Sensing Soft Robot Shape Using IMUs: An Experimental Investigation

Josie Hughes[1(✉)], Francesco Stella[2], Cosimo Della Santina[2,3,4], and Daniela Rus[1]

[1] Distributed Robotics Lab, CSAIL, MIT, Cambridge, USA
josieh@mit.edu
[2] Cognitive Robotics Department, Delft University of Technology, Delft, Netherlands
[3] Informatics and Mathematics Department, Technical University of Munich, Munich, Germany
[4] Institute of Robotics and Mechatronics, German Aerospace Center (DLR), Cologne, Germany

Abstract. Shape estimation of soft robotic systems is challenging due to the range of deformations that can be achieved, and the limited availability of physically compatible sensors. We propose a method of reconstruction using Inertial Measurement Units (IMUs), which are mounted on segments of a deformable manipulator. This approach utilizes the piecewise constant curvature model in combination with the quaternion data from IMUs to allow for accuracy reconstruction and closed-loop control. A key strength of this approach is that it is hardware agnostic, and could be used on any soft structure to provide pose reconstruction and controllability. We explore this approach experimentally on a growing, extendable 3D printed continuum body structure, demonstrating that high accuracy reconstruction that can be achieved.

Keywords: Soft manipulation · Kinematic control · Shape estimation

1 Introduction

Within the domain of soft robotics, continuum body manipulators offer particularly exciting capabilities, with applications ranging from surgery, compliant exploration and human like environmental interactions [4,12]. To achieve such capabilities there is firstly the challenge of the design and fabrication of the system [6]. However, there is then the second key challenge of developing the artificial brains to control the robot [5]. In this regard a central problem is that of perception, since understanding the robot shape is critical for control. However, accurately measuring and reconstructing the shape of a soft robot without relying on exteroceptive sensing techniques is very challenging [9].

There is a significant body of related work focusing on shape and pose reconstruction of continuum body structures. Many proprioceptive techniques for such robots rely on soft sensors which are custom or specific to the particular physical manifestation of the manipulator [8]. The use of learning techniques [14,15] or mixed strategies [16], are often required due to the complex nonlinear characteristics of these sensors. More recently approaches such as model predictive

B. Siciliano et al. (Eds.): ISER 2020, SPAR 19, pp. 543–552, 2021.
https://doi.org/10.1007/978-3-030-71151-1_48

control [2], and computational methods [1] have been shown to perform well for trajectory optimization of soft robots.

In light of this existing work, and the challenges that remain, we focus on the problem statement of providing accurate and reliable proprioception to soft robots. We believe that Inertial Measurement Units (IMUs) are a feasible solution for equipping soft robots with preconception capabilities, without altering the soft nature of the system, and without requiring the implementation of complex machine learning techniques. Existing work has shown how IMUs can be used for accurate reconstruction of rigid robots [13] and UAVs [11], and has also been widely demonstrated for human pose reconstruction [13]. Extending these capabilities to the domain of soft robots, would provide a 'universal' proprioceptive solution which could be used across a wide number of soft arms and continuum structures. To work towards this goal, this work makes the following contributions:

- A theoretical framework for using IMU sensor data to enable the reconstruction of the shape of a soft continuum manipulators, based upon the piecewise constant curvature model.
- Development of a extensible, flexible, multi-segment, continuum body manipulator to demonstrate this approach. We will contextually test and benchmark against the use of encoders for proprioception [7].
- Experimental results that quantify the accuracy that can be achieved when using IMUs for reconstruction, and for closed loop control of a continuum body manipulator.

In the remainder of this paper we first introduce the technical approach and methods for IMU based reconstruction. We introduce the robot platform that has been developed to explore this approach. Following on from this we show the results of applying the approaches to the robot platform demonstrating the effectiveness and accuracy that can be achieved.

2 Technical Approach and Methods

Intertial Measurament Units (IMUs) sense 3-axis linear acceleration and angular velocity. They also include a magnetometer which senses the direction of the magnetic field. Although standard methods to fuse these sources of information are prone to drift over time, recently proposed techniques have proven able to reduce this problematic accumulation of error to a minimum. Such techniques have been shown to be particularly effective in the case of sensing orientation. For example, the Mahony filter in [11] has shown that drifts can be limited to only the local direction of the gravity field. For the case of continuum body robots, the output from these filters is not the only information that we have regarding the shape of the soft robot.

