**LITERATURE REVIEW**

Charles DeLorey

CID: 01965560

1. **Introduction and Problem Statement**

Robots made of soft materials have been part of the robotics domain for the past few decades. As their uses and advantages become more well known, so too has the need for innovative robotics sensing and control systems increased. In areas such as prosthetics and minimally invasive surgery (MIS), rigid-body robotics is the state of the art. Recent developments in soft robotics have enabled better sensing and control, which is slowly moving soft robots into a popular area of robotics research. This is also revealing many avenues where soft robotics may be applied to improve upon the situation of the field currently maintained by rigid-body robots. The following literature review presents related work in soft robots (specifically applied to the relevant subdomains of prosthetics and MIS), along with control and sensing methods for soft robots. Electrical impedance tomography (EIT) is presented as a promising sensing modality for soft robots. The review then details a project plan in which a soft robot actuator will be implemented with a closed-loop control and EIT sensor subsystem. It will then be evaluated to assess the performance of an EIT-based soft robot actuator.

1. **Soft Robotics**

Soft robotics is a specialization in robotics using soft and flexible materials. Though the term “soft robot” was first used in an article on soft actuators from 1990, there have in fact been soft robotic systems designed since the 1950s [1] . It must be addressed, however, what the precise draws are for soft robots. With the advancements of fabrication and 3D printing technologies, it is possible to create articulated or otherwise agile robot manipulators using stiff materials [2]. Indeed, there are many segment-based articulated robot manipulators deployed specifically in medical applications [3]. They can also be made using biocompatible materials, so what precisely makes soft robots so appealing? The compliant nature of the materials that make up soft robots is what defines them as “soft” and is what enables their key feature: a gentler interaction with objects and the environment. This is of course desirable as soft robots are safer than rigid-body robots in scenarios where the robot must not exert undue forces [4], such as in human-robot interaction (HRI) and MIS. Since the materials used in soft robots comply with objects, they are also better at object grasping tasks [4].

Soft actuators have also been applied to wearable technologies, where the device must be comfortable to use and actuate in a way that will not be harmful to the user. Rehabilitation and assistive devices using pneumatic soft actuators have been developed to restore hand functionality to the wearer [5]. On a larger scale, soft robot exosuits are being developed for rehabilitation to restore mobility to individuals with muscle or neurological diseases, as well as military applications to improve the performance of soldiers carrying heavy weight [6]–[8]. Soft or compliant materials are ubiquitous in nature, with examples of soft manipulators found in animals like octopus and earthworms. These soft robotic systems are made of compliant materials which allow for actuation based on pneumatic, hydraulic, or mechanically underactuated systems, depicted in Figure 1. In the animal world, soft mechanical systems in animals have evolved over many years to be energy-efficient and to be able to adapt to different stimuli [9]. A recent development in 3D printed soft robotics is 4D printing, whereby materials or subsystems are incorporated into the print itself [10]. Figures 1 and 2 show soft actuation methods and examples of soft robot manipulators in various applications, respectively.

Diagram

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Figure 1: Four actuation methods in soft robotics. (a) transverse tensile actuation, (b) longitudinal tensile actuation, (c) pneumatic artificial muscle, and (d) fluid elastic actuator. Image from [4].

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Figure 2: Example soft robots, including multi-fingered grippers (a, d, e, g), continuum robots (b, f, h), granular jamming gripper (c), and a soft rehabilitation glove (i). Image from [4].

