Model Predictive Control of an Underdamped, Pneumatically Actuated, Soft Robot with Flexible Links for Unmodeled Environments

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2 Overview Chart

Model Predictive Control of an Underdamped, Pneumatically Actuated, Soft Robot with Flexible Links for Unmodeled Environments

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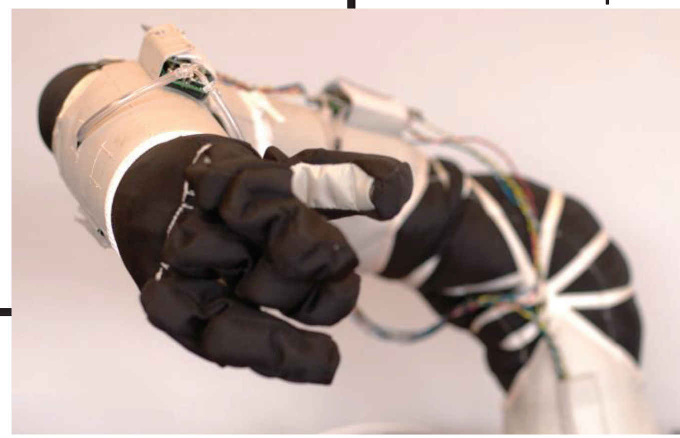
Research Objectives

- Develop optimal control methods (Model Predictive Control) for soft robots to enable fast, precise motion despite the difficult underdamped dynamics of the system.
- Apply these control methods to achieve unprecedented performance in real and unmodeled environments for soft robot manipulation and locomotion.
- Test the controllers in realistic and useful scenarios (such as equipment maintenance or installation, or exploration of rugged terrain), that will have wide applicability to future space missions.



Soft, underdamped, pneumatically controlled robot from Otherlab.

Approach

- Model soft robots using approximate linear, pseudo-rigid body, and non-linear models.
- Incorporate models with Model Predictive Control (MPC) using state-of-the-art real-time optimization for manipulating unmodeled objects.
- Compare MPC to other state-of-the-art controllers for underdamped systems.
- Build new capabilities on top of low-level MPC controllers such as 1) collaboration between different soft robots and 2) soft robot locomotion.

Potential Impact

- Capable robots can provide significant benefits for space exploration in terms of human assistance and collaboration, rugged terrain exploration, or equipment maintenance.
- The proposed controllers will enable cheaper, lighter (10 times lighter), smaller (10 times smaller packing volume) robots for important missions.
- The proposed control methods and testing will also be applicable in other important areas such as search and rescue or disaster relief.

3 Scientific/Technical/Management Section

3.1 Relevance

3.1.1 Relation to Call and Proposed Topic

The main objectives of our proposal and their relation to the proposal solicitation can be described as follows:

1. Develop optimal control methods for underdamped, underactuated, soft robots that allow fast and precise motion despite the difficult natural dynamics of the system.

2. Apply these control methods to achieve unprecedented performance in real and unmodeled environments for underdamped robot manipulation and locomotion.

3. Test the controllers we develop in realistic and useful scenarios (such as equipment maintenance or installation, or exploration of rugged terrain), that will have wide applicability to future space missions as well as other crosscutting domains such as natural disaster relief or search and rescue missions.

These control methods will use recent advances in convex optimization to implement model predictive control with explicit models of the robot compliance to achieve smooth and fast motion control of soft robots with low inertia and inherent compliance. This approach is in contrast to current low-pass filtering techniques (input smoothing), impulse command methods such as input shaping (which trade off a decreased rise-time for an increase in sensitivity to parameter variation), or open loop optimal control where the full trajectory must be known prior to execution and solution times may be too long for on-line updates. Our approach uses a forward model of the robot dynamics (including compliance) to predict over a short time horizon the effect of control inputs. It then selects the optimal inputs for that small horizon. In our prior work with rigid robots that have compliance at the joints (see [47, 48]), we have found MPC to be robust to modeling error (plus or minus 50% of the nominal mass values). MPC can also be used to explicitly define constraints that limit velocity and mitigate unexpected contact with the world which will further increase the utility of our proposed controllers for soft machines in close proximity to each other, people or other important and delicate equipment.

For the first two years of research we will focus on using a two-armed pneumatically actuated robot and applying our controllers to perform manipulation tasks such as:

- non-dexterous grasping of an object with known mass, but unknown geometry
- interacting with unmodeled objects and environments
- interacting with compliant systems including other robots and or materials such as fabric or insulation

For the third year of research, we will focus on building on top of our existing controllers for a pneumatically-actuated quadruped robot for tasks like:

- traversing flat and rough terrain using virtual models (often called virtual model control)
- performing simultaneous manipulation and locomotion

We expect that our progress will be a major step towards allowing soft robots to explore environments, perform maintenance, or work collaboratively with other robot agents or human partners without significantly increasing the limited payload and volume constraints that exist for space missions.

