Feasibility of using a Long Short-Term Memory Network for Robotic Catheter Control*

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INTRODUCTION

Coronary artery disease (CAD) is one of the major cardiovascular diseases threatening human health worldwide and is responsible for around 20% of deaths in the developed countries [1]. Patients suffering from CAD experience different levels of chest pain, shortness of breath, fatigue, or irregular heartbeat. Cardiac catheterization is widely performed to treat CAD. In this procedure, a flexible catheter is steered along the aorta until it reaches the left and right coronary arteries. Next, a guidewire is employed to cannulate the occlusion area [2].

Accurate control of flexible catheters is vital in interventions. Nevertheless, precise steering is difficult in practice. Amongst other factors, hysteresis is a major cause of imprecision regardless of actuation technologies. Hysteresis generates a complex non-linear multi-valued relation between input commands and the response of the catheter distal tip. In the past, researchers endeavored to model and compensate for the hysteresis in catheters based on mathematical modeling [3], where a complex identification process is imperative. In comparison, Neural Networks (NNs) are appealing for their ability to accurately represent complex nonlinear behavior, albeit dependent on the specific application. This makes them feasible for modeling and compensating nonlinear systems. In this work, the feasibility of employing a NN to deliver precise catheter control in presence of a hysteresis-affected actuation system is investigated.

METHODS

The output of a system suffering from hysteresis depends on both the current and past inputs, typically described as a time series of hysteresis loops. Long Short-Term Memory (LSTM) proposed in [4] is an effective tool for processing sequential information since it takes historical information into account and utilizes this knowledge to predict the behavior at future time steps. Therefore, LSTM is logical to be used in this work. In the following, the LSTM was first trained based on real hysteresis data collected from an experimental setup and then validated on that setup as well.

Pneumatic Artificial Muscles (PAMs) show good promise in intervention tools thanks to its advantages e.g. large bandwidth, easy fabrication, and lightweight. Nevertheless, hysteresis is a major challenge when using PAMs, thus

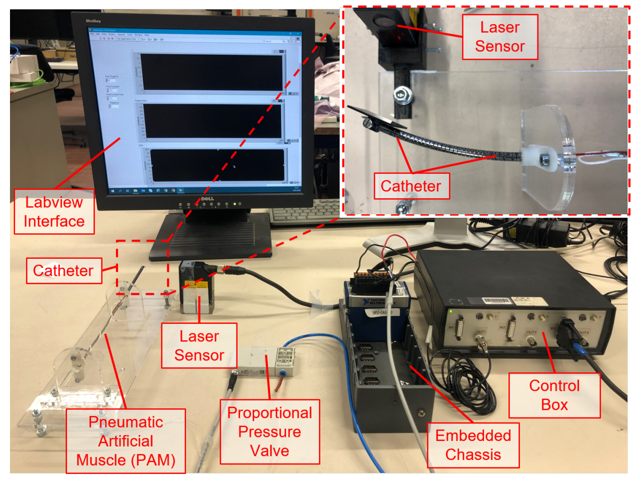

Fig. 1. The experimental setup for hysteresis data collection and LSTM performance validation. A close-up demonstrates the bending configuration of the catheter when the PAM is inflated.

compensation of hysteresis originating therefrom based on LSTM is investigated. To collect training data for the LSTM, an experimental setup was developed (Fig. 1). The setup contains a one-DOF Nitinol distal catheter segment with an embedded PAM. The PAM is attached off-center to the catheter tip. When increasing the pressure, the PAM contracts and pulls via a steel cable on the catheter tip, