Control of a Soft Redundant Manipulator Under Variable Loading Through Localized Online Learning

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***Summary*—Commonly used model-based approaches often have low tolerance to unmodelled loading, resulting in significant error. In this study we employ a nonparametric learning-based method that can approximate and update the inverse model of a redundant two-segment soft robot in an online manner. The performance of the control framework was evaluated by tracking of a 3D trajectory with an unknown mass added to the robot tip. The results indicate that the proposed controller could effectively adapt to the disturbance and continue to track the desired trajectory accurately.**

I. Introduction

The introduction of robots constructed from hyper-elastic materials and embedded with fluidically driven chambers have given rise to a new class of robots that have gained prevalence in specialized applications like surgical intervention [1]. Subsequently, the growth of soft robotics field has sparked research focused on modelling the behavior of soft robots.

The piecewise constant curvature (PCC) approach is commonly used to approximate the kinematic mapping of soft robots [2]. Although the use of PCC still remains predominant, any loading to the robot that results in non-circular bending invalidates the PCC assumption. Fully utilizing the conformability and maneuverability of soft continuum robots while also maintaining end-effector accuracy is still technically challenging.

A path towards this goal is through learning-based approaches, which have gained popularity in soft robotics for their ability to bypass the difficulties in modelling uncertain internal and external dynamics. A number of NN-based approaches have been used to learn the inverse kinematics of soft continuum robots [3], however the presence of external disturbances was not accounted for in these studies.

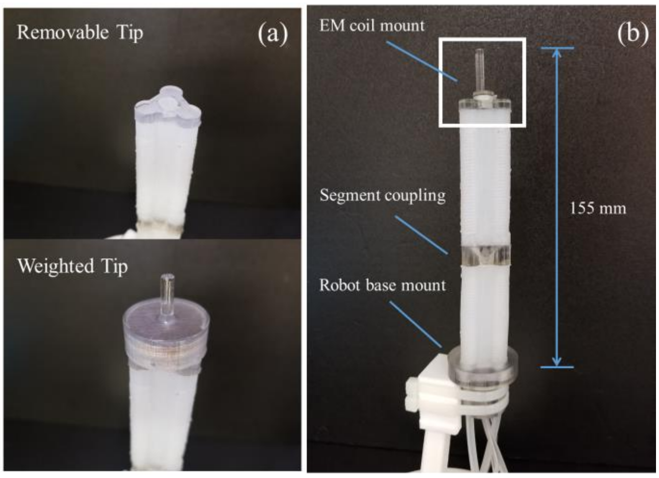

Fig. 1. (a) Plug-in tip allowing easy switching to a weighted tip for our experimental validation. (b) Two-segment soft continuum robot coupled with 3D-printed components.

Recently, Lee et al. [4] proposed a generic control framework based on [5] that is able to directly learn the inverse model of a soft continuum robot for task-space control. The algorithm utilizes locally-weighted linear models that are updated in an online manner, allowing adaptation to external disturbances. In this study, we extend the control framework in [4] to a multi-segment soft continuum robot, addressing the redundant nature of multiple bending segments.

II. Methods

A. Implementation of Online Learning Algorithm

The objective is to control the soft robot accurately in the task space motion transition coordinate Δs_k, while under unknown loading. For this reason, an online learning algorithm based on the work found in [5] is adapted for usage on our

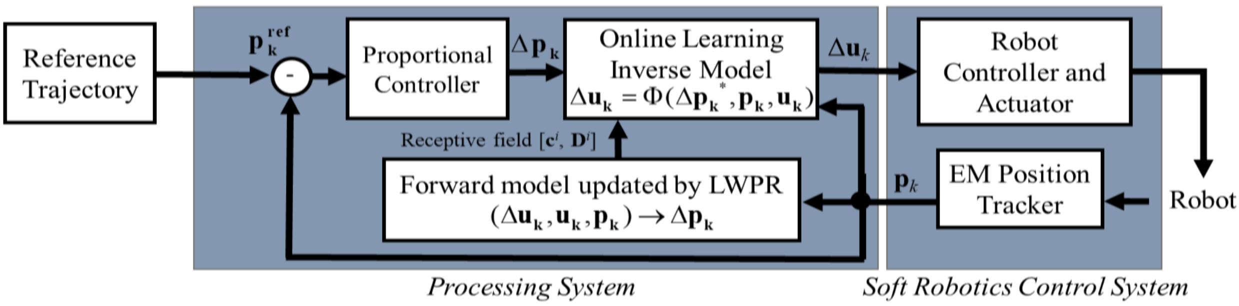

Fig. 2. Proposed system architecture to enable online updating of the learned controller.

This work is supported in part by the Croucher Foundation, the Research Grants Council (RGC) of Hong Kong (17202317, 17227616 and 27209515), the UK Engineering and Physical Sciences Research Council (EP/P010040/1, EP/N031768/1, EP/L016796/1, EP/L00058X/1), the European Union Horizon 2020 Research and Innovation Programme (671653), Aptorum Group Limited and Signate Life Sciences Limited.

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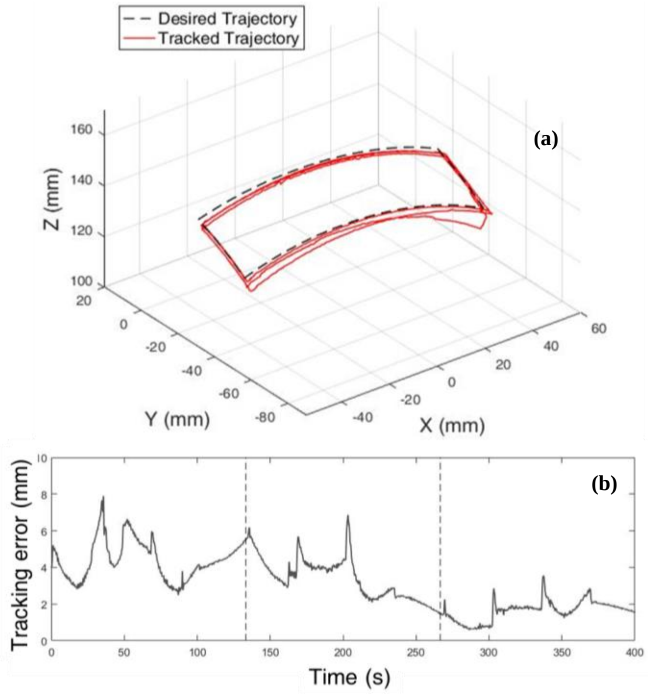

Fig. 3. Experimental results for trajectory tracking with additional tip loading, using the pre-trained model and updating with online learning: (a) Actual tracked trajectory and the desired trajectory. (b) Euclidean tip tracking error over time. Cycles are separated by the vertical dotted lines.

redundant two-segment soft continuum robot. The goal of the algorithm is to estimate the global inverse mapping of the soft robot by combining a set of localized linear controllers. This technique is based on the idea that in a localized region of robot configuration, a valid inverse solution can be obtained because the inverse kinematics mapping forms a convex function.

Initially, we aimed to acquire an appropriate local linearization of the robot forward motion mapping $(p_k, \Delta u_k, u_k) \rightarrow \Delta p_k$, which relates the tip position p_k, change in chamber pressures Δu_k, and chamber pressures u_k to the change in tip position Δp_k, which is nonlinear in general. Such local linearization can determine how many linear models are required to approximate the motion mapping, and the valid region of each linear model. The localized regression method, Locally Weighted Projection Regression (LWPR) [6], is employed to learn the forward motion mapping. For each piecewise linear forward model we assign a linear controller to approximate the global inverse mapping, using the same local valid regions. We wish to determine the local inverse transition models also positioned in p_k and u_k space, with parameter β^i_{IK}.

To estimate a global inverse model of the system, the local inverse controllers are combined in a weighted sum, acting as the Jacobian inverse for the manipulator:

$$\Delta u_k = \frac{\sum_{i=1}^{n} w^i(p_k, u_k)\left[\Delta p_{ref,k}, p_k, u_k\right]\beta^i_{IK}}{\sum_{i=1}^{n} w^i(p_k, u_k)} \quad (1)$$

III. Experiments, Results and Discussion

A. Experimental Platform

A two-segment soft robot was molded using silicone rubber (Dragon Skin 10, Smooth-on Inc.) and had 3 actuation chambers per segment, which were equally spaced around the section perimeter. Each segment was able to bend approximately 100 degrees omnidirectionally. The *x-y-z* robot tip and base position was tracked by an electromagnetic (EM) tracking system (NDI Medical Aurora) with an update rate of 40 Hz. The online learning algorithm was implemented in the Matlab environment, applying the open-source library for LWPR [7]. In order to effectively generate a functional global controller, pre-training data that sufficiently characterizes the robot's workspace and possible configurations was obtained. Initially, 80 random waypoints were used to pre-train the global inverse model. The proposed system architecture is shown in **Fig. 2.**

B. Trajectory Tracking Experiment with Tip Load

An additional tip mass was added to the robot tip, as illustrated in **Fig. 1(a)**. The total additional mass was 14.2 g and was not previously presented to the model during pre-training. The real-time data obtained from the tracked tip position and actuator volumes were input to the online learning algorithm, enabling incremental improvements to the overall learned inverse model. The average frequency of the online updates was 23 Hz. Improvements to tracking could be observed in the results presented in **Fig. 3**. The mean absolute tracking error of every cycle could be seen to decrease significantly, starting at ±4.42 mm in the first cycle and reducing to ±1.63 mm in the third cycle.

IV. Conclusions and Future Work

Overall, online learning of the original pre-trained model could be seen to improve the tracking performance through continuous online updating of the inverse model, even in the presence of a previously unknown external disturbance. Our future work includes further extension of the proposed control framework to three or more segments of a soft robot and incorporation of a greater number of task space variables to improve the manipulability of the robotic system. We also aim to integrate alternative sensing modalities such as FBG-based fiber optics in place of the heavily tethered EM system.

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