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Estimating the Configuration of a Continuum Dexterous Manipulator with Variable Curvature Bending Using Partial Shape-Sensing

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Abstract

Reliably estimating the shape of variable curvature continuum dexterous manipulators (CDMs) is necessary to use these devices in biomedical applications. Embedding shape-sensing elements have been shown to effectively measure the shape of constant curvature CDMs. This paper explores several methods for estimating the configuration of variable curvature CDMs. Experiments bent the CDM in varying configurations, applied an external load, and measured the configuration. Three methods are described that use the measurements from simulated shape-sensing elements. Analyses included varying the number and placement of the shape sensors. The results showed at least three shape-sensing elements are necessary to predict manipulator configuration, with one method demonstrating average error less than 0.35 mm for a CDM under an external load. The presented techniques offer promise for successfully predicting, tracking, and controlling CDM configuration during surgery.

I. INTRODUCTION

Continuum dexterous manipulators (CDMs) have increasing visibility in a number of medical applications (e.g., [1]–[4]). Many of these applications do not require the manipulator to withstand large internal (e.g., tools inserted through a lumen) or external forces. For variable curvature CDMs exposed to time-varying unknown external loads (such as that investigated in this paper), existing kinematic and dynamic algorithms relying solely on actuator position may not effectively estimate the shape.

We previously described a variable curvature CDM for orthopedic surgery using revision total hip arthroplasty (THA) as an example application [5], [6]. Osteolysis—bone degradation due to wear of the implant components—is a cause of around 13% of revision THAs [7], and, if left untreated, can result in component loosening or fracture. The CDM accesses the lesion through screw holes in the acetabular (pelvic) component of the hip implant (Fig. 1) to achieve over 94% coverage of a sample lesion geometry [6], [8], [9]. Inserting tools such as brushes, water jet, and suction, through the manipulator lumen, may allow the surgeon to more effectively treat the osteolysis than conventional rigid tools alone.

Understanding the shape of the CDM is key to a successful surgery. Visual feedback would be the most viable option; however, concerns of x-ray radiation limit the amount of available visual feedback. Other described shape estimation techniques for variable curvature manipulators include (a) dynamic approaches (e.g., [10]–[14]) requiring measurements of external loads; (b) empirical models [15], which may not offer appropriate accuracy and fail when the manipulator interacts with the environment; or (c) optimization techniques [15], [16] requiring knowledge of the manipulator tip. An alternative approach is shape-sensing technology such as piezoelectric sensors [17], fiber Bragg grating sensors [18], or other strain sensors [19]. This paper analyzes the number and placement of general shape-sensing elements to estimate manipulator configuration for variable curvature manipulators. Section II briefly describes the manipulator. Section III defines models for incorporating shape-sensing elements into estimating the manipulator configuration, and describes physical experiments conducted to test these models. Finally, this paper discusses the experimental results and concludes with a brief discussion.

II. BACKGROUND

Two nested nitinol tubes are press fit to form the CDM structure. Each of the two cable channels contained between the nested tubes hold a single braided or solid steel wire that bend the CDM when pulled, resulting in variable curvature along the length of the manipulator. The choice of notch pattern—cut using wire EDM—constrains the manipulator to planar bending along its 35 mm flexible section. The manipulator has an outer diameter of 6 mm and a large inner lumen of 4 mm diameter [5], [6].

We have previously described the manipulator kinematics as a series of rigid pin joints along the length of the manipulator [9], [15]. The kinematic configuration is given by

$\Theta = [\theta_i] \in \mathbb{R}^{27}$, with notch points p_j defined along the length of the manipulator in the xz -plane (Fig. 2).

