Model-free Soft-Structure Reconstruction for Proprioception using Tactile Arrays

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***Abstract*—Continuum body structures provide unique opportunities for soft robotics, with the infinite degrees of freedom enabling unconstrained and highly adaptive exploration and manipulation. However, the infinite degrees of freedom of continuum bodies makes sensing (both intrinsically and extrinsically) challenging. To address this, in this paper we propose a model-free method for sensorizing tentacle-like continuum soft-structures using an array of spatially arranged capacitive tactile sensors. By using visual tracking, the relationship between the tactile response and the 3D shape of the continuum soft-structure can be learned. A data set of 15000 random soft-body postures was used, with recorded camera-tracked positions logged synchronously to the tactile sensor responses. This was used to train a neural network which can predict posture. We show it is possible to achieve proprioceptive awareness over all three axis of motion in space, reconstructing the body structure and inferring the soft body head's pose with an average accuracy of $\approx 1\mathrm{mm}$ in comparison to the visual tracked counterpart. To demonstrate the capabilities of the system, we perform random exploration of environments limiting the work-space of the sensorized robot. We find the method capable to autonomously reconstruct the reachable morphology of the environment without the need of external sensing units.**

***Index Terms*—Modeling, Control, and Learning for Soft Robots; Force and Tactile Sensing; Soft Sensors and Actuators**

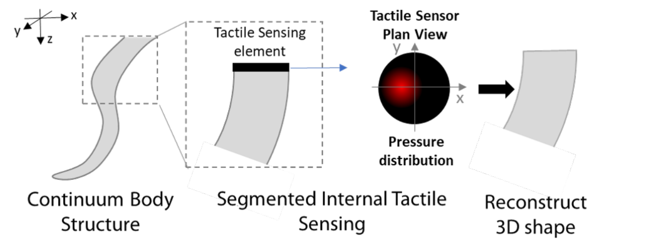
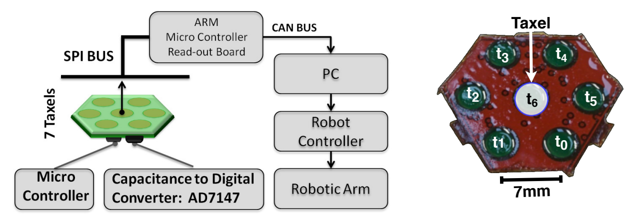


Fig. 1: Role of tactile sensing to allow reconstruction of passive systems. The deformation of the continuum body structure leads to internal pressure distributions which allow 3D reconstruction.



(a) (b)

Fig. 2: (a) The CySkin technology architecture. (b) The CySkin patch used for the experiments.

I. INTRODUCTION

THE advent of soft robotics has changed the robotics landscape, enabling rapid and low cost prototyping and providing resilience to external disturbance and internal failures [1], [2]. One key remaining challenge is the extrinsic and intrinsic sensing of soft bodies to provide environmental information which is key for complex environmental interaction. Considerable work has focused on the development of tactile sensing approaches [3], [4] and soft manipulators for environmental exploration [5]. There has been minimal investigation on how the inherent compliance of soft structures can be exploited to achieve environmental awareness [6], [7].

The use of fully soft continuum body structures for manipulation has been demonstrated with the creation of octopus tentacle systems [8], [9]. These adaptable manipulators take advantage of the intrinsic compliance of soft structures, exploiting environmental interactions in the process. However, the potentially infinite degrees of freedom offered by soft continuum body structures make it challenging, and often impossible, to accurately determine their spatial configuration, or proprioceptive awareness [10]. For environmental interactions to be understood in this context, it is necessary to develop sensing techniques capable of reconstructing the configuration of a soft continuum body. Research on the configuration reconstruction of such bodies has mainly been driven by tactile [11]–[13] and medical applications [14].

