Evaluation of Sampling-Based Optimizing Planners for Outdoor Robot Navigation

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Abstract—Sampling-Based Optimal(SBO) path planning has been mainly used for robotic arm manipulation tasks. Several research works have been carried out in order to evaluate performances of various SBO planners for arm manipulation. However, not much of work is available that highlights performances of SBO planners in context of mobile robot navigation in outdoor 3D environments. This paper evaluates performances of major SBO planners in Open Motion Planning Library(OMPL) for that purpose. Due to large number of existing SBO planners, experimenting and selecting a proper planner for a planning problem can be burdensome and ambiguous. SBO planner’s probabilistic nature can also add a bias to this procedure. To address this, we evaluate performances of all available SBO planners in OMPL with a randomized planning problem generation method iteratively. Evaluations are done in various state spaces suiting for different differential constraints of mobile robots. The planning setups are focused for navigation of mobile robots in outdoor environments. The outdoor environment representation is done with prebuilt OctoMaps, collision checks are performed between a 3D box representing robot body and OctoMap for validation of sampled states. Several evaluation metrics such as resulting path’s length, smoothness and status of acquired final solutions are selected. According to selected metrics, performances from different SBO planners are presented comparatively. Experimental results show the significance of parallel computing towards quicker convergence rates for optimal solutions. Several SBO methods that take advantage of parallel computing produced better results consistently in all state spaces for different planning inquiries.

Index Terms—Sampling-Based Optimal planning, path planning, outdoor robot navigation.

I. INTRODUCTION

Path planning is one of the essential steps for navigating a robot from its current pose to a desired pose in space while avoiding obstacles. Various approaches to solve planning problem has been proposed over the years. Sampling-Based Optimal(SBO) planning is one of these approaches that got attention of researchers in recent years due to its effectiveness while planning in complex, high dimensional state spaces. SBO planners aims to minimize or maximize an objective function, the ultimate goal is to get a valid plan with the lowest cost or highest award depending on the selected objective function. In SBO planning, the objective function is mostly a cost function, where the amount of cost can be dependent on different properties of the path such as shortness, smoothness or estimated energy consumption along path.

Fig. 1. Sample planning results from evaluated SBO planners in SE3 state space, the ground is uneven hence the contour like shapes

The path planning problem is well studied and established for the most part. However, due to different topological structures and scales of environments, increased dimensions of states for different types of robots, path planning is still a relevant research area particularly in robotics. There isn’t one general method or framework that can cope with all different planning problems, different groups of planners are better suited to different situations. Therefore it is important to systematically evaluate planners for mobile robots rigorously. Lack of work in literature that focuses SBO path planning performance analysis for outdoor robot path planning has been main motivation behind this study. Some of the main contributions of this work are listed as follows.

- To the best of our knowledge, we are first to present a detailed evaluation of SBO planners that particularly focuses on outdoor robot navigation, with realistic planning times towards actual application. Evaluations are carried out for robots with different kinematic constrains.
- We present comparative results from all major SBO planners with randomized iterative approach that can better capture behaviour of probabilistic SBO planners.
- The environment representation enables to analyze response of SBO planners for navigation in 3D, plans can go through light ramps, slopes and elevations within defined boundaries.
This paper is a result of an empirical study of state-of-the-art SBO planners and their behaviours under different state spaces. The evaluations are performed in different state-spaces suited for all well known robot kinematics. In section III gives a brief overview of SBO planners subject to evaluation, in section IV the metrics and setup for evaluation are described. Finally, in section V a discussion related to acquired results and in section VI conclusions drawn from this study are provided.

II. RELATED WORK

SBO planning methods are extended on top of basic path planning algorithms into more challenging scenarios and diverse applications [9]. Complete path planning algorithms existed as early as 1979 [24], but the complexity of the these approaches made it hard for practical use. With arrival of cell decomposition methods such as Brooks and Lozano-Perez [5] and Potential Fields methods [20] the requirement of completeness was relaxed to resolution completeness, that is the algorithm will return a valid path if one exists with a finely set resolution for the decomposed cells representing environment. These algorithms proved to work well in practical use cases [12]. However, for the problems with higher number of dimensions and scales, cell decomposition based methods suffered due to increasing number of cells which caused impractical computation times. Cell decomposition methods used a complete representation of the environment it operated in. A predefined complete representation of environment resulted in extensive computation time, making these methods unfeasible for high dimensional state spaces.

