Planning Practical Paths for Tentacle Robots

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Abstract: Robots with many degrees of freedom with one fixed end are known as *tentacle robots* due to their similarity to the tentacles found on squid and octopus. Tentacle robots offer advantages over traditional robots in many scenarios due to their enhanced flexibility and reachability. Planning practical paths for these devices is challenging due to their high degrees of freedom (DOFs). Sampling-based path planners are a commonly used approach for high DOF planning problems but the solutions found using such planners are often not practical in that they do not take into account soft application-specific constraints during the planning process. This paper describes a general sample adjustment method for tentacle robots, which adjusts the randomly generated nodes within their local neighborhood to satisfy soft constraints required by the problem. The approach is demonstrated on a planar tentacle robot composed of ten Robotis Dynamixel AX-12 servos.

1 INTRODUCTION

Tentacle robots (see Figure 1), also known as snake or serpentine robots, are manipulator robots with many degrees of freedom (DOFs). Such devices have received considerable attention from the robotics community due to their applicability in a wide range of different domains. Surveys on tentacle robots are provided in (Transeth et al., 2009) and (Rollinson and Choset, 2011). Tentacle robots are often an attractive alternative to traditional robotic systems for difficult terrains and challenging grasping scenarios. These applications include search and rescue missions in complex urban environments, planetary surface exploration, minimally invasive surgery, and inspection of piping and nuclear systems (Choset and Henning, 1999; Gayle et al., 2007; Buckinham and Graham, 2011). Unlike traditional manipulator robots which tend to have small numbers of DOFs, tentacle robots utilize redundant DOF's in order to enhance their ability to deal with complex environments and tasks.

Path planning is a fundamental problem for nearly all the robotic systems. The basic robot path planning problem involves finding a path for a robot to get from ‘here’ to ‘there’ while avoiding any obstacles in a static environment. It has been proven that the basic path planning problem is PSPACE-complete in the dimensionality of the DOFs possessed by the robot (Reif, 1979; Canny, 1988). As a consequence, a number of probabilistic sampling-based planners have been developed to solve high-dimensional real-world path planning problems (a summary is provided in (Tsianos et al., 2007)) such as the planning problem encountered with tentacle robots.

Since it can be hard to plan a path for robots with many DOFs, most methods for high DOF robots aim at finding any solution within a reasonable time. With the development of sampling-based algorithms and their application in practice, the focus has shifted to considering the quality of the path obtained (Raveh et al., 2011; Geraerts, 2006; Kim et al., 2003; Garber and Lin, 2002; Wein et al., 2005; Bayazit, 2003; Song et al., 2001; Karaman and Frazzoli, 2011). A shortcoming of basic sampling-based planning approaches is that they often obtain highly ‘non-optimal’ solutions since they rely upon randomization to map or explore the search space. Although these algorithms may find a valid solution, that solution may not be practical in that it does not meet soft constraints that exist within the problem domain. Furthermore, it has been proven that standard PRM and RRT are not asymptotically optimal, i.e. the cost of the solution returned by the algorithm will not converge to the optimal cost as the number of samples increases (Karaman and Frazzoli, 2011).

The need to properly represent and use soft constraints is particularly important for redundant DOF robots such as tentacle devices. For these devices the high number of DOFs provide the opportunity to deal with complex environments and to produce solutions that are not only correct (e.g., they grasp the object through free space, for grasping tasks) but that

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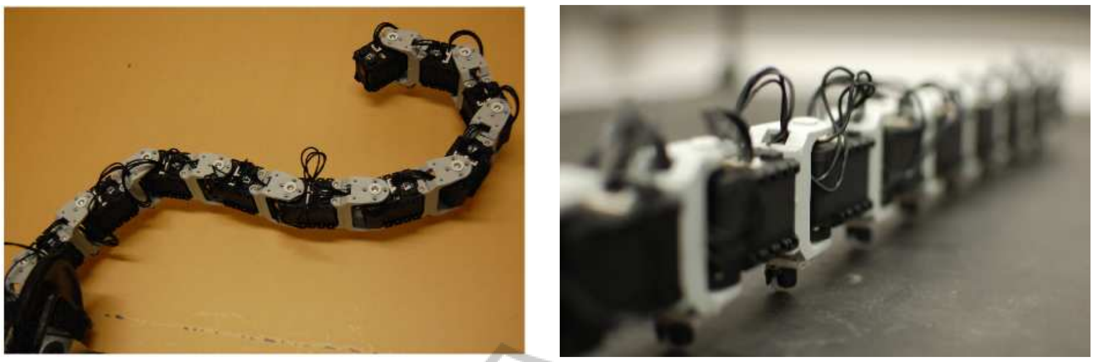


Figure 1: A planar tentacle robot with ten links.

they also optimize other requirements of the problem space. One common way of taking these constraints into account is to use an appropriate controller that takes the path identified by the path planner as input and then integrates the soft constraints while following the path (Bruce and Veloso, 2005; Kobilarov and Sukhatme, 2005). There are many issues with this approach. Perhaps most critically the paths produced may be infeasible for a real robot. For example, following the path produced may require that the robot move extremely slowly in order to minimize the influence of dynamics and other physical constraints. These controllers are also system specific, and it can be very hard to develop a good 'general' controllers or to know which controller to use for which task.

