A Framework for Unknown Environment Manipulator Motion Planning via Model Based Realtime Rehearsal

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Abstract:

In this paper, we propose a novel framework for unknown environment planning of manipulator type robots. Unknown environment motion planning, by its nature, requires a sensor based approach. The problem domain of unknown environment planning, when compared to model based approaches, is notoriously harder (NPHARD) in terms of demanding technical depth especially for difficult cases. The framework we propose herein is a sensor based planner composed of a sequence of multiple MBPs (Model Based Planners) in the notion of cognitive planning using realtime rehearsal. That is, one can use a certain model based planner as a tactical tool to attack location specific problems in overall planning endeavor for an unknown environment. The enabling technology for the realtime rehearsal is a sensitive skin type sensor introduced in the paper. We demonstrate the feasibility of solving a difficult unknown environment problem using the introduced sensor based planning framework.

Keywords: *sensor based planning, randomized sampling, unknown environment motion planning, collision avoidance, cognitive planning.*

1. Introduction

Unknown environment motion planning is one of the most daunting tasks in path planning study. Sensor based approaches have been the dominant trends in the study of unknown environment planning for decades. When it comes to unknown environment planning, a planner calls for continuous perception and planning, thereby closing the loop between sensation and actuation. For instance, SLAM (Simultaneous localization and Motion planning) is one of the trends to solve mobile robot navigation problems in unknown environments.

In manipulator planning especially for unknown environments, similar notion is applicable to solve difficult cases. For instance, in [1], 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.

Another example is introduced in [2], where simultaneous path planning with free space exploration is proposed using a skin type sensor. In their approach, a robot is assumed to be equipped with a sensitive skin.

The roadmap approach proposed by Yu and Gupta [3] 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.

Sensor based planners have been advanced by numerous technological breakthroughs in sensor technology including laser scanner, vision sensor, proximity sensor, etc. Despite of advanced today's sensor technologies, unknown environment planning still falls short of a fullfledged solution especially to tackle difficult cases. On the other hand, model based planners are also limited in their capability to deal with certain cases of planning problems due to the absence of realtime environment mapping capability.

Sensitive skin [3] proposed by Lumelsky and innovated thereafter by Chung and Um [5] poses itself as a tool to bridge the gap between the model based planning and unknown environment planning domains. It is unique in that it can either report impending collision with any part of the body at any moment or impart a realtime environment mapping capability during the course of planning operation. Endowed with such uniqueness, sensitive skin will result in a SLAM capability for many degrees of freedom robotic manipulators.

In addition, *we believe that the sensitive skin is unique in that many advanced strategies studied in the model based planning problem domain can be utilized to solve unknown environment planning problems, including problems with difficult cases.* We also believe that if a sensor based planner utilizes model based planning strategy in case sensitive manner, majority of the planning problems can be resolved (See Figure 1).

To that end, we propose a novel framework of sensor based planning constituting the totality as a sequence of model based planners using a sensitive skin and realtime rehearsal in cognitive sense. *In each step of sequence, one can use a particular model based planer tailored to attack location specific problems perceived by the realtime sensing capability of a skin type sensor.* The notion of cognitive sense of planner imparts the decision capability so that the planner can select the best strategy case by case in each local area to increase the probability of overall convergence (See Figure 2).

For instance, if the perceived local area at a step is with a reasonably open space, one can choose PRM [4] or RRT [7] for fast sampling with evenly distributed sample points. But importance sampling or adaptive sampling [8] can be selected for path findings in areas with difficulties. For better results in narrower passages with many degrees of freedom, bridge test algorithm [9] can be selected for more effective path search.