This led to development of Sampling-Based(SB) planners such as Kavraki and Latombe [18], Kavraki et al. [19] and LaValle [22]. Instead of relying on full representation of the environment, SB methods samples a series of states while performing a collision check for each of this state to ensure validity of generated states. The way each of SB planner samples a state differs. The probabilistic characteristic of these methods contradicts with completeness of these methods. However, SB planners are probabilistically complete [19] meaning that, if a valid solution exists the planner will return one as the number of sampled states approaches to infinity [2]. Initial SB planners were not cost-aware, however with introduction of novel methods by Karaman and Frazzoli 2011 [17], a new milestone that led to numerous research efforts on SBO planners was reached. In next section we enhance our discussion on SBO planning in next section, each SBO planner subject to our evaluation is highlighted with its unique property.

III. SAMPLING-BASED OPTIMAL PLANNERS

Planning is a core component of autonomous robot’s software stack alongside Perception and Control. It is a process of estimating series of consecutive valid, collision-free states(or poses) that will drive the robot to a desired pose safely. Here, SBO approach might be particularly useful while planning in mid-scale outdoor environments (e.g. 100 x 100 meters) with 3D structures such as ramps, elevations that can’t be represented in 2D, hence inconvenient to use 2D grid cell based methods for such environments. In following we take a close look at existing SBO Methods and their characteristics.

Two of well established Sampling-Based(SB) planners are Rapidly-Exploring Random Trees(RRTs) [22], and Probabilistic RoadMaps(PRMs) [19]. Although employing some common structures RRTs and PRMs differs from each other in the way they construct a graph(or tree for RRT) for connecting start $S_{start}$ to goal $S_{goal}$ pose. A major difference of PRM over RRT is that it can be used as multiple-query planner, while RRT is suited for single-query online planning. Depending on characteristic of the environment this can be useful or vice-versa. A robot that operates in a highly dynamic environment, may not benefit much from the multiple-query feature of PRMs, whereas an online single-query RRT could be practical.

Generating a valid plan with an SB planner is possible (if one exists) most of the time. Several variants of RRTs has been deployed to robotic platforms [4], [30], and it has been proven useful for practical use cases. In many cases though, the quality of this valid paths are crucial to the overall behaviour of a system. Therefore, it is important to systematically define and evaluate quality of a generated path. SBO path planning tries to address this by using various optimization techniques.

On the high level, SBO planners operates similarly, that is by randomly sampling a series of states in the state space, making sure that generated states are valid(collision-free). A path is then constructed by connecting start state $S_{start}$ to a goal state $S_{goal}$ through sampled valid states with the minimal cost. Below we list some common procedures that a typical SBO planner employs.

- **Sampling**: It is a process of generating sample states in the state space, the randomized state generation has proved to greatly simplify planning in high dimensional state spaces.
- **Objective cost calculation**: At this step, the aim is to find a numerical cost of taking robot from a state $S_a$ to $S_b$. The calculation of this cost will depend on the defined objective, e.g. for path length, this cost can be Euclidean distance between $S_a$ and $S_b$.
- **Collision checking**: It is mostly a Boolean function, which checks whether a defined robot body volume is in collision with its environment at a sampled state. This step takes most part of execution time [15].
- **Nearest neighbor search**: Based on selected objective cost, this procedure calculates nearest neighbor or minimal cost to a newly generated sample.

Some initial works towards SBO planning relied on different heuristics, e.g. by using a biased model to grow RRTs in low-cost regions [53]. Berenson et al. introduced Transition-RRT(T-RRT), which was designed to steer the exploration of RRT by considering stochastic global optimization method.

Karaman and Frazzoli [17] extensively investigated optimality of popular SB methods, RRTs and PRMS. The analysis
concludes that the resulting solutions by these planners under normal circumstances converges to a non-optimal value almost at all times. Despite this fact, the authors purposed two new milestone approaches known as RRT* and PRM*. These two planners are provably asymptotically optimal, meaning that the cost returned by these planners converges to optimum value almost at all times. The proof of asymptotic optimality led to whole another effort in order to improve the quality guarantees of SBO planners. Recent works focused on improving the convergence rate to optimality and better initial solutions. Some essential properties of RRT* and PRM* can be summarized as follows.

**RRT***:

RRT* differs from original implementation in a sense it restructures the tree by considering the total cost of that particular sample to the start state, whereas in RRT a valid newly sampled state is just added to the nearest node in the tree. This property makes RRT* path cost-aware and leads much shorter and smoother paths with a cost of increased computation.

**PRM***:

PRM* does not sample states with a fixed radius as in PRM; instead the radius is set to be a function of state space dimensions and characteristic of state space. This leads to sparse and quick exploration of large collision free areas, as well dense exploration in narrow nooks finally leading increased exploration capabilities.

