Visual Servo Control of a Soft Continuum Robot using Gaussian Process Regression

Ge Fang, Xiaomei Wang, Kui Wang, Kit-Hang Lee, Denny K.C. Fu, and Ka-Wai Kwok

I. Introduction

Bio-inspired continuum robots made of totally soft materials have attracted increasing research interests nowadays because of their high dexterity and compliance, which enables safe interaction with environments [1]. However, the inherent nonlinear property and infinite degrees of freedom challenge the precise control of soft robots. To replicate the adaptability of these systems in practical applications, accurate and efficient controllers are in great demand.

Majority of existing controllers used model-based approaches, which rely on approximations, such as constant curvature [2], or complicated analytical procedures like Cosserat rod theory [3] and Finite Element Modeling [4]. However, the assumptions may be invalid for systems with high nonlinearity or external disturbance while a complicate analytical model may be not computational suitable for real-time control. Model-free approaches, directly learn the kinematics or dynamics from sensory data, intuitively should fare better in this case. In our previous work, an efficient incremental nonparametric learning technique, locally weighted projection regression (LWPR), was used to solve the inverse problem. The proposed controller showed good performance on a redundantly fluid-driven soft continuum robot, which enables a 3D orientation tracking accuracy within the mean error of 2.49° [5]. However, LWPR may require manual tuning of many hyperparameters in order to achieve small approximation error. Gaussian process regression (GPR) would be a more efficient nonparametric learning technique for accurate approximation of nonlinear functions [6]. Compared to LWPR, the hyperparameters of GPR can be automatically determined by maximizing the likelihood of the prediction distribution. GPR is also relatively simple to be constructed in an incremental form for online update, which could adapt to unknown external disturbance.

To control the motion of soft robot, accurate sensory feedback also plays an important role. Eye-in-hand camera allows a self-contained setup. Not only does it enable instant video feedback due to the robot motion, but it also provides the operators with an intuitive perception of environment. However, a hand-eye calibration procedure may be necessary, if model-based control method is adopted. To this end, in this project, we intend to combine GPR with an uncalibrated eye-in-hand camera with the aim at controlling a soft continuum robot without using any predefined model of its robot kinematics.

II. Method

Robot task space of our visual servo task is defined in image plane. The displacement between adjacent image frames is estimated using a template matching method, which compares the coherence between the template and a sliding window. GPR is utilized to establish the inverse mapping from the task space to the actuation space. The redundancy is addressed by pre-processing the sampling dataset so that it can only produce one inverse solution. To close the control loop of image-based visual servo, actuation command is calculated through the learned inverse mapping given the error displacement between the current position and target position.

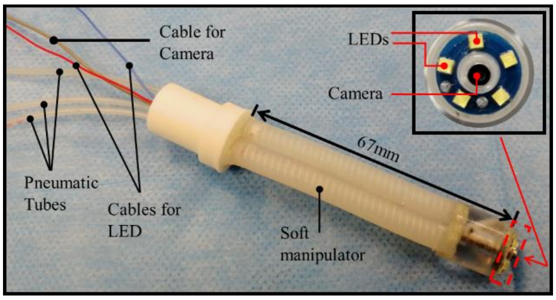

Fig. 1. Pneumatic-driven soft manipulator mounted with an endoscopic camera and five LEDs at its tip, of which the cables are routed and housed inside the inner channel.

III. Experiments and Results

A. Experiment platform

A pneumatically driven soft continuum robot made of silicon elastomer (**Fig. 1**) was used to validate our controller. Three individual fiber-reinforced chambers enable robot bending at an angle >90°, creating a workspace in 3D. An

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G. Fang, X.M. Wang, K. Wang, K.H. Lee, D.K.C. Fu and K.W. Kwok are with the Department of Mechanical Engineering, The University of Hong Kong, Hong Kong; (Email: fangge@connect.hku.hk).

endoscopic camera is mounted at the robot tip, which is surrounded by five LEDs for illumination. Experimental setup of the visual servo test is illustrated in **Fig. 2**.

