Research Proposal

Huaiyuan Rao
Georgia Institute of Technology

I. Background

Safety is of the highest importance for control systems and is often prioritized above other performance requirements. Especially in the field of robotics, conducting safety-critical autonomous control is vital. However, for different types of robots, safety has different meanings. For example, safety for a mobile robot means avoiding collisions with obstacles when moving in hazardous environments. For medical robots, safety means operating without causing harm to patients, which requires high control accuracy. So we must confront several key challenges: (1) Real-world robot system have complex and time-varying uncertainties, which require some robust methods to model them (e.g. Gaussian Process). (2) Robot control tasks need control-theoretic guarantees such as safety and stability, which require a framework to unify different control methods' theoretical results (e.g. Reinforcement learning combined with optimal control). (3) Generalization of designed control algorithms, which need to maximize control method's compatibility on robot systems.

Given these challenges, my research vision is to establish a foundation for safe control that facilitates the long-term autonomy of robot systems. In pursuit of this vision, my research goal will focus on **constructing a unified algorithmic and theoretical framework that can formulate safe control problem to a optimization problem and using novel control strategy to solve them.**

II. Literature Review

There are two common methods used in safety critical robot control problem: Control Barrier Function (CBF) and Hamilton-Jacobi (HJ) reachability analysis. The latter one is a value function-based approach, which formulates the reachability of a target set as an optimal control problem, which can be sovled numerically by using the dynamic programming principle. But HJ reachability analysis mainly suffer two problems [1]: the first is constructing the value function by numerical methods suffer from the curse of dimensionality. Secondly, the resulting safe optimal control policy is generally overly conservative when applied directly. In the other hand, CBF is known for its efficiency that verify and enforce safety properties in the context of (optimization based) safety-critical controllers [2]. It often comes up with construct a hand-crafted CBF (e.g. a circle barrier) in mobile robot control tasks. Then it formulates a CBF-QP problem to minimize

Finished Work
[1]https://github.com/Rhyme0730/RL_LQR_Continuum_Robots
[2]https://github.com/Rhyme0730/RL-CBF-RRTX

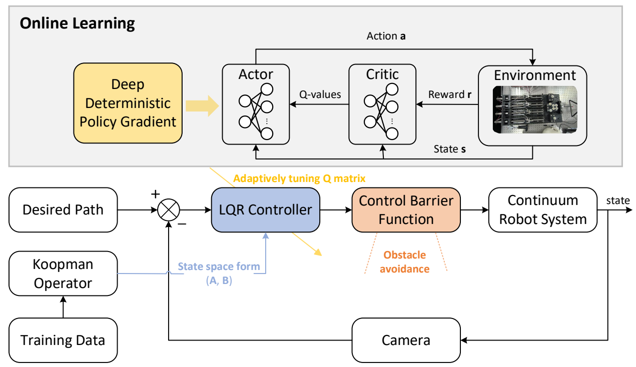

Fig. 1. Control diagram of DDPG-LQR.

the applied control input while not violating the constraint, in other words, we need to find the "minimum effort" controller which is stable in the sense of Lyapunov. Additionally, in some nonlinear systems, when the system's relative degree larger than 1, we may need to redesign a higher order CBF.

Reinforcement learning (RL) has been used successfully in numerous robotics applications [3], [4]. RL typically assumes that the underlying control problem is a Markov decision process (MDP), and an RL agent must explore a vast number of states (exploration & exploitation) during training to develop a meaningful control policy. Many researchers are now focusing on safe reinforcement learning (RL) control in robotics [5]. Most approaches leverages a model-based safety framework which serves to prevent the exploration of unsafe states (e.g., [6], [7]) by projecting the action taken by the RL agent onto a safe-set of actions. They generally combine safe control methods (e.g., LQR, MPC, PID) with RL agents (e.g., DQN, DDPG, TRPO). These safe control methods guide the training process of the RL agents, preventing them from entering unsafe regions and enhancing the effectiveness of the trained control policy. For both CBF and safe RL control, I have completed two projects during my M.S. studies and am preparing them for publication. ([1]RL-LQR (Fig. 1), [2]RL-CBF-RRT^X (Fig. 2)).

III. Future Directions

My future work is centered around leveraging safe control in autonomous systems: developing unified frameworks which yield useful theory, practical algorithms, and novel real-world capabilities. It can be detailed as follow.