A more general approach is to augment sampling-based path planning with mechanisms to provide paths that are both correct but that also optimize soft constraints. Such augmentation could take place at different points in the path planning algorithm. Here we concentrate on optimizations performed during the sampling phase of the algorithm. Specifically we perturb each randomly generated sample within its local neighborhood in order to enhance compliance with the soft constraints. We show that this often leads to more practical paths for the robot. The framework described here is intended to be robot independent, but the approach is described and tuned here towards capabilities and tasks associated with the planar tentacle robot shown in Figure 1.

This paper is structured as follows: Section 2 reviews existing sampling-based planning algorithms that address the path quality problem and the current methods used to plan paths for tentacle robots. Section 3 formulates the practicality of paths in terms of soft constraints and describes constraints particularly critical for tentacle robots. In Sections 4 and 5, path planning strategies are developed to find paths of user-preferred qualities based on this formalism. Section 6 includes comparison results from applying the practicality-based approach and basic PRM to different test environments using both real and simulated tentacle robots. Finally Section 7 summarizes the work and provides possible directions for future research.

2 RELATED WORK

2.1 Sampling-based Path Planning

Instead of computing an exact representation of the planning space, sampling-based planners generate samples and test motions in configuration space. Such planners usually represent motions as a graph as in the Probabilistic Roadmap Method (PRM) (Kavraki et al., 1996; Kavraki et al., 1998), or as a tree as in the Rapidly-exploring Random Tree (RRT) (LaValle and Kuffner, 2000). These methods are probabilistically complete and it is not guaranteed that these planners will find a path even though one exists, but if they do find a path the path will take the device from the initial configuration to the goal. With the development of the sampling-based algorithms and their application in practice, focus in the research community has shifted to considering the quality or practicality of the computed path. Randomized path planning algorithms addressing the path quality problem can be divided into three broad categories based on where practical issues are integrated within the algorithm: pre-processing, post-processing, and customized learning.

Pre-processing Approaches. Pre-processing approaches consider the specific preferences of desired paths in the pre-processing phase, i.e. during the roadmap construction phase before a query is made. Because of its probabilistic nature, the PRM roadmap often contains nodes and edges that lack practical usage or are redundant. Aiming at finding shorter paths with higher clearance, Nieuwenhuisen and Overmars (Nieuwenhuisen and Overmars, 2004) proposed to add nodes and edges to create "useful" cycles, which provide short paths and alternative paths in different homotopy classes. Based on this work, a PRM variant also attempts to retract nodes and edges to the medial axis for generating high clearance paths (Geraerts, 2006).

Post-processing Approaches. Given a path found by the sampling-based path planner, post-processing approaches modify the path in accordance with the required practicality preference by adding new nodes, smoothing it, eliminating unnecessary loops or detours, etc. Path pruning and shortcut heuristics are common post-processing techniques for creating shorter and smoother paths (Hsu, 2000; Geraerts, 2006). Two retraction algorithms are presented to add clearance to a given path, one based in the workspace and the other one based in the configuration space (Geraerts and Overmars, 2005). Post-processing algorithms may take multiple paths as inputs rather than just a single one. For example, the path merging algorithm described in (Raveh et al., 2011) computes a path with improved quality by hybridizing high-quality sub-paths from the initial input paths. The algorithm considers the generalized formulation of path quality measures rather than specific requirements.

Customized Learning. Although post-processing algorithms have shown some success in improving the path quality and can be used by all the path planners, the final path depends on the original paths, i.e. they cannot find alternative routes that deviate considerably from the original ones. To avoid this problem, customized learning algorithms integrate the requirement for path quality in the learning phase. For example, Kim et al. (Kim et al., 2003) use an augmented version of Dijkstra's algorithm to extract a path from a roadmap on criteria other than path length.

The approach of initially finding an approximate solution is utilized by the Fuzzy PRM (Nielsen and Kavraki, 2000), Lazy PRM (Bohlin and Kavraki, 2000), IRC (Iterative Relaxation of Constraints) (Bayazit, 2003) and C-PRM (Customizable PRM) (Song et al., 2001) algorithms where the roadmap nodes and edges are not validated, or are only partially validated, during roadmap construction. During the learning phase, the path is searched by strengthening the constraints (obstacle collision, path length or other specified preferences) iteratively. These methods are designed to decrease the roadmap construction costs, while only increasing the query costs slightly.

