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Simulation, Design and Control of a Soft Robotic Arm with Integrated Bending Sensing

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Abstract— **The utilization of soft robotic arms/fingers, which are inherently safe and passively compliant, has been an active research area in robotics. This paper studies a rigid robotic arm and compliant soft gripper with integrated sensing and control for use in object manipulation tasks. A brief outline of the method used to implement the approximate soft mechanics of a compliant gripper within the rigid-body simulation of Gazebo [1] is described, followed by the implementation of the embedded strain sensors required for the sensing of the soft gripper within ROS [2].**

A further method of soft gripper pose estimation, making use of the embedded sensor readings and a model-based approach, is then described, and implemented, within ROS and evaluated to gain an approximate understanding of how the method performs within a simulation environment and possibly in real use cases. Many avenues for further research may stem from this project, including further evaluation across wider use cases, additional systems built upon the pose estimations acquired and whether the method is feasible in real use cases when used in conjunction with a physical gripper.

I. INTRODUCTION

A. Why soft robotics?

Currently, within the robotics domain, there is a large amount of interest surrounding the research, development, control and applications of soft robotics. Soft robotics can provide many benefits over their conventional, rigid counterparts due to their inherent compliance and adaptability towards unknown environments.

Soft robotics revolves around implementing flexible materials and compliant actuation methods into a design. Traditionally, rigid materials such as metals and hard plastics with moduli in the range 10^9–10^{12} Pa have been used [3] in conjunction with rigid actuators to perform fast, precise and repetitive tasks [4] with high degrees of stiffness and have found use in many applications [5]. Alternatively, soft robotics aims to use flexible materials (silicone, rubber), with moduli comparable to biological materials in the order of 10^4–10^9 Pa [3], [6] in order to create machines that are compliant by design [7] such that they can easily deform while remaining mechanically resilient [6]. The advantages of such characteristics allow the robot to be equipped for unpredictable situations by embedded adaptability, not into the control systems, but rather the material properties and structure of the body itself [4]. This allows soft designs to adapt to their environments more readily without the need for complex sensing and control systems [7] and is particularly useful in simplifying grasping operations [3]. The flexible structure can passively adapt to objects being handled [7] and improve interactions with soft materials [1] while still maintaining the ability to apply significant force [6] as well as allowing safer human-robot interactions due to their soft structure [3], [7], [8]. The simplifications soft robotics require in sensing and control lend themselves to low-cost and inexpensive manufacturing [7]–[9] which can be further reduced as, for many grasps, only one degree of actuation is required [7] due to the infinite degrees of freedom the soft structure provides [5]. With these advantages, the field of soft robotics has many applications, but in regard to soft robotic arms and grippers involved in this paper, they lend themselves to applications requiring interaction with delicate and variable geometries such as surgery, healthcare, delicate pick-and-place scenarios, and human-robot interaction in industry [4], [9], [10].

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B. Sensing and Feedback

While considerable research has been focused on the construction and actuation of soft robotics, there still exists a substantial challenge in embedding and utilising sufficient feedback to fully realise the potential benefits through the use of these compliant manipulators.

In order for soft robots to expand their capabilities, the use of embedded sensors is needed to allow for position and force feedback that can then be used to develop efficient control systems. Making use of feedback sensors can enable control systems to potentially obtain more information about the environment, improve reliability, detect targets as well as improve control when handling fragile objects with the use of tactile force sensors [6], [10], [11].

Embedding sensors within soft robotics continues to be a significant challenge as the sensors themselves must not hinder the compliance and mobility of the gripper and so most conventional methods used in rigid robotics are no longer viable [6], [12]. [3] highlights some of the ways in which soft sensors have been developed for integration with other soft materials to various degrees of success but in recent years, the development of 3D printable filaments that are both flexible and conductive has enabled new production techniques to be employed. [11] made use of both conductive and non-conductive TPU filaments to build a gripper with fingertip strain sensors that can be used for tactile feedback which allows both the position on the gripper and magnitude of the exerted force to be read. Meanwhile, [10] made use of directly 3D printing embedded strain sensors [13] within the length of a 3D printed pneumatic gripper to give feedback

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on the curvature of the finger. Both of these implementations [10], [11] highlight the two predominant feedback types being utilised, namely tactile and curvature feedback. This paper focuses on the later feedback type and attempts to use such curvature feedback to predict the shape and pose of the given gripper by utilising a model-driven approach.