* 1. **Prosthetics**

Applications of soft robotics in prosthetics are especially enticing, as they offer a delicateness that rigid-body robots are not always able to attain. Also, they generally have fewer heavy or cumbersome parts (reducing carrying weight) and in many cases simplify the grasping procedure for a given object. A rigid robotic hand would need additional sensor capabilities to dynamically regulate the forces it applies, which is necessary if interacting with delicate objects or humans [11]. The additional force sensors add to the weight of the device. On the other hand, a soft prosthetic would result in safer interactions, and significantly reduce the number of sensors and subsystems housed in the hand [11]. Common actuation methods include pneumatic, hydraulic, and cable driven. In [11], a low-weight soft prosthetic hand was developed using an underactuated cable design, with potentiometers on each shaft to measure position. While an effective design, it does not fully leverage the compliant material from which the hand is made. In contrast, some animals have a combination of soft and more rigid materials which when inflated in particular ways create different shapes, thus enabling more complex multidimensional movements [12]. Enabling soft actuators to be designed directly for their intended purpose(s) allows for more creation of 3D printed shape-changing actuators, fitting within the aforementioned 4D printing [10]. Perhaps beyond the scope of the sensing portion of the project, multiple soft manipulators have been designed with solid sensing capabilities. [13] presents a soft gripper with integrated sensors for detecting not just force, but proprioceptive, temperature, and haptic feedback as well. The gripper is capable of recognizing when an object it holds is being disturbed, however the sensing methods used do not provide much information for each actuated finger. For example, a rough understanding of where an arbitrary length of the actuator is relative to the base. In prosthetics, ample dexterity is important to make the device as natural and unintrusive to use as possible for the patient. Proprioception, the awareness of one’s body, is another feature lost in prosthetics but reclaimed using a learning algorithm and integrated sensors [14]. Design of the fingers and fingertips to increase surface area and maneuverability enables certain grasping configurations [15]. Furthermore, [15] demonstrates a finger configuration which can manipulate an object while holding it, something a biological hand would be capable of; however, their design focus is a 4-finger cross arrangement, not anthropomorphic. [16] presents an anthropomorphic soft prosthetic hand design that incorporates the soft finger joints into the design itself, to mimic the degrees of freedom (DoFs) found in human fingers. To improve the performance of a pinch grasp, 3D printed fingernails and small bumps on the index finger and thumb are added for increased grip [16].

* 1. **Minimally Invasive Surgery**

Soft robots in the medical field find themselves in MIS for many different purposes, taking different forms: continuum robots, with an “infinite” number of joints, akin to an octopus tentacle; peristaltic robots, which move via an “inching” procedure like earthworms; and indeed, serial robots with made up of links and joints [17]. The latter behaves like a standard rigid-body robot, except the links can be stiffened or softened, enabling further compliance. One prominent example of such technology is the STIFF-FLOP project, a MIS soft serial robot with variable stiffness accomplished by granular jamming in individual segments making up the length of the robot [18]. This was one of the first robot systems to leverage stiffness to improve functionality in confined MIS scenarios, by enabling individual segment stiffening for retracting tissue in the region of interest. Many other systems have since been developed around variable stiffness in surgery, including iterations on the segmented variable stiffness design from STIFF-FLOP [19], each using different methods to mitigate the drawbacks associated with the technique. Instead of a jamming medium, materials with shape memory capabilities are used to direct the robot’s form [20]. Similarly, intricate cable-driven robots using unique joint designs enable accurately controlled manipulator motion, readily applicable to MIS [21]. Also, magnetic fields have been used to precisely control the end effector of a MIS robot [22]. For tasks requiring deployment *in vivo*, devices have been made that can collapse and expand once in the region of surgical interest [23]. Haptic feedback, a large area of research in MIS, applies sensor systems to augment the surgical experience during Robotic MIS (RMIS) [24].

1. **Control Systems for Soft Robots**

Controlling a rigid-body robot is relatively straightforward, as the design of the robot can be reduced to a series of links, and the target location has 6 degrees of freedom (3 translational, 3 rotational). Soft robots do not follow these same mechanics and dynamics, meaning new sensing and control methods must be developed. As a system such as a continuum robot can be thought of as having infinite degrees of freedom, control schema must make certain assumptions regarding the robot, which can be provided either through training or from a model of the robot [25]. An important distinction to be made is where the control comes from. The two groups of control methods are model-based or analytical controllers, and model-free or data-driven controllers [25]. The following sections describe the differences between the two and present their advantages and disadvantages.

* 1. **Model-Based Control of Soft Robots**

In soft robotics, model-based controllers (also referred to as “FEM in loop”) are the most ubiquitous for their reliability and ease of use [25]. FEM in loop models can approximate physical robots, even those comprised of multiple different compliant materials [26]. This modeling approach has excellent scalability in the number of sensors or DoFs used for a particular application. Additionally, it handles changes to the design better than model-free approaches, in which you would need to start all over. Assuming the problem is well-defined and not likely to change, it is even possible to apply models which are not a soft manipulator [27]. Though it will be discussed in the next section, machine learning (ML) methods can be applied to model-based approaches. [28] presents a reinforcement learning (RL) agent which learns a closed-loop control policy from open-loop control policies generated by a supervised learning neural network being provided ground truth closed-loop actions. The closed-loop policies are then applied to a model as well as a physical robot for validation. Neural networks have also been used to map states and inputs to outputs, able to create a model-based controller for nonlinear models of soft robots [29].

