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Manipulator Path Planning in Unknown Environments using Model Based Planners: Conversion Criteria and IPA Sensor Implementation

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***Abstract*—** Path planning in unknown environments such as Mars or underwater are not only challenging but also daunting tasks. While significant advances are made for mobile platforms, manipulator motion planning in unknown environments still falls short of full fledged solutions due to the uncertainty and complexity of higher order configuration spaces. Most feasible solutions proposed so far are either modeling unknown environments in realtime or applying randomized model based planners with sensitive skin type sensors. Although solving unknown environment planning problems with randomized model based approaches seems very promising, no systematic study has been reported as to how to adopt model based planners into the sensor based problem domain effectively.

In this paper, we study the adoption issues of model based planners to tackle sensor based planning problems, and hence provide conversion guidelines from one to other problem domain. In addition, we discuss the range effect of the sensitive skin type sensor, IPA, for on-line planning in unknown environments. Some experimental results in an unknown environment are presented in the paper as well.

Keywords – sensor based planning; randomized sampling; unknown environment motion planning; collision avoidance

I. INTRODUCTION

UNKNOWN environment motion planning is one of the most daunting tasks in path planning study. Sensor based approach has been the dominant trend in the study of unknown environment planning for decades. Applications of sensor based planning include navigations in underwater or unexplored planets. In this section, we first investigate how traditional sensor based planning strategies have been evolved so far. In addition we study the conversion criteria of model based planners (MBP) to solve sensor based planning (SBP) problems.

Traditional sensor based approaches

Two main trends are often observed in sensor based motion planning studies. On one hand, algorithmic research on bug-like robots, mostly in the context of 2D workspace or configuration space, has been a trend in sensor based approaches. For instance, Lumelsky proposed sensor based planning algorithms while focusing on the worst case path length in 2D manipulator problems [1]. The completeness of the planning algorithm is proven, in general, by the upper bound of travel distance. Since the upper bound of Euclidean travel distance is the major interest in the context of 2D planar robots, expansion of the theory to higher degrees of freedom robots is limited significantly.

One significant breakthrough made in this area, though, is the development of the sensitive skin by Cheung and Lumelsky [2]. In their paper, the obstacle contour following technique is proposed as a means to guide a robot in unknown environments. The sensitive skin that covers the entire body enables it to obtain a normal vector to the tangent plane at a contact point of a c-space obstacle. The original sensation means proposed in [2] had evolved to what is known as "modularized skin patches" [3], where flexible paper-like sensor patches are made to comply with virtually any geometric contour for collision detection and motion planning purposes. Further development of the sensitive skin has been reported in [4] using semiconductor manufacturing technology.

One major contribution of the sensitive skin in motion planning research is that it bridges the gap between two problem domains: model based planning and sensor based planning. That is, due to the capability of a random sampling in higher order c-space by the sensitive skin in realtime, the majority of the model based planners can be adopted to solve the problems in unknown environments.

Recent trends in sensor based approach

The major trends identified are to use model based planner to solve sensor based problems. In [5], Lee and Choset promoted the GVG concept to HGVG to solve higher order unknown environment planning problems. The main point of study is to introduce a new roadmap (HGVG) construction method by which a systematic roadmap of free configuration space can be incrementally constructed using line-of-sight sensor data. The main contribution of the work is that it enables higher degree unknown environment planning using the HGVG map-building strategy. The weakness would be that of requiring vast amount of memory storage for map building, especially for redundant manipulators or for a large scale search operation.

Another example is introduced in [6], where simultaneous path planning with free space exploration is proposed using a skin type sensor. In their approach, a robot

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is assumed to be equipped with a sensitive skin. The Lazy-PRM, one of the model based methods is utilized to tackle unknown environments. Like the HGVG method, they also build a map of a free c-space for further planning of the robot's movements. Authors in this paper claimed that any model based method can be used for unknown environment planning with a proper modification as long as a robot is equipped with sensitive skin. *However, some critical issues are identified when using a model based planner to solve unknown environment planning problems* (see next section).

Another notable study is a novel approach called SRT (Sensor-based Random Tree) method [7], which is primarily inspired by RRT (Rapidly exploring Random Tree), but modified for sensor based planning problems. Due to the nature of the RRT, the SRT utilizes a goal-oriented exploration strategy based on random action selection. The contribution of the paper is that, the SRT algorithm, using one of the most successful model based methods (RRT), and collision avoidance capability of an imaginary sensor that provides a safe free c-space sampling, demonstrated a way to find a practical solution for unknown environment path planning.