Historically, exteroceptive sensing technologies, such as cameras, have been predominantly used for soft body shape reconstruction [15]–[17]. These methods, however, are inapplicable in scenarios where it is impossible or impractical to set-up sensing units external to the soft body. More recently, sensors which are capable of measuring curvature and bending have been used, with early work showing how fiber optic curvature technology can be used to sense bending and twist [18]. Electroactive polymeric sensors have also been used to sense bend angles and rates in prostheses [19], while in [20], fluid-resistive bending sensor were developed for flexible pneumatic balloon actuators. Additionally, work in strain sensor technology has shown how proprioceptive

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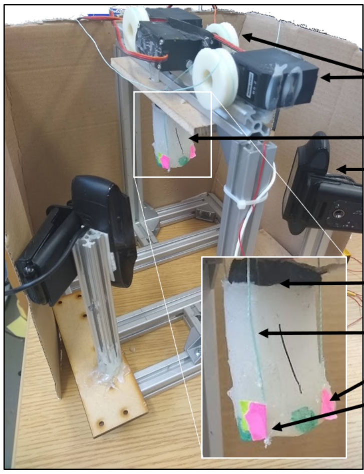


Fig. 3: Experimental setup showing the flexible soft body, location of the sensor, vision tracking system and the servo control and tendon system.

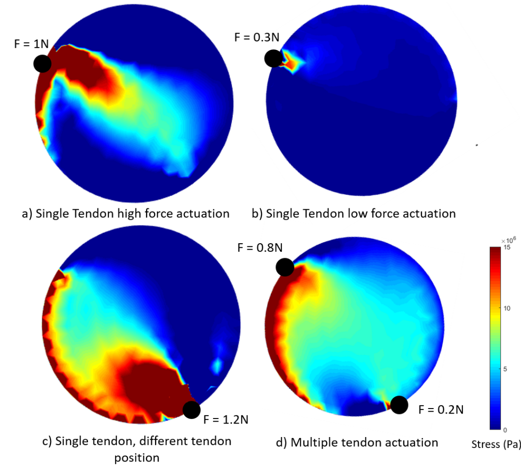


Fig. 4: Results from FEM experiments showing the stress distribution at the top of the sensorized body. a), b) and c) show the resulting stress distributions when actuating a single tendon with a force of 1N, 0.3N and 1.2N respectively. b) shows the stress distribution a two-tendon actuation, applying a force of 0.8N and 0.2N in two different locations.

curvature information can be retrieved and used for partial reconstruction of soft continuum bodies [21], [22]. Despite the progress, integration into soft robot technologies is limited. Additionally, the technologies developed allow discrimination of different preset states, such as bending, twisting and pushing, but do not obtain sufficient information for the full configuration reconstruction of a soft body. Recent work has shown how flexible force sensors can be embedded in soft robotics manipulators, obtaining information useful in task such as grasping and object recognition [23], [24]. However, this force sensing technology allows the curvature in only one axis to be measured.

To solve the proprioceptive problem, it is necessary to devise a method capable of reconstructing the spatial configuration of continuum soft materials over all axis of deformation, while maintaining the soft body characteristics (e.g. stretch and bend). We propose that by integrating a tactile sensor array at the base of a tentacle-like continuum soft body, it is possible to use the distributed change in pressure over the surface of the sensor, induced by the change in posture of the body, to retrieve the 3D position of the tentacle end-point. Through this method, the position estimation can thus be used to reconstruct the shape and configuration of the soft continuum body. This is summarized in Fig. 1.

To demonstrate these hypotheses we sensorize a soft tentacle-like body segment using capacitive tactile sensing technology. Using a simple feed-forward Neural Network, the mapping from the spatial response of the tactile sensor and the deformation of the continuum body can be obtained. This allows deformations to be sensed along all axes in 3D space, whilst maintaining the *soft* properties of the body (e.g. bend and stretch). By understanding the body structure, we demonstrate how this can enable exploration and reconstruction of the system's work-space.

The ability to understand the shape of a continuum body structure has the potential to impact work including medical robotics, soft robotic exploration and enables control of continuum structure which was previously not possible. To the authors knowledge, this is the first soft-robotic sensorization method based on capacitive tactile sensing technology, which is capable of sensing accurate deformation along all three dimensional axis in space.

In this paper, Section II presents the methods developed, including the capacitive tactile sensing technology, continuum structure design and experimental set-up. The results are reported in Section III which characterize the performance of the system. Additionally, a case study of environmental exploration through body posture inference is presented. The paper concludes with a discussion in Section IV.