An analogous way to define the manipulator configuration is to use a “backbone curve” comprised of orthonormal reference frames [20], [21]. Let $\phi(s, t)$ be tangent to the curve at a point s and time t . The kinematic description [20] applied to this manipulator is

$$\phi(s, t) = \sum_{i=1}^{27} a_i(t) H(s - \mathcal{L}_i) \quad (1)$$

$$\kappa(s, t) = \frac{\partial \phi}{\partial s} = \sum_{i=1}^n a_i(t) \delta(s - \mathcal{L}_i) \quad (2)$$

$$x_{ee} = \sum_{i=1}^{27} L_i \sin \phi(\mathcal{L}_i, t) \quad (3)$$

$$z_{ee} = \sum_{i=1}^{27} L_i \cos \phi(\mathcal{L}_i, t) \quad (4)$$

Here, $H(\cdot)$ is the Heaviside unit step function, κ is the curvature, a_j are the relative joint angles, L_j are the link lengths, $\mathcal{L}_i = \sum_{j=1}^i L_j$, s is the length along the manipulator and $[x, y]^T$ is the end-effector position. Thus, the curvature can be modeled at each pin joint as the relative corresponding joint angle.

III. METHODS

A. Data collection

We collected data for two sets of experiments: (1) free bending ($n = 149$ images) and (2) an external load applied to the manipulator ($n = 9$ images). For free bending, data collection followed that described in [15]: tension was applied to one cable (while the other cable remained slack) to achieve some configuration. The maximum applied tension was 22.2N. To apply an external load, both drive cables were tensioned and a reasonable external load was applied (Fig. 3). Both data collection procedures used an overhead camera to capture manipulator configuration.

The free bend scenario employed a piecewise-rigid 2D/3D registration procedure to identify manipulator configuration from each static image [15], [22]. We used manually-digitized notch points in the loaded images to geometrically estimate the manipulator configuration. While accurate for describing the manipulator configuration, both of these approaches lead to high gradients in joint angles. To smooth the joint angles, we performed an energy minimization procedure previously shown to effectively predict smooth joint angles [15]. This method minimized the sum-squared of joint angles while constraining the tip position; additionally minimizing the variance (not tested) may afford even smoother results. The joint angles and associated notch positions resulting from the energy minimization were used as the gold-standard in this experiment.

B. Configuration prediction

We implemented three simple methods for estimating manipulator configuration. Each method used curvature measurements (i.e., relative joint angles, κ in (2)) at k known sensor locations ($s_1, s_2, \dots, s_k$) and predicted the remaining configuration, $\tilde{\kappa}(s)$. Since the link lengths (except the last link) are equal, define $s \in \{1, 2, \dots, 27\}$ (the pin joint index), rather than normalized arc length. The curvature sensor positions were chosen to exclude both the base and the tip, as these measurements may not be physically realizable. The method descriptions are as follows:

Method A

Linear interpolation; for those points outside of the measured range, choose constant curvature.

$$\tilde{\kappa}(s) = \begin{cases} \kappa(s_1) & s < s_1 \\ \frac{\kappa(s_i) - \kappa(s_{i-1})}{s_i - s_{i-1}} (s - s_{i-1}) + \kappa(s_{i-1}) & s_{i-1} \leq s \leq s_i \\ \kappa(s_k) & s > s_k \end{cases}$$

Method B

Same as Method A, but extrapolate the curvature past the last known curvature.

$$\tilde{\kappa}(s) = \begin{cases} \kappa(s_1) & s < s_1 \\ \frac{\kappa(s_i) - \kappa(s_{i-1})}{s_i - s_{i-1}} (s - s_{i-1}) + \kappa(s_{i-1}), & s_{i-1} \leq s \leq s_i \\ \frac{\kappa(s_k) - \kappa(s_{k-1})}{s_k - s_{k-1}} (s - s_k) + \kappa(s_k), & s > s_k \end{cases}$$

Method C

Same as Method A, but extrapolate the curvature prior to the first known curvature.

$$\tilde{\kappa}(s) = \begin{cases} \frac{\kappa(s_2) - \kappa(s_1)}{s_2 - s_1} (s - s_1) + \kappa(s_1) & s < s_1 \\ \frac{\kappa(s_i) - \kappa(s_{i-1})}{s_i - s_{i-1}} (s - s_{i-1}) + \kappa(s_{i-1}) & s_{i-1} \leq s \leq s_i \\ \kappa(s_k) & s > s_k \end{cases}$$

Method D

Fit a third-order polynomial among the points of known curvature. In cases where only three points of curvature are used, this will underfit the data.