2.2 Path Planning for Tentacle Robots

There has been relatively little work devoted explicitly to tentacle robot path planning. One approach is based on the definition of *tunnels* in the workspace (Chirikjian and Burdick, 1990). Methods from differential geometry are then used to guarantee that the tentacle is confined to the tunnels, and therefore avoids any obstacles. This work does not prescribe any strategy for constructing the tunnels. Later, it was proposed to use the results of the Generalized Voronoi Graph (GVG) approach to construct the *tunnels*. Motion planning is then achieved via a nose-following approach which allows the end-effector to move along the GVG followed by the rest of body (Choset and Henning, 1999).

Sampling-based planning algorithms such as PRMs and RRTs are popular because of their success in a wide range of applications and in high-dimensional configuration spaces. This makes them an appealing choice for tentacle robot path planning, but they still suffer from the problem of generating less than optimal paths of the robot. Aiming at finding *realistic* paths for highly articulated chain a physics-based sampling strategy is presented in (Gayle et al., 2007). The method exploits the coherence between joint angles via the "adaptive forward dynamics" framework in order to determine which joints have the greatest impact on the overall motion. Then, only the most important joints are simulated. The samples are then biased by using constraint forces designed to avoid collisions while moving toward the goal (similar to the potential field approach). Simulations show that the planner was able to find more natural paths than the PRMs and RRTs that used straight-line local planners.

3 PROBLEM STATEMENT

In basic path planning (Latombe, 1991), given a robot $\mathcal{A}$, a static workspace $\mathcal{W}$ containing a set of obstacles, an initial configuration θ_{init} and a goal configuration θ_{goal}, the objective of path planning is to determine a feasible path $\mathcal{P}$ between θ_{init} and θ_{goal}. The definition of feasible paths only considers geometric constraints that arise from collision with obstacles and is often inadequate to describe realistic path planning problems.

Soft constraints can be added to the basic path planning problem in a number of different ways. Following the PDDL3.0 approach (Gerevini and Long, 2005), the syntax for soft constraints can be broken down into two components: (i) the identification of the soft constraints; and (ii) the description of how the satisfaction or lack of these constraints affects the quality of the result. Similar to the descriptions of hard constraints, soft constraints are also described using predicates of the planning problem. Each binary soft constraint is associated with a violation penalty weight such that paths, or portions of paths that satisfy different subsets of soft constraints can be compared. Let $\mathcal{S}$ be the set of soft constraints. The following are typical soft constraints for tentacle robots described in terms of inequalities between the value computed from the robot's configuration and a corresponding threshold λ:

Safe Clearance from Obstacles (SCO). A soft constraint for keeping a safe clearance from the obstacles (Zghal and Dubey, 1990) is given by

$$\left(\sum_{i=1}^{N}\frac{1}{D_i}\right) \leq \lambda_{SCO} \tag{1}$$

where D_i is the distance between the i-th link of the manipulator and obstacles, and λ_{SCO} is the predefined upper bound (similar to λ_{JLA} and λ_{PEE} below);

Joint Limit Avoidance (JLA). A soft constraint for joint limit avoidance (Zghal and Dubey, 1990) is given by

$$\left(\sum_{i=1}^{N}\frac{\theta_{i,Max}-\theta_{i,Min}}{(\theta_{i,Max}-\theta_i)(\theta_i-\theta_{i,Min})}\right) \leq \lambda_{JLA} \tag{2}$$

where $\theta_{i,Max}$ and $\theta_{i,Min}$ are the maximum and minimum permissible joint angles and θ_i is the current joint angle for the i-the joint.

Precision of End-Effector (PEE). It is often required to ensure the precision with which a tentacle robot approaches a point or follows a path defined by the pose of the end-effector (EEF) (Hill and Tesar, 1997). Let $x \in \mathbb{R}^m$ represent the output position vector of the EEF and $\theta \in \mathbb{R}^n$ the vector of joint angles of the robot. An infinitesimal error in the EEF position can be mapped from the joint errors through:

$$\Delta x = J\Delta c \tag{3}$$

where the $m \times n$ matrix J, called the Jacobian, is a geometrically dependent structure relating the joint errors to the output errors (Manseur, 2006; Khalil and Dombre, 2002). The Euclidean norm of the EEF error is therefore bounded above by

$$\frac{||\Delta x||}{||\Delta c||} \leq \sigma_{max} \tag{4}$$

where σ_{max} is the Jacobian's maximum singular values. A soft constraint for the generalized EEF precision can be defined by bounding σ_{max}:

$$\sigma_{max} \leq \lambda_{PEE} \tag{5}$$

Note that we do not attempt to distinguish degrees of satisfaction of a soft constraint – we are only concerned with whether or not the constraint is satisfied. However, a soft constraint may be counted multiple times depending on the number of the violation occurrences exhibited while executing the path. Let $\mathbb{P}$ denote the set of all feasible paths. Here we define the cost function that describes the overall practicality of a path and then define the path planning with soft constraints using the cost function.