3.1.2 Relation to Improvements at System Level

Current robot technology for space missions such as DLR's Rollin' Justin [10, 11], or NASA's Robonaut 2 [18, 19], is mostly based on rigid robot linkages which usually have compliance at the joint (i.e. impedance control). Although these robots are incredibly capable in terms of hardware, they are heavy, take up a large volume, and despite having compliance at the joints have relatively high inertia which still limits how quickly they can move around delicate equipment or human collaborators in order to mitigate unexpected impacts and high contact forces. In contrast, the testbed we are proposing is approximately 10 times lighter than Robonaut 2 (330 lbs vs 33 lbs) which has significant benefits for space travel. Additionally, because our testbed is inflatable, the storage volume for space missions is approximately 10 times smaller than a platform like the new Baxter robot from Rethink Robotics (a 3'x2'x1' storage box versus a 4'x4'x4' box).

However, despite the reduction in transportation size and weight, the current performance of underactuated platforms is generally considered to be lower than even the recent generation of torque controlled robot arms (e.g. WAM, Robonaut 2, Meka M1, PR2). Our proposed research will provide a substantial improvement in control performance and would put underactuated, soft robots on par with other torque controlled robots while still being over 10 times lighter and over 10 times smaller in volume for easier and more realistic transport on space missions. Additionally, the intrinsic safety of lower inertia and compliant manipulators increases the likelihood of these platforms working with human collaborators on dangerous and difficult missions. If we can fit more of these soft robot platforms in the same space as one rigid robot, then there is also the opportunity to pack multiple robots for redundancy in case of failure and for collaboration between robots for difficult or heavy tasks. The possibility of having multiple robots capable and available for maintenance means that astronauts can focus more on high-level cognitive problems. It also means that when necessary, a single person could accomplish the work of many in collaboration with the robots.

Finally, the cost of this platform is between $20k-$30k versus $2.5 million for the current cost of Robonaut 2. Admittedly, the hardware on Robonaut 2 is designed for space operation, and this testbed is not yet. However, we expect that if we can show with our control methods that soft machines can compete with rigid robots in terms of performance, there would still be a large cost benefit to using this type of platform.

3.2 Related Research and Capabilities

3.2.1 Comparison with State-of-the-art

Recently, there has been a greater emphasis in research on robots using joint impedance control to interact with humans and the environment (see [4, 5, 15, 26, 27, 30, 31, 35, 51, 80, 98]). However, in uncertain or unmodeled environments, the performance of these robots in terms of speed is fundamentally limited by the inertia of their rigid links. Our approach of improving the performance for control of a soft, inflatable robot directly addresses the issue of inertia and mitigates unintended consequences of unexpected contact.

Other researchers have focused on control for manipulators with flexible links using methods such as open loop input shaping [7, 17, 55, 63, 83, 90], inverse dynamics or differential flatness [53, 69], sensor-based feedback or nested feedback loops [59, 64, 75, 93, 96], linear quadratic regulators [68], or neural network control [74, 85, 87, 88]. For the most part however, these methods try to compensate for underdamped oscillation in systems with much higher natural frequencies than our soft robot (i.e. stiffer links). A few attempts at using MPC to address this problem exist (see [12–14, 86]), but almost all of the previous work, including that on MPC, is limited to one link, two links, or parallel robot structures. In contrast, our work will develop controllers from the onset that are designed for a complete 14 degree-of-freedom soft robot in order to manipulate and interact with the environment without a pre-defined trajectory or stringent accuracy requirements for the dynamic models.

For robot locomotion of both bi-pedal and quadrupedal platforms (sometimes in conjunction with manipulation), we can group the related work into inverse dynamics for control [33, 73], stochastic and optimal control [16, 25, 52], Poincaré-based (or limit cycle) methods [28, 60, 77], whole-body motion control [54, 76, 78], planning-based foot placement [6, 9, 38, 65, 97], Zero Moment Point methods [29, 42, 92], reactive control for following nominal trajectories [8, 61, 71, 91], virtual model control (including SLIP models) [34, 50, 66, 70, 95], or some mixture of these approaches that often include hybrid dynamics [24, 32, 39, 67, 72, 81, 84]. One of the most successful approaches for locomotion in rough terrain has been the use of virtual models to one degree or another which has been used both in academia and industry (see Cheetah and BigDog robots from Boston Dynamics). Far fewer researchers have looked at soft or flexible robots and tensegrity structures to locomote (see [40, 56, 79, 89]). Our approach (in terms of testbed form and robustness) is most related to these. Other approaches for bi-pedal locomotion and manipulation of the world that already use model predictive control for rigid robots and assume that they can explicitly model the world, including where, when and what type of any possible contact (see [22, 23]). We deem this to be unrealistic for real-world scenarios and expect that our proposed lower-level controllers would serve as a useful foundation for any kind of higher-level control such as theirs.

