Safe Model-based Control from Signal Temporal Logic Specifications Using Recurrent Neural Networks

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Introduction

Temporal logics are widely used as specification languages for robotic systems due to their rich expressivity and similarity to natural language. In this work, we apply model-based Reinforcement Learning (RL) to simultaneously learn the system dynamics and a control policy that satisfies a given Signal Temporal Logic (STL) task. Compared with existing approaches, our algorithm:

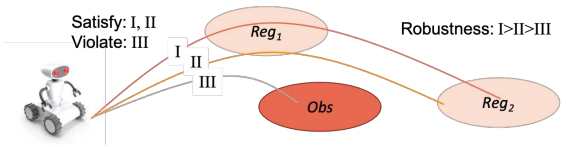
- requires no demonstrations (as opposed imitation learning);
- is data-efficient compared to model-free RL approaches;
- enables real-time execution after training;
- utilizes Control Barrier Function (CBF) to improve safety.

Signal Temporal Logic

STL, which is defined over real-valued signals, can express complex, time-related task specifications. Informally, an STL formula ϕ is made of:

- predicates: $l(x_t) \geq 0$, $x_t \in \mathbb{R}^n$;
- logical operators: $\wedge$ (AND), $\vee$ (OR), $\neg$ (NOT);
- temporal operators: $\mathbf{U}_I$ (until), $\mathbf{F}_I$ (eventually), $\mathbf{G}_I$ (always), where I is a time interval.

Qualitative semantics: whether a formula is satisfied;
Quantitative semantics (robustness): how strongly a formula is satisfied.
Example: $\mathbf{F}_{[0,5]} Reg_1 \wedge \mathbf{F}_{[5,10]} Reg_2 \wedge \mathbf{G}_{[0,10]} \neg Obs$.



Problem Formulation

Given:

- an STL formula φ with time horizon T;
- a control affine system with **unknown dynamcis** $x_{t+1} = f(x_t) + g(x_t)u_t$;
- a distribution p for the initial condition x_0,

find optimal parameters W^* for a Recurrent Neural Network (RNN) control policy $u_t = \pi(x_{0:t}, W)$ that maximizes the expected STL robustness $\rho(x_{0:T}, \varphi)$ over distribution p:

$$\begin{aligned} W^* &= \arg\max_W E_{p(x_0)}[\rho(\varphi, x_{0:T})] \\ \text{s.t. } & x_{t+1} = f(x_t) + g(x_t)\pi(x_{0:t}; W), t = 0, \ldots, T-1 \end{aligned} \tag{1}$$

Remark: We use RNN because memory is necessary for the controller [1].

Model-Based Safe Policy Search

System Model Learning:
We use a probabilistic model to reduce the effect of model bias, which is implemented as neural networks $\mathcal{F}$ and $\mathcal{G}$ with **dropout** layers [2]:

$$\hat{x}_{t+1} = \mathcal{F}(x_t; W_f, Z_f) + \mathcal{G}(x_t; W_g, Z_g)u_t,$$

- W_f, W_g: neural network parameters;
- Z_f, Z_g: dropout masks.

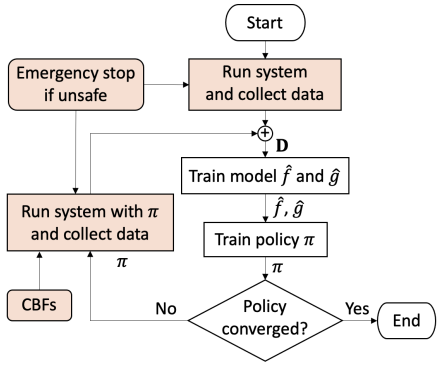
Run the system and collect transition data to simutaneously train the two neural networks. When running the system, **CBFs** are used **under the consideration of model uncertainty** to improve safety.

Control Policy Improvement:
Substitute the learned model to (1) and solve the optimization problem. In specific, we

- use the model to roll out the trajectory;
- compute the STL robustness and its gradient;
- update the policy using the gradient.

At each optimization step, sample a new set of initial states and system dropout masks. Use the mean value to approximate the expectation.

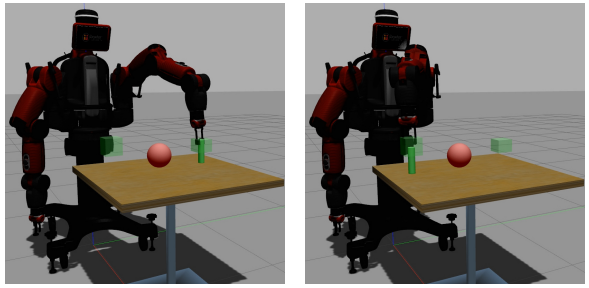
Model-Based Safe Policy Search:
Repeatedly train the system model and the control policy (called a cycle) until convergance.