II. METHODS

A. Tactile Sensing Technology

The tactile sensor used for the experiments is described in [25]. The sensor uses capacitive transduction organized in a layered structure: the lower layer consists of the positive electrode, which is mounted on a Flexible Printed Circuit Board (FPCB). A small air chamber act as dielectric and the upper layer is a ground plane made with conductive Lycra. The tactile sensor is made up of a number of tactile elements ($taxels$) geometrically organized in triangular modules.

In the experiments we use an hexagonal shaped module, hosting 7 taxels (Fig. 2b), as well as the Capacitance to Digital Converter (CDC) chip (namely, the AD7147 from Analog Devices) for converting capacitance values to digital. The CDC chip can measure variations in capacitance values with 16 bits of resolution. All the modules are interconnected and communicate through an SPI bus to a read-out board which performs a preliminary processing of the tactile sensor data and send them to the PC through CAN bus (Fig. 2a) with a sensitivity of $0.32\,\mathrm{pF}$. In this context, the normal forces exerted on the sensor produce variations in capacitance reflecting the varied pressure over the taxel positions. A sensor reading, or tactile image, from the tactile sensors described is produced at $20Hz$, and corresponds to a 7-dimensional array,

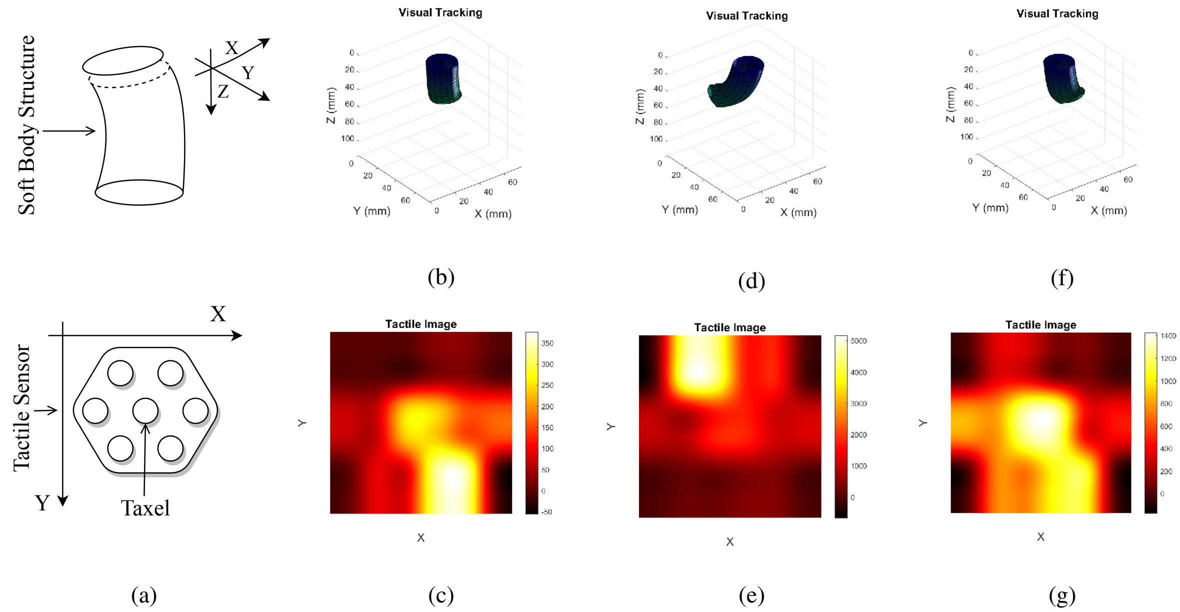


Fig. 5: Raw tactile image pressure sensing, induced by the change in posture of the soft body. (a) shows the coordinate system for each corresponding row in the figure. Fig. (b), (d) and (f) show the visually tracked soft body pose in three different motor-induced poses. Fig. (c), (e) and (g) show the corresponding tactile images, where increasing brightness implicates higher sensed pressure.

where each element contains the capacitance variation value of the corresponding taxel within the patch.

