Optimizing Heart Valve Surgery with Model-Free Catheter Control

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INTRODUCTION

Minimally Invasive Surgery (MIS) is nowadays the most widely adopted approach for treating structural heart disease. Despite the superior safety achieved, and efficacy, MIS procedures are technically demanding, requiring a high level of dexterity to precisely maneuver the catheter and thus showing a notoriously steep learning curve. To address these issues, we aim at introducing a variable shared autonomy robotic platform for intra-procedural support, by robotizing the commercial MitraClip^{TM} System (MCS). The MCS allows the treatment of mitral regurgitation by percutaneously implanting a clip that grasps the valve leaflets with a tendon-driven catheter. In this paper we propose a position control strategy that guarantees good trajectory tracking in the intracardiac phase of the procedure, i.e. from the transseptal puncture to the positioning of the clip in the valve, see Fig. 2. In the field of control of catheter robots, a good model of the system is key to obtaining reliable control. Several model-based control approaches have been proposed in the literature [1]. The constant curvature model is the best-known one but implies significant and oversimplifying assumptions about the catheter. The Cosserat Rod model, on the other hand, aims at providing a higher-fidelity description of the robot's behavior, but it is too computationally expensive to be usable online [2], [3]. Data-driven model-free controllers represent a valid alternative to analytical models, considering their potential in model uncertainties that strongly influence soft robot control [3]. In [4], authors proposed a formulation for learning the inverse kinematics of a continuum manipulator while integrating the end-effector position feedback. In this paper, we present a Neural Network based Inverse Kinematic Controller (IKC), shown in the scheme in Fig. 1, to control the tip position of the catheter. The inputs of the net are the target tip pose at the next time instant $\bar{\boldsymbol{p}}_{k+1}$, the current state of the 3 motors, $\boldsymbol{q}_k$, and the current tip pose $\boldsymbol{p}_k$, while the output is the state of the 3 motors at the next time instant $\boldsymbol{q}_{k+1}$. Our goal is to build a robust control starting from the state-of-the-art one applied to the MCS presented in [5] by X. Zhang et all. Moreover, we characterize the control model proposed, by testing its performance robustness at different motors' velocities.

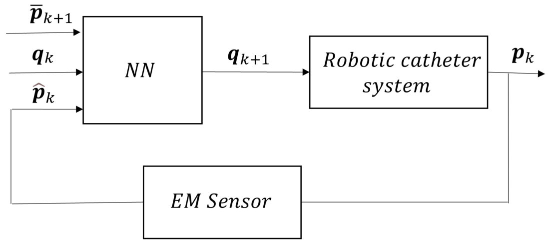

Fig. 1 Scheme of the Inverse Kinematic Controller. The inputs are the desired pose at time $k+1$, $\bar{\boldsymbol{p}}_{k+1}$, the current servomotors position, $\boldsymbol{q}_k$, and the current tip pose $\hat{\boldsymbol{p}}_k$, measured by the Electromagnetic (EM) sensor. The tip pose is expressed as a vector with the position and orientation expressed as a quaternion. The output is the position of the servomotor at the next time instant, $\boldsymbol{q}_{k+1}$.

MATERIALS AND METHODS

The proposed control exploits the Multi-Layer Perceptron (MLP) neural network to learn the non-linear map:

$$(\bar{\boldsymbol{p}}_{k+1}, \boldsymbol{q}_k, \hat{\boldsymbol{p}}_k) \rightarrow (\boldsymbol{q}_{k+1}). \tag{1}$$

In order to identify the aforementioned map, we explored the whole catheter's workspace ",i.e. the intracardiac-simulated environment within the robot can move from the transseptal puncture site to the Mitral Valve (see Fig. 2)," and we built a representative data set where known configurations of the motors' state were mapped to the corresponding tip poses, which were measured by using the Electromagnetic (EM) Sensor Aurora® NDI. In order to make the measurement of the tip pose independent from the magnetic field generator position, we referred the tip pose with respect to a fixed sensor at the base (Fig. 2). The data acquired were then sampled and processed, obtaining a final training data set of 3500 points. The architecture of the implemented MLP features an input layer of 17 neurons ($\bar{\boldsymbol{p}}_{k+1}, \boldsymbol{q}_k, \hat{\boldsymbol{p}}_k$), two hidden layers of respectively 56 and 60 neurons with hyperbolic tangent activation functions, and an output layer of 3 neurons ($\boldsymbol{q}_{k+1}$) with linear activation functions. The system is composed of a set of two Nema 23 Stepper motors (JoyNano), and one linear actuator Nema 17 Bipolar Stepper Motor (Sainsmart) that are used respectively to pull tendons, for bending the catheter in mediolateral (ML) and anteroposterior (AP) planes, and to move the tip in the forward direction (LIN). Each motor is controlled by a DM556 driver (Jadeshay) and connected to an Arduino Uno microcontroller. To study the performances of the