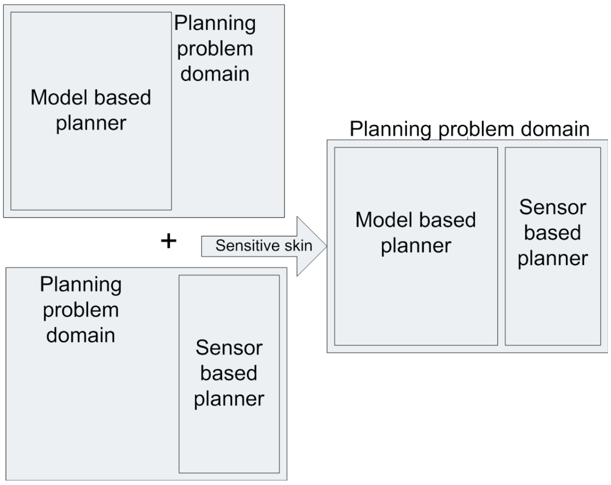


Fig. 1. Sensitive skin as a tool to bridge the gap of two planning domains.

The new framework proposed in this paper is to host multiple MBPs as tactical tools within which the best local algorithm will be eclectically selected based on spatial examination. Therefore, of importance in the proposed planner is the cognitive sense of spatial perception for the optimality in the MBP selection process.

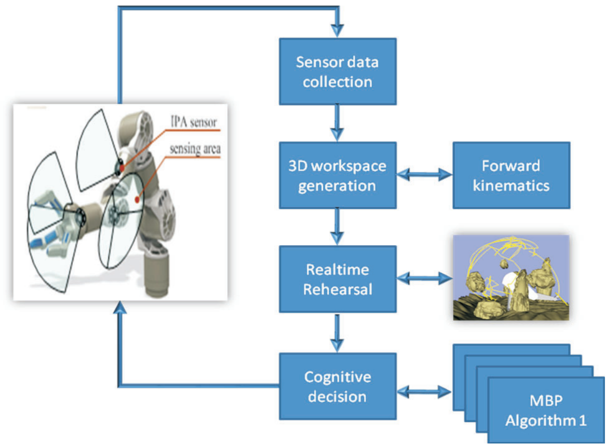


Fig. 2. Concept of sensor based planning framework.

When the planning expands its scope to perception and action, sampling and path finding problems will fall into a cognitive problem domain. In recent literatures, evidenced often is a trend of the probabilistic motion planning expanding its scope from planning to perception and action in c-space for better manipulability. As detailed in [10], for example, the planner moves the mobile base to a less clustered area to obtain better manipulability to achieve higher success ratio in grasping path planning. In [11], next best view search is discussed to increase the success ratio in which the constructed 3D spatial information of a work space is utilized.

In the framework we propose, for demonstration purpose, global planning objective is rather simple and similar to that of the potential field planner, thus the robot is simply biased toward a goal seeking the shortest path, while the local planning objective is divided into perception and action objectives as below.

Perception objective:
Obtain environmental affordance.

Action objective:
In crowded area, increase traversability.
In less crowded area, increase manipulability and observability.

The environmental affordance we measure is the spatial distribution of sampled spaces. To that end, the realtime rehearsal via a sensitive skin type sensor takes place to generate a local c-space map and to examine the spatial distribution affordance. Increased manipulability and observability as well as traversability result in probabilistically higher reachability to the goal position. In order to meet the action objective, we propose an action schema of multiple MBPs, among which the best suitable one will be exercised.

In summary, the robotic action selection will occur as the action schema in local area, which is cognitively connected to the perception stage by the affordance relations. Before we discuss the proposed framework, the details of the IPA skin sensor are discussed in section II, followed by the algorithm with simulation results in III.

2. IPA Skin sensor

The enabling technology for the realtime rehearsal is a sensitive skin type perception sensor, namely IPA (Infrared Proximity Array) skin sensor from DINAST (Figure 3). Included in Figure 4 are some demonstration pictures of the IPA skin sensor capability. The 3D depth measurement capability of the sensor is shown in pictures at upper left and right corners. With this capability, the proposed framework enables instantaneous 3D virtual map generation for locally sensed areas. Lower left side picture depicts a test for finger tracking function of the IPA sensor to demonstrate a realtime operation capability. Finally the one on the lower right corner is the reconstructed 3D surface map of a human face to show precision surface modeling capability of the IPA sensor.

From the unknown environment planning standpoint, the IPA skin sensor is unique in that it can impart a collision shield (See Figure 5) to an entire manipulator so that the IPA equipped robot can sample an arbitrary c-space in realtime, thereby perform realtime collision check in work space. One example of an IPA sensitive skin equipped robot is shown in Figure 6.