3.2.2 Perceived Impact on Knowledge in Field of Manipulation for Soft Machines

Successful completion of the proposed research will result in a true paradigm shift for manipulation and control of robots, especially in close proximity to people and in other unmodeled environments. We expect that the most immediate impact will be that robots will begin to be used in many applications that were previously considered infeasible due to the required cost of robot usage in terms of time or money, cost of specialized instrumentation or sensors for safety, or lack of mechanical robustness of the robot. This shift will come because we can now have light-weight, low-inertia, cheap, robust robots that can more safely interact with people and their environment. Although this shift will allow us to perform more useful tasks around and for people, it will also open up new avenues in research from basic controls and estimation research, to human robot interaction, to human-machine interfaces.

After initial development of the dynamic models and controllers, our focus will be on practical implementation of control for soft robots in uncertain environments. However, we expect that research on modeling, and stability for these systems is also an area where we can contribute to current knowledge for soft robots and controlling them using MPC. This research and approach to robotics will also open new doors for questions about modeling unilateral contact and velocity constraints for robot control if we allow and expect contact in unmodeled environments and interactions.

3.3 Proposed Innovations

Our proposed innovation is to apply recent advances in convex optimization (see [21, 36, 37, 57, 58]) to form tractable, high performance control methods for low inertia, underdamped, soft robots. Specifically, we expect to show that we can use a form of optimal control called model predictive control (MPC) to accurately and quickly move a soft, low-inertia robot arm to a desired position or through a desired trajectory. We expect to generalize our results to large degree of freedom robots (14+) by working from the beginning on a real platform as opposed to working in theory or simulation alone (although we will use both of these tools). The focus on a real platform will help to ensure that our methods are also robust and applicable to future NASA missions and that we satisfy the three objectives listed in Section 3.1.1.

Secondary innovations that we are proposing include developing methods that would allow soft robots to work together or work with a human partner subject to constraints and underdamped dynamics. We also expect to develop variable impedance control for mitigating unexpected collisions by varying impedance on-the-fly instead of using iterative learning techniques which are currently prevalent, but not applicable to unmodeled environments and non-repeated motion. We also expect that our results from year one and two as well as the mechanical robustness of the proposed testbed (see Section 3.4.3 and http://youtu.be/zML1XyJxX8I) will allow us to develop locomotion control algorithms without fear of damaging the equipment in the third year. We will combine the controllers for locomotion and manipulation to perform useful tasks (such as installation or maintenance on equipment with other robots) that are not usually considered for robots due to complexity or difficulty of the task.

3.3.1 Effect on Space Science, Travel and Exploration

Because our proposed testbed is lightweight and compact for storing when not in use, developing controllers that result in high performance soft machines that are easy to deploy and safe for human coworkers will make space exploration immediately more viable. We expect that given our proposed work, multiple robots could be commanded by a single astronaut or even work collaboratively with the astronaut when necessary using direct physical interaction without fear of injury or unexpected high impact forces. Being able to use multiple of these robots due to their compliance and robustness should result in reduced risk during missions with human astronauts.

Additionally, the robustness and current low-cost of this platform in combination with our proposed controllers make it ideal to send on scouting or reconnaissance missions in uncharted and rough terrain areas. We expect that the result of our work will be that these soft robots will be capable of manipulating unknown objects and traversing unmodeled and rough terrain quickly and efficiently. These are currently tasks that are still extremely difficult and slow for rigid, high inertia robots. The recent DARPA Robotics Challenge showed that even the most successful teams moved slowly and carefully to locomote or manipulate the world.

In our case however, if we are successful at moving rapidly while controlling underdamped oscillation, the robot can move quickly without concern for serious damage due to falling or impact.

3.3.2 Path to Further Development and Crosscutting Potential

For most of our tests we expect to have a human-in-the-loop for at least supervisory control. However, future development should focus on more autonomous behavior or better human-machine interfaces for controlling these robots from a space station until autonomy (AI) methods can perform more robustly. We believe that developing better intermediary control (sometimes called shared control) between the robot and the human giving commands will be useful. This is however work that is mostly outside the scope of this proposal except for our proof-of-concept applications.

We also expect to eventually use our controllers for robots to directly interact with human collaborators in the same way that we will develop methods to interact with other robot agents and unmodeled environments. This is a fruitful area for future development and crosscutting potential so that we have robots that can safely perform in-home assistance tasks for older adults or people with motor impairments (such as activities of daily living or general home maintenance).

Finally, we believe that the proposed controllers and hardware have a great crosscutting potential for use in natural disaster response, war-torn countries and first responder scenarios. These platforms could even be dropped into a remote disaster zone and provided with mechanisms to inflate and then look for survivors or help rescue workers that are already on the ground.

