INTEGRATING SIMULATED TENSEGRITY MODELS WITH EFFICIENT MOTION PLANNING FOR PLANETARY NAVIGATION

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ABSTRACT

One of the more interesting advancements in prototype robotics are tensegrity-based robots. These robots use compression elements and tension cables to create lightweight structures that can reconfigure their shape. While these capabilities are good for transport of the robot and costs of materials, they complicate planning and control of locomotion. With so these dynamic and reconfiguring parts, both simulating the motions of the robot and planning future motions become more challenging. New software packages and state-of-the-art planning algorithms are helping to address these challenges, but have yet to be used in tandem. This work shows the interaction of these two advancements in control and planning for tensegrity-based robots.

1 INTRODUCTION

Tensegrity-based structures have been proposed as flexible robotic systems [1], [2]. They provide compliance and load-distribution, which allow for dynamic maneuvers and reconfiguration over difficult terrains while maintaining structural integrity. Nevertheless, controlling tensegrity robots is challenging. There has been exciting progress on providing locally valid gaits [3], in some cases through the use of pattern generation principles [1], [4], and has been evaluated on physical robots (see Fig. 1). These breakthroughs allow moving the robot in a desired direction. It has not been possible, however, to purposefully navigate or reconfigure for longer horizon paths.

The generation of purposeful motions requires global planners, which reason over long horizons, consider terrain complexity, and provide diverse paths for science teams. Such methods have to deal with the high dimensionality of the system, the effects of contacts with the ground on the system's dynamics, and noisy actuation. A promising solution to this planning problem involves using sampling-based motion planners [5], [6], which have been shown to be successful when dealing with high-dimensional robots. It is also the case that under certain conditions, these sampling- based methods can achieve asymptotic optimality [7]. The asymptotic optimality property states that given sufficient computation time, the probability that these sampling-based algorithms return the optimal solution approaches one. In practice, the solutions returned by these algorithms are close to optimal in a short amount of time. Until recently, these desirable properties could not be achieved in the case of highly dynamical systems, such as tensegrity robots.

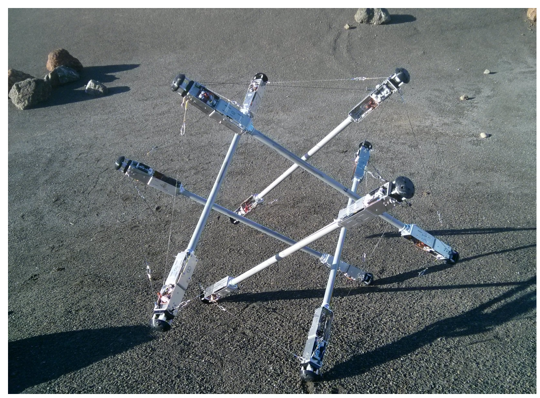

Figure 1: SUPERball prototype from NASA Ames Research Center [3].

A more recent development is an algorithm that provides asymptotic optimality for systems with dynamics [8]. By making use of selective deletion of previously stored waypoints, the tree data structure used in the algorithm can focus computation on high-quality paths. Using this method, finding paths of increasing quality for systems with dynamics or physically-simulated systems is now possible in a reasonable amount of time. In addition, this method can operate while planning under uncertainty by using a particle representation to model multimodal belief distributions and nonlinear dynamics [9].

For simulating the high-dimensional tensegrity robots, a software tool called the NASA Tensegrity Robotics Toolkit (NTRT) has become available to simulate tensegrity robots through the use of a physics engine [10]. Such simulations require significant computational resources due to the complex dynamics and contacts (tension cables, terrain contacts, shared force loads). The benefit of this expensive simulation is that it is shown to accurately approximate the real-world prototypes. The integration of NTRT with the sampling-based methods described above provides an initial step toward long horizon planning capabilities for tensegrity robots.

