A Study in Soft Robotics: Metrics, Models, Control, and Estimation

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A Study in Soft Robotics:

Metrics, Models, Control, and Estimation

Levi Thomas Rupert

A dissertation submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

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ABSTRACT

A Study in Soft Robotics: Metrics, Models, Control, and Estimation

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Doctor of Philosophy

Traditional robots, while capable of being efficient and effective for the task they were designed, are dangerous when operating in unmodeled environments or around humans. The field of soft robotics attempts to increase the safety of robots thus enabling them to operate in environments where traditional robots should not operate.

Because of this, soft robots were developed with different goals in mind than traditional robots and as such the traditional metrics used to evaluate standard robots are not effective for evaluating soft robots. New metrics need to be developed for soft robots so that effective comparison and evaluations can be made. This dissertation attempts to lay the groundwork for that process through a survey on soft robot metrics. Additionally we propose six soft robot actuator metrics that can be used to evaluate and compare characteristics and performance of soft robot actuators. Data from eight different soft robot rotational actuators (five distinct designs) were used to evaluate these soft robot actuator metrics and show their utility.

New models, control methods and estimation methods also need to be developed for soft robots. Many of the traditional methods and assumptions for modeling and controlling robotic systems are not able to provide the fidelity that is needed for soft robots to effectively complete useful tasks. This dissertation presents specific developments in each of these areas of soft robot metrics, modeling, control and estimation. We show several incremental improvements to soft robot dynamic models as well as how they were used in control methods for more precise control. We also demonstrate a method for linearizing high degree of freedom models so it can be simplified for use in faster control methods for better performance. Lastly, we present an improved continuum joint configuration estimation method that uses a linear combination of length measurements. All these developments combine to help build the “fundamental engineering framework” that is needed for soft robotics as well as helping to move robots out of their confined spaces and bring them into new unmodeled/unstructured environments.

Keywords: soft robot, robotics, control, metrics, evaluation, Model Predictive Control, MPC, Input Shaping, estimation, continuum, optimal control
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CHAPTER 1. INTRODUCTION

More and more people are looking to introduce robots into unmodeled environments or areas where the robots will be working with or around humans or delicate equipment [1]. Traditional robotic systems have rigid links and actuators which can be dangerous in these environments [2]. Many current robots in use today have high-torque actuators, heavy and rigid members, and few or no force sensors. They are very capable of performing the tasks that they were built and programmed to do, but are a significant danger to humans when operating in a shared space. Currently most robots must be confined in spaces that have been highly modeled and that restrict access to humans during operation so as to limit potential damages or injury. In an effort to bring robots into more environments including operating around humans, many researchers have looked at ways to produce safer robots by mitigating danger to humans through tactile sensors, active force control, developing lightweight manipulators [3], [4], adding compliance at the joints [5] as well as other approaches [6].

A growing solution that is being explored is adding compliance to the robotic systems [7], [8], [9], [10]. The robotics community has started exploring the field of soft robotics which uses naturally compliant materials in the structure and/or actuation of the robots, thus making the robots safer to operate in unmodeled/unstructured environments. Soft robotics has the potential to revolutionize the robotics world by bringing robots into these new environments.

To encourage the development of soft robotics the National Science Foundation has recently put out an Emerging Frontiers in Research and Innovation (EFRI) solicitation on the topic of soft robotics. In it they said, “While there have been numerous demonstrations of the exciting potential of soft robotics, a fundamental engineering framework is needed to fully realize the promise of these pioneering results. Such a framework would guide the emergence of a new field of soft robotics...” [11]. Additionally, the emerging technology of soft robots is another approach to making robots that are safer and can have meaningful human-robot interactions. As stated in
the EFRI solicitation “Such robots promise substantial advantages over traditional rigid robots in accomplishing open-ended tasks in an unstructured environment and in physical interfaces with biological organisms, including humans,” [11]. This new area of robotics is broad and extremely varied as shown in this survey paper of the current state of soft robots [7]. The paper shows that each soft robot has its specific focus and design, however the scope of this dissertation is soft robot serial manipulators.

We propose that there are four principles that are needed to build a fundamental engineering framework for soft robots. They include creating soft robot metrics, models, techniques for control and estimation. This work presents developments in all four of these key areas.

1.1 Contributions and Dissertation Organization

Many of the contributions in this dissertation have been published in peer-reviewed venues and those chapters will be presented in that form. This dissertation has the following contributions in the areas of soft robot metrics, models, control and estimation and is organized as follows. Section 1.2 presents the robot platforms used in this dissertation as well as a general overview of Model Predictive Control (MPC) which is the dominant control method used in this dissertation. Chapter 2 discusses the lack of and dire need for soft robot metrics on a manipulator and actuator level. It also presents a survey of members of the soft robotics community that we use as an initial set of metrics to facilitate exploration of soft robot metrics. During this initial investigation into soft robot metrics it became abundantly clear that an initial approach was to focus on soft robot actuators. In Chapter 3 we present a published paper on metrics for fluidic soft robot rotary actuators. We propose the following six metrics as well as present data from eight different actuators supporting the choice for these six metrics.

- Maximum Torque
- Torque-to-Mass Ratio
- Efficiency
- Parasitic Stiffness
- Variable Stiffness
• Maximum Range of Motion

We also present three metric evaluation criteria (MEC) that are used to evaluate the value of each metric and which can be used in future work to evaluate new soft robot metrics. Chapter 4 is a conference paper that compares two low impedance joint control methods on Baxter, input shaping and MPC. We show that MPC is able to limit oscillations more than input shaping during full single-DoF and multi-DoF movements. Although not a specifically soft robot control method, it was the building block for many of our later efforts in soft robot control. Chapter 5 presents several soft robot models and their use in MPC controllers. The different models and control methods have been published in a few different co-authored journal articles and conference papers. In Chapter 6 an improved method for estimating the joint configuration of continuum joints using optimized placement of length sensors and using a linear combination of their measurements is demonstrated. We were able to show in simulation that with only three length sensors, the median joint error as a percent of the range of motion was as low as 0.262% for a soft continuum robot with non-constant curvature. Lastly is the conclusion in Chapter 7, where we discuss potential future work and applications of the contributions. Note that in this dissertation all matrices are uppercase bold while all vectors are lowercase bold and all constants are lowercase non-bold.

The main contributions of this dissertation are

• Development of six proposed soft robot actuator metrics and methods for how fluidic rotational actuators are evaluated using the metrics

• Development of antagonistic torque model for antagonistic pneumatic actuators.

• Development of the novel concept of overlapping length sensors to improve the estimation of a continuum joint’s state

• Creation of the Weighted Averaging Method (WAM): A method for using overlapping sensors to significantly improve continuum joint estimation resulting in an estimate that reduces error by a factor of eleven when using two sensors on a joint rather than using a single sensor

with the full list of contribution as follows, organized by chapter and by publication venue. All contributions listed here are direct contributions we have have made in each publications.
Chapter 2

  - A survey of the important soft robot metrics for five different tasks

Chapter 3

  - A brief survey of soft robot actuators and metrics
  - A justification of the necessity for soft robot actuator metrics
  - Development of six proposed soft robot actuator metrics and methods for how fluidic rotational actuators are evaluated using the metrics
  - An application and evaluation of the metrics using data from eight different soft robot actuators (five of which use distinctly unique actuation methods, while the others include variations in material or geometry)

Chapter 4

  - Development of a Model Predictive Control (MPC) method for smooth motion control of a full seven degree of freedom
  - Extension and testing of input shaping to a seven degree of freedom robot using feedback linearization
  - Significant reduction in overshoot and residual oscillation of a compliant robot while maintaining compliance
  - Comparison between performance of the Cartesian MPC and multi-degree of freedom input shaper

4
– Cartesian motion without the need for a trajectory or path planner to mitigate overshoot or stay within actual torque or joint limits

Chapter 5


  – Inclusion of first-order pressure dynamics in dynamic model for pneumatic soft robot actuators
  – Development of antagonistic torque model for antagonistic pneumatic actuators.


  – Development of the Coupling-Torque method for linearizing high degree of freedom dynamic models
  – Formulation of MPC for robots with significant compliance at the joints using the Coupling Torque linearization
  – Implementation of the Coupling-Torque method on the soft robot Nightcrawler


  – Extension of MPC method for simulations position and stiffness control to multiple degrees of freedom
  – Demonstration that end-effector displacement decreased by approximately 50% when we commanded a stiffness set point of 40 N·m/rad to our controller rather than 30 N·m/rad. This showed that our active stiffness control method significantly affected the system behavior of soft robots
Chapter 6


- Development of the novel concept of overlapping length sensors to improve the estimation of a continuum joint’s state

- Creation of the Weighted Averaging Method (WAM): A method for using overlapping sensors to significantly improve continuum joint estimation resulting in an estimate that reduces error by a factor of eleven when using two sensors on a joint rather than using a single sensor

- Development of two methods for determining the placement of overlapping length sensors on a continuum joint, and an objective comparison of their performance

1.2 Hardware, Platforms and Model Predictive Control Background

In this work there are several measurement systems, robot platforms, soft robot actuators, and general control methods used. The next section describes the measurement systems used including two motion capture systems. Next, the robotic platforms are described which consist of several soft robot platforms, soft robot actuators and one traditional robot platform. Lastly the most common control method used in this dissertation, Model Predictive Control, is described.

1.2.1 Measurement Systems

The two motion capture systems used in this dissertation include a standard inferred motion capture system and a system that uses the HTC Vive virtual reality (VR) system. The inferred system is from Motion Analysis and has eight infrared cameras and small infrared reflective balls that we arranged in unique patterns that are then tracked as rigid bodies. The Vive system is similarly used to estimate pose with the controllers and trackers being the rigid bodies that are tracked. Through the tracking of the rigid body markers we are able to measure and estimate the joint angles of the soft robots used in this work using the method described by Hyatt et al. [12].
1.2.2 Robot Platforms

**Baxter**  Baxter is a collaborative robot with two seven-Dof arms, built by Rethink Robotics [5] (see Figure 1.1). Baxter is a more traditional robot platform but has joints that use Series Elastic Actuators. These increase its compliance which helps to reduce the impact forces and thus increase Baxter’s ability to operate safely around humans and in unmodeled environments.

![Baxter from Rethink Robotics](image)

**Grub**  The Grub is a single DoF robot that is constructed out of fabric by Otherlab (see Figure 1.2). Its links and actuation chambers have no rigid parts but are inflated to provide structure and actuation. Each chamber consists of an airtight plastic bladder inside the strain limiting fabric.
layer. As the chambers on each side are pressurized they cause a torque, providing antagonistic actuation to the joint. Both links of the Grub have a shared, continuous elastomeric bladder which adds stiffness to the joint and limits the maximum torques achievable by the joint.

**King Louie**  King Louie is a multi-DoF extension of The Grub and shares all the same structural and actuation characteristics (see Figure 1.3). It has two four-DoF arms and a single-DoF at its waist but which is fixed for all experiments in this work. Like the Grub, each of King Louie’s arms
have a single continuous bladder, thus adding to the joint stiffness of each joint. Also the hoses for each actuator passes through the joints adding additional stiffness.

**Nightcrawler and Kaa** Nightcrawler and Kaa, like the Grub and King Louie, are made of fabric and have antagonistic actuators (see Figure 1.4a and 1.4b). Nightcrawler is a three-DoF robot while Kaa has six-DoF. Once again the structure uses air pressure to provide rigidity and the joints are pneumatically actuated and have an antagonistic nature. There are few differences between
Nightcrawler/Kaa and King Louie/The Grub. First, each link has its own bladder instead of a single continuous bladder for all the links, thus decreasing the stiffness of each joints. Second, the actuators were redesigned to be more efficient, enabling an increased payload. King Louie has a payload of about 13.3 N at a distance of 1 m while Kaa has a payload of about 26.7 N at 1.5 m.

**Antagonistic Actuators** In Chapter 3 we display data from the following four antagonistic actuators found in Figure 1.5. The top two actuators are continuum actuators capable of two DoF actuation. They both consist of four actuators arranged in a square with each actuator at the corners of the square. The bottom right actuator is the Grub while the bottom left actuator uses a similar actuation mechanism as Kaa and Nightcrawler but has an actual pin joint about which it rotates. Additionally the actual actuator is made from rubberized fabric which is air tight instead of a fabric that contains an air tight bladder inside.

**Fluidic Elastic Actuators** In Chapter 3 we also use and display data from several fluidic elastic actuators. They are single-chamber actuators that bend as they are pressurized. They were 3D printed out of TPU and NinjaFlex (white and blue actuators in Figure 1.6 respectively).

### 1.2.3 Model Predictive Control

The most common control method used in this dissertation is Model Predictive Control (MPC). MPC is a form of optimal control, although a sub-optimal version. The sub-optimality is due to the strategy of optimizing over a finite time-horizon and then implementing the control input for only the first time step in the predicted trajectory. In spite of MPC’s sub-optimal nature, in practice we are able to get good system performance because we are incorporating feedback into an optimal control scheme. MPC uses an optimization routine that minimizes a cost function that is subject to certain constraints such as joint limits and joint velocities. At the next time step, the optimization is reformulated for the next finite time horizon using new measurements of the current state to solve for the next control input. The main differences between a linear quadratic regulator (LQR) and MPC is that LQR looks over an infinite time-horizon and has only the constraints of the system dynamics, whereas MPC optimizes over a finite time-horizon and, in theory, can have any constraints the optimization can handle. This control method has been used successfully
in the chemical processing industry for some time and is now gaining traction in other areas of application due to the advancement in computer processing power and optimization algorithms. As will be shown in Chapters 4 and 5, MPC is an effective method of control for soft robots.
Figure 1.4: Soft robot platforms developed and built by Otherlab.
Figure 1.5: Large soft robot actuators used in this work. (a) Blow-molded Continuum actuator (b) Bead Continuum actuator (c) Rubberized Rotary Elastic Chamber actuator (d) Fabric Rotary Elastic Chamber actuator
Figure 1.6: Fluidic Elastic Actuators used in this work from left to right: Large TPU, Medium TPU, Small TPU and Small NinjaFlex.
CHAPTER 2. METRICS

2.1 Metrics Introduction

As the field of soft robotics grows and develops there will be a need for more informed and better metrics. All engineering fields have developed methods to examine and analyze their realms of interest. For example in the field of control theory principles like observability, controllability, and stability exist to help characterize different systems. Currently no soft robot specific metrics exists for that allow us to compare two different platforms or two different actuation methods. In traditional robotics there are several metrics that help to define how a particular robot will perform at a given task such as reachability, manipulability, accuracy, repeatability, and maximum payload to name a few. While some of these may be applied to soft robots, soft robots have unique capabilities and mechanics that require additional metrics to allow for effective evaluation and comparison.

While many measurements can be used to compare soft robots, it is important that the metrics chosen do not just enable classification but allow for actual evaluation. Additionally, effective metrics can only be defined when a goal or purpose for the metric is first defined. For example, the volume of several soft robots can be compared but it would not be a good metric unless the volume of the robot will affect the performance of a robot for a defined goal or purpose. Also the method of actuation of a soft robot, i.e. cable actuation, fluidic, or electro-static, can be used to compare soft robots but this is only a classification instead of actual evaluation relative to a task. Therefore it is necessary to be able to evaluate comparative metrics at a high (or task) level to avoid simple classification. To evaluate potential metrics for soft robots we have developed three criteria that can be used. These are the Metric Evaluation Criteria (MEC) with the following criteria and descriptions:

• Task Utility - How well can a given metric inform the user about the direct utility of a soft robot component in terms of a task or application?
• Design Comparison - How well can a given metric allow for the exploration of the trade offs that are present during the design of a soft robot component?

• Information - Does a given metric allow for more/different information to be described for a soft robot component?

We first focused on developing metrics for soft robot manipulators and on picking metrics that would help determine the Task Utility of a soft robot manipulator. We picked five tasks and many different metrics that could describe the performance of a soft robot manipulator in performing those tasks. To reduce the number of metrics from 15 to 20 to a more manageable number of metrics we developed a survey where we asked the soft robotics academic community to rank the importance of seven different metrics relative to five different tasks. The details of the survey and a summary of the results are included in Sections 2.2 and 2.3 respectively. The survey asked the users to evaluate the importance of different metrics as they could be used to evaluate the performance of a robot manipulator completing a specified task. While tasks and metrics have the potential to be used for all robot manipulators the users were asked to focus on only applying the metrics to soft robot manipulators.

Through the study and analysis of survey results it quickly became clear that an important building block for evaluating any soft robot design had to start with evaluating the potential actuators to be used. This led us to develop the three MEC discussed earlier and six soft robot actuator metrics that can be used to evaluate fluidic rotational soft robot actuators. These metrics and their evaluation using the MECs are presented and discussed in detail in Chapter 3. These soft robot actuator metrics provide a fundamental level of metrics that can be used, allowing for the higher level metrics found in the survey to build on them.

2.2 Soft Robot Manipulator Metrics

To determine which metrics the soft robotics community considered most important, we used a weighted scoring method which is commonly used in the engineering design process. The weighting was calculated as follows. For each individual who considered the metric as Extremely Important, the metric was given 4 points, for Very Important it was given 3 points, for Moderately Important 2 points, for Slightly Important 1 point, and 0 points for Not at all Important. The
average of the points (the sum of the total points divided by the number of responses) was then used as the final score for the metric with respect to the task.

The five different tasks that we had in the survey were as follows.

- **Vibration Task** - A task where the end effector or the base of a robot is experiencing large vibration (e.g., high frequency and/or large magnitude) such as a sanding task.

- **Wiping Task** - A task where a robot wipes a surface, whether an end effector or other parts of the manipulator are used. An example includes the cleaning of a solar panel.

- **Intentional Impact Task** - A task where a robot is intentionally impacting something, such as hammering.

- **Incidental Impact Task** - A task where a robot unintentionally makes contact with something. This is a worst-case scenario where a robot may slip and impact the ground, another robot, or human while performing another task.

- **Pick and Place Task** - The standard pick and place task where a robot picks up an object and places it at a different location

The survey was presented to the soft robotics academic community using the robotics-worldwide mailing list [13]. We had between 18 and 21 responses for each question as not all participants answered every question. The average experience of the survey takers in the field of robotics was 6.9 years with an average experience with robotic manipulators being 6.3 years and the average experience with soft robotics being 3.7 years.

The full results, including the original survey, is included in Appendix A and at https://bit.ly/38xe0fn while a summary is included here in the following section. Also included in Appendix A are definitions of the metrics.

### 2.3 Survey Results

The following tables summarize the survey results. Each entry in the table represents the number of individuals from the survey that ranked the corresponding metric with the corresponding level of importance (e.g., as seen in Table 2.1 the metric *Modes of Vibration* had two individuals
rank its importance as *Extremely Important*). The average importance score was calculated by multiplying each row by the their respective row weightings (4 points, 3 points, etc.), summing the columns and dividing by the total number of samples.

### 2.3.1 Vibration Task

For the Vibration task the survey results show that the highest ranked metric was the *compliance* metric which also had a low standard deviation compared to the rest of the metrics. *Repeatability* was the next highest ranked metric but was only slightly higher than the next three metrics *compliance at end effector (EE), resonant frequency ratio*, and *force control*. The one metric that did not seem very important to most who took the survey was *modes of vibration* signifying that most of the researchers felt this would not determine the performance or a soft robot during a vibration task. The spread of the average for the highest ranked metric to the lowest was 0.9 points (see Table 2.1).

### 2.3.2 Wiping Task

The highest ranked metric for the wiping task was also *compliance at the EE*. The next two metrics, *force control* and *hardness/softness*, had the same average importance and were ranked second highest. The metric that the respondents felt was least important to capturing the performance of a Wiping task for a soft robot was the metric *time to completion*. The spread of the average for the highest ranked metric to the lowest was 0.85 points (see Table 2.2).

### 2.3.3 Intentional Impact Task

The highest ranked metric for this task was the *maximum impact energy*. The next highest ranked metric was *maximum force*. These two metrics also had the lowest standard deviation meaning there was the most consensus between the survey takers about the importance of these metrics. Two metrics, *compliance* and *tolerance about trajectory*, both scored the lowest for this task. The spread of the average for the highest ranked metric to the lowest was 0.84 points (see Table 2.3).
Table 2.1: Vibration Task Survey

<table>
<thead>
<tr>
<th>Modes of Vibration</th>
<th>Compliance at EE</th>
<th>Resonant Force Frequency Ratio</th>
<th>Force Control</th>
<th>Compliance</th>
<th>Maximum Force</th>
<th>Repeatability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Important (4 pts)</td>
<td>2</td>
<td>5</td>
<td>5</td>
<td>7</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Very Important (3 pts)</td>
<td>6</td>
<td>8</td>
<td>8</td>
<td>6</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td>Moderately Important (2 pts)</td>
<td>7</td>
<td>6</td>
<td>6</td>
<td>4</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>Slightly Important (1 pts)</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Not at all Important (0 pts)</td>
<td>1</td>
<td>0</td>
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Table 2.2: Wiping Task

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<th>Reachability</th>
<th>Time to Completion</th>
<th>Hardness/Softness</th>
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<td>10</td>
</tr>
<tr>
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<td>Compliance</td>
<td>Maximum Velocity</td>
<td>Hardness/Softness</td>
<td>Tolerance about Trajectory</td>
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</tbody>
</table>
2.3.4 Incidental Impact Task

This task had two metrics that tied for the highest ranked metric, *maximum impact energy* and *compliance at the EE*. The metric *compliance* was ranked just below the top two metrics showing it was also considered very important. The two metrics, *maximum velocity* and *strength of links/joints* were scored the lowest for this metric. The spread of the average for the highest ranked metric to the lowest was 0.73 points (see Table 2.4).

2.3.5 Pick and Place Task

The highest ranked metric for the Pick and Place task is the *steady state error*. The next highest was *disturbance rejection*. The metric that was the least important was *maximum acceleration*. The spread of the average for the highest ranked metric to the lowest was 0.95 points (see Table 2.5).

2.4 Discussion

By analyzing the results of the survey we aim to enable the development of soft robot metrics and we at least show this in the case of soft robot actuators in Chapter 3. The top-ranked metric from each task are the following:

- Compliance (Vibration Task)
- Compliance at EE (Wiping Task, Incidental Impact)
- Maximum Impact Energy (Intentional Impact, Incidental Impact)
- Steady State Error (Pick and Place)

Note that the metrics Compliance at EE and Maximum Impact Energy were ranked highest for two tasks.

2.5 Conclusion

We would like to note that this survey is subjective and falls within the realm of engineering design. However, as often happens in engineering it is useful to start development from good
Table 2.4: Incidental Impact Task

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<tr>
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engineering intuition and this survey provides that intuition. These rankings can be used to inform the community which metrics should be explored first for use in evaluating soft robot manipulators for specific tasks.
CHAPTER 3. PERFORMANCE METRICS FOR FLUIDIC SOFT ROBOT ACTUATORS


3.1 Introduction

Promising characteristics of soft robots include the ability to safely interact in unmodeled and unstructured areas around sensitive equipment, materials, or humans. Many of the proposed safety benefits of soft robots derive from their compliant actuation and structure, their reduced mass, and their compliant external surface. Despite the commonalities in many soft robot designs, many researchers continue to develop new types of actuators (involving novel actuation methods, geometries, materials, or combinations) without a clear way to compare their performance. These new designs include actuation methods ranging from tension cables, to Shape Memory Alloys (SMA), to fluidic actuation. Not only are there different methods used to provide power for the actuators but the style and shape of the many actuators differ.

Despite a variety of soft robot actuators, there is currently no systematic way for someone to determine which actuator will be most advantageous for a prescribed application or to design different actuators based on required performance specifications. This is due to the lack of a standardized method for comparing different soft robot actuators. For the design and control of soft robotic actuators to emerge as an engineering methodology, a set of metrics for comparison needs to be established. This article attempts to lay the groundwork for that process and encourage a broader discussion about engineering design and evaluation for soft robotics, specifically soft robot actuators.

The contributions of this chapter are as follows:

• A brief survey of soft robot actuators and metrics
• A justification of the necessity for soft robot actuator metrics

• Development of six proposed soft robot actuator metrics and methods for how fluidic rotational actuators are evaluated using the metrics

• An application and evaluation of the metrics using data from eight different soft robot actuators (five of which use distinctly unique actuation methods, while the others include variations in material or geometry)

While not a direct contribution of this chapter to the soft robotics field, we also include a case study as an example of how the metrics can be implemented to evaluate the actuators with respect to a specific task.

It is important to note that while the data and analysis of the actuators is of significance, it is not the main focus of this work. The data are used to support the development of the six proposed soft robot actuator metrics. Also of note is that while these metrics and methods are only validated for fluidic rotational soft robot actuators, we discuss methods for adapting them to other types of soft robot actuators in Section 3.4. The chapter is organized as follows.

We first describe the state of the art with respect to soft robot actuators as well as the state of the art for soft robot actuator metrics in Section 3.1.1. We then define our metrics and describe how they are measured in Section 3.2.1. Next we develop the methods that we use in this chapter to validate the metrics including a scoring method as described in Section 3.2.2. In Section 3.2.3 we describe the actuators that will be used in this work to validate the proposed metrics, as well as any actuator specific variations to the methods used to measure the metrics. Section 3.2.4 introduces a case study where we provide an example of using the proposed metrics to select actuators for an example task. Next, Section 3.3 shows the results of the tests and discusses the different metrics, how they differentiate the variety of actuators, along with an evaluation of the metrics. The details and analysis for the case study are presented in Section 3.3.9. Lastly, Section 3.4 concludes the chapter, discusses the limitations of the work, and discusses potential applications and future work.

3.1.1 Related Work

Various actuator types exist in the field of soft robotics have their advantages and disadvantages, however most of the actuators that lift significant loads use either tendon actuators or fluidic
actuators (see [14–18]). In this chapter, we focus on fluidic actuators as they represent a prominent portion of the soft robot actuators being developed. The following section reviews the current state of art for fluidic soft robotic actuators in more detail. However, many of the metrics described in this chapter could be adapted to non-fluidic actuators.

