

Hybrid System Analysis and Control of a Soft Robotic Gripper with Embedded Proprioceptive Sensing for Enhanced Gripping Performance

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Soft robots are considered to have infinite degrees of freedom based on their structural compliance, providing high adaptability to the environments, and recent study has focused mostly on advancement of their physical designs for increasing the adaptability. However, interaction itself with the environment has not been taken into serious account in previous studies despite the importance in applications. A soft robot as a hybrid system described by both discrete and continuous states is considered and a method of analysis for enhanced manipulation is proposed. The method is tested with a soft gripper composed of a pneumatic bending actuator and an embedded soft sensor for a task of object gripping. The optimum sensor location on the actuator based on the calibration map obtained from the actuator characterization is first determined. Using the sensor information, the interaction with the environment (i.e., object) classified into four discrete states is understood. In addition, a control strategy to find the best position to grip the object based on the estimated states is developed. The gripper is able to successfully complete the task using the proposed method for three test scenarios with different initial conditions and control parameters. Finally, the results are demonstrated with supporting videos.

to various shapes of objects to be gripped. From the kinematic point of view, soft robots can generate complex motions with high degrees of freedom (DoFs) at a small cost (in terms of the number of actuators or control inputs) by utilizing their inherent property of compliance.^[1–3] Considering the necessity of interactions between robots and environments, this feature is highly advantageous as robots can easily change their physical configurations depending on the surroundings and situations whether intentionally or unintentionally. Furthermore, the structural compliance allows for interactions with the environments in a passive and adaptive manner so that the safety for both the robots and the surroundings including humans can be guaranteed, which encouraged researchers to incorporate compliant mechanisms into various applications. Object manipulation is one of the most widely explored areas, and the first step of manipulation is to grip an object.^[4–6] To successfully grip the target

1. Introduction

Compared with conventional robots made of motors, rotational joints, and rigid linkages, soft robots are composed of compliant materials and structures. A remarkable feature of soft robots is that they can deform both actively and passively to conform

object in this case, the robotic system has to adapt its shape to the object only with a limited number of active DoFs (i.e., actuators).^[7–9]

There has been an approach to address this problem using under-actuated robotic hands that can easily conform various objects with different shapes.^[10–12] In this case, most studies have focused on analyzing the static models of robots to figure out the generated forces and the geometries for determining the best design parameters for given tasks.^[13,14] A mechanically programmable design with mechanical selectors incorporated in an under-actuated robotic hand has also been proposed to extend the grasping capabilities.^[15] However, the rigid link-joint structure inevitably constrains the motion of the robots and limits the reachable target regions in these approaches. Some researchers have partially adopted elastic elements into the structure to address the above limitation, in which the physical constraints can be averaged out at the desired configuration.^[16]

However, soft robotic hands that are fully (or mostly) composed of elastic materials have a much higher capability of handling various objects, thanks to their unconstrained deformation with an infinite number of DoFs.^[17–20] Although various types of soft robotic hands or fingers have been developed, an analysis on the extended grasping capability has not been investigated enough yet. The difficulty comes from the complex configuration

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or the nonlinear kinematics of the structure with a large number of DoFs. Compared with a conventional rigid robot whose body configuration can be clearly expressed with a finite number of joint angles, the analytic expression for the configuration of a soft robot in general requires many approximations or a high computational power.^[21–24] An accurate but fast analysis of the system if possible will be thus highly useful for performing high-level manipulation tasks. The good news is that we can describe the system only with a small number of state variables despite the large number of DoFs as long as the task or the environment is defined. To be specific, the number of the states can be determined by the dimension of the given environment. Therefore, instead of trying to develop a general infinite dimensional model for a soft robot, analyzing its reduced form based on the given environmental conditions will offer a greater efficiency in modeling.

In the case of a simple elastic beam that could be a basic form of a soft gripper's finger, shown in **Figure 1**, an infinite number of curvature variables (continuous distribution) are necessary to describe the state (i.e., shape) of the beam (Figure 1a). However, once the control input and the environment of the system are defined, only a finite number of variables will be enough. For example, a pneumatic bending actuator with a single pressure input and a fixed environment (i.e., wall) (Figure 1b) needs only a single variable to express the state, as there exists only a single state. This means the distributed curvatures along the length of the finger are fully coupled with each other, and the coupled motion can be determined by the single input. Although the shape of the actuator can no longer be expressed by the single state if the environment has its own DoF (Figure 1c), it still requires a finite number of states.

Therefore, the infinite dimensional configuration space of the elastic beam can now be reduced to a finite dimensional space, allowing us to analyze the system more accurately and efficiently, which is highly useful in practical applications with soft robots.

In this work, a gripper system composed of a soft robotic finger and an object will be expressed as a dynamic system with a state variable x and an input u . In general, the state evolution of a continuous system can be written with a differential equation as

$$\dot{x} = f(x, u) \quad (1)$$

However, in the case of the system in Figure 1b,c, the motion of the finger starts to deviate from its original trajectory upon contact even though the trajectories shown in the figure are continuous. Such a system with two distinguished states can be simply described with an additional discrete state variable as

$$\dot{x} = f(q, x, u) \quad (2)$$

The variable q indicates whether the system (i.e., finger) is in contact with the environment (i.e., wall) or not. The system described in Equation (2) is called a hybrid system, in which there exist both continuous and discrete state variables.^[25,26] This approach has been frequently adopted for analyzing motions in conventional robotics that switch their states or “modes” of the motion.^[27–29]

Given that the system is expressed in a hybrid model comes the problem of estimating the hybrid states. In other words, a sensor (or a limited number of sensors) needs to both detect a contact and estimate the shape of the finger. Although visual tracking systems have been widely used as a method of feedback in these types of problems, they are sometimes limited due to the need of additional devices or spaces, and some of them are even slow, expensive, and inaccurate.^[30–33] In this study, by taking advantage of the deformable feature of the soft robot, we estimate the high-dimensional but coupled states of the system using a single embedded proprioceptive soft sensor.^[34–37] The concept of proprioception comes from biological muscle systems, where a muscular unit internally detects its stretch or stress by the embedded sensing elements inside, such as muscle spindles or Golgi tendon organs.^[38,39] We first understand how the deformations (outputs) are distributed along the finger according to the state and then we suggest the estimation strategy based on the mapping from the state to the outputs.

This article starts with a simplified problem and its modeling of the soft gripping system, followed by the definitions of the state space for the hybrid system and the task to be conducted. Experiments were then conducted to characterize the deformation according to the input of the system. The result determines

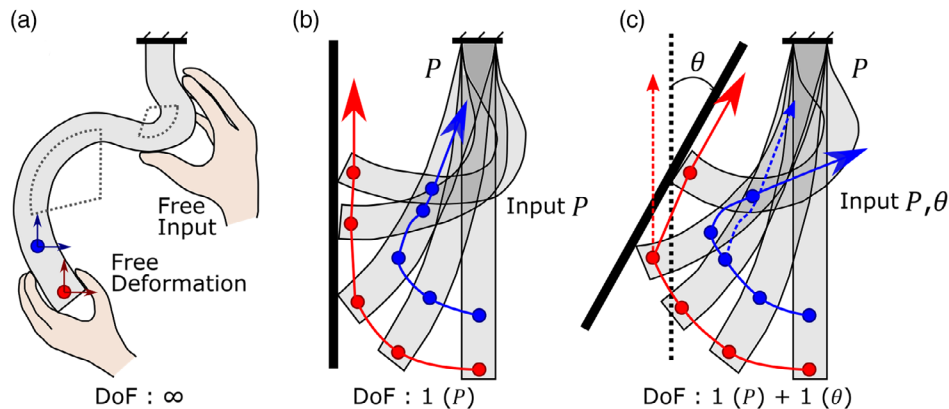


Figure 1. DoF of an elastic beam. a) An elastic beam can be deformed freely with an infinite number of DoFs in general. However, when the control input of the beam and the environment are fixed, only a finite number of DoFs are necessary to describe its shape. b) For a pneumatic bending actuator of one pressure input and a fixed environment (i.e., wall), only one variable is sufficient for describing the system. c) If the environment has its own DoF, the system has an extra DoF.

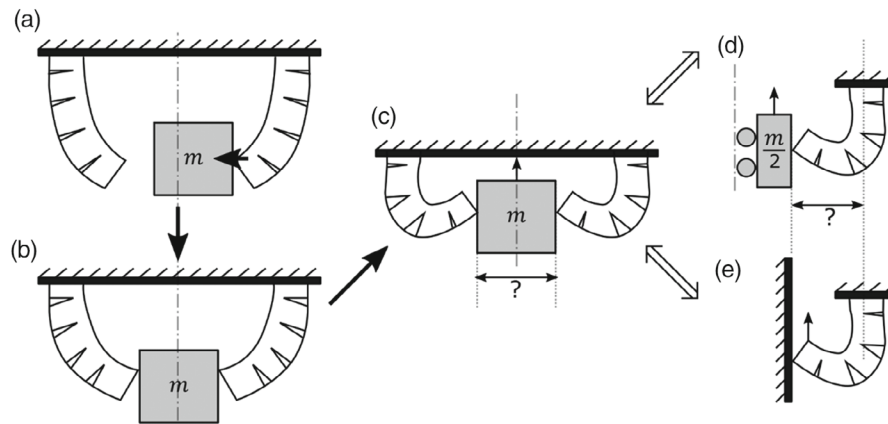


Figure 2. Definition of an object manipulation problem with a soft pneumatic gripper. a) An object at an arbitrary position between two fingers can be b) aligned to the center line by increasing the internal pressures of both fingers equally. c) The gripping motion by the two fingers is equivalent to d) a lifting-up motion of half of the object in the vertical direction or to e) a climbing-up motion of the fingertip on a frictionless wall assuming both the force generated by the finger and the friction between the finger and the object are large enough.

the sensor placement and the estimation strategy. Finally, the control result for the gripping task is presented, which validates the core contribution of this study: estimation of hybrid states of a soft robotic system using a proprioceptive sensing mechanism.

2. Problem Definition and Modeling

2.1. A Soft Robotic Gripper

The problem we are interested in modeling with a hybrid system approach is a soft robotic gripper with the simple manipulation task of lifting up an object, as shown in **Figure 2**. A robotic gripper with two soft pneumatic actuators (i.e., fingers) and an object to be gripped are shown in **Figure 2a**. We assume that the shape of the target object is cubic for simplicity in this problem but leave the size and the position of the object unknown. To grip the object, the actuators can move in the horizontal direction. When we pressurize both fingers, the object moves to the center between the two fingers (**Figure 2b**). If the pressure further increases, the bending motion of the fingers generates forces in both the horizontal and the vertical directions, resulting in lifting up the object (**Figure 2c**). We can simplify the system to a half based on the symmetry, replacing the object with a new one that weighs half of the original object, and can move the new object freely only in the vertical direction (**Figure 2d**). Assuming the mass of the object is small and the force generated by the finger and the friction between the fingertip and the object are both large enough, we can consider only the kinematics of the finger. Then, the system for analysis and modeling is equivalent to a single pneumatic bending actuator climbing up a fixed vertical wall without friction (**Figure 2e**).

The simplified system with variables is shown in **Figure 3**. The only difference in this configuration from **Figure 2e** is that the base has an active DoF in the horizontal direction. Depending on the distance to the wall (or the object), the base of the finger can approach or retreat from the wall to find an optimal location for successfully climbing up (i.e., gripping the object). d_{base} and d_{tip} are the distances to the wall from the base and from the tip of the finger, respectively, and θ is the bending

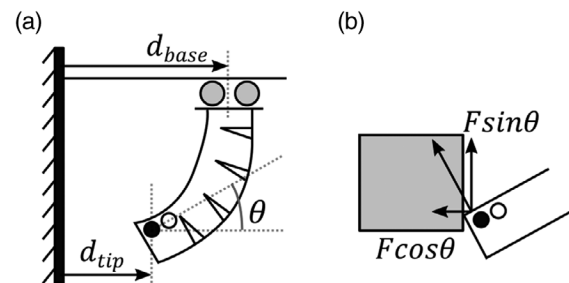


Figure 3. a) Definition of the coordinate system and the configuration variables. b) The tip orientation (θ) of the finger is important as it determines the direction of the gripping force.

angle of the finger measured by the black and white dots at the tip about the horizontal axis, which is important for successful gripping as it determines the direction of the force (**Figure 3b**).

2.2. States and Measurement of the System

To successfully complete the gripping task, the system has to find the right values for d_{base} and θ . As θ is determined by the input pressure P to the actuator, although d_{base} can be directly adjusted, P and d_{base} become the system inputs. To close the loop for control, we now need real-time information on d_{tip} and θ for estimating the control variables d_{base} and θ . Although they can be easily measured by visual tracking, incorporating vision data into an online controller makes a system slow, bulky, and expensive in general. We thus used a simple proprioceptive soft sensor embedded in the finger for measuring local strains, to estimate d_{tip} and θ in real time, which will be discussed later.

By adjusting the system inputs P and d_{base} , we can achieve different physical configurations of the finger, as shown in **Figure 4a**. A contact between the tip and the wall can be made by increasing P or by decreasing d_{base} , and the configurations of the finger that just start making a contact are shown in the diagonal elements in red circles. **Figure 4b** shows the actuator bending and making a contact with the wall. The shape of the

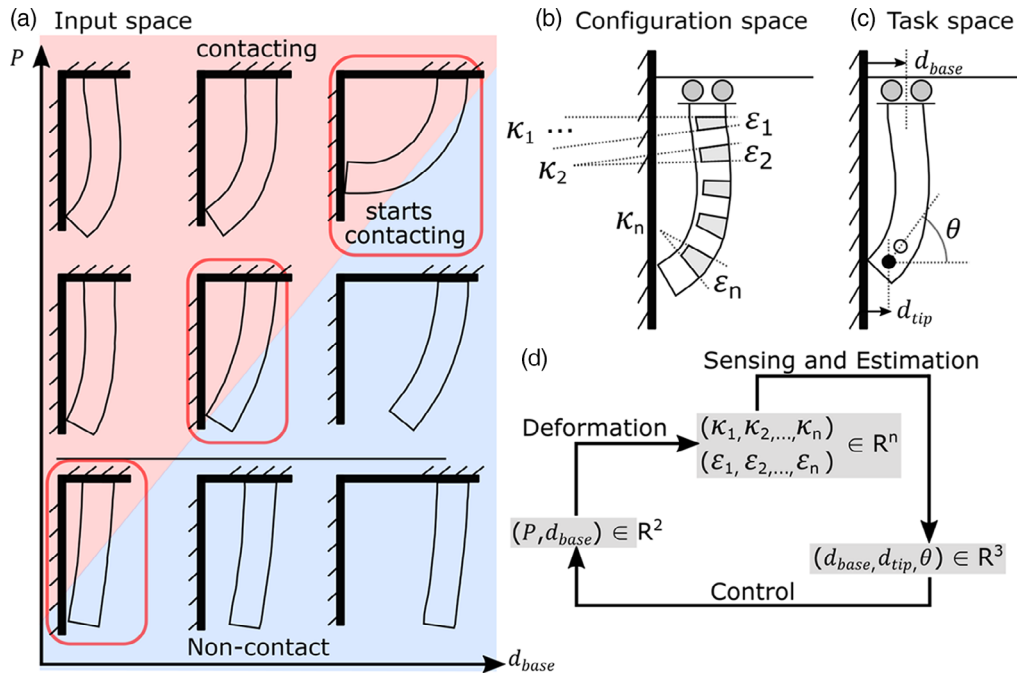


Figure 4. Three-state spaces of the system. a) Input space (P, d_{base}) and the shapes of the actuator with different input pairs. A contact occurs in the upper-left region (pink area) of the plot. b) The configuration space of the actuator can be expressed with n piecewise constant curvatures or strains. c) The task space of the actuator. d) The variables in each space can be transformed into those in the other spaces. The loop schematically describes how the estimation and control of the system occurs.

finger can be determined by the curvature distribution along the length, which can be discretized into the n piecewise constant curvatures. The n curvature values can be obtained from n strains of the corresponding segments on the finger. As it is enough to estimate the task space variables (Figure 4c) if the measurable dimension of the configuration space is larger than the dimension of the input space, we can utilize the estimated values for control. The overall procedure is shown in Figure 4d.

3. Hybrid System Analysis

In this section, we formally define the system in Figure 3 and suggest a control strategy for gripping. The system cannot be described as a simple continuous system, as its dynamics and the sensor responses are different depending on whether there is a contact or not. We first define three discrete states of the actuator.

3.1. Discrete States for the Actuator

$$q = (q_1, q_2, q_3) \in \mathbb{Q} \quad (3)$$

$$\mathbb{Q} = \{(\text{non-contact}, \text{pressurize}, \text{stay}), (\text{contact}, \text{pressurize}, \text{stay}), (\text{non-contact}, \text{depressurize}, \text{approach}), (\text{non-contact}, \text{depressurize}, \text{retreat})\} \quad (4)$$

where $q_1 \in \{\text{non-contact}, \text{contact}\}$: contact status of the finger with the wall, $q_2 \in \{\text{pressurize}, \text{depressurize}\}$: status of pressure input to the finger, and $q_3 \in \{\text{approach}, \text{retreat}, \text{stay}\}$: motion of the finger base.

The discrete states have only four values, as shown in Equation (4). The system undergoes discrete “transition” or “jump” from one state to another. In between the jumps, i.e., while the system is not moving in a single discrete state, the evolution of the continuous states occurs, which has to be defined.

3.2. Continuous States

$$X = (P, d_{base}, d_{tip}, \theta, \tau) \in \mathbb{R}^5 \quad (5)$$

where $P \in [0, P_{max}]$: Input pressure, $d_{base} \in \mathbb{R}_+$: finger base position (distance from the wall), $d_{tip} \in \mathbb{R}_+$: fingertip position, $\theta \in \mathbb{R}$: fingertip orientation (angle), and $\tau \in \mathbb{R}_+$: internal clock time between transitions.

With the defined discrete and continuous states earlier, the gripping task can be formulated.

3.3. Task

$$\begin{aligned} &\text{Reach } \tau > T_{move} \\ &\text{while} \\ &(q = (\text{contact}, \text{pressurize}, \text{stay})) \wedge (\theta \leq \theta_{max}) \wedge (P \leq P_{max}) \end{aligned} \quad (6)$$

It is regarded as a success when the actuator climbs up the wall (i.e., pressurizing) for a longer period than T_{grip} while maintaining contact in the upward direction ($\theta \leq \theta_{max}$), where θ determines the direction of the force from Figure 3. As the upper limit of the angle guarantees the lifting-up motion of the actuator, we can assume the gripper conducts both grasping

and lifting motions. However, the functional requirements could be different depending on the situations whereas the formulated task defined here represents only one example among many. To complete the task, we have to control the system so that the state evolves in a proper direction. The control input variables, either discrete or continuous, are defined here.