B. Soft Continuum Body Design and Sensor Embedding

A continuum soft body segment has been developed by casting EcoFlex 00-30 silicone in a 3D printed mould. This soft ‘finger’ (height = 50cm, radius = 15mm) is controlled by three tendons equally distributed around the finger, and which allow full position control of the soft body.

The capacitive tactile sensor module described in Section II-A is placed at the base of the cylindrical finger. Thus, the capacitive sensor taxels are uniformly distributed along one of the circular surfaces of the elastomeric finger. The sensor placement allows pressure patterns to be sensed at the top of the finger when deformations are induced along its body.

To perform the experiments, we devised a set-up by which the soft continuum finger is suspended at the top of a cubical frame (Fig. 3). The hexagonal tactile sensing module is thus placed between the base of the finger and the top metal beam of the cage. Three servos are placed above the top beam, each connected to a tendon to allow the continuum structure to be deformed. Two cameras are mounted in adjacent corners of the frame. The cameras face the finger in orthogonal directions, and perform visual tracking of markers on the finger’s head, to reconstruct the posture of the continuum body (Fig. 3). Both visual tracking and tactile images are logged synchronously throughout the experiments.

C. Sensor Pressure Distributions and Visual Tracking

When the tendons are actuated by the servos, the finger’s change in posture induces changes in the distributed pressure on the sensors surface. To demonstrate how these vary for different poses of the soft structure, we have modelled the soft structure and pressure distributions through FEM. The soft continuum body structure has been modelled as a third order reduced polynomial with a modulus of E=1.4 MPa, which has been shown to provide the closest model to the true behaviour [26]. We use a Cosserat model to represent the interaction between the tendon and the soft body. The surface pressure for a given force applied to a tendon can be simulated. The simulation was performed through the MATLAB FEM toolbox. The force applied by a tendon changes the magnitude and area of the pressure distribution at that location (as shown by Fig. 4 (a), (b) and (c)). Similarly, by combining different tendon actuation, more complex pressure distributions can be observed (Fig. 4 (d)), reflecting the type of actuation both in magnitude and location. Following the hypothesis, the pressure distribution is here indicative of the posture of the soft body, determined by the specific tendon actuation.

This approach has also been shown experimentally (Fig. 5) where the tactile image represents the pressure distribution on the sensor’s surface for different finger configurations, as retrieved and reconstructed by the camera tracking system.

The tracking system performs 3D tracking of markers placed at the head of the soft finger. Given the shape and make of the soft continuum body, the reconstruction of the body’s configuration consists of a logarithmic interpolation between the base of the finger, sensed when the finger is at rest, and the tracked x-y-z positions thereafter.

III. RESULTS

A. Soft-body configuration Learning from Visual Tracking

We perform experiments where the soft finger is actuated by random combinations of servo angles, reaching arbitrary

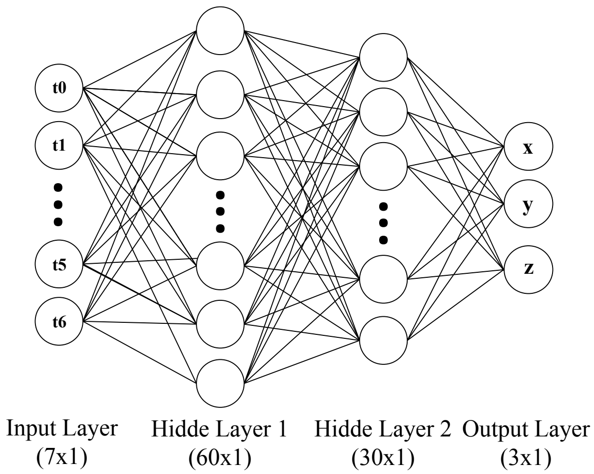


Fig. 6: Neural Network for tactile learning.