2 EXPERIMENTAL SETUP

This work integrates the NTRT simulator [10] with the recent framework for belief space planning [9] to perform robust long-horizon planning for tensegrity robots. To the best of the authors knowledge, this is the first time it has become possible to plan for tensegrity robots while taking dynamics into account, i.e., not just in a quasi-static manner as in [11]. It is also possible to consider state uncertainty as part of the planning process.

The tensegrity evaluated in the planning method is the SUPERball [3], which is a prototype robotic platform built at NASA Ames Research Center. This structure has six rigid components arranged to mimic a icosohedron shape. These rigid elements are modeled as dynamic rigid bodies with 6 degrees of freedom each (three translational components, three rotational components, and their corresponding velocity terms). Movement is achieved by contracting the cables that connect the rigid elements. These contractions create forces on the rigid elements that cause the entire structure to reconfigure. Given enough change in the structure, rolling will occur, thus achieving locomotion.

2.1 **Algorithm**

Algorithm `SPARSE_BELIEF_TREE`($\mathbb{B}$,$\mathbb{U}$,b_0,N)

$G = \{V \rightarrow \{b_0\}, E \rightarrow 0\}$;
for N *iterations* **do**
  $b_{selected} \leftarrow$ `SelectNode` ($\mathbb{B}$,V);
  $b_{new} \leftarrow$ `Random_Prop` (b_{select}, $\mathbb{U}$);
  if `IsNodeLocallyBest` (b_{new}, S) **then**
    $V \leftarrow V \cup \{b_{new}\}$;
    $E \leftarrow E \cup \{\overline{b_{select} \rightarrow b_{new}}\}$;
    `Prune_Dominated_Nodes`(b_{new}, V, E);

Figure 2: Algorithmic framework for high-level motion planning.

The high level planning methodology is provided in Fig. 2. Given an initial belief $\mathbf{b_0}$ taken from the space of beliefs **B**, the algorithm generates a tree of paths that use control inputs from the control space **U** to move the robot to the goal. The algorithm operates in a manner that first tries to explore the state space quickly, searching for successful paths. Then, because of the properties of the algorithm, the path will be improved given more computation time.

At a high level, the algorithm works using some basic primitives. First, an existing node in the tree is selected. This node is then extended using random control inputs to generate a new node. Finally, if this new node is collision-free and has a good path cost, the node will be added to the tree. For more details about the algorithm, see [8], [9].

2.2 **Implementation Details**

When moving to planning under uncertainty, the correct representation of uncertainty must be chosen. In many other domains, a Gaussian distribution is chosen, but is not appropriate for highly dynamical systems, such as tensegrity robots. This is due to their nonlinear behavior that likely will cause the uncertainty to follow multi-modal distributions, i.e. have multiple probability peaks rather than one. For this reason, a particle-based representation is chosen, where a set of particles approximate the underlying probability distribution.

Because a particle representation is used when planning under uncertainty, the computational cost of planning is increased significantly. Each particle must be simulated independently of the other particles, meaning NTRT must be called for each particle. Since this simulation is the dominant computation even when planning without uncertainty, improvements need to be made to make simulations faster. By taking advantage of the independence of the particles, a parallel extension can be performed, where multiple particles can be extended at the same time.

3 EVALUATION

The integration of NTRT with a sampling-based planner requires significant computational resources. This is mostly due to a basic primitive that a sampling-based planner requires, the forward propagation primitive. This forward propagation primitive in most cases is fast, but is a computational bottleneck when a physics engine is used. This is the case when using NTRT and this influences the planning time.

In this section, different scenarios are constructed where the tensegrity robot must traverse from its start position to a goal region. A simple problem is shown first, which is only the task of moving from the start to the goal. Then, invalid regions are introduced, where the center of mass of the robot cannot intersect. These regions could represent unsafe traversal areas due to environmental factors, such as low sunlight or difficult terrain. Finally, the challenges related to planning under uncertainty are explored, along with some observations.

