idSTLPy: A Python Toolbox for Active Perception and Control

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\textbf{Abstract}—This paper describes a Python toolbox for active perception and control synthesis of probabilistic signal temporal logic (PrSTL) formulas of switched linear systems with additive Gaussian disturbances and measurement noises. We implement a counterexample-guided synthesis strategy that combines Bounded Model Checking, linear programming, and sampling-based motion planning techniques. We illustrate our approach and the toolbox throughout the paper with a motion planning example for a vehicle with noisy localization. The code is available at https://codeocean.com/capsule/0013534/tree.

\section{I. INTRODUCTION}

The recent decade has seen more intelligent systems in our day-to-day lives, but many of them are still pre-programmed or only work well in controlled environments. Next-generation intelligent systems need to recognize their surrounding environments, make predictions of the environment behavior, and purposely take actions to improve confidence in their belief of environment states. This process is known as an active perception: the intelligent system explicitly explores the environment to collect more information about the environmental behavior \cite{1}.

Since the process of active perception involves both actions and perceptions, we propose to specify an active perception task as probabilistic signal temporal logic (PrSTL) formulas, which combine real-time temporal logic with chance constraints. Then the active perception problem can be solved as a controller design for a given PrSTL specification with uncertain and differential constraints.

Existing PrSTL controller synthesis methods include mixed-integer Second-Order Cone Programming (SOCP) \cite{2,3}, sampling-based optimization \cite{4}, and heuristic-search based \cite{5}. SOCP and sampling-based methods provide satisfying controllers for a convex fragment of PrSTL, but do not incorporate a perception model in the system dynamics. Thus these algorithms cannot synthesize controls to gather more information, and therefore are not considered active perception methods.

In this paper, we introduce idSTLPy: a software toolbox for active perception and control developed based on our recent work in \cite{6,7}. This toolbox is an open-source software package for designing the trajectory of an intelligent system with active perception from temporal specification and hybrid dynamics. Unlike other methods, this toolbox synthesizes controllers that consider the effects of observation on the belief dynamics. Hence, the planned trajectory includes motions that reduce the uncertainty about the state variables to achieve the task, i.e., active perception.

Our current development is inspired by several toolboxes for symbolic control in the literature, such as TuLip \cite{8}, Linear Temporal Logic MissiOn Planning (LTLMoP) \cite{9} and Open Motion Planning Library \cite{10}, which support the design of controllers for deterministic hybrid systems from Linear Temporal Logic (LTL) formulas. However, to our best knowledge, idSTLPy would be the first toolbox that tackles active perception and control for stochastic systems.

The current version of idSTLPy models the stochastic system behavior as a switched linear system with Gaussian noises. This model allows us to inherit the computational efficiency and soundness of Kalman filtering. Additionally, these systems help to represent complex behaviors of physical systems interacting with logical rules or controllers. Therefore, these switched systems allow us to model several real-life problems.

The software is written in Python. Our basic idea is to combine Bounded Model Checking (BMC) with sampling-based motion planning to separate logical and dynamical constraints. We propose abstractions that approximate the belief dynamics. Unlike other methods, this toolbox synthesizes controllers that consider the effects of observation on the belief dynamics. Hence, the planned trajectory includes motions that reduce the uncertainty about the state variables to achieve the task, i.e., active perception.

This paper is structured as follows: Section \textbf{II} briefly describes the preliminaries, Sections \textbf{III} and \textbf{IV} give the overview of the toolbox with an example. Finally, Section \textbf{V} concludes the work.

\section{II. PRELIMINARIES}

\textbf{A. System}

We consider switched linear control systems as follows:

\begin{equation}
\begin{aligned}
x_{k+1} &= A_{q_k} x_k + B_{q_k} u_k + W_{q_k} W_k, & W_k \sim \mathcal{N}(0, I) \\
y_k &= C_{q_k} x_k + n_{q_k}(x_k) V_k, & V_k \sim \mathcal{N}(0, I),
\end{aligned}
\end{equation}