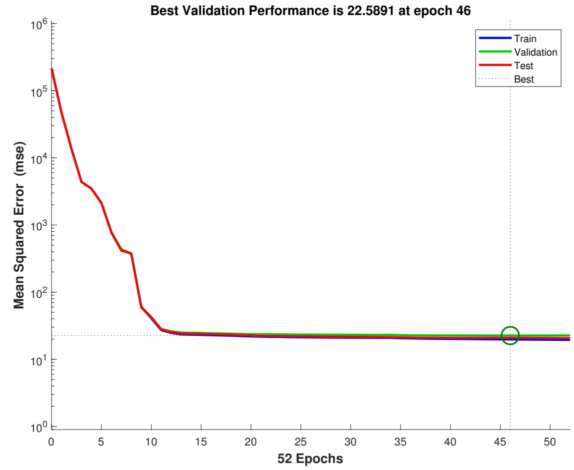


Fig. 7: Neural Network training and validation curves.

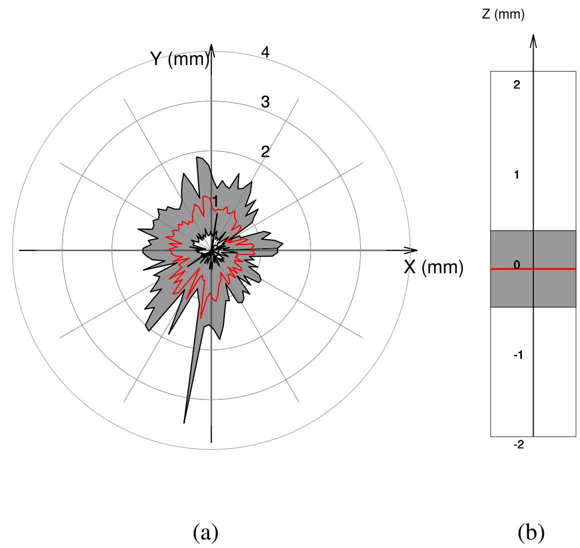


Fig. 8: The error (red line) and standard deviation (gray area) of the finger (a) in x-y coordinates, and (b) in z coordinates, as compared to the corresponding visually tracked positions.

points in space. The cameras, placed on the aluminum frame, perform visual tracking and retrieve the configuration of the 3D finger for each set of servo angles. Concurrently, tactile images from the capacitive tactile sensor array are recorded and stored for each configuration. The actuation of the finger is run autonomously for a total of 15000 random configurations. A Neural Network is used to map the tactile sensor responses directly to the finger head positions. Given the servo and tendon placement, stretching postures could not be achieved unless manually induced. As such, the network was not trained on stretch prediction.

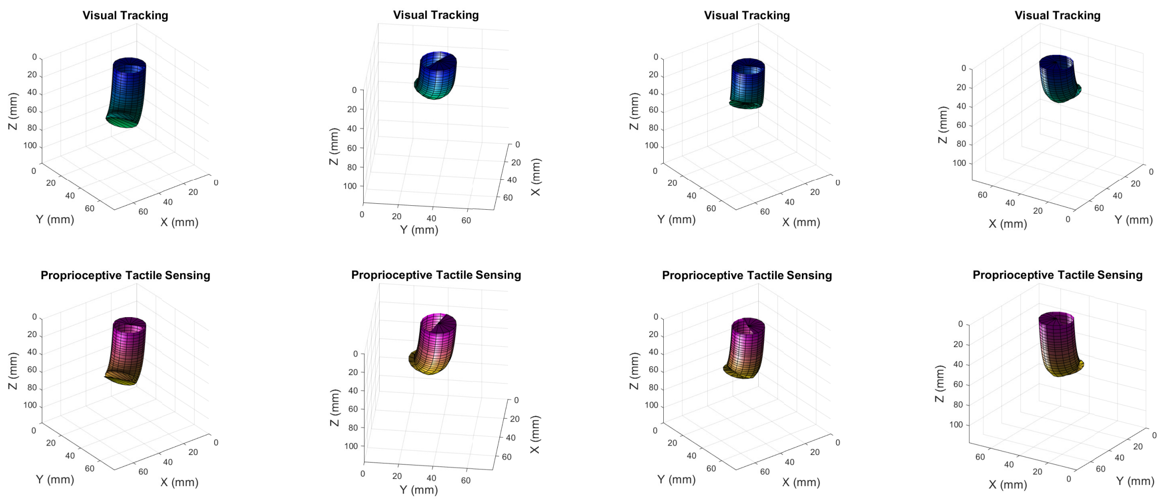
The Neural Network is a fully connected feed-forward network with an input layer of 7 units, to read tactile image information, two hidden layers of respectively 60 and 30 units, and an output layer of 3 units, returning an $x - y - z$ position in space, corresponding to the camera tracked outputs, and relative to the learned finger configuration (Fig. 6). The non-linearity for all units is a $tanh$, with a Glorot uniform initialization [27]. The design of the network is here secondary to the main research goal, with this specific implementation enabling testing, to identify whether it is possible to accurately determine the deformation of the finger vie the capacitive tactile sensor array sensing.