3.1 Traversal Planning

For an initial test, a plan for moving without invalid regions is performed. The best path in this setup is as close to a straight-line as possible. This is not directly achievable given the dynamics of the robot. An example planned trajectory that considers terrain is shown in Fig. 3. An example path planning tree is shown in Fig. 4 where the paths shown are for the center of a rod in the structure. The goal for the robot is the top right of the figure. The tree illustrates the inherent dynamics of the SUPERball and how moving in straight lines is difficult even on flat terrain.

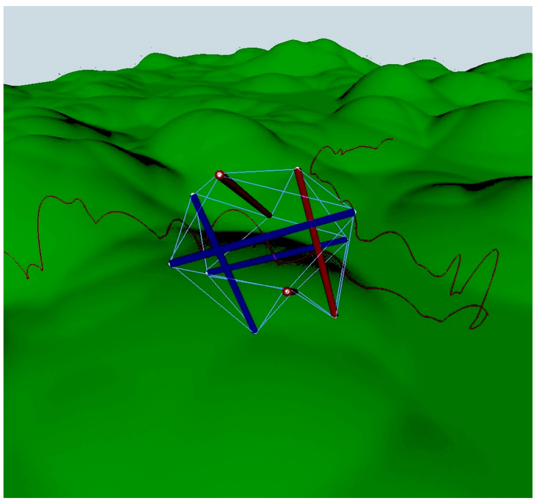

Figure 3: An example path for the SUPERball tensegrity robot. This path also considers the terrain effects through the physics simulator.

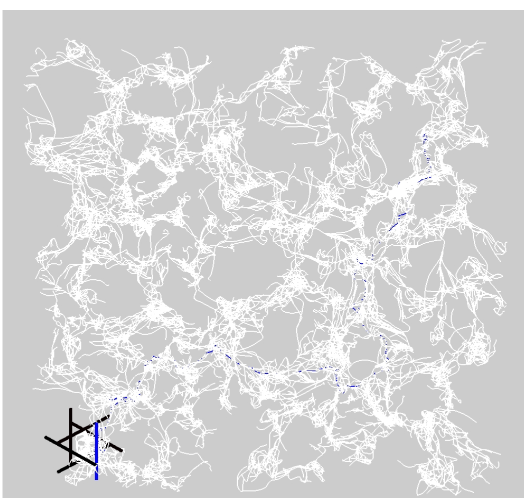

Figure 4: An example tree computed from the motion planner. This example has no invalid regions.

3.2 Navigation Around Obstacles

In order to get closer to real mission objectives, a series of invalid regions are defined for the robot. The center of mass of the robot cannot overlap with the invalid regions. The goal is to move to a position that is nearby the start point, but requires movement around obstacles. This highlights the need for high-level planners. An illustration of the motion planner's tree is shown in Fig. 5.

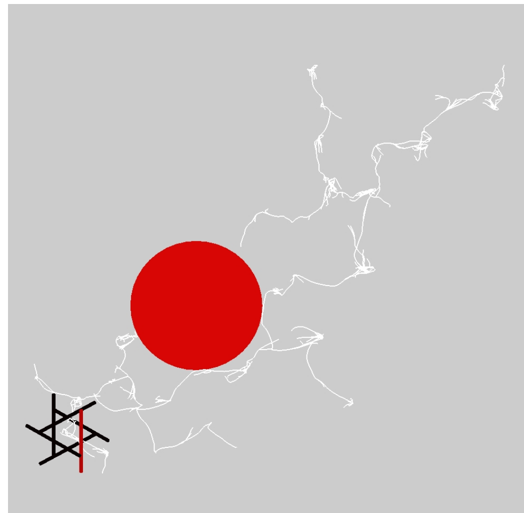

Figure 5. An example tree computed from the motion planner. This tree has to avoid the red region, which causes the robot to move around it. Invalid regions could correspond to craters or inescapable areas.