In summary, IPA sensor endows the reatlime rehearsal capability to a multi-DOF robotic manipulator with following features.

1. Collision shield
2. Realtime workspace mapping

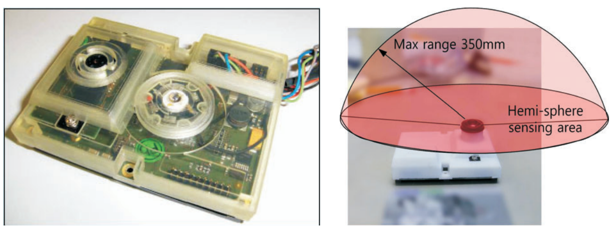


Fig. 3. IPA skin sensor, sensing range.

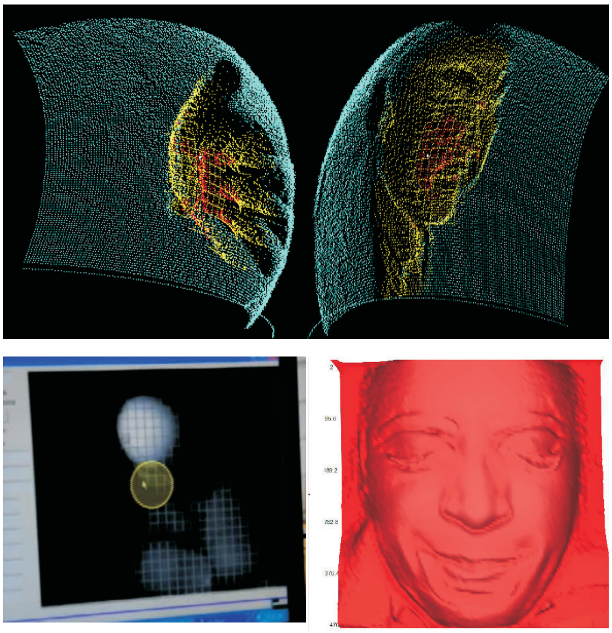


Fig. 4. IPA skin sensor demonstration.

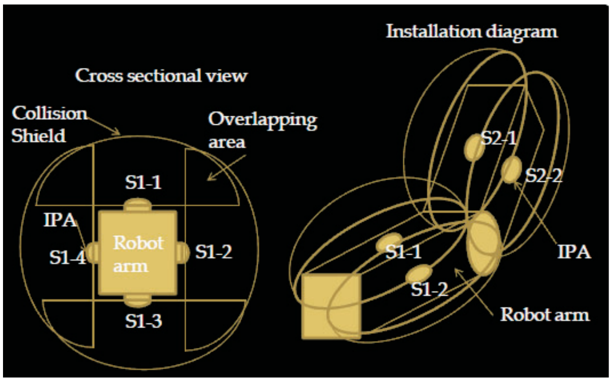


Fig. 5. The concept of collision shield.

Fig. 6. IPA sensitive skin installation on Adept robot.

2.1. IPA sensitive skin sensor specification.

IPA sensitive skin is a DSP technology based smart sensor with sensor array of about 0.3 million sensors in synch with each other. At the moment, the refresh rate of the sensor is 20 ms for realtime operation. The sensor itself is compact in size, thus can comply with any surface configuration with a 3D realtime surface modeling power to support advanced motion planning capability. Detailed sensor spec is in Table 1.

The frame rate of the IPA sensitive skin is adjustable depending on applications at the cost of resolution loss. Active retina principle can also be adopted for regional magnification for high variant areas. In addition, IPA sensitive skin is equipped with a fish eye lens with image dewarping capability, thus imparting complete hemi-sphere coverage for maximum sensibility (Figure 3).

Table 1. IPA sensitive skin sensor specification.

