Adaptive Safe Behavior Generation for Heterogeneous Autonomous Vehicles Using Parametric-Control Barrier Functions (Student Abstract)

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Abstract

Control Barrier Functions have been extensively studied to ensure guaranteed safety during inter-robot interactions. In this paper, we introduce the Parametric-Control Barrier Function (Parametric-CBF), a novel variant of the traditional Control Barrier Function to extend its expressivity in describing different safe behaviors among heterogeneous robots. A parametric-CBF based framework is presented to enable the ego robot to model the neighboring robots behavior and further improve the coordination efficiency during interaction while enjoying formally provable safety guarantees. We demonstrate the usage of Parametric-CBF in behavior prediction and adaptive safe control in the ramp merging scenario.

Introduction

Safety in terms of collision avoidance is an important topic for autonomous systems and adopting safety-critical control into the domain of autonomous driving presents many new challenges. To ensure provable safety guarantee, surrounding robots are often assumed to be fully cooperative or passively moving with constant velocity in the collision avoidance scenario (Wang, Ames, and Egerstedt 2017; Ames et al. 2019). However, in a more realistic setting when an ego robot operates in an environment with unknown robots, it is desired for the ego robot to take observations and infer the underlying safe behavior strategy of the others, and then compute its own behavior accordingly to achieve improved safety and task efficiency. How to improve the expressivity of autonomous vehicles' safe-critical controllers, so that the modeled behaviors can be better understood by surrounding drivers remains an open problem.

Motivated by these considerations, we focus on the learning and safe design for interaction of heterogeneous autonomous vehicles in ramp merging scenario. This paper extends our previous work on CBF-based merging control (Lyu, Luo, and Dolan 2021) and presents the following **contributions**: 1) We propose the novel idea of Parametric-CBF, a variant of traditional CBF that gives a richer safe behavior descriptions; 2) We present a novel safe adaptive merging algorithm that integrates the safe behavior prediction of heterogeneous robots and safe control for the ego robot using the learned parameters of the Parametric-CBF, yielding improved task efficiency with safety guarantee.

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Traditional CBF One of the most important properties of CBF is its forward-invariance guarantee of a desired safety set. Consider the following nonlinear system in control affine form: $\dot{x} = f(x) + g(x)u$, where $x \in \mathcal{X} \subset \mathbb{R}^n$ and $u \in \mathcal{U} \subset \mathbb{R}^m$ are the system state and control input with f and g assumed to be locally Lipschitz continuous. A desired safety set $x \in \mathcal{H}$ can be denoted by the following safety function: $\mathcal{H} = \{x \in \mathbb{R}^n : h(x) \geq 0\}$. Thus the control barrier function for the system to remain in the safety set can be defined as (Ames et al. 2019): Given the aforementioned dynamical system and the set $\mathcal{H}$ with a continuously differentiable function $h : \mathbb{R}^n \to \mathbb{R}$, then h is a **Control Barrier Function (CBF)** if there exists a class $\mathcal{K}$ function for all $x \in \mathcal{X}$ such that $\sup_{u \in \mathcal{U}} \{L_f h(x) + L_g h(x)u\} \geq -\kappa\big(h(x)\big)$, where $\dot{h}(x, u) = L_f h(x) + L_g h(x)u$ with $L_f h, L_g h$ as the Lie derivatives of h along the vector fields f and g. The resulting safe behavior near the boundary of $h(x) = 0$ is determined by the selected class $\mathcal{K}$ function, e.g. $\kappa(h(x)) = \gamma h(x)$ commonly used in (Ames et al. 2019) with $\gamma \in \mathbb{R}^{\geq 0}$ as a CBF design parameter. As motivated in (Djaballah et al. 2017), this particular form as $\kappa(h(x)) = \gamma h(x)$ is limited in describing complicated system behaviors when approaching to the boundary of $h(x) = 0$, and thus a more general form capturing a richer nonlinear behavior descriptions is needed.

Parametric-Control Barrier Function

Definition 0.1. Given the aforementioned dynamical system and the set $\mathcal{H}$ with a continuously differentiable function $h : \mathbb{R}^n \to \mathbb{R}$, then h is a **Parametric-Control Barrier Function (Parametric-CBF)** for all $x \in \mathcal{X}$ such that $\sup_{u \in \mathcal{U}} \{\dot{h}(x, u)\} \geq -\alpha H(x)$, where parameter vector $\alpha = [\alpha_1 \quad \alpha_2 \quad \dots \quad \alpha_n] \in \mathbb{R}^n$ with $\forall \alpha_p \in \mathbb{R}^{\geq 0}$ for $p \in [n]$, $H(x) = \begin{bmatrix} h(x) & h^3(x) & \dots & h^{2n-1}(x) \end{bmatrix}^T, n \in \mathcal{N}$.

In Parametric-CBF, $\kappa(h(x))$ is constructed as a weighted polynomial function $\kappa(h(x)) = \alpha H(x)$ with $H(x)$ as a set of basis functions containing independent odd-powered power functions $h^{2p-1}(x)$, which are individually used as class $\mathcal{K}$ functions (Ames et al. 2019; Wang, Ames, and Egerstedt 2017). This regulates how fast the states of the system can approach the boundary of the safe set and is char-

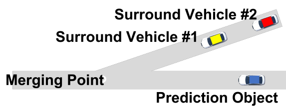

Figure 1: Prediction Scenario. The blue car on the main road is the prediction object whose driving style needs to be estimated.

acterized by the weights distribution α to achieve a richer description of the system's behavior.

