Gaussian Belief Space Planning for Articulated Robots

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Our work is motivated by applications where robots need to robustly complete navigation and manipulation tasks in the presence of significant uncertainty, which would require the robot to perform information gathering actions in order to minimize the effects of uncertainty. This problem is often formalized as a Partially Observable Markov Decision Process (POMDP), finding globally optimal solutions for which is known to be intractable. *Belief space* planning, which applies traditional planning and control algorithms in an augmented belief space comprising of both the robot state and the uncertainty associated with it, has emerged as an effective approach for computing locally optimal solutions to the POMDP problem [2].

However, for planning in belief spaces, collision detection needs to be performed in a probabilistic sense by considering collisions with respect to all possible states that the robot could be in. Prior work has only considered point robots or spherical approximations of the robot geometry to simplify collision detection in the belief space, thus limiting their applicability. We extend the belief space planning framework to plan for general robots such as articulated robots operating under the assumption of Gaussian models of uncertainty.

Our key insight for dealing with collisions in belief spaces involves the use of *sigma hulls*, which are convex hulls of the robot geometry transformed according to the unscented transform [1] of the Gaussian uncertainty. The unscented transform also serves the dual purpose of propagating the Gaussian belief using an unscented Kalman filter (UKF).

We adopt the approach of Platt et al. [2] to use sequential quadratic programming (SQP) to compute locally optimal trajectories in the belief space. As opposed to the standard practice of dealing with collisions as costs in the optimization framework, which can often lead to tedious parameter tuning for each problem to get out of collision, we strictly enforce them by incorporating them as (hard) constraints using a penalty method [3]. We show that the collision avoidance constraints can be locally approximated by convex constraints using the sigma hulls, and we derive how to efficiently compute this convex approximation analytically.

Fig. 1 provides an overview of our framework for Gaussian belief space planning framework for general robots. We formulate the objective in terms of costs that penalize the uncertainty in the robot state and minimize the total control effort expended along the trajectory. We also impose constraints on the optimization for collision avoidance and to ensure that the belief dynamics are satisfied. The optimization then computes a locally optimal trajectory in belief space. As is standard in nonlinear optimization for control, we follow the model predictive control (MPC) paradigm of re-planning after every time step based on the belief state estimated using observations obtained during execution. This allows the robot to correct for perturbations as they occur while operating under considerable uncertainty.

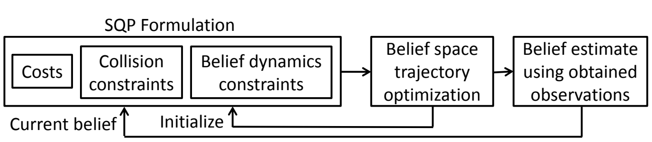
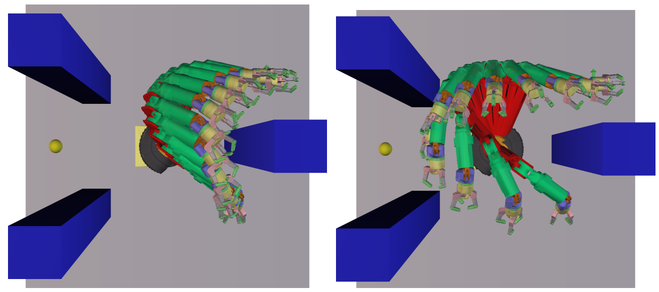


Fig. 1. Overview of our Gaussian belief space planning framework.



(a) (b)

Fig. 2. Simulated trajectory traces for a 7-DOF manipulator (Barrett WAM arm) moving in a constrained environment with obstacles (blue). The robot localizes itself based solely on distance of the robot end-effector from a landmark (yellow sphere) in the environment, with the signal strength decaying quadratically with the distance. (a) Naïve trajectory optimization [3] produces a trajectory that avoids collisions with obstacles but is oblivious to the uncertainty in the robot state. (b) With Gaussian belief space planning, the robot executes a trajectory that leads it first to the landmark for better localization before reaching the target with significantly reduced uncertainty.

Fig. 2 shows the advantages of using belief space planning over naïve trajectory optimization methods [3] for a 7-DOF manipulator moving in a constrained environment with obstacles. Belief space planning explicitly accounts for the uncertainty in the robot state and is able to compute motion plans that maximize information gathering actions (visiting the landmark) to minimize the effects of uncertainty. Our method computes a locally optimal trajectory in a 35 dimensional belief space with a high fidelity articulated robot model in under 10 seconds.

In conclusion, we proposed a method for efficiently dealing with collisions while planning for articulated robots in Gaussian belief spaces using sigma hulls. We believe that this is an important first step to facilitate efficient belief space planning for a large class of robots including household and surgical robot manipulators and humanoid robots.

References

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