Cost Function. Consider a feasible configuration $\theta \in \mathcal{C}_{free}$, where $\mathcal{C}_{free}$ is the free configuration space, i.e θ meets all the hard constraints, e.g., not colliding with the surrounding obstacles and staying within the joint limits. Given a soft constraint s, the cost function of the configuration $cost_s : \mathcal{C}_{free} \rightarrow [0,1]$, i.e. a $cost_s(\theta) \in [0,1]$ can be computed for each $\theta \in \mathcal{C}_{free}$. This cost function can be continuous or discrete. In its simplest version, the cost function $cost_s$ is binary, which is 0 when the soft constraint is satisfied by θ, and 1 when violated.

Furthermore, given a set of soft constraints $\mathcal{S}$ with associated violation penalty weights, the cost of the feasible configuration is the summation of the penalty weights of all the cost of soft constraints that are violated by θ, defined as

$$cost : \mathcal{C}_{free} \rightarrow \mathbb{R}_{\geq 0},\ cost(\theta) = \sum_{s\in\mathcal{S}} w(s)\cdot cost_s(\theta) \tag{6}$$

where $w(s)$ is a positive value that represents the violation penalty weight associated with the soft constraint s. A path $\mathcal{P}$ of length l is represented by a unit-speed parametric function $\tau : [0,l] \rightarrow \mathcal{C}_{free}$ with $\tau(t) = \theta_t \in \mathcal{P}$. Then the parametric cost function can be defined:

$$v : [0,l] \rightarrow \mathbb{R}_{\geq 0} v(t) = cost \circ \tau(t) = cost(\theta_t) \tag{7}$$

Given a feasible path $\mathcal{P}$, its cost is the integral of the cost of all the configurations along the path, defined as

$$cost : \mathbb{P} \rightarrow \mathbb{R}_{\geq 0},\ cost(\mathcal{P}) = \int_0^l v(t)dt \tag{8}$$

A discrete approximation of the integral leads to

$$cost : \mathbb{P} \rightarrow \mathbb{R}_{\geq 0},\ cost(\mathcal{P}) \sim \frac{1}{n}\sum_{k=0}^{n-1} v\left(\left(\frac{k}{n-1}\right)l\right) \tag{9}$$

Which provides a cost function that penalizes paths with sections that violate the soft constraints provided.

Algorithm 1: Roadmap Generation with Soft Constraints.

```
 1: $V \leftarrow \emptyset$
 2: $E \leftarrow \emptyset$
 3: for $i = 1, ..., n$ do
 4:     $\theta_{rand} \leftarrow$ sampling with soft constraints
 5:     $V \leftarrow V \cup \{\theta_{rand}\}$
 6: end for
 7: for all $v \in V$ do
 8:     $X \leftarrow Near(G = (V, E), \theta_{rand}, r)$
 9:     for all $x \in X$ do
10:         if $(v, x) \vDash \mathcal{H}$ then
11:             $E \leftarrow E \cup \{(v, x), (x, v)\}$
12:         end if
13:     end for
14: end for
15: return $G = (V, E)$
```

Path Planning with Soft Constraints. Given a path planning problem $(\mathcal{A}, \mathcal{W}, \theta_{init}, \theta_{goal})$, a set of soft constraints $\mathcal{S}$ with corresponding penalty weights and a cost function *cost*, generate a feasible path $\mathcal{P}$ such that $cost(\mathcal{P})$ is minimized. Report failure if no feasible path can be found.

4 SAMPLING WITH SOFT CONSTRAINTS

PRM was designed to answer multiple path queries for a high-DOF robot in cluttered environments. In order for the algorithm to find not only correct paths but also paths that minimize violations of soft constraints the basic method must be refined. Here we describe the integration of the node-based soft constraints in the sampling phase of the PRM.

Following (Kavraki et al., 1998), the PRM roadmap generation is outlined in Algorithm 1. During node generation, instead of choosing completely random configurations, our sampling method with soft constraints (i.e. *SamplingSC* and *SamplingHCSC*) is called (line 4) and the new configuration that satisfies some or all the soft constraints is added to the set of vertices V. Connections are then attempted between vertices within a distance r using a simple straight-line local planner.

It is observed that for a collision-free node to be useful for path planning it must be part of a connected free region. Within any region we can expect some locations to be more practical than others. Ensuring that more practical nodes are chosen during the seeding process while still sampling the space sufficiently densely to construct paths is likely to improve overall path practicality, at least as measured by the node-based soft constraints.

Given that a node was found to be feasible we can search within a local region of this node to enhance the practicality of this node. In order to take advantage of this, the planner adjusts a node within its free space to states with fewer soft constraint violations before adding them to the roadmap. For efficiency reasons, and for generality of the approach, we follow the philosophy of randomness of the PRMs to make the adjustment. We present two node adjustment strategies *SamplingSC* and *SamplingHCSC* as outlined in Algorithm 2 and 3.

