Enhancing Lattice-based Motion Planning with Introspective Learning and Reasoning

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Abstract

Robust and safe robots operating outside of controlled environments require not only awareness of the robot’s own actions, but also the current ability to execute those actions and how the execution is expected to vary in motion planning, this translates to well-calibrated safety margins for collision checking Safety is expressed as probabilistic safety in the context of motion under uncertainty.

In this work we are concerned with introspective learning and reasoning about controller performance over time. Normal controller execution of the different actions is learned using machine learning techniques with explicit uncertainty quantification, for safe usage in safety-critical applications. Monitoring for anomalies verifies, at runtime, that the learned models remain valid for collision checking in the motion planner.

While a motion plan is being executed, the presented approach allows for explicit awareness of controller performance under normal circumstances, and detection of unexpected and potentially dangerous behavior in abnormal circumstances. Having learned a more accurate model of execution variability, the safety margins can be reduced while maintaining the same safety as before. This, in turn, also leads to shorter and more efficient plans. Evaluation is made on the nonlinear dynamics of a quadcopter in accurate 3D simulation using system identified parameters.

Introduction

Uncontrolled Real-world Environments

One of the challenges in such environments is varying uncertainty over time, which can be decomposed into three factors:

- Dynamic perception uncertainty
- Dynamic action stochasticity
- Dynamic environmental uncertainty (the environment evolves)

Challenges in Robotics

- What is normal behavior?
- Is the robot behaving normally?
- Safe, but not task effective?
- Are learned models safe to use?

Our Approach

Learn models of execution variations from action sequences
Monitor execution with respect to models during deployment
Use models with explicit uncertainty quantification for tight safety-bounds
Monitor models with respect to executions during deployment

Our Contributions

We present a general approach for enhancing lattice-based motion planning methods with (1) learning models of normal motion primitive execution, (2) using the learned models to improve collision checking effectiveness during planning and (3) efficiently monitor the motion primitive execution for abnormalities.

Since both collision checking and abnormality detection are safety-critical the learning is performed using machine learning techniques with explicit uncertainty quantification from probabilistic machine learning. The monitoring for abnormalities also verifies at runtime that the learned models remain valid for collision checking in the motion planner.

Method

The motion planner in [2] plans safe (collision free) trajectories with respect to both static and dynamic obstacles. That the plans are indeed safe to execute depends on how well-calibrated the safety margins are. A safety margin can be divided into three main parts, reflecting the uncertainties from the robot's perspective of:

- the state of the world
- the control execution
- the behavior of others

\[ \text{Collision} = \text{State} + \text{Execution} + \text{Behaviors} \]

Lattice-based motion planning use graph search to find full trajectories made up of local trajectories (motion primitives). Motion primitives are optimised offline using numerical optimal control. We consider 104 different motion primitives in total. For every motion primitive \( \gamma_i \), we collect all trajectories consisting of these motion primitives, where \( \gamma_i \) is the middle one.

Using methodology from probabilistic machine learning, we estimate a unimodal model that spans the variability of \( \gamma_i \) by

\[ \mathcal{S}_i = \mathcal{O}_s + \mathcal{O}_e + \mathcal{O}_b \]

where \( \mathcal{S}_i \) is the resulting safety margin, \( \mathcal{O}_s \) is the state space, \( \mathcal{O}_e \) is the execution uncertainty, and \( \mathcal{O}_b \) is the behavior uncertainties.

Results

The standard approach in the literature is to use a sphere for \( \mathcal{O}_s \), capturing the aggregate of \( \mathcal{O}_e \) and \( \mathcal{O}_b \), with a single use baseline invariant to time. We use this baseline \( \mathcal{O}_s \), and condition two more with tighter bounds, \( \mathcal{O}_e \) (different for each primitive) and \( \mathcal{O}_b \) (also varying over time). For a meaningful comparison with our proposed variability model, we probabilistically ground the baselines by assuming a Gaussian likelihood over the observations centered on the primitive reference trajectory (i.e. relative translation is zero).

Safety margin components are defined as centered p-Probability Regions (p-PR).

Abnormality detection: Model the rate of leaving the p-PR of a random variable. Monitor that failure rate \( p \) is likely.

Conclusions / Summary

With increased autonomy of cyber-physical systems, the need for integrated introspection capabilities is of growing importance. Such capabilities allow a robot to self-monitor and to react to unexpected changes in circumstances in the environment. This is paramount if robots are supposed to operate safely in unstructured, dynamic and complex environments.

We present an integrated approach for learning and monitoring the execution of motion actions, motion primitives, within the lattice-based motion planning paradigm. Interesting future works is robust online learning of motion primitive execution models, as well as learning such models for different situations e.g. windy and non-windy conditions for multi-modal operations.

System Perspective

Efficiency, effectiveness and safety are competing qualities, and in safety-critical applications the required degree of safety makes it very challenging to achieve useful levels of efficiency and effectiveness. To this end we investigate a holistic perspective on agent motion in complex and dynamic environments. The perception-action loop of an intelligent agent can be decomposed into different components in several ways. In our long-term endeavor we take a holistic perspective of motion and motion patterns - mostly in terms of trajectories - and have made contributions within Perception & Anticipation, Decision Making & Control and Runtime Verification. An important contribution is an integrated whole, made possible by compatible mathematical languages and models from logic, probability theory and machine learning. We use extensive simulation as a valuable and necessary complement to field robotics experimentation. Below is an overview of our AI Robotics stack in ROS (Robot Operating System).

References