Other SBO planners subject to evaluation in our work bases on above two with slight modifications, we will lightly mention their general characteristics. LazyPRM* is a combination of [17] and [3]. Number of nodes to connect are not fixed but is determined automatically based on coverage of the state space [33]. SPARS [7] and SPARStwo [6] are also built on top of PRM*, these methods suggest finite-sized nodes within roadmap which might provide near-optimality properties. If the optimality is relaxed to near-optimality, sparser graphs can provide solutions meeting near-optimality requirement. This lead to several advantages such as reduced resources used to solve the planning problem and decreased rate of node addition into roadmap.

RRTX [27] is a variant of RRT*, the nodes in the tree are rewired only if the cost is being reduced by a specified margin (known as epsilon), this improves the convergence of solution. RRTsharp [1], bases on Rapidly-exploring Random Graphs(RRG), it improves the convergence rate by keeping stationary information of sampled vertices, by doing this RRTsharp can achieve better estimations of potential optimal paths. InfromedRRT* [11] narrows down tree exploration space to boundaries of a prolate hyperspheroid, a prolate hyperspheroid is n-dimensional symmetric ellipse that is constructed around current optimal plan. As the search space is reduced to region around optimal plan, the converge rate improves significantly. SST [23], an enhancement of RRT* tries to address optimal kinodynamic planning when there is no access to two-point boundary value problem(BVP) solver, BVP is required to get desirable property for systems with dynamics.

A more recent SBO approach, Batch Informed Trees (BIT*) [10] uses a unified structure that is composed of both graph and trees, this leads to a few advantages such as being able to use heuristics like one in A* [13] to prioritize tree expansions towards the goal with high quality paths. An extension of BIT*, Advanced BIT*(ABIT*) [32], combines an advanced graph-based search with an RRT* like planner for faster convergence rate. Another variant of BIT*, AIT* [31], uses an asymmetric bidirectional search where both of the searches continuously inform each other, this leads to quicker initial solutions.

According to authors [16] Fast Marching Tree (FMT*) is an SBO planner that converges to optimal solutions faster than PRM* and RRT*. The approach utilizes recursive dynamic programming to form a tree from probabilistically sampled states.

Anytime solution optimization by Luna et.al. [25] is a generic method that wraps around one or more SBO planner. The method applies an iterative path simplification, shortening process. In case of multiple SBO planner, it is capable of generating hybrid paths if they are to yield shorter solutions. Another approach CFOREST [26], wraps a parallelized framework around single-query SBO planners e.g. RRT*. Separate trees are grown from different threads while these threads communicate with each other, every time a better path is found by a thread, other threads are also informed. This leads a significant speedup of convergence towards optimal plans. The end result paths are shorter and smoother.

### IV. Experiments

#### A. Evaluated Planners

OMPL is an open source C++ library that contains many of state-of-the-art SBO planning algorithms. Its abstract interface allows for quick deployment of many SB and SBO planners with little effort in terms of lines of code. At the time of writing, all available SBO planners in OMPL (see Table I) [33] were selected for the evaluation. These includes very recent SBO planners such as AIT* [31], ABIT* [32]. All SBO planners were evaluated with their default settings. Planners with parallelization capabilities such as CFOREST and AnytimePartShortening(APS) were used with 8 instances of RRT* in the background.

#### B. Scenarios and Evaluation Setup

For the collision checking, we use Flexible Collision Library(FCL) [28]. The environment is represented with an OctoMap [14], a memory efficient tree data structure that holds 3D occupancy information of environment in a probabilistic manner. Collision checking is performed between a 3D bounding box that represents robot body and a prebuilt OctoMap of the environment. We evaluate planners in OctoMaps which were generated from Gazebo [21] simulator.
The simulated environment may consists of an even/uneven ground plane with various objects such as houses, lamb posts and plants in. Figure 1 shows an corresponding OctoMap of such environment with sample results from several SBO planners.

During the experiments, we use a randomized goal and start pose generation within defined state space boundaries. The validity of these start and goal poses were acquired by collision check status between a 3D box representing robot’s body and OctoMap at start and goal poses. In order to make sure that an actual valid plan exists between randomly generated start and goal poses, a planning request was made from start to goal pose with a sufficient amount of timeout (10 seconds).

The actual benchmarking was initialized only if there existed a valid plan from random start to random goal pose. In Final phase, RRT* planner with a very large amount of timeout (500 seconds) was used to create a ground truth plan, this ground truth plan was used as base for comparison of results from all SBO planners.

The length of ground truth plans and resulting plans from SBO planners were normalized to 100 meters as seen in Figures 2, 6. This allows to simpler interpretation of SBO planner’s performance for length objective.