Algorithm 2 : SamplingSC (random sampling with soft constraints).

```
 1: repeat
 2:     $\theta_{rand} \leftarrow$ a randomly chosen configuration in $\mathcal{C}$
 3: until $\theta_{rand} \vDash \mathcal{H}$
 4: $\theta_{new} \leftarrow \theta_{rand}$
 5: for $i \leftarrow 1, ..., k$ do
 6:     $d \leftarrow \mathcal{N}(0, r^*)$
 7:     $\theta_i \leftarrow$ a random configuration at distance $d$ from $\theta_{rand}$
 8:     if $\theta_i \vDash \mathcal{H}$ and $cost(\theta_i) < cost(\theta_{new})$ then
 9:         $\theta_{new} \leftarrow \theta_i$
10:     end if
11: end for
12: return $\theta_{new}$
```

Algorithm 3: SamplingHCSC (random sampling with hill-climbing soft constraint satisfaction).

```
 1: repeat
 2:     $\theta_{rand} \leftarrow$ a randomly chosen configuration in $\mathcal{C}$
 3: until $\theta_{rand} \vDash \mathcal{H}$
 4: $\theta_{new} \leftarrow \theta_{rand}$
 5: $u \leftarrow$ a random direction
 6: for $i \leftarrow 1, ..., k$ do
 7:     $\theta_i \leftarrow$ move $\theta_{new}$ in the direction of $u$ by step size $d_{step}$
 8:     if $\theta_i \vDash \mathcal{H}$ and $cost(\theta_i) < cost(\theta_{new})$ then
 9:         $\theta_{new} \leftarrow \theta_i$
10:     else
11:         return $\theta_{new}$
12:     end if
13: end for
14: return $\theta_{new}$
```

In *SamplingSC*, for each randomly generated node θ_{new} that satisfies all the hard constraints, a user specifies the number k of attempts to adjust θ_{new} to reduce the soft cost. New samples are generated in θ_{new}'s neighborhood according to the normal distribution $\mathcal{N}(0, r^*)$, where the scale r^* (similar with the radius r used to in Algorithm 1) is chosen based on the assumed local complexity of the configuration space. Each of these new samples is first tested for compliance with the hard constraints (collision free in most cases). If the test passes then the soft constraints are applied. The valid node with minimum cost (i.e. it satisfies soft constraints the most) from this sample is then added in the roadmap.

Note that during the node adjustment step k nodes are not added to the roadmap. Rather, each node is augmented up to k times while retaining fixed the total number of nodes. Choosing k is an application-specific issue. On the one hand, k should not be too small, because we want to give our planner a good chance to make an improvement. On the other hand, making k too large increases the running time unnecessarily. In essence we assume that within some radius (defined by r^*) of a node, there exists a common homotopic path. In this work we assume a single r^* but clearly it would be possible to set $r^* = f(\theta)$ for complex non-homogeneous environments or to set $r^* = g(n)$ according to the density of the sampling.

SamplingHCSC is a greedy strategy that can be considered as an alternative to *SamplingSC*. Instead of attempting to reduce the cost of a sample once, the *SamplingHCSC* iterates the maximum of k steps toward a random direction u until a hard constraint is violated or the cost stops decreasing. The random direction u incorporates all of the degrees of freedom of the robot.

Once the roadmap $\mathcal{R}$ is constructed, finding a path between θ_{init} and θ_{goal} involves connecting these points to $\mathcal{R}$. If they do not belong to the same connected component, then more nodes need to be generated for $\mathcal{R}$ to connect the components to which θ_{init} and θ_{goal} belong. If this cannot be accomplished after a maximal number of trials then failure is reported. Otherwise, it proceeds to the next phase: extracting an optimal path from $\mathcal{R}$. Given the nature of the **cost** function of paths, it is possible to use Dijkstra's algorithm (Kim et al., 2003) to find the minimum cost path in $\mathcal{R}$ from θ_{init} to θ_{goal}.

5 POSTPROCESSING WITH SOFT CONSTRAINTS

Path smoothing is a commonly used post-processing method that improves a found path. Path pruning and shortcut heuristics are common path smoothing techniques for creating shorter and smoother paths. The shortcut method tries to iteratively improve the path by replacing a part of the path with a shorter local path. In each iteration, the path is randomly split in three parts. Let a and b denote the begin and end configurations of the middle part. If the local path $LP(a,b)$ is collision-free, then the local path replaces the middle part. Due to their simplicity, shortcut algorithms have been widely used to improve the quality of paths computed by randomized planners (Geraerts and Overmars, 2007).

The goal of traditional shortcutting method is to find a shorter path that is in the same homotopy class of an existing path. However, this can bring the robot close to an obstacle or violate other soft constraints. We augment the shortcut algorithm with soft constraints (shown in Algorithm 4) which compares the cost of the new local path and the original part of the path before replacement. We expect that this method will be slower than the original heuristic as the cost comparison takes extra computing time. However, we expect that the resultant path will be more practical.

