lateral position.

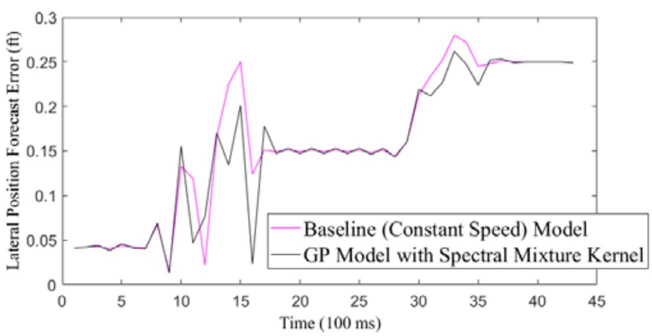

Fig. 2. Lateral position tracking error comparison of SM-kernel GP and baseline (constant speed) models during a lane-change maneuver from NGSIM (I-80) dataset

3. CONCLUDING REMARKS

In this abstract, we have proposed a stochastic hybrid framework based on DHSA and non-parametric Bayesian notions to model the states of the remote vehicles as stochastic disturbance components, which could be utilized in order to design a more robust stochastic MPC in the host vehicle. More specifically, it has been proposed to augment the baseline constant speed forecasting model with a non-parametric Bayesian model, i.e. GPs, during the special driving moments where the baseline model accuracy deviates from its normal level. For instance, lane change maneuvers which introduce some non-linearities in the lateral position trend over time, might not be modeled with a good precision by the constant speed (linear position) model. Thus, taking a hybrid modeling approach which switches between the baseline and GP in an online adaptive manner seems a better solution than using each of these models individually. However, one challenge here is defining a criterion which enables the model to automatically detect the switching moments. It seems that using other parameters, such as heading or steering angle which are highly correlated with the lateral movements, in conjunction with the speed could be a good starting point to tackle this problem. We are currently investigating the design of such hybrid forecasting methods.

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