* 1. **Model-Free Control of Soft Robots**

In contrast to FEM in loop, controlling a soft robot through a data-driven approach is not as common. The unpredictability inherent to soft (and/or not fully actuated) robots means it is difficult to produce a robust and reliable controller [25]. However unlike model-based, data-driven approaches are much simpler, and for many purposes a model-based controller may be an unnecessary simplification of the problem. Model-free approaches also lend themselves to fabrication methods which use novel actuation methods [30]. As seen in the previous section, ML methods such as neural networks are effective when trying to make sense of the large quantities of data produced by a soft robot. In [31], a neural network is used to describe the kinematics and track the trajectory of a continuum robot, all without knowing the kinematics of the robot. Model-free approaches have even been applied to mobile multi-limbed soft robots, as they can be used to learn high level robot locomotion controls, instead of the low level and difficult kinematics required to move a soft robot [32]. While model-based approaches may have difficulty with semi-soft robots, or articulated soft robots (ASRs), a model-free approach still does not need a lot of knowledge of the robot in order to develop a control scheme [33]. ML-based or data-driven controllers are what are applied to the 4D soft robots discussed in [10], where the integrated sensors are well suited to dynamic closed-loop controllers but could use a model-based controller instead.

Both model-based and model-free approaches produce robust soft robot controllers, the exact choice and parameters being determined by the complexity and variables of the problem. For prosthetics applications, both approaches offer clear benefits: the adjustability of model-based versus the simplicity of model-free.

1. **Electrical Impedance Tomography**

In electrical impedance tomography (EIT), known voltages and currents are applied between an arrangement of electrodes, and the conductivity of the space and material between them is found [34]. This technique has applications in fields as far from medicine as geophysics [34]. EIT is attractive for clinical applications due to its non-invasive nature, lack of radioactive agents, and real-time imaging capability. Figure 3 below depicts a simplified EIT test environment, where the yellow ovals are being detected in the light blue conductive medium using current injected from the left, and voltage detected on the right.

Diagram

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Figure 3: Simple example of EIT, showing the current injection, objects in conductive medium, and the measurement electrodes. Image from [35].

EIT systems benefit from hardware and software that enable high resolution data acquisition, as well as functionality for different imaging targets [34], [36]. For the purposes of imaging, it is the inverse EIT problem which is used. The inverse problem is the reconstruction of detected objects from signals measured on the electrodes. Figure 4 below shows an EIT reconstruction image, an application of EIT for real-time lung monitoring in pediatrics [37].

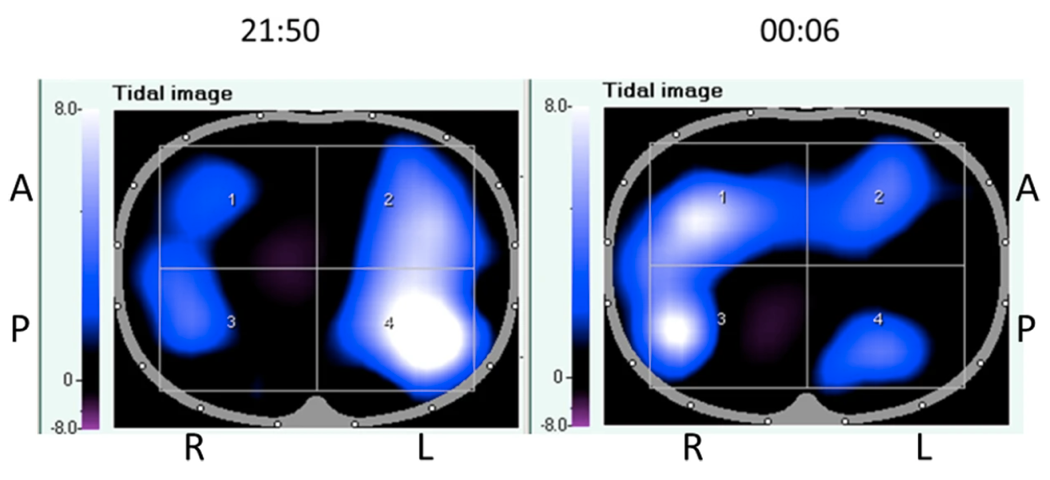


Figure 4: EIT images from a pediatrics patient, showing sequential lobar collapse. The brighter the image, the greater the impedance change. Images from [20] [37].