Algorithm 4: Shortcut with Soft Constraints (discrete path $\mathcal{P} = \theta_0, \theta_1, \ldots \theta_{m-1}$).

```
1: loop
2:     $a, b \leftarrow$ two random indices in $[0, m)$ and $(a < b)$
3:     $\mathcal{P}_1 \leftarrow \theta_0, \ldots \theta_{a-1}$
4:     $\mathcal{P}_2 \leftarrow \theta_a, \ldots \theta_b$
5:     $\mathcal{P}_3 \leftarrow \theta_{b+1}, \ldots \theta_{m-1}$
6:     if $LP(\theta_a, \theta_b) \models \mathcal{H}$ and $cost(LP(\theta_a, \theta_b)) < cost(\mathcal{P}_2)$
       then
7:         $\mathcal{P} \leftarrow \mathcal{P}_1 \cup LP(\theta_a, \theta_b) \cup \mathcal{P}_3$
8:     end if
9: end loop
```

6 EXPERIMENTAL VALIDATION

This section describes experiments of the algorithm using a real tentacle robot and its simulation. The planar tentacle robot is composed of ten Robotis Dynamixel AX-12 servos (Figure 1). The robot is approximately 67cm long when it lies straight. One end of the robot is fixed and rollers have been installed to reduce friction between the robot and the table top. The algorithms were implemented within Lavalle's Motion Strategy Library (LaValle, 2006), and run on a Mac running OS X with 3.06 GHz Intel Core 2 Duo processor and 2 GB memory.

Only one single soft constraint (SCO, JLA, and PEE as discussed in Section 3) is considered in each experiment. The penalty weight for each soft constraint is set to 1. The thresholds are set as follows: $\lambda_{sco} = 15, \lambda_{jla} = 50, \lambda_{pee} = 1000$.

Comparisons between the basic path planning and path planning with soft constraints minimizing a cost function are illustrated in Figure 2. The scene shows a simulation of the tentacle robot operating in a workspace comprising two obstacles. The path planners attempt to compute possible paths that takes the

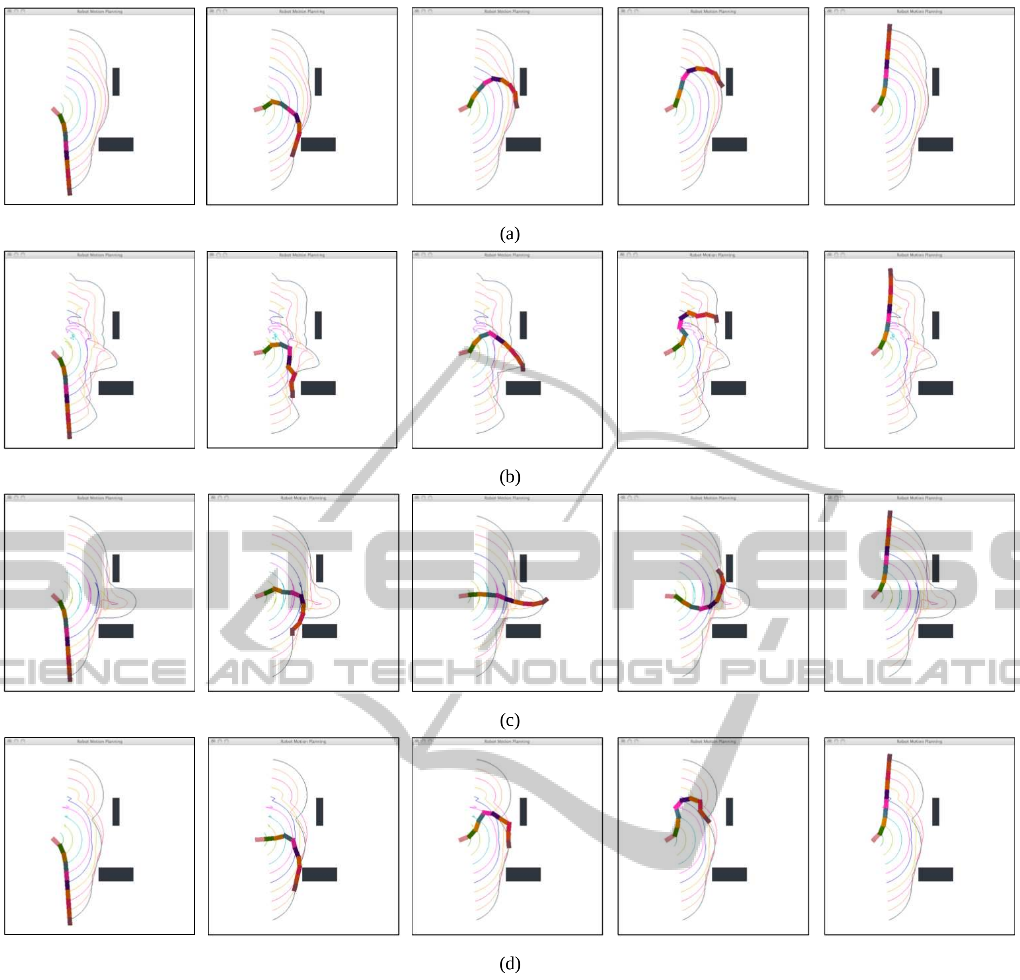


Figure 2: Path planning in a workspace with two rectangular obstacles. Comparison between (a) basic path planning; (b) path planning with soft constraints keeping safe clearance from obstacles (SCO); (c) path planning with soft constraints avoiding joint limits (JLA); (d) path planning with soft constraints maximizing precision of the end-effector (PEE).