Description	Specification
Size	6.5cm x 4.5cm x 4cm
Sensing range	350mm
Sensing rate	20Hz at 640*480 resolution
Measurement error	±8mm at 350mm
Viewing angle	hemi-sphere complete coverage

2.2. Cross talk prevention between modules

Prevention of crosstalk between sensor modules is one concern when multiple IPA sensitive skin sensors are put together for a collision shield. For instance, IR light emitted from one sensor can be seen by another IPA module as an object, which results in a false alarm. In order to prevent crosstalk, a higher level control logic is in need for robust sensing and 3D mapping. Figure 7 shows the firing diagram based on groups of sensors that has little or no correlation in sensitivity due to geometric configuration. The higher level controller will drive each group of sensors in sequence to prevent crosstalk based on the firing diagram in. The firing diagram will result in 50% increase in sampling time due to the sequential IR light emission. Frequency modulation can be used for minimum loss in sampling time if more groups of sensor are needed.

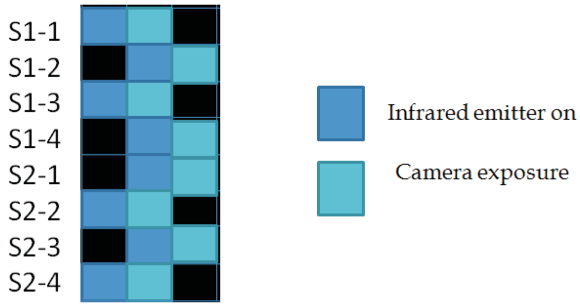


Fig. 7. Multiple Sensor Firing Diagram for crosstalk prevention.

3. RRT-Cabomba planner

The planner we propose to implement the concept in Figure 2 and to maximize the usefulness of the IPA sensitive skin is a RRT variant, namely RRT-Cabomba. The planner resembles how a natural aquatic cabomba stretches in water (Figure 9). RRT-Cabomba searches an unknown space based on local probing via the IPA skin and develops a local map in a virtual workspace perceived in sensing range. In each local virtual workspace, RRT-Cabomba grows RRT to examine spatial distribution.

Depending on the result of the spatial distribution, RRT-Cabomba will determine which MBP is the most suitable for the sensed local area. Search completeness in local area will be granted as long as each MBP used is a complete planner, but the global search completeness has yet to be proved as a whole. The sensor model (Figure 8) used for simulation is similar to the IPA sensitive skin depicted in Figure 3, but in 2D plane.

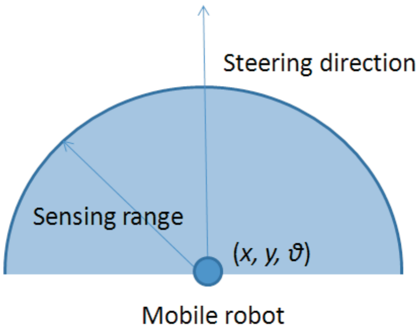


Fig. 8. Sensor model.

RRT-Cabomba Natural cabomba

Fig. 9. RRT-Cabomba.

In summary, the RRT-Cabomba is a planner with the following logic.

RRT-cabomba

1. *Sensor data collection*
   Sense a local workspace.
2. *Virtual workspace generation*
   Generate a local virtual environment with measured 3D depth information.
3. *Realtime rehearsal*
   Grow an RRT in local virtual environment established in step 2.
4. *Cognitive decision*
   Measure the spatial distribution of the grown local tree. Determine which MBP is the most suitable for the sensed area.
5. *Advance the robot*
   Move the robot to the next position depending on the MBP strategy chosen at step 4.
6. *Convergence check*
   Check if the goal position is reached. If not, loop back to step 1.

In step 1, we apply a global algorithm such that the cabomba tree is steered toward the goal position by controlling the sensing direction biased toward the goal position. Steering toward a goal generally, but not always, yields faster convergence to the goal at the cost of being entrapped at local minima. Sensor data collection is necessary to build a complete local environment model to fully grow a c-space RRT in each movement.