### 3.1.1.1 Fluidic Soft Robot Actuators

One of the earliest fluidic actuators is the Pneumatic Muscle Actuator (PMA) or McKibbon actuators [19,20]. These actuators use a cylindrical strain limiting outer layer and a cylindrical flexible internal bladder. When pressurized the PMAs naturally minimize the ratio of volume to surface area thus contracting. The relationship between pressurization and loads has been thoroughly explored and documented [20]. PMAs continue to be used in the design of new soft robotic actuators [21] due to their use of lightweight and simple elements. PMAs are most often used in multiples of two where they are arranged in an antagonistic format so that the PMAs pull in opposite directions. It is the difference in forces/torques that then causes a net force/torque on the load.

Another subset of fluidic actuators are Fluidic Elastic Actuators [22, 23] which rely upon the elastic nature of the material from which they are fabricated. They often have several chambers which are flexible and deformable with strain limiting sections that help to transfer the pressure in the chambers to create forces and/or motion. They are used in a myriad of applications including grasping [24], large body motion [22], and even locomotion [23, 25].

Rotary Elastic Chambers (REC) [15, 26, 27] are able to provide rotary motion similar to traditional motor actuators but they do so without any gearing or moving seals. They have been used to show reliable control and to perform simple tasks [12, 15]. Rotary Elastic Chambers are also antagonistic in nature.

Continuum actuators are another type of soft robot actuator. Many continuum actuators in the literature use tendons to cause motion or exert force, while others use fluid power [28–32]. Continuum actuators have no defined center of rotation and even some Fluidic Elastic Actuators are considered continuum actuators. Many continuum actuators are distinctive in their ability to bend in two degrees of freedom (DOF) with a single mechanism. Some continuum actuators have a third DOF as they can also grow in length [30].
Other fluidic actuators include origami inspired artificial muscles [33] which use a folding skeleton that is housed in a sealed skin. The folding skeleton provides the path for actuator motion as air is removed from the skins. Many different motions can be achieved by changing the geometry of the origami skeletons and has been shown to achieve linear as well as grasping motions. Another fluidic actuator that is able to grow and is based on the principle of eversion. Hawkes et al. [34] developed an actuator that is made of an inverted thin membrane that can be deployed from a roll. As air is added to the roll the internal pressure causes the roll to evert which results in growth. The authors were able show the ability to control the direction of growth of the actuator through changing the length of material at the tip of the actuator.

While not a complete survey, the majority of the different types of fluidic soft robot actuators are represented above. In this chapter we use our proposed metrics to compare different types of Fluidic Elastic Actuators, Rotary Elastic Chambers, and fluidic continuum actuators.

In the next section we discuss the current state of soft robot actuator metrics.

### 3.1.1.2 Actuator Metrics Related Work

The area of soft robot metrics is a new and emerging field. Mosadegh et al. [35] developed five parameters to characterize the performance of their actuator relative to the original design from the Soft Robotics Toolkit [36]. However, the focus of the chapter was on a new specific type of soft robot actuator design while our chapter is focused on the development of general soft robot actuator metrics. Similarly, Krause et al. [37] developed a test bed for testing and evaluating Fluidic Elastic Actuators. However, this test bed does not appear to generalize well to any other type of soft robot actuator so that its application is limited.

Joshi and Park [38] present methods and experiments to characterize a Fluidic Elastic Actuator in multiple directions and loading conditions. This is a significant step in the direction of developing metrics for soft robot actuators as it starts to establish a method for characterizing and comparing soft robot actuators, albeit limited to a single type of actuator. Agarwal et al. [39] develop some metrics for a subset of soft robot actuators by surveying the current literature of assistive wearable devices. Using designs found in the current literature they developed metrics from which they were able to base their new design. They showed that their new design was able
to meet their metric objectives as compared to the surveyed literature. Their scope was also limited to a specific type of soft robot actuator, wearable assistive devices, and does not generalize well.

Morzadec et al. [40] used soft robot finite element models to evaluate soft robot designs using a torque based fitness function. They then used an evolutionary algorithm to iterate upon the design to find an “optimal” design of a deformable leg for a locomotive robot before they built the robot. Although the metric that was used is specific to their use, this shows the potential of using a metric to aid in the design of soft robots through computer aided tools. By having a common set of metrics across many metrics the tools can also become more general and useful for the soft robotics community.

Garriga-Casanovas et al. [41] developed a method for describing Fluidic Elastic Actuator soft robotic actuators with the intention of unifying the way they are described across the literature. In it they discuss how different design parameters affect metrics such as force and deflection. In our work, we instead look directly at developing metrics that can be used for comparison across many different soft robot actuators and not at how the design of actuators affect their performance with respect to metrics. We expect that developing a solid foundation of well-defined metrics as proposed in this chapter will lead to superior and more robust design tools for soft robot actuation.

3.2 Materials and Methods

We first discuss our proposed metrics and the methods used to collect data and calculate the metrics for our actuators. Next, we present the methodology that we used to evaluate these metrics. Then we describe the actuators that we used to collect data, calculate metrics, and then evaluate those metrics. Last we present an example case study of how the proposed metrics could be used to select an actuator for a given task.

3.2.1 Soft Robot Actuator Metrics and How They Are Measured

We propose the following soft robot actuator metrics along with their descriptions and methods for measurement.

- Maximum Torque
- Torque-to-Mass Ratio
• Efficiency

• Parasitic Stiffness

• Variable Stiffness

• Maximum Range of Motion

In the results section of this work we also use the mass of each actuator as a baseline metric for evaluation of our proposed metrics.

We do not claim that this is a complete or exclusive set of metrics for all soft robot actuators, nor do we claim that the methods we use to measure them are the best for all actuators. However, we show that these metrics generalize and allow comparison between different fluidic rotational actuators. All the metrics are chosen to be agnostic to control methods or the dynamics of the systems, therefore all measurements are taken at static values after any transient dynamics have subsided. This provides the best comparison between actuators using these specific metrics. Combined metrics for actuation plus control is outside the scope of this chapter, but is a significant subject for future research.

The following equipment was used to gather the data for all of the experiments:

• Motion tracking system (either infrared cameras with sub mm accuracy, or HTC Vive trackers with sub cm accuracy for static measurements [42]) to accurately track the pose of the actuators’ top and base.

• 6 DOF force and torque (FT) Sensor from ATI Technologies (Axia80-M20)

• Pressure control system that has embedded electronics, pressure sensors, valves, and a Real Time computer (RTPC)

• Computer to record data

• Scale for weighing actuators

All the data from the motion tracking computer and RTPC were transmitted using Robot Operating System (ROS) messages with time stamps which enabled us to time sync them for analysis. During
post processing for every metric we extracted data corresponding to the same positions and ranges to be used for all calculations.

The relative angular deflections of the actuators are calculated from the pose of their top and base using the method described in Hyatt et al. [12]. Additionally each actuators’ base is mounted solidly to keep the base from moving during actuation and force measurements. We did not use a standard fixture between all the actuators due to the widely varying designs of each actuator. This meant that most actuators required their own unique fixture. The exception to this approach was that all of the Fluidic Elastic Actuators had the same fixture. The processes described are adaptable to many different types of actuators due to this fact. Standardization of the fixturing and measurement method itself seems difficult given the wide variety of actuators. However, we do expect that reporting on noise and repeatability characteristics of a measurement device and fixture is likely important for future results that use the metrics we present in this chapter to be general.

3.2.1.1 Maximum Torque

Just as it is important to know the torque limits of an electric motor or hydraulic actuator, it is crucial to know the torque limits for soft robot actuators. For fluidic rotational actuators, the two major contributions to their maximum torque is first, the actuator’s ability to convert pressure to force and second, the maximum pressure the actuator can handle without failing.

The Maximum Torque was found by controlling the actuator to its maximum operating pressure and letting the actuator come to rest. The authors then used the FT sensor to push the actuator back to its un-deflected (or neutral) configuration. The measurement was taken once the system was at rest and all transient dynamics had died out.

3.2.1.2 Torque-to-Mass Ratio

The Torque-to-Mass Ratio compares the weight of the actuator to its maximum torque. This metric includes the weight of all the elements of the joint that are integrated into the actuator as a system. Many applications for soft actuators involve them being mounted on a mobile platform, attached on the distal end of another actuator, or some other mode where the actuator’s full mass is being actuated. Therefore for each application, the full mass that is being accelerated should
be used. If it is just the distal end of the actuator being accelerated, the mass associated with that segment should be used. Similarly, if the full actuator will be actuated by another actuator then the full mass should be used. Any part of the system that can have a another device or model be substituted in its place it should not be included in the mass measurement. For example, the actuators presented in this chapter need pressure regulators, pumps, tubing and controlling electrical hardware to have a fully functioning actuator. Since the actuators could still work with any type of functioning pressure regulator, valves, tubing or pressure controlling electrical hardware that met the specifications, these were not included in the mass of the actuator since they did not affect the performance or function of the actuator. Only tubing that was self contained in the actuator was included in the mass measurement. Section 3.2.3 discusses what masses we use for our metric evaluations.

The mass of the actuators were measured using a scale, which was then combined with the previously defined Maximum Torque to calculate the Torque-to-Mass Ratio. The ratio is calculated by dividing the Maximum Torque by the mass of the actuator.

For the actuators used in this chapter the sections highlighted in red in Figure 3.1 are the sections used for the mass and Torque-to-Mass Ratio metrics. These sections were selected as we assume the full actuator will be accelerated and they represent the minimum required components for the actuators to be used. If any other parts were left out from the sections highlighted in red the actuators would be structurally unsound. As stated before no pumps, or pressure regulators were part of the mass measurements and only tubing that was an integrated part of the actuators was included.

### 3.2.1.3 Efficiency

All motors used in traditional robots have a known efficiency. For soft robot actuators this measurement should also be used as a method to compare performance. The standard measure of efficiency is a ratio of the energy output of an actuator divided by the energy input for the actuator. For fluidic soft robot actuators we must define an equivalent energy input for the system as well as a way to measure the energy output of the system.

For pressure driven soft robot actuators, when at a static state, i.e. at equilibrium, pressure can be used as a measurement of the energy density of a system. We therefore used pressure as
a measurement of the energy that we put into the system. As described in the Kinetic Theory of Gases [43] the average molecular kinetic energy of a system is directly proportional to the pressure and volume.

\[ E = \frac{3}{2}PV \]  

(3.1)

Since we are interested in the change in kinetic energy as the actuators are pressurized we take the difference as follows.

\[ \Delta E = E_2 - E_1 \]  

(3.2)

where

\[ E_i = \frac{3}{2}P_iV_i \quad i = 1, 2 \]  

(3.3)
\( E_1 \) is the energy of the actuator when its internal pressure is equal to that of the atmosphere, and \( E_2 \) is the energy of the actuator when actuated to any other pressure. Additionally, the pressure and volume at state 2 can be expressed as a change from state 1 as follows:

\[
P_2 = P_1 + \Delta P
\]

\( V_2 = V_1 + \Delta V \) \hspace{1cm} (3.4)

By substituting in Equations 3.4 and 3.5 into Equation 3.3 and substituting those into Equation 3.2 the following equation for the change in energy is calculated.

\[
\Delta E = \frac{3}{2}(\Delta PV_1 + P_1 \Delta V + \Delta P \Delta V)
\]

Equation 3.6 should be used instead for soft robots that undergo significant change in volume as their internal pressure increases.

To determine efficiency, we also need to calculate the energy output of the system. The energy output of a system is usually measured by how much work is done. However, we take static measurements at the same angular position each time (the undeflected position) and since there is negligible change in volume we assume that no work is being done. We instead measure the force that is being produced by the actuator. Knowing the geometry of the actuator, we calculate the torque produced by the actuators. The units for efficiency will be N·m/J as it is the relationship between energy in the actuator to static torque produced by the actuator. Although N·m and J have the same base units \( \left( \frac{\text{kg} \cdot \text{m}^2}{\text{s}^2} \right) \) values greater than one are possible because it is not a direct
measurement of the work in compared to the work out of the actuator. This is due to the static nature of this metric.

It is important to note that this metric neglects any of the losses that occur during the process of pressurization for the following two reasons. First, the compressor or flow losses that occur prior to the actuator are independent of the actuator design and so should not be used for making actuator comparisons. Second, this metric is a static measurement, therefore any dynamic losses (like flow losses) of the actual actuator are also neglected. Additional dynamic measures of efficiency are worth investigating in future work.

To calculate efficiency as previously described, the data gathering was completed using the following steps:

1. Two motion tracking frames were initialized to be in the same orientation on the bottom and top of the actuators in their un-deflected or neutral configurations.

2. The actuators were controlled to a known pressure and the actuator was allowed to come to rest.

3. The FT sensor was then used to push the actuators back to the approximately un-deflected state while recording data (i.e. pressures, pose of top and base, angular deflections, forces and torques).

4. The FT sensor was removed and the actuator was allowed to deflect under the actuation load from the pressure until the actuator came to a rest again.

5. The pressure in the actuators was than incremented and the actuator was allowed to come to rest.

6. Steps 3 through 5 were repeated until the actuators maximum operating pressure was reached.

For the antagonistic actuators one side was controlled to a constant low pressure while the other was incremented.

A video showing an example of how the data were taken for the Fluidic Elastic Actuators can be found here https://youtu.be/KPYLk_J_qxA.
3.2.1.4 Parasitic Stiffness

Most soft robot actuators use elastic elements in their construction which results in an inherent spring force. When unactuated, the spring force will return the actuator to a neutral pose or natural equilibrium configuration. At positions away from neutral this stiffness reduces the torque available from the actuator and is parasitic in nature. Generally, torque loss due to parasitic stiffness increases with deflection from the neutral pose. This stiffness is a property of the material and geometry of the actuator and depending on the geometry of the actuator is independent of the pressure in the actuator. It should be measured while at an un-pressurized state. The units are those for standard rotational stiffness, N·m/rad.

Understanding the parasitic stiffness enables soft robot designers to know how their torque changes over the operational space of their actuator. Some applications may require a minimal parasitic stiffness while other applications may only require that the available torque over the operational space be higher than a given threshold. Combining this metric with the Maximum Torque metric can help estimate the torque capabilities over the whole range of motion of the actuator.

The parasitic stiffness was measured through the following process:

1. Two motion tracking frames were initialized to be in the same orientation on the bottom and top of the actuators in their un-deflected or neutral configurations.

2. The FT sensor was used to push the actuators to a known and consistent displacement while the actuators are fully vented allowing for no pressure differential to build through compression of the chambers.

3. The FT sensor was removed and actuator was allowed to come to rest at the zero configuration.

4. Steps 2 and 3 were repeated several times while recording data (pose of top and base, angular deflections, forces and torques) in order to calculate an average parasitic stiffness.
3.2.1.5 Variable Stiffness

As many soft robot actuators are only able to produce force or torque in a single direction, they are often combined into antagonistic actuators. Therefore, many of the antagonistic soft fluidic actuators have the ability to vary their stiffness by adjusting the average pressure in their antagonistic chambers. As this average pressure is increased or decreased the stiffness also increases or decreases. Gillespie et al. [44] and Best et al. [45] show that this stiffness can be controlled while still controlling joint angles. This is a distinct advantage of antagonistic actuators over traditional motor actuators and therefore a metric capturing this distinction is critical.

This metric measures the ability an actuator has to vary stiffness. For this metric we report how changing the average energy in the chambers affects the stiffness of the actuators. Similar to the Efficiency metric we relate the pressure in the chamber to the potential energy in the system through the volume contained in the actuator as described in Equation 3.2. The units of this metric are a rotational stiffness per average energy in the chamber, N·m/(rad·J)

The variable stiffness was measured in a method similar to the efficiency metric using the following process:

1. Two motion tracking frames were initialized to be in the same orientation on the bottom and top of the actuators in their un-deflected or neutral configurations.

2. Opposing chambers of the actuators were controlled to a known common pressure and the actuator was allowed to come to rest at the neutral configuration.

3. The FT sensor was used to push the actuators to a known and approximately consistent displacement while recording data.

4. The FT sensor was removed, the pressure in the actuators was than incremented and the actuator was allowed to come to rest again at the zero configuration.

5. Steps 3 and 4 were repeated until the actuators maximum pressure was reached.
3.2.1.6 Maximum range of motion

As many servo motors or rotary sensors have a limited range of motion, for many applications it is important to know the range of motion for soft robot actuators. When designing a new soft robot actuator or selecting one for a given application the range of motion is a critical consideration. This measurement will be reported as a positive or negative range from their neutral configuration with the following format [Minimum Angle, Maximum Angle] and will be in radians (rad).

This range of motion was measured by bending each actuator to its maximum displacement. For all the antagonistic actuators, except the Blow-molded continuum actuator, this was done while at atmospheric pressure. The high parasitic stiffness of the Blow-molded continuum actuator required that a single chamber was pressurized to bend it to its limits. The Fluidic Elastic Actuator actuators range of motion were also measured while pressurized to their maximum pressure.

The range of motion metric for the Fluidic Elastic Actuator actuators used in this chapter (described in Section 3.2.3.2) is only one-sided as they can only bend in a single direction.

3.2.2 Metric Evaluation Criteria

One of the objectives of this chapter is to determine the ability of each proposed metric to quantify the performance of soft robot actuators. Each Metric Evaluation Criteria (MEC) is chosen to enable the development of general metrics that allow for effective comparison across the many different features and details that make each actuator unique. The MEC that will be used are the following:

• Design Comparison

• Task Utility

• Information
3.2.2.1 Design Comparison

The MEC examines how well each metric allows for exploration of the tradeoffs that are present during design of novel soft actuators.

3.2.2.2 Task Utility

The Task Utility MEC evaluates how the metric can inform the user about the direct utility of the actuator in terms of a task or application. Although this may seem like a trivially important metric, we feel that it must be included as an MEC. If a metric cannot compare the usefulness of an actuator with respect to a task it is not a valid metric.

3.2.2.3 Information

This MEC explores if the metric has different information about the actuators when compared to other metrics.

Each metric will be evaluated for each MEC with a binary choice. Yes if the metric satisfies the MEC or No if it does not. It is understood by the authors that these evaluations are somewhat subjective but are based on Engineering Judgment as is common for many engineering design tasks that require creativity that is nonetheless grounded in math, physics, etc. (see [46]). In addition, future work on quantifying how well these or other metrics meet the proposed MECs is important work.

3.2.3 Actuators Used In this Work

This section describes the fluidic actuators used in this chapter. The two major different types of fluidic actuators used in this work are antagonistic and non-antagonistic. Each type will be discussed in the following subsections as well as any specifics for calculating metric values for the different actuators. A video of the actuators and their actuation can be found here https://youtu.be/OT_D5Rq1Ii8.

A list of the different actuators in this work includes the following:

- Bellows Continuum Joint
– Blow-molded Continuum
– Bead Continuum

• Rotary Elastic Chamber
  – Rubberized Rotary Elastic Chamber
  – Fabric Rotary Elastic Chamber

• Fluidic Elastic Acutators
  – Large TPU
  – Medium TPU
  – Small TPU
  – Small NinjaFlex

3.2.3.1 Antagonistic Actuators

The two types of antagonistic actuators used in this work are first, bellows continuum actuators, and second, Rotary Elastic Chamber actuators, shown in Figure 3.1.

Bellows Continuum Actuators  The bellows continuum actuators provide a force from each pneumatic chamber that is related to the pressure in the bellows, resulting in a torque about the bottom plate of the actuator. Each joint in the case of our experiments has four independently controlled bellows. As the torques of all four actuators are summed a resultant torque causes movement in either (or both) of the two DOF. Both of the bellows continuum actuators we use in this chapter are built with four actuators arranged in a square pattern such that the cross-section of the four actuator chambers form a square or diamond.

The continuum actuator in Figure 3.1 (a) is made from blow-molded plastic bellows and identified in the rest of the chapter as the Blow-molded Continuum actuator. The blow-molded bellows have a high stiffness and therefore a high return force to their neutral configuration.

The other continuum actuator in Figure 3.1 (b) is made of rubberized fabric that was heat welded into bellows and is identified in the rest of the chapter as the Bead Continuum actuator.
The fabric from which this actuator is made has very little stiffness and therefore when this actuator is not pressurized it has negligible stiffness and collapses to its joint limits under its own weight.

Although the continuum actuators are two DOF actuators, we will only report the range of motion for a single bending plane. This is reasonable since the continuum actuators used in this work have an approximately identical range of motion for any plane in which they are bent.

Rotary Elastic Chamber Actuators  The Rotary Elastic Chamber actuators (as described in Section 3.1.1) used in this work behave and rotate similar to a traditional pin joint actuator. The Rotary Elastic Chamber actuator in Figure 3.1 (c) is made of the same rubberized fabric as the bead continuum actuator but is heat welded into bellows. It is identified in this chapter as the Rubberized Rotary Elastic Chamber actuator. This actuator, similar to the Bead Continuum actuator has no stiffness and when it is not pressurized it moves to its joint limits under its own weight.

The last Rotary Elastic Chamber actuator, see Figure 3.1 (d), is built entirely out of fabric with internal bladders which, as they expand in the fabric, cause rotation about a fabric center of rotation. It is identified in the chapter as the Fabric Rotary Elastic Chamber actuator.

Each of the antagonistic actuators in this work was designed and built by Otherlab Inc.

3.2.3.2 Non-Antagonistic Actuators, Fluidic Elastic Actuators

The non-antagonistic actuators used in this work are Fluidic Elastic Actuators and are shown in Figure 3.2. They have simple pneumatic chambers with geometry that allows them to bend in a single direction as the pressure in the chamber increases. We built three different sizes (differentiated in the chapter by small, medium, and large) as well as one size in two different materials using 3D printing techniques. The Medium Fluidic Elastic Actuator is 1.25 times larger than the Small Fluidic Elastic Actuator in all dimensions while the Large Fluidic Elastic Actuator is 1.5 times larger than the Small Fluidic Elastic Actuator. The two different materials are a clear TPU which has a Shore Hardness of 95A [47] and the other is NinjaFlex which has a Shore Hardness of 85A [48].

While we explore only two dimensions of the design space, (i.e. size and material), many others could have been chosen. However, as stated previously, the purpose of this chapter is to develop general metrics that can be used to evaluate actuators across many dimensions of the
design space. As shown in Section 3.3 our limited design variations are able to show that the proposed metrics can enable effective Design Comparison.

In Table 3.1 we have included some dimensions of the different actuators to provide a sense of scale.

### 3.2.4 Case Study

To demonstrate how these metrics can be used to evaluate actuators for a task we have included an example case study. Using a given task we analyze the metrics to evaluate which actuators would be of most value for that task.

In 2017 we took a survey of the soft robotics academic community using the [13] and received 20 anonymous responses. Instead of fabricating a scenario for the example case study we instead use this survey as the basis for the case study. This survey asked the soft robotics
Table 3.1: Dimensions of each actuator. The dimensions of the bounding box includes that part of the actuators that is outlined in red in Figure 3.1

<table>
<thead>
<tr>
<th>Actuator</th>
<th>Bounding Box 1 x w x h (m)</th>
<th>Maximum Pressure kPa</th>
<th>Mass kg</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fabric Rotary Elastic Chamber</td>
<td>0.191 x 0.191 x 0.305</td>
<td>102.0</td>
<td>1.52</td>
</tr>
<tr>
<td>Rubberized Rotary Elastic Chamber</td>
<td>0.191 x 0.191 x 0.102</td>
<td>104.6</td>
<td>1.28</td>
</tr>
<tr>
<td>Blow-molded Continuum</td>
<td>0.191 x 0.191 x 0.206</td>
<td>450.0</td>
<td>1.92</td>
</tr>
<tr>
<td>Bead Continuum</td>
<td>0.229 x 0.229 x 0.382</td>
<td>171.6</td>
<td>8.44</td>
</tr>
<tr>
<td>Large TPU Fluidic Elastic Actuator</td>
<td>0.0244 x 0.0244 x 0.172</td>
<td>238.2</td>
<td>0.0736</td>
</tr>
<tr>
<td>Medium TPU Fluidic Elastic Actuator</td>
<td>0.0204 x 0.0204 x 0.143</td>
<td>244.6</td>
<td>0.0446</td>
</tr>
<tr>
<td>Small TPU Fluidic Elastic Actuator</td>
<td>0.0163 x 0.0163 x 0.114</td>
<td>248.9</td>
<td>0.0251</td>
</tr>
<tr>
<td>Small NinjaFlex Fluidic Elastic Actuator</td>
<td>0.0164 x 0.0164 x 0.119</td>
<td>243.5</td>
<td>0.0377</td>
</tr>
</tbody>
</table>

community to rank the importance of several metrics as they related to five different tasks. For the case study we focus on the results of survey for a Wiping Task which was defined as “A task where a robot wipes a surface, whether an end effector or other parts of the manipulator are used. An example includes the cleaning of a solar panel.”

The survey participants ranked the importance of a metric as it pertained to a task as either Extremely Important, Very Important, Moderately Important, Slightly Important or Not at all Important. As the focus of this chapter is developing actuator metrics the full results of the survey are not included but the full survey data can be found here https://bit.ly/38xe0fn.

To determine what metrics the community felt were most important, we used a weighted scoring method which is commonly used in engineering design process. The weighting was calculated as follows. For each individual who considered the metric as Extremely Important, the metric was given 4 points, for Very Important it was given 3 points, for Moderately Important 2 points, for Slightly Important 1 point, and 0 points for Not at all Important. The average of the points (the sum of the total points divided by the number of responses) was then used as the final score for the metric.

In Section 3.3.9, we present the results of the survey for the Wiping task and the analysis performed in the case study. Although the survey metrics are designed for a full robot manipulator, with some assumptions, most of them can be related to the actuator metrics proposed in this chapter. By using these relations we are able to evaluate the suitability of the actuators presented in this chapter based on the requirements defined for the wiping task.
### 3.3 Results

In the following sections (3.3.1 through 3.3.7) we present an analysis of the data we collected from different soft robot actuators along with an evaluation of each metric using the Metric Evaluation Criteria (MEC) discussed in the previous section.