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where \( x_k \in \mathbb{R}^n \) are the state variables, \( u_k \in \mathcal{U} \subseteq \mathbb{R}^m \) are the input variables, \( \mathcal{U} \subseteq \mathbb{R}^m \) is a polytope, \( y_k \in \mathbb{R}^p \) are the output variables. Each system location \( q \in Q = \{1, 2, \ldots, N\} \) is defined by a noise function \( q : \mathbb{R}^n \to \mathbb{R}^n \), and constant matrices \( A_q \in \mathbb{R}^{n \times n}, B_q \in \mathbb{R}^{n \times m}, \) and \( C_q \in \mathbb{R}^{p \times n} \) with proper dimensions. We assume that the system is subject to mutually uncorrelated stationary Gaussian additive disturbances \( V_k \sim \mathcal{N}(0, I_n) \) and \( W_k \sim \mathcal{N}(0, I_p) \), where \( I_n \) is the identity matrix with dimension \( n \). Note that this dynamical system can arise from linearization and sampling of a more general continuous system. In such a case, we denote the sampling period as \( T_s \), where \( T_s = t_{k+1} - t_k \) for all \( k \in \mathbb{N}_{\geq 0} \). We assume that the uncertainty is stable, meaning that the uncertainty does not increase infinitely over time.

### B. Trajectory

The system in Eq. (1) is probabilistic. This means that the dynamics result into a random process \( X_k \) that represent probabilities over the state variables \( \text{prob}(X_k = x_k) \). We call this random process as belief state. A belief trajectory \( \beta \) is defined as a sequence \( X_0, q_{0:k}, u_{0:k}, Y_k \ldots \) A transition \( X_k \xrightarrow{q_k,u_k} X_{k+1} \) represents the process of applying a command \( q_k \in Q \) and input \( u_k \in \mathcal{U} \) at instant \( k \) and waiting for an observation \( y_{k+1} \) at instant \( k + 1 \) to update the next belief state \( X_{k+1} \).

### C. Probabilistic Signal Temporal Logic

We specify the requirements of a system belief trajectory using PrSTL formulas. These formulas are defined recursively according to the following grammar:

\[
\phi := \pi_k^1 \lor \pi_k^2 \lor \phi_1 \land \phi_2 \\
\varphi := \phi_1 \lor \phi_2 \lor \phi_1 U_0 \lor \phi_2 \lor \phi_1 R_0 \varphi_2 \lor \phi_2 R_0 \varphi_2,
\]

where \( \pi \) is a predicate, \( \varphi_1, \varphi_2, \) and \( \varphi_3 \) are PrSTL formulas, and \( \phi_1, \phi_2, \) and \( \phi_3 \) are PrSTL state formulas. Predicates can be one of two types: atomic and probabilistic. An atomic predicate \( \pi_k \) is a statement about the belief system locations and is defined by a subset \( Q \subseteq Q \) of locations. A probabilistic predicate \( \pi_k^k \) is a statement about the belief \( X_k \) defined by a linear function \( \mu : \mathbb{R}^n \to \mathbb{R}^n \) and a tolerance \( \epsilon \in [0, 0.5] \). The operators \( \lor, \land, \) \lor \land \) are Boolean operators, conjunction, and disjunction, respectively. The temporal operators \( U \) and \( R \) are LTL operators until and release, respectively. In PrSTL, these operators are defined by an interval \( [a, b] \subseteq \mathbb{N}_{\geq 0} \). We assume that PrSTL state formulas forms a full-dimensional region in the state space \( \mathbb{R}^n \).

We denote the fact that a belief trajectory \( \beta \) satisfies an PrSTL formula \( \varphi \) with \( \beta \models \varphi \). Furthermore, we write \( \beta \models k \varphi \) if the trajectory \( X_k \xrightarrow{q_k,u_k} X_{k+1} \ldots \) satisfies \( \varphi \). Formally, the following semantics define the validity of a formula \( \varphi \) with respect to the trajectory \( \beta \):

- \( \beta \models k \pi_k^k \) if and only if \( k = 0 \) or \( q_{k-1} \notin Q \).
- \( \beta \models k \pi_k^2 \) if and only if \( p(\mu(x_k) \leq 0) \geq 1 - \epsilon \).
- \( \beta \models k \varphi_1 \lor \varphi_2 \) if and only if \( \beta \models k \varphi_1 \) or \( \beta \models k \varphi_2 \).
- \( \beta \models k \varphi_1 \land \varphi_2 \) if and only if \( \beta \models k \varphi_1 \) and \( \beta \models k \varphi_2 \).
- \( \beta \models k \varphi U_{[a,b]} \) if and only if \( \beta \models k \varphi \) for all \( \exists k' \) s.t. \( k + a \leq k' \leq k + b \), \( \beta \models k' \varphi_2 \), and \( \beta \models k \varphi_1 \land \varphi_2 \).
- \( \beta \models k \varphi R_{[a,b]} \) if and only if \( \beta \models k \varphi_1 \) and \( \beta \models k' \varphi_2 \) for all \( \exists k' \) s.t. \( k + a \leq k' \leq k + b \), \( \beta \models k \varphi_1 \land \varphi_2 \).
- \( \beta \models k \varphi \) if and only if \( \beta \models 0 \varphi \).