The network is trained over 52 epochs, with the 15000 tactile images in input and corresponding x-y-z visually tracked positions for target outputs. 75% of the data was used for training while 15% was used for validation and 10% for testing. Fig. 7 shows the training error, validation and test performance of the network during learning. The network trained over 52 epochs, before halting due to early stopping, and reaching a lowest validation error of $22.589px$ and test error of $22.732px$. Given cameras' placement with respect to the finger position, a pixel corresponds to $\approx 0.13mm$

B. Tactile Proprioceptive analysis

For testing purposes we retrieve 2000 previously unseen finger configurations, with corresponding tactile images and visually tracked head positions. Fig. 9 shows the compared finger deformation reconstruction of four different finger test configurations, based on the camera visual tracking and the proprioceptive tactile sensor response after learning.

The close correspondence between the true position and that estimated by the tactile sensors clearly demonstrates how the embedded capacitive tactile sensor is capable of matching the performance of the external camera tracking. In Fig. 8 we compare the error of the tactile sensor, over all axis within its work-space, to the ground truth retrieved by visual tracking. In a 'reachable' work-space of $\approx 40X40mm$ in x-y space, and $\approx 30mm$ in z (or height), from the figure it is possible to see how, on average, the tactile prediction after learning is within $1mm$ from its ground truth counterpart, retrieved from visual tracking. The experiments show how the tactile sensor array is capable of capturing the information relative to the deformation of the soft continuum fingers, with levels of accuracy near $1mm$ on average in all axis of deformation.



(a) (b) (c) (d)

Fig. 9: Shape reconstruction based on the proprioceptive tactile sensing as compared to visual tracking.

C. *Tactile Proprioceptive Work-space Exploration*

As previously mentioned, it is often the case that the conditions surrounding a deployed robotics system do not allow the installation of exteroceptive sensing mechanisms, like cameras. After learning, we halt the camera tracking system and undertake experiments where the sensorized finger is randomly actuated within unknown work-spaces. Initially, The finger is actuated over 2000 random servo angles, whilst free to move within its own environment. After, the soft continuum body is placed within a semi-closed and closed off environment, where vision based reconstruction methods are not possible. In the first instance, the finger is placed in a cuboid with three missing faces (Fig. 10c), and is further actuated over 2000 random configurations. In the second instance, the experiment is repeated with the finger placed within a space in the shape of a cuboid with two missing faces (Fig. 10e). Figures 10b, 10d and 10f show the x-y positions of the soft finger, as predicted by the Neural Network using only the sequential tactile images recorded. The finger explored spaces in Fig. 10f and Fig 10d are significantly smaller than the full work-space explored explored in Fig. 10b. Remarkably, the retrieved x-y positions accurately match the work-space explored by the sensorized soft structure in shape, as can be seen by comparing Fig 10c with Fig. 10d and Fig. 10e with Fig. 10f. The figure illustrates how through autonomous exploration and proprioception, it is possible to accurately retrieve the state of the work-space surrounding the soft finger.

IV. CONCLUSIONS

Retrieving the spatial configuration of soft continuum materials is currently a challenge. Over the past few decades, various methods have been devised, however, these methods are only capable of discriminating between preset states, or can sense deformations along one axis in space. We have devised a novel method to retrieve deformation information based on capacitive tactile sensing technology, where we embedded a capacitive tactile sensor array to read pressures at the base of a soft continuum cylindrical body, or finger. Experiments were performed, where the soft continuum body was deformed by actuating three attached tendons concurrently. The resulting material deformation allowed the finger's head to reach an arbitrary point in 3D space within its work-space. A camera tracking system was used to track the head of the finger synchronously to retrieving pressure patterns at its base, through the tactile sensor array.

