Tokyo Institute of Technology
School of Engineering

Myopically verifiable probabilistic certificate for long-term safety and its autonomous driving application

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Abstract: In this talk, we will first introduce our recent work that focused on barrier function-based approaches for the safe control problem in stochastic systems. With the presence of stochastic uncertainties, a myopic controller that ensures safe probability in infinitesimal time intervals may allow the accumulation of unsafe probability over time and result in a small long-term safe probability. Meanwhile, increasing the outlook time horizon may lead to significant computation burdens and delayed reactions, which also compromises safety. To tackle this challenge, we define a new notion of forward invariance on ‘probability space’ as opposed to the safe regions on state space. This new notion allows the long-term safe probability to be framed into a forward invariance condition, which can be efficiently evaluated. We build upon this safety condition to propose a controller that works myopically yet can guarantee long-term safe probability or fast recovery probability. The proposed controller ensures the safe probability does not decrease over time and allows the designers to directly specify safe probability. This framework can also be adapted to characterize the speed and probability of forward convergent behaviors, which can be of use to finite-time Lyapunov analysis in stochastic systems. Building upon the above framework, we will then present an adaptive safe control method that can adapt to changing environments, tolerate large uncertainties, and exploit predictions in autonomous driving. The use of long-term safe probability provides a sufficient outlook time horizon to capture future predictions of the environment and planned vehicle maneuvers and to avoid unsafe regions of attractions. The resulting control action systematically mediates behaviors based on uncertainties and can find safer actions even with large uncertainties. This feature allows the system to quickly respond to changes and risks, even before an accurate estimate of the changed parameters can be constructed. The safe probability can be continuously learned and refined. Using more precise probability avoids over-conservatism, which is a common drawback of the deterministic worst-case approaches. The proposed techniques can also be efficiently computed in real-time using onboard hardware and modularly integrated into existing processes such as predictive model controllers.

Bio: Yorie Nakahira is an Assistant Professor in the Department of Electrical and Computer Engineering at Carnegie Mellon University. She received B.E. in Control and Systems Engineering from Tokyo Institute of Technology and Ph.D. in Control and Dynamical Systems from California Institute of Technology. Her research interests include the fundamental theory of optimization, control, and learning and its application to neuroscience, cell biology, smart grid, cloud computing, finance, and autonomous driving. Her group website can be found here: https://www.cmu.edu/ece/learning-control/index.html.