A Method for Sensorizing Soft Actuators and Its Application to the RBO Hand 2

Vincent Wall Gabriel Zöller Oliver Brock

Abstract—The compliance of soft actuators makes manipulation safer and simplifies control. But their high flexibility makes sensorization challenging, because traditional rigid-link solutions no longer apply. From the large space of possible deformations, a subset already provides valuable insights about the actuator state. We present a method for sensorization of soft actuators that, for a given application, finds an effective layout from a set of sensors. The method is applied to the PneuFlex actuators of the RBO Hand 2. It identifies a layout of four liquid metal strain sensors and one pressure sensor to predict actuator deformation in three dimensions: flexional, lateral, and twist. Finally, the layout is used to build a sensorized RBO Hand 2. It can detect passive shape adaptation while grasping and reveal failure cases during manipulation, e.g. slipping fingers while opening a door.

I. INTRODUCTION

Soft robotics has had significant impact in a number of areas of robotics, ranging from grasping [1] to locomotion [2]. This impact stems from desirable properties of soft robotic systems: they are inherently safe and, when properly designed, increase robustness to uncertainty while reducing the requirements for perception and control. This is maybe most easily seen in robotic hands, where the use of softness has become the standard design paradigm [1], [3], [4]. When grasping with these hands, their softness lets the hand passively adapt to the shape of the grasped object, effectively without explicit sensing or control.

But there is also a price to pay for softness when it comes to sensing. Due to their ability to deform in many different ways, the configuration of a soft robotic system can only be described accurately by a very large number of parameters. Many sensors would be required to determine all of them. In addition, most traditional sensor technology, e.g. joint and motor encoders [5] or inelastic tactile sensing [6], are not suitable for the integration with soft actuators. At the same time, extrinsic sensing, e.g. through visual tracking [7], [8], limits the field of operation and is susceptible to (self-) occlusions. Still, there is an unbroken need for sensing in soft systems. As we will see in Section IV, even applications particularly well-suited for the soft robotics paradigm still benefit substantially from sensing. Taken together, sensing— and in particular proprioception—remains an open problem in soft robotics.

In this paper we present a method for sensorizing soft actuators. We use soft, flexible and stretchable strain sensors that can be integrated into soft actuators without negatively affecting their advantageous properties. Recognizing the fact that a very large number of such sensors would be required to fully reconstruct the shape of the actuator, we propose a method by which we identify the most appropriate placement of sensors, given a number of target deformation modes of particular relevance in a given application. We validate the proposed method in the context of grasping with the RBO Hand 2 [1]. Given three deformation modes deemed important for manipulation, we determine an appropriate sensor layout and confirm it in real-world experiments. Our results demonstrate that the proposed method enables the sensorization of soft actuators for applications in which it is not necessary to reconstruct all aspects of deformation.

II. RELATED WORK

A. Flexible Sensors

The compliance of soft actuators introduces new requirements for the sensor technologies. The sensors need to be as flexible as the actuator to not restrict them. For the human hand several flexible sensors have been developed. They can measure contact and bending by means of bi-metallic strips, carbon-infused silicone, and dielectric stretchable thin-metal films [9]–[11]. Even though these sensors are flexible and stretchable enough for the human hand, they are still not elastic enough to be used with soft actuators, which often exhibit stretch of more than 200% [1].

Recently, the use of liquid metal made it possible to
build strain sensors that can withstand elongation typically observed in soft actuators. Metal alloys, like eutectic gallium-indium (EGaIn), are liquid at room temperature and can be used to detect strain through change in resistance. Various patterns have been proposed to sense contact and multi-axial strain using silicone-embedded EGaIn [12]–[15]. These sensors are promising candidates for the integration with soft actuators.

To calculate the optimal placement of strain sensors on soft structures, Culha et al. [16] have developed a computational method. It is, however, based on voxel models which are not available for most soft actuators.