The roadmap approach proposed by Yu and Gupta [8] solves sensor-based planning problems for articulated robots in unknown environments. They incrementally build a roadmap that represents the connectivity of free C-spaces. But the usefulness of collision sensor attached on the end-effector is uncertain to detect all the possible collisions.

A sensor-based planning version of the Ariadne's Clew algorithm proposed in [9] utilizes the sensor based approach for incremental search for free spaces and computes a path to a goal configuration for a 2-link planar robot. The authors utilize the postulated approach in [10], assuming that the workspace is partially known a priori.

One thing noticeable in the course of literature survey for the sensor based motion planning was that planning strategies borrowed from the model based approaches are utilized without caution for adoption to the sensor based problem domain. From the planning perspective, each domain is believed to have uniqueness in terms of problem definition and research point of interest. For instance, in unknown environments, obtaining a complete analytic solution is difficult due to the uncertainty of the environments. Obtaining a complete solution requires a complete map of the free c-space of a given workspace, which, in turn, is impractical due to the uncertainty of sensing and measurement process (model based planning itself is known as NP-HARD).

That said, we shall discuss conversion criteria of a model based planner to tackle an unknown environment planning problem with the assumption that the robot is equipped with sensitive skin.

II. CONVERSION CRITERIA FROM MBP TO SBP

Random sampling in c-space is the main idea for the majority of the probabilistically complete model based planners. In order to discuss the conversion criteria from MBP TO SBP, we will focus our study on random sampling strategy by which a sensitive skin equipped robot is able to sample randomly in high DOF c-space. In the following section, we study the conversion criteria from MBP domain to SBP domain. Some of the criteria are necessary conditions, but some are recommended. We provide rationale for those necessary conditions.

First, *Random sampling in unknown environments needs to be performed simultaneously with step motions of robot in sequential manner.* Since no world model is available a priori, the only way to sample in unknown environments is to move sensors whose sensing range is greater than zero along with each step motion. Therefore, this condition is a necessary condition. For instance, the RRT blossom method [11], one of the successful parallel sampling approaches, is not applicable for sensor based unknown environment planning. This is simply because of the fact that multiple presence of a robot is not possible in real world.

Second, *non-uniform sampling is not preferable in unknown environments since preprocessing is not feasible without a world model*. However, for sensitive skin type sensors, difficulty measure of the current c-space configuration by counting the number of sensors reporting impending collision would be possible. Therefore, this is a recommended condition. In addition, adaptive sampling can be cautiously adopted for smart steering meriting the history of the sampled data.

Third, *free c-space registration is necessary for completeness of the search operation*. Since the road-map generation such as PRM is neither feasible nor efficient (if done by preprocessing) in unknown environments, explored free c-spaces need to be recorded for search completeness in planning operation (see [12]). Therefore, this is a necessary condition for the search completeness.

Two necessary conditions and one recommended condition are identified so far. Other thoughts are given to consider sampling strategies based on the conditions addressed above; one is lazy search and another is multi-directional approach as detailed below.

laziness in collision checking becomes popular in the model based planning, but it may not be useful for sensor based planning. Laziness, by nature, postpones the collision checking until it is absolutely necessary. *In the sensor based planning, however, each sample point needs to be connected in realtime to continue search operation.* Therefore, this condition violates the first condition in the conversion criteria.

M*ulti-directional sampling approach often found in model based approaches is not feasible due to the nature of on-line sampling of the sensor based planning*. Even if multiple robots are used for bi-directional or multi-directional samplings, technically there is no guarantee of successful rendezvous between multiple parties due to unpredictable progression of each party. This also violates the first condition of the conversion criteria. In summary, the conversion criteria discussed so far is detailed in Table 1. One can use this table as a guidance to check if a MBP is suitable for SBP problem domain, or to convert a MBP to solve SBP problems.

Table 1: Conversion criteria of a model based planner for random sampling in unknown environments.