As examples of the ability of our metrics to enable Design Comparison we present specific comparisons between similar actuators of different sizes as well as similar actuators made of different materials.

Additionally we use the rest of our results to present the importance of each metric with respect to the MECs for Task Utility and Information. Again the scope of this work is not to quantify precisely how these specific actuators perform, but to develop metrics by which soft fluid-driven actuators can be compared. Thus enabling a standardized method for discussing soft fluid-driven robot actuator performance. Table 3.2 summarizes the results of all the experiments for each actuator with respect to the different metrics.

Additionally, for making comparisons between the TPU Fluidic Elastic Actuators for the metrics and their performance based on a variation in their scale, we have plotted the ratios of the different TPU Fluidic Elastic Actuators in Figure 3.3. This is done by dividing the values for each metric for the Small, Medium and Large TPU Fluidic Elastic Actuators by the value for each metric of the Small TPU Fluidic Elastic Actuator. We plot all the metrics in the same plot as a ratio so that a more effective visual comparison can be performed. By analyzing the varying slopes shown on Figure 3.3, a gross relationship between variation in actuator scale and each metric can be determined.
Figure 3.3: Plot of the metric values for the scaled TPU Fluidic Elastic Actuators divided by the metric values of the Small TPU Fluidic Elastic Actuator. The non-linear nature of most of the metrics means that there is not a one to one mapping between scaling and what the resultant metric will be.

### 3.3.1 Mass

Although the mass of the actuators is not one of our proposed metrics, we use it as a means of comparison with the other metrics we are recommending.

**Design Comparison** When comparing the mass of the Fluidic Elastic Actuators as shown in Table 3.2, as expected, the scaled versions of the TPU actuators are larger and scales approximately linearly with the geometry. The NinjaFlex Fluidic Elastic Actuator has a similar size to the Small TPU Fluidic Elastic Actuator but has 50% more mass.
From Figure 3.3 it can be seen that as the scale increases the mass increases but at a higher rate. This can be seen by the steeper slope from Medium to Large Fluidic Elastic Actuator as compared to going from the Small to Medium.

The Rotary Elastic Chamber actuators have similar masses so no significant comparison can be made. While the continuum joints do have significantly different masses, their method of construction do not allow for good comparison using the Mass Metric. Much of the difference in mass is due to the top and bottom cap of the Bead Continuum actuator and not a variance in design.

The differences found in the slope of the Fluidic Elastic Actuators show that this metric does allow for comparison and Design Comparison MEC and is evaluated as Yes for the mass metric.

**Task Utility**  The mass metric provides relevant data that can be used to guide selection for different applications. Therefore it is useful in terms of Task Utility as the mass of the robot is often an important factor for many soft robot applications therefore the Task Utility MEC is evaluated as Yes for the mass metric.

**Information**  The Information MEC compares each metric to the other metrics to examine if the metric in question provides any new information. Both the mass metric and the Torque-to-Mass Ratio metric provide similar information about mass. So for the Information MEC only one can be used to satisfy the MEC. The authors feel that the Torque-to-Mass Ratio metric is a better candidate and evaluate the Information MEC for the mass metric as No. A more detailed discussion of this reasoning is found in Section 3.3.3.

Although this metric does have its use, it does not satisfy all three MEC and we therefore do not recommend it as a metric.

<table>
<thead>
<tr>
<th>Mass</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Design Comparison</em></td>
</tr>
<tr>
<td><em>Task Utility</em></td>
</tr>
<tr>
<td><em>Information</em></td>
</tr>
</tbody>
</table>

47
3.3.2 Maximum Torque

Of the antagonistic actuators the Blow-molded Continuum actuator has the ability to produce the largest maximum torque of 63.90 N·m at a pressure of 450.0 kPa as per the manufacture’s specifications. The Fabric Rotary Elastic Chamber has the lowest maximum torque of 22.51 N·m at 102.0 kPa as per the manufacturer’s specifications. The maximum torque from the Fluidic Elastic Actuators was significantly smaller but this is expected from the relative size of the actuators.

**Design Comparison** Increasing the scale of the Fluidic Elastic Actuators did increase the maximum torque and as seen in Figure 3.3 where there is only a slight inflection as the scale keeps increasing. This can be seen by the almost constant slope for the Maximum Torque Metric in Figure 3.3.

The Small TPU Fluidic Elastic Actuator had a 1.69 times higher Max Torque than the Small NinjaFlex Fluidic Elastic Actuator. This shows that varying material can have a significant effect on the performance of an actuator with respect to this metric. A similar trend can be seen for the Rotary Elastic Chamber actuators. There is a significant increase in Maximum Torque from the Rubberized Rotary Elastic Chamber as compared to the Fabric Rotary Elastic Chamber. This demonstrates that this metric satisfies the Design Comparison MEC and is evaluated as Yes.

**Task Utility** Because many applications or tasks for which these actuators would be used have a payload requirement this metric is also important in terms of the MEC of Task Utility. We evaluate the Task Utility MEC as Yes for the Maximum Torque metric.

**Information** Lastly when comparing the other proposed metrics, this metric does share information with the Torque-to-Mass Ratio metric. As discussed previously we feel the Torque-to-Mass Ratio metric better satisfies the Information MEC with respect to mass. Therefore the Max Torque metric provides new information about the Maximum Torque of each actuator that is not readily available from the Torque-to-Mass Ratio exclusively. Therefore the Maximum Torque metric satisfies the Information MEC and is evaluated as Yes.
### 3.3.3 Torque-to-Mass Ratio

The joint with the greatest Torque-to-Mass Ratio is the Small TPU Fluidic Elastic Actuator with the Rubberized Rotary Elastic Chamber being the next highest with a close third of the Medium TPU Fluidic Elastic Actuator (see Figure 3.4). The obvious lowest is the Bead Continuum actuator, and although it has a high Max Torque, its large mass severely affects its Torque-to-Mass Ratio.

**Design Comparison**  
It can be noted that as the actuators were scaled to be larger the Torque-to-Mass Ratio decreased. As is shown in Figure 3.3, an increase in scale from the Small to Medium and from Medium to Large results in a decrease in the Torque-to-Mass Ratio. This comparison shows how this metric satisfies the Design Comparison MEC and is therefore evaluated as *Yes*.

**Task Utility**  
Many applications are sensitive to the mass of the actuators used. This metric will help guide the selection of an actuator that will have the required payload while also limiting the mass of the actuator. We evaluate the Task Utility MEC as *Yes* for the Torque-to-Mass Ratio metric.

**Information**  
The mass, Maximum Torque and Torque-to-Mass Ratio metrics all have somewhat redundant information relating to the torque output and mass of the actuators. However, to satisfy the Information MEC each metric must have new information that other metrics do not. Therefore only two of the three metrics can satisfy the Information MEC as there are two independent variables. We chose Maximum Torque and Torque-to-Mass Ratio because they are stronger candidates with respect to the other MECs. Both Maximum Torque and Torque-to-Mass Ratio can be used better for Design Comparison and Task Utility. We therefore evaluate the Information MEC as *Yes* for the Torque-to-Mass Ratio.
3.3.4 Efficiency

Figures 3.5 and 3.6 show the efficiencies of all the actuators that we tested. As stated previously, we measure efficiency as the change in energy in the system as compared to the change in torque output. This correlates to the slopes of the data found in Figures 3.5 and 3.6. Because the
antagonistic actuators can accept much higher input pressures (therefore containing more energy) than the Fluidic Elastic Actuators they were separated into two plots for readability.

As previously stated, the antagonistic actuators have much higher energies than the Fluidic Elastic Actuators. However, this does not mean that they are always more efficient as is shown in Table 3.2. The actuator with the largest efficiency that we tested is the Rubberized Rotary Elastic Chamber (REC). Interestingly the two Continuum actuators, the Bead Continuum and Blow-molded Continuum actuators had very similar efficiency. Of additional note is that three of the Fluidic Elastic Actuators, the Large, Medium and Small TPU Fluidic Elastic Actuators had higher efficiencies than the Fabric Rotary Elastic Chamber actuator.
Figure 3.6: Relationship between energy and torque for the fluidic elastic actuators (FlEA). As the size of the actuator increases the amount of efficiency of the actuator decreased.

**Design Comparison**  As the Fluidic Elastic Actuators were scaled up in size, the Efficiency did not increase, but in fact decreased as seen in Figure 3.3. However, it does seem that there is a slight change in slope as the Fluidic Elastic Actuator was scaled from Medium to Large as compared to scaling from Small to Medium. This suggests that the efficiency may start to increase again as the size continues to increase. Additionally, the Small TPU Fluidic Elastic Actuator is essentially two times more efficient than the Small NinjaFlex Fluidic Elastic Actuator. This kind of comparison shows the importance of evaluating the type of material used for soft robot actuators and how the metrics presented enable this comparison.
As seen in Figure 3.5 the efficiencies for the antagonistic actuators are similar with the exception of the Fabric Rotary Elastic Chamber. The efficiency of the Fabric Rotary Elastic Chamber is less than half the efficiencies of the other antagonistic actuators.

As can be seen by these comparisons, this metric satisfies the Design Comparison MEC and is evaluated as Yes.

**Task Utility** Any application that has a limited supply of energy or pressure would consider the efficiency of an actuator when making a selection. Therefore this metric satisfies the Task Utility MEC and is evaluated as Yes.

**Information** This metric uses the energy which is unique from any of the other metrics discussed in this work. So the Information MEC is evaluated as Yes for this metric.

<table>
<thead>
<tr>
<th>Efficiency</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Design Comparison</strong></td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Task Utility</strong></td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Information</strong></td>
<td>Yes</td>
</tr>
</tbody>
</table>

### 3.3.5 Parasitic Stiffness

As discussed in Section 3.2.3 the Rubberized Rotary Elastic Chamber and Bead Continuum actuators have practically no parasitic stiffness and will not be discussed in this section. The Blow-molded Continuum actuator had by far the largest parasitic stiffness while the other actuators’ ranges were similar.

**Design Comparison** For the Fluidic Elastic Actuators, as the size of the actuator increased the parasitic stiffness also increased from the Medium to the Small, but it decreased from the Medium to the Large Fluidic Elastic Actuator. This variation in parasitic stiffness shows not only how the selected material affect the stiffness of the actuator, but how the geometry of the actuator will affect the stiffness as well.

Additionally, the difference in stiffness between the Fabric Rotary Elastic Chamber and the Blow-molded Continuum actuator is of significance. The trade-off between stiffer plastic and less...
stiff fabric is very apparent when comparing these two actuators with respect to Parasitic Stiffness. For this reason we evaluate the Design Comparison MEC as Yes for the Parasitic Stiffness metric.

**Task Utility** As the parasitic stiffness reduces the available torque when the actuators are bent, for many applications it is important to know how much torque is available over the desired range of motion. The parasitic stiffness metric will allow us to quantify if a soft robot actuator will have an acceptable stiffness for the range of motion of the task. Thus this metric satisfies the Task Utility MEC as is evaluated as Yes.

**Information** While the Variable Stiffness metric also measures stiffness, they measure the stiffness of a soft robot actuator from different sources. Therefore the unique information found in this metric shows that it satisfies the Information MEC and we evaluate it as Yes.

<table>
<thead>
<tr>
<th>Parasitic Stiffness</th>
<th>Design Comparison</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Task Utility</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Information</td>
<td>Yes</td>
</tr>
</tbody>
</table>

### 3.3.6 Variable Stiffness

As shown in Table 3.2 and Figure 3.7, the Fabric Rotary Elastic Chamber, Rubberized Rotary Elastic Chamber, and Bead Continuum actuators all have similar Variable Stiffness capabilities. However, the Blow-molded Continuum actuator is incapable of large changes in stiffness.

There is a significant difference in performance between the Blow-molded Continuum actuator and the other antagonistic actuators. The test on every actuator was performed in the exact same way and exploring this difference and its root cause is beyond the scope of this chapter. However, the difference is clear.

**Design Comparison** By changing the material and design between the two continuum actuators, there is a significant difference in potential variable stiffness. This means that simply because the actuators are antagonistic in nature, does not mean that they will allow significant changes in stiffness, even if other similar actuators do. Using this metric we are able to effectively compare
Figure 3.7: The variable stiffness relationship between pressure and stiffness for the antagonistic actuators.

the two continuum actuators showing that effective Design Comparison is enabled by this metric. Therefore we evaluate the Design Comparison MEC as Yes for this metric.

**Task Utility**  For any application that requires a variable stiffness joint this metric is essential. Therefore we evaluate the Task Utility MEC as Yes for the Variable Stiffness metric.

**Information**  As previously mentioned this metric does deal with stiffness like the previous metric, but it is a different type of stiffness that comes directly from actuator geometry (such as surface area) and applied pressures. Therefore this metric provides unique information and therefore satisfies the Information MEC and is evaluated as Yes.
### 3.3.7 Maximum range of motion

The range of motion of the antagonistic actuators were all similar while the Fluidic Elastic Actuators had much more variance. The Fabric Rotary Elastic Chamber and Bead Continuum joints have the largest range of motion with $[-1.57, 1.57]$ rad, while the Small TPU Fluidic Elastic Actuator has the smallest range of motion of $[0, 1.60]$ rad.

**Design Comparison** As the Fluidic Elastic Actuators were scaled, the Maximum range of motion scaled at a constant rate as shown in Figure 3.3. Although this does allow for some Design Comparison the linear nature is somewhat trivial. However, when comparing the Fluidic Elastic Actuators, the Small NinjaFlex Fluidic Elastic Actuator (when inflated to its maximum operating pressure) had the highest range of motion with $[0, 2.03]$ rad while the similarly sized Small TPU Fluidic Elastic Actuator had the lowest range of motion of $[0, 1.60]$ rad. The difference in material had a much larger impact on the Maximum range of motion than the scaling and thus allows for a significant Design Comparison. Therefore this metric satisfies the Design Comparison MEC and we evaluate it as Yes.

**Task Utility** Because the range of motion of an actuator determines its workspace, it is key to understanding the range of motion when selecting an actuator for an application. The Task Utility MEC is evaluated as Yes for this metric.

**Information** As none of the other metrics can be used to determine the data in this metric, this metric satisfies the Information MEC and is evaluated as Yes.
Table 3.3: Summary results from the metric evaluation using the MEC.

<table>
<thead>
<tr>
<th>Evaluation Category</th>
<th>Mass</th>
<th>Maximum Torque</th>
<th>Torque-to-Mass Ratio</th>
<th>Efficiency</th>
<th>Parasitic Stiffness</th>
<th>Variable Stiffness</th>
<th>Maximum range of motion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design Comparison</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Task Utility</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Information</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable Stiffness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design Comparison</td>
</tr>
<tr>
<td>Task Utility</td>
</tr>
<tr>
<td>Information</td>
</tr>
</tbody>
</table>

3.3.8 Metric Evaluation

Table 3.3 summarizes the results of the metrics’ evaluations. All of the proposed metrics, with the exception of mass, satisfied all three MECs. This shows that they are good metrics for soft robot actuators and can be used for making design comparisons, selecting actuators for different applications, and differentiating how different soft robot actuators perform.

3.3.9 Case Study

To show how the proposed metrics would be useful in selecting soft robot actuators for an actual task, or even potentially designing new actuators for a given task, we next present the metrics as applied to our case study from Section 3.2.4. The results of the analysis of the survey for the wiping task are included in Table 3.4. The seven metrics that were scored for the wiping task survey were:

1. Compliance at the End Effector (3.2 points)
2. The Hardness/Softness of the material making contact (3.05 points)
3. The ability to perform Force Control (3.05 points)
4. Compliance of the Joints and Links (2.9 points)
5. The Reachability of the serial manipulator (2.75 points)
The ability of the serial manipulator to maintain a Tolerance about a Trajectory (2.75 points)

The Time to Completion of the desired wiping task (2.75 points)

As the two metrics, Tolerance about Trajectory and Time to Completion are dynamic measures and depend heavily on the controller and dynamics of the system, we will not explore them in this case study. To relate the manipulator metrics from the survey to the actuator metrics some assumptions have been made and will be stated as necessary.

Both of the compliance metrics from the survey are related to the Variable Stiffness metric proposed in this chapter as the compliance of a manipulator is directly tied to the compliance of the actuators ([49] section 21.6). Because there is no compliance value or range specified we assume that a manipulator that has the ability to vary its compliance over the widest range will provide the most utility. By having a variable stiffness actuator the compliance can be adapted for varying scenarios of a wiping task. To satisfy this metric the Blow-molded Continuum joint can be ruled out since it has almost no ability to vary stiffness. However, the other three antagonistic actuators seem like possible candidates.

The Hardness/Softness metric from the survey does not directly correlate to any of the metrics proposed in this chapter. However, the hardness of an object is related to its deflection properties by the modulus of elasticity, and as discussed in section 3.3.5, the stiffness of the material from which the actuators are made has a correlation to the Parasitic Stiffness. We also assume that for a wiping task the hardness of the actuators should be minimized so that any impact forces can be reduced. Therefore, looking at the Parasitic Stiffness, the Blow-molded Continuum joint can be ruled out again due to its high Parasitic Stiffness and the Rubberized Rotary Elastic Chamber and Bead Continuum joint have rigid plastic elements that remove them as ideal candidates. Therefore the Fabric Rotary Elastic Chamber is the best choice out of the antagonistic actuators that provide variable stiffness outputs.

The ability to have force control is related to the Maximum Torque metric proposed in this chapter. The larger the maximum torque that an actuator can achieve, the wider the range of force control that is theoretically possible. While the resolution of the force control is also a factor to consider, for this analysis we are assuming that a wide range of force control is of higher value and the resolution of the force control is adequate. Future work could include metrics that deal with
control resolution for soft robot actuators. Therefore, for the force control metric, the Rubberized Rotary Elastic Chamber may be the best choice based on the Maximum Torque metric.

The Reachability metric of the survey can be directly related to the range of motion metric proposed in this chapter. Generally the larger the range of motion of the actuators the higher the Reachability of the full serial manipulator will be. The Fabric Rotary Elastic Chamber and Bead Continuum actuators have the highest range of motion of \( \pm 1.57 \) rad and would be the best candidates based on this metric. However the Bead Continuum joint is a slightly better choice due to its two degrees of freedom bending. It is important to note here that in the case of applying these metrics to robot design (and not just selection of existing actuators), there can be interaction between the metrics. For example, having a large range of motion may also require long soft robot links to achieve good reachability. Having good reachability does not mean that the designed manipulator would be able to lift the actual load of the soft robot designed. This then ties back to the Maximum Torque metric and we can see how the desired value for that may need to increase if the weight of the manipulator increases. However, the proposed metrics so far cover this use case completely and would allow that trade-off in the design space if properly modeled.

As with many design decisions the engineer must make a choice on how to weight the importance of each metric. Based on the weighting we calculated from the survey, and if selecting only from the actuators presented in this chapter, we would choose the Fabric Rotary Elastic Chamber for a serial manipulator used to perform wiping motions while in contact. These choices satisfy the Compliance metric, the Hardness/Softness metric and the Reachability metric. The design trade-off in this case requires sacrificing the actuator’s ability to perform Force Control in favor of the other metrics.

It should be noted that these may not be the optimal actuators for this task as the comparison in this chapter is limited to only eight actuators. However, by using these metrics with accurate models during the actuator design phase, an optimal actuator can be designed and selected for a desired task. Although it did not include actuator design, this type of design optimization was shown for the whole kinematic structure of a soft robot manipulator in Bodily et al. [32].

For this case study we are not proposing that the survey, the scoring method used, or our assumptions are the only or best methods for determining which metrics should be used to evaluate actuators for a task. As the task is more clearly defined, or if any of the assumptions change, then
the final analysis and actuator choice would also change. Instead, we are providing an illustrative example of how the metrics can be used to select appropriate actuators for a given task.

3.4 Discussion

This chapter is a step towards developing a unifying method to compare and evaluate soft robot actuators. This is necessary since there is currently no standard in the literature to enable comparison between soft robot actuators. We accomplish this by first developing a method of evaluating potential metrics using the Metric Evaluation Criteria which include Design Comparison, Task Utility, and Information. By using the MECs we were able to show that the metrics proposed in this work are effective metrics for fluidic soft robot rotational actuators. In our case study we also demonstrated how the metrics could be used to evaluate the actuators in this chapter for the given task, thus showing how these metrics facilitate design and comparison of new and existing soft robot actuators within an engineering methodology.

It is important to note that while we have demonstrated the efficacy of these metrics for fluidic rotational actuators these metrics can be modified/adapted for use with other types soft robot actuators.

For non-fluidic rotational soft robot actuators only the Efficiency and Variable Stiffness metrics will need significant modification. For both metrics it will be necessary to develop a method for measuring the potential energy of the system and the torque output during a static loading scenario. However once this has been done, the metrics in this chapter are applicable for any other type of rotational soft robot actuator.

The metrics can also be adapted for soft robotic actuators that do not have rotational motion profiles. For linear actuators the metrics can be modified by replacing all torque and rotational measurements with force and linear measurements respectively. We readily acknowledge that the metrics described in this chapter may not be adaptable to all soft robot actuators. As the motion profiles of the soft robot actuators become less general the metrics that need to be used to evaluate those actuators will also become less general. Examples of these actuators include twisting actuators and actuators that use eversion [34] as their actuation method. As more actuation methods (i.e. fluidic, electrostatic, etc.) and actuation modes (i.e. rotational, linear, twisting, etc.)
are developed it will be important to develop metrics to start comparing them and characterizing their performance. What we have demonstrated in this chapter is an important step in that effort.

### 3.4.1 Conclusion

Future work includes using the metrics developed here to evaluate additional soft robot actuators to enable the soft robotics community to make more rigorous comparisons between different soft robot actuation methods and designs. Some additional metrics that we feel should be explored include reliable life cycle, motion repeatability, and safety to name a few. As the metrics in this chapter are limited to static metrics, in future work it will also be important to develop dynamic metrics (related to actuator bandwidth and control bandwidth for soft actuators). Additionally the metrics presented can be expanded to encompass all soft robot actuators and not only fluidic rotational actuators as described above. We further expect that new potential soft robot applications will emphasize and clarify additional necessary requirements for comparison and evaluation of potential actuators. Therefore, despite having developed six soft robot actuation metrics as well as guidelines for evaluation, we fully expect this set of guidelines to further mature as the field of soft robotics continues to grow.

### 3.5 Acknowledgements

We would like to thank Ryan Larson, Adam Wagner, and Spencer Diehl for designing and fabricating the Fluidic Elastic Actuator actuators. We also sincerely thank Otherlab Inc. for their long collaboration and making this work possible by designing and building all of the antagonistic actuators. We also thank the reviewers of this chapter for the important feedback that has significantly strengthened the chapter and improved its generality.
Table 3.4: Survey analysis results for the wiping task from a total of 20 responses. Each entry represents the tally of individuals that ranked the corresponding metric with the corresponding level of importance (e.g. Compliance at EE had seven individuals rank its importance at "Extremely Important" etc.). The average importance score is calculated by multiplying each row by the their respective row weightings (4 points, 3 points, etc.), summing the columns and dividing by the total number of samples (20).

<table>
<thead>
<tr>
<th></th>
<th>Compliance at EE</th>
<th>Force Control</th>
<th>Compliance</th>
<th>Tolerance about Trajectory</th>
<th>Reachability</th>
<th>Time to Completion</th>
<th>Hardness/Softness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extremely Important (4 pts)</td>
<td>7</td>
<td>9</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Very Important (3 pts)</td>
<td>10</td>
<td>4</td>
<td>9</td>
<td>7</td>
<td>7</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>Moderately Important (2 pts)</td>
<td>3</td>
<td>6</td>
<td>5</td>
<td>6</td>
<td>6</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Slightly Important (1 pts)</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Not at all Important (0 pts)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td><strong>Average Importance Score</strong></td>
<td><strong>3.2</strong></td>
<td><strong>3.05</strong></td>
<td><strong>2.9</strong></td>
<td><strong>2.75</strong></td>
<td><strong>2.75</strong></td>
<td><strong>2.35</strong></td>
<td><strong>3.05</strong></td>
</tr>
<tr>
<td><strong>Standard Deviation</strong></td>
<td><strong>0.68</strong></td>
<td><strong>0.97</strong></td>
<td><strong>0.83</strong></td>
<td><strong>0.94</strong></td>
<td><strong>0.94</strong></td>
<td><strong>0.85</strong></td>
<td><strong>0.80</strong></td>
</tr>
</tbody>
</table>
CHAPTER 4. COMPARING MODEL PREDICTIVE CONTROL AND INPUT SHAPING FOR IMPROVED RESPONSE OF LOW-IMPEDANCE ROBOTS


4.1 Introduction & Motivation

As humanoid robots operate more commonly in close proximity to people, we would expect to see an increased need for the number of robots that exhibit low impedance behavior for safety reasons. This low impedance (either from active control or from passive element design) will make the high-level control and planning methods used for robots very different from current position control methods. This is especially the case when comparing them with robots in factories that perform precision tasks. Unfortunately low impedance often means losing the ability to accurately and quickly track a joint command without oscillation. This makes the robot less useful for performing meaningful tasks and operating in close proximity to human counterparts. Without sacrificing compliance for safety reasons, we will need to increase the precision and efficiency of such compliant robots. We show in this chapter that implementing methods such as input shaping and MPC can improve the robot’s overall performance in terms of time-efficient task completion while maintaining robot compliance.

We present two methods for improving the step response of a compliant serial manipulator. We use Model Predictive Control (MPC) and input shaping to effectively control the Baxter robot from Rethink Robotics that has both active and passive compliance (see Figure 4.1 for images of Baxter). MPC is a form of optimal control that uses a model of the dynamic system and an optimization formulation to determine the best control input which minimizes a cost function subject to real world constraints. We compare this controller to an input shaper which is a command gen-
operation technique for oscillatory systems. We show that the MPC controller effectively reduces residual oscillations, improves tracking of a step input, and is less sensitive to modeling error than the input shaper.