### B. Sensorized Soft Actuators

Only very few studies of sensorized soft actuators have been published. Homberg et al. [17] presented a three-fingered pneumatic hand, equipped with commercially available resistive flex sensors. A single sensor in each finger provides feedback about its curvature, which is used to recognize objects during grasping. Bilodeau et al. [18] included liquid metal strain sensors directly into the fabrication process of a pneumatic four-fingered gripper. They use the sensor measurements in conjunction with the actuation pressure to detect if an object was grasped. Farrow and Correll [19] published a design for an easily customizable liquid metal strain sensor. It uses EGaIn injected into prefabricated silicon tubes for simple and robust manufacturing. Attached to a pneumatic actuator they show how the actuation pressure and strain measurement allow to estimate the diameter of cylindrical objects.

All of these solutions use only a single sensor per actuator and can consequently only detect movement in the plane of actuation. However, the key feature of soft actuators is their passive compliance. For this reason most interactions cause deformations in more than one dimension. For many manipulation tasks perception of additional deformation dimensions offers valuable insights about the grasp. Depending on the expected tasks, additional sensing is therefore required.

### III. Method

To be able to fully reconstruct the shape of a soft actuator, a very large number of sensors would be necessary. In many applications, however, the space of relevant deformations is only a subset of all possible deformations. We therefore propose a method to sensorize soft actuators, which, given a specific application, finds the most appropriate sensor layout.

This section describes the general process for any soft actuator in six steps. In Section IV this method is applied to the RBO Hand 2. Each subsection of method and application correspond to the same step.

#### A. Target Selection

Initially, all application-relevant variations to the actuator’s state have to be identified. For many manipulation tasks this will be some form of deformation of the actuator. But any other measurable physical property, e.g. contact location, is permissible. For the grasping application, we chose to sensorize the RBO Hand 2 for the identified deformation modes shown in Figure 2.

#### B. Redundant Sensor Layout

Approximate modeling and human intuition is used to generate an initial, redundant layout of sensors for the selected deformations. Through minor variation in the placement of similar sensors redundancy is introduced. Figure 3 shows the redundant sensor layout that was selected for the PneuFlex actuators of the RBO Hand 2.

#### C. Obtaining Training Data

In order to perform supervised learning in the next step, labeled training data is required. For this the soft actuator is manipulated in ways that are expected to occur in the envisioned application. Meanwhile the sensor data and ground truth of the target deformation are recorded. Part of the recorded training data is shown in Figure 4.

#### D. Supervised Learning

The training data is used to learn a mapping from sensor data to the deformation of the actuator. The choice of learning algorithm depends on the type of target data. The quality of the sensor layout is evaluated with the prediction error of the trained model on an independent validation set. Figure 5 shows an excerpt of the learned PneuFlex deformation estimation.

#### E. Layout Reduction

The redundant sensor layout is reduced to find the most appropriate set of sensors for the task. For this a variant of the Recursive Feature Elimination (RFE) algorithm [20] is applied, which excludes the least relevant sensor in each
iteration. By using a subset of the already recorded data, no new measurements need to be made. The reduction is repeated until only a single sensor is left. Two steps of the applied layout reduction are shown in Figure 6.

F. Final Layout

The validation error of each intermediate layout during the reduction steps indicates its quality. The sensor layout with the lowest error offers the most accurate mapping of sensor data to deformations. It is chosen as the final layout. The result for the PneuFlex actuator is visualized in Figure 8.

IV. APPLICATION TO THE RBO HAND 2

The proposed method is now applied to sensorize the PneuFlex actuators of the RBO Hand 2. All subsections correspond to the respective step of the general method described in Section III.

A. Target Selection

To determine the relevant deformation we observed the RBO Hand 2 during common manipulation tasks (Figure 2). From all possible deformations, the following three were the most descriptive for the actuator’s state:

1) **Flexional**: A displacement in the actuated direction.
2) **Lateral**: The finger bends to the side.
3) **Twist**: A rotation about the longitudinal axis.

B. Redundant Sensor Layout

**Sensor Types:** Farrow and Correll [19] presented a very flexible liquid metal strain sensor that works well with PneuFlex-like actuators. Its thin design has little influence on the actuators compliance and is able to withstand large stretch. The process is easily adjustable to specific sensor shapes. Detailed fabrication instructions can be found in [19].