Each method was tested on both the free bend and loaded manipulator. We chose five different sets of known curvature sensor locations, with between two and five sensors distributed along the length of the manipulator ranging from $s = 5$ to $s = 25$ (Table I). For each combination of method and curvature sensor location, we estimated the manipulator configuration. The Euclidean distance between the predicted notch points $\tilde{p}_i$ and the known notch points p_i defined the error along the length of the manipulator.

IV. RESULTS

Configuration prediction error depended on the sensor position (Fig. 4); moreover, this response changed based on the CDM configuration (e.g., loaded or unloaded) (Fig. 4, Table II). Example average prediction errors were very high when only two points of curvature were assumed to be measured (i.e., $s_{known} = (9, 18)$). However, the errors when three, four, and five points of curvature were known were very similar (Fig. 5). Method C offered the best prediction, overall (Table II). Errors for loaded and unloaded configurations were similar, suggesting reproducibility of this approach regardless of CDM configuration (Fig. 5).

V. DISCUSSION AND CONCLUSIONS

This work defined and tested various algorithms that use shape-sensing to estimate the configuration of a variable curvature CDM. Experimental testing bent the manipulator into realistic configurations, both with and without external loads. From these configurations, shape-sensing elements were simulated to measure curvature at known locations. The known curvature drove the algorithms to define the manipulator configuration and results were compared with the actual configuration.

The results showed that at least three points of known curvature (i.e., three curvature sensors) are required to achieve sub-millimeter accuracy (Fig. 5). In the loaded conditions, the discrepancy between two and three curvature sensors is especially noticeable. Generally, Method C proved to be the overall best choice among the three methods tested. In all cases with at least three curvature estimates, the average error was no more than 0.35 mm (Table II). Maximum error varied based on the location of the known curvature sensors. Liu et al. [18] have embedded fiber Bragg gratings into the CDM, and future work should apply these algorithms to the strain measurements reported by the sensors.

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Fig. 1.

An envisioned procedure for computer-assisted revision surgery for total hip arthroplasty. The manipulator is inserted through the screw holes of the acetabular component to treat the osteolytic lesion located behind the implant.

Fig. 2.
The manipulator kinematics with pin joints (*) and points $p_i(o)$ identified [15].

Fig. 3.
Example manipulator configuration before (left) and after (right) external load.

(a) $s_{known} = (5, 15, 20)$ (b) $s_{known} = (5, 15, 25)$ **Fig. 4.**

Example error distribution, $\|p_i - \tilde{p}_1\|$, along the length of the manipulator for an unloaded manipulator with three points of curvature. The tip of the manipulator occurs at point index 29 and 30 (Fig. 2).

Fig. 5.

Error in predicting CDM configuration ($\|p_i - \tilde{p}_i\|$, with error bars of one standard deviation) for (a) unloaded and (b) loaded cases. The maximum error is denoted by the $\times$. Curvature sets map to those in Table I.

TABLE I

Tested known curvature sensor locations

Set ID	Curvature sensor locations, s_{known}
i	(9, 18)
ii	(5, 15, 20)
iii	(5, 15, 25)
iv	(5, 12, 19, 25)
v	(5, 10, 15, 20)
vi	(5, 10, 15, 20, 25)

TABLE II

Configuration prediction errors (mm): method C

Loaded?	s_{known}	Mean (st dev)	Mean of max	Max
No	(9, 18)	1.05 (0.95)	2.90	5.26
	(5,15,20)	0.15 (0.14)	0.54	1.08
	(5,15,25)	0.13 (0.09)	0.21	0.47
	(5,12,19,25)	0.13 (0.09)	0.19	0.46
	(5,10,15,20)	0.17 (0.19)	0.73	1.33
	(5,10,15,20,25)	0.13 (0.10)	0.24	0.51
Yes	(9, 18)	1.21 (0.79)	3.03	3.74
	(5,15,20)	0.20 (0.20)	0.57	0.85
	(5,15,25)	0.35 (0.45)	1.39	2.03
	(5,12,19,25)	0.23 (0.26)	0.73	1.20
	(5,10,15,20)	0.16 (0.15)	0.53	0.74
	(5,10,15,20,25)	0.18 (0.19)	0.50	0.88