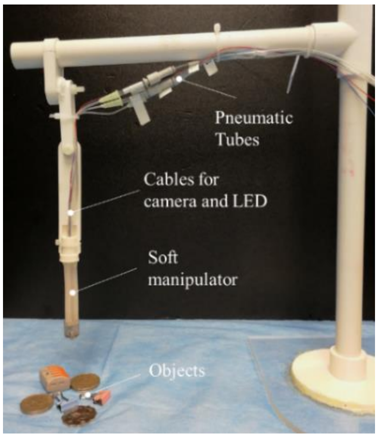

Fig. 2. Experimental setup for the visual servo task.

B. *Tracking Accuracy*

Point-to-point tracking was conducted. **Fig. 3** presents the robot configurations and image frames obtained at the initial and final positions, respectively. The robot was initially vertically positioned. A start point was manually selected at [320, 348] in the image plane of 400×400. Around the start point, a 100×100 template pattern was created and denoted by a red box in image frames. The desire point was at the image plane center, [200, 200]. The robot was controlled to reach the selected target at its image plane center in a 100×100 block. **Fig. 4a** shows a trajectory of the tracking trace from a start point to its goal. **Fig. 4b** gives the error in unit of pixel against each time step. Our soft manipulator finally aims at the target point previously selected within an error <10 pixels.

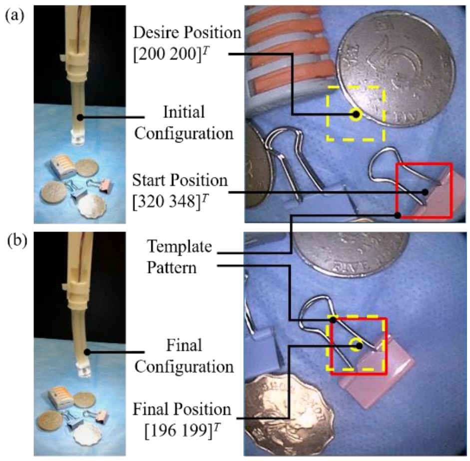

Fig. 3. **(a)** Initial robot configuration viewing on the objects through its endoscopic camera (Left). A target point was manually selected in the corresponding camera image (Right); **(b)** Robot tracing the selected target at its image plane center, thus reaching it as a final configuration.

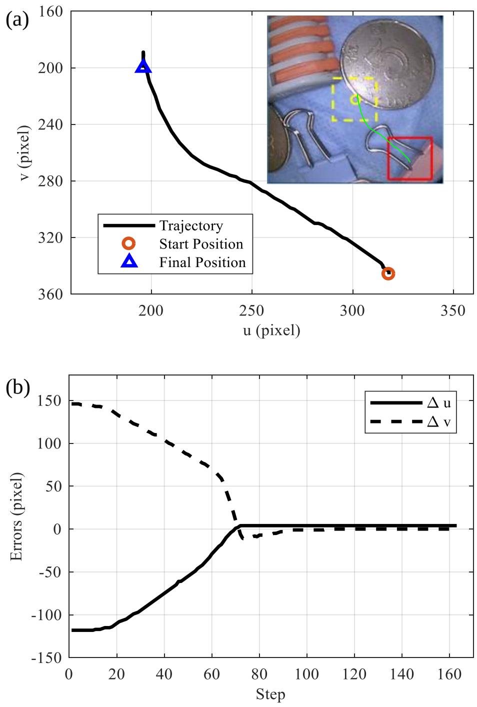

Fig. 4. Performance of tracking on a target point defined on image plane: **(a)** Resultant trajectory traveled along the template pattern detected/matched; **(b)** Vertical and horizontal error measured from the actual position of target position at each time step.

IV. Conclusion

This paper presents a learning-based control method for eye-in-hand visual servo control. Complicated analytical modelling procedure or hand-eye calibration could be avoided with the use of our GPR-based controller. Experimental results demonstrate that the soft continuum robot could track a target position promptly within an error smaller than 10 pixels using the proposed controller.

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