Additionally we use a pressure sensor for the pressure inside the actuator’s air chamber. Such a sensor is required for actuation anyway, so it does not add complexity.

**Sensor Placement:** Currently no reliable deformation model exist for the PneuFlex. Therefore, the initial, redundant sensor layout is created based on intuition and observation of the actuator. Strain is most effectively measured along the path of maximum stretch. In case of the PneuFlex the stretch is visible by observation of the rubber hull. This gives an indication of where to place the sensors. Through slight variations of similar sensors, redundancy is introduced.

The redundant sensor layout is shown in Figure 3. It consists of ten strain sensors: two on the back, three on the sides, and five wrapped around the finger diagonally.

C. Obtaining Training Data

**Sensor Data:** A LabJack U6 data acquisition system is used to record data from the ten strain sensors and a Freescale MPX-series pressure sensor. All data are recorded at 20 Hz.

**Deformation Data:** Ground truth about the actuator shape is recorded using a motion capture system (MoCap) by Motion Analysis. Markers on the base and the fingertip are used to track the deformation of the actuator in 3D-space. The system’s ten cameras operate at 100 Hz.

The magnitude of each deformation mode is extracted from the MoCap data by calculating the transformation between the initial resting position of the actuator’s fingertip and its current pose in each frame. Flexional deformation is expressed as the angle of the fingertip’s rotation in the actuation pane. Lateral deformation is quantified as the offset of the fingertip in millimeters that occurs perpendicular to the actuation pane. Twist is the angle of rotation about the actuators longitudinal axis (base to fingertip).

**Conducting the Experiment:** The experiment consists of five trials, with five steps of inflation pressure each. Pressures are selected equidistant from 0 kPa (deflated, straight) to 200 kPa (maximally inflated). The step order is randomized to eliminate the risk of temporal effects.

Before each step a calibration movement (one complete inflation and deflation) helps to account for small sensor offsets, caused by unreliable electrical sensor connections.

At each pressure level the actuator is deformed manually by applying forces to the fingertip. The movements are chosen to mimic the deformation we observed during grasping experiments. They cover both individual and combined occurrences of the three deformation modes.\(^1\)

Figure 4 shows the training data for a single pressure step. The different phases of calibration, inflation, manual deformation, and deflation are marked by vertical lines.

D. Supervised Learning

We apply polynomial regression learning methods from the Scikit-learn toolbox [21] to the recorded training data. Of the five complete trials, one trial is randomly selected as

\(^1\)Video of the experiment at https://youtu.be/Rvkl-5AEKLs
sensor readings used as training data

deformations used as target data

Fig. 4. Training data for a single pressure step from the test set. The horizontal segments indicate the phases: I: Calibration, II: Inflation, III: Manual deformation, IV: Deflation

Fig. 5. Estimation of the three deformation modes on part of the test set compared to the actual deformation

E. Layout Reduction

Our implementation of the RFE algorithm works by comparing \( n \) alternative layouts of \( n-1 \) sensors, where \( n \) is the number of sensors at the beginning of each iteration. In each layout one sensor is left out. The layout with the lowest MSE across all regression parameters (polynomial degree and interaction features) is selected and used in the next iteration. This repeats until only one sensor is left.

Figure 6 shows the results for the first reduction to 10 sensors and a later iteration to find the best 5-sensor layout. The columns represent reduced layouts. The label indicates which sensor is left out. The rows show the different parameterizations of the regression algorithm. The MSE for each layout and algorithm is represented by a colormap. The lowest MSE value is indicated with a yellow ’X’.

F. Final Layout

The result of each reduction step is summarized in Figure 7. It shows the MSE for the best layout-regression combinations for each number of sensors. The lowest value across all sensor sets is marked with an arrow. This represents the layout with the most effective sensors for the chosen three deformation modes. When using fewer sensors not enough variation in the data can be explained and both training and validation error increase. When using more sensors, however, the divergence of the two errors indicates an overfitting of the regression to the training data.