Parametric-CBF based Control and Prediction

Safe Control In this work, we use the same system dynamics to describe vehicles as in our previous work (Lyu, Luo, and Dolan 2021). The safe controller is formulated as a quadratic programming for heterogeneous multi-vehicles with the control input u_i. The objective function $\min_{u_i \in \mathcal{U}_i} ||u_i - \bar{u}_i||^2$ represents minimally deviation control from the nominal control input $\bar{u}_i$, where i, j are the indices of the pairwise vehicles. The actuation constraint $U_i^{min} \leq u_i \leq U_i^{max}$ represents the maximum and minimum allowed acceleration. The Parametric-CBF based safety constraint is formulated as $\dot{h}_{ij}(x,u) + \alpha_i H_{ij}(x) \geq 0$, where $\alpha_i = [\alpha_{i,1} \dots \quad \alpha_{i,n}]$, $H_{ij}(x) = \left[h_{ij}(x), \dots, h_{ij}^{2n-1}(x)\right]^T, n \in \mathcal{N}$. We consider the particular choice of pairwise vehicle safety function $h_{ij}(x)$ and safety set $\mathcal{H}_i$ as: $\mathcal{H}(x) = \{x \in \mathcal{X} : h_{ij}(x) = ||x_i - x_j||^2 - R_{safe}^2 \geq 0, \forall i \neq j\}$, where x_i, x_j are the positions of each pairwise set of vehicles and $R_{safe} \in \mathbb{R}^+$ is the minimum allowed safety distance.

Behavior Pattern Prediction We assume each heterogeneous robot carries the aforementioned safe controller with different parameters α_i reflecting their various safe control behaviors, e.g. how aggressive they are in engaging collision avoidance scenario. Here we consider the behavior prediction task for ego vehicle i over prediction object j, who is interacting with a set of other vehicles. To that end, the ego vehicle is able to observe the behavior of the prediction object j and obtain the interactive dataset $\mathbb{D} = \{\dot{h}_{jk}^t, h_{jk}^t\}_{t=1}^m$ calculated from the observations during m time steps (the position and velocity of the prediction object and its surrounding vehicles). Given that, the ego robot i could perform ridge linear regression to find estimated $\bar{\alpha}_j$ for the prediction object j as: $\bar{\alpha}_j = \arg\min_{\alpha_j} \sum_{t=1}^m \left\|\dot{h}_{jk}^t - \alpha_j H_{jk}^t\right\|_2^2 + r\|\alpha_j\|_F^2$, where r is a regularizer parameter and $\|\alpha_j\|_F$ is the Frobenius norm of the estimate parameter α_j.

Simulations

Behavior Pattern Prediction The interactive driving scenario is shown in Fig. 1. The task here is to predict the driving style, i.e., the Parametric-CBF parameter vector α, of the prediction object, based on observations over its interaction with surrounding vehicles. The prediction result is shown in Fig. 2(a). It is observed that the prediction results converge over time as more data points are collected. The learned parameter vector α reaches convergence in only 10

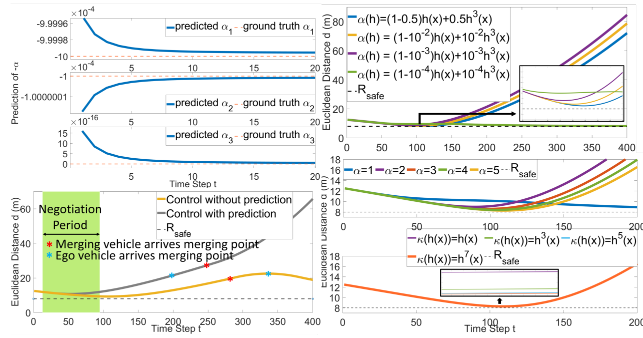

Figure 2: a.(top left) Learnt driving style α of the prediction object. b.(bottom left) Comparison of control with prediction in the loop and without prediction. c.(top right) Performance comparison of traditional CBF with different choices of $\kappa(h(x))$. d.(bottom right) Comparison of different constructions of Parametric-CBF.

time steps, which is 0.1s, indicating it is computationally efficient enough to be applied in real-time applications.

Richer Safe Behavior Characterization To demonstrate the advantage of Parametric-CBF over traditional CBF in terms of behavior description richness in the safe control task, comparison of traditional CBF (Fig. 2(c)) and Parametric-CBF (Fig. 2(d)) is conducted. The two vehicles interaction scenario has the ego with various underlying safe controllers on the main road and the merging vehicle with the same driving style α on the ramp. It is observed that, Parametric-CBF outperforms the traditional CBF in terms of richer description of the generated behavior with more distinct variations caused by changes in relative weights of different order component functions.

Improved Task Efficiency To show how the Parametric-CBF-based prediction can contribute towards more efficient safe control, safe behaviors generated with prediction knowledge and without prediction are compared in Fig. 2(b). The difference between two trials is whether the ego vehicle estimates the merging vehicle's driving strategy through observations during interactions and choose adaptive strategy in terms of driving aggressiveness accordingly. It is observed that the use of prediction significantly improve the ego vehicle's task efficiency by 39.6% and the overall coordination task efficiency by 16.1%, greatly reducing traffic congestion.

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