Our specific contributions include the following:

- Development of Model Predictive Control for smooth motion control of a full seven-degree-of-freedom compliant robot.
- Extension and testing of input shaping to a seven degree of freedom robot using feedback linearization.
- Significant reduction in overshoot and residual oscillation of a compliant robot while maintaining compliance.
- Comparison between performance of the Cartesian MPC and multi-degree of freedom input shaper.
- Cartesian motion without the need for a trajectory or path planner to mitigate overshoot or stay within actual torque or joint limits.
4.1.1 Literature Review

Many researchers are exploring the ability of robots to work with and around humans [50], [51], [52]. Typical industrial robots are not well suited to work in close proximity to humans due to their high torque capabilities, rigid links, and large masses [53]. A common method for developing safer robots is to make them compliant [8, 9, 54, 55]. This is done through several methods that include but are not limited to active compliance control [10], [56], passive compliance actuators [9], and using flexible links or mechanisms instead of rigid links [55, 57].

In terms of prior research for compliant robot control, in [58] they use a State Feedback Damping Controller that is able to function for at least three joints of the seven-degree-of-freedom (DoF) compliant robot. However, from their system description, they do not have any mechanisms for handling limited actuation or state and actuation constraints. Input shaping or command shaping is an open-loop method for controlling flexible and underdamped structures that has been successfully used to control compliant robots and mechanisms for low DoF systems [59]. Input shaping has previously been shown to remove oscillations when moving free swinging suspended objects [60] as well as controlling a two-link flexible robot [61]. Input shaping was also used by the authors in [55] to reduce the residual oscillation of their single link robot in simulation and on a physical system. The authors of [61] used feedback linearization to remove the non linearities of a two DoF system which allowed them to effectively use input shaping as a linear control method. In [62] they also used feedback linearization and input shaping to control a flexible single link manipulator in simulation and show that by removing the non-linearities the input shaping scheme was greatly improved. We show in this chapter that a Zero Vibration and Derivative (ZVD) input shaper [59] for a seven-DoF robot with feedback linearization does not respond well to nominal modeling error. We would expect similar limitations in terms of disturbance rejection for other open-loop optimal control methods when compared to our model predictive controller.

Another control method for flexible robots that is gaining attention due to improvements in the efficiency of current optimization algorithms [63], [64], [65] is Model Predictive Control (MPC). The authors in [66], [67], [68] use MPC to control flexible links and to reduce residual oscillation and improve tracking on a four link, a single link and a two link mechanism respectively. In [67] and [68], they show results in both simulation and on hardware while [66] has results only in simulation. In [69], they use MPC to control a compliant soft robot, but they make no effort
to minimize overshoot or oscillation like in the work in this chapter. The authors of [68] also use an unconstrained optimization while [66] and [67] utilize the potential of MPC and include constraints. Our approach is most similar to this work, but is applied to a full seven-DoF humanoid robot.

In terms of organization of this chapter, in Section 4.2 we describe the nomenclature for this work as well as the method and controller formulation of our input shaper and Model Predictive Controller. In Section 4.3 we describe the experimental setup including the hardware we used and the tests we conducted, while the results of the experiments on hardware are shown and discussed in Section 4.4.

4.2 Method

We define the nomenclature and all variables used for this work in Table 4.1. Bold upper case variables are matrices while bold lower case variables are vectors, and any non-bold variables are scalars.

This section includes the formulation of our input shaper and model predictive controller. These controllers were designed with the assumption that the arms have relatively low mechanical impedance at the joints and that the impedance can be modeled as springs and dampers that are linear in joint space as follows (Equation (4.1)).

\[ \tau = K_p(q_{\text{des}} - q) - K_d \dot{q} \] (4.1)

The variables \(q, \dot{q}, \text{ and } q_{\text{des}}\) (joint angle, joint velocity, and commanded joint angle) are \(n\) length vectors and \(K_p\) and \(K_d\) are \(nxn\) diagonal matrices that are the proportional and derivative gains respectively.

4.2.1 Feedback Linearization and Input Shaping

Our input shapers were formulated and implemented for each joint individually using feedback linearization. Our approach was similar to that of [61] where input shaping is successfully adapted to two links through feedback linearization, however our implementation of input shaping
Table 4.1: Nomenclature and variable definitions.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_d$, $B_d$</td>
<td>Discrete time linear approximations of the dynamics for a robot arm</td>
</tr>
<tr>
<td>$M(q)$</td>
<td>Configuration dependent robot joint-space inertia matrix</td>
</tr>
<tr>
<td>$F(\dot{q})$</td>
<td>Coulomb and viscous joint friction terms</td>
</tr>
<tr>
<td>$J(q)^T f$</td>
<td>Contact force at the end effector</td>
</tr>
<tr>
<td>$K_p$</td>
<td>Diagonal joint stiffness matrix</td>
</tr>
<tr>
<td>$K_d$</td>
<td>Diagonal joint damping matrix</td>
</tr>
<tr>
<td>$C(\dot{q}, q)$</td>
<td>Coriolis and centrifugal matrix terms</td>
</tr>
<tr>
<td>$G(q)$</td>
<td>Configuration dependent gravity joint torques</td>
</tr>
<tr>
<td>$I$</td>
<td>Lumped parameter moment of inertia</td>
</tr>
<tr>
<td>$R$</td>
<td>Diagonal weighting matrix for MPC</td>
</tr>
<tr>
<td>$q, \dot{q}, \ddot{q}$</td>
<td>Joint angles, velocities and accelerations</td>
</tr>
<tr>
<td>$q_{\text{min}}/\text{max}$</td>
<td>Minimum/ Maximum joint angle limits</td>
</tr>
<tr>
<td>$q_{\text{des}}$</td>
<td>Commanded joint angles sent to the joint impedance controller</td>
</tr>
<tr>
<td>$\Delta q_{\text{des}}$</td>
<td>Change in commanded joint angles sent to impedance controller</td>
</tr>
<tr>
<td>$\Delta q_{\text{cmd}}$</td>
<td>Vector of commanded goal joint steps</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Joint torques for each joint</td>
</tr>
<tr>
<td>$T_c, T_p$</td>
<td>Number of time steps in the prediction models where we have control authority and where we do not respectively</td>
</tr>
<tr>
<td>$u$</td>
<td>Input for MPC formulations, $q_{\text{goal}}$, for single DoF application and $\Delta x_{\text{des}}$ for seven DoF application</td>
</tr>
<tr>
<td>$\tau_{\text{max}}$</td>
<td>Maximum joint torques at each joint</td>
</tr>
<tr>
<td>$\alpha, \gamma$</td>
<td>Scalar weightings for MPC</td>
</tr>
<tr>
<td>$\Delta T$</td>
<td>Discrete time step in seconds, determined by the control rate</td>
</tr>
<tr>
<td>$\Delta \tau_{\text{max}}$</td>
<td>Maximum allowed change in torque at each time step</td>
</tr>
<tr>
<td>$J_x(q, \dot{q})$</td>
<td>Geometric Jacobian used to describe Cartesian velocity for the end effector</td>
</tr>
<tr>
<td>$q^\uparrow, q^\downarrow$</td>
<td>Upper and lower bound on the second joint for seven DoF MPC cost function</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>Damping ratio</td>
</tr>
<tr>
<td>$\omega_n$</td>
<td>Natural frequency for a single joint</td>
</tr>
</tbody>
</table>

was for four joints of a seven-DoF compliant robot since the last three joints were not underdamped for the input shaping.

In this section we formulate the ZVD input shaper by first explaining the feedback linearization process in Section 4.2.1.1, derive the dynamic models in Sections 4.2.1.2 and 4.2.1.3 and then lastly, we formulate the input shapers in Section 4.2.1.4.
4.2.1.1 Feedback Linearization

Feedback linearization is used to simplify the dynamics of a nonlinear system to behave instead like a linear system [70]. We implemented feedback linearization to make each joint act independently as a linear second order system. We then implemented a ZVD shaper to shape the inputs of each joint independently.

We derived our dynamic model using Equation (4.2) which is for a robot with rigid links and no contact forces except at the end effector (see [71]):

\[ \tau = M(q)\ddot{q} + C(q, \dot{q})\dot{q} + F(\dot{q}) + G(q) + J(q)^T \mathbf{f} \]  \hspace{1cm} (4.2)

Neglecting friction, assuming the robot experiences no contact forces, and assuming that a low-level controller compensates for gravity, (which is the case for the Baxter robot), we are left with

\[ \tau = M(q)\ddot{q} + C(q, \dot{q})\dot{q} \] \hspace{1cm} (4.3)

Neglecting friction is something that is more reasonable for SEA torque-controlled systems like Baxter as opposed to highly geared industrial robots and we make the same assumption for MPC. To feedback linearize the system, we apply the following control torque

\[ \tau = M(q)[K_p(q_{des} - q) - K_d\dot{q}] + C(q, \dot{q})\dot{q} \] \hspace{1cm} (4.4)

which when substituted into Equation (4.3) yields the simple dynamics

\[ \ddot{q} = K_p(q_{des} - q) - K_d\dot{q} \] \hspace{1cm} (4.5)

By applying the torque given in Equation (4.4) at a rate of 500 Hz and assuming a perfect model, we not only simplify the joint dynamics to be as given in Equation (4.5), but also decouple each joint from every other joint in the arm because \( K_p \) and \( K_d \) are diagonal matrices. With each joint decoupled from the rest we are able to shape commands for each joint using input shaping. It should be noted that performance for the feedback linearization degrades in the cases of torque saturation and significant modeling error.
Input shaping is an open-loop method of control that generates command inputs based on
the known desired path and the system’s dynamics to attain a desired trajectory or goal while
mitigating oscillation. The input shaper generates a series of impulses and convolves them with
the desired goal command to cancel any vibrations that a system might experience [59]. Implemen-
tation of this method requires a knowledge of the path and the system’s natural dynamics prior to
execution so that a correct input can be determined. If the desired path or load changes, a new
shaped input needs to be formed. Also because this control method is open loop there is no ability
for it to reject disturbances. This is similar to many open-loop optimal control methods but in
comparison is not a limitation of MPC implementations which is one benefit of MPC over other
optimal control methods. Figure 4.2 (a) shows the general control scheme that we used with our
input shaper.

![General control block diagrams for controllers. (a) Input shaper block diagram. (b) MPC block diagram.](image)

We implement a Zero Vibration and Derivative (ZVD) shaper for the input shaper. A ZVD
was chosen as opposed to a ZV shaper because it is more robust to modeling error at the cost of
taking slightly longer to reach a goal. The equations used to calculate the impulse magnitudes and
times are found in detail in [59] but we describe our implementation in Sections 4.2.1.2, 4.2.1.3 and
4.2.1.4. We formulated an independent input shaper based on the feedback linearized model found in Equation (4.5) for all but the last three joints. These joints were excluded because with gains low enough to cause them to be underdamped, they cannot even achieve commanded positions due to actual dynamics of those joints. The last three joints are therefore better modeled as over damped systems whose inputs do not need to be shaped.

4.2.1.2 Second-Order Single-Joint Dynamic Model

In order to first test whether input shaping was a viable option for mitigating oscillation on our robot arm, we first implemented a single-DoF ZVD shaper for the first joint of the robot which requires no feedback linearization. Using the joint spring-damper model from Equation (4.1), we assumed a second-order model for a rotary mass-spring-damper. This included treating a given joint and subsequent links as a lumped model, represented by

\[
\ddot{q} + \frac{k_d}{T} \dot{q} + \frac{k_p}{T} q = \frac{k_p}{T} q_{des}
\]  

(4.6)

We let \( \omega_n = \sqrt{\frac{k_p}{T}} \) be the natural frequency of the system, and \( \zeta = \frac{k_d}{2 \sqrt{k_p}} \) be the damping ratio where \( I \) is the moment of inertia for the full robot arm. We use these values in Section 4.2.1.4 to develop our input shaper for one joint.

4.2.1.3 Second Order Multiple Joint Dynamic Model

After successfully testing a ZVD shaper on a single joint, we developed the full 4 DoF ZVD shaper. Here we used the feedback linearization as explained in Section 4.2.1.1. This allowed each joint to be treated independently as a simple linear second order system where the overall dynamic equations are given by Equation (4.5). Because \( K_d \) and \( K_p \) are diagonal, this is a set of \( n \) decoupled ordinary differential equations.

We calculated \( \omega_{ni} = \sqrt{\frac{k_p}{K_{pi}}} \) to be the natural frequency of the \( i \)th DoF of the system, and \( \zeta_i = \frac{k_{di}}{2 \sqrt{k_{pi}}} \) the damping ratio. We use these values in Section 4.2.1.4 to develop our input shaper for multiple joints.
4.2.1.4 ZVD Input Shaper

By finding \( \omega_n \) and \( \zeta \) for both the single joint and feedback linearized cases we are able to represent the dynamics of each system

\[
\ddot{q}_i + 2\zeta\omega_n \dot{q}_i + \omega_n^2 q_i = \omega_n^2 q_{des,i}, \forall i = 1, 2, 3, 4
\]  

(4.7)

We can now use Equation (4.8) which is described in [59] to develop a ZVD shaper. The three discrete input impulses of a ZVD shaper are represented as the amplitude \( A_j \) and the implementation time of the \( j^{th} \) impulse \( t_j \). \( K \) is defined in Equation (4.9) and \( T_d \) is the damped period (Equation (4.10)).

\[
A_1 = \frac{1}{(1 + K)^2} \text{ at: } t_1 = 0
\]

\[
A_2 = \frac{2K}{(1 + K)^2} \text{ at: } t_2 = .5T_d
\]

\[
A_3 = \frac{K^2}{(1 + K)^2} \text{ at: } t_3 = T_d
\]

(4.8)

\[
K = \exp\left( -\frac{\zeta \pi}{\sqrt{1 - \zeta^2}} \right)
\]

(4.9)

\[
T_d = \frac{2\pi\sqrt{1 - \zeta^2}}{\omega_n}
\]

(4.10)

Letting \( \Delta q_{cmd} \) be the desired change in joint configuration, the final open loop commands that are then sent to the low-level impedance controller for a step input are given by

\[
q_{des} = q(t_0) + A_1 \Delta q_{cmd}
\]

\[
q_{des} = q(t_0) + (A_1 + A_2) \Delta q_{cmd}
\]

(4.11)

\[
q_{des} = q(t_0) + (A_1 + A_2 + A_3) \Delta q_{cmd}
\]

Our results for these input shapers are described in Section 4.3.2.
4.2.2 Model Predictive Control

In this section we formulate the model predictive controller. This is done in two parts, we first derive the dynamic model and then formulate the convex optimization equations.

4.2.2.1 Dynamic Model

For the dynamic model, we make the same assumptions as stated in section 4.2.1 to simplify the model and make it more tractable for linear MPC resulting in Equation (4.3). We also assume that over the short time horizon used in our controller, the joint-space mass matrix \( M(q) \), the Coriolis matrix \( C(q, \dot{q}) \) and the geometric Jacobian \( J_x(q, \dot{q}) \) of the end effector are varying slowly and can be assumed to be constant over the model predictive control horizon.

Substituting \( \tau \) from Equation (4.1) into Equation (4.3) results in Equation (4.12):

\[
K_p(q_{des} - q) - K_d \ddot{q} = M(q)\ddot{q} + C(q, \dot{q})\dot{q}
\]  

(4.12)

Solving for \( \ddot{q} \) gives

\[
\ddot{q} = M(q)^{-1}[K_p(q_{des} - q) - K_d \dot{q} - C(q, \dot{q})\dot{q}]
\]  

(4.13)

We represent the dynamics in state space form as

\[
\begin{bmatrix}
\ddot{q} \\
\dot{q}
\end{bmatrix} = A
\begin{bmatrix}
\ddot{q} \\
\dot{q}
\end{bmatrix} + B q_{des}
\]  

(4.14)

where

\[
A = \begin{bmatrix}
M(q)^{-1}(-K_d - C(q, \dot{q})) & M(q)^{-1}(-K_p) \\
1 & 0
\end{bmatrix}
\]  

(4.15)

and

\[
B = \begin{bmatrix}
M(q)^{-1}K_p \\
0
\end{bmatrix}
\]  

(4.16)
We transformed this state-space form from continuous time domain to the discrete domain using the matrix exponential [72] where

\[ A_d = e^{A \Delta T} \]  

(4.17)

and

\[ B_d = (A_d - I)A^{-1}B \]  

(4.18)

so that the complete discrete state space equation is

\[
\begin{bmatrix}
\dot{\mathbf{q}}(k+1) \\
\mathbf{q}(k+1)
\end{bmatrix} = A_d \begin{bmatrix}
\dot{\mathbf{q}}(k) \\
\mathbf{q}(k)
\end{bmatrix} + B_d \mathbf{q}_{\text{des}}(k)
\]  

(4.19)

We used the parameters needed for calculating this dynamic model (such as mass and center of mass for each link) as provided by the manufacturer. We expect that performing system identification could further improve our performance.

### 4.2.2.2 Controller Formulation

MPC is a form of optimal control that is technically suboptimal because it minimizes a cost function over a finite time-horizon and then applies only one step of the resulting control input for that horizon. At the next time step, the optimization is reformulated for the same length finite time horizon using new measurements of the current state before solving for the next control input. Despite being suboptimal, in practice we are able to get very good system performance with MPC because we are incorporating feedback into an optimal control scheme that includes realistic physical constraints on actuation and state variables. MPC’s placement in our control scheme can be seen in Figure 4.2 (b). For our MPC controllers we use CVXGEN [63] to generate code to solve the optimization problem. The optimization formulations are described in Equations 4.20 - 4.26.

We first developed a single joint MPC controller as a test case with slight modifications from our final Cartesian controller in order to compare against the one degree of freedom input shaper. It calculates a change in \( \mathbf{q}_{\text{des}} \) to move the joint to a desired \( \mathbf{q} \). The MPC objective function and constraints for this case are defined by Equations (4.20), (4.22), (4.24), (4.25), (4.26), where
\[
\text{minimize} \\
q_{\text{des}}/\Delta q_{\text{des}}
\]
\[
g(q, \dot{q}, u)
\]  
(4.20)

**subject to:**
\[
\begin{bmatrix}
\dot{q}[k+1] \\
q[k+1]
\end{bmatrix} = A_d \begin{bmatrix} \dot{q}[k] \\
q[k]
\end{bmatrix} + B_d (q_{\text{des}}[k] + \Delta q_{\text{des}}[k]) \quad \forall k = 0, 1 \ldots, T_c
\]
(4.21)
\[
\begin{bmatrix}
\dot{q}[k+1] \\
q[k+1]
\end{bmatrix} = A_d \begin{bmatrix} \dot{q}[k] \\
q[k]
\end{bmatrix} + B_d (q_{\text{des}}[k]) \quad \forall k = T_c, T_c + 1 \ldots, T_c + T_p
\]  
(4.22)
\[
q_{\text{des}}[k+1] = q_{\text{des}}[k] + \Delta q_{\text{des}}[k]
\]  
(4.23)
\[
|K_p (q_{\text{des}}[k] - q[k]) - K_d \dot{q}[k]| \leq \tau_{\text{max}}
\]  
(4.24)
\[
|(K_p (q_{\text{des}}[k+1] - q[k+1]) - K_d \dot{q}[k+1]) - (K_p (q_{\text{des}}[k] - q[k]) - K_d \dot{q}[k])| \leq \Delta \tau_{\text{max}}
\]  
(4.25)
\[
q_{\min} \leq q[k+1] \leq q_{\max}
\]  
(4.26)

\(T_c = 10\), \(T_p = 0\), \(u = q_{\text{goal}}\), where \(q_{\text{goal}}\) is a vector of desired joint angles, and \(q_{\text{des}}\) is the manipulated variable. For this single joint case Equation (4.20) is defined as Equation (4.27) and the weightings \(N\), \(O\), and \(P\) are scalars.

\[
\sum_{k=0}^{T_c} \|q_{\text{goal}} - q[k]\|^2_N + \|q[T_c]\|^2_O + \|q_{\text{goal}} - q[T_c]\|^2_P
\]  
(4.27)

The constraints are defined as follows. Equation (4.22) is the dynamic model predictions, Equation (4.24) is the actuator torque constraints, while Equation (4.25) is a constraint on the amount that the torque can change at each step. The final constraint is Equation (4.26) which is a joint limit constraint. The controller ran at approximately 100 Hz.

We next developed a MPC Cartesian controller that solves for the needed change in commanded joint angles that will result in a desired change in Cartesian position of the end effector. The MPC control law for our seven-DoF robot is computed by minimizing the cost function as defined in Equation 4.28 where \(T_c = 3\) and \(T_p = 2\), \(u = \Delta x_{\text{des}}\), where \(\Delta x_{\text{des}}\) is a desired change in Cartesian end effector location, and \(\Delta q_{\text{des}}\) is the manipulated variable.
\[
\alpha \| \Delta x_{\text{des}} - J_x(q[T_c + T_p + 1] - q[0]) \|_2 \\
+ \sum_{k=0}^{T_c} \| \Delta q_{\text{des}}[k] \|_R^2 \\
+ \gamma^* \text{neg}(q_\uparrow - q[T_c + T_p + 1][2]) \\
+ \gamma^* \text{neg}(q[T_c + T_p + 1][2] - q_\downarrow)
\] (4.28)

The first term in Equation (4.28) is a quadratic cost on the difference between the desired change in Cartesian end effector location \( \Delta x_{\text{des}} \) and an approximation, using the Jacobian, of the change in Cartesian end effector location from the beginning of the horizon to the end, \( J_x(q[T_c + T_p + 1] - q[0]) \). The second term is a quadratic cost on the input \( \Delta q_{\text{des}} \) weighted by \( R \). The final two terms in Equation (4.28) were added to keep the second joint of the robot in a preferred range of joint angles. When running previous versions of the MPC controller the second joint would drift over time, putting the arm into configurations which limited the feasible solutions for new commanded positions. They add cost only when the terms inside the \( \text{neg}(\cdot) \) function are negative by taking the magnitude of the negative term. Term three represents an upper bound \( (q_\uparrow) \) and term four is a lower bound \( (q_\downarrow) \). The weightings \( \alpha, \gamma, \) and \( R \) were tuned by hand.

Our cost function is subject to the constraints in Equations (4.21), (4.22), (4.23), (4.24), (4.26). Equation (4.25) was not used for the seven DoF robot tests. The constraints are defined as follows. Equation (4.21), (4.22) and (4.23) are the dynamic model predictions, while Equation (4.24) is the actuator constraint and Equation (4.26) are the joint constraints. We ran the controller at 20 Hz.

4.3 Experimental Setup

4.3.1 Hardware

Our testbed for this research was Rethink Robotics’ Baxter platform which runs the Robot Operating System (ROS) [73]. Our research focus was on reducing the residual oscillations while maintaining the ability to quickly track a Cartesian step command. Our testing revolves around showing this capability. To control Baxter, we used the provided torque control interface and the state estimation \( (q, \dot{q}) \) as provided by Rethink Robotics.
Baxter’s passive compliance comes from its series elastic actuators (SEAs) [74] which have a spring between the actuator and the link load. We increase the compliance of Baxter by implementing a low level, low gain, joint impedance controller which introduces active compliance at the joints. The impedance controller takes the form of Equation (4.1) which was explained in Section 4.2. In addition to introducing added compliance, this helps to decouple the inertia of each link from the more distal links given unexpected contact.

### 4.3.2 Testing

An initial step response test was performed on a single joint to validate our methods for input shaping and MPC. Figure 4.3 displays the results of the test. While the ZVD shaper was
able to reduce settling time compared to the normal impedance controller, the MPC was able to do so with a faster rise time and less overshoot. We then moved on to subsequent tests that were developed to show the capabilities of both input shaping and MPC to reduce residual oscillation over the nominal simple impedance controlled case and to compare input shaping to MPC for the seven DoF case.

To test MPC we gave a step input in Cartesian space for a commanded end effector position to the MPC controller and recorded the response. While most controllers will need a path planner or trajectory generator to convert the task from Cartesian space to joint space, our MPC controller does not need this. It also does not require slewing of the desired goal position, although it can be accommodated to improve performance. The tests for input shaping and impedance control consisted of commanding a step in joint space for each joint. The initial and final angles were determined by the initial and final resting angles of the MPC tests in order to make the tests comparable. The results reported are the distance from the original position of the end effector to the commanded position of the end effector. We ran three tests to compare MPC, the ZVD shaper and the nominal impedance controller. The first two were large steps of 1.1 meters in magnitude and the last was a smaller step of about .25 meters. The results from the two large step inputs can be seen in Figs. 4.5 and 4.6. A video of test 4.6 can be found at https://youtu.be/hB-9Lb0ZINw. Results from the third smaller step input can be seen if Figure 4.4. Figure 4.1 shows initial and ending configurations that were used for the step test.

It was a possibility that MPC was able to accomplish the results shown by effectively stiffening the robot joint control. However, to verify that the MPC controller did not change the stiffness of the robot a simple test was conducted to measure the Cartesian stiffness of the MPC and the nominal impedance controller. Step inputs of 10 cm in x and y were given to both controllers while their motion was opposed by a force sensor. Measuring displacement and force after one second, the Cartesian stiffnesses were estimated. The results as found in Table 4.2 demonstrate that the low-gain nominal impedance controller and MPC exhibit similar compliance.
4.4 Results and Discussion

The results of our tests show that MPC and the ZVD shaper were able to improve the response of the seven-DoF arm over the nominal impedance controller as would be expected. Table 4.3 reports many of the key indicators of how the controllers performed on each test.

Both MPC and the ZVD shaper were able to reduce the percent overshoot but this reduction of oscillation was significantly better for the MPC controller. The input shaper was able to perform very well for a small step but performed only marginally better than the nominal impedance controller for large steps while MPC seems to have consistent behavior for either large or small steps. The largest percent overshoot that MPC had was 0.43% which happened on the small step (see Figure 4.4). The smallest percent overshoot for the ZVD shaper was 0.70% also for the small step.