C. Simulation

While easily accessible and performant solutions exist to simulate rigid robotics alongside their control systems, this is not the case when utilising soft components. Through the integration of compliant actuators and sensors within these existing rigid simulations, further rapid prototyping, development and verification of soft robotics and their control systems can be more easily undertaken to create more advanced systems that can fully utilise the many benefits that soft components can provide.

The FEM (Finite Element Method) has been used to accurately simulate soft robotics previously [5], [14] and the SOFA [15] (Simulation Open Framework Architecture) toolkit has successfully been used to accurately simulate soft robotics as shown in [14]. Despite this, there are a few issues highlighted in [5] that suggest this approach may not be suitable for this work, one of which is that integrating both rigid and soft robotics within the same simulation environment can be difficult to achieve. Furthermore, the use of rigid body approximations require less background knowledge in material science and can run much faster [14] so are likely a better choice for interactive task manipulation simulation whereas a FEM approach may be better suited for actuation design and verification [5].

As such, an implementation of such compliant systems within ROS and Gazebo, two widely used platforms for rigid robotic simulation and control, that can simulate the soft characteristics of these interactions, to a degree of accuracy for task simulation, would prove useful for more accessible compliant robotics simulation and can make use of the work presented in [5].

II. Implementation

A. Simulation

A similar approach to that used in [5] was used to simulate the soft mechanics of a gripper. This requires each finger of the gripper to be segmented into a number of pieces, each connected via a compliant joint, modelled through the use of a physics plugin for the Gazebo physics engine to simulate the mechanics of an in-extensible pneumatically actuated soft gripper.

Firstly, finger segmentation is achieved by including a custom ‘finger’ component within the URDF (Unified Robot Description Format) file that can be parsed before the simulation is started. The component contains information about the geometry, characteristics and number of segments the finger should utilise. The parsing script then segments the finger, interpolating the geometry and characteristics along the length of the finger, with the number of segments being user defined such that the simulation is accurate and stable enough for task simulation while being suitably performant. 12 segments were utilised through the use of this project to give a good balance between these two requirements on the used system.

Once generated, each joint relating to a soft finger required the soft physics characteristics to be applied at every simulation time-step. This required a physics plugin that could directly interact with the Gazebo physics engine to alter the behaviour of these specific joints. This plugin is called to update once per time-step and iterates through all the soft joints and applies an opposing spring force following Hooke’s Law (1), the same as was used in [5], to simulate the spring forces within the elastic material that the gripper is composed of. While this assumption of a linear relationship between force and displacement may not hold true for real printed grippers due to differing geometries and materials, this plugin could still be utilised to apply an opposing force following any curve, whether that is modelled or determined experimentally.

$$F = Kx \tag{1}$$

B. Sensing and Feedback

To provide feedback for the soft gripper within the simulation, sensors needed to be added to the fingers in order to expand the capabilities of the gripper and control systems. As such, a ROS node was developed that can receive the joint states from the simulation and provide simulated strain sensor readings that can be passed to the gripper control node for further use.

When the simulation joint states are received within a ROS node, it simply states the angle of each joint, not the 3D position. This means forward kinematics were required to iterate through the joints and determine their positions. Once the positions are determined, a point can be placed on the path for each strain sensor, each side of the joint along its normal, as can be seen in Fig. 1. Alternatively, a single side may be required to utilise strain sensors if the opposing side is constrained such that it cannot extend, and as such, its length is always known, as demonstrated in [12]. Finally, in order to get a strain value, the distance between the points along each sensor’s path is totalled and divided by the resting distance to get an extension ratio. In this case, a simple linear relationship between extension and the sensor’s reading is used but this could be altered to follow the curve of an experimentally determined strain sensor response.

C. Pose Estimation

In order to extend the functionality of the soft gripper, the feedback given from the strain sensors must be interpreted. As mentioned previously, there have been many ways in which the free-bending curve can be determined from the strain sensor readings using experimental results to fit regression or neural network models. While this can be useful for simple object detection, more complex curvatures, when

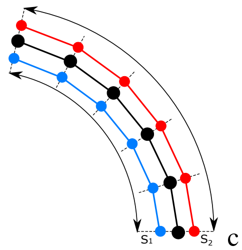


Fig. 1: Layout of strain sensors along each side of gripper joints and links Black=Simulation Joints, Red/Blue = Points along strain sensors path.

the gripper is no longer in a free-bending situation, struggle to be accurately modeled with this method.

