# Robot Motion Planning with Uncertainty

The Challenge

The motion of a robot in response to commanded actions often cannot be precisely predicted with certainty. Whether maneuvering a vehicle over unfamiliar terrain, steering a flexible needle through human tissue to deliver medical treatment, or guiding a micro-scale swimming robot through turbulent water, the underlying motions cannot be predicted with certainty. But in many of these cases, a probabilistic distribution of feasible outcomes in response to commanded actions can be experimentally measured. This stochastic information is fundamentally different from a deterministic motion model. Though planning shortest feasible paths to the goal may be appropriate for problems with deterministic motion, shortest paths may be highly sensitive to uncertainties: the robot may deviate from its expected trajectory when moving through narrow passageways in the state space, resulting in collisions. We are developing new methods that explicitly consider the effects of uncertainty and optimize a robot's actions to maximize the probability it achieves its goal.
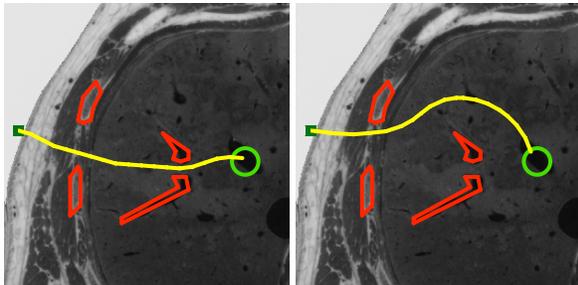
Our planner steers a flexible, bevel-tip medical needle to a simulated clinical target in the liver while avoiding obstacles such as bones and critical vessels. Considering uncertainty (right) more cleanly avoids obstacles and significantly increases the probability of success compared to shortest path plans (left).

The Approach

We have developed a variety of approaches to address this problem. One of them, the Stochastic Motion Roadmap (SMR), is a new motion planning framework that explicitly considers uncertainty in robot motion. The planner takes in as input the obstacles, the goal location, and a motion uncertainty model for the robot. The output is a policy, a plan defined by actions that are a function of the robot's current state at a given time. A plan execution is successful if the robot does not collide with any obstacles and reaches the goal. The idea is to compute plans that maximize the probability of success.

To ensure that the framework is generally applicable to a wide variety of robots and problems, we use a sampling-based approach. Our framework builds on the highly successful approach used in Probabilistic Roadmaps

(PRMs): a learning phase followed by a query phase. During the learning phase, a random (or quasi-random) sample of discrete states is selected in the state space, and a roadmap is built that represents their collision-free connectivity. During the query phase, the user specifies initial and goal states, and the roadmap is used to find a feasible path that connects the initial state to the goal, possibly optimizing some criteria such as minimum length. However, an underlying assumption of prior work is that the collision-free connectivity of states is specified using boolean values rather than distributions.
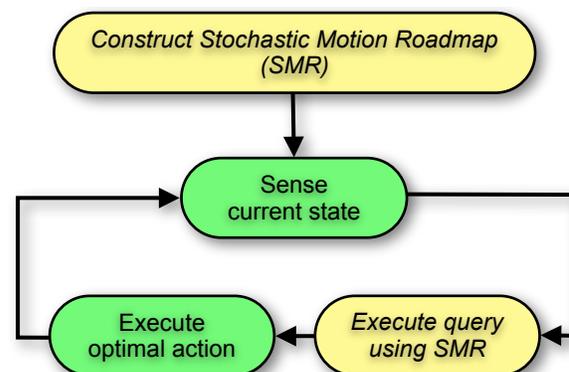

Planner workflow. Stages in italics are implemented in the planning framework while the other stages are performed by the robot.

In our SMR framework, we explicitly consider uncertainty in robot motion by combining a sampling-based roadmap representation of the state space with a stochastic model of robot motion. The input to our method is a geometric description of the workspace and a motion model for the robot capable of generating samples of the next state that the robot may attain given the current state and an action. We require that the motion model satisfy the Markovian property: the distribution of

the next state depends only on the action and current state, which encodes all necessary past history. As in PRMs, the method first learns the state space by generating random samples and checking for collision with obstacles. We then sample the robot's motion model to build a stochastic motion roadmap, a set of weighted directed graphs with vertices as sampled states and edges encoding feasible state transitions and their associated probability of occurrence for each action.

The focus of our motion planning method is not to find a feasible plan, but rather to find an optimal plan that maximizes the probability that the robot will successfully reach a goal. Given a query specifying initial and goal states, we use the SMR to formulate a Markov Decision Process (MDP) where the "decision" corresponds to the action to be selected at each state in the roadmap. We solve the MDP using dynamic programming to generate a plan, which is defined as a policy providing the optimal action to perform given the current state. Because the roadmap is a discrete representation of the continuous state space and transition probabilities, the computed optimal actions are approximations of the optimal actions in continuous space that converge as the roadmap increases in size.

We applied the SMR framework to the medical challenge of steering flexible needles through soft tissues around obstacles to reach clinical targets. Steerable needles, a new class of flexible bevel-tip medical needles being developed, have the potential to enable new medical procedures by allowing clinicians to steer to targets inaccessible to traditional stiff needles. As in many medical applications, considering uncertainty is crucial to success of the procedure: the needle tip may deflect from the expected path due to tissue inhomogeneities that cannot be detected prior to the procedure. Due to uncertainty in predicted needle/tissue interactions, needle steering is ill-suited to shortest-path plans that may guide the needle through narrow passageways between bones or critical tissue such as blood vessels or nerves. By explicitly considering motion uncertainty using an SMR, we obtain solutions that result in possibly longer paths but that improve the probability of success.
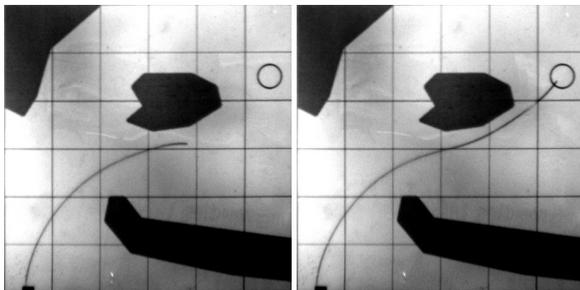
Our planner steers a flexible, bevel-tip medical needle through a physical tissue model with properties similar to real tissues. The needle tip successfully avoids obstacles and reaches a target.

Project Members

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Selected Publications

Jur van den Berg, Sachin Patil, and Ron Alterovitz, "**Motion Planning Under Uncertainty Using Iterative Local Optimization in Belief Space**," *International Journal of Robotics Research*, vol. 31, no. 11, pp. 1263-1278, Sep. 2012.

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Keywords

Robotics; motion planning; path planning, uncertainty; Markov Decision Processes; optimization; medical robotics; steerable needles; minimally invasive surgery; procedure planning

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