No. of issue	description
Necessary	conditions
1	Sequential sampling (no lazy, no multi-direction)
2	C-space registration
Preferable	conditions
	Uniform sampling (adaptive sample is possible)

III. IMPLEMENTATION EXAMPLE

In this section, we demonstrate an example of adopting a model based planner to tackle sensor based problems in an unknown environment referring to the conversion criteria in Table 1. The target planner is the SBL (Single-query, Bi-directional, Lazy in collision checking) planner [6] developed for a model based search in geometrically complex environments. First, we summarize the goal and objective followed by definitions and modification details of overall algorithm and other relevant algorithms in light of the conversion criteria discussed in section II.

Target system: sensitive skin equipped manipulator.
Goal: modify a model based algorithm to a sensor based algorithm.
Objectives:
1. Satisfy all the conversion criteria in Table 1.
2. Minimize change in the algorithm

The second objective may not result in optimal algorithm for unknown environment planning. However, since the focus of study lies in the conversion from one to other problem domain, we propose minimization in change as an objective for demonstration purpose.

Modified SBL planner for sensor based planning

Problem definitions and notations for the SBL planner are kept intact except the problem domain (from model based to sensor based planning). The followings are the definitions from SBL planner.

C: configuration space of a robot normalized as $[0,1]^n$
F ($\subseteq C$): free spaces in C
q: current configuration in C, q_{init}(initial q), q_{goal}(final q)
$d = L_\infty$ – the metric used for n-D cube
$B(q,r)=\{q'\in C|d(q,q')<r\}$: neighborhood of q of radius r
τ : a path in C
T : a tree in C
Sr : sensing range of implemented sensors

Overall Algorithm

First we modify the overall algorithm, while minimizing change. The modified overall algorithm of the SBL planner is as follows.

Algorithm PLANNER (q_{init}, q_{goal})
1. Install q_{init} as the roots of T.
2. Repeat s times
   2.1 EXPAND-TREE
   2.2 $\tau \leftarrow$ CONNECT-TREE
   2.3 If $\tau \neq nil$ then return τ
3. Return failure

Notice that the first step is modified by the first criteria in Table 1, thus no tree will be grown from the goal position. In addition, the functions, EXPAND-TREE, and CONNECT-TREE are modified accordingly as follows.

Tree expansion

The modified algorithm for tree expansion is shown below.

Algorithm EXPAND-TREE

Repeat until a q_{new} has been generated
1. For i=1,2,… until $i<s$
   1.1 Pick a configuration q uniformly at random from $B(q_{last}, \rho/i\ (<Sr))$
   1.2 If q is collision-free
      1.2.1 $\tau' \leftarrow$path connection q_{last} and q_{new}
      1.2.2 if TEST-SEGMENT (τ') = collision free then install it in T as a child of q_{last}.
2. q_{new}=nil, then
   2.1 Pick a milestone m from T at random, with probability $\pi(m)$
   2.2 Assign m as a q_{last}, and goto step 1

In the above algorithm, q_{new} is a new milestone, q_{last} is the last milestone installed in T, and ρ is the distance threshold constrained by the sensing range. The search radius, ρ/i, enables an adaptive sampling to cope with difficult areas. In on-line sampling, there is only one tree (criteria #1 in Table 1), thus switching between trees is not required. In addition, in the original SBL planner, a new milestone m in T is selected for random branch expansion. In sensor-based search, however, random branching may not be feasible, since it causes frequent backtracking or repetitive motion along the same path. Instead, in the modified algorithm, the search operation of q_{new} always takes place from the latest configuration to let the robot move forward for exploration. This eventually minimizes the non-regression characteristics of the tree-like road map, thus affecting the search performance.

A new milestone m is identified only when there is no free space available from the current configuration after certain number of iteration (see line 2 in EXPAND-TREE).

This allows a backtracking mechanism when the robot is stuck in local minima. Another notable change is to constrain the radius of q by the sensing range, *Sr. For on-line sampling, the planner checks the collision by sensor and thus the radius of search for* q_{new} *must be constrained by the sensor.* In addition, since a robot, equipped with sensitive skin, is able to check a collision in realtime, connection of each milestone is done in realtime as well (line 1.2.1 and 1.2.2), rather than by a lazy collision check method. A temporary path, τ' connecting q_{new} and q_{last}, is tested for a realtime collision check.

Tree connection

The modified tree connection algorithm is shown below.