where the temporal operators are indexed by its delay \( a \in \mathbb{N}_{\geq 0} \) and deadline \( b \in \mathbb{N}_{\geq 0} : a < b \leq \infty \). We can derive other operators such as \( true(\equiv \pi^0) \), \( false(\equiv \pi^\bot) \), always \( (\equiv_{[a,b]} \pi = \bot R_{[a,b]} \varphi) \) and eventually \( (\equiv_{[a,b]} \pi = \forall U_{[a,b]} \varphi) \).

### D. Problem Formulation

A practical problem definition for active perception and control synthesis from PrSTL specification is a feasibility problem of the form:

\[
\text{find } \xi \text{ s.t. } \xi \models \varphi, \text{ prob}(X_0 = x) \sim \mathcal{N}(\bar{x}, \Sigma^x), \\
X_{k+1} = A_{q_k} X_k + B_{q_k} u_k + W_{q_k} W_k, \\
Y_k = C_{q_k} X_k + n_{q_k}(x_k) V_k, \\
y_{k+1} = \text{arg max prob}(Y_{k+1} = y_{k+1} | X_k, q_k, u_k), \\
q_k \in Q, u_k \in U, W_k \sim \mathcal{N}(0, I_n), V_k \sim \mathcal{N}(0, I_p),
\]

where \( \xi \) is a belief trajectory, \( \varphi \) is a PrSTL formula, \( \text{prob}(X_0 = x) \) is the initial condition (a priori belief), and \( \text{arg max}_{y_{k+1}} \text{prob}(Y_{k+1} = y_{k+1} | X_k, q_k, u_k) \) is a practical approximation called Maximum Likelihood Observation (MLO) \( [11] \), \( [7] \).

### III. dSTLPy Overview

Our toolbox implements the approach in \( [7] \) illustrated in Fig.\ref{fig}. The basic idea is to construct deterministic abstractions (i.e., TS and \( T^S \)) and to use counterexample-guided synthesis \( [12], [13] \) to satisfy both the PrSTL specification \( \varphi \) and the dynamics of System \( [11] \). Two interacting layers, discrete and continuous, work together to overcome nonconvexities in the logical specification \( \varphi \) efficiently. At the discrete layer, a discrete planner acts as a proposer, generating discrete plans by solving a BMC \( [14], [15] \) for the given specification (i.e., \( (\varphi\text{LTL}) : TS \times TS_{fair,1} \times \cdots \times TS_{fair,N} = \mathcal{E}(\varphi\text{LTL}) \)). We use an iterative deepening search to search first for shorter satisfying plans, thus minimizing undue computation. We pass the satisfying discrete plans to the continuous layer, which acts as a teacher. In the continuous layer, a sampling-based search is applied to check whether a discrete plan is feasible. If the feasibility test does not pass, we construct a counterexample (i.e., \( TS_{fair,i} \)) to discard infeasible trajectories. Then we add this counterexample to the discrete planner and repeat this.
process until we find a solution or no more satisfying plans exist.

In this approach, we proposed a SPARSE-RRT [16] – a sampling-based motion planning variant for active perception. The execution of this method is defined by a timeout in seconds (rTt_timeout), a distance to consider that two states are near (delta_near), a distance to drain near states (delta_drain), a goal bias (goal_bias), a minimum (min_num_of_steps) and a maximum (max_num_of_steps) number of steps for each iteration. Intuitively, for each candidate solution, we execute the proposed RRT for rTt_timeout seconds. During the execution, we randomly sample a state and take an existing trajectory that the last state is sufficient near (delta_drain) and has less uncertainty (i.e., active perception). Next, we randomly select a target state with probability goal_bias to be in the goal (i.e., task planning) and synthesize control inputs for an horizon between min_num_of_steps and max_num_of_steps. If the new trajectory has the last state to be in the goal (i.e., task planning) and synthesize control inputs for an horizon between min_num_of_steps and max_num_of_steps. If the new trajectory has the last state to be in the goal (i.e., task planning) and synthesize control inputs for an horizon between min_num_of_steps and max_num_of_steps.