3.4 Technical Approach

3.4.1 Control Methods for Dramatically Improving Soft Machine Performance

In order to accomplish high performance and high bandwidth control of soft robots, we will use three main control methods, 1) Model Predictive Control (MPC), 2) Linear Matrix Inequalities (LMI) and 3) Virtual Model Control (VMC). The majority of our proposed work will use MPC which when given a cost function, a dynamic model of the system, and constraints on states and actuation variables, calculates the optimal thing to do over a short time horizon. Because it is relevant for our proposed testbed, we are assuming that torque or force control for most soft robots can be executed as follows:

$$\boldsymbol{\tau}_{control}(\boldsymbol{K}_p, \boldsymbol{K}_d, \boldsymbol{q}_{des}) \quad = \quad \boldsymbol{K}_p(\boldsymbol{q}_{des} - \boldsymbol{q}) - \boldsymbol{K}_d\dot{\boldsymbol{q}} + \hat{\boldsymbol{G}}(\boldsymbol{q}) \tag{1}$$

The inputs to determine the applied control torques ($\boldsymbol{\tau}_{control}$) are $\boldsymbol{K}_p, \boldsymbol{K}_d, \boldsymbol{q}_{des}$. Where $\boldsymbol{K}_p$ and $\boldsymbol{K}_d$ are m by m dimensional gain matrices and m is the number of degrees of freedom (or joints) on the robot, $\boldsymbol{q}, \dot{\boldsymbol{q}}$ are the joint states (angles and velocities), $\boldsymbol{q}_{des}$ is the set of desired joint angles and $\hat{\boldsymbol{G}}(\boldsymbol{q})$ is gravity compensation torques. For our platform, $\hat{\boldsymbol{G}}(\boldsymbol{q})$ should be fairly small which is another benefit of soft robots in that errors in gravity compensation have a smaller effect and gravity compensation in general uses less of our available control bandwidth. This formulation enables us to use torque control, is nominally stable if no updated commands are sent, and also enables us to vary the impedance of our torque control online. We can then formulate the forward prediction model as follows:

$$\begin{bmatrix} \dot{\boldsymbol{q}}[t+1] \\ \boldsymbol{q}[t+1] \end{bmatrix} = f(\dot{\boldsymbol{q}}[t], \boldsymbol{q}[t]) + g(\boldsymbol{q}_{des}[t], \boldsymbol{f}_{contact}) \tag{2}$$

where t_0 is the current time step and t varies from our current time step in discrete intervals to some time in the future, $f()$ and $g()$ are functions which can usually be represented as a linear matrix operations on the states and inputs (i.e. commonly seen in control systems as $\boldsymbol{Ax}$ and $\boldsymbol{Bu}$), and $\boldsymbol{f}_{contact}$ represents any external contact with the world. See [47] for more details on a specific model. The important take-away from Equation 2 is that we can represent the dynamic robot model as a discrete-time state difference equation. This allows us to form the following optimization problem:

$$
\begin{aligned}
&\underset{\boldsymbol{q}_{des}}{\textbf{minimize}} \quad h(\dot{\boldsymbol{q}}[t], \boldsymbol{q}[t], \boldsymbol{q}[t_0]) \\
&\textbf{subject to} : (for\ t = t_0 \ldots t_0 + H) \\
&\begin{bmatrix} \dot{\boldsymbol{q}}[t+1] \\ \boldsymbol{q}[t+1] \end{bmatrix} = f(\dot{\boldsymbol{q}}[t], \boldsymbol{q}[t]) + g(\boldsymbol{q}_{des}[t], \boldsymbol{f}_{contact}) \\
&actuation\ limits \\
&user-defined\ constraints
\end{aligned}
\tag{3}
$$

where H represents a discrete number of time steps into the future and $h()$ is a cost function that is user-defined but usually relates to a desired joint or end effector position, "$actuation\ limits$" is a constraint on our actuator and "$user-defined\ constraints$" are anything that we can express in terms of our states or inputs. We have found in previous work [47, 48] that excellent control can be obtained with a fairly simple model that captures the main dynamics. Although it is expected that improving the dynamic model (as long as it is tractable in real-time) for prediction will improve overall performance to some degree. For this reason, we will investigate 3 main different types of models to enable model predictive control. We will look at linearized models that include only the compliance at the joints, linear pseudo-rigid body models that can model the non-linear deflection with multiple linear underactuated elements, and nonlinear models that are simplified and tractable for control (such as the assumed modes method). In [48], we showed that for a real impedance controlled arm, we were able to control contact forces while reaching to a goal location in unmodeled clutter using MPC. However, in simulation we also showed that using small time horizons (1-10 steps) allowed us to control the position of a single link and then a four link planar arm with significant compliance at the joints. Even more interesting was that our results in terms of control effort looked surprisingly like input shaping commands, but were subject to realistic actuation and joint velocity constraints that we had imposed. We believe that this preliminary work shows great promise for our proposed approach.

Invariably, using any of these models effectively will require system identification. However, traditional methods using a trajectory that excites the natural dynamics and fits the dynamic parameters for a rigid body may not apply. Particularly because although we have pressure and joint position sensing on our testbed, the underactuated and compliant nature of the links means that we will not have ground truth for a given trajectory. In fact, even for rigid robots, literature on system identification methods often admits that "[un]realistic parameters can be obtained," (see Chapter 14 of [82]). We will use a small motion capture system to measure the output of the arm at multiple points along each link given a trajectory that sufficiently excites the dynamics. We will then formulate off-line optimizations to identify parameters for each of the above noted models that would allow us to have a forward model of the dynamics.