Simulation Results

We simulated a Baxter robot, which has a 7 DOF manipulator. $x_t \in \mathbb{R}^{14}$ is the joint angles and velocities, $u_t \in \mathbb{R}^7$ is the torques. Consider the following STL formula for a Pick and Place task with obstacle avoidance:

$$\begin{aligned} \varphi_1 = & \left(\mathbf{F}_{[0,\frac{2.5}{\Delta t}]}(\mathbf{G}_{[0,\frac{0.5}{\Delta t}]}\mathbf{p} \in R_{pick})\right) \wedge \left(\mathbf{F}_{[\frac{3}{\Delta t},\frac{5.5}{\Delta t}]}(\mathbf{G}_{[0,\frac{0.5}{\Delta t}]}\mathbf{p} \in R_{place})\right) \\ & \wedge (\mathbf{G}_{[0,\frac{6}{\Delta t}]}\mathbf{q} \in V_{30}) \wedge (\mathbf{G}_{[0,\frac{6}{\Delta t}]}p_x > x_{body}) \wedge (\mathbf{G}_{[0,\frac{6}{\Delta t}]}p_z > h_{tb}) \wedge (\mathbf{G}_{[0,\frac{6}{\Delta t}]}\mathbf{p} \notin Obs) \end{aligned}$$



(a) Pick **(b)** Place

Testing results including success rate γ, unsafe rate β, mean robustness $\bar{\rho}$:

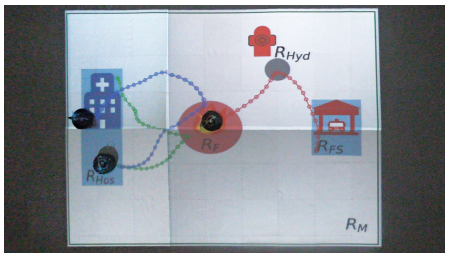
	w/ CBF			w/o CBF		
	γ	β	$\bar{\rho}$	γ	β	$\bar{\rho}$
Cycle 1	0%	10%	-0.4807	0%	24%	-0.7224
Cycle 2	2%	0%	-0.0973	14%	5%	-0.0880
Cycle 3	14%	0%	-0.0235	22%	0%	-0.0071
Cycle 4	83%	0%	0.0169	87%	0%	0.0192
Cycle 5	100%	0%	0.0401	100%	0%	0.0419

Testing results show that our algorithm achieves a high success rate, and the use of CBFs greatly reduces unsafe rate. Training costs 50 minutes, with 180 system runs (a small number compared with model-free methods)

Experiment Results

We used 3 ground vehicles in a fire fighting scenario:

$$\begin{aligned} \varphi_2 = & \wedge_{k=1}^{2}\left(\mathbf{F}_{[0,\frac{8}{\Delta t}]}(p^k \in R_F) \wedge \mathbf{F}_{[\frac{8}{\Delta t},\frac{15}{\Delta t}]}(p^k \in R_{Hos})\right) \wedge \mathbf{F}_{[0,\frac{10}{\Delta t}]}(p^3 \in R_{Hyd}) \\ & \wedge \mathbf{G}_{[\frac{10}{\Delta t},\frac{15}{\Delta t}]}(p^3 \in R_F) \wedge_{i,j\in\{1,2,3\},i\neq j} \mathbf{G}_{[0,\frac{15}{\Delta t}]}(\|p^i - p^j\|^2 \geq d^2) \wedge_{k=1}^{3} \mathbf{G}_{[0,\frac{15}{\Delta t}]}(p^k \in R_M). \end{aligned}$$



Scan for the video of the simulation and experiment:

- Collected 2372 transition data in 4 cycles of training (20 minutes), with the system running for about 13 minutes.
- Policy execution times: $0.01s$, which enables **real time control**.
- Success rate: 100%.

References

[1] W. Liu, N. Mehdipour, and C. Belta, "Recurrent neural network controllers for signal temporal logic specifications subject to safety constraints," *IEEE Control Systems Letters*, vol. 6, pp. 91–96, 2021.

[2] Y. Gal and Z. Ghahramani, "Dropout as a bayesian approximation: Representing model uncertainty in deep learning," in *international conference on machine learning*. PMLR, 2016, pp. 1050–1059.