A. Systems

A system (a.k.a., switched system) is composed of a finite set of system modes. Each system mode is also a dynamical system that inherit the behavior of a linear control system (LCS, i.e., \( x_{k+1} = Ax_k + Bu_k \)) as illustrated in Fig. 2. We can have three types of dynamical behavior. If the output dimension is zero, i.e., \( p = 0 \), the system mode is a linear belief system (LBS). In this behavior, there is no active perception because we assume no observation. Otherwise, if the output dimension is non-zero (i.e., \( p > 0 \)), we have a partially observable linear belief system (POLBS). In turn, a POLBS can have a linear noise function (POLBSWithLinNoise, i.e., \( n(x) = V \)) or a nonlinear noise function (POLBSWithNonLinNoise).

We can create any one of the linear belief systems using the function mk_lbs(A, B, W, C = None, V = None), where \( C \) and \( V \) are optional parameters, and \( V \) can be a constant matrix or a function that returns a matrix. Similarly, we can construct a switched system using the function sys.mk_switched_sys(system_modes), where system_modes is a list of linear belief systems. We declare a dynamical system in our example in Listing 1 lines 8-12.

B. Variables

Due the hybrid nature of switched systems, we have two variable types: real-valued and discrete. As illustrated in Fig. 3 a real-valued variable is also a linear expression. A linear expression over a variable \( x \in \mathbb{R}^n \) is a multiplication between a constant vector \( h \in \mathbb{R}^n \) and the variable plus a constant \( c \in \mathbb{R} \): \( h^T x + c \). For example, variable \( x \in \mathbb{R}^2 \) is also...
import idstlpy as stl
import numpy as np

q = stl.mk_variable(size=1, dtype=int)
x = stl.mk_variable(size=2, dtype=float)
u = stl.mk_variable(size=2, dtype=float)

problem = stl.Problem(
    switched_system=stl.mk_switched_sys(
        A=np.identity(x.size), B=0.25 * np.eye(x.size, u.size), W=np.zeros((2, 2)),
        C=np.identity(2), V=lambda state: ((1 / 10) * (5 - state[0]) ** 2 + 0.001) * np.identity(2))
    ),
    control_domain=stl.logical_and(u[0] >= -1.0, u[0] <= 1.0, u[1] >= -1.0, u[1] <= 1.0).region,
    initial_state=stl.to_belief(mean=np.array([0, 2.5]), cov=np.diag([0.1, 0.1]))
    stl_formula=stl.until(
        stl.logical_and(q == 0, stl.prob(x[0] >= -1) >= 1 - 0.01, stl.prob(x[0] <= 5) >= 1 - 0.01,
        stl.prob(x[1] >= -1) >= 1 - 0.01, stl.prob(x[1] <= 4) >= 1 - 0.01, name='free_space'),
        0, 240,
    ),
    always(0, 40,
        stl.logical_and(q == 0, stl.prob(x[0] >= -0.25) >= 1 - 0.05, stl.prob(x[0] <= 0.25) >= 1 - 0.05,
        stl.prob(x[1] >= -0.25) >= 1 - 0.05, stl.prob(x[1] <= 0.25) >= 1 - 0.05,
        name='target'))
)

solution = problem.solve(rrt_timeout=60, delta_near=2, delta_drain=0.5, goal_bias=0.25,
    min_num_of_steps=3, max_num_of_steps=15)

for i in range(problem.switched_system.system_modes.size):
    problem.switched_system.system_modes[i].compute_finite_horizon_lqr(horizon=5, Q_final=np.identity(2), Q=np.identity(2), R=0.05*np.identity(2))

xi_sim, xi_real = problem.switched_system.simulate(
    reference_trajectory=solution, num_of_steps=solution.num_of_steps, real_initial_state=np.array([0.5, 2.75]),
    real_system=stl.mk_switched_sys([stl.mk_lcs(A=np.identity(2), B=0.25 * np.identity(2))])
)

Listing 1: Motion Planning Example

C. Constraints

An PrSTL formula atom is a constraint over the discrete and real-valued variables. We illustrate the inheritance of different constraint objects in Fig. 4. We call a constraint defined as an equality over discrete variables \( q = \alpha \) as discrete predicate (DiscretePredicate implements \( \pi_\alpha \)), where \( \alpha \in \mathbb{N} \). On the other hand, if the constraint is defined over a real-valued variable, this constraint is convex (ConvexConstraint). Particularly, a linear inequality over the variable (i.e., \( h^T x + c \leq 0 \)) is a linear predicate (LinearPredicate). Similarly, a inequality over the probability of a linear predicate (i.e., \( \text{prob}(h^T x + c \leq 0) \geq 1 - \epsilon \)) is a probabilistic linear predicate (ProbabilisticLinearPredicate).