With this in mind, an investigation into a model-based approach, in which the gripper fingers are approximated to the arc of circles rather than the data-driven approaches mentioned, was undertaken. This method was shown in [12] when estimating the size of objects where the approximation would extend well to the use case, given the spherical object shapes, and produced repeatable and accurate results. Whether such success would transfer to a more general use case was largely unknown and, while there was no strong evidence of this approach being utilised in more general cases previously, initial results were promising and so further investigation into the applicability of this method was undertaken.

The first stage in this approach is to calculate the length of each strain sensor from the strain value given. In this case, as they are modeled with a linear response, this simply requires multiplying by the known resting length as shown in (2).

$$length = strain \times restLength \tag{2}$$

Fig. 2 shows the problem to be solved with the corresponding two strain sensor lengths. Note the necessity for a known distance between the strain sensors in the bending plane, shown as Δ_R.

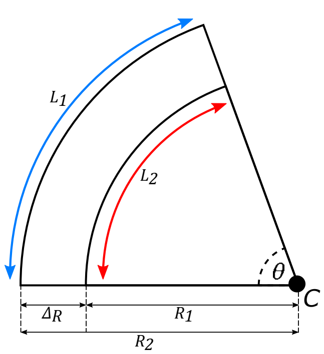


Fig. 2: Visual representation of double arc representation. Both radii and arc angle can be derived from the two arc lengths and the known radius difference.

$$R = l \times \theta \tag{3}$$

Given that both arcs share the same angle θ, the same centre C and are a known distance apart Δ_R, with the use of the equation for an arc (3), the radii and angle of each arc can be calculated as follows:

$$R_1 = L_1\theta$$

$$R_2 = L_2\theta \quad while \quad R_2 = R_1 + \Delta_R$$

$$\theta = \frac{R_1}{L_1} = \frac{R_2}{L_2} = \frac{R_1}{L_2} + \frac{\Delta_R}{L_2}$$

As such, when solved for R_1 we reach the equation:

$$R_1 = \frac{L_1\Delta_R}{L_2 - L_1} \tag{4}$$

While R_2 can easily be found due to the known Δ_R

$$R_2 = \frac{L_1\Delta_R}{L_2 - L_1} + \Delta_R \tag{5}$$

Finally, with both R_1 and R_2 now known, θ can easily be found as follows:

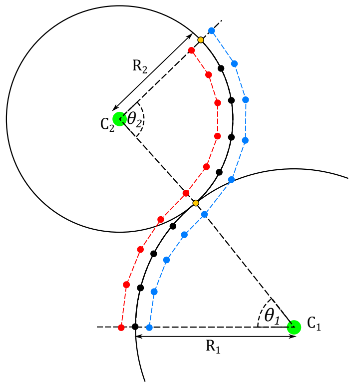
$$\theta = \frac{R_1}{L_1} = \frac{R_2}{L_1} \tag{6}$$

Given that the angle of the finger's base is also known from the rigid attachment point, the position of the arc center can be found by following the normal vector for the known radius to find point C also shown in Fig. 2.

Now the center of the arcs, the arc angle and the radii are all known, the finger can be plotted to follow the curve through the middle of these two arcs. Furthermore, given the simulation uses discrete joints separated by a known link length, the estimated joint positions can be re-mapped onto the curve such that the error between the estimate and ground truth can be calculated along the length of the whole finger and not just the fingertip position.

As will be highlighted in the results for this paper, this method worked very well in free-bending scenarios and gave good results when compared to the simulation ground truth. While this was a good step, this could also be achieved with a data-driven approach and still had the same pitfall as it would fail to estimate accurately when the gripper was in contact with objects and no longer free-bending or deviated from an arched trajectory. Further expansion of this method was needed to give accurate results when the gripper was no longer in a free-bending situation. This was achieved through the use of multiple sensors along the length of the finger, each of which could estimate another arc section around another center and, by concatenating these arcs, a more intricate and accurate estimate could be obtained, even when being deformed due to contact with objects and external forces. Fig. 3 shows how simply splitting the finger into two sections can allow for opposing curvatures to be modelled while additional splitting can continue to improve the accuracy.