Development of robot models and state variables with which we can forward predict the state of the robot, will allow us to formulate model predictive control laws. We will investigate cost functions that range from having a goal in joint space, to Cartesian space and that minimize time to reach the goal. In general, we may find that exploiting the full underdamped dynamics of the arms will require us to abandon straight line motion for more time efficient trajectories. This will obviously be application dependent and foundational principles for control of these soft robots is one of the expected results from our exploratory research.

So far, we have assumed that we have known dynamic parameters and payload in order to use MPC. However, it is more realistic to assume that we will have disturbances. Examples of this include change in gravity on different planets or possibly altitudes for different missions. Additionally, change in end-effector payload weight (i.e. picking something up) will have a drastic effect on the dynamics due to a change in the natural frequency of the system. This must be accounted for online using adaptive model techniques commonly referred to as Model Identification Adaptive Control. After first developing MPC for moving the soft robot for point-to-point motion and manipulating a known payload, we will include these techniques and test with more realistic disturbances and unknown parameters.

After initial testing of those capabilities and models, we expect to focus on applications and extensions to improve manipulation performance when operating in unmodeled and dynamic environments where we may make unexpected contact and or need to collaborate with a person or other robot. We will again use MPC, but this time as a mid-level controller, to formulate costs that represent collaboration and constraints with respect to other agents or manipulated objects. We may need to make assumptions about the location of other agents or their intent that can be relaxed in future work where we would include force and proximity sensing. We will also examine using variable impedance at the joints to mitigate unmodeled impact forces

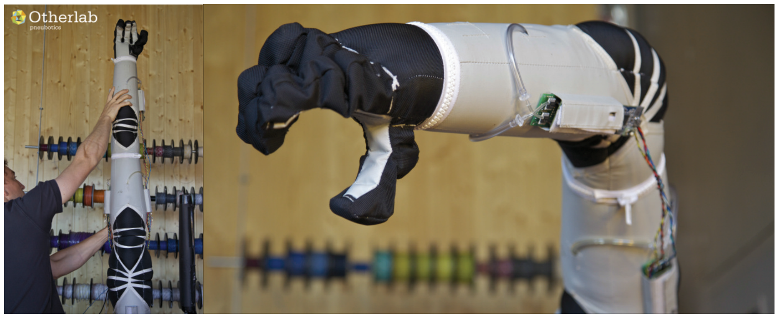


Figure 1: Example of a pneumatically actuated, soft robot arm produced by Otherlab.

while still defining higher stiffness in preferred directions. Preferred directions may come from constraints in collaborative manipulation or from a pre-defined desired trajectory. We will use linear matrix inequalities to formulate the problem in terms of an eigenvalue problem which will allow us to have cross coupling in both the stiffness and damping matrices ($\boldsymbol{K}_p, \boldsymbol{K}_d$) while requiring the eigenvalues of these matrices to give a certain stability margin. After implementing and testing for a single degree-of-freedom testbed, we will adapt our methods to a full arm where we expect to see the most benefit of having variable stiffness. Testing, experimentation and validation for all of the proposed work in manipulation is outlined in the next section.

In the final year of this proposed work, we will develop controllers for locomotion with a soft robot. Initial attempts at mobility will use virtual model control (VMC) which has been successful for locomotion both in academia (see Section 3.2.1) and in industry (Big Dog and Cheetah from Boston Dynamics). The main premise of virtual model control is that we represent the way we want the system to perform as a simplified dynamic model and then attempt to make the system behave according to this model. Virtual model control will be a baseline for the beginning of our work. We expect that the form of the virtual models that we use will vary greatly and depend mostly on the form of our quadruped and the performance of our underlying MPC that we will have developed in years one and two. Developing this control method first for flat terrain and then for rough terrain will allow us to incrementally improve our approach through practical application of our controller.

3.4.2 Testing and Experimentation

All testing and experimentation corresponds directly with specific milestones and relevant sub-tasks that are described below in Section 3.5. Rather than repeating that information, we will summarize by saying that we expect that at the end of both the second and third years, we will test our control methods in realistic scenarios using teleoperation. We will identify scenarios that are important to NASA missions through input of different NASA sites and personnel. These tasks can be seen as the culmination of our research in manipulation and mobility and they will likely relate directly to equipment maintenance, installation or exploration of rugged terrain environments.

3.4.3 Facilities and Testbed Hardware Description

Dr. Killpack's research group is housed in a research facility that has adequate room for 3-4 robots as well as 6-7 students. This space has cargo door access for bringing in materials to simulate real environments, available air pressure for pneumatic control and network capability for control communication between different robots. We also have a 3D printer for prototyping parts, and access to normal machine shop equipment (drill-press, mills, CNC machines, etc) through the university. In addition, we have two Baxter robots from Rethink Robotics that we will be using as input devices for controlling the soft robot during teleoperation testing of our controllers. Finally, we have support for and access to exceptional computing resources at BYU for large numbers of simulation trials.