Using the piecewise constant curvature (PCC) approximation we can identify the full shape of each segment from a function which has just two variables. Consider a number of reference frames attached as in Fig. 1, on for the end of each segment plus one at the base. Let R^i_{i-1} be the rotation matrix and t^i_{i-1} the

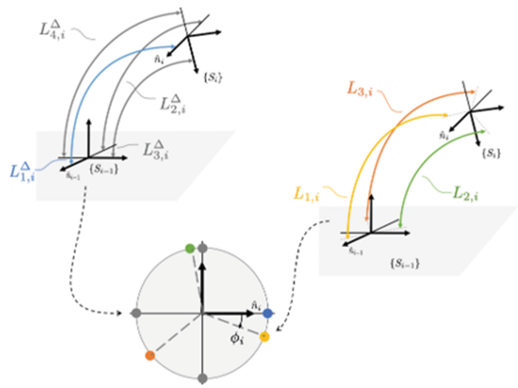

Fig. 1. Model and reference frames for the manipulator.

translation mapping the reference frame at base of the $i-$th segment to the one attached to its tip.

According to the description proposed in [3], the posture of the $i-$th segment can be described through the two banding variables $\Delta_{\mathrm{x},i}, \Delta_{\mathrm{y},i} \in \mathbb{R}$ and the total length of the segment L_i. More specifically the orientation is described by the rotation matrix $R_{i-1}^{i}(\Delta_{\mathrm{x},i}, \Delta_{\mathrm{y},i}, s_i) =$

$$\begin{bmatrix} 1+\frac{\Delta_{\mathrm{x},i}^2}{\Delta^2}\left(1-\cos\left(s_i\Delta_i\right)\right) & \frac{\Delta_{\mathrm{x},i}\Delta_{\mathrm{y},i}}{\Delta^2}\left(1-\cos\left(s_i\Delta_i\right)\right) & -\frac{\Delta_{\mathrm{x},i}}{\Delta}\sin\left(s_i\Delta_i\right) \\ \frac{\Delta_{\mathrm{x},i}\Delta_{\mathrm{y},i}}{\Delta^2}\left(1-\cos\left(s_i\Delta_i\right)\right) & 1+\frac{\Delta_{\mathrm{y},i}^2}{\Delta^2}\left(1-\cos\left(s_i\Delta_i\right)\right) & -\frac{\Delta_{\mathrm{y},i}}{\Delta}\sin\left(s_i\Delta_i\right) \\ \frac{\Delta_{\mathrm{x},i}}{\Delta}\sin\left(s_i\Delta_i\right) & \frac{\Delta_{\mathrm{y},i}}{\Delta}\sin\left(s_i\Delta_i\right) & 1+\left(1-\cos\left(s_i\Delta_i\right)\right) \end{bmatrix}, \tag{1}$$

and the position by the vector

$$t_{i-1}^{i}(\Delta_{\mathrm{x},i}, \Delta_{\mathrm{y},i}, L_i, s_i) = \frac{L_i}{\Delta_i^2}\begin{bmatrix} \left(1-\cos\left(s_i\Delta_i\right)\right)\Delta_{\mathrm{x},i} \\ \left(1-\cos\left(s_i\Delta_i\right)\right)\Delta_{\mathrm{y},i} \\ \sin\left(s_i\Delta_i\right)\Delta_i \end{bmatrix}, \tag{2}$$

where $\Delta_i = \sqrt{\Delta_{\mathrm{x},i}^2 + \Delta_{\mathrm{y},i}^2}$. The local coordinate along the segment is $s_i \in [0,1]$, with 0 referring to the base, and 1 to the tip (see Fig. 1). Since we have an IMU at the base and tip of each continuum body segment, we can use the posture provided by a stack of Mahony filters [10] to extract the global posture of each reference frame $\hat{R}_0^i$. We then evaluate the relative posture $\hat{R}_{i-1}^{i} = \left(\hat{R}_0^{i-1}\right)^{-1}\hat{R}_0^i$. Finally, we can extract the parameterization of each segment by properly inverting (1) for $s_i = 1$. We propose to do that by evaluating the configuration of the segment as the solution of the optimization problem