3.4. Inputs

$$u = (u_1, u_2, T_{\text{move}}) \quad (7)$$

$$u_1 \in \{1, -4\}: \text{Pressure differential} \\ (\text{pressurize, depressurize})$$

$$u_2 \in \{1, -1, 0\}: \text{Base position (distance) differential} \\ (\text{approach, retreat, stay}) \quad (8)$$

$$T_{\text{move}} \in \mathbb{R}_+: \text{Time for base moving}$$

In **Figure 5**, the transitions between the discrete states are represented by the arrows and the continuous evolution (dynamics) is formulated inside the states. The condition for the transition and the reset map of each transition is shown in the beginning (tail) and the end (head) of the arrow, respectively.

3.5. Continuous Evolutions

Increase or decrease in the internal pressure of the finger is determined by $u_1 (\dot{P} = u_1)$, and the relative motion between the wall and the actuator is determined by u_2 and T_{move} . Before the internal clock ($\tau = 1$) reaches T_{move} , the wall moves in the direction of u_2 . The remaining variables d_{tip} and θ evolve in an autonomous manner inside each state.

3.6. Guard Condition, Reset Map, and Discrete Transitions

1) *(non-contact, pressurize, stay) → (non-contact, depressurize, approach)*: If the internal pressure of the finger reaches the maximum value before contact occurs, it means that the finger is located too far away from the wall to grip the object. The finger approaches the wall for T_{move} with depressurization (transition occurs). As there is no measured θ at this point, T_{move} is set as a preset constant. 2) *(non-contact, pressurize, stay) → (contact, pressurize, stay)*: During the state *(non-contact, pressurize, stay)*, the sensor signal keeps being evaluated to detect the contact. When a contact is detected, the position of the finger base is estimated ($\hat{d}_{\text{base}}$) from the input pressure at the moment and stored. The transition occurs, and the tip orientation is estimated ($\hat{\theta} = \theta(P, \hat{d}_{\text{base}})$). 3) *(contact, pressurize, stay) → Task completion*: While maintaining a contact, increase in input pressure for T_{grip} means a success of the task. 4) *(contact, pressurize, stay) → (non-contact, depressurize, approach)*: If the input pressure reaches the maximum value before T_{grip} , it means that the actuator is too far away from the wall to grip the object. The actuator then approaches the wall for T_{move} with depressurization (transition occurs). The estimated $\hat{\theta}$ in the former state determines the duration to move (T_{move}). 5) *(contact, pressurize, stay) → (non-contact, depressurize, retreat)*: If the estimated $\hat{\theta}$ is larger than θ_{max} , it means that the finger is too far away from the wall to grip the object. The actuator retreats from the wall for T_{move} with depressurization (transition occurs). The estimated $\hat{\theta}$ in the former state determines the duration to move (T_{move}). 6) *(non-contact, depressurize, approach)/(non-contact, depressurize, retreat) → (non-contact, pressurize, stay)*: After adjusting the distance ($\hat{d}_{\text{base}}$), go back to the initial state and repeat the procedure.

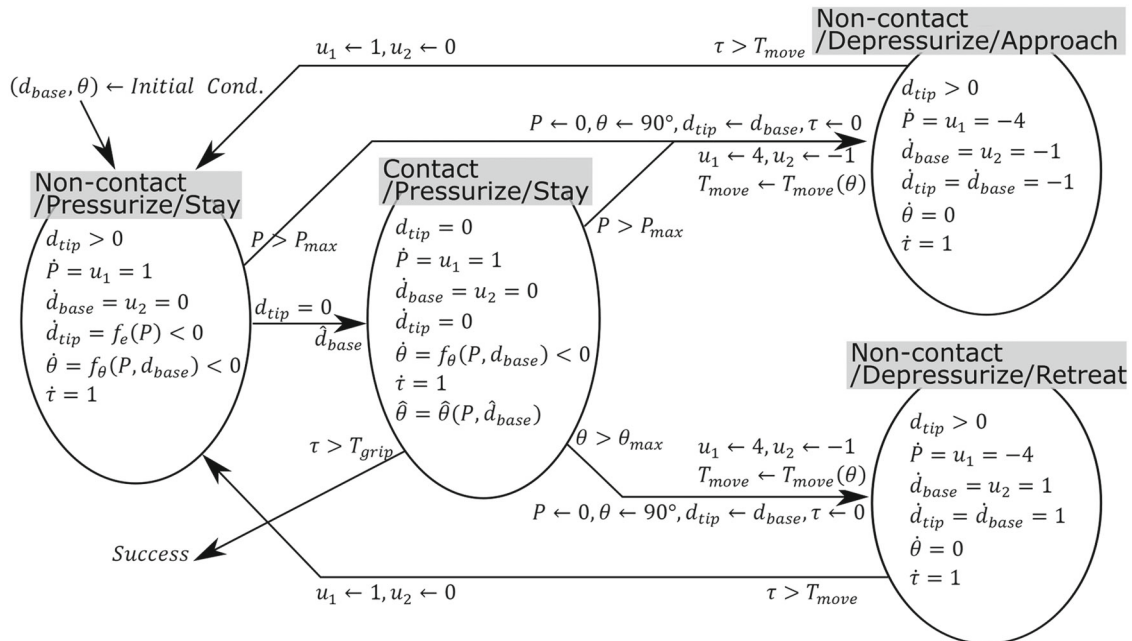


Figure 5. Hybrid system with four discrete states. The transitions between the states are expressed with arrows. A guard condition to enable a transition to another state was provided in the beginning (tail of the arrow) of each transition, and a reset map for the state after the transition was provided at the end (head of the arrow) of the transition. Continuous evolution of continuous states is formulated inside each discrete state.

4. Sensor Placement, Contact Detection, and Estimation

Control of the earlier system (i.e., determining u_1 , u_2 , and T_{move}) requires estimation of the continuous states. The internal pressure P and the clock τ can be measured directly from the pressure regulator of the pneumatic pump and from the control loop, respectively. However, the geometric states of the actuator, such as the base and the tip positions (d_{base} and d_{tip}) and the orientation (θ), have to be estimated from the measurement of physical deformation, which requires a soft sensor to be embedded in the actuator. As shown in Figure 4a,b, the 2D inputs (P and d_{base}) determine the configuration of the actuator whose shape can be expressed by n -dimensional curvature distribution. In this work, we set five candidate locations for the soft sensor (i.e., $n = 5$) that are equally spaced along the length of the actuator and then find the best location among the five by experimentally characterizing the task and the configuration spaces of the actuator. After embedding the sensor at the selected location in the actuator, the task state variables are estimated using the characterization data of the soft sensor, and the estimated values are compared with the reference values.