Algorithm CONNECT-TREE

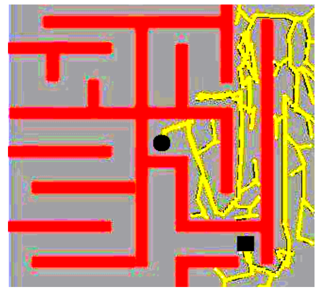
1. $m \leftarrow$ most recently created milestone
2. $m' \leftarrow q_{goal}$
3. If $d(m, m') < \rho$ then
   3.1 Connect m and m' by a bridge w
   3.2 $\tau \leftarrow$path connection q_{init} and q_{goal}
   3.3 Return τ
4. Return *nil*

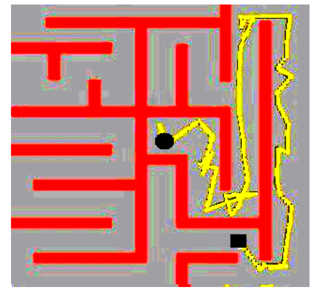
To minimize the change of the SBL algorithm, we kept every step of the CONNECT-TREE algorithm intact except replacing the algorithm of selecting m' in step 2. One benefit of the on-line sampling is the absence of the path testing process since sensors can immediately report collision up to the sensing range in c-space. However, for simulation, we check collision of a direct path between q_{new} and q_{last} by the function TEST-SEGMENT before installing a q_{new} in T. In the following section, we demonstrate some simulation results with the SBL algorithm modified for sensor-based planning.

IV. Simulation Results of an Adopted Planner

2D simulation with a disk-like robot in unknown environments

In order to replicate a similar c-space environment, an experimental environment has been setup in 2D space. A simple disk-like robot is used for simulation in the notion of similarity of the c-space and the workspace. Fig. 1 and Fig. **2** illustrate examples of found paths using the model based algorithm and the sensor based algorithm respectively. Two algorithms are compared by several performance indices as shown in Table 2. Measured performance indices include planning time (P.T.), standard deviation of the planning time (Std), node of initial and goal trees (Ti, Tg), milestones in the roadmap (Nr. Mil), milestones in the found path (Mil-P), collision check points (Tcc), sampled milestones (S.M.), and collision check time (cc time). Each data of Table 2 is obtained by 30 runs for statistical confidence. As is shown in the table, the planning time for the modified SBL algorithm is greater since it checks the collision in realtime rather than by lazy approach. The number of milestones, however, is less for the modified SBL because of the fewer number of branches. As is seen by the standard deviation of planning time, the search time is more consistent for the original SBL algorithm due to the nature of gradual space occupation.





(circle: Start point, rectangle: goal point)

Fig. 1: Model based alg. Fig. 2: Sensor based alg.

Table 2: Performance measure for 2D example

Type	P.T.	Std	Ti	Tg	Nr. Mil	Mil – P	T cc	S.M.	cc time
SBL	15	1,61	146	189	335	19	626	624	0,06
M. SBL	23,3	7,9	86	1	87	11	265	263	0,02

The modification of the algorithm by criteria #1 is the primary reason for less consistent search time, since it does not allow gradual occupation of the free c-spaces. However, since a robot would have to visit each milestone multiple times by the original SBL for even growth of the tree, the large number of milestones on the tree (Nr. Mill in Table 3) may result in a longer travel distance in real world, thus leading to a longer path planning time.

Sensing range effect study by 3D simulation with a 6 DOF robot in unknown environments

In order to investigate the performance of the proposed sensor based planner, a simulation setup has been made for a 6 DOF robot. The robotic manipulator is assumed to be equipped with the sensitive skin and placed at complex unknown environments. An arbitrary shaped rocky environment mimics either underwater environments or unexplored planets. Fig. 3 and Fig. 4 represent start and goal configurations respectively. Fig. 5 illustrates a found path by the modified SBL algorithm viewed from different angles.

In unknown environment planning, the performance of the planner is significantly affected by the sensor performance. One of the performance measures of the sensor is its sensing range, since the planner can obtain quantitatively different amount of information of an unknown environment depending on the sensing range. *Therefore, the primary interest of the unknown environment simulation lies in the effect of the sensing range in search operation.* The sensing range in the modified SBL algorithm corresponds to the variable ρ in the algorithm which represents the sampling range. That is, larger the sensing range of a sensor becomes, bigger the variable ρ is for each sampling operation. As is shown in Table 3, the sensing range is changed from 10% to 20% of the configuration space, *C*. First, as shown in Fig. 6, the planning time has a decreasing tendency as the sensing range is increasing, thus larger sensing range of a point automaton in unknown environments may result in shorter planning time.