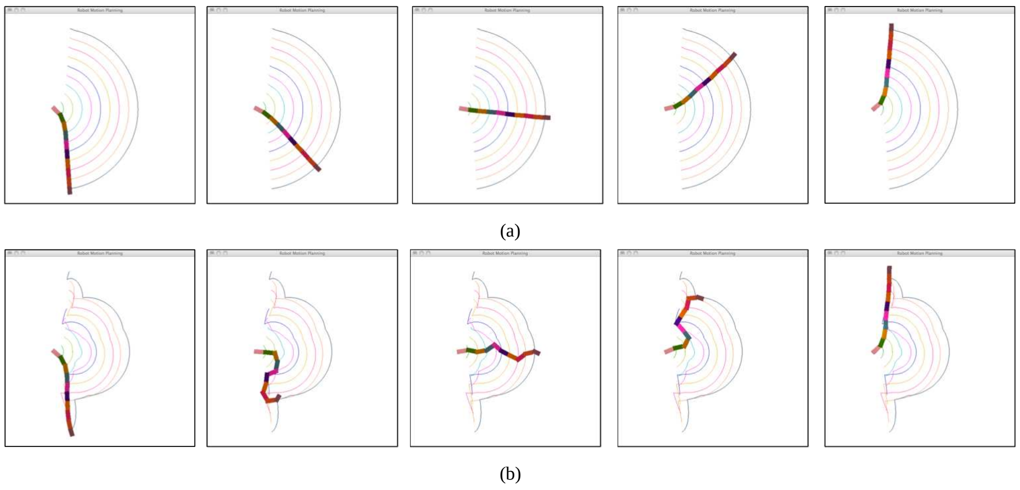
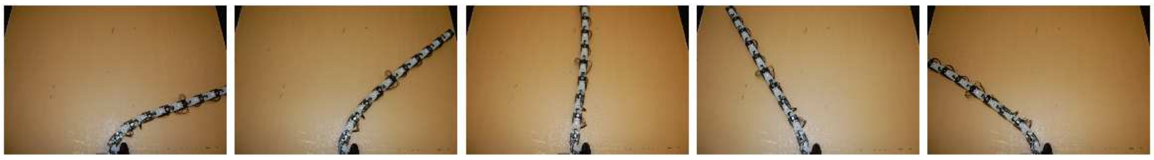
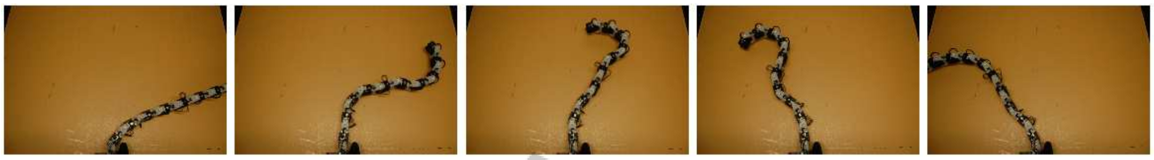


Figure 3: Path planning in the absence of obstacles. Comparison between (a) basic path planning and (b) Path planning with soft constraints maximizing the precision of end-effector (PEE).

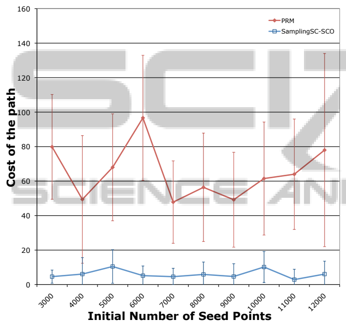


(a)

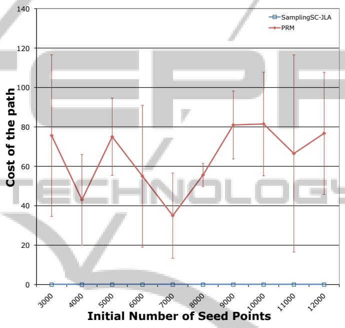


(b)

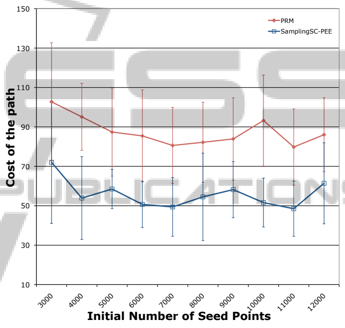
Figure 4: Snapshots of the tentacle robot executing the paths computed by: (a) basic path planning and (b) Path planning with soft constraints maximizing the precision of end-effector (PEE).