4.1. Experimental Setup and Prototype

The experimental setup is shown in Figure 6a. To determine the sensor location, we used a vision tracking system first. The distance between the wall and the finger base (d_{base}) can be controlled by moving the horizontal position of the finger. However, for more accurate tracking of the finger motion, the position of the finger was fixed to maintain the same distance to the camera. We instead moved the wall installed on the 1D motorized stage, pretending the motion of the finger base. For vision tracking, multiple markers were attached on the actuator body and the wall. The green marker on the wall determines the origin of the system and the distance to the base (d_{base}). The red markers at the tip determine the position (d_{tip}) and the orientation (θ) of the fingertip. The blue markers are for measuring local strains of the five candidate locations along the length of the actuator.

The design of the finger used in the experiment is shown in Figure 6b. On the top side of a pneu-net bending actuator,^[40] an extra silicone layer was attached for embedding a soft strain

sensor.^[41,42] The extra layer was made of a much softer elastomer material (Ecoflex 00-30, Smooth-On, 100% modulus: 69 kPa) than that of the remaining body of the finger (Dragon Skin 30, Smooth-On, 100% modulus: 593 kPa) so that the effect of the sensor layer on the bending stiffness is negligible. On the surface of the extra layer, a microchannel was embedded, filled with conductive fluid (eutectic gallium–indium, eGaIn).^[42–44] When the actuator is internally pressurized, bending occurs along the finger body, with the inextensible layer on the bottom side of the finger being a neutral axis. As the sensor layer on top is located off the neutral axis, the embedded microchannel is stretched with bending, resulting in increases in its electrical resistance that can be easily converted to a strain value.

4.2. Characterization of Task and Configuration Spaces

Figure 7 shows the characterization result with color maps of the task space variables (d_{tip} and θ) and the configuration space variables ($\epsilon_1 - \epsilon_5$). All the data for characterization were collected by vision tracking in this stage. Figure 7a shows the finger model with five candidate locations for embedding a soft strain sensor. The dotted lines on the color maps in Figures 7b–d are the contact boundaries, where the fingertip starts to make a contact with the wall, determined by the tip position (i.e., $d_{\text{tip}} = 0$) from the vision data. As expected, only a small input pressure is required to make a contact if d_{base} is small, but a higher input pressure is necessary for a larger d_{base} for contact (Figure 7b). Also, the tip orientation (θ) continuously changes along the contact boundary (Figure 7c).

The strain plots in Figure 7d show that the closer to the base the sensor is located, the more the sensor signal is affected by d_{base} , indicating that ϵ_1 is the most effective location to estimate d_{base} , as we already know P as an input pressure. Therefore, we can reliably estimate the configuration variables d_{base} and θ from ϵ_1 and P , respectively. Figure 7e shows the different behaviors of the actual finger prototype with varied input pairs of d_{base} and P , consistent with Figures 7b,c.

4.3. Estimation of Task Space Variables with Embedded Soft Sensor

Following the result in Section 4.2, a soft strain sensor was embedded at the location of ϵ_1 in Figure 7a. Figure 8a shows

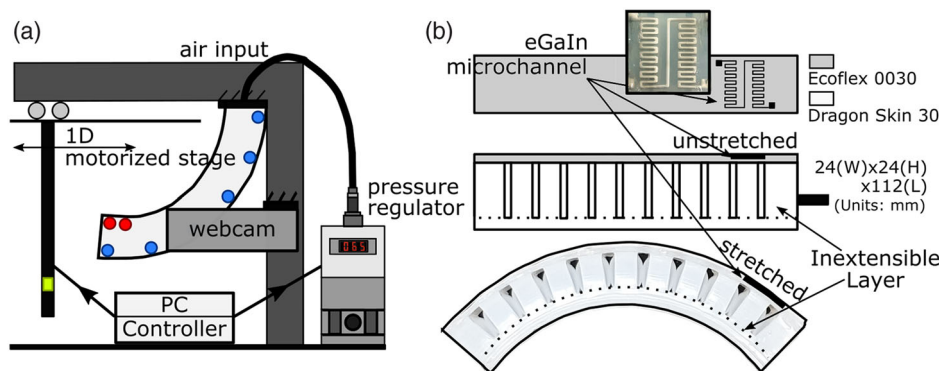


Figure 6. a) Experimental setup. b) Design of the soft actuator used in the experiment with an embedded proprioceptive soft sensor.