With the additional sensors, there is a compromise in additional connections, more complex construction of the finger and more computational cost in estimating the pose.



c

Fig. 3: Demonstration of using multiple strain sensors to model finger from multiple arcs allowing for opposing curves as well as varying radii to be modelled.

The evaluation phase covers the benefits of additional sensors, which in a simulation environment have negligible negative effects, and highlights the potential improvements in accuracy that may be achieved that, during real use, may be unnecessary and cause more complications in the construction of the gripper.

D. *Force Estimations*

Given the position estimations can now be determined, the next stage is to calculate the force being exerted along the length of the gripper. This is done by first, predicting the position of the gripper assuming it is free-bending, and as such, only the spring forces are opposing the pressure. As mentioned previously, Hooke's law is being used to model the spring forces applied by the material's stiffness and so this can be rearranged to solve for the displacement given the known input pressure and spring constant (7).

$$x = \frac{F}{K} \tag{7}$$

With this, the predicted displacement of each joint in the finger at the applied input pressure can be compared against that observed from the estimated finger shape. If an external force is being applied to the finger, the difference in displacement can be used within the original Hooke's Law equation to calculate this, therefore the force exerted by each joint within the finger can be calculated. It is worth noting that this effectively predicts the grasping torque being exerted along the length of the finger to the rest of the finger, not the contact force being applied to the grasped object directly. The final result of both the pose and force estimation can be seen in Fig. 4 where one side of the gripper is free-bending while the other is being obstructed resulting in varying and opposing radii along the length of the gripper, requiring multiple strain sensors and arcs to reconstruct the pose.

E. *Control*

The ability to estimate the pose of the gripper as well as the forces being applied externally provides suitable feedback channels that can be used by further control systems. To

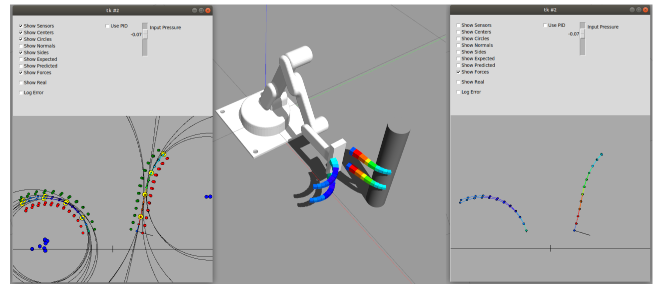


Fig. 4: Demonstration of pose and force estimation outputs. Central window shows the simulation window, colours represent force being applied along the fingers. The left shows the estimation outputs with detailed visualisation of the underlying construction method, right shows the same estimations without the additional visualisation, simply the estimated pose and same colour mapping to represent the applied force.

demonstrate this, a PID controller was integrated that could control the input pressure to the gripper in order to maintain a target distance between the fingertips of the gripper. This would be useful in many pick and place operations where delicate objects should not be grasped too heavily or to confirm the gripper is opened completely before attempting to grasp an object. Due to the elastic nature of the gripper, the controller had to be carefully tuned in order to dampen any resonance. If the controller is not dampened enough then the gripper would continue to oscillate around the target setpoint, possibly indefinitely, while if the system is over-dampened then the controller would not reach the setpoint or take too long to reach it.

There are countless other ways in which the pose estimation feedback produced could be interpreted and used for much more complex tasks far beyond what has been shown, much of which is unfortunately beyond the scope of this paper.

III. EVALUATION

In order to evaluate the applicability and potential use cases of this pose estimation method, a variety of scenarios, some of which are purely demonstrative and others corresponding to real use cases for such a gripper, were constructed and run through to assess the performance of the predictions. As was mentioned during the implementation of the finger pose estimation method, by utilising multiple strain sensors along the length of each finger, the estimation can predict a curvature of varying radii to best fit the real pose. To address this factor, each scenario is run with 1-4 strain sensors along the length of each finger to further analyse how the number of sensors affects the estimation accuracy with some interesting results.

Two numerical outputs will be given from the tests. Firstly the error in fingertip position (Fingertip Error) between the simulation ground-truth and the estimated position will be used as this will be a useful metric to analyse the potential for use within pick and place situations as well as for object manipulation where a precise, more dexterous and sensitive approach is needed. Secondly, the average error for all joint positions along the length of the finger (Pose Error) will be used to determine how well the estimation matches the curve and shape of the gripper, not just the position at the tip, which will be useful in power grasping scenarios such as pick and place uses where less dexterity is needed but a more secure and firm grip is needed. The accuracy in which the pose of the gripper can be estimated during these grasping scenarios is important as it could allow for further advancements in soft gripper controls such as size and shape detection of the grasped object.

