PhD Research Project Extended Abstract

Spatio-Temporal Learning, Reasoning and Decision-Making with Robot Safety Applications

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Cyber-physical systems such as robots and intelligent transportation systems are heavy producers and consumers of trajectory data. Making sense of this data and putting it to good use is essential for such systems. When industrial robots, intelligent vehicles and aerial drones are intended to co-exist, side-by-side, with people in human-tailored environments safety is paramount. Safe operations require uncertainty-aware motion pattern recognition, incremental reasoning and rapid decision-making to manage collision avoidance, monitor movement execution and detect abnormal motion. We investigate models and techniques that can support and leverage the interplay between these various trajectory-based capabilities to improve the state-of-the-art for intelligent autonomous systems.

Consider a vehicular traffic scenario where a vehicle enters a T-crossing. The vehicle being a physical object traverses a continuous-time trajectory $x : \mathbb{R} \to \mathbb{R}^D$ as it makes a left turn. This trajectory is not directly observable by the vehicle nor an external observer. The uncertainty of the trajectory state $x(t)$ over time points t is represented as a probability distribution over trajectories

$$p\big(x(\cdot)\big)$$

and observed states at $t_0, \dots, t_K$ are samples from the marginal distribution

$$\hat{x}_{\leq t_K} = \hat{x}_{t_0}, \dots, \hat{x}_{t_K} \sim p\big(x(t_0), \dots, x(t_K)\big).$$

Reconstructing $x(t)$ from observations (both for interpolation and extrapolation) without underestimating the uncertainty in $x(t)$ is important for many safety applications (e.g. safe collision avoidance, abnormality detection). Gaussian process regression[4] is one class of methods well suited for this kind of inference.

Consider the case where a vehicle is observed to make the same kind of turn multiple times, or where multiple vehicles are observed to make the same kind of turn. The observations consists of a set of J sampled trajectory-observations (one for each executed trajectory) $\hat{X} = \left\{\hat{x}^j_{\leq t^j_K}\right\}_{j=1}^{J}$. Given previous observations $\hat{X}$, the current time-point t_K and observations $\hat{x}_{t_0,\dots,t_K}$ we would like to:

1. Model the motion pattern spanned by $\hat{X}$ as a distribution over trajectories (e.g. for abnormality detection) without underestimating the uncertainty,

$$p(X(\cdot)|\hat{X}), \tag{1}$$

where $X(\tau)$ is a trajectory over time parametrization $0 \leq \tau \leq 1$, and a continuous-time trajectory alignment model mapping state to τ (for comparing trajectories),

$$p(\tau_0, \dots, \tau_K | \hat{x}_{t_0,\dots,t_K}, \hat{X}). \tag{2}$$

2. Classify $x(t)$ according to categories $c = 1, \dots, C$ of motion patterns (such as left turn, aggressive left turn, right turn etc.) for every time-point t

$$p(c(\cdot)|\hat{x}_{t_0,\dots,t_K}, \{\hat{X}_c\}_{c=1}^{C}) \tag{3}$$

3. Runtime-verify constraints over $x(t)$ (e.g. is the current position precise enough? Is an imminent collision unlikely? Are previously made predictions similar enough with what happened? Are predictions unlikely to underestimate uncertainty?)

$$\big\{p(x(\cdot)|\hat{x}_{t_0,\dots,t_N})\big\}_{N=0}^{K}, t_K \models \text{constraint}(x(t)) \tag{4}$$

4. Motion planning and re-planning in real-time of reference trajectories $x_0(t)$ which result in efficient and safely executed motion $x(t)$, where safety can be

$$\forall t \quad p(x(t) \in \mathcal{X}_{free}(t)) \geq p_{threshold} \tag{5}$$

where $\mathcal{X}_{free}(t)$ is the free space which is time dependent (dynamic obstacles).

In [5] we propose a model for (1) better suited for sets of trajectories than previously proposed models, and techniques for online learning of this model. Alignment of continuous-time trajectories is necessary for multi-trajectory analysis, for example [2]. In [9] we propose a motion pattern model (**1.**) extending [5] with a temporal alignment part (2). We consider learning of and inference in large-scale motion pattern structures as sequences[9] in a road network and as directed graphs[7]. We propose a generative classifier (**2.**) in [9] for associating sub-trajectories to respective motion pattern category (see also examples in [7]). **Interesting research directions** are **(a)** intra-category clustering (e.g. different velocity profiles of the same kind of left turn), **(b)** clustering of trajectories to automatically learn categories (left turn, right turn, etc.), **(c)** infer motion pattern graph structures (through clustering and motion pattern model learning of individual segments), **(d)** clustering and learning of motion patterns that are similar across for example a large city (e.g. similar left turns in different crossings) and are generalizable to new unseen regions/situations.

In robot safety it is important to integrate logical and probabilistic reasoning for uncertainty-robust, rapid and anticipatory decision-making and awareness. In [8] we investigate extensions to stream reasoning for incremental reasoning over probabilistic state information and over predictions for runtime-verification for safety in robotics (**3.**). This work is followed by [10] in which we propose and formalize Probabilistic Signal Temporal Logic (ProbSTL) together with efficient incremental reasoning algorithms with associated correctness proofs. We investigate reasoning over uncertain physical signals such as trajectories and prove properties and guarantees of conclusions drawn based on sampled trajectories. **Interesting research directions** are **(a)** learning safety constraints as ProbSTL formulas, **(b)** integration with Machine learning (ML) for directed and effective learning based on distance to constraint violations, **(c)** controller synthesis based on probabilistic constraints as opposed to regular STL constraints and **(d)** integration into Big data and ML production systems for probabilistic monitoring as opposed to the deterministic monitoring commonly in use today.

Lattice-based motion planning (LBMP) has been one of the most frequently used planning techniques in real implementations for autonomous vehicles [3] and conceptually it works by finding a sequence of translation-invariant compatible trajectories from a set of available motions forming a plan from start state to goal state. In [1] we extend LBMP into a general optimization-based receding-horizon lattice-based motion planning framework with collision avoidance functionality for both complex 3D environments and moving obstacles with real-time performance (**4.**). In [6] (*submitted*) we model actual plan execution (**1.**) to improve the collision predictions in the motion planner (**4.**) and to runtime-verify (**3.**) that executions are not abnormal and that the models are not deteriorating. **Interesting research directions** are **(a)** to learn a representative set of motion patterns of other agents, **(b)** to infer intent and likely current motion plan of other agents, **(c)** to integrate (a) and (b) into the collision avoidance prediction during planning and **(d)** to integrate **3.** to runtime-verify operations and trigger emergency-behaviors (or contingency functionality) in case of abnormalities.

References

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