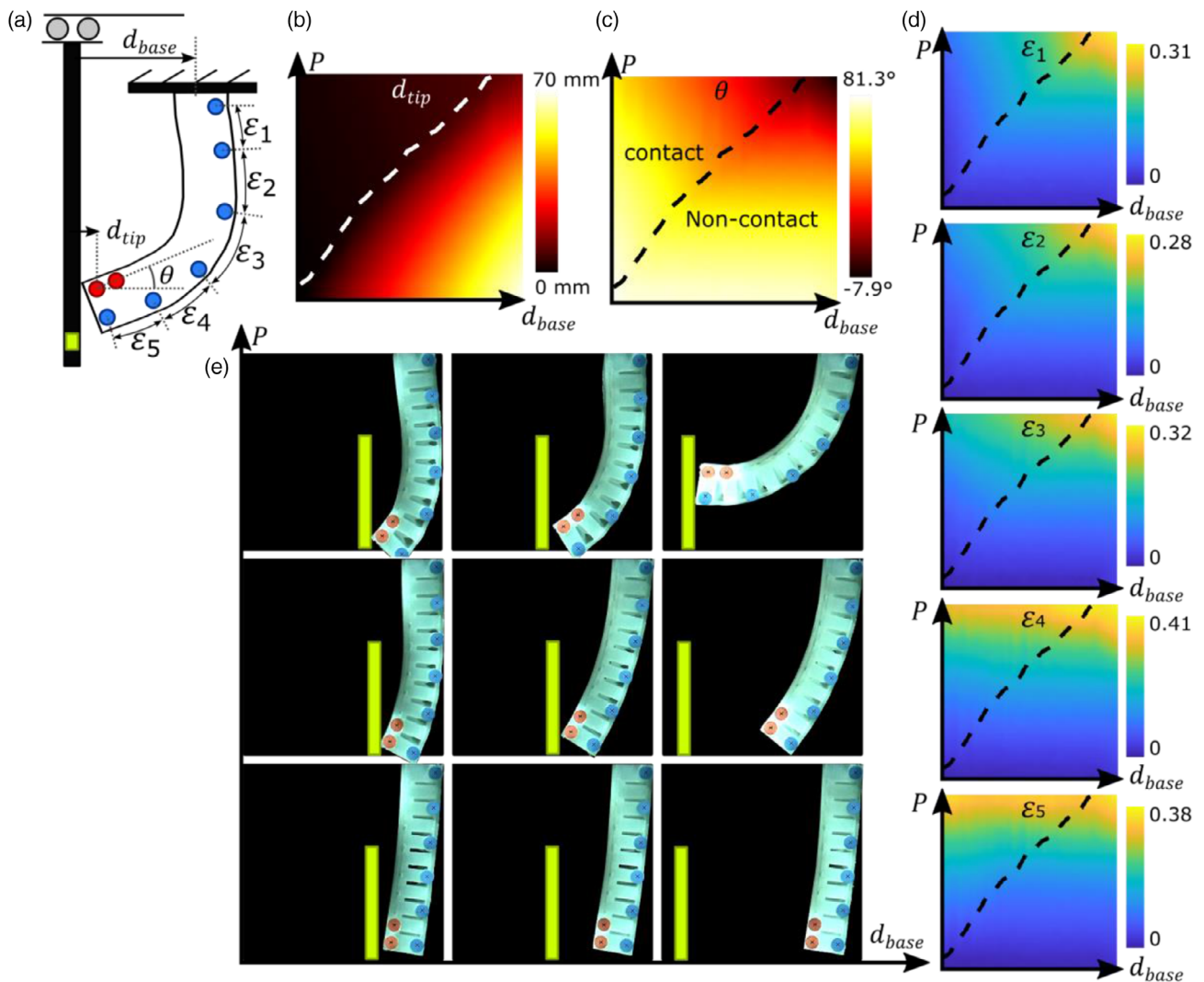


Figure 7. Characterization of the task and the configuration spaces. a) Finger model with five sensor location candidates. Color map plots of b) the position and c) the orientation of the fingertip and d) the strains at the five sensor locations with varied input pairs of P and d_{base} . The dotted lines are the boundaries of contact, which were determined from the tip position (d_{tip}) by vision data. e) Shapes of an actual finger prototype with varied input pairs of P and d_{base} .

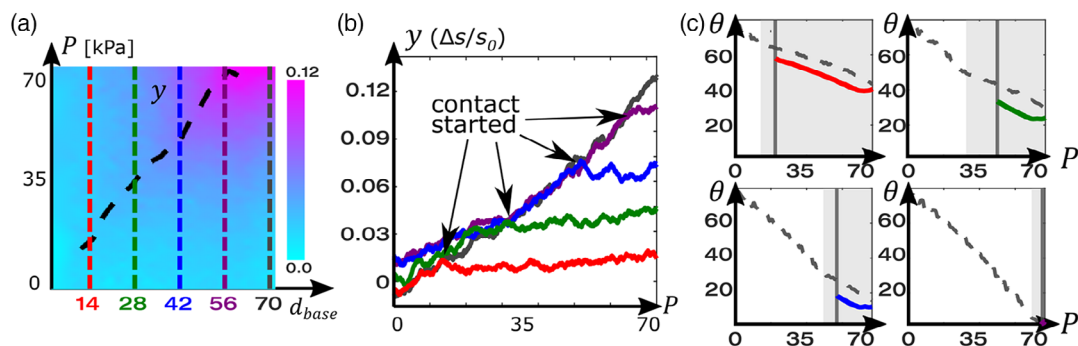


Figure 8. a) Sensor signal plot at the selected sensor location (ϵ_1 in Figure 7a). The signal is similar to the predicted result in Figure 7b. b) Sensor signals at several finger base positions (d_{base}). The dark grey curve of free motion ($d_{base} = 70$ mm) can be a reference signal for detecting a contact. c) Estimation results. There are delay and errors with underestimation in detecting a contact and estimating θ , which is due to the positive threshold used in the detection method.

the color map plot of the embedded sensor signal, which looks similar to ϵ_1 plot in Figure 7d. For five different d_{base} values, the sensor signals (y) are shown again in Figure 8b. If the distance is large enough ($d_{\text{base}} = 70$ mm), no contact occurs even though the pressure is increased to the maximum value, as shown with the dark grey curve in Figure 8b. As the distance (d_{base}) decreases, the fingertip starts to make a contact at certain pressure levels, and the contact pressure level decreases as d_{base} decreases. From these contact starting points, the sensor signal starts to deviate from the dark grey curve.

We now set the dark grey curve as a reference signal and let the internal pressure of the actuator increase when the base position (d_{base}) is given. If the deviation is larger than a certain threshold, we can say that a contact occurs. Plugging the pressure value at this point into the regression model of the dotted contact boundary in Figure 7, we can estimate the distance ($\hat{d}_{\text{base}}$). Now, having the $\hat{d}_{\text{base}}$ value, we can calculate the estimated $\hat{\theta}$ from the color map in Figure 7c.

With this strategy, we estimated the value of θ on line for the four distances in Figure 8a except for the reference ($d_{\text{base}} = 70$ mm) curve. During estimation, only the sensor signal, the reference signal (dark grey curve), and the regression models (the θ map and the dotted boundary in Figure 7c) were used, and no vision data was referred to. Figure 8c show the result. The dotted grey line is the reference value, which was calculated from the vision data after the experiment. The shaded region represents the reference contact region. The vertical lines indicate the input pressures, where the contacts start to occur, detected on line (i.e., the points where the sensor signal starts to deviate from the reference more than the threshold). Estimation of θ starts after this point.

Although estimation was reliable, there was a delay in detecting the contact. In other words, the vertical line appears at a slightly higher pressure than the left boundary of the shaded region in Figure 8c. This is because we set the threshold for the deviation larger than 0. Although the delay can be reduced by lowering the threshold, a certain level of a positive threshold is necessary relative to the noise level of the sensor. The error of the estimated θ can be described in the same context. If there is a delay in contact detection, it means that the pressure where the contact is detected is larger than the actual starting level. In the same way, we find the $\hat{d}_{\text{base}}$ value larger than the true value from the contact boundary of Figure 7c. Referring to the θ map in Figure 7c, large pressure and $\hat{d}_{\text{base}}$ make the final estimation of θ smaller than the true value. Those errors can be compensated by tuning the gain or the offset when making a feedback input with $\hat{\theta}$. The algorithm and the result of closed-loop control using $\hat{\theta}$ are discussed in the next section.