We can apply the Boolean conjunction operator \( \wedge \) over and probabilistic linear predicates (i.e., the function \( \text{logical_and}(*args) \)). The resulting constraint is a convex

\[^1\text{In Python language, } *args \text{ means a variable number of arguments.} \]
region over the state (if arguments are LinearPredicates) or belief state space (if arguments are ProbabilisticLinearPredicate). A convex region has a property that defines a polytope or a belief cone as illustrated in Fig. 5. We declare a convex region and take its region that defines the input domain (a polytope) in our example in Listing 1 line 13.

1) Polytopes: A polytope $\mathcal{P} \subseteq \mathbb{R}^n$ is a set in $\mathbb{R}^n$ defined by the intersection of a finite number of closed half-spaces, i.e., $\mathcal{P} := \bigcap_i \{x \mid \mu_i(x) \leq 0\}$, where $\mu_i \in H(P)$ is a linear function $\mu_i : \mathbb{R}^n \rightarrow \mathbb{R}$ such that $\mu_i(x) := h_i^\top x + c_i$, $H(P)$ is the set of linear functions that defines the polytope $P$, $h_i \in \mathbb{R}^n$ and $c_i \in \mathbb{R}$ are constants. We can also represent a compact polytope $\mathcal{X} \subseteq \mathbb{R}^n$ as the convex hull of its vertices, i.e., $\mathcal{X} = \text{conv}(V(\mathcal{X}))$, where $V(\mathcal{X})$ is a set of vertices.

2) Belief Cone: We call the reciprocal of polytopes in the belief state space as belief cones. These cones $B \subseteq \mathbb{R}^{n(n+1)}$ are intersection of a finite set of second order cones about the multivariate Gaussian distribution parameters (i.e., mean $\hat{x} \in \mathbb{R}^n$ and covariance $\Sigma_x \in \mathbb{R}^{n \times n}$) that satisfies a conjunction of a finite set of probabilistic linear predicates (i.e., $\bigwedge_i \text{prob}(\mu_i(x) \leq 0) \geq 1 - \epsilon_i$). For simplicity, we will denote that a Gaussian random variable $X_k \sim \mathcal{N}(\hat{x}_k, \Sigma_x)$ satisfy a probabilistic linear predicate $\text{prob}(\mu_i(x) \leq 0) \geq 1 - \epsilon_i$ by $X_k \models \mu_i(x) \leq 0 \geq 1 - \epsilon_i$. Therefore, a belief cone is defined as:

$$B := \{b \in \mathbb{R}^{n(n+1)} : \bigwedge_i X_k \models \text{prob}(h_i^\top \hat{x}_k + c_i \leq 0) \geq 1 - \epsilon_i\}$$

$$:= \bigcap_i \{h_i^\top \hat{x}_k + c_i + \Phi^{-1}(1 - \epsilon_i)\sqrt{h_i^\top \Sigma_x h_i} \leq 0\},$$

(5)

where $b \in \mathbb{R}^{n(n+1)}$ is the Gaussian distribution parameter variable, $h_i^\top \in \mathbb{R}^n$, $c_i \in \mathbb{R}$ and $\epsilon_i \in [0, 0.5]$ are constants, $\Phi(v)$ and $\Phi^{-1}(p)$ are the cumulative distribution and quantile functions of the standard Gaussian distribution $V \sim \mathcal{N}(0, 1)$, i.e., $\Phi(v) = \text{prob}(V \leq v)$ and $\Phi^{-1}(p) < v$ if and only if $p \leq \Phi(v)$. We can easily see that $X_k \models \text{prob}(h_i^\top \hat{x}_k + c_i \leq 0) \geq 1 - \epsilon_i$ if and only if $h_i^\top \hat{x}_k + c_i + \Phi^{-1}(1 - \epsilon_i)\sqrt{h_i^\top \Sigma_x h_i} \leq 0$ from Gaussian distribution properties such as linear transformation and the quantile function definition.