EIT has been applied as a flexible sensing method for its noninvasiveness, biocompatibility, together with the ability to use any electrically conductive material as a sensor. This sensing technique is particularly attractive in soft robotics as it is able to function well in soft materials, and in systems with large deformable surfaces. Additionally, the materials used in EIT are low-cost and generally compatible, as the fluid medium can be a simple saline solution. Other soft or flexible sensors have been developed using different materials. Optical fibers have been used, however due to their linear nature they are best applied in continuum robots [38]. Sensors based on the variable resistance of stretched metal have also been investigated, however their materials not necessarily suitable for medical soft robots [39]. The advantages of electrical impedance tomography over other sensing methods is its low cost and material requirements while having great applicability and range of sensitivity [35]. For example, EIT has been investigated as a modality to produce a malleable touch sensitive sensor, to create a “skin” for a robot [35]. Similarly, [40] presents and evaluates an EIT-based artificial skin, which is able to detect differently sized objects as well as perform on a curved surface. It is in these kinds of relatively larger surface area applications where EIT is able to perform better than flex or bend sensors, making them better suited to surface-concerning sensing in soft robotics. Moreover, EIT has been applied to MIS for sensing size and stiffness of tissue regions of interest [41]. Of course, since the material through which EIT is performed can be a fluid, this enables an EIT sensor system to bend and flex along with the actuated portions of soft robots. With such a design, EIT-based sensing of any size and region could be attained, with only the EIT elements [42], [43]. Just as EIT can sense touch, it can also sense deformation of a structure into which it is incorporated. EIT can be applied to problems where the boundaries of the area in question are not static and therefore must be compensated [44]. More recently, this technique has been applied to soft robotic actuators and was able to produce EIT images of their movement [45]. Despite the benefits, EIT does have some disadvantages. It does not provide exceptional spatial resolution, nor can it represent the difference between an area of touch and the pressure applied to that area [35]. Nevertheless, EIT remains a promising and relatively unexplored sensing modality in soft robots.

1. **Project Plan**
   1. Describe in detail the intended actuator for this project.
      1. Finger-sized and shaped actuator with integrated electrodes for EIT sensing. Possibly with an integrated force sensor to provide detailed grasping or touch feedback.
   2. Experiment with electrode placement for optimal EIT readings of actuator.
      1. Using EIDORS and/or through prototyping a simple actuator, identify optimal placement and solidify actuator design and purpose.
   3. Develop closed-loop control of the actuator, using a model-free approach.
      1. Acquire optical tracking data of actuator as ground reference data points.
      2. Create machine learning closed loop control to learn relationship between electrode readings and actuator angle/movement.
         1. The shape of the deforming actuator will make voltage changes, which will then produce a distinct EIT image.
         2. *To be determined*: whether the voltages alone will be enough as inputs to the ML agent, or if the EIT images will be necessary.
         3. *To be determined:* whether different ML algorithms or techniques improve the performance of the controller.
   4. Test actuator and control system.
      1. Evaluate actuator capabilities:
         1. Mechanical limits
         2. Reaction speed
         3. Strength
         4. Sensitivity
      2. Control loop capabilities:
         1. Speed
         2. Resolution
         3. Number of actuators that can be controlled at once
   5. If feasible within the scope of the project, assemble a multi-fingered gripper using the newly created actuators and evaluate its mechanical performance as well as performance of the closed-loop control approach devised in C.
2. **Methods**
   1. The EIT data acquisition will be accomplished with a power source and sensing electronics, following the system detailed in [21] [36].
   2. Fabrication of the compliant material will be completed using a 3D printed mold to cast a flexible and biocompatible medium such as silicone. Preliminary prototypes will likely be made using a material that is easily formed into the desired shape, such as laser-welded thermoplastic.
   3. To acquire image data, a computer vision system using MATLAB will be devised and allowed to get as much data as possible from the actuator. A closed-loop controller, likely a Python-based machine learning algorithm (implemented with Scikit-learn [46]) will then use this data and the EIT data from the actuator to create a learned model of the robot.
   4. To validate this system, both the physical robot and the EIT sensor system driving it will be interrogated as to their robustness and their exact functionalities in actuating and measuring deformation, as well as simple grasping tasks.

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