5. Control

5.1. Control Strategy

The pseudocode in **Algorithm 1** shows the implementation of the state evolution, transitions, task completion, feedback input, and the control strategy described from Sections 3 and 4.

Algorithm 1. Control code.

```

get reference sensor signal of free motion  $y(P)$ 
move the wall to the initial position
Initial state is (non-contact/pressurize/stay)
 $u_1 \leftarrow 1, u_2 \leftarrow 0$ 
while not SUCCEED
    update internal time  $\tau \leftarrow \tau + d\tau$ 
    update pressure  $P \leftarrow P + u_1 P$ 
    update wall position  $d_{\text{base}} \leftarrow d_{\text{base}} + u_2 d_{\text{base}}$ 
    read sensor signal  $y$ 
    if state is (non-contact/pressurize/stay)
        if  $P \geq P_{\text{max}}$ 
            update  $u_1 \leftarrow -4, u_2 \leftarrow -1, T_{\text{move}} \leftarrow 10$ 
            go to state (non-contact/depressurize/approach)
        if  $|y(P) - \text{ref}(P)| > \text{threshold}$ 
            calculate  $\hat{d}_{\text{base}} = \hat{d}_{\text{base}}(P)$ 
            go to state (contact/pressurize/stay)
    else if state is (contact/pressurize/stay)
        calculate  $\hat{\theta}(P, \hat{d}_{\text{base}})$ 
        if  $\tau \geq T_{\text{grip}}$ 
            SUCCEED
        if  $P \geq P_{\text{max}}$ 
            update  $u_1 \leftarrow -4, u_2 \leftarrow -1, T_{\text{move}} \leftarrow K_1 \hat{d}_{\text{base}}$ 
            go to state (non-contact/depressurize/approach)
        if  $\hat{\theta} \geq \theta_{\text{max}}$ 
            update  $u_1 \leftarrow -4, u_2 \leftarrow 1, T_{\text{move}} \leftarrow K_2 \hat{\theta}$ 
            go to state(non-contact/depressurize/retreat)
    else if state is (non-contact/depressurize/approach)
        if  $\tau \geq T_{\text{move}}$ 
            update  $u_1 \leftarrow 1, u_2 \leftarrow 0$ 
            go to (non-contact/pressurize/stay)
    else if state is (non-contact/depressurize/retreat)
        if  $\tau \geq T_{\text{move}}$ 
            update  $u_1 \leftarrow 1, u_2 \leftarrow 0$ 
            go to (non-contact/pressurize/stay)

```

5.2. Results

Using the above algorithm, we conducted control experiments for three different initial conditions and feedback inputs (**Figure 9**). In each subfigure, the first two subplots show the input pressure (P) and the sensor signal (y) with the reference signal (blue line) of the noncontact free motion. When the sensor signal starts to deviate from the reference signal (vertical line), the pressure at the moment is stored and $\hat{d}_{\text{base}}$ is calculated from the regression model (dotted line of Figure 7c). In the third subplot, the four discrete states in Equation (4) (and Figure 5) are shown with four integer values from 1 to 4 in order. While maintaining the contact in the state (contact/pressurizing/staying), θ is estimated. The estimated value $\hat{\theta}$ determines whether to jump out of the current state