When measuring the pose error a mean absolute error metric was used to give an average error in millimeters for the joints in the finger. Furthermore, due to slight instabilities in the simulation, the timestep of the physics simulation was decreased to improve the consistency of the measurements while each position was held across 100 samples and averaged to give a much more representative value.

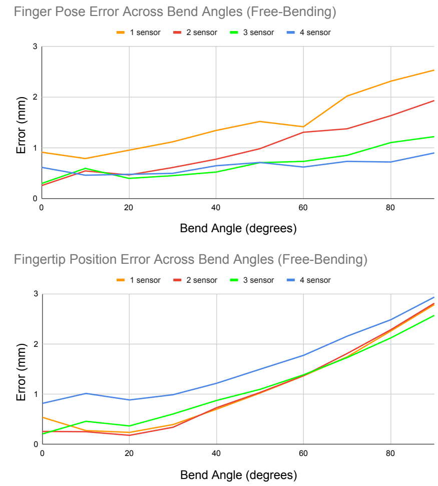


Fig. 5: Free-bending results, top graph shows the average error for the whole finger while the lower graph shows the error of the fingertip.

A. Free-Bending Tests

The first scenario is simply the gripper in a free-bending scenario and the results can be seen in Fig. 5. As can be seen from the top graph, when estimating the pose of the finger from the strain sensor readings, each joint position can be estimated to within 3 millimeters with just a single sensor while additional sensors improve the accuracy of this reading, although the difference between 3 and 4 sensors appears to be less significant. When looking at the error in fingertip position estimations, the number of sensors appears to have little effect on the accuracy and a higher number appears to be slightly detrimental at lower bend angles. This is possibly because, in free-bending scenarios, the finger curvature very closely follows a circular shape and as such, even a single sensor can approximate this well, as was the case in [12], meanwhile, with an increased number of sensors, the cumulative error is increased at lower bend angles where little force is being applied to each segment of the finger and the simulation is slightly less stable.

While these results are useful, this was still possible with a data-driven approach and so further tests are needed to show the sensor in contact with objects to assess the accuracy when being deformed externally.

B. Obstructed and Object Manipulation Tests

Four further test scenarios were created, two of which are demonstrative with a static object blocking either the inside grasp of the gripper or the outer extension of the gripper. The other two represent a simple grasping operation that may occur in a pick and place operation, one of a box shape and another uneven and non-uniform object. As the objects will be obstructing the motion of the gripper, the bend angle cannot be used so the input force is used instead. This gives a good representation of the accuracy over various poses as at lower inputs, the curvatures in the finger are shallower while, as the force increases, the gripper deforms to the surface of the object more and so a greater variation in large and small radius curvatures are seen.

The pose error tests can be seen in Fig. 6 while the errors in fingertip position can be seen in Fig. 7 showing some significant results.

Clearly, the use of a single strain sensor is insufficient to reconstruct the pose or fingertip position of the gripper with this method once it is deformed away from a circular shape by an obstruction. Interestingly, the difference in accuracy between 2, 3 and 4 sensors is much less significant in both metrics and so, given the additional complications including each additional sensor, certainly shows that the number of sensors should be strongly considered in relation to the application.

While the most significant improvement can be seen by moving from a single sensor to 2 sensors, a 4mm improvement in average pose errors and a 6mm improvement in fingertip position error can still be achieved by utilising 4 sensors over 2. This demonstrates that the increased resolution still provides a use but with diminishing returns when accounting for the increased complexity but may, nevertheless, be vital where maximal precision is required.

All four graphs are scaled equally to better highlight the difference between scenarios and can be seen during the testing in the screenshots shown in Fig. 8.

IV. Conclusion

The implemented soft gripper and corresponding control systems provide a system that is capable of task simulation, utilising the inherent compliance, adaptability and improved grasping capabilities of soft grippers for pick and place operations. Furthermore, extended sensing capabilities, in the form of simulated strain sensors, have been embedded within the simulated soft gripper to provide additional feedback with which investigation into advanced control systems could take place.