The ZVD shaper did have significantly faster rise times than MPC but it came at the cost of significant overshoot which was as high as 9.52% as compared to MPC’s 0.08% overshoot for the same test. Settling time for the ZVD shaper also seemed to be faster than MPC for most cases but again the residual oscillation of the ZVD shaper outweighs the better performance in settling time. It should be noted however that MPC tended to have faster settling times as compared to the nominal impedance controller which would allow it to complete tasks more quickly. In addition, the performance of MPC is a direct result of tuning the weights on terms in the cost function. We would expect that if overshoot were acceptable in some scenarios, it should be possible to tune MPC for faster rise times.

MPC had some steady state error ranging from 1 to 2.5 cm in magnitude. This error can be reduced by implementing and tuning an integrator that will drive the steady-state error to zero. Steady state error in the input shaper is due to modeling error in the feedback linearization but it has a lower magnitude of about 1 cm. We measured the stiffness of the MPC controller and the results are in in Table 4.2 and show that MPC controller does not increase the stiffness of the robot over that of the impedance controller with MPC having its smallest stiffness at 234 N/m, while the impedance controller had a smallest stiffness of 262 N/m.

It is worth noting that most of the oscillation in the ZVD shaper seemed to be a result of error in the feedback linearization. The results that we presented were obtained using dynamic parameter values from the manufacturer and both controllers used the same model and parame-
Table 4.2: Stiffness

<table>
<thead>
<tr>
<th></th>
<th>MPC Stiffness</th>
<th>Impedance Control Stiffness</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>234 N/m</td>
<td>262 N/m</td>
</tr>
<tr>
<td>Y</td>
<td>323 N/m</td>
<td>445 N/m</td>
</tr>
</tbody>
</table>

Table 4.3: Step Test Results

<table>
<thead>
<tr>
<th>Test</th>
<th>95% Rise Time (s)</th>
<th>98% Settling Time (s)</th>
<th>Percent Overshoot</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MPC</td>
<td>ZVD</td>
<td>Imp.</td>
</tr>
<tr>
<td>1</td>
<td>2.58</td>
<td>0.61</td>
<td>0.58</td>
</tr>
<tr>
<td>2</td>
<td>1.80</td>
<td>0.70</td>
<td>0.60</td>
</tr>
<tr>
<td>3</td>
<td>1.37</td>
<td>0.78</td>
<td>0.35</td>
</tr>
</tbody>
</table>

ters for dynamic predictions providing a good comparison of the robustness of MPC and feedback linearization with ZVD input shaping. Much of the overshoot and oscillation is largely due to model/plant mismatch and torque saturation limits. MPC however appears to be much less sensitive to errors in the model (which we would expect for a closed-loop control method) and includes torque saturation limits in the formulation of the optimization constraints. We expect that better performance of the feedback linearization and ZVD input shaper can be obtained by performing system identification for dynamic parameter values.

4.5 Conclusion

The ZVD input shaper and model predictive controller were able to reduce oscillations, MPC much more than the input shaper, and track a step input better than a nominal impedance controller. Although input shaping had lower settling and rise time as compared to the nominal controller, its significant residual oscillation makes it impractical for mitigating oscillation for a seven DoF arm. MPC however, was able to track the step input as well as retain the compliance of the nominal impedance control. An additional benefit of MPC is that it is able to take Cartesian goals and transform them into joint actuation without any inverse kinematics or trajectory planning. Both the nominal controller and the ZVD input shaper would need this additional step. This leads to the possibility of performing tasks without computational cost for inverse kinematics or
trajectory planning. Future work for MPC includes extending the formulation to include complete pose control (position and orientation at the end effector) in order to actually test real task performance. We also expect to identify improved dynamic model parameters that will benefit both MPC and the feedback linearized ZVD shaper. As our model predictive controller is further developed it will help compliant robots perform useful tasks with improved time efficiency while retaining low stiffness for operation in close proximity to humans and human environments.
Figure 4.5: Large step response in Cartesian space for the MPC controller (about 1.1 m step). Test 1: Step from high to low, back to front, and left to right.
Figure 4.6: Large step response in Cartesian space for the MPC controller (about 1.1 m step). Test 2: Step from low to high, front to back, and right to.
CHAPTER 5. SOFT ROBOT MODELING AND CONTROL

The contents of this chapter are published in


5.1 Introduction

Most control methods depend on an accurate system model in order for them to be effective when controlling the states of the system. Soft robots have many characteristics that make modeling the dynamics more complicated than traditional robots. These include their compliant actuators, compliant links, their complicated actuation mechanics, and their general non-linear nature. To work with these more complicated models, less classical control methods are often employed such as Model Predictive Control and other model based methods.

In this chapter we demonstrate a progression of models that enable better control of soft robots. We also show how these models were used in model based control methods for the control of the robots King Louie, the Grub, and Nightcrawler which are described in Section 1.2.
The layout of this chapter is as follows. First, in Section 5.2 we present a background of the initial soft robot models that were developed to control the Grub and King Louie. Next, in Section 5.3 the inclusion of pressure dynamics in the model is presented. In Section 5.4 we demonstrate the development of an antagonistic torque model that is then used to improve control for both the Grub and King Louie. Then in Section 5.6 a linearized dynamic model, that was developed in collaboration with Jon Terry, is described and demonstrated, including showing how it improves the control of MPC for systems with a large number of states. Lastly in Section 5.7 the integration of the linearized dynamic model and a position and stiffness controller developed by Charles Best is demonstrated.

A list of the contributions shown in this chapter are as follows:

• The development of an initial soft robot dynamic one DoF model
• The development of a simple impedance controller for soft robots with antagonistic actuators
• The formulation of a dynamic pressure model for fluid-driven soft robots
• The development of an antagonistic torque model for fluid-driven antagonistic soft robots
• The formulation of the Coupling Torque (CT) method, a linearized dynamic model for large state and high DoF systems as well as its formulation for a MPC controller
• The integration of the CT method with a simultaneous position and stiffness controller for a four-DoF soft robot

### 5.2 Initial Soft Robot Modeling

As described before it is important to have a representative model for controllers to be as effective as possible. We started initially by developing simple models for these antagonistic soft actuators.

These initial modeling attempts focused on the dynamics of a single joint modelled as an inverted pendulum and used the equations of motion

\[I\ddot{q} + K_d\dot{q} + mg\frac{L}{2}sin(q) = \tau\]  (5.1)
where $I$ is the moment of inertia of the distal link, $K_d$ is the damping coefficient of the joint, $m$ is the mass of the distal link, $g$ is the gravity constant, $L$ is the length of the distal link, $q$ is the generalized coordinate for the joint angle, and $\tau$ is the actuator torque from the antagonistic actuators. To obtain a good control law a reliable model for $\tau$ was needed.

Initial control models used a simple torque impedance model

$$\tau = K_s (q_{des} - q)$$

where $K_s$ is the spring constant of the joint, $q_{des}$ is the desired joint angle, and $q$ is the current joint angle. The control method just needed to choose an effective $q_{des}$.

The initial approach to modeling $q_{des}$ for an antagonistic actuator for control was developed by Best et al. (2015) [75]. They developed a mapping between the two steady state pressures in the antagonistic actuators to a steady state angle (see Figure 5.1). The process to develop this mapping was as follows:

1. Deflate both chambers.

2. Set the desired pressure in both chambers to 1 psig.
3. Fill each chamber to the desired pressures.

4. Once the system has reached a steady state pressure and angle, record the angle.

5. Deflate both chambers.

6. Increase the desired pressure in first chamber by 1 psig.

7. Repeat steps 3-6 until the max pressure is reached in the first chamber.

8. Increase the desired pressure in the second chamber by 1 psig and set the desired pressure in the first chamber to 1 psig.

9. Repeat steps 3-8 until the max pressure in the second chamber is reached.

While they were able to find a mapping between the opposing pressures to an angle there is no direct mapping from an angle to two pressures, which is needed for angle control. Best et al. simplified the approach by adding a constraint that allowed them to have a one-to-one mapping between a single joint angle and a unique pair of pressures for each chamber by using the following equations. For a pressure $P^+$, $P^-$ and $P$, they defined

$$P^+ = 14 + P \tag{5.3}$$

and

$$P^- = 33 - P \tag{5.4}$$

with the constraint

$$1 \leq P \leq 18 \tag{5.5}$$

Where $P^+$ is the pressure in the chamber that causes positive rotation, $P^-$ is the pressure in the chamber that causes negative rotation, and $P$ is the constraint that simplifies the mapping. The constants 1, 18 and 33 are used because the control method used absolute psi as the pressure control units and these values keep the system operating in range of 1 to 15 psig. This reduced the mapping to a 2D function as shown by Figure 5.2. Then using curve fitting tools Best et al. found the following relationship between $P$ and the steady state angle $q_{des}$. 

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The coefficients \( s_1, s_2, s_3 \) and \( s_4 \) were calculated from the empirical data using a curve fitting tool.

These Equations, 5.1 - 5.6, were then used in both an LQR and MPC controllers to control the Grub and King Louie. For King Louie they treated each joint as a separate system and had an independent controller for each one. Using this initial model and controllers, reasonable initial joint angle performance was achieved given the complexities of the soft robot, however improvements to the model were needed (see [75] for the full performance results).

### 5.3 Pressure Dynamics

One of the major issues that was noticed with the first controller developed by Best et al. was that the commanded pressure and the actual pressure were not the same but had dynamics that were not being captured (i.e., delay between the time when the actual pressure reached the
commanded pressure). This tended to produce some overshoot and oscillation. It became apparent that the pressure dynamics of the pressure controller were significant and could not be ignored. The pressure dynamics of the pressure controller were therefore modeled as a simple first order system:

$$\dot{P}(t) = \alpha P(t) + \beta P_{des}(t)$$  \hspace{1cm} (5.7)

where $\dot{P}$ is the time rate of change of the pressure in a given chamber, $P$ is the current pressure in the chamber, $P_{des}$ is the current set-point for the pressure controller, and where $\alpha$ and $\beta$ are the constants describing the dynamics of the pressure control system. The values for $\alpha$ and $\beta$ were found through analysis of empirical data. The pressure of the chamber $P$ would asymptotically approach $P_{des}$ at a rate dictated by $\alpha$ and $\beta$. Modeling these pressure dynamics was done in collaboration with Charles Best and Morgan Gillespie.

Using the newly developed pressure dynamic model Gillespie et al. [76] developed a new method to calculate $q_{des}$ using a linearized version of the full pressure to angle map found in Figure 5.1. Using the following planar relationship they developed an equation relating the two chamber’s pressures to a single steady state angle.

$$q = \alpha_1 + \alpha_2 P^+ + \alpha_3 P^-$$  \hspace{1cm} (5.8)

The constants $\alpha_1$, $\alpha_2$, and $\alpha_3$ are coefficients that describe a plane that is tangent to the operating point on the original pressure-to-angle map shown in Figure 5.1. They then used Equation 5.8 for both $q$ and $q_{des}$ as shown here.

$$q_{des} = \alpha_1 + \alpha_2 P_{des}^+ + \alpha_3 P_{des}^-$$  \hspace{1cm} (5.9)

Equation 5.8 and 5.9 were then substituted into Equation 5.2 following equation for $\tau$.

$$\tau = K_s(\alpha_2(P_{des}^+ - P^-) + \alpha_3(P_{des}^- - P^-))$$  \hspace{1cm} (5.10)

The revised model was implemented in an MPC control scheme and shown to improve the average rise time, settling time and overshoot. Gillespie et al. were able to show that they could
also control the stiffness using the same model by varying a target pressure for each antagonistic chamber (see [44] for the full performance results).

5.4 Torque Model

The next progression in the modeling occurred when we focused on characterizing the torque based directly on pressure instead of through the original quasi-static relationship that mapped pressures to angles. This new modeling approach assumed that the total torque ($\tau$) of each joint was the difference of the torques produce by each chamber and the torque due to the stiffness of the fabric joint as shown in the following equation and represented in Figure 5.3.

$$\tau = \tau^+ - \tau^- - \tau_{\text{stiffness}}$$ (5.11)

One chamber provides positive torque ($\tau^+$) and the other chamber provides negative torque $\tau^-$. This is analogous to the human muscle structure where you have an agonist muscle and an antagonist muscle per joint. The difference between the two torques, the positive torque and the negative torque, produces a total torque on the link. Many soft robot antagonistic actuators also have a torque that is due to the stiffness of the joint as expressed by $\tau_{\text{stiffness}}$ in Equation 5.11.

To determine the form of the relationship between pressure and torque we built a test rig for the Grub as shown in Figure 5.3. We used the following test procedure to measure the torque produced by the Grub at various pressures and joint angles:

1. Mount the Grub securely in the test rig
2. Mount a force sensor at the desired angle
3. Pressurize a single chamber to the desired pressure
4. Record the force measurement
5. Increase the pressure by 1 psia
6. Repeat steps 3-5 starting with a pressure of 15 psia until a pressure of 30 psia is tested
7. Remount force sensor at the next angle
8. Repeat steps 3-7 for the following angles \([+60^\circ, +30^\circ, 0^\circ, -15^\circ, -30^\circ, -45^\circ, -60^\circ, -90^\circ]\)

The results are shown in Figure 5.4. The torque from the joint is found by multiplying the measured force by the moment arm \(l\). After analyzing the data it was apparent that the torque due to stiffness was also part of the data. This stiffness torque is what influenced the parasitic torque metric found in Chapter 3 and its importance to soft robot actuator design became very apparent from this data. To have an accurate relationship between the pressure in the chamber and the torque produced we preformed a test to measure the stiffness torque of the actuator.

We performed this test by deflating both chambers and measuring the force output of just the passive joint at a variety of angles. In an effort to understand and eliminate the possible effects of hysteresis we performed the test three times. Once by starting at \(-80^\circ\) and measuring the stiffness force at increments of 20° and ending at \(+80^\circ\). We then performed the same test starting at \(+80^\circ\), decremented the angle at increments of 20° and ending at \(-80^\circ\). Lastly we randomized the order of the measurements and made stiffness measurements at the same angles as the other two times. As shown in Figure 5.5 the relationship between the angular deflection from 0° and force is strikingly linear even with the slight hysteresis seen.

Using the linear fit of angle to force we compensated for the measured forces in the initial pressure to force test found in Figure 5.4 by subtracting the stiffness force at the measured angle.
This produced a fairly linear final relationship between pressure and force output as shown in Figure 5.6. For these tests all pressures were measured and reported in absolute psi.

Given this linear relationship, we modeled the torque from a single actuator using

\[
\tau^+ = \gamma^+ P^+ \\
\tau^- = \gamma^- P^- \tag{5.12}
\]

and where the torque from an actuator, + or − respectively (causing motion in the positive or negative direction by convention), is the pressure in the chamber \( P \) multiplied by a constant coefficient \( \gamma \). Due to the linearity of the data found in Figure 5.5 we model the stiffness torque (\( \tau_{\text{stiffness}} \)) as

\[
\tau_{\text{stiffness}} = K_s q \tag{5.14}
\]

where \( K_s \) is the stiffness coefficient which correlates to the slope of the line from Figure 5.5.
Finally substituting Equations 5.12 - 5.14 into Equation 5.11 gives the full torque model as

$$\tau = K_s q + \gamma^+ P^+ - \gamma^- P^-$$

(5.15)

Often the pressure to torque coefficients ($\gamma$) are equal due to the symmetry of the actuators and Equation 5.15 can be simplified to

$$\tau = K_s q + \gamma(P^+ - P^-)$$

(5.16)

This torque model was integrated into the equations of motion to give

$$I \ddot{q} + K_d \dot{q} + mg \frac{L}{2} \sin(q) = K_s q + \gamma(P^+ - P^-)$$

(5.17)

$$\dot{p}^+ = \alpha P^+ + \beta P^+_{des}$$

(5.18)
We then used these equations of motion in an MPC control scheme to control both the Grub and King Louie (see [77]). It should be noted that for King Louie we controlled each joint independently as its own MPC controller with the assumption that each link was an inverted pendulum like the Grub. This MPC approach is referred to as the four-state MPC as each joint has four states, angular position ($q$), angular velocity ($\dot{q}$), and the pressures in the two actuation chambers ($P^+$ and $P^-$), as opposed to the two-state MPC as demonstrated previously which only had angular position and angular velocity as states. In this application the torque from gravity was found to be three orders of magnitude less than the other terms, due to the low mass of the fabric actuators, and it was removed from the dynamic equations reducing them to

$$I\ddot{q} + K_d\dot{q} = K_s q + \gamma (P^+ - P^-)$$  \hspace{1cm} (5.20)
\[ \dot{P}^+ = \alpha P^+ + \beta P^+_{\text{des}} \]  
\[ \dot{P}^- = \alpha P^- + \beta P^-_{\text{des}} \]  

The cost function for the MPC controller for the horizon \( T \) is

\[ \arg\min_{P^{+\text{des}}, P^{-\text{des}}} \sum_{k=0}^{T} \left( \| q_{\text{des}} - q[k] \|^2_Q + \| \dot{q}[k] \|^2_R + \| P^+[k] - P_T \|^2_S + \| P^-[k] - P_T \|^2_S \right) \]  

subject to the equations of motion as constraints (see Equations 5.20 - 5.22) as well as

\[ q_{\text{min}} \leq q \leq q_{\text{max}} \]  
\[ P_{\text{min}} \leq P^{+\text{des}}, P^{-\text{des}} \leq P_{\text{max}} \]  
\[ \| \Delta P^{+\text{des}}, \Delta P^{-\text{des}} \| \leq \Delta P_{\text{max}} \]

where \( Q, R, \) and \( S \) are manually tuned scalar weights, \( P_T \) is a target pressure, \( q_{\text{min}} \) and \( q_{\text{max}} \) are joint limits, \( P_{\text{min}} \) and \( P_{\text{max}} \) are bladder pressure limits, \( \Delta P^{+\text{des}}, \Delta P^{-\text{des}} \) is the change in desired pressure from the previous time step, and \( \Delta P_{\text{max}} \) is the maximum change allowed in the desired pressure per time step. The slew rate constraint (Equation 5.26) prevents valve chatter. The MPC controller was run at a rate of 300 Hz with a horizon of \( T = 20 \) time steps.

5.4.0.1 Results

By including the pressure dynamics and the relationship between pressure and torque, the performance of the MPC controllers from the two-state MPC to the four-state MPC improved as shown in Figure 5.7 and 5.8 (for both the Grub and King Louie). While there was some increase in the average rise time, there was a 15.13% improvement in the average settling time and a 843.35% decrease in the overshoot (see Table 5.1 for more details).

To demonstrate the robustness of this model and controller we performed two repeatability tests using King Louie. In the first one we defined three joint configurations, along with an initial joint configuration, that we controlled King Louie to (see Figure 5.9 for images of the different joint configurations). We commanded the arm to go to each location ten times. We then calcu-
Figure 5.7: Comparison of performance of the Grub using the two-state MPC described in [75] and the four-state mpc that includes equations relating torque and pressure.

<table>
<thead>
<tr>
<th></th>
<th>Average Rise Time</th>
<th>Average Settling Time</th>
<th>Average % Overshoot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two-state MPC</td>
<td>1.319 s</td>
<td>2.985 s</td>
<td>24.408%</td>
</tr>
<tr>
<td>Four-state MPC</td>
<td>1.360 s</td>
<td>2.592 s</td>
<td>2.587%</td>
</tr>
<tr>
<td>Improvement</td>
<td>-3.02%</td>
<td>15.13%</td>
<td>843.35%</td>
</tr>
</tbody>
</table>

lated the repeatability using the radial distance that would encompass 99.8% of the end effector measurements given the exact joint commands. A motion-capture system was used to measure the joint angles (see [12] for details) and end-effector position but was not used for end-effector control such as visual servoing. As shown in Table 5.2 the repeatability for the three different positions was under 3 cm. One of the 30 trials had an error in the controller and joint estimation code and was therefore discarded as an outlier.
Figure 5.8: Comparison of performance of King Louie using the two-state MPC described in [75] and the four-state mpc that includes equations relating torque and pressure.

Table 5.2: The repeatability measures for reaching to three different joint configurations.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Repeatability (cm)</td>
<td>0.43</td>
<td>2.8</td>
<td>2.6</td>
</tr>
</tbody>
</table>
Figure 5.9: The initial joint configuration and the three commanded joint configurations for the position controller repeatability tests: (a) King Louie, initial joint configuration; (b) King Louie, joint configuration 1; (c) King Louie, joint configuration 2; and (d) King Louie, joint configuration 3.

We also tested the repeatability of the controller while manipulating an unknown payload. For a traditional rigid robot, we would expect no significant changes to the performance, but due to the low mass and compliance of King Louie there may be a significant effect. Our test had King Louie grab a ball with an approximate diameter of 18 cm in joint configuration 2 and then drop...
it in a bucket at joint configuration 1 as shown in Figure 5.10. We repeated the test ten times and the arm was successful at grabbing the ball and placing it in the bucket nine out of the ten times. During the single failed attempt the ball hit the edge of the bucket. A video of these trails is available at https://youtu.be/p30jKn7_pV4.

Figure 5.10: The initial joint configuration and the final joint configuration for King Louie grabbing a ball and placing it in a bucket: (a) the initial joint configuration for grabbing the object and (b) the final joint configuration for releasing the object.

5.5 MPC for a 3-DoF Soft Robot

To try to improve control performance we made some changes to the model that is used in MPC. Instead of using a single joint model we started using a model of the full dynamics of a multi-joint soft robotic manipulator in the MPC controller. This model is based on the standard equations of motion of a serial manipulator given by

\[
M(q)\ddot{q} + C(q, \dot{q})\dot{q} + F(\dot{q}) + G(q) + J(q)^Tf = \tau
\]  

(5.27)
where \( M(q) \) is the mass matrix, \( q, \dot{q}, \ddot{q} \) are vectors of joint angles, velocities, and accelerations respectively, \( C(q, \dot{q}) \) is the Coriolis matrix, \( F(\dot{q}) \) is the friction, \( G(q) \) is torque due to gravity, \( J(q)^T f \) are contact forces and \( \tau \) is the applied joint torques.

We first focused on controlling the three DoF manipulator Nightcrawler as shown in in Figure 5.11. For this work we assume that the friction forces can be approximated by a viscous damping term \( K_d \dot{q} \) where \( K_d \) is a diagonal matrix that has the damping coefficients for each of the joints. Additionally there are no contact forces so we also remove that term for this application. The description of the input torque that we used for Nightcrawler is given by

\[
\tau = K_p q + \tau^+(P^+) - \tau^-(P^-) \tag{5.28}
\]

where \( K_p \) is a diagonal matrix that models the joint stiffness that results from the geometry and material properties of the actuators, \( \tau^+(P^+) \) and \( \tau^-(P^-) \) are torques caused by all the positive or negative acting actuators respectively. As stated in Equations 5.12 and 5.13 we model the
torque from pressure as a linear relationship. We also use the first-order model for pressures in the chambers as shown in Equation 5.7. Substituting Equation 5.28 into Equation 5.27 and solving for \( \dot{q} \) and \( \dot{P} \) results in the following set of ODEs:

\[
\ddot{q} = M^{-1}[K_p q - (C + K_d)\dot{q} - G(q) + K_\gamma^+ P^+ - K_\gamma^- P^-] \tag{5.29}
\]

\[
\dot{P}^+ = K_\alpha^+ P^+ + K_\beta^+ P_{\text{des}} \tag{5.30}
\]

\[
\dot{P}^- = K_\alpha^- P^- + K_\beta^- P_{\text{des}} \tag{5.31}
\]

We have removed the state dependencies for each matrix for readability and all \( K \) matrices are diagonal matrices that contain the different coefficients for the respective joint pressures. These were found by doing system identification using empirical data.

The state variable equations for this platform are defined as

\[
\dot{x} = Ax + Bu - M^{-1}G \tag{5.32}
\]

where

\[
x = \begin{bmatrix} \dot{q} & q & P^+ & P^- \end{bmatrix}^T \tag{5.33}
\]

\[
u = \begin{bmatrix} P^+_{\text{des}} & P^-_{\text{des}} \end{bmatrix}^T \tag{5.34}
\]

\[
A = \begin{bmatrix}
-M^{-1}(C + K_d) & M^{-1}K_p & M^{-1}K_\gamma^+ & M^{-1}K_\gamma^- \\
I & 0 & 0 & 0 \\
0 & 0 & K_\alpha^+ & 0 \\
0 & 0 & 0 & K_\alpha^-
\end{bmatrix} \tag{5.35}
\]

and
\[ B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ K^+ & 0 \\ 0 & K^- \end{bmatrix} \] (5.36)

For each control step we assume that the state dependant variables like \( M \) and \( C \) are fixed over a given horizon providing a linear approximation across a control horizon. For this reason we refer to this method as the Fixed-State (FS) method. We discretize the dynamic model using the matrix exponential to give

\[ x_{k+1} = A_d x_k + B_d u_k \] (5.37)

We used the following cost function for the MPC optimization:

\[
\begin{align*}
\arg\min_{P^+, P^{-}} & \sum_{k=1}^{T} \| q_{\text{des}} - q[k] \|^2_Q + \| \dot{q} \|^2_R + \| P^+ - P_T \|^2_S + \| P^- - P_T \|^2_S \\
\text{subject to} & \quad q_{\text{min}} \leq q[k] \leq q_{\text{max}} \quad \forall k = 1 \ldots T + 1 \\
& \quad P_{\text{min}} \leq P^+[k] \leq P_{\text{max}} \quad \forall k = 1 \ldots T + 1 \\
& \quad P_{\text{min}} \leq P^-_{\text{des}}[k] \leq P_{\text{max}} \quad \forall k = 1 \ldots T + 1 \\
& \quad -\Delta P \leq P^+_{\text{des}}[k+1] - P^+_{\text{des}}[k] \leq \Delta P \quad \forall k = 0 \ldots T \\
& \quad -\Delta P \leq P^-_{\text{des}}[k+1] - P^-_{\text{des}}[k] \leq \Delta P \quad \forall k = 0 \ldots T 
\end{align*}
\] (5.38)

subject to the dynamic equations and the following equations as constraints:

\[
\begin{align*}
q_{\text{min}} & \leq q[k] \leq q_{\text{max}} \quad \forall k = 1 \ldots T + 1 \\
P_{\text{min}} & \leq P^+[k] \leq P_{\text{max}} \quad \forall k = 1 \ldots T + 1 \\
P_{\text{min}} & \leq P^-_{\text{des}}[k] \leq P_{\text{max}} \quad \forall k = 1 \ldots T + 1 \\
-\Delta P & \leq P^+_{\text{des}}[k+1] - P^+_{\text{des}}[k] \leq \Delta P \quad \forall k = 0 \ldots T \\
-\Delta P & \leq P^-_{\text{des}}[k+1] - P^-_{\text{des}}[k] \leq \Delta P \quad \forall k = 0 \ldots T 
\end{align*}
\] (5.39 - 5.43)

where \( T \) is the prediction horizon, \( Q, R, \) and \( S \) are 3x3 diagonal, positive semi-definite weighting matrices, \( P_T \) is a 3 \times 1 vector of target pressures that helps keep the joints at a nominal stiffness for control, \( q_{\text{min}} \) and \( q_{\text{max}} \) are 3 \times 1 vectors of the minimum and maximum joint limits respectively, \( P_{\text{min}} \), and \( P_{\text{max}} \) are 3 \times 1 vectors of the minimum and maximum pressures respectively, and \( \Delta P \) is a limit on the slew rate of the pressure commands.
Although this control method included more accurate dynamics, the performance was not as good. As shown in Figure 5.12 there is significant error when trying to control the 3 DoF soft robot platform Nightcrawler. There is significant steady state error and movement in one joint causes error in another joint as seen in the plot at times around 30, 50 and 70 seconds. Additionally the controller was only able to run at a maximum rate of 20 Hz even with a prediction horizon of size $T = 10$. Finally, tuning one joint for better performance resulted in degradation of performance for another joint.