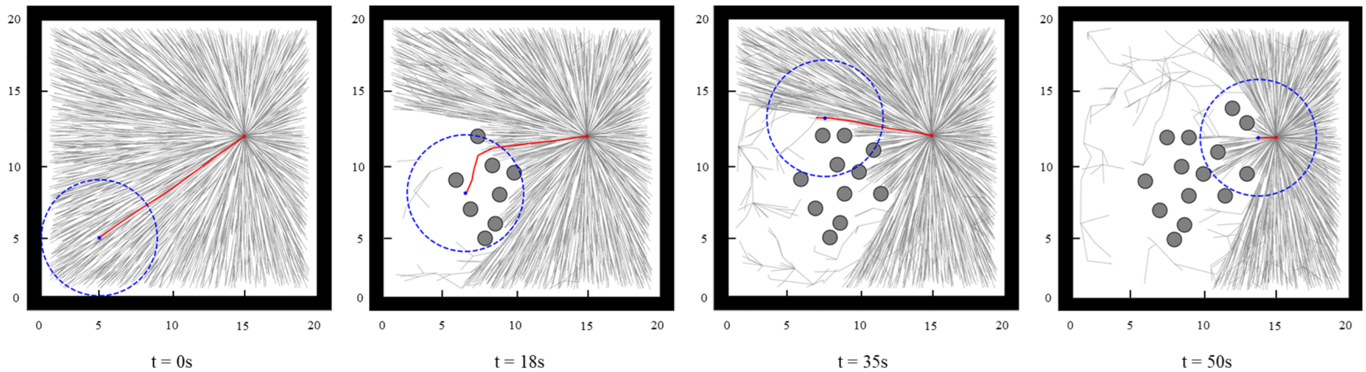

Fig. 2. Collision-free navigation of an dubin vehicle navigating in an unknown environment using RL-CBF-RRT^X.

A. Using data-driven methods to get robots system model

My M.S. research found that a large quantities of robots system are hard to get full model dynamics (e.g. continuum robots, blimps, etc.). It is hard to use mathematical formula to describe the highly nonlinearity's impacts (e.g. internal friction) on the robot system. Common methods such as linearization around system equilibrium point and traditional system identification methods (ordinary least squares) show its limit on nonlinear robot systems. So using learning methods like machine learning or [1]Koopman operator is a better choice. Therefore, I am keen to develop a principled learning framework that learning model from data and integrates learned model with control theory.

B. Safe learning based control for robots in complex environments

My research will continue to explore the intersection of learning and control theory, in other words, combining reinforcement learning with control while guarantee safety and better control performance. Common control methods may fail while robot system work in hazardous environment, thus using learning methods such as RL to overcome this issue is feasible. But the compatibility is another thing we need to consider. For instance, if we get good control performance on certain robot system and only training using data generated from it. How can we generalize this control method to other robot system? Thus I want to construct a unified framework to provide theoretical foundations in learning and control.

C. Formulating and sovling control problem from convex and nonconvex optimization perspective

Convex optimization focuses on minimizing (or maximizing) a convex function over a convex set, and it has significant applications in areas such as LQR, MPC and robust control methods. However, in real-world applications, the problems we encounter are often nonconvex. Recent advances in nonconvex optimization algorithms, including heuristic methods and machine learning techniques, are enhancing their applicability in control systems, such as adaptive control. My goal is to study both convex and nonconvex optimization and integrate them to solve complex control problems effectively.

References

[1] J. J. Choi, D. Lee, K. Sreenath, C. J. Tomlin, and S. L. Herbert, "Robust control barrier–value functions for safety-critical control," in *2021 60th IEEE Conference on Decision and Control (CDC)*, pp. 6814–6821, IEEE, 2021.

[2] A. D. Ames, S. Coogan, M. Egerstedt, G. Notomista, K. Sreenath, and P. Tabuada, "Control barrier functions: Theory and applications," in *2019 18th European control conference (ECC)*, pp. 3420–3431, IEEE, 2019.

[3] J. Kober, J. A. Bagnell, and J. Peters, "Reinforcement learning in robotics: A survey," *The International Journal of Robotics Research*, vol. 32, no. 11, pp. 1238–1274, 2013.

[4] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, "Deep reinforcement learning: A brief survey," *IEEE Signal Processing Magazine*, vol. 34, no. 6, pp. 26–38, 2017.

[5] L. Brunke, M. Greeff, A. W. Hall, Z. Yuan, S. Zhou, J. Panerati, and A. P. Schoellig, "Safe learning in robotics: From learning-based control to safe reinforcement learning," *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 5, pp. 411–444, 2022.

[6] J. F. Fisac, A. K. Akametalu, M. N. Zeilinger, S. Kaynama, J. Gillula, and C. J. Tomlin, "A general safety framework for learning-based control in uncertain robotic systems," *IEEE Transactions on Automatic Control*, vol. 64, no. 7, pp. 2737–2752, 2018.

[7] Z. Li, U. Kalabić, and T. Chu, "Safe reinforcement learning: Learning with supervision using a constraint-admissible set," in *2018 Annual American Control Conference (ACC)*, pp. 6390–6395, IEEE, 2018.