$$\arg\min_{\Delta_{\mathrm{x},i}, \Delta_{\mathrm{y},i} \in \mathbb{R}^2} ||R_{i-1}^{i}(\Delta_{\mathrm{x},i}, \Delta_{\mathrm{y},i}, 1) - \hat{R}_{i-1}^{i}||_{\mathrm{F}}^2, \tag{3}$$

where $||\cdot||_{\mathrm{F}}$ is the Frobenius norm, and $R_{i-1}^{i}(\Delta_{\mathrm{x},i}, \Delta_{\mathrm{y},i}, 1)$ is as in (1). This is evaluated by starting from the initial guess

$$\begin{aligned}\Delta_{\mathrm{x},i} &= \frac{1}{2}(\hat{R}^i_{i-1}[3,1] - \hat{R}^i_{i-1}[1,3]) \arccos(\hat{R}^i_{i-1}[3,3]) / \sin(\arccos(\hat{R}^i_{i-1}[3,3])),\\ \Delta_{\mathrm{y},i} &= \frac{1}{2}(\hat{R}^i_{i-1}[3,2] - \hat{R}^i_{i-1}[2,3]) \arccos(\hat{R}^i_{i-1}[3,3]) / \sin(\arccos(\hat{R}^i_{i-1}[3,3])),\end{aligned} \tag{4}$$

where $\hat{R}^i_{i-1}[j,k]$ is the element of $\hat{R}^i_{i-1}$ positioned at row j and column k. Note that if the PCC hypothesis were perfectly fulfilled, than $R^i_{i-1}(\Delta_{\mathrm{x},i}, \Delta_{\mathrm{y},i}) = \hat{R}^i_{i-1}$ - i.e. this would be the global minimum of (3). Yet the real system will likely have a non perfectly constant bending. Therefore, we use standard gradient descent method to locally refine the guess. In this way the residual drift is tamed by the constraints imposed by the kinematic model. Finally, full postures (i.e. both orientation and position) of each point along the segment can be retrieved by substituting back the parameterization into (1). Note that under PCC hypothesis the total length of the segment L_i can be expressed as average of the length of the three actuated segments, which in turn is know from the motor encoders.

In this way the IMU can be used to evaluate full posture, instead of orientation only. Finally, the extracted configuration can be used to regulate the end effector configuration of the robot through kinematic feedback controllers. We extend here the inverse kinematics approach introduced in [7, Sect. 2C], by using the error between desired tip configuration and the measured one, rather than computing the value off-line.

3 Experimental Platform

To validate this algorithm we have developed a single segment, continuum body manipulator based upon our previous work [7]. The actuation system consists of a compliant tri-axial rack and pinion system formed from flexible 3D printed rack elements (Fig. 2). On this motorised platform we have the three rack and pinion mechanisms, each controlled by a DC motor equipped with a quadrature encoder. A PID controller has been implemented to allow a the length of the legs of the manipulation to be set. By varying the length of flexible track between the tip and the base for each of the flexible backbones, the orientation and location of the tip can be controlled in 3D space. This allows for both growth and change in length of the robot, and also motion of the movement of the tip in 3D space. Using the encoders, the approximate position of the end-effector can be controller using the piecewise constant curvature approximation, as previously shown in [7]. Multiple, independent stages of this manipulator can be combined together to generate larger systems, and the properties of the 3D printed racks can be varied to control the bending properties. We have equipped the manipulator with two 9 Degrees of Freedom (DoF) IMUs (BMO005), mounted on the base and the tip of the manipulator, with the two aligned in the Z axis. The IMUs have been calibrated, and the 4 axis quaternions were sampled 10 Hz. Initial readings were discarded to ensure the magnetometer is calibrated. Patterns of reflective motion tracking markers have been mounted on the two stages of the robot, to allow the ground truth of the position of the robot to be captured using a motion tracking experiments. The location of the sensors and markers is highlighted in Fig. 2.