The main testbed that we will be using for developing and testing our controls is part of a new class of all-fluidic, membrane-based robotics that Otherlab (the company who produces the platform) is calling Pneubotics. The robot is constructed entirely out of compliant fabric and a prototype for a single arm can be seen in Figure 1. Both the structure and the actuation of the robot are derived from pressurized fluid. This means there are no drive trains, motors, bearings, shafts or sliding surfaces. Each joint is controlled with two pneumatic chambers. The result is a method of compliant joint torque control (see http://youtu.be/yc8M7yD7R3g). If pressure increases in both chambers then the overall stiffness of the joint increases. This type of robot and actuation allows for high strength to weight ratios where the original Pneubotic arm developed under the DARPA Maximum Mobility and Manipulation program was able to manipulate objects over 2x its own weight. However, the underdamped nature of the arms is what sets the stage for our research on controlling soft robots.

During the first year, we will be using a robot torso with 2 degrees of freedom and two 5 degree of freedom arms. Each arm can carry a payload of about 4-5 kg at 1 meter of extension. In the second year, we will use another pneumatically actuated robot torso from Otherlab that has a 14 kg payload at 1 meter. This will allow us to adapt our initial control algorithms and apply them to tasks with heavier loads. In addition, having both platforms will be the basis for developing mid-level controllers to allow collaboration in manipulating a single object. In the last year, we will use a quadruped, fabric-based robot, also purchased from Otherlab, to apply our same control techniques to traversing rough terrain. We expect that our methods for manipulation and mobility will be robust to uncertainty and variation, but we also expect that the platform itself will be robust to damage from rough terrain and unexpected impact (see http://youtu.be/zML1XyJxX8I). In addition risks of hardware failure are minimal as most failure modes would be modular (i.e. replacement of a bladder or single valve).

3.5 Work Plan

In this section we define milestones for a three-year funding period. The required tasks to achieve those milestones and a corresponding time line are in Section 3.5.2.

3.5.1 Defined Milestones

Milestones	
1	Identify model parameters for predicting the end-effector position and orientation given the joint torques, positions and velocities (includes quantifiable numbers for accuracy of different models).
2	Demonstrate that the soft robot testbed can perform point-to-point motion smoothly and quickly with model predictive control using at least one of the models identified in milestone 1.
3	Perform objective comparisons between MPC and other methods for point-to-point motion.
4	Confirm that performance for manipulation of known mass (but unknown geometry) for trajectory tracking and time efficiency is comparable to point-to-point performance in free space.
5	Show performance for manipulation with unknown mass or other disturbances using our adaptive algorithms and MPC is comparable to performance with a known mass.
6	Perform testing for a realistic manipulation task using teleoperation with human-in-the-loop.
7	Test variable impedance algorithms for improvements in unexpected contact force reduction.
8	Develop and test control of multiple robots for object manipulation that is more time efficient and task effective than operating a single agent for a given task.
9	Perform final testing for manipulation capabilities that include multiple aspects of our developed algorithms in a realistic scenario.
10	Test control methods for locomotion of a quadruped robot across flat terrain.
11	Test controllers for traversing uneven terrain (this includes having developed approaches for climbing up, going down and using arms to maneuver and manipulate as well).
12	Perform testing for a combined manipulation and mobility task using teleoperation interface.

3.5.2 Defined Tasks and Time Line

Task Number	Description	Milestone
1	Set up motion capture system, optimize trajectories and take system ID data.	1
2	Develop dynamic models and perform initial testing of flexible links in simulation	1
3	Fit dynamic models that we develop to captured data and evaluate model performance	1
4	Formulate relevant cost functions and constraints for MPC, then generate and tune controller code	2
5	Implement other state of the art controllers for comparison (input shaping, feedback linearization, open loop optimal control)	3
6	Testing and tuning all controllers for point to point motion	3
7	Compare performance for point to point motion with different control methods including robustness to modeling error and/or disturbances.	3
8	Mount and calibrate a 3D sensor or camera (for user input) for testing actual manipulation of unmodeled objects.	4
9	Development of teleoperation interface for manipulating an unknown object either through a Baxter robot already in our lab, or through a GUI interface.	4
10	Perform testing and tuning for unknown object with known mass.	4
11	Development of adaptive models and terms for varying load and errors in gravity compensation	5
12	Test controller for manipulation of unmodeled object with unknown mass and other disturbances.	5
13	Develop scenario and physical environment for testing realistic manipulation scenario.	6
14	Develop on-the-fly variable impedance control algorithms using linear matrix inequalities and optimal control to mitigate unexpected high forces from accidental collision for a single joint	7
15	Develop on-the-fly variable impedance control algorithms with LMIs for full 12 degrees of freedom.	7
16	Test performance of variable impedance algorithms in comparison to a constant joint impedance for the manipulation task 13 with unmodeled contact.	7
17	Adapt all algorithms and progress for 2nd pair of arms with higher payload.	8
18	Develop coordinated control algorithms for two arms to manipulate the same object	8
19	Extend coordinated control to allow up to n-arms manipulating the same object.	8
20	Test coordinated control and show that completing a real task with this controller is more efficient than 1) trying to have two operators and 2) using only a single arm to perform the work.	8
21	Develop final test scenario, environment and metrics before testing (should be based on real task or need from NASA space missions).	9
22	Using new, low-level MPC developed for manipulation, wrap virtual model control (VMC) around it as a mid-level controller to do walking with a quadruped on flat terrain.	10
23	Test and tune for soft robot walking/running on flat ground.	10
24	Model and incorporate dynamics from interaction with ground into manipulation framework to allow simultaneous locomotion and manipulation of objects.	12
25	Adapt our virtual model controller for rough terrain traversal.	11
26	Test and tune VMC on real rough terrain.	11
27	Develop controllers that include arms with legs to move across really rough terrain (i.e. climbing up).	11
28	Test rough terrain traversal on real rough terrain.	11
29	Develop methods for descending step slopes.	11
30	Test rough terrain descent without damaging platform.	11
31	Develop scenario and physical environment for testing realistic manipulation plus mobility scenario.	12