3.3 Planning Under Uncertainty

The following table outlines the performance of planning in the state space and the belief space. For increasing computation times, the largest distance that can be traversed is reported. The increased computational cost planning under uncertainty has relative to just path planning severely reduces exploration capabilities. Both sets of experiments use a single computer core for computation.

	Time/ Dist.	Time/ Dist.	Time/ Dist.
State Space Planning	1 min/14m	2 min/31m	3 min/71m
Belief Space Planning	2 min/4m	4 min/12m	6 min/14m

A trajectory computed in the belief space is shown in Fig. 6. Due to noise in actuation, different final states may be reached, which composes a belief over the actual state of the robot, illustrated as transparent shapes of the robot. Planning in belief space has higher computational cost relative to state space planning, but provides the benefit of robustness to errors.

Another interesting property that was discovered while planning under uncertainty is that the SUPERball can inherently reduce its uncertainty with specific motions. This behavior arises due to the different faces that can be touching the ground at any given time. Even with small errors in actuation, a similar resting state can be achieved by not changing control inputs too rapidly. In addition, the set of particles quickly diverges and clusters into multiple modes (see Fig. 7 for an example). It may be possible to exploit this behavior in an intelligent way to help reduce overall uncertainty when executing a trajectory in the real world.

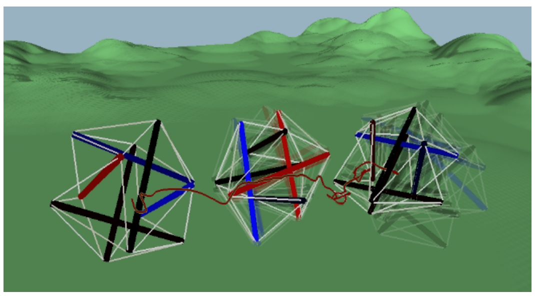

Figure 6: An example trajectory computed when planning under uncertainty. The transparent versions of the SUPERball show different possible futures given uncertain actuation.

Figure 7: A single set of particles that represent one belief distribution. This distribution is multi-modal. The dynamics of the system naturally create these situations.

4 DISCUSSION

The integration of a simulator for tensegrity robots with motion planning techniques allows for more diverse robot trajectories to be computed. It also allows for those trajectories to be more dynamic and not limited to being quasi-static. There are some interesting research directions to explore as well.

4.1 Implementation Efficiency Concerns

One of the most obvious drawbacks discovered when planning with the physics engine is that the computational cost of planning is large. Especially in the case of planning under uncertainty, there is a lot of work to be done to make planning faster. This work takes advantage of parallelism to achieve faster times, but alternatives should be explored. It might be possible to find a different representation for the probability distributions that is not particle-based. If this is possible, much of the computational cost can be reduced. Another possible direction is looking into more approximate models of tensegrity robots for long horizon planning. Then, the full simulator can be used more as a verification tool than planning primitive.

4.2 Algorithmic Additions

Much of the integration between the simulator and the planner assumes that there is no knowledge other component. The planner considers the simulator as a "black box" that given a start state, an end state is provided as output. If more knowledge about the underlying workings of the simulator is given to planning, more efficiency may be gained. By maximizing the usefulness of each iteration of the planner, the resulting paths will have better quality. This addition could be further parallelization, biasing the search region, or even moving into a replanning framework.

Another way to improve the integration is to better focus the search process to promising controls and integrating this high-level planning method with efficient local gaits that have been recently developed [3]. This work uses random control inputs to the robot, while more intelligent control inputs will more effectively move the robot. The question then becomes, what are the set of diverse local gaits that allow for locomotion in the largest amount of cases? This question is the focus of ongoing work.

Acknowledgement

This research has support from a NASA Space Technology Research Fellowship No. NNX13AL71H and NASA's Game Changing Developments SUPERball Task.

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