(a)



(b)



(c)

Figure 5: Cost comparison of the paths found by PRM and *SamplingSC*, when the soft constraints are: (a) SCO; (b) JLA; (c) PEE. Cost of the path is measured as the summation of the binary cost of the configurations along the discretized path. Results are averaged for 20 independent runs for each case. Standard deviations are shown.

robot from the lower space to the upper one while avoiding obstacles. Figure 2(a) shows a path computed by the traditional PRM followed by the traditional shortcut method. The path is correct and is relatively short. Figure 2(b) shows a path computed by our path planner minimizing SCO, which encourages to keep the robot a minimum distance away from the obstacles. Figure 2(c) shows a path minimizing JLA, which tries to minimize the deviation between each joint. Therefore the robot becomes straight when passing the gap between the two obstacles.

In practice the precision of tentacle robots is a critical issue for it to accomplish tasks and the precision issue becomes more critical when the robot has more joints. Here we use PEE as the soft constraint in path planning and try to find paths that the robot can follow more precisely. As discussed in Section 3 we can increase the precision of the end-effector by reducing the maximum singular value σ_{max} of the Jacobian matrix. It has been observed that σ_{max} is maximized when the robot is straight, and it decreases when the robot bends. A result path is shown in Figure 2(c). The difference is more obvious in the case shown in Figure 3 where there is no obstacle in the scene. Most path planners will compute a path shown in Figure 3(a) that directly takes the path from the start to the goal while the robot stays straight all the way. However, maximizing the PEE gives a more complex solution as shown in Figure 3(b). The effectiveness of the method was further validated on the real tentacle robot, to which we passed different computed paths and it shows that our method outperforms basic PRM in terms of precision of the robot in practice. See Figure 4 for snapshots from the execution of these experiments.

To test our algorithm's performance on different soft constraints, we compare the practical path alghorithm with the basic PRM using the problem shown in Figure 2. We compare the *SamplingSC* algorithm with a single soft constraint applied against the basic PRM. Each algorithm was tested with various numbers of seed points as described in Figure 5. By sampling with soft constraints the average cost of the path is decreased significantly when compared to the basic PRM in all the three cases. The *SamplingSC* method also shows more stability (smaller standard

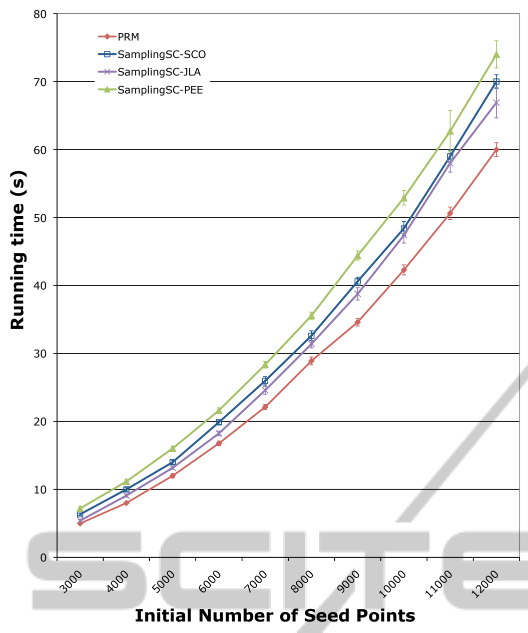


Figure 6: Comparison of the running time of the basic PRM and *SamplingSC* with soft constraints being SCO, JLA and PEE. Results are averaged for 20 independent runs for each case. Standard deviations are shown.

deviations) than the basic PRM in the path quality they achieve. Figure 6 compares the running time of constructing the basic PRM and the roadmap with different soft constraints for the test model. It shows that the roadmap generation with soft constraints takes more time to compute than the PRM algorithm since the node adjustment involves an increased number of collision checks and computation to check the soft constraints.

7 SUMMARY AND FUTURE WORK

Path planning is an important but intractable problem in Robotics. Sampling-based path planning algorithms are successful in solving high-dimensional problems. However, their ability to find paths that meet certain soft constraints is still limited. In many applications, it is also required to find a path that is safer or more precise than other alternative paths.

This paper describes an approach to the problem of planning practical paths for tentacle robots in terms of soft constraints and develops sample adjustment strategies for sampling-based path planners to take into account these soft constraints. The planner adjusts each randomly generated node in a random direction within its local neighborhood to increase its practicality (i.e. reduce its cost). Then the new node with competitive practicality replaces the initial node in the roadmap.

We have shown the effectiveness of our approach using both a simulated and real tentacle robot. Three soft constraints are used separately in the test model. Although the resultant path is not optimal due to the randomness of the planner, it shows significant improvement over the path computed by the basic PRM.

Currently we only considered node-level soft constraints to express the practicality of each node, i.e. a configuration of the robot. For many problems the transition of the adjacent configurations should also meet certain requirements, such as the smoothness of the transition and the acceleration of the movement. Ongoing work includes developing path planners to address such edge-level practicality issues.

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