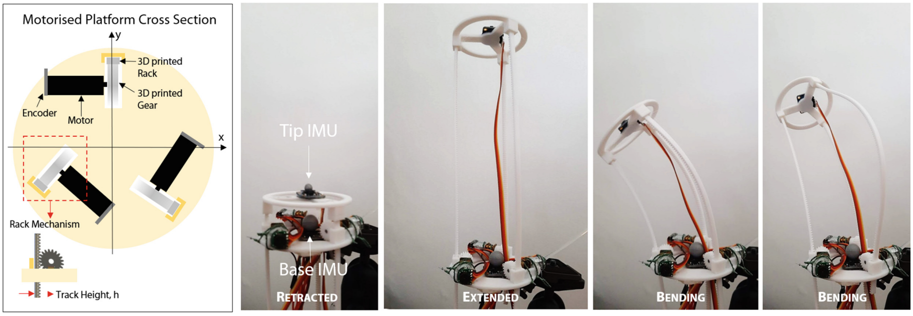

Fig. 2. Design of the actuation stages of the manipulator showing the triaxial motors and 3D printed tracks. Accompanied by pictures showing the range of motions and actions that can be achieved using the manipulator. The placement of the IMUs is highlighted.

It is important to underline here that encoders are a sensing technology that is specific to this design, and are general not feasible for other kind of soft robots. Conversely, implementation of IMUs on a soft robot would be agnostic of the actuation method providing versatility.

4 Results

In this section we first explore the performance of open loop pose reconstruction when using the IMUs on the robot system. Following on from this, we then implemented closed loop control as proposed above to increase the positional accuracy of the robot.

4.1 Pose Reconstruction

In the first experiments we consider the accuracy with which the pose can be reconstructed using the IMU sensor data. The end effector was systematically moved around the working space of the manipulator in the x, y and z axis by varying the demanded encoder positions. During this experiment the true 6 DoF position of the end effector and base of the manipulator was captured using motion capture, and the data from the tip and base IMU was also recorded. Using the methods identified in Sect. 2, the pose of the robot was reconstructed over this period using the IMU data.

In Fig. 3 we show a number of poses of the robot overlaid with a reconstruction of the robot that has been calculated using the IMU data. These results show that there is a close similarity between the shape of the manipulator and the reconstruction. We also see a high accuracy in the estimation of the prediction of the location of the tip of the end effector.

To quantify the performance of the pose reconstruction over the entire workspace of the robot, a comparison between the true pose of the end effector

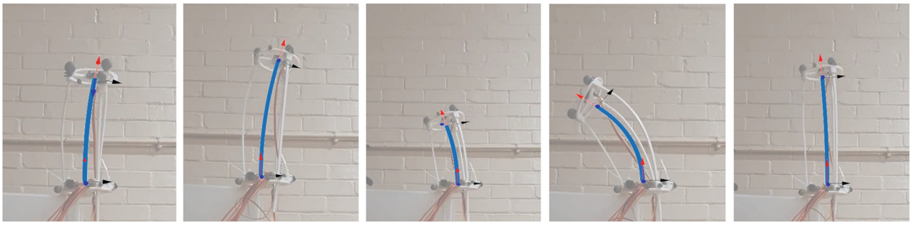

Fig. 3. Comparison between real pose of the robot, and reconstructed pose determined using the IMU data.

(as determined by motion capture), and the pose as estimated using the IMU data has been calculated. The error when reconstructing the location is evaluated by computing the Euclidean distance between the end effector position as reconstructed from the IMU and the true location. Over the entire recording, the reconstruction had a mean accuracy of 2.7 cm, with an accompanying standard deviation of 1.2 cm. For reference, the total length of the robot segment was approximately 20 cm. The error in reconstructing the orientation was evaluated by computing the norm of the relative rotation between the motion capture frame and the IMU based frame, i.e. $|q_{MC} conj(q_{IMU})|$, where q_{MC} and $conj(q_{IMU})$ are the quaternion vectors of the motion capture and the complex conjugate of the IMU quaternion projected on the PCC kinematic model respectively. The recorded accuracy of the orientation has a mean of 0.92 and a standard deviation of 0.12. In this context, a result of 1 represent perfect reconstruction of the orientation. In the context of deformable robots and the variety of different motions that can be achieved with the end effector, this offers an accuracy that would assist in enabling many tasks.

4.2 Closed Loop Control

To experimentally test using the IMU data for closed loop control, the end-effector of the robot has been set to move to a variety of positions along the x, y and z planes within the work-space of the robot. This was performed using encoder only ‘open loop control’, where the position was determined by setting specific demand encoder values, and also closed loop control using the IMU data in addition. The visual results are shown in Fig. 4 where the motion in each axis is shown for both the open loop and closed loop motion strategies. It can be observed that the IMU based control shows a far closer match to the expected motion path. When only the encoder based approach is used slippage between the gears and rack, and other causes of error lowers the positional accuracy significantly. This is particularly the case for poses which are further from the base of the robot, or poses which require large amounts of bending.