5.6 Linearized Dynamics: Coupling Torque

The next improvement in modeling was to use a different linearization method called the Coupling Torque (CT) method. In the FS method the dynamic model includes cross-coupling terms in the joints, where as the CT method allows the coupling terms of the dynamics of the arm to be accounted in an more efficient manner, allowing for the control for each joint to be optimized independent of the other joints for a given time horizon. In the standard dynamic model as described in Equations 5.29 - 5.31 coupling occurs through the torques generated from the motions of the other links in the arm, which are expressed mathematically through the Coriolis and inertial terms. In contrast, the CT method includes coupling torques from the other links as constant disturbance input terms over the MPC horizon duration. This allows the CT method to be highly computationally scalable to more degrees of freedom as compared to the FS method. Much of the computation gains come from the fact that instead of running a single computationally expensive optimization, you can run $n$ smaller and faster optimizations in parallel for any $n$ DoF soft robot.

Jon Terry, the co-developer of this method, explored how the CT method compared to a traditional Taylor Series (TS) linearization. This comparison was performed by simulating the full seven DoF of Baxter during a 20 degree step in commanded position of the first three joints using a torque impedance model as described in Equation 5.2. It was found that the Coupling Torque method matched the full non-linear dynamics of the Fixed-State method closer than the Taylor Series method of linearization did (see [78] for details).
Figure 5.12: MPC with three DOF using the Fixed-State method controlling Nightcrawler
5.6.1 CT Dynamic Equations

The equations that are used for forward prediction using the CT method are as follows for joint \( i, \forall 1 \ldots n \) where \( n \) is the number of joints:

\[
x_{k+1,i} = A_{mpc,i} x_{k,i} + B_{mpc,i} u_{k,i} + d_{mpc,i}
\]

(5.44)

where the terms are defined as follows:

\[
A_{mpc,i} = \begin{bmatrix}
a_{i,i} & a_{i,j_1} & a_{i,j_2} & a_{i,j_3} \\
a_{j_1,i} & a_{j_1,j_1} & a_{j_1,j_2} & a_{j_1,j_3} \\
a_{j_2,i} & a_{j_2,j_1} & a_{j_2,j_2} & a_{j_2,j_3} \\
a_{j_3,i} & a_{j_3,j_1} & a_{j_3,j_2} & a_{j_3,j_3}
\end{bmatrix}
\]

(5.45)

\[
B_{mpc,i} = \begin{bmatrix}
b_{i,i} & b_{i,j_1} \\
b_{j_1,i} & b_{j_1,j_1} \\
b_{j_2,i} & b_{j_2,j_1} \\
b_{j_3,i} & b_{j_3,j_1}
\end{bmatrix}
\]

(5.46)

with

\[
\begin{align*}
  j_1 & = i + n \\
  j_2 & = i + 2n \\
  j_3 & = i + 3n
\end{align*}
\]

The other terms are defined as follows:

\[
x_{k,i} = \begin{bmatrix}
q_{k,i} & q^+_k & q^-_k
\end{bmatrix}^T
\]

(5.47)

\[
u_{k,i} = \begin{bmatrix}
P^+_{k,i} & P^-_{k,i}
\end{bmatrix}^T
\]

(5.48)

\[
d_{mpc,i} = \begin{bmatrix}
q_{i,i} & q^+_i & q^-_i & d^+_{p,i} & d^-_{p,i}
\end{bmatrix}^T
\]

(5.49)
where

\[
d_{q,i} = q_{1,i} - a_{i,j}q_{0,i} - a_{i,j1}q_{0,i} - a_{i,j2}P_{0,i}^+ - a_{i,j3}P_{0,i}^- - b_{i,j}P_{des,0,i}^+ - b_{i,j}P_{des,0,i}^- - M(q_0)^{-1}G(q_0)_i
\]

(5.50)

\[
d_{q,i} = q_{1,i} - a_{j1,i}q_{0,i} - a_{j1,j1}q_{0,i} - a_{j1,j2}P_{0,i}^+ - a_{j1,j3}P_{0,i}^- - a_{j2,i}P_{0,i}^+ - a_{j2,j1}P_{0,i}^- - b_{j1,i}P_{des,0,i}^+ - b_{j1,i}P_{des,0,i}^- - b_{j2,j1}P_{0,i}^+ - b_{j2,j1}P_{0,i}^-
\]

(5.51)

\[
d_{p^+_i} = P_{1,i}^+ - a_{j2,i}q_{0,i} - a_{j2,j1}q_{0,i} - a_{j2,j2}P_{0,i}^+ - a_{j2,j3}P_{0,i}^- - a_{j3,i}P_{0,i}^+ - a_{j3,j1}P_{0,i}^- - b_{j1,i}P_{des,0,i}^+ - b_{j1,i}P_{des,0,i}^- - b_{j2,j1}P_{0,i}^+ - b_{j2,j1}P_{0,i}^-
\]

(5.52)

\[
d_{p^-_i} = P_{1,i}^- - a_{j3,i}q_{0,i} - a_{j3,j1}q_{0,i} - a_{j3,j2}P_{0,i}^+ - a_{j3,j3}P_{0,i}^- - a_{j3,j3}P_{0,i}^+ - a_{j3,j3}P_{0,i}^- - b_{j1,i}P_{des,0,i}^+ - b_{j1,i}P_{des,0,i}^- - b_{j2,j1}P_{0,i}^+ - b_{j2,j1}P_{0,i}^-
\]

(5.53)

\[a_{i,j} \text{ and } b_{i,j} \text{ are the entries in the } i\text{th row and } j\text{th column of } A_d \text{ and } B_d \text{ from Equation 5.37. } d_{mpc,i} \text{ is the torque generated from the motion of the other links. When implemented in the controller, } d_{mpc,i} \text{ is calculated at the current states and then held constant over the MPC prediction horizon.}

To reiterate, the significance of this method is that it reduces the state variable matrix \( A_d \) \((mn \times mn)\) to \( A_{mpc} \) \((m \times m)\), where \( m \) is the number of states and \( n \) is the number of links. This greatly simplifies the MPC optimization, which improves computational tractability.

5.6.2 CT-MPC Derivation

The MPC algorithm that was used for the CT method first calculates the current states and model using the methods described in Section 5.6.1. Then we send the model, current states and cost function weights to an optimization routine which returns the control inputs and predicted corresponding states that minimize the cost function for a given horizon. The length of the horizon (in time) is determined by the number of time steps given to the optimizer, and the rate at which the controller is run. Only the inputs returned for the first time step are sent to the actuators on the
platform, then the resulting updated states (which are measured or estimated) are sent to the MPC
optimization and the process is repeated.

The MPC optimization for Nightcrawler used the following cost function and constraints:

$$\arg\min_{P_{\text{des}}^{+}, P_{\text{des}}^{-}} \sum_{k=0}^{T} \left( \| q_{\text{goal}} - q_{k} \|_{\lambda_1}^2 + \| P_{\text{des},k+1}^{+} - P_{\text{des},k}^{+} \|_{\lambda_2}^2 \right)$$

$$+ \| P_{\text{des},k+1}^{-} - P_{\text{des},k}^{-} \|_{\lambda_2}^2 \right) + \| \dot{q} \|_{\lambda_3}^2$$

(5.54)

s.t.

$$x_{k+1,i} = A_{\text{mpc},i} x_{k,i} + B_{\text{mpc},i} u_{k,i} + d_{\text{mpc},i}$$

$$q_{\text{min}} \leq q_{k,i} \leq q_{\text{max}} \quad \forall k = 0 \ldots T$$

$$P_{\text{min}} \leq P_{\text{des},k,i}^{+} \leq P_{\text{max}} \quad \forall k = 0 \ldots T$$

$$P_{\text{min}} \leq P_{\text{des},k,i}^{-} \leq P_{\text{max}} \quad \forall k = 0 \ldots T$$

$$P_{\text{des},k+1,i}^{+} - P_{\text{des},k,i}^{+} = 0 \quad \forall k = T - 5 \ldots T$$

$$P_{\text{des},k+1,i}^{-} - P_{\text{des},k,i}^{-} = 0 \quad \forall k = T - 5 \ldots T$$

(5.55)

where $q_{\text{goal}}$ is the target angle, $\lambda_1$, $\lambda_2$ and $\lambda_3$ are weights and $T$ is the horizon length (set to 20 time steps in this work).

The first term in Eq 5.54 drives the joint angles to a desired position, the second and third terms limit the rate at which the pneumatic actuation can change, and the last term limits the velocity of the arm at the final time step to reduce overshoot and residual oscillation. The first constraint in Eq 5.55 is the dynamics of the system. The second constraint restricts the optimization’s search space to physically feasible pressures for the actuators. The last constraint requires that the actuation pressure not change for the last five steps of the horizon, making the controller behave in a less greedy manner which results in smoother performance.
5.6.3 CT-MPC Results

Both the FS-MPC and CT-MPC methods were tested on three the DoF platform Nightcrawler. Figure 5.13 shows the results of the CT-MPC on Nightcrawler running at 200 Hz with step commands of $30^\circ$ for Links 1 and 3 and a $20^\circ$ step for Link 2. The CT-MPC has excellent performance with very little overshoot or residual oscillation. These results are significant because, as stated in Section 5.5, Nightcrawler has additional mass and dynamics that are more difficult to control than King Louie.

As shown in the previous section, when testing the FS-MPC there was significant steady state error even when using ramp trajectories instead of the step trajectories shown for CT-MPC. Additionally the controller could only be run at a rate of 20 Hz compared to the 200 Hz of the CT-MPC method. Also as the different weights for each joint were tuned they would adversely effect the performance of the other joints. With additional tuning the FS-MPC may have been able to perform as well as, or better than, the CT-MPC, but these results emphasize the strength of using a simpler model that is also simpler to tune.

The Coupling Torque method was developed jointly with Jon Terry. As stated previously Jon Terry additionally performed a thorough analysis, comparing the standard TS linearization method, the FS method and CT method to the simulated dynamics of Baxter performing a $20^\circ$ step in joint angle of the first three joints. He was able to show that the CT method was able to match the performance of the FS method and outperform the TS method. Additionally he was able to show an improvement of control for all seven-DoF of Baxter using an MPC controller using the CT method as compared to the MPC method described in Chapter 4. A more detailed explanation can be found here [78].

5.7 Multi DoF Position and Stiffness Control

This section describes how we extended the simultaneous position and stiffness control method to multiple DoF by using the CT-MPC method. This work is described in Best et al. (2020) [45] and was a collaboration between Charles Best and the author of this dissertation. Charles Best developed a method for simultaneously controlling position and stiffness of antagonistic antagonistic actuators. He proved the method for a single DoF on the Grub and for multiple
Figure 5.13: CT-MPC on Nightcrawler for three joints.

DoF on King Louie [79]. The multi-DoF controller however used the older MPC method that models each joint as decoupled inverted pendulums that have no interactions.
Using the CT-MPC method we performed simultaneous estimated stiffness and position control for the right arm of King Louie. In addition to controlling the stiffness and position for four joints for a series of step inputs, we also show that the end effector stiffness actually changes when stiffness in the joints is changed as deflection was reduced by 46.4% when the arm was commanded at 40 N·m/rad stiffness rather than 30 N·m/rad stiffness. This corresponds to a reduction from 17.9 cm of deflection to 12.2 cm. For the work on King Louie the source pressure was regulated to approximately 39.7 psia (274 kPa).

5.7.1 Implementation

For multi-degree-of-freedom (multi-dof) control, we combined the stiffness formulation for a single joint with recent work on making multi-dof MPC more tractable as described in the previous section. Best et al. derived a stiffness estimate by taking the partial derivative of the torque model described in Equation 5.15, (which torque model is a contribution of this dissertation), with respect to joint angle. The resulting equation for stiffness and its time derivative that was found are as follows:

\[
k = \gamma^+\mu^+P^+ + \gamma^-v^-P^-
\]

\[
\dot{k} = \alpha k + \gamma^+\mu^+(\theta)\beta P_{des}^+ + \gamma^-\mu^-(\theta)\beta P_{des}^- - \dot{\theta}(\gamma^+(\mu^+(\theta))^2P^+ + \gamma^-((\mu^+(\theta))^2P^-)
\]  

(5.56)

where

\[
\mu^{+,-} = \frac{M^{+,-}}{\alpha + \beta}
\]

(5.57)

\[
M^{+,-} = M^{+,-}\theta + b
\]

and \(b\) are coefficients that relate the angle of a joint to the volume of the respective actuator and \(\alpha\) and \(\beta\) are the pressure coefficients from Equation 5.7. The values for \(M^{+,-}\) and \(b\) were empirically found and a full derivation can be found in Best et al. [45].

The stiffness state equation was added to the other states and equations as defined in Equations 5.32-5.36.

The cost function used for each individual joint (since we ran four parallel MPC controllers with King Louie according to the CT-MPC formulation) was
\[
\min_u J(x) = \sum_{t=1}^{T} \left( ||\dot{\theta}[t]||_{Q_{\text{vel}}}^2 + ||\theta[t] - \theta_{\text{goal}}||_{Q_{\text{pos}}}^2 \right. \\
+ ||k[t] - k_{\text{goal}}||_{Q_{\text{stf}}}^2 + ||\Delta P_{0,\text{des}}[t]||_{R_0}^2 \\
+ ||\Delta P_{1,\text{des}}[t]||_{R_1}^2 + ||\Delta k[t]||_{Q_{\text{dstf}}}^2 \right),
\]

where \( \theta_{\text{goal}} \) is the desired angle, \( k_{\text{goal}} \) is the desired stiffness, \( Q_{\text{vel}} \) is the velocity weighting, \( Q_{\text{pos}} \) is the position error weighting, \( Q_{\text{stf}} \) is the stiffness error weighting, \( R_0 \) is the weighting on the change in \( P_{0,\text{des}} \), \( R_1 \) is the weighting on the change in \( P_{1,\text{des}} \) and \( \Delta k[t] \) is the change in \( k \). The cost function Equation 5.59 is subject to the constraint Equations 5.60:

\[\begin{align*}
\theta_{\text{min}} & \leq \theta_i[t] \leq q_{\text{max}} \quad \forall t = 0 \ldots T \\
P_{\text{min}} & \leq P_{i}^{+}[t] \leq P_{\text{max}} \quad \forall t = 0 \ldots T \\
P_{\text{min}} & \leq P_{i}^{-}[t] \leq P_{\text{max}} \quad \forall t = 0 \ldots T
\end{align*}\]

where \( \theta_{\text{min}} \) and \( \theta_{\text{max}} \) are joint limits. The cost on \( \Delta k[t] \) with the weight \( Q_{\text{dstf}} \) was added to reduce oscillations about the desired stiffness trajectory. One other minor change that was needed for this formulation was the method of linearization and discretization as seen in the constraint Equation 5.61. The state equations for \( \dot{\theta}, \theta, P^+, \) and \( P^- \) are all linear and not dependent on stiffness \( k \) so these equations were discretized using the matrix exponential. When we attempted to linearize and discretize the stiffness equations in the same manner, we got poor prediction and control performance. Therefore, instead of using the CT method like we did for the rest of the dynamic equations, we linearized (using the Taylor Series) and discretized (using a first-order Euler approximation) the stiffness equation as follows:
\[ k[t + 1] = k[t] + \left( \frac{\partial k}{\partial \dot{\theta}} (\dot{\theta}[t] - \dot{\theta}[1]) + \frac{\partial k}{\partial \theta} (\theta[t] - \theta[1]) \right. \\
+ \left. \frac{\partial k}{\partial P_0} (P_0[t] - P_0[1]) \right) \\
+ \frac{\partial k}{\partial P_1} (P_1[t] - P_1[1]) \\
+ \frac{\partial k}{\partial P_{0,\text{des}}} (P_{0,\text{des}}[t] - P_{0,\text{des}}[1]) \\
+ \frac{\partial k}{\partial P_{1,\text{des}}} (P_{1,\text{des}}[t] - P_{1,\text{des}}[1]) + \dot{k}[1] \Delta t \] (5.61)

When applied to each joint on King Louie, the controller weights and the first order pressure model coefficients were tuned manually for each joint for best performance and the results can be seen in Table 5.3. Tuning MPC effectively for a MIMO system, especially with a large number of degrees of freedom remains an open problem. The process for picking weights and parameters for each joint may also be improved with system identification.

MPC was implemented at 200 Hz to track a step command in position for each joint while maintaining a commanded stiffness as well (a constant value in this case). The results can be seen in Figure 5.14.

Looking at Figure 5.14, stiffness is tracked well for all four joints for the duration of the test. Position tracking is good for Joints 2, 3, and 4 but Joint 1 shows poorer tracking. There is almost 7° overshoot after the step at 15 seconds and the joint moves a few degrees in the wrong direction after the step at 30 seconds. One reason for this may be because it is assymmetric when compared to the other joint configurations. The orientation of Joint 1 with the shoulder makes it so this joint works directly against gravity and because it is the first joint, the inertia effects from the other links are most apparent. However, this test still shows that the proposed formulation is tractable and gives reasonable performance while still being able to control at 200 Hz for a multi-dof soft robot arm.

Even though stiffness is controlled to a desired value for each joint, the actual stiffness of the joint is not expected to be the estimated value exactly. For good estimation of joint stiffness as seen in Equation 5.57, accurate torque coefficients \((a_0 \text{ and } a_1)\) and a good angle to volume...
Table 5.3: MPC weights and parameters used for each joint on King Louie

<table>
<thead>
<tr>
<th>Joint 0</th>
<th>Joint 1</th>
<th>Joint 3</th>
<th>Joint 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q_{vel} )</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>( Q_{pos} )</td>
<td>1200.0</td>
<td>800.0</td>
<td>500.0</td>
</tr>
<tr>
<td>( Q_{st,f} )</td>
<td>0.2</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>( Q_{dst,f} )</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>( R_0 )</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>( R_1 )</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>( \theta_{max} )</td>
<td>20°</td>
<td>120°</td>
<td>120°</td>
</tr>
<tr>
<td>( \theta_{min} )</td>
<td>−120°</td>
<td>−120°</td>
<td>−120°</td>
</tr>
<tr>
<td>( c_0 )</td>
<td>−2.65</td>
<td>−2.65</td>
<td>−5.301</td>
</tr>
<tr>
<td>( c_1 )</td>
<td>2.65</td>
<td>2.65</td>
<td>5.301</td>
</tr>
</tbody>
</table>

relationship \((M_i \text{ and } b)\) would have to be determined. Because of the construction of King Louie’s arm, these parameters are difficult to determine for each joint. Instead, the grub parameters were used and tests were performed to show that overall arm stiffness can be increased or decreased as seen in the next section. Future work where actuator designs allow for these coefficients to be determined analytically from geometry would greatly simplify this problem.

### 5.7.2 Stiffness Test

The stiffness of King Louie’s arm was tested by commanding a joint angle for each joint and a single stiffness to be applied to all the joints. Once all the joints achieve the stiffness and joint angles, a 4 lb weight was applied to the end effector as a step input. Figure 5.15 shows the arm in the initial position and the arm at maximum deflection for a commanded stiffness after the weight has been applied. The desired joint angles for this configuration are \( \theta_1 = −30° \), \( \theta_2 = 60° \), \( \theta_3 = 20° \), and \( \theta_4 = 20° \).
The maximum deflection was measured by first recording the XYZ coordinates of the end effector before the load is applied and then tracking the end effector coordinates using Vive (see Chapter 1 for description of Vive) data for the end effector location during the joint controller response to the step input in load. The deflection vector can then be calculated by subtracting the initial coordinate vector from the end effector coordinates that give the maximum displacement during the transient response from the disturbance load. The deflection magnitude for the test is then the magnitude of the deflection vector with the biggest Euclidean norm. This test was completed for stiffnesses from 20 N·m/rad to 40 N·m/rad in increments of 5 N·m/rad. For each tested stiffness, five trials were completed and the median value can be seen in Figure 5.16.
The data shown in Figure 5.16 show a clear downward trend in deflection as stiffness is increased from 30 to 40 N·m/rad (or the overall trend from 20-40). This means that controlling joint stiffness affects end effector stiffness in a predictable way as we would expect, although perhaps not with the correct predicted end effector stiffness. Additionally, controlling at a single constant stiffness as was done in this trial defeats the purpose of using variable stiffness actuators. A higher fidelity model that accounts for the link and joint interactions could be used to determine what stiffnesses are best for specific objectives and tasks. Although the overall trend of maximum deflection decreases from 20 N·m/rad to 40 N·m/rad, the behavior between 20 N·m/rad and 30 N·m/rad is not expected and may be attributable to link deflection and other unmodeled effects in the soft robot dynamics.
5.8 Conclusion

In this work we were able to show a trend of higher fidelity models that resulted in better, more accurate, and faster control methods. We were also able to show that the CT-MPC method is adaptable and it is possible to include even more states like the joint stiffness and perform effective control of position. This modeling work has laid the foundation from much of the current and future publications and controls work found in the RaD lab. As the fidelity of soft robot models continue to increase the control performance will also continue to increase.

Some potential future areas include more accurate pressure dynamics, a higher fidelity pressure to torque model that also considers the current joint angle and potentially developing better techniques for handling coupling terms in the dynamics.
CHAPTER 6.  IMPROVED CONTINUUM JOINT CONFIGURATION ESTIMATION USING A LINEAR COMBINATION OF LENGTH MEASUREMENTS AND OPTIMIZATION OF SENSOR PLACEMENT


6.1 Introduction

Continuum joints are becoming a common style of robotic joint, especially in the world of soft robotics. These joints bend continuously along their length and offer the ability to form complicated shapes, operate in cluttered environments, and can be compliant which increases the inherent safety of the robot.

While being able to form complicated shapes and easily deform is one of continuum joints biggest strengths, it is also one of the attributes that make them the hardest to use in practice. Current approaches for sensing the configuration of continuum robots include many different methods such as motion capture, optical sensors, and length sensors (see Section 6.1.1 for a review of many of the methods used for sensing continuum joint’s state). Many of these state-of-the-art methods operate under assumptions that limit their ability to estimate the full kinematic position of a continuum joint in non-laboratory settings, (e.g. settings where the joint undergoes actual loads during a useful task that cause unanticipated bending). In this work we focus on methods that use measurements of the length of a continuum joint to estimate the configuration of the joint. Many of the previous methods in the literature assume that the bending of the joint is constant curvature. This assumption readily breaks down as soon as any actual loads are applied to the joint. Of particular note, is when the robot is in the s-shape bending as shown in Figure 6.1 (see proximal joint). For any method using a single length measurement and a constant curvature assumption, the measurement in this scenario will result in an estimate of zero deflection.
The most accurate way to sense the full configuration of a continuum joint using length sensors, would be to divide the joint into infinitesimal segments and have each of those segments be monitored by length sensors. For every sensor that is added to the joint, the constant curvature assumption can be applied to that smaller segment. By having every segment covered by its own sensor the full configuration could be reconstructed by treating those segments as pieces of a kinematic chain.

This method is not feasible for a real system due to mechanical, electrical and computational limits. However it does suggest that it may be possible to increase the number of sensors to get more accurate pose estimation of a continuum joint while still remaining within the mechanical, electrical and computational constraints of a real system.

However, if sensors are simply placed end to end along the joint, estimation will still be limited to the maximum number of sensors that will be allowed by the physical constraints of the system. Our hypothesis was that by using measurements from sensors that have overlapping coverage of the same discrete joint segments, whether literal discrete segments like the robot shown in Figure 6.1, or representative segments of a soft robot, a more accurate estimate can be accompl-
plished. In this paper, we show that by overlapping sensors on the joint, more information can be gained without the cost of adding a sensor for every representative segment.

We propose and demonstrate two new methods of estimating the configuration of a continuum joint using measurements from overlapping length sensors. The first method averages the per segment length of the sensors for each sensor monitoring a segment, we call this the Equally-Weighted Averaging Method (E-WAM). The second method estimates the segment configuration by using a linear combination of the per segment lengths of all the sensors on the continuum joint, we call this the Weighted Averaging Method (WAM). The weights for the WAM method are found by performing a linear regression as discussed in Section 6.2.5.

To determine the placement of the overlapping sensors, we developed a heuristic placement method as well as an Evolutionary Algorithm (EA) that determines optimal sensor placement for a joint. We compare the results of these two placement methods in this paper.