Fig. 3: Start configuration

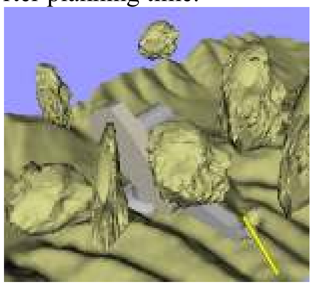


Fig. 4: Goal configuration

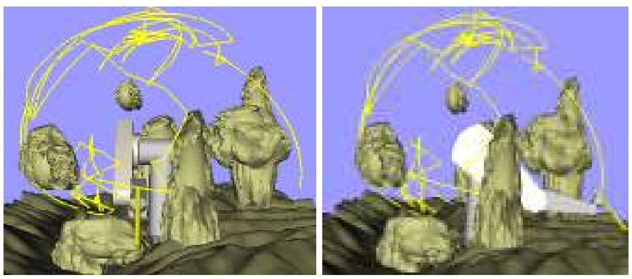


Fig. 5: Found path in a 3D unknown environment

Table 3: Performance measure for 3D simulation (30 runs per each sensing range)

S.R.	P.T.	std	Ti	Tg	Nr Mill	Mill on P	Tcc	S.M.	cc Time
0.100	488	231	6599	1	6600	57	10784	10782	5
0.125	379	519	2330	1	2331	63	3858	3865	4
0.150	118	134	2124	1	2125	54	3817	3815	1
0.175	229	212	1070	1	1071	44	2078	2076	3
0.200	107	116	854	1	855	41	1754	1752	1

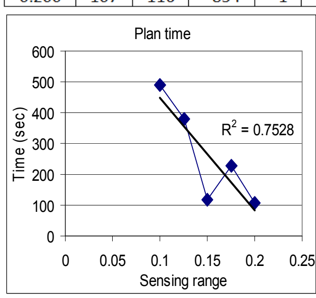


Fig. 6: Plan time,

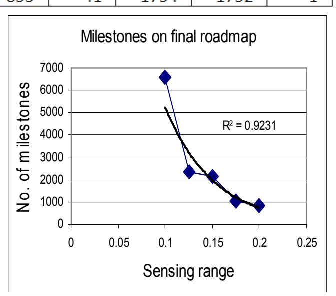
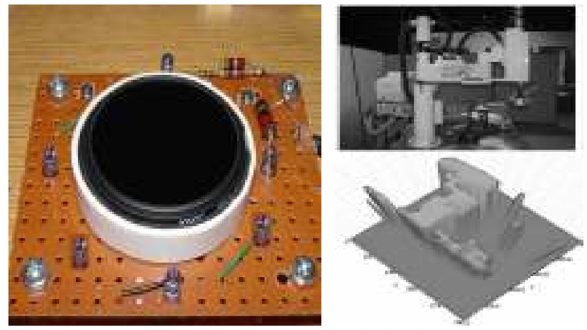


Fig. 7:Milestones on final roadmap

Notice also that the number of milestones on the roadmap has exponentially decreased as the sensing range increased (Fig. 7). This is due to the exponential increase of search points by multiple DOF C-Space. This concludes that the sensing range of a sensor used in an unknown environment plays a key role in search performance. As a result, one can say that the hardware of a sensor system is as important as the planning software in unknown environments.

V. Experiments with IPA Sensors

A series of experiments are carried out to demonstrate the performance of the Modified-SBL planner for unknown environment motion planning. Sensors used for the experiments are the IPA (Infrared Proximity Array) sensors [13] that are capable of detecting collision for unknown environment path planning.