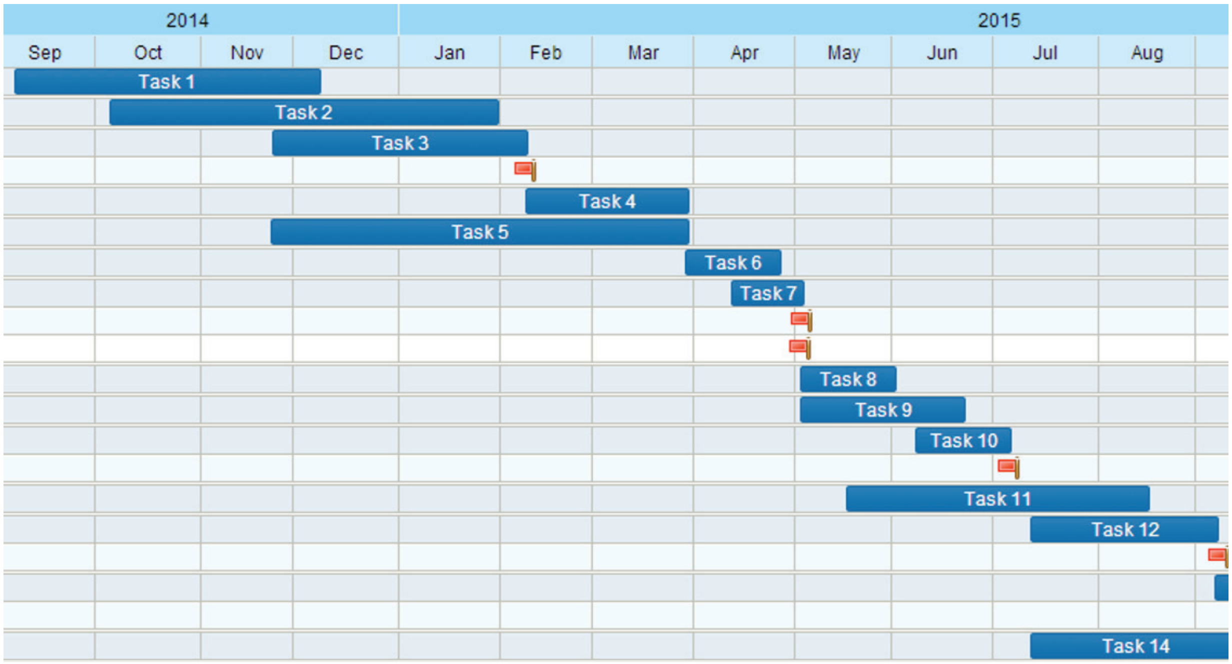


Figure 2: Year 1 time line for proposed work.

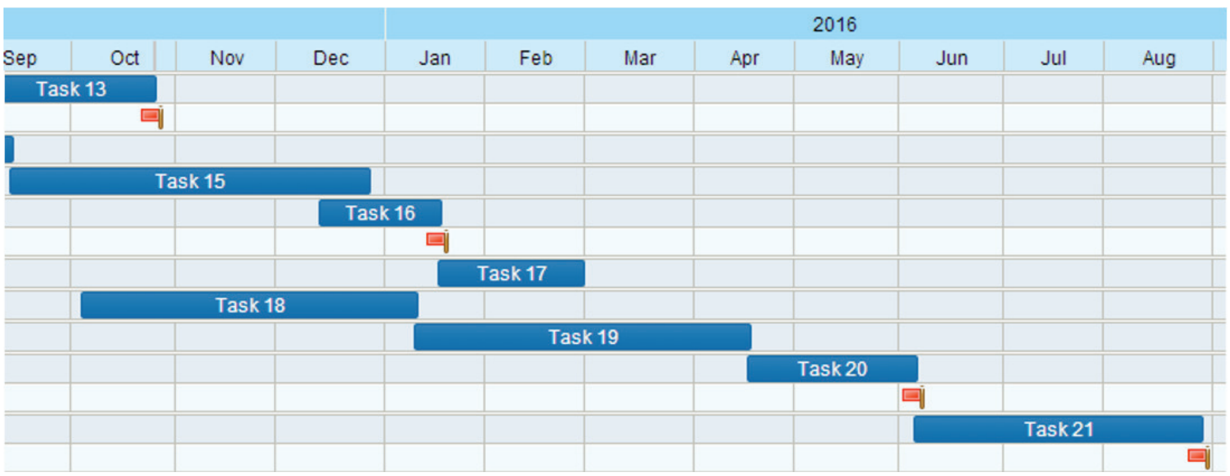


Figure 3: Year 2 time line for proposed work.