The planners are evaluated in various state spaces; SE3, SE2, REEDS-SHEEP [29], DUBINS [8]. The variety of these state spaces are intentionally selected to meet existing kinematic structures of grounds robots, e.g. Differential-Drive, Omni-Drive, Ackermann etc. as well as to confirm consistency of planners under different constrains. Paths in REEDS-SHEEP [29] and DUBINS state spaces particularly suits robots with Ackermann kinematics. We also perform evaluations in SE3 for uneven terrains such as one depicted in Figure 1. The benchmark scripts are written in C++ and are interfaced with OMPL. A YAML file format is used to specify and configure parameters for different state spaces and other parameters benchmarks requires. This allows efficient testing of different planners in various state spaces. All configuration parameters are highlighted below, description of each parameter is given in red color.

| Planner | configuration |
|---------|---------------|
| RRT*    | # amount of time allowed for planner to get a solution |
| LazyPRM* | interpolation parameter 120 # uniformly interpolate the final path |
| octomap | "octomap" # ROS topic to subscribe for an OctoMap |
| selected_state_space | "SE2" # other options are; "OMPL","SE3","SE2" |
| selected_planners | ["RRT*", "PRMstar", ...] # includes all planners given in Table 1 |
| state_space_boundaries | # sampling is always within these boundaries |
| sample | # in meters |

### C. Evaluation metrics

There are few important metrics to assess quality of resulting plans. Most essential ones being the length, execution time, availability of exact solution etc. SBO planner’s execution time is quite ambiguous and needs an explanation here. SBO planners uses a timeout parameter, initially some amount of this time is used to construct a valid plan (if one exists), after a valid plan is found the remaining time is utilized for getting lower cost paths, at the end all time is utilized. Despite being crucial indicator of a planner’s performance, we cannot really set execution time as a metric since SBO planners utilize all given time to construct most optimal plan even after a valid plan is found. All planners timeouts were set to 1 second for all state spaces. Metrics of evaluation and their short descriptions are given as follows.

- **status**: whether a solution (exact or approximate) was found
- **solution length**: real length of the resulting solution path
- **solution smoothness**: the smoothness of path is calculated by sum of angles between consecutive path segments, the lower this sum the smoother path is. For instance a perfectly straight line will result in smoothness value of 0.0

### V. Discussion and Results

It must be noted that given enough amount of timeouts, each planner’s performance will be reasonable and similar. Therefore we used a rather strict timeout amount of 1 second to challenge and reveal performance differences among SBO planners. We generated 25 random planning problems with minimum euclidean distance between start and goal pose being 85 meters. To reduce bias related to probabilistic nature of planners each planner was inquired to make a plan for each problem 4 times, resulting total number 100 runs. The resulting figures are presenting results from 100 runs.

DUBINS and REEDS-SHEEP spaces are suitable while planning for car-like robots. DUBINS state space particularly suits for forwards-only motions while REEDS-SHEEP also allows backwards motions in generated plans. SE3 state space was considered for evaluating planners in non-flat environments, e.g. in figure 1. In SE3, the resulting paths z axis can elevate/decrease within defined boundary. As can be seen from Figures 2 and 6, planning in motion constrained space is much harder. Compared to SE2, the lengths and smoothness
In general, planners perform better in relaxed SE2 and SE3 compared to DUBINS and REEDS-SHEEP in terms of providing a valid plan with given amount of time, this can be best seen from performance of FMT in figure 6 compared to figure 2. CFOREST and APS’s parallelization approach seems to have a significant effect for quicker convergence towards optimal plans. In case of increased complexity in state spaces, as in DUBINS or SE3, FMT* planner was not able to provide a valid plans within required timeouts. In simpler cases though(e.g. SE2) FMT* was able to provide valid plans.
with average lengths and smoothness, see figures 7, 8 and 10. SBO planners that are variants of RRT, performed dominantly better in terms of shorter and smoother plan generation in all state spaces.

VI. CONCLUSION

In this work we evaluated the performances major state-of-the-art SBO planners in various state spaces with a randomized fashion. The evaluation setup was particularly aimed for planning of outdoor ground robots. For convenience, OctoMaps were generated from simulation, the study faced two limitations, inability to do evaluation in larger scale environments (e.g. 1000 x 1000 meters) due to increased memory requirements and lack of suitable real data to be used as OctoMap. Despite these, the planners performances are little affected by the environment data, provided experimental results show strength/drawbacks of SBO planners in different use-cases. A general conclusion of this work can be drawn as, parallelized approaches such as CFOREST, AnytimePartShortening etc. leads to consistency in generated plans and acceptable computation times (1 second for 85+ meter planning inquiries) for low speed ground robots.

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