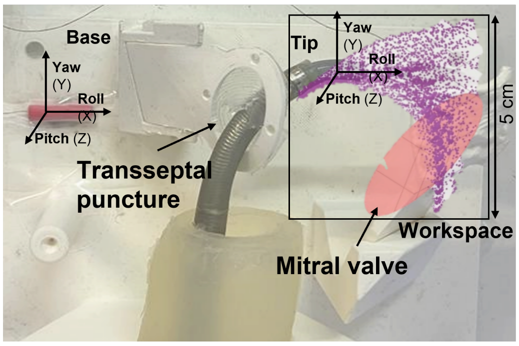

Fig. 2 MitraClip^{TM} System. The image shows the entire catheter workspace after the transseptal puncture approaching the mitral valve, in the intracardiac phase. The reference systems of the base (fixed point) and tip are also shown.

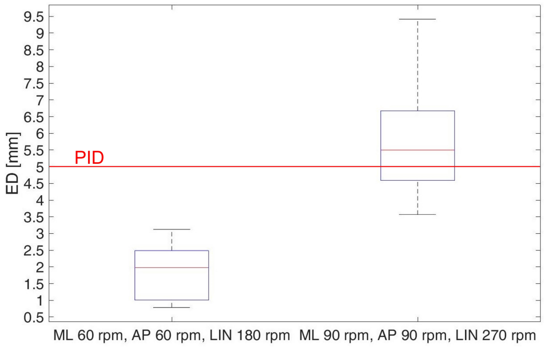

Fig. 3 Box plots show the distribution of the ED, (2), using the IK controller at two motors' velocities. The red line represents the mean ED obtained by [5], with the PID controller.

proposed IK controller, the system was tested in tracking five desired trajectories. The trajectories were recorded independently from the data-set acquisition. For all of them, the catheter moved from the transseptal puncture site to the final target on the mitral valve, see Fig. 2, following different paths. Moreover, two different motors' velocities (60 rpm for AP and ML motors, 120 rpm for LIN one, 90 rpm for AP and ML, then 270 rpm for LIN) were set to simulate slow and fast actuation and characterize the controller behavior. Each trajectory was repeated 3 times at each speed, and the results were averaged. To evaluate the performance of the control for the path following the Euclidean Distance (ED) was used:

$$ED = \sqrt{(\hat{x}_k - \bar{x}_k)^2 + (\hat{y}_k - \bar{y}_k)^2 + (\hat{z}_k - \bar{z}_k)^2} \qquad (2)$$

between the desired position of the tip $[\bar{x}_k, \bar{y}_k, \bar{z}_k]$ and the measured one $[\hat{x}_k, \hat{y}_k, \hat{z}_k]$.

RESULTS

Our study compared the performances of data-driven model-free control with the PID model-based control proposed by [5]. The box plots in Fig. 3 show the distribution of the estimated position error ED with the proposed IKC applied for the two motors' velocities tested. The median of the error with slower motors' velocities is 1.98 mm, with respect to the 5.5 mm obtained at higher velocity. Moreover in Fig. 3 is reported with a red line the mean value of the error obtained with the PID controller in [5], which is 5 mm. The data-driven controller outperformed the PID when the motors velocities are set to small values, with an average improvement in tracking error of 3.02 mm. Overall, the results suggest that data-driven model-free control can be a promising alternative to model-based control in challenging scenarios.

DISCUSSION

In conclusion, this paper introduces a machine learning model-free kinematic controller for continuum tendon-driven robots and the preliminary validation results of a robotic-assisted system in comparison with a PID state-of-the-art control. Experimental results demonstrated the effectiveness of the proposed method in path tracking if we stay under a curtain motor's velocity. Future works may compare the proposed method with other controllers based on a data-driven model. Additionally, another promising alternative could be the implementation of a data-driven controller which exploits a different architecture, such as the Radial Basis Function Neural Network [6], which could be useful to compensate for modeling uncertainties and unknown external disturbances, thus achieving better tracking performance. Recurrent Neural Networks [7] could be also a suitable solution for controlling our system, since their ability to capture temporal characteristics.

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