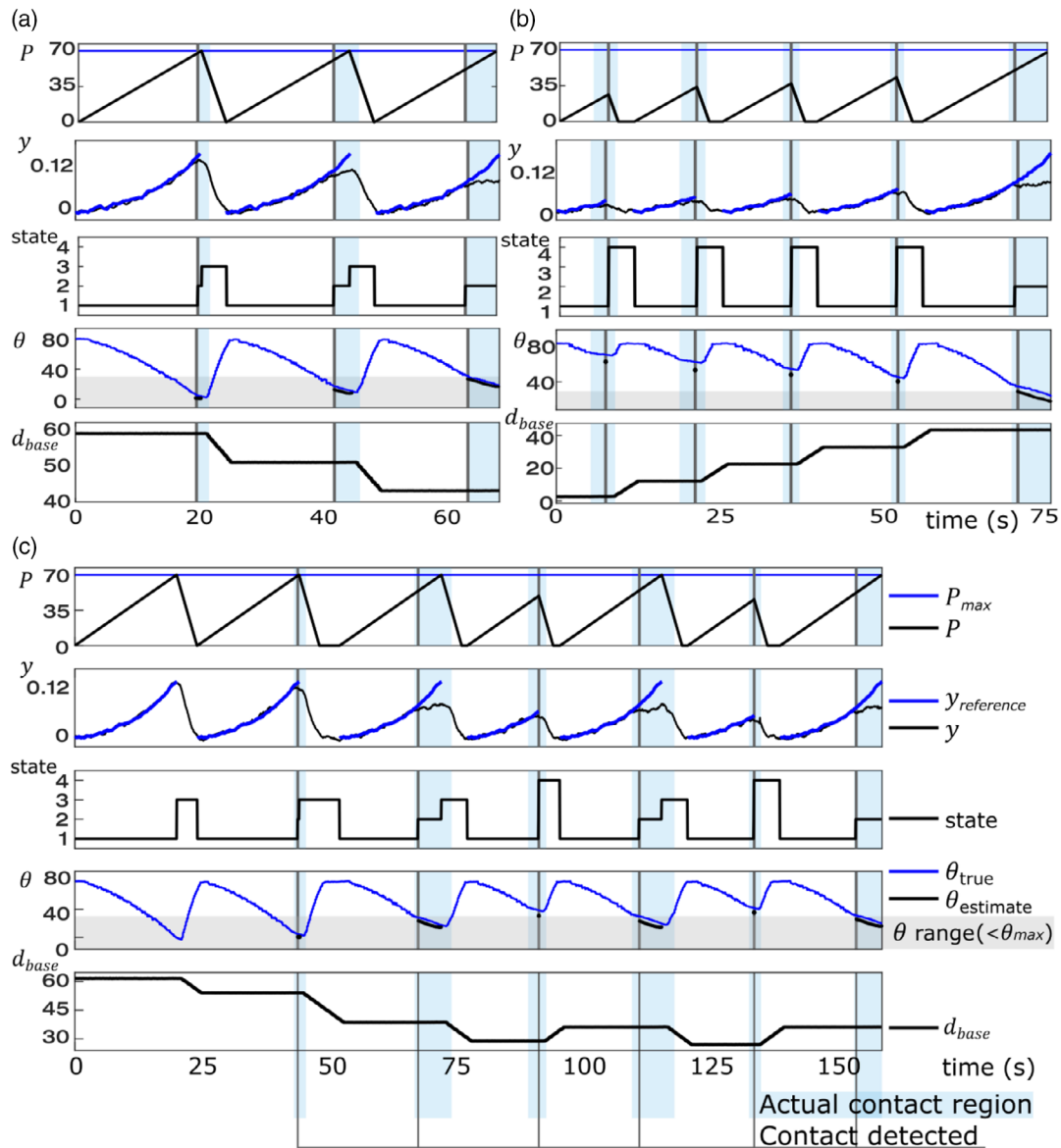


Figure 9. Control results with a,b) $\theta_{\max} = 36^\circ$, feedback input $T_{\text{move}} = 4$, and c) $\theta_{\max} = 30^\circ$, feedback input $T_{\text{move}} = 4 + 0.05(\theta_{\text{desired}} - \hat{\theta})$. At the ends of all three cases, the gripper successfully completed the gripping task.

or not and the feedback input for the next state. The blue shaded region is the true contact region. The grey region of the θ plot shows the allowable θ range as defined in the task. The blue line in the same plot shows the true θ value. As shown in Figure 8, the detection has the delay and the estimated $\hat{\theta}$ has negative errors. In the case of Figure 9a,b, the input T_{move} was set as a constant value, which determines the distance to move to the wall. In other words, the $\hat{\theta}$ value only affected the discrete inputs of u_1 and u_2 that determine the “direction” of the input but not the continuous input for the “magnitude.” The finger moved with a small incremental step for each transition.

Figure 9a shows the case of a “too-far” initial condition (Supporting Video 1, Supporting Information). While increasing the pressure in state 1 (*non-contact/pressurize/stay*), the

finger made a contact. After detecting the contact, the state transition was made to state 2, (*contact/pressurize/stay*). In state 2, before the clock reaches $T_{\text{grip}} (= 5 \text{ s})$, the pressure saturates and the controller jumps to state 3 (*non-contact/depressurize/approach*) for reducing the distance. After repeating the process once again, d_{base} was adjusted to the proper value and the task was completed.

Figure 9b shows the case of a “too-close” initial condition (Supporting Video 2, Supporting Information). The contact occurred whereas the pressure was increased (from state 1 to state 2). Just after transition occurred, however, $\hat{\theta}$ turned out to be larger than the $\theta_{\max} (= 36^\circ)$, so the state immediately moved to state 4 (*non-contact/depressurize/retreat*). This adjustment process was repeated four times before the task was completed.

In the above two cases $\hat{\theta}$ was not reflected to the magnitude of the feedback input. The magnitude was preset to a small incremental value such that the trajectory of d_{base} , the “solution” of the system, could “converge” to the desired value. However, this strategy does not guarantee the convergence of the solution in general if the target range is small. Also, if the target is too far away from the finger in the initial condition, the convergence is very slow.

In Figure 9c, the target condition was harsher, i.e., $\theta_{\text{max}} = 30^\circ$ (Supporting Video 3, Supporting Information). The control input, T_{move} , was determined by the difference of the target value of θ from the estimated value multiplied and added by a gain and an offset, respectively. The trajectory of the solution d_{base} converged into the allowable position after oscillation between state 3 and state 4.

6. Discussion

The entire process of system description, analysis, and control of the soft pneumatic gripping system described in this work was fundamentally aimed to find the optimal position and orientation of the fingertip to successfully grip an unknown object by evaluating the relative fingertip angle at the contact point. More specifically, our approach tries to place the contact force at the fingertip inside the friction cone of the object surface.^[22,45,46] To deliver this key concept, we assumed a simple system of a cubic object and 1D interaction (Figure 3). In this simplified system, the surface normal of the object is always fixed and the fingertip force lies on the 1D trajectory (red line of Figure 1b). To place the fingertip force inside the fixed friction cone, control of the position of the finger base (d_{base}), while evaluating the angle between the fixed surface normal and the force, was suggested as a strategy. The angle was estimated by sensing the local strain of the finger while contact occurred.

However, if we generalize our approach for more complex applications, the surface normal of the object is not fixed anymore and rather unknown, which means we have more states to estimate and control. Then, we have to add more sensors, such as fingertip force sensors,^[44,47] or increase the control dimension with additional DoFs of the gripper base. In addition, the current model of a single-finger system should be extended to a multifingered gripper to accommodate the arbitrary shape of the object.^[17–19] In this case, the structural compliance of the soft gripper will be a great benefit in preventing the system from being bulky with too many DoFs or fingers, as the gripper can easily adapt its shape to and conform the object.

Furthermore, it is always possible for the object to slip during the gripping process, caused by different reasons, such as the weight, the surface curvature, or the low friction of the object, in practical applications. This will introduce uncertainties to the suggested model, and it will be impossible to include all the possibilities in the model. However, monitoring the history of the sensor signals or the motion of the robot may provide useful information to address this issue, which is often used in hysteresis analysis and modeling,^[48–51] and it will be one of the areas of future work.

7. Conclusion

To address real-life manipulation issues with a soft pneumatic gripper, particularly related to contact interaction, we went through a process of modeling, analyzing, and controlling the gripper system along with estimation of its physical configuration. For taking advantage of the safe and compliant characteristics of soft robots during interaction with the environment, it is important to efficiently detect whether contact has occurred or not. For solving the problem without external devices, we first investigated the state spaces and the systematic description of the gripping system, where hybrid state variables, including discrete variables that categorize the gripping motion into four states, were defined. With proper sensor placement and experimental calibrations, the system was able to estimate the variables as well as obtain the information on the contact. Finally, the performance of the proposed method was demonstrated utilizing the sensor information and the state estimations. The gripper successfully completed the gripping task for three control scenarios with different initial conditions.

This study has its contribution in that the configuration of a soft bending actuator under contact interaction was analyzed and estimated using a simple sensing mechanism. The concept was experimentally validated with a simplified gripping system composed of a single pneumatic gripper and an embedded proprioceptive sensor. The result presented in this article will open a rich space for future research on modeling and control of soft robots.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

hybrid systems, proprioceptors, soft grippers, soft pneumatic actuators, soft sensors

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