The primary contributions of this paper are:

1. The novel concept of overlapping length sensors to improve the estimation of a continuum joint’s state.

2. WAM: A method for using overlapping sensors to significantly improve continuum joint estimation resulting in an estimate that reduces error by a factor of eleven when using two sensors on a joint rather than using a single sensor.

3. Two methods for determining the placement of overlapping length sensors on a continuum joint, and an objective comparison of their performance.

All of the methods and theory that we develop in this paper are based purely on kinematics and static loading conditions. We confirm and demonstrate our contributions using a Piece-Wise Constant Curvature continuum joint kinematic simulation. Future work would include implementing this on actual hardware and in dynamic environments.

The remainder of this paper is organized as follows, Section 6.1.1 discusses related literature on sensor design and estimation for continuum actuators, as well as methods for determining optimal sensor placement. Section 6.2 discusses the assumptions we used and develops the models, theory and algorithms for our estimation methods. Section 6.3 presents the results of the estimations methods and Section 6.4 discusses the results and possible applications for future work.
6.1.1 Related Work

The focus of this paper is estimation for a discrete-segment continuum joint. Although there are many types of soft robot joints (including discrete segments [80], compliant continuum joints with discrete rigid components [81], and fully soft-bodied robots [82]), we have chosen to develop our methods for discrete segments because 1) it matches our actual development hardware, and 2) most soft robot joints could be represented to varying degrees of fidelity by a discrete-segment model where the kinematics are approximated with a series of representative constant curvature segments, regardless of actual construction.

Related literature can be divided into two main areas: 1) soft robot configuration estimation; 2) soft robot sensor placement.

6.1.1.1 Soft Robot Configuration Estimation

Of the two areas covered in this paper, by far the most literature exists relative to novel sensors for soft robot configuration estimation. We therefore describe prior work that uses different methods of construction or physical phenomenon to estimate soft robot configuration. We also describe methods used to estimate the actual bend angle or pose.

A significant amount of the research in soft robot configuration estimation has required using motion capture systems with infrared cameras and reflective tracking dots [82, 83], electromagnetic field detectors [84–86], or virtual reality tracking hardware [87]. However, using this type of sensor constrains the mobility of the soft robot to operate solely within the range of the motion capture system.

Resistance-based sensing is often used with conductive material or fabrics that are assembled in a way such that the resistance of a circuit varies as the bend angle of the robot changes. Examples use methods ranging from commercial flex sensors [88], to conductive thread [89–91], or yarn [92], to conductive silicone that is cut using principles from kirigami [93]. There are multiple examples of this approach (see [94–99]).

Many papers have focused on using optical methods that tend to revolve around novel combinations or topologies for Fiber Bragg Grating (FBG) sensors (see [100–103]). However, other related methods focus on the basic idea of using optical fibers in general (see [104–106]).
Using optical frequency domain reflectometry combined with added optical gratings the authors in [107] were able to show that they could improve configuration estimation when in contact or with non-constant curvature for medical applications.

Some methods have relied on photo diodes [108], or combined the strength of traditional camera or ultrasound images in conjunction with optical fibers (see [109, 110]). Other researchers used camera-based methods directly to detect contact, or estimate deformation for a deformable link, but with rigid joints [111].

Other physical phenomenon used include capacitance [95, 112–114], inductance [115–117], magnetism [88], impedance [118], or a combination of gyroscope, accelerometer and magnetometer in an inertial measurement unit (IMU) package [87].

Similar to our efforts to include multiple sensors to improve configuration estimation, there are some researchers who have used overlapping sensors to improve performance. Specifically, Li et al. [119] used a dual array FBG scheme to improve estimation accuracy. While Felt et al. [115] used two circuits and measured change in inductance to improve estimation of lateral motion for a continuum joint.

As near as we can tell, all of the previous sensors and estimation methods (minus those that give a global pose such as motion capture) seem to focus on estimating curvature or linear motion only, which does not account for deformation that we would expect when these platforms are heavily loaded. Some methods enable detection of contact, but this is used as a way to relate discrepancies in curvature to a contact event, rather than using the loading condition to more accurately estimate the joint configuration with a non-constant curvature assumption. However, there is some literature where the configuration of flexible members experiencing a point load is estimated using accurate Kirchoff or Cosserat rod models and additional sensor information (such as cameras or force-torque data). In Rucker and Webster [120] they use an Extended Kalman Filter in conjunction with a Cosserat rod model which requires a measurement of the tip pose and applied forces. While in Borum et al. [121] the authors use external cameras to help solve for the configuration of a flexible member that can have multiple equilibrium positions (due to bifurcation) by formulating the problem as a geometric optimal control solution. This solution includes estimates for the forces and torques applied at the tip to cause the deformation. In both cases, the
deformation was restricted to being planar and was caused by an external force at the tip, rather than being included as part of a potentially self-contained soft robot control scheme.

In Trivedi and Rahn (2009) [122] and Trivedi and Rahn (2014) [123], the authors solve for the configuration of the OctArm robot platform with unknown payloads using Cosserat rod models and three different sensing methods (e.g. force-torque sensors and an inclinometer at the base, multiple cable encoders, and multiple inclinometers along the manipulator) to constrain and solve initial value or ODE problems with given boundary conditions. The method was effective, but required varying levels of accurate knowledge about soft robot parameters depending on the sensing method used and was again restricted to planar applications (although not due to limits in formulation). In addition, this formulation would require additional sensors across the arm if a distributed load were applied (not at the tip or end effector). Similar work uses Cosserat rod models [124] or Kirchoff elastic rod models [125, 126] combined with force sensing at the base of the flexible member in order to estimate soft robot configuration or interaction forces and stiffnesses.

These model-based methods hold great promise and could likely be incorporated with our model-free method. However, additional benefits of our method are that even without a complex soft-body model, it performs quite well and is able to handle loading conditions that are not limited to the tip of the flexible member. Any additional information derived from an accurate model within an estimation scheme such as a Kalman filter would likely improve the results shown in this paper.

Finally, using different modalities, many researchers have used neural networks to map sensor output to joint configuration for optical sensors [127], FBG sensors plus ultrasound images [109], pressure readings [128], tactile arrays [129], or linear potentiometers [130–132]. In Lun et al. [133] they develop a flexible sensor using fiber Bragg gratings that when combined with a learned model can be used to accurately reconstruct the surface of a soft robot, but this is not applied specifically to a soft robot. Many of these methods learned a mapping to estimate full pose for the tip of one, or sometimes multiple joints. However, one of the main limitations is that there is no relation or intuition between the data and the black box model that is produced. Also, if the manipulator were to carry a larger load, additional data with the load in place would likely need to be collected, especially if the joint deformed in a way that violated constant curvature.
assumptions. Information about the load (e.g. overall mass and distribution of mass) may also
have to be included in the training data to make the approach general. Because our approach is
based on fitting parameters to shapes that are caused by many different loading conditions, we
expect this approach to potentially generalize more easily.

6.1.1.2 Sensor Placement

The general problem of sensor placement (number of sensors and relative positioning) is
often approached using a metric of observability in order to improve estimator design (see [134–
136]). However, observability may not always be the best metric and sensor placement based on
simple models and heuristics is an open research problem [137].

For our specific contributions, we focus on sensor placement in the context of soft robot
configuration estimation. Some researchers have followed the previously mentioned approach of
relating soft robot sensor placement to observability [138]. In this case they use a differential
representation of the continuum robot’s kinematic equations. However, the robot is a concentric
tube robot which appears to be unloaded, in contrast to the work we present. In Tapia et al. [139],
they require hyperelastic material models and finite element discretizations to simulate nonlinear
behavior of a given soft robot with expected loading. This is similar to our method with two main
differences. Our loading and deformation models are much simpler and the proposed optimization
in that paper requires the sensors to be integrated with the actual fabrication of the soft robot,
unlike ours which can be added after the fact and only needs to measure length. Other relevant
work includes Deustschmann et al. [140] where the authors optimize the attachment points for
length sensors to estimate the pose of a 6-DoF continuum-joint robot head. This required a beam
finite element model with a fixed load (the robot head) and the data was fused with IMU. Finally,
in Kim et al. [141] they use FBG sensors and an optimization with a similar notion to our weighted
reconstruction, using their own set of basis functions. However, the type of optimization presented
does not necessarily translate to overlapping sensors (which we have found to be very beneficial in
the results presented in this paper).
6.2 Materials and Methods

In this section we describe the methods used to develop the simulated continuum robot configuration, estimate the continuum robot configuration from the attached sensors, and develop the evolutionary algorithm used to find the optimal sensor placement along the continuum robot joint.

6.2.1 Continuum Joint Configuration

For a general continuum joint there are three degrees of freedom, bending about two orthogonal axes and extension along an axis orthogonal to the two bending axes. As long as one bending degree of freedom exists, in which the center of rotation stays constant for the bending range, the joint can be considered a continuum joint.

In our work, we focus on continuum joints that have a fixed length/height and two bending degrees of freedom. The continuum joint hardware shown in Figure 6.1, is used as the basis for models in this paper, is made up of bending segments of a fixed height. We assume that these segments bend with piece-wise constant curvature. The theory is that the curvature change in one segment is small enough that it can be assumed to have constant curvature. It should be noted that the methods discussed in this paper can be adapted for joints that are not actually made of smaller constant curvature segments by splitting the joint into virtual segments.

Due to our fixed length assumption as the joint bends there exists a neutral axis or spine at the center of the joint that does not change lengths. This is represented by the black line in Figure 6.2.

We use the $uvh$ states developed by Allen et al. [142] to describe the configuration space and pose of a single continuum joint segment under the constant curvature assumption (displayed graphically in Figure 6.2). This parameterization is based on Screw Theory. The full configuration of the continuum joint is described by the $uvh$ parameters of the series of smaller segments that make up the joint. The parameter $u$ describes bending about the local x-axis and $v$ describes bending about the local y-axis for each segment. The variable $h$ is the length of the neutral axis which we keep constant for the purposes of this paper. According to Allen et al., the arc angle, $\phi$, is equal to the magnitude of the rotation axis, $w = [u, v, 0]$. 

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6.2.2 Sensor Arrangement

As stated previously, for this application we are simulating sensors that measure the change in length of the joint as it undergoes bending. By using constant curvature assumptions we can calculate the pose from the sensors length measurements as will be described in Section 6.2.3.

The continuum joint has two sets of sensors that run the length of the joint and start at the base at $0^\circ$ and $-90^\circ$ on the circumference of the joint as shown in Figure 6.3. These locations allow each set of sensors to independently measure the two degrees of freedom ($u$ and $v$) as the mounting points correspond to the directions of the bending axis. Thus bending about each axis will only be measured by a single set of sensors.
Each set of sensors in our simulations contain between one and six sensors which are aligned such that they are parallel to the neutral axis of the continuum joint in the unbent configuration. Additionally, we modeled each joint using twelve to forty-eight segments of equal length. The sensors were placed such that they cover a series of consecutive segments. This series can be a minimum of one segment or a maximum of the total number of segments representing the joint. An example of a set of three sensors is shown in Figure 6.4.
Figure 6.4: An illustration of showing three possible bending states of a continuum joint, the segment indexing used in this paper, and a possible sensor configuration.
For a sensor configuration to be considered for our simulated experiments, each segment must be covered by a minimum of one sensor. For the joints simulated in this paper, both degrees of freedom had identical sensor placements although this is not a requirement for successful configuration estimation of a two degree of freedom continuum joint.

6.2.3 Pose Estimation

As mentioned in Sections 6.2.1 and 6.2.2, the bending section of the continuum joint is divided into smaller segments that are small enough that we can assume constant curvature. Additionally each of these segments is covered by at least one length sensor located at a fixed distance away from the neutral axis.

The work developed by Allen et al. [142] also describes how to estimate the angle of bending for a continuum joint with constant curvature that is monitored by a length sensor. We apply this method to our discrete sections by using Equations 6.1 and 6.2 which convert the length of a tendon, \( l \), located at a fixed radius from the neutral axis of the joint to a joint angle, \( u \) or \( v \), given the height of the segment, \( h \).

\[
\begin{align*}
    u &= \frac{l_{\text{tendon at } 0^\circ} - h}{\text{radius}} \\
    v &= \frac{-h + l_{\text{tendon at } -90^\circ}}{\text{radius}}
\end{align*}
\]

As defined in Allen et al. [142] \( w \) is defined as \([u, v, 0]\) and whose magnitude equals \( \phi \). Therefore \( \phi \) represents the total magnitude of the deflection angle as shown in Equation 6.3

\[
\phi = \sqrt{u^2 + v^2}
\]

The full homogeneous transformation matrix for the \( uvh \) parametrization is described in Allen et al. [142]. We use this to compute the position of the end of each link along the kinematic chain of segments that makes up the complete pose of the bending section of the continuum joint.

This approach is used for each estimation method described in Section 6.2.5. Although each sensor covers several constant curvature segments, these segments may not have the same curvature. Thus at least some error is introduced. The tendon length \( l \) of a segment is calculated
by dividing the full sensor by the number of segments that it covers. This tendon length is referred to as a "virtual tendon length.”

Given every segment’s angle of deflection the length of a simulated sensor is calculated by summing the "virtual tendon lengths” for each segment that the sensor covers. The "virtual tendon lengths” are calculated by solving for the respective \( l \) found in equations 6.1 and 6.2.

### 6.2.4 Loading Conditions

Since the motivation of this paper is to improve the estimation of continuum joint poses under real-world loading conditions, we examine four loading conditions that encapsulate the majority of situations experienced by a cantilevered continuum joint with a fixed mounting. The loading conditions are listed as follows:

- **End Force Load**: This loading condition simulates contact at the end of the joint (Figure 6.5 (A)).
- **Uniformly Distributed Load**: This loading condition simulates joint deflection due to gravity (Figure 6.5 (B)).
- **End Force Load with a Moment**: This loading condition simulates a load at the end of the joint with a torque created by the joints actuators resulting in an s shape (Figure 6.5 (C)).
- **Constant Curvature**: While not explicitly a loading condition, this represents the joint being actuated such that all segments reach their maximum range of motion (ROM).
Figure 6.5: (A) End Force Load, (B) Uniformly Distributed Load, (C) Beam with One End Fixed and the Other End Guided. \( L \) is the arc length of the full joint, \( F \) is an end load amount, \( w \) is a distributed load, and \( M_0 \) is a moment.
We treat the continuum joint as a cantilevered beam and apply each of the given loading conditions. The Finite Element Analysis (FEA) program ANSYS was used to simulate the resulting deformation of the modeled beam.

We use Beam 188 elements which were divided into \( m \times 3 \) elements, where \( m \) is the number of the constant curvature segments in the joint. For each loading condition the load and/or moment was incrementally increased until the desired deflection of the first segment was reached.

It is important to note that we used the FEA solution for all of the loading except for the constant curvature case as the angles of deflection for each segment are all the same and thus known.

We then adapt these nonconstant curvature simulations to our actual Piecewise Constant Curvature (PCC) joint model. This is done by recording the total deflections from the FEA model at the beginning and end of each segment. Then the difference between the deflection at the beginning of a segment and the end of the segment is calculated. This difference is then set as the bending angle for that Constant Curvature segment as shown in equation 6.4.

\[
\phi_i = \theta_{i+1} - \theta_i \quad \forall \quad i = 1, \ldots, m
\]  

(6.4)

Figure 6.6 demonstrates a continuum joint undergoing a force load and the deflection angles, \( \theta_i \) that can be used to calculate the relevant joint angles \( \phi_i \)

![Figure 6.6: Illustration of the method used for adapting a continuous bending model to a Piece-wise Constant Curvature model.](image)
Due to the computational demands of the finite element analysis (FEA), we found solutions for a specific set of joint deflections. This was performed for every loading condition where the first segment was set to the maximum ROM which was incremented from $-8^\circ$ to $+8^\circ$ in increments of $\frac{1}{8}^\circ$. For any modeled deflections that were between the original FEA solutions a linear interpolation was used. Using this method, a maximum per segment error bound of $0.0285^\circ$ was calculated for the linear interpolation. This was calculated using the worst case scenario (maximum difference between two points used for interpolation) in terms of error. Specifically, the error bound was found by summing the difference between joint angle FEA solutions used for interpolation and then dividing by the number of segments. We did not need to use the interpolation method for the constant curvature loading case as each segment’s angle would be the maximum ROM.

6.2.5 Estimation Methods

In this section we describe the estimation methods used in the simulated experiments. We experimented with simulating four different sensor configurations for gathering state data and used two different methods for state estimation.

6.2.5.1 Sensor Configurations

When describing the configuration of sensors along the length of a continuum joint, we use a pair of two numbers inside square brackets to represent the sensor’s starting segment and ending segment as such $[\text{starting segment} - \text{ending segment}]$. Figure 6.4 shows the indexing of the joint segments on this 12 segment continuum joint. The segment numbering is started at the most proximal segment which is labeled segment 0 and the rest of the segments are incrementally labeled until the last segment. Using our method of describing a sensor configuration on a joint, the red sensor is $[0-11]$, the blue sensor is $[1-3]$, and the green sensor is $[6-8]$.

Single Sensor The Single Sensor configuration, henceforth abbreviated as SS, involves using a single sensor that spans the entire length of a joint, to measure the overall joint angle of a continuum joint. This method relies on the assumption of constant curvature along the entire length of the joint.
for state estimation. This method represents the bare minimum amount of sensing that a continuum joint can have for state estimation with length sensors.

**End-to-End** The End-to-End Sensor configuration, henceforth abbreviated as EE, involves multiple sensors that are placed along the length of the joint with every segment covered and no overlap. The method for algorithmically determining the sensor placement involves dividing the number of segments by the number of sensors and rounding down. That is the default number of segments each sensor will cover. If there is a remainder from dividing the number of segments by the number of sensors, that remainder is evenly distributed among the sensors closest to the distal end of the joint. For example, a 12 segment joint with 5 sensors would have sensors that cover the following segments [0-1], [2-3], [4-5], [6-8], and [9-11].

**Heuristic Overlap** The Heuristic Overlap configuration, henceforth abbreviated as HO, involves multiple sensors aligned in a regular pattern along the joint, with each sensor overlapping with its neighboring sensors for two segments. The sensor placement is determined by first finding the EE sensor configuration and expanding each sensor’s starting and ending index by one segment. Note, sensors that cover the first or last segment on the joint are not expanded past the ends of the joint. For example, a 12 segment joint with 5 sensors would have sensors that cover the following segments [0-2], [1-4], [3-6], [5-9], and [8-11].

**Optimized Overlap** The Optimized Overlap configuration, henceforth abbreviated as OO, is a sensor configuration that is determined by an evolutionary algorithm we developed. The evolutionary algorithm is described in Section 6.2.6. This configuration represents the best possible sensor configuration for a given number of sensors.

### 6.2.5.2 State Estimation Methods

For each estimation method, we estimate the angle of deflection for each individual segment of the continuum joint which then allows for the estimation of the full configuration of the joint. This is accomplished by estimating the length that a single sensor would be if it was monitoring
just that individual segment, henceforth known as the "virtual sensor length". We have developed three methods for performing this estimation.

**DEM (Direct Estimation Method)**  For sensor configurations that have no overlap, we estimate the virtual sensor length of a segment by simply dividing the length of the sensor covering it by the number of segments that sensor covers. This method assumes that all of the segments covered by a sensor have the same angle of deflection.

**E-WAM (Equally-Weighted Averaging Method)**  For sensor configurations that have overlap, we have two methods of estimating the virtual sensor length of a joint segment, the first of which we call E-WAM. The E-WAM method takes the per segment lengths of all the sensors covering a segment and averages them to estimate the length of the virtual sensor for that segment.

**WAM (Weighted Averaging Method)**  The second method for estimating the virtual sensor length, $l_{est}$, of a joint segment on a robot that has overlapping sensors is WAM. This method uses a weighted linear combination of all of the sensors on the robot to find the virtual sensor length for each segment, the hypothesis being that the sensors that do not cover the segment still provide additional information about its state. Each segment has a separate weight for each sensor on the joint as shown in equation 6.5.

$$l_{est,i} = \sum_{j=0}^{n} w_{i,j} \cdot \frac{l_j}{p_j}$$  

where $i$ is the $i^{th}$ segment, $n$ is the number of sensors on a joint, $w_{i,j}$ is the weighting on the $i^{th}$ segment for the $j^{th}$ sensor, $l_j$ is the full length of the $j^{th}$ sensor, and $p_j$ is the number of segments the $j^{th}$ sensor spans.

We find these weights by applying the robust linear regression algorithm from Scipy ([143]) to deflection angle data we simulated from the continuum joint under 30 different loading samples ($s$) for each of the 4 loading conditions ($c$) for a total of 120 data points per joint segment. The 30 different loading samples are calculated by varying the ROM used in the loading conditions as describe in the following equation.
\[ ROM_{\text{loading},i} = -\frac{1}{s} ROM_{\text{max}} + i \frac{2ROM_{\text{max}}}{s}, \forall i = 1, \ldots, s \] (6.6)

We use the scipy `least_squares` function with the loss condition set to “soft l1” and the “f_scale” condition set to 0.1. Our residuals function can be seen in Equation 6.7 where \( S \) is the matrix of collected sensor data, \( w_i \) is a vector of the weights for which we are solving, and \( l_i \) is the length of a virtual sensor covering that segment.

\[ \text{residual} = Sw - l_i \] (6.7)

Matrix \( S \) takes the form shown in Equation 6.8. Each row is made up of the sensor values from one of the simulated loading cases. The sensor data in the matrix is normalized and denoted as \( \bar{s} \), where \( \bar{s}_j = \frac{l_j}{p_j} \).

\[
S = \begin{bmatrix}
\bar{s}_{1,\text{case}1} & \bar{s}_{2,\text{case}1} & \cdots & \bar{s}_{n,\text{case}1} \\
\bar{s}_{1,\text{case}2} & \bar{s}_{2,\text{case}2} & \cdots & \bar{s}_{n,\text{case}2} \\
\vdots & \vdots & \ddots & \vdots \\
\bar{s}_{1,\text{case}m} & \bar{s}_{2,\text{case}m} & \cdots & \bar{s}_{n,\text{case}m}
\end{bmatrix}
\] (6.8)

Vector \( w_i \) takes the form shown in Equation 6.9.

\[
w_i = \begin{bmatrix}
w_{i,\text{sensor}1} \\
w_{i,\text{sensor}2} \\
\vdots \\
w_{i,\text{sensor}n}
\end{bmatrix}
\] (6.9)

Vector \( l_i \) takes the form seen in Equation 6.10.

\[
l_i = \begin{bmatrix}
l_{i,\text{case}1} \\
l_{i,\text{case}2} \\
\vdots \\
l_{i,\text{case}m}
\end{bmatrix}
\] (6.10)
6.2.6 Evolutionary Algorithm

To find the optimal sensor placement on a continuum joint, we implemented an Evolutionary Algorithm (EA) from the DEAP (Distributed Evolutionary Algorithms in Python) Library [144].

The goal of our algorithm is to find the optimized sensor placement for a given continuum joint with a fixed number of sensors. Prior to running the EA, we define the continuum joint on which we will be optimizing the sensor placement by setting the total length of the joint, the number of segments, and the total range of motion of the continuum joint.

The EA itself is the eaSimple function from the DEAP library, which handles iterating over the specified number of generations, selection, mating and mutation with built-in options or the ability to define your own functions. We chose to do 10 generations and discuss our choices for selection, mating and mutation in Section 6.2.6.4.

6.2.6.1 Defining an Individual

To represent an individual we used a list of integers with a length of two times the number of sensors. For example, a continuum joint with 12 segments and two sensors could be represented as [0, 7, 4, 11]. In this list, each sensor is represented by a pair of numbers. The first two numbers represent the starting segment index of the first sensor and the ending segment index of the first sensor. The second two numbers represent the starting and ending index of the second sensor. For a given sensor number $i$, the starting index is $2i$ and the ending index is $2i + 1$. If the ending index is lower than the starting index, they are automatically swapped to be in the correct order by our algorithm. The sensors cover the full segments of both the starting and ending segment. In other words the sensor starts on the bottom of the starting segment and ends at the top of the end segment.

6.2.6.2 Creating the population

To create the population, we create 500 individuals each with an attribute list that is two times the number of sensors long with random integers generated at every index of the attribute list.
We experimented with seeding the population with individuals that have sensors lined up end to end or start with a Heuristic overlap but found no noticeable improvement in the EA's performance.

6.2.6.3 Evaluating the Fitness

To evaluate the fitness of an individual we use a cost function that sums the deflection angle error of all \( m \) joint segments, for all \( s \) loading samples of a loading conditions, for all \( c \) loading conditions giving us the cost function seen in Equation 6.11. Our goal is to minimize the cost of an individual.

\[
\text{cost} = \sum_{i} \sum_{j} \sum_{k} (|\phi_{\text{actual},i,j,k} - \phi_{\text{estimated},i,j,k}|) \tag{6.11}
\]

Additionally, when evaluating an individual, we first determine whether or not a sensor configuration is a valid configuration. For our purposes, valid means that each segment on the joint is observable i.e. covered by at least one sensor. If this criteria is not met, the individual’s fitness score is set to the maximum which is the maximum joint error possible ((2 \( \times \) ROM) multiplied by \( c, s, \) and \( m \)). Intuitively, this means that the estimation was off by the maximum possible amount for each segment in each loading simulated.

We also experimented with including the Cartesian position and orientation of the end effector of the joint in the fitness score. However, due to its direct correlation with the individual deflection angles we found that this did not improve overall performance for the optimization.

6.2.6.4 Selection, Mating, and Mutation

Selection is performed though a tournament selection process as provided by the DEAP library, \texttt{deap.tools.selTournament(individuals, k, tournsize, fit_attr=“fitness”)}, where the method is passed a list of individuals (individuals) and the size of the tournament (tournsize).

The mating is performed by using a one point crossover algorithm provided by the DEAP library, \texttt{deap.tools.cxOnePoint(ind1, ind2)}, where “ind1” and “ind2” are two individuals that are to be mated. The algorithm randomly chooses a place for crossover to happen. Crossover then occurs by swapping the elements between the two individuals that are right of the selected element. This
method cannot choose the last element so there will always be some crossover (see Figure 6.7 for an example of one point crossover). We set the crossover probability to 0.7.