The final sensor layout chosen by our method for the PneuFlex actuator has a total of five sensors: the four strain sensors #2–left (full length), #3–right (half length), #5–top (half length), and #7– single twist (radial), plus the pressure sensor of the actuator. The final layout and the sensorized PneuFlex are shown in Figure 8.

V. CASE STUDY

The RBO Hand 2 has four identical PneuFlex actuators as fingers. (Palm and thumb are not considered here, as they are differently shaped actuators.) We built a sensorized version, with fingers using the final sensor layout. The sensorized hand was then tested in two manipulation tasks: grasping a spherical object and pulling a door handle (Figure 9).
1) Grasping: To analyze the effect of the sensorization during compliant grasping, we performed a simple grasp of a spherical object. One would expect to see in the deformation data the twist of the fingers that passively adapt their shape to the sphere.

Figure 10 shows the result of the deformation estimation during the grasp. Each subplot shows one deformation mode for all four fingers. Three observations are marked with arrows in the plots:

- **Arrow I:** The index finger has a noticeably larger flexional deformation compared to the other fingers. This indicates that it is not participating in the grasp.
- **Arrow II:** All four fingers show different levels of lateral deformation. The slight slope in the graph of the little finger, however, indicates that the finger is slowly slipping.
- **Arrow III:** The twist of the middle finger can be seen in the last subplot. This is a good example of passively compliant grasping.

2) Pulling: In a second manipulation task we used the sensorized RBO Hand 2 to pull the handle of a door. The soft fingers are not strong enough to hold on to the handle.

Figure 11 shows the estimated deformation of the sensorized hand while pulling a door handle. The four marked sections are discussed in V.-2.
handle and start to slip. With successful sensorization, the estimated deformations should show the slippage in the flexional component, as the fingers bend away and finally slip off the handle.

The estimation of the finger deformations in Figure 11 nicely shows how this can be detected by the sensorized hand. The subplots are organized by finger and each shows all three deformations. Four notable situations are visible from the data:

- **Situation I**: Three fingers make contact with the door handle. The little finger shows no additional deformation because it misses the handle.
- **Situation II**: The three fingers close around the handle and start pulling. They begin to slip, which can be seen in the flexional deformation.
- **Situation III**: The middle and ring finger slowly twist away. Then the ring finger slips off the handle. (The temporary drop in lateral deformation and twist of the ring finger at second 12 can be attributed to a pinched-off strain sensor at the fingertip.)
- **Situation IV**: The middle finger also slips off the handle and bumps into the ring finger. Both fingers show sudden deformations.

VI. DISCUSSION

The proposed method is based on a initial definition of relevant deformation modes, for which an appropriate sensor layout is determined. Depending on the application, additional deformation modes may become relevant. Possible extensions are localization of contact along the actuator and failure cases, e.g. buckling of the actuator due to high loads. As long as good representations can be found, the same method can be used to generate appropriate sensor layouts.

One frequent source of error were faulty sensor readings due to broken links between the liquid metal core of the sensor and the required wiring. Even small movements of the link occasionally resulted in complete interruption of the electric signal. However, there have been promising advances in the material sciences, investigating for example biphasic metal films, that might resolve these issues [22, 23].

VII. CONCLUSION

The compliance of soft actuators makes their sensorization useful but also challenging. While the complete space of possible deformations is very large, the ability to sense a subset of task-relevant deformations already offers useful insights. We have presented a general method for the sensorization of soft actuators. It systematically reduces an initially redundant set of sensors to find the most appropriate sensor layout for a given task. We have applied this method to the PneuFlex actuator and found a sensor layout that consists of four liquid metal strain sensors and one pressure sensor. With it we can perceive the actuators deformation in three dimensions: flexional, lateral, and twist. Finally we built a sensorized RBO Hand 2 with four sensorized PneuFlex fingers. We validate the results of the sensorization in two manipulation tasks. The sensorized hand can detect shape adaptation in compliant grasps and discover grasp failures due to slipping fingers.

REFERENCES