IPA assembly 3D depth data by IPA

Fig. 8: IPA sensor

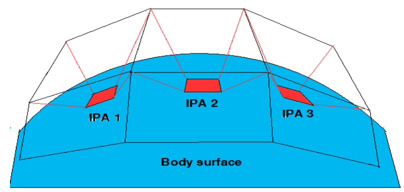
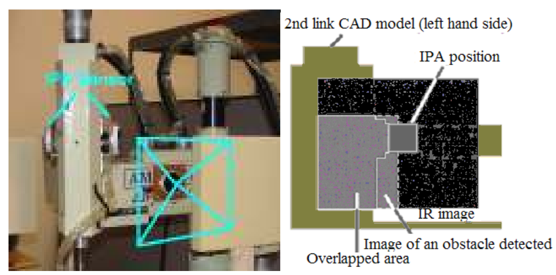


Fig. 9: Shield for collision checking by multiple IPAs



Sensor installation Obstacle detection

Fig. 10: IPA sensor application

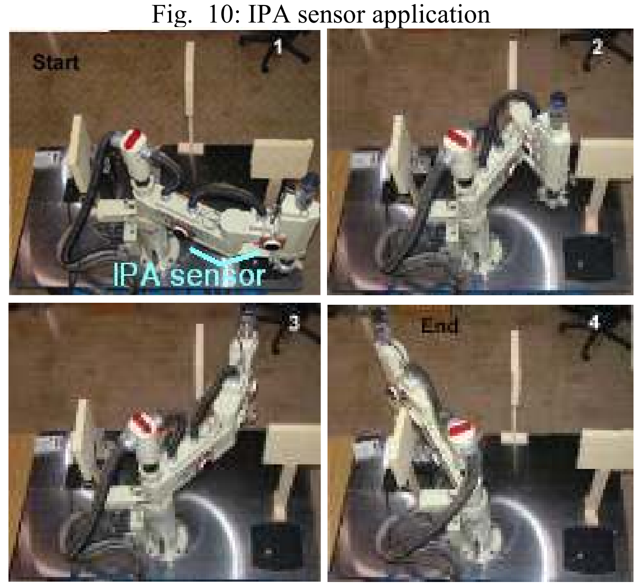


Fig. 11: Motion planning experiment with no world model

One IPA patch is composed of a CCD sensor array, an infrared filter, and infrared LEDs. A CCD sensor array, responding to the various light spectrum including visible light and infrared light is encapsulated securely in a cylindrical plastic mold (Fig. 8, left). The depth data on the right hand side is a Scara robot detected by IPA (refer to [13] for details). By using multiple IPA sensors, an invisible shield can be formed for collision checking (see Fig. 9). The collision checking capability by the invisible shield allows a random sampling in higher order c-space for a manipulator motion planning.

A two-link planar robot is used for experiments. Four IPA patches are installed on both sides of each linkage (Fig. 10). For experiments, three unknown obstacles are placed randomly in the workspace of the robot. Collision check is done by overlapping the linkage CAD data with the sensor data to identify an imminent collision (Fig. 10, right). In Fig. 11, four intermittent moments during the motion are captured and presented including the start (1) and the end (4) states. Although, the robot collided with the unknown obstacles in multiple occasions, M-SBL planner demonstrated about 90% success rate in the series of the planning demonstrations (See Table 4 for the planning result of 30 successful runs). The reason for failures is primarily because one IPA does not completely cover the dimension of one side of the linkage (See Fig. 10, right).

Table 4: Performance measure for on-line planning (30 runs)

P.T	std	Ti	Tg	Nr Mill	Mill on P	S.M.
728	376	9123	1	8220	132	28592

In addition, some difficult situations such as narrow passages have been tested, but the success ratio was low (< 30%) due to the uncertainty of the sensor data and inability of the modified SBL algorithm to handle difficult areas. One recommendation is to further develop the IPA for fine surface modeling capability of detected objects and to incorporate the optimization algorithm in [14] for object surface following strategy.

VI. CONCLUSION

In this paper, we surveyed sensor based and model based planners including recent trends of probabilistic sampling method to plan manipulators in unknown environments.

The main contribution of the paper is to study the conversion rules of a model based planner to solve an unknown environment problem with sensitive skin. SBL algorithm is used to provide a conversion example. In the series of experiments, it turned out that the original SBL algorithm outperformed the modified SBL planner in planning time. In addition, the planning time for sensor based planner version varies more due to the absence of non-regression property of the random tree roadmap. However, due to the large number of milestones of the original SBL roadmap, the travel distance eventually becomes longer than that of the modified SBL, resulting in longer planning time in real world applications.

The impact of sensing range in sensor based planning has been examined as well, concluding that the sensing range of a used sensor plays a key role in unknown environments.

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