Figure 6.7: Example of one point crossover for an individual where \( m = 12 \) and \( n = 2 \). One point crossover is initialized though the random selection of where crossover happens. Then the crossover occurs by swapping the sides that are to the right of where crossover was chosen to happen. It should be of note that this method may take parents that have all the segments covered by sensors and make children who do not have segments that are covered by sensors.

Mutation occurs using the method `deap.tools.mutUniformInt(individual, low, up, indpb)` found in the DEAP library where “individual” is the individual to be mutated, “low” and “up” are
the lower and upper bound, respectively, that an attribute can be set to, and “indpb” is the independent probability that each element of the attribute will be mutated. Therefore if an individual is selected for mutation each element of the individual’s attribute (the sensor list) has a chance to randomly mutate to a value in the closed set [“low”, “up”] based on a uniform distribution. We set the mutation probability to 0.5

6.2.7 Experiments

We had four hypotheses that we tested and analyzed for general trends.

1. Increasing the number of sensors on a joint for a given placement method and estimation method will improve the accuracy of the state estimation.

2. Overlapping the sensors can provide more information about the configuration of the joint and will therefore improve configuration estimation for continuum joints.

3. Using a weighted linear combination of the overlapping sensor data can decrease the state variable estimation as compared to an equally weighted linear combination. Additionally, the weights can be found using linear regression.

4. An evolutionary algorithm can be used to determine the optimal placement of overlapping sensors that will further improve state estimation for continuum joints.

To prove generality of our solutions and to test the hypotheses being proposed, we generated 80 different joints by varying the number of segments and the max ROM per segment. We varied the two variables as shown in Table 6.1 to generate the 80 different joints. From here on in this paper, when we mention ROM, we are referring to the range of motion of the segment, not of the whole joint, unless explicitly stated otherwise.

For each of the hypotheses presented above, we perform simulated experiments that compare the performance of a sensor placement or state estimation method on all 80 joints. We compare the performance of the methods by simulating the joints in 40 different poses and comparing the aggregate error of the joint segments angle error (our cost function) normalized for number of segments $m$, max ROM, loading conditions $c$, and loading samples, $s$. The 40 different poses come from the 4 different loading cases ($c = 4$) and ten sample poses ($s = 10$). We then multiply by 100
Table 6.1: The different parameters and their values that were simulated.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Segments</td>
<td>12, 16, 20, 24, 28, 32, 36, 40, 44, 48</td>
</tr>
<tr>
<td>Max ROM per Segment (degrees)</td>
<td>±1, ±2, ±3, ±4, ±5, ±6, ±7, ±8</td>
</tr>
</tbody>
</table>

to get the average joint segment angle error as a percent of ROM for a given joint. (see Equation 6.12)

\[
Average \% Error of ROM = \frac{cost}{c \cdot s \cdot m \cdot ROM_{\text{max}}} \tag{6.12}
\]

With the exception of the base case of a single sensor, we performed all of our simulated experiments with two, three, four, five, and six sensors to study how the results change as more sensors are added. For the first hypothesis, we compare the average percent error of ROM when using the DEM on the simulated joints for the SS placement and two to six sensors in the EE placement. For the second hypothesis we study the effects of overlap by comparing the results of the EE placement method with the DEM estimation method versus the HO placement method with the E-WAM estimation method. The third hypothesis tests our WAM method by comparing the WAM method and the E-WAM method on the joints with HO sensor placement. The final hypothesis tests our evolutionary algorithm by comparing the HO and OO sensor placement methods while using the WAM estimation method. Section 6.3 presents and discusses the results of the simulated experiments.

6.3 Results

This section reports the results of the tests described in Section 6.2.7. To make it easier to compare all of our results, we created a bar graph that summarizes the tested sensor placement and estimation methods, shown in Figure 6.8. We also report the original data used to generate the bar graph in Table 6.2.
Figure 6.8: This bar graph shows the median results for all of the simulated joints’ Average % Error of ROM (defined in Equation 6.12) of all the joint’s segments. Quartile bars are included to show the spread of the results.

We have also included a case study to help visually show the effectiveness of the different estimation methods for the different loading cases. Figure 6.9 shows how well different estimation methods are able to reconstruct the actual configuration of the joint under the three real-world loading cases.

6.4 Discussion

The results of these simulated experiments strongly support our first, second, and third hypotheses. The results also loosely support our fourth hypothesis. For all of the analyses listed in this discussion, the data behind Figure 6.8 can be found in Table 6.2.

Our first hypothesis, that increasing the number of sensors on a joint for a given placement and estimation method will improve the accuracy of the state estimation, is somewhat intuitive. As we can see in Figure 6.8, as the number of sensors increases, the error, as a percent of the range of motion, generally decreases. This hypothesis is most strongly supported by the EE with DEM and HO with E-WAM state estimation methods. For these methods, the decrease in error resembles an exponential decay. While six sensors was the maximum number of sensors we used
Table 6.2: Average segment error as a percent of the range of motion, normalized over all of the
deflection modes used for evaluation of performance. SS - Single Sensor, EE - End to End,
HO - Heuristic Overlapping, OO - Optimized Overlapping, DEM - Direct Estimation
Method, E-W AM - Non-Weighted Averaging Method, W AM - Weighted Averaging
Method.

<table>
<thead>
<tr>
<th>Sensors</th>
<th># Sensors</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS, DEM</td>
<td>Median</td>
<td>16.71</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>3rd Quart.</td>
<td>16.92</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>1st Quart.</td>
<td>16.16</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>EE, DEM</td>
<td>Median</td>
<td>-</td>
<td>8.309</td>
<td>5.423</td>
<td>4.033</td>
<td>3.178</td>
<td>2.634</td>
</tr>
<tr>
<td></td>
<td>3rd Quart.</td>
<td>-</td>
<td>8.321</td>
<td>5.465</td>
<td>4.077</td>
<td>3.212</td>
<td>2.672</td>
</tr>
<tr>
<td></td>
<td>1st Quart.</td>
<td>-</td>
<td>8.281</td>
<td>5.305</td>
<td>3.931</td>
<td>3.105</td>
<td>2.592</td>
</tr>
<tr>
<td>HO, E-W AM</td>
<td>Median</td>
<td>-</td>
<td>7.561</td>
<td>4.504</td>
<td>3.090</td>
<td>2.342</td>
<td>1.914</td>
</tr>
<tr>
<td></td>
<td>3rd Quart.</td>
<td>-</td>
<td>7.735</td>
<td>4.720</td>
<td>3.230</td>
<td>2.538</td>
<td>1.993</td>
</tr>
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<td></td>
<td>1st Quart.</td>
<td>-</td>
<td>7.277</td>
<td>4.280</td>
<td>2.878</td>
<td>2.257</td>
<td>1.784</td>
</tr>
<tr>
<td>HO, W AM</td>
<td>Median</td>
<td>-</td>
<td>1.552</td>
<td>0.262</td>
<td>0.0915</td>
<td>0.0434</td>
<td>0.0366</td>
</tr>
<tr>
<td></td>
<td>3rd Quart.</td>
<td>-</td>
<td>2.086</td>
<td>0.364</td>
<td>0.112</td>
<td>0.0538</td>
<td>0.0475</td>
</tr>
<tr>
<td></td>
<td>1st Quart.</td>
<td>-</td>
<td>1.403</td>
<td>0.181</td>
<td>0.0653</td>
<td>0.0289</td>
<td>0.0228</td>
</tr>
<tr>
<td>OO, W AM</td>
<td>Median</td>
<td>-</td>
<td>1.542</td>
<td>0.238</td>
<td>0.0836</td>
<td>0.0368</td>
<td>0.0315</td>
</tr>
<tr>
<td></td>
<td>3rd Quart.</td>
<td>-</td>
<td>2.063</td>
<td>0.362</td>
<td>0.106</td>
<td>0.0506</td>
<td>0.0437</td>
</tr>
<tr>
<td></td>
<td>1st Quart.</td>
<td>-</td>
<td>1.389</td>
<td>0.175</td>
<td>0.0427</td>
<td>0.0220</td>
<td>0.0215</td>
</tr>
</tbody>
</table>

in our experiments, we expect the decrease in error for a given continuum joint to plateau when
the number of sensors is greater than or equal to the number of segments. For example, a twelve
segment joint using EE and DEM with thirteen sensors would not be any more accurate than a joint
with twelve sensors given our assumptions. In the real world, with imperfect sensors, this may not
be true because having two sensors monitoring a single segment may allow filtering or averaging
to get more accurate information out of the two sensors than a single sensor alone.

While the trend of increasing the number of sensors leading to a decrease in error is consist-
tent across all the simulated experiments, we also noticed a steep decline in error for HO and OO
using the WAM method when going from two sensors to three sensors, with an effective plateau
in performance from four to six sensors. We attribute this plateau to the effectiveness of the WAM
method to accurately estimate the state with a smaller number of sensors. Four or more sensors
seems to add redundant information to the estimation method resulting in only minor decreases in
error.
Our second hypothesis states that by overlapping length sensors on a continuum joint, we are able to obtain more information about its configuration and therefore better estimate said configuration. Referencing Figure 6.8 again, we can see that all cases of HO or OO had lower errors than the EE placement method for a given number of sensors. This confirms that overlapping sensors does indeed allow us to more accurately estimate the configuration of the joint.

We first analyze why there is an improvement from using EE with DEM to HO with E-WAM. This is performed using the term ”region of estimation”, which refers to groups of segments on the continuum joint which are estimated to have the same deflection angle and therefore the same curvature. In a simplified example, a continuum joint with two sensors with EE placement only has two distinct regions of estimation, the segments covered by the first sensor and the segments covered by the second sensor. A continuum joint with two sensors using the HO placement has three distinct regions of estimation, the segments covered exclusively by the first sensor, the
segments covered exclusively by the second sensor and the segments covered by both sensors. The E-WAM method is essentially the DEM method but it averages the overlapping sensors that are covering a segment. This creation of additional estimation regions is what allows the HO method to have lower error than the EE method, even when using a simple estimation method such as E-WAM.

Our third hypothesis, which is the main contribution of this paper, is that a weighted linear combination of overlapping sensor data can significantly reduce state estimation error when compared to simpler estimation methods such as E-WAM and DEM. The reduction in error from HO with E-WAM to HO with WAM shown in Figure 6.8 and 6.9 is dramatic. This data is highlighted in Table 6.3. We can easily see how overlapping sensors creates additional regions of estimation with the simple estimation method E-WAM. The WAM method takes that one step further by using linear regression to derive unique sensor value weights for estimating the state of each segment, thus creating a distinct region of estimation for each segment. This means that each joint segment can have a unique estimated deflection angle with minimum of two sensor. To achieve this with E-WAM \( m - 1 \) sensors are needed, where \( m \) is the number of constant curvature segments of the joint. For example, the proximal most segment is always bent at an angle that is greater than or equal to the bending angle of the next most proximal segment. This can be expressed by the WAM method when it calculates slightly different weights for segments zero and one, even though they may be covered by the same set of sensors.

Furthermore, the WAM method allows for sensors that are not covering a segment to provide information about the robot state. By using a linear combination of all the sensor measurements on the joint, not just the ones covering the segment, WAM is able to significantly reduce the deflection angle estimation error as compared to E-WAM. For example, if the proximal segments have a sensor reading associated with a negative bending angle and the distal segments have a sensor reading associated with a positive bending angle, that information can be captured by the weights of the WAM method to determine that there will be a point of inflection in the middle of the joint and therefore middle segments will have small deflection angles in this situation.

Our final hypothesis was that an evolutionary algorithm could be used to determine the optimal placement of overlapping sensors such that state estimation will be further improved than using WAM with the Heuristic Overlap. This hypothesis is only loosely supported by the data.
Table 6.3: Table highlighting the difference in median error as a % of ROM between HO with E-W AM and HO with W AM. The bold values shown in the table highlight the improvements between the two methods being compared.

<table>
<thead>
<tr>
<th>Number of Sensors</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>HO with E-W AM Median Error as % of ROM</td>
<td>7.561</td>
<td>4.504</td>
<td>3.090</td>
<td>2.342</td>
<td>1.914</td>
</tr>
<tr>
<td>HO with W AM Median Error as % of ROM</td>
<td>1.552</td>
<td>0.261</td>
<td>0.0915</td>
<td>0.0434</td>
<td>0.0366</td>
</tr>
<tr>
<td>Decrease in Median Error as % of ROM</td>
<td><strong>6.009</strong></td>
<td><strong>4.243</strong></td>
<td><strong>2.9985</strong></td>
<td><strong>2.2986</strong></td>
<td><strong>1.8774</strong></td>
</tr>
</tbody>
</table>

Table 6.4: Table highlighting the difference in median error as a % of ROM between HO with W AM and OO with W AM. The bold values shown in the table highlight the improvements between the two methods being compared.

<table>
<thead>
<tr>
<th>Number of Sensors</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>HO with W AM Median Error as % of ROM</td>
<td>1.552</td>
<td>0.262</td>
<td>0.0915</td>
<td>0.0434</td>
<td>0.0366</td>
</tr>
<tr>
<td>OO with W AM Median Error as % of ROM</td>
<td>1.542</td>
<td>0.238</td>
<td>0.0836</td>
<td>0.0368</td>
<td>0.0315</td>
</tr>
<tr>
<td>Decrease in Median Error as % of ROM</td>
<td><strong>0.010</strong></td>
<td><strong>0.0240</strong></td>
<td><strong>0.00790</strong></td>
<td><strong>0.0066</strong></td>
<td><strong>0.0051</strong></td>
</tr>
</tbody>
</table>

collected in our simulated experiments. Since the bars in Figure 6.8 are so small, the data comparing HO and OO with W AM are highlighted in Table 6.4. There is always a reduction in error when using OO instead of HO, however that reduction is very small. We mainly attribute this to the WAM method being able to estimate the shape so accurately that it is difficult to reduce the error even further using “optimal” sensor placements. We also believe the HO placement method already provides a fairly optimal, even coverage of all the segments on the joint. The largest reduction in error observed occurs when using three sensors. We believe the benefits of OO peak at three sensors because it is when using more than three sensors with HO there is already excellent coverage of the segments and when using two sensors there aren’t many possible configurations so there is only a modest reduction in error from optimizing.

In conclusion, we have shown that state estimation of a continuum joint can be significantly improved by using the WAM estimation method on overlapping sensors which are placed on the continuum joint according to a simple heuristic. Using this method with only three sensors yielded a median joint angle error (as a percentage of the range of motion) of 0.262%. Increasing the number of sensors further reduced the state estimation error to under 0.1%. We have also shown that the simple heuristic overlap performs almost as well as an optimized overlapping arrangement.
determined by an evolutionary algorithm with the median error (as a percent range of motion), being less than 0.025% for all cases tested.

Some sources of error in this work could come from the shapes of the joints in the real world not being as ideal as the simulated ones we used for testing. This would mean that the median errors determined in this paper would be slightly higher when implemented on hardware even with ideal sensors. Even with this introduction of uncertainty, we are confident the reduction in error seen from using WAM in simulation will translate to large, real world reductions in error. A simple way to improve the estimation would be to collect test data from the hardware and perform linear regression on that data rather than simulated data. Nonetheless, future work will entail implementing these sensor placement and configuration estimation methods on hardware and testing their capabilities for a non-idealized sensor. Given noise or other possible sources of error introduced by the hardware, this will be important to prove that the approach is as effective in the real world as is predicted by these kinematic and static loading simulations.
CHAPTER 7. FUTURE WORK AND CONCLUSION

As stated previously soft robot metrics need to continue to be developed and expanded. The soft robot survey we performed can be used as a starting place for developing soft robot metrics for full systems. Metrics that also consider specific control methods can also be developed, thus allowing for better comparisons between different soft robot platforms for different tasks/applications. The soft robot actuator metrics can be extended from fluidic rotary actuators to different types of soft robot actuators including non-fluidic actuators and linear actuators. Furthermore, metrics that start to consider the dynamics of soft robot actuators need to be developed for a proper comparison of soft robot actuators. As more actuation modes (i.e., rotational, linear, twisting) and actuation methods (i.e., fluidic, electrostatic, tendon driven) are developed it will be important to develop metrics that allow for effective evaluation and comparison.

Continued development and refinement of the models and control methods used in soft robotics is crucial for the advancement of this field. Potential future work in this area includes developing more accurate pressure dynamics for the antagonistic rotary elastic chambers such as those on Kaa, King Louie or the Grub. There is currently no method to model impacts and how they affect the pressure in the chambers. Also as more soft robot actuation methods are developed, new kinematic and dynamic models that accurately describe the new methods will need to be developed. These models can then be used in model predictive controllers or other model base controllers for more precise control. Additional control methods such as Non-linear MPC, Model Reference Adaptive Control and other methods should also be explored and compared to expand the capability of soft robots.

To continue the development of the WAM method it should be tested and validated on hardware. This will include developing methods to accommodate for real world factors such as noise and other uncertainties associated with fabrication of hardware. Additional estimation methods should also be implemented for soft robot applications including Extended Kalman Filters,
Unscented Kalman Filters or even Particle Filters. These methods can use the dynamic models described above and WAM to further improve the estimate of the actual state of a soft robot.

7.1 Conclusion

In this dissertation we have shown developments in four key areas of soft robotics that are needed to build a “fundamental engineering framework”, soft robot metrics, models, estimation, and control. We demonstrated the need for soft robot metrics and laid a foundation for further development through six actuator metrics that can be used for fluidic rotary soft robot actuators. This was accomplished by demonstrating these metrics on eight different soft robot actuators with five unique designs and using the Metric Evaluation Criteria to show their efficacy as metrics.

Several developments in soft robot models were presented including a first order pressure dynamics model, an antagonistic torque model for fluidic antagonistic actuators, and a novel method for linearizing high DoF systems. We then demonstrated how these models were used in several control methods to effectively control the position and stiffness of soft robots. We also made a comparison between two control methods, MPC and input shaping, showing that while each could reduce the overshooting of a compliant robotic manipulator, the MPC controller had an overshoot of only 0.26% as compared to an overshoot of 5.80% for input shaping.

Lastly, we demonstrated a method for high fidelity estimation of a continuum joint with non-constant curvature bending. We showed that it is possible to overlap length sensors and combine them using a novel method (WAM) to achieve low estimation error. Through this method of combining measurements we achieved a median estimation error of 0.262% of the range of motion of a joint segment using 3 sensors as compared to 16.71% error with a single sensor.

All these developments combine to help make progress towards a “fundamental engineering framework” that is needed for soft robotics. These developments are also helping move robots out of their confined spaces and bring them into new unmodeled/unstructured environments. This work is a step in helping to achieve the reality of robots being able to work safely and closely with humans.
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[81] Rone, W. S., and Ben-tzvi, P., 2013. Multi-Segment Continuum Robot Shape Estimation Using Passive Cable Displacement. 119


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Soft robots were developed with different goals in mind than traditional robots and as such the traditional metrics used to evaluate standard robots are not as effective in evaluating soft robot performance. The purpose of this questionnaire is to query the robotics community on what they think are good metrics for soft robotic manipulators. The survey involves rating different metrics/measurements on their importance when evaluating the performance of robots during five different tasks. These metrics/measurements do not always inherently denote good or bad performance but can be used to define desired performance. The metrics/measurements can then be used in different ways including the design and evaluation of soft robot hardware as well as tuning soft robot controllers.
Figure A.2: Survey Page 2
Vibration Task
A task where the end effector or the base of the robot is experiencing large vibrations (e.g., high frequency and/or large magnitude) such as a sanding task shown below.

Please identify the importance of the metrics/measurements below in determining the performance of this task. In other words, an important metric/measurement is one where the performance of the task could not be assessed without it.

Metric Descriptions:
- Modes of Vibration: The modes of vibration that are excited during a given vibration task.
- Compliance at End Effector (EE): The compliance at the end effector.
- Resonant Frequency Ratio: The ratio of the resonant frequency of the manipulator to the frequency of vibration.
- Force Control: The resolution and accuracy of the force control during a vibration task.
- Compliance: The compliance of the joints and links.
- Maximum Force: The maximum possible force output during a vibration task.
- Repeatability: The repeatability of the desired action while performing a vibration task.

<table>
<thead>
<tr>
<th></th>
<th>Extremely important</th>
<th>Very important</th>
<th>Moderately important</th>
<th>Slightly important</th>
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<td>Resonant Frequency Ratio</td>
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<td>Maximum Force</td>
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<td>Repeatability</td>
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</tbody>
</table>

Are there any redundant metrics/measurements that can be eliminated or combined?

Are there any metrics/measurements that have been missed and what would their importance score be?
### Wiping Task

A task where the platform wipes a surface whether it uses its end effector or other parts of its structure. An example would be the task of cleaning a solar cell.

![Image of robot performing a wiping task](image_url)

Please identify the importance of the metrics/measurements below in determining the performance of this task. In other words, an important metric/measurements is one where the performance of the task could not be assessed without it.

**Metric Descriptions:**
- **Compliance at End Effector (EE)** - The compliance at the end effector.
- **Force Control** - The resolution and accuracy of the force control during a wiping task.
- **Compliance** - The compliance of the joints and links.
- **Tolerance about Trajectory** - The ability of a platform to stay within a tolerance while following a trajectory.
- **Reachability** - The reachable workspace of the platform.
- **Time to Completion** - The time it takes to complete a wiping task.
- **Hardness/Softness** - The hardness/softness of the surface of the platform that is making contact.

<table>
<thead>
<tr>
<th>Metric</th>
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<th>Slightly Important</th>
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</tbody>
</table>

Are there any redundant metrics/measurements that can be eliminated or combined?

Are there any metrics that have been missed and what would their importance score be?
Intentional Impact
A task where the robot is intentionally impacting something such as hammering.

Please identify the importance of the metrics/measurements below in determining the performance of this task. In other words, an important metric/measurement is one where the performance of the task could not be assessed without it.

Metric Descriptions:
- **Maximum Impact Energy**: The maximum energy transferred from an impact.
- **Maximum Force**: The maximum possible force output during an intentional impact task.
- **Strength of Links/Joints**: The maximum force a joint/link can take before deforming or breaking.
- **Compliance**: The compliance of the joints and links.
- **Maximum Velocity**: The maximum velocity achievable for a platform/mover.
- **Hardness/Softness**: The hardness/softness of the surface of the platform that is making contact.
- **Tolerance about Trajectory**: The ability of a platform to stay within a tolerance while following a trajectory.

<table>
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<tr>
<th>Metric Descriptions</th>
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<th>Moderately important</th>
<th>Slightly important</th>
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<td>Hardness/Softness</td>
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<td>Tolerance about Trajectory</td>
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</tbody>
</table>

Are there any redundant metrics/measurements that can be eliminated or combined?

Are there any metrics/measurements that have been missed and what would their importance score be?
Incidental Impact
A task where the robot unintentionally makes contact with something. This is a worst-case scenario where the robot may slip and impact the ground, another robot, or human while performing another task.

Please identify the importance of the metrics/measurements below in determining the performance of this task. In other words, an important metric/measurement is one where the performance of the task could not be assessed without it.

Metric Descriptions:
- **Hardness/Softness**: The hardness/softness of the surface of the platform that is making contact.
- **Compliance**: The compliance of the joints and links.
- **Maximum Impact Energy**: The maximum energy transferred from an impact.
- **Compliance at End Effector (EE)**: The compliance at the end-effector.
- **Disturbance Rejection**: How well a robot rejects disturbances or recovers from disturbances.
- **Maximum Velocity**: The maximum velocity achievable for a platform/controller.
- **Strength of Links/Joints**: The max force a joint/link can take before deforming or breaking.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Extremely important</th>
<th>Very important</th>
<th>Moderately important</th>
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<td>Maximum Impact Energy</td>
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Are there any redundant metrics/measurements that can be eliminated or combined?

Are there any metrics that have been missed and what would their importance score be?
Pick and Place Task
The standard pick and place task where a robot picks up an object and places it in a different location.

Please identify the importance of the metrics/measurements below in determining the performance of this task. In other words, an important metric/measurement is one where the performance of the task could not be assessed without it.

Metric Descriptions:
- Steady State Error - The steady state error from the commanded trajectory.
- Overshoot - The percent overshoot from a commanded trajectory.
- Time to completion - The time it takes to complete a pick and place task.
- Efficiency - The ratio of the output power of the actuators to the input power.
- Rise Time - The rise time for a commanded trajectory.
- Disturbance Rejection - How well a robot rejects disturbances or recovers from disturbances.
- Maximum Acceleration - The maximum acceleration a robot can achieve while remaining stable.

<table>
<thead>
<tr>
<th>Metric Descriptions</th>
<th>Extremely important</th>
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<td>Rise Time</td>
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Are there any redundant metrics/measurements that can be eliminated or combined?

Are there any metrics/measurements that have been missed and what would their importance score be?
Table A.1: Page 2: Years in Robotics

<table>
<thead>
<tr>
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Average 6.91  6.30  3.67
Table A.2: Vibration Task: Full results for the survey from the vibration task including mean and standard deviation (STD).

<table>
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<tr>
<th>User</th>
<th>Modes of Vibration</th>
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<th>Force Control</th>
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Table A.3: Wiping Task: Full results for the survey from the wiping task including mean and standard deviation (STD).

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Mean: 2.14 2.76 2.76 2.76 3.00 2.70 2.80
STD: 1.06 0.94 0.94 1.14 0.79 0.80 1.01
Table A.4: Intentional Impact Task: Full results for the survey from the Intentional Impact task including mean and standard deviation (STD).

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Mean | 3.58 | 3.32 | 2.84 | 2.74 | 2.84 | 2.79 | 2.74 |
STD  | 0.69 | 0.75 | 1.12 | 1.28 | 0.90 | 0.79 | 1.15 |
Table A.5: Incidental Impact Task: Full results for the survey from the Incidental Impact task including mean and standard deviation (STD).

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Table A.6: Pick and Place Task: Full results for the survey from the Pick and Place task including mean and standard deviation (STD).

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