In step 2, piecewise information from each sensor is put together to form a complete virtual environment. Cartesian coordinate with orientation of each sensor on the manipulator body is obtained *via* forward kinematics. Obtained data of each sensor are then mapped and projected in a virtual environment for workspace object construction followed by a realtime rehearsal. Growing a c-space RRT with respect to a constructed local workspace provides the result of realtime rehearsal for collision in workspace, and at the same time, generates sampled nodes in c-space. We utilize *nth* order standard distance distribution as a measure of spatial distribution in Step 4 as detailed below.

$$\sigma_N = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\theta_i - \theta_{mean})^2}$$

where θ_i is the sampled nodes of i_{th} joint and θ_{mean} is the mean value of θ_i. σ_N, if larger than $\sigma_{threshold}$, signals an open c-space, or crowded space otherwise. The value of $\sigma_{threshold}$ is determined empirically. In our case, 0.3 yields reasonable performance (maximum value is 0.5). For step 5, in our simulation, we only use following two MBPs for open and crowded cases.

MBP #1 (Open c-space): Move to a node closest to the mean values of sampled nodes.
MBP #2 (Crowded c-space): Move along the θ axis with largest standard deviation in c-space.

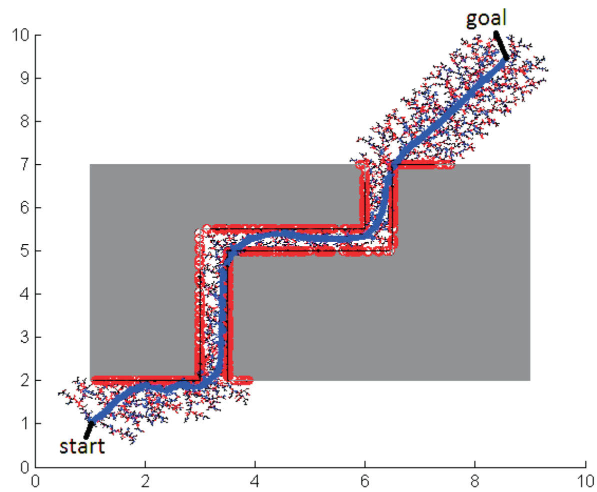
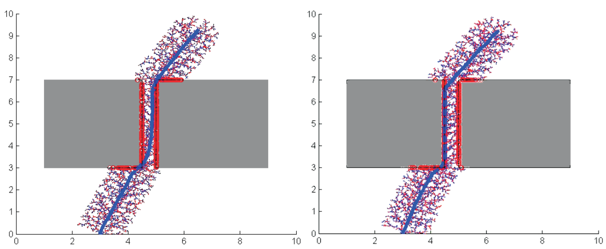


Fig. 10. RRT-Cabomba for difficult area path search test.



Original RRT-cabomba RRT-cabomba switching to bug algorithm in crowded area

Fig. 11. Comparison between original and one with bug algorithm.

For *MBP #1*, as mentioned earlier, moving to a mean value of θ_i offers probabilistically best location for next move in terms of maneuverability for each joint, thus may increase reachability as well. The *MBP #2* is chosen for reasonable traversability, but can be replaced with variety of other MBP algorithms feasible for specific needs in each local area.

One execution example of RRT-cabomba is shown in Figure 10.

Table 1. Results of two algorithms

Algorithm	Original RRT - Cabomba	RRT-Cabomba with bug algorithm
Search time	125 s	155 s
Total collision nodes	6838	5892
Total collision free nodes	21218	21162
Total No. of nodes	28056	27054

Here we use the identical sensor model as the physical IPA skin sensor, hemisphere frontal sensing range with 3 DOF (x, y, θ) mobility.

One big drawback of RRT-Cabomba is not being able to handle local minima problems effectively due to the global steering algorithm. Global steering mechanism in a completely unknown environment is still a daunting and not a fully addressed issue. Therefore, in this study, we focus more on reasonable search results for a completely unknown environment with RRT-Cabomba planner in conjunction with the IPA skin sensor, leaving the global completeness of the algorithm a future work. As for the algorithm complexity, since RRT-Cabomba uses mixture of local algorithms depending on the situation, the complexity varies as the planner changes. For instance, if the local planner selected is the RRT planner, than it has the same complexity of RRT in the local area. However, although c-space construction is known to be polynomial in the geometric complexity for unknown environments, the proposed algorithm effectively generates c-space map as the robot explores the environment. Therefore the c-space construction is not the bottleneck of the algorithm.