To quantitatively compare the performance of the two different control approaches, the 3 DoF position of the end effector was measured when moved in the three axes (as in Fig. 4), and the euclidean distance error between the

Fig. 4. Graphical comparison of the motion that is achieved when using open loop (encoder only control), and closed loop control using IMU feedback. This is shown for motion in the vertical Z axis, horizontal X axis, and horizontal Y axis.

demand and true position measured. Each pose was repeated 5 times to test and evaluate the reliability, with the results shown in Fig. 5. We see that on average the closed loop controller halves the position error. As seen in the pictorial results this is particularly the case for larger motions where the flexible racks of the robot are most bend. For very low height, or less extreme motions, for example in low heights in the z axis the accuracy for both methods is high, however, for more expansive motions the IMU based closed loop control becomes increasing important. Considering the mean accuracy of the pose reconstruction (2.7 cm), the IMU based closed loop control achieves a precision which is in line with this.

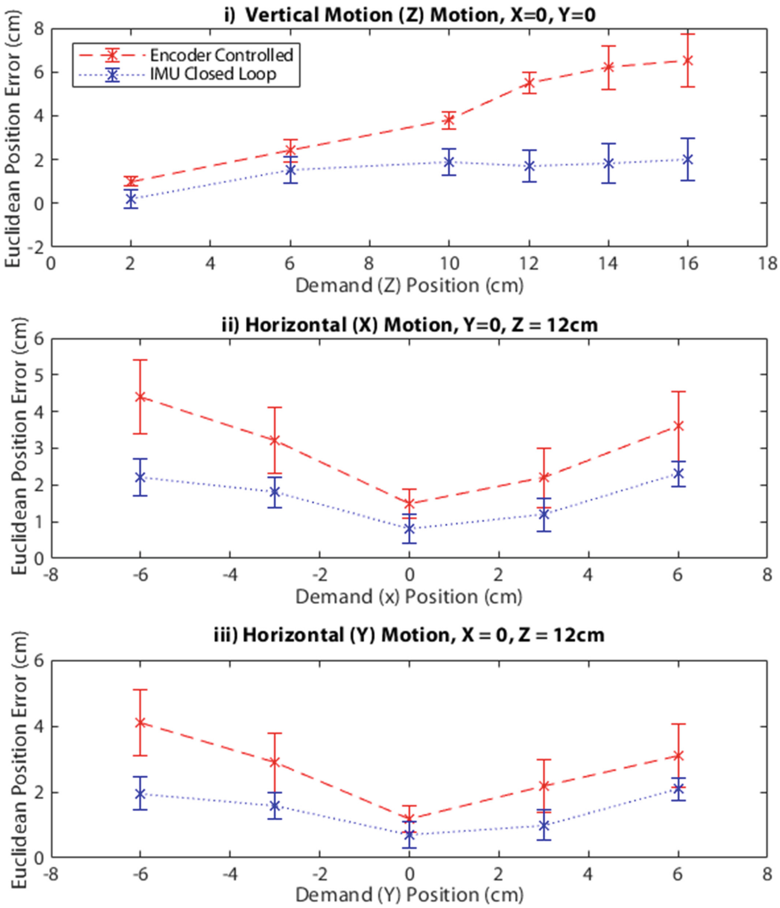

Fig. 5. Quantatative comparison between the performance of the open loop vs. closed loop control for motion in the X, Y, and Z axis.

5 Discussion and Conclusions

In this work we introduced a new method for combining the feedback from IMUs on a deformable manipulator with the PCC model. This constrains the IMU response, minimizing the effects of drift commonly observed when using the response from IMUs. This approach was demonstrated on a growing, deformable manipulator for both pose reconstruction and closed loop control of position. It was shown how the pose could be reconstructed with an mean error of 2.7 cm in position. Using this ability to reconstruct the pose closed loop control using the IMUs was applied to significant reduce the error in positioning.