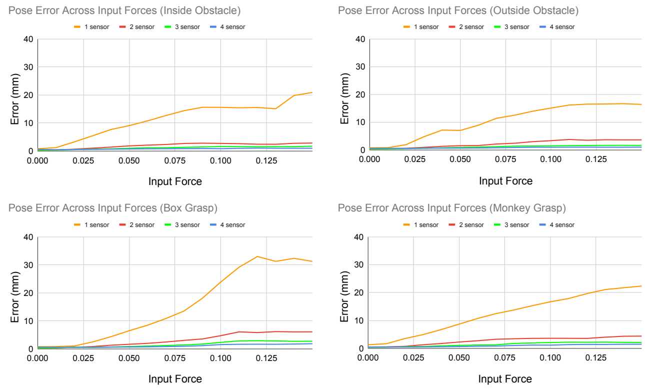


Fig. 6: Pose error results across varying scenarios showing similar trends, crucially, the necessity for at least 2 sensors to estimate the pose when the gripper is deformed externally.

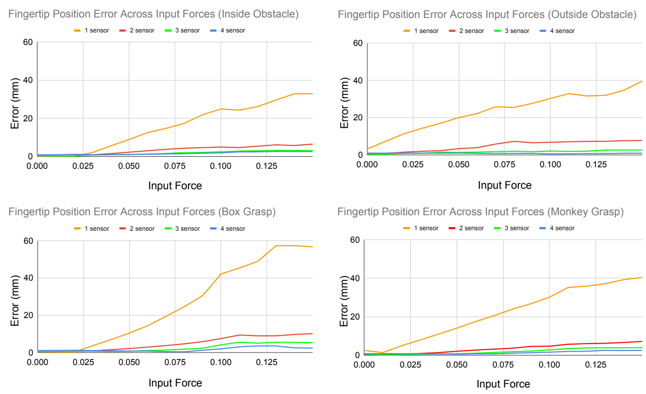
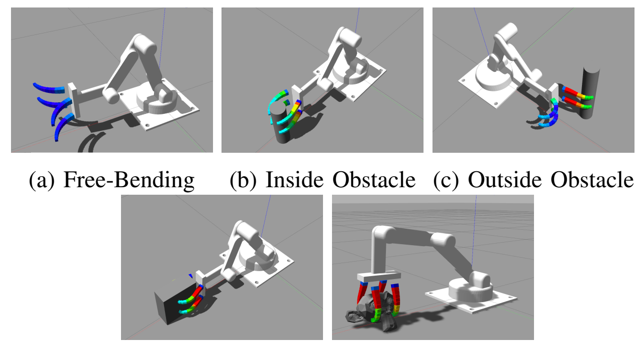


Fig. 7: Fingertip position error results across varying scenarios showing similar trends as Fig. 6.

A model-driven pose estimation method has been developed in which the approximate position and shape of the gripper's fingers can be calculated with the feedback from the embedded strain sensors, giving accurate results in free-bending scenarios with a single sensor. Further investigations showed that, through the use of multiple strain sensors, this method could be extended to accurately estimate the pose of the gripper in more general cases, where the use of two strain sensors could vastly improve the estimation capabilities across multiple test scenarios while, with the use of four strain sensors, the estimations can be accurate to within an average of +/-2mm, a useful finding given the recent advancements in soft gripper construction and embedded strain sensors that may facilitate this.

It is important to highlight that the conclusions drawn from these methods are based solely on the simulation results. As such, further work to confirm the accuracy of the soft-body approximations as well as the applicability of the proposed pose-estimation method outside of the simulation domain is necessary to verify any effectiveness within real, physical use cases. With this in mind, the methods shown in the paper provide potential preparatory work that can be explored with physical development, comparing against the accuracy of the simulation as well as the pose-estimation, particularly as the pose estimation follows assumptions that hold true in the simulation world but not necessarily for the physical equivalent. Providing this is shown to be suitably accurate for control system and task simulations, future works could build on this implementation of pose estimation to produce advanced control systems that can detect collisions, delicately handle fragile objects or incorporate object size and shape recognition from the available feedback.



(a) Free-Bending (b) Inside Obstacle (c) Outside Obstacle

(d) Box Grasp (e) Monkey Grasp

Fig. 8: Demonstration of each of the testing scenarios from within the simulation

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