D. PrSTL formula

We implement a PrSTL formula as classes shown in Fig. 6. An STLAtomicProposition implements a PrSTL state formula $\phi$, meaning that it represents the conjunction (i.e., $\text{logical_and}(*args)$) over a list of ProbabilisticLinearPredicate and Boolean formula (i.e., using $\text{logical_and}(*args)$ or $\text{logical_or}(*args)$) over DiscretePredicate, meaning that it is defined by a convex region and a set of valid system modes. In plain English, a trajectory $\xi$ satisfies an STLAtomicProposition at instant $k$ if it reaches a belief state in the convex region using one of the valid system modes. We declare two STLAtomicProposition in our example in Listing 1 lines 16-17 and lines 20-21.

An STLAnd object represent the conjunction (i.e., $\text{logical_and}(*args)$) of a list of STLFormulas containing at most one STLAtomicProposition. On the other hand, an STLOr object is a disjunction (i.e., $\text{logical_or}(*args)$) of a list STLFormulas but containing an arbitrary number of STLAtomicProposition. An STLUntil object is an PrSTL formula with until operator $\varphi_1 U [a, b] \varphi_2$, and STLRelease object is an PrSTL formula with until operator $\varphi_1 R [a, b] \varphi_2$. We obtain these formulas using the functions: until($\varphi_1, a, b, \varphi_2$), eventually($a, b, \varphi$), release($\varphi_1, a, b, \varphi_2$), always($a, b, \varphi$). We declare a formula in our example in Listing 1 lines 15-22.

E. Solution

The object Problem wraps the implementation of the approach presented in Section III. A solution could be empty (None in Python) if the algorithm did not find a trajectory that satisfies the specification. However, if such a trajectory is found, the algorithm returns an object that implements this trajectory. Since the solution is a trajectory of the approximated transition system [7], the returned trajectory is a ProbabilisticTSTrajectory. This object implements methods to extract data from the trajectory such as: get_mean, get_cov, get_control, get_action that returns the belief state mean, the belief state covariance, the control, and the action from the trajectory. We can use these methods to extract a trajectory tracking strategy. We declare a problem in our example in Listing 1 lines 7-23 and solve it in Listing 1 lines 24-25.

We can simulate the execution of this planned trajectory. The planned trajectory is the result of an approximated belief dynamics where the observations are the MLO. Hence, we propose to use a linear feedback law to adjust the belief state during the execution to track the planned trajectory. Specifically, we implemented a receding horizon control (RHC) strategy with a finite horizon discrete time Linear Quadratic Regulator (LQR) to track the belief mean values.
compute_finite_horizon_lqr(horizon, Q_final, Q, R)

for each system mode, where $Q_{final}, Q \in \mathbb{R}^{n \times n}$ are positive-semi-definite contract matrices and $R \in \mathbb{R}^{m \times m}$ is a positive definite matrix. Next, we call the method simulate from SwitchedSystem object. This method simulates the system real_system initialized at real_initial_state for num_of_steps steps while using the linear feedback law to track the planned trajectory reference_trajectory. In the running example, we track the mean of the estimated belief with cost function $J = \sum_{k=0}^{\text{horizon}-1} \hat{x}_k^\top Q \hat{x}_k + \hat{u}_k^\top R \hat{u}_k$, where $Q = I_2$ and $R = 0.05 I_2$ and the horizon $h = 5$, as shown in Listing 1 lines 27-32.

The result is shown in Fig. 7. The blue trajectory is the planned trajectory in the belief space. This trajectory approximates the observation as maximum likelihoods. However, we observe a very different observation during the execution, which is the purple trajectory in the figure. As a result, the belief trajectory during the execution is slightly different, the orange trajectory in the figure. However, this trajectory satisfies the specification, and the resulting state (in red) also is within the expected result. Since the maximum likelihood approximation is close to the most likely belief trajectory, a simple tracking strategy is, in general, sufficient to enforce the planned trajectory during execution.

V. CONCLUSIONS AND FUTURE WORK

In this work, we presented a Python toolbox for controller synthesis from PrSTL specifications. We considered problems with a switched linear system with Gaussian noises. We illustrated our approach on a simulation of robot motion planning under noisy localization. In this example, we showed that the planned trajectory satisfied both the task and active perception requirements.

We will focus on two directions in future work. One direction is to extend to other probabilistic hybrid systems and also consider probabilistic switching. Another direction is to drop the MLO approximation during the planning without a conservative assumption.

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