By introducing this IMU based proprioceptive sensing approach, we provide a universal approach for control and reconstruction of soft, curvature based continuum manipulators. The IMUs can be easily integrated or applied to manipulators of any form factor, including soft of highly performance structures. Using the sensor feedback allows for accurate reconstruction and closed loop control.

Further work could explore the use of IMUs in multi segment robot structure, and also on robots with other actuation methods to validate it across other designs. As this method is highly scaleable it would be possible to create a complex, many-segmented continuum body robot structure. The use of the IMU based pose reconstruction could aid exploration of complex environments when using soft robots. This IMU based method could also be extended to other continuum body structure such as grippers, or soft walkers for proprioceptive sensing.

Acknowledgments. We would like to acknowledge grant NSF EFRI (1830901) which made this work possible.

References

1. Bern, J.M., Banzet, P., Poranne, R., Coros, S.: Trajectory optimization for cable-driven soft robot locomotion. In: Robotics: Science and Systems (2019)
2. Bruder, D., Gillespie, B., Remy, C.D., Vasudevan, R.: Modeling and control of soft robots using the koopman operator and model predictive control. arXiv preprint arXiv:1902.02827 (2019)
3. Della Santina, C., Bicchi, A., Rus, D.: On an improved state parametrization for soft robots with piecewise constant curvature and its use in model based control. IEEE Rob. Autom. Lett. **5**(2), 1001–1008 (2020)
4. Della Santina, C., Catalano, M.G., Bicchi, A.: Soft Robots, pp. 1–14. Springer Berlin Heidelberg, Berlin, Heidelberg (2020). https://doi.org/10.1007/978-3-642-41610-1_146-1
5. Della Santina, C., Katzschmann, R.K., Bicchi, A., Rus, D.: Model-based dynamic feedback control of a planar soft robot: trajectory tracking and interaction with the environment. The International Journal of Robotics Research, p. 0278364919897292 (2019)
6. Hughes, J., Culha, U., Giardina, F., Guenther, F., Rosendo, A., Iida, F.: Soft manipulators and grippers: a review. Front. Rob. AI **3**, 69 (2016)

7. Hughes, J., Della Santina, C., Rus, D.: Extensible high force manipulator for complex exploration. In: 2020 3rd IEEE International Conference on Soft Robotics (RoboSoft), pp. 733–739. IEEE (2020)
8. Hughes, J., Iida, F.: Tactile sensing applied to the universal gripper using conductive thermoplastic elastomer. Soft Rob. **5**(5), 512–526 (2018)
9. Katzschmann, R.K., Della Santina, C., Toshimitsu, Y., Bicchi, A., Rus, D.: Dynamic motion control of multi-segment soft robots using piecewise constant curvature matched with an augmented rigid body model. In: 2019 2nd IEEE International Conference on Soft Robotics (RoboSoft), pp. 454–461. IEEE (2019)
10. Mahony, R., Hamel, T., Pflimlin, J.M.: Nonlinear complementary filters on the special orthogonal group. IEEE Trans. Autom. Control **53**(5), 1203–1218 (2008)
11. Mahony, R., Kumar, V., Corke, P.: Multirotor aerial vehicles: modeling, estimation, and control of quadrotor. IEEE Rob. Autom. Mag. **19**(3), 20–32 (2012)
12. Rus, D., Tolley, M.T.: Design, fabrication and control of soft robots. Nature **521**(7553), 467–475 (2015)
13. Santaera, G., Luberto, E., Serio, A., Gabiccini, M., Bicchi, A.: Low-cost, fast and accurate reconstruction of robotic and human postures via imu measurements. In: 2015 IEEE International Conference on Robotics and Automation (ICRA), pp. 2728–2735. IEEE (2015)
14. Scimeca, L., Hughes, J., Maiolino, P., Iida, F.: Model-free soft-structure reconstruction for proprioception using tactile arrays. IEEE Rob. Autom. Lett. **4**(3), 2479–2484 (2019)
15. Thuruthel, T.G., Shih, B., Laschi, C., Tolley, M.T.: Soft robot perception using embedded soft sensors and recurrent neural networks. Science Robotics, vol. 4, no. 26 (2019)
16. Truby, R.L., Della Santina, C., Rus, D.: Distributed proprioception of 3D configuration in soft, sensorized robots via deep learning. IEEE Rob. Autom. Lett. **5**(2), 3299–3306 (2020)