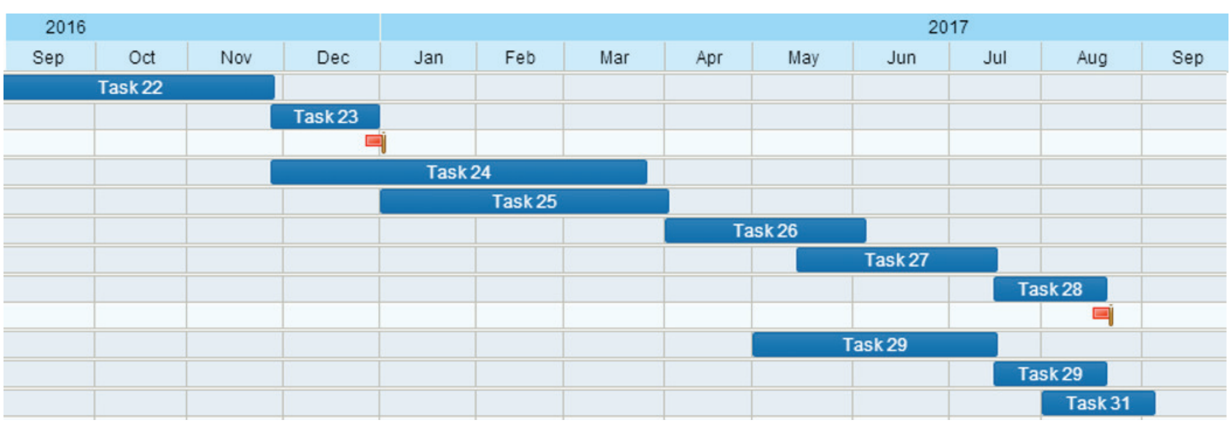


Figure 4: Year 3 time line for proposed work.

3.6 Technology Readiness Level

3.6.1 Current TRL

The initial rating for technology readiness is a 1 for this work. Although components of this work have been successfully used in the past (i.e. MPC on a rigid robot arm), there exists very little work on using MPC to control flexible robot arms at high speeds with accurate trajectories.

3.6.2 Expected TRL at End of Funding

We expect a technology readiness level of 3-5 for manipulation at the end of this work. We will have moved from basic principles and concepts of the proposed controllers to analytical models that match our real world data for a soft robot and allow us to demonstrate utility of controllers in at least somewhat realistic environments. We will also have tested aspects of our proposed controllers in relevant environments (unknown, unmodeled and in proximity to other robot agents).

For mobility the final rating of technology readiness level will be between a 2 or 3. We will apply initial ideas to control for locomotion which will allow us to perform testing for proof-of-concept scenarios like traversing rough terrain. We will also have performed initial testing of the coupling between mobility and manipulation for the complete underdamped system. We expect that this testing for mobility, although preliminary, will result in further concept generation for new locomotion control of soft robots.

3.7 Management Structure

3.7.1 Personnel and Proposed Contribution

The proposed research will be accomplished at Brigham Young University under the direction of Dr. Killpack with three graduate students and two undergraduate students. In addition, two specific collaborations will serve to strengthen our approach and make available a wealth of experience in modeling of flexible and compliant systems. As per the requirements of appendix number NNH14ZOA001N-14ECF-B1, these collaborations do not include financial support for the collaborators, but rather will be reflected in joint publications and discussions on the proposed work.

- PI - Dr. Marc D. Killpack
  - As PI, Dr. Killpack will lead the research efforts and focus on expected outcomes and milestones listed in Section 3.5. His expertise lie in the fields of robot manipulation, contact modeling, tactile sensing and optimal control of robots in uncertain environments. Although familiar with modeling of flexible systems, this is an area where collaboration will both strengthen the work and increase the likelihood of success for innovative advancements over the current state-of-the-art.
- Collaborator - Dr. Wayne J. Book
  - Dr. Book is an expert on modeling and control of flexible robots and has written the chapter on the topic in the comprehensive Springer Handbook of Robotics manual. He has also published over 80 papers and has over 40 years of experience in this research area (as well as over 200 papers on human-robot interaction). His expertise in using the assumed modes method to model the arm and compare against other linear and nonlinear models as well as his expertise in human-machine interfaces is important to our proposed approach.
- Collaborator - Dr. Larry Howell
  - Dr. Howell is an expert in modeling compliant mechanisms. His expertise in this domain will be invaluable for modeling the soft robot in order to forward predict the motion using linear elements that represent the nonlinear response of such a compliant mechanism. He has written the most cited book on compliant mechanisms and has published over 200 papers in the area of compliant mechanisms.

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