Local minima avoidance with bug algorithm

In order to demonstrate the versatility of the RRT-Cabomba, in this case to tackle the local minima problem, we change the *MPB #2* to the bug algorithm. The bug algorithm proposed by Dr. Lumelsky [12] and improved thereafter has a unique property of global convergence in 2D and 3D unknown environments. For higher order manipulator path problems, one can utilize algorithms introduced in [8], [9], [13]. These algorithms deal with difficult cases in higher order path problems.

In step 4, if σ_N is smaller than $\sigma_{threshold}$, we switch the local strategy to the bug algorithm. Shown in Figure 11 and Table 1 is the results of the previous RRT-Cabomba and the one with the bug algorithm. No significant statistical difference is evidenced in running performance.

Notice though that the second planner follows the wall of the first obstacle it encountered because of the bug algorithm engaged in crowded areas. In order to demonstrate the local minima avoidance capability of the RRT-Cabomba, another simulation set is prepared. Shown in Figure 12 is an execution example with the bug algorithm as the second MBP. As demonstrated in the figure, a group of MBPs in conjunction with realtime rehearsal produces reasonable results in a difficult unknown environment case.

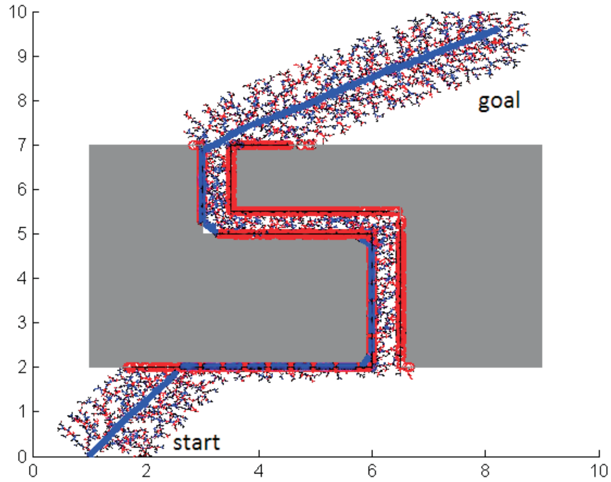


Fig. 12. Local minima avoidance with bug algorithm as a crowded area search strategy.

Table 2. Local minima avoidance simulation.

Algorithm	RRT-Cabomba with bug algorithm
Search time	**187 s**
Total collision nodes	**11512**
Total collision free nodes	**25562**
Total No. of nodes	**37074**
Total foot steps	**50**

One limiting factor of the RRT-Cabomba from the implementation perspective in real world is the realtime rehearsal for advancing a manipulator without interruption when continuous motion is needed. In order to perform the realtime rehearsal, however, virtual world generation with 3D-depth measure of a local area followed by a realtime rehearsal with RRT in local area has to take place with zero time lag. In the previous simulation with a computer equipped with an Intel Core 2 CPU at 2.13 GHz and 2Gb RAM, each foot step takes 3.7 second in average, meaning the robot in the real world has to wait for 3.7 second in each step motion for path search. This bottleneck can be tackled with several improvements in implementation such as faster computer, smaller step size, distributed simulation and so forth. However, the algorithm needs to be significantly improved for a full scale, 6 DOF robotic manipulator operating in a completely unknown environment.

4. Conclusion

A novel manipulator path search framework with a sensitive skin type sensor for a completely unknown environment planning, especially for difficult cases with local minima, has been investigated. To that end, a novel IPA sensitive skin has been developed and demonstrated its capabilities in the paper.

The proposed algorithm, RRT-Cabomba, provides a unique solution for difficult unknown environment planning cases by merging sensor based planning and model based planning ideas for maximum synergy. In RRT-Cabomba, multiple MBPs can be employed to tackle local area specific planning problems. Cognitive decision making has been studied with realtime rehearsal for each step motion to eclectically select the best possible local strategy in each step. For the feasibility test of the proposed algorithm, a series of simulations has been performed and the results are shared in the paper.

Time-lag in simulation due to expensive calculations would be a bottleneck for a real world implementation, but for the proof of the usefulness, the concept of realtime distributed simulation of the proposed algorithm is under investigation at the moment. In addition, real world implementation with IPA sensitive skin is under consideration for future work.

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