Research Topic Proposal

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1 Introduction

Motion planning is a fundamental problem for autonomous robot navigation. While smoothness and optimality of trajectory plays key role in effectiveness of planning and robot's ability to perform complex maneuvers, an ability to plan fast can be critical for navigation in the unknown or changing environments which might include other robots or humans operating in the area. Currently planning in unknown environment constructs a leading edge of research.

2 Related works

The task of planning in high-dimensional space is classified as a PSPACE-hard problem [1]. One way to considerably save in computation time is to sample the configuration space instead of explicitly constructing obstacles. Incremental sampling-based methods PRM* and RRT* [2], found success in this area. Both build a path very fast by uniformly selecting states from a state space and connecting them satisfying feasibility conditions. Unlike their original versions [3], PRM* and RRT* continue searching for shorter path after finding initial one and thus are asymptotically optimal. RRT-Connect [4] is another widely accepted variant, which grows two RRTs from the start and goal states simultaneously. That allows for a very fast search of initial path, but typically not-optimal. Informed-RRT* [5] tackles that problem and incrementally improves the best found trajectory by shrinking the sample space using ellipsoidal heuristic derived from the current best path cost. Recently proposed Informed-RRT*-Connect [6] successfully combines these approaches and builds an algorithm for 2, 3 and 6 Degree of Freedoms (DoFs), that benefits from bidirectional method, path length informed sampling space reduction and pruning operation minimizing the cost function. However, due to stochastic nature of the algorithm initial path can still be heavily sub-optimal even for the obstacle-free environment and lead to longer convergence rate. In case of real-time planning that means that the optimal path might not be found on time.

2.1 Real-time planning

To allow for real-time execution onboard an autonomous agent it is important that the solution is found in less time that is needed for its execution. Trading off search completeness for optimality and speed rapidly exploring random trees proved to be effective in finding a path, typically not optimal, very quickly [4], and further with a proper heuristic applied it can converge to an optimal solution over time. That fits real-time planner requirements very well. Further in their Quad-SDK framework for planning in static environments [7] Joseph Norby et al. show that decoupling of the planning problem, first considering global planning for rigid body trajectory, and then performing the footstep planning, helps reduce the problem complexity and increase both overall convergence rate and quality of the solution.

In anytime planning framework [8] Van Den Berg et al. reuse all prior knowledge about obstacles and plan over space-time space propagating obstacles over time. It was found useful to perform the CoM planning over a static environment while planning collision-free repairing based on the observations of the dynamic obstacles. Similar approach is adapted by Francesco Grothe et al. in recent work [9], where given the full knowledge of the environment dynamic obstacles are propagated over time and planning is performed over space-time state space. Search is performed iteratively for the time planning horizon by building RRT from the start state and RRTs from the goal regions intersected by the horizon.

In [10] Dave Ferguson et al. argue about availability of the complete information about the obstacles and provide another replanning method that allows to retain reusable parts of the RRTs by removing only newly-invalid edges and regrowing the trees to avoid dynamic obstacles. Their implementation was able to solve a joint planning problem for 10 cars trajectories avoiding collisions and static obstacles over a state space of size 10^{54} within 13 seconds. Although these planners make a good advancement towards collision-free planning under uncertainty and even consider multi-agent setup, they still require prior assumptions about the environment and obstacles to reduce dynamic problem to static by obstacles prediction or by assuming partial knowledge of the map.

A good attempt to adjust planning to dynamic environment is made in recent work [11], where Yicheng Chen et al. explore adaptive heuristics for sampling based on the feedback from previous operation. Their algorithm adjusts probability of growing RRT directly to the goal state depending on the presence of the obstacles detected during the previous tree extension. This method converges faster in obstacle-free environment than prior RRT-based approaches but still suffers from blindness in irregular cases when heuristic parameter is forced to be adjusted too often.

2.2 Kinodynamic

Unfortunately in non-holonomic robot models straight-line connections between a pair of states might not lead to a valid trajectory due to the system's differential constraints, but luckily EXTEND operation of an RRT-based algorithm allows to apply any requirements on the trajectory and solve optimization problem or plan kinodynamic motion over an obstacle-free stretch. Provided with the height from the sampled state within this operation the global plan can be supplied with motion primitives for the local planner to plan footsteps.

[12] successfully extends RRT* to Dubins vehicle and double integrator models. Kinodynamic RRT* [13] additionally incorporates cost-to-go term along with the optimal control strategy and solves the two-point boundary value problem per each new state added to the RRT. Authors also suggested that strong correlation of velocity and orientation should be reflected in sampling which can lead to even better convergence rate and smoother solutions. The work [3] implements vector field guided heuristic in application to planning for quadrotors, it shows improvements to smoothness of the trajectory by restricting sampling space to the cone of potential field that directs RRT growth towards the goal state. Kinodynamic approach to planning proposed by [14] steps towards hierarchical planning too and first builds a trajectory for centroidal dynamics, after that validates it according to collision avoidance, bounds on position and dynamic equilibrium, and applies a steering method.

3 Conclusions

Randomized sampling-based planners proved their success in tackling the curse of dimensionality. Among advantages of RRT-based algorithms are rapidness, probabilistic completeness, assymptotical optimality (for optimal variants) and scalability. That makes them a good fit for real-time planning in unknown or dynamic environment. Recently introduced Adaptively Dynamic RRT*-Connect algorithm [11] solves the planning problem for UAV in known environment with dynamic obstacles but its prunning-reconnection mechanism presents a good base for extension for other applications in unknown and dynamic environments given an ability obtain or perceive the immediate surrounding of the robot. In this work Y. Chen et al. make an assumption based on prior sampling result, thus if previously no obstacles were between the newly-sampled node and the tree, the next sampling was pulled closer to the goal state with higher probability. For the area in the proximity of the robot such check and adjustment could easily be done precisely with camera or just LiDAR.

Due to their stochastic nature RRT-based algorithms bring advantage of eventually exhausting all the state space given, even if some areas won't give a meaningful exploration. To tackle that a proper heuristic can help focus or guide the search and reduce the sampling space in the desired direction. In [11] this role played the best path cost, in [3] potential field guided RRT growth towards the goal state. While direct trajectory towards the goal might not be feasible due to obstacles, a better velocity-guided sampling might help build smoother solution. Developing this idea further one might expect that propagating velocity influence from the previous state could smooth the path even further. This can help avoid typical winding paths appearing in RRTs due to its stochastic nature, in cases where a straight line is the obvious best solution. Comparing to the well-known rewiring operation [2], which slows down the search by adding a loop, velocity propagation should add no more than O(1) of additional computational cost.

Furthermore, given the information about initial direction the sampling space can be reduced in the fashion of Informed-RRT* [5] for the initial part of the RRT from the start state. This estimation can be obtained from the onboard sensors. Additionally observable obstacle-free area can allow for direct sampling and steering planning reducing the sampling space for the rest of the path.

Not many global planning approaches take advantage of perception commonly available onboard of many autonomous robots, but this direction is attracting attention in modern research and provides ideas for perception-aware global planning algorithms for kinodynamic systems in dynamic and unknown environments.

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