By using the camera tracking system as a supervisor we have shown how it is possible to autonomously learn the body configuration and the work-space of the soft structure, through the random actuation of the finger. The capacitive tactile sensing technology is used to achieve a proprioceptive kinaesthetic understanding of the soft structure, allowing a Neural Network to guess the head position of the cylinder within $1mm$ from its visually tracked position. Moreover, the system was shown to be reliable against external disturbances and interactions, as demonstrated during the random exploration of closed spaces, where the actuated body would unavoidable collide with the surface of the surrounding walls. We have shown how it is possible for the finger to perform autonomous explorations of work-spaces where cameras are impractical to use. Finally, the method of embedding the tactile sensor into the continuum body allows for the inherent soft properties of the continuum material to be maintained (e.g. stretch and bend). This work has the potential to enable and assist with many applications, such as medical exploration, e.g. provide postural feedback, or the resolution of exploratory and manipulation tasks.

After demonstrating the principles of both the sensor integration and learning, and the capabilities of the system to predict the configuration of the soft structure with high levels of accuracy, future work will include the extension of the actuation system to allow for twists and stretch. Moreover, we will focus to extend this sensorization method to include multiple sensors, at different levels, within a continuum soft body, possibly enabling the sensing of twists, bends and double

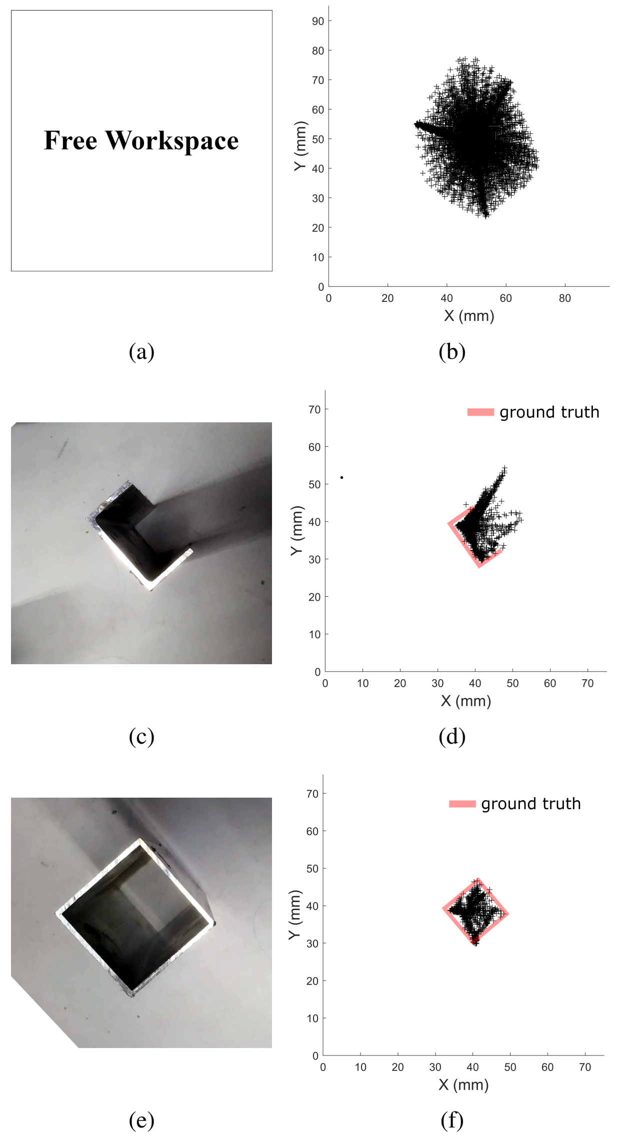


Fig. 10: Work-space reconstruction after random exploration. (a) shows the work-space explored when the finger was free to move over its reachable work-space. Figures (d) and (f) show respectively the reached positions when the soft finger was placed inside the cuboidal object shown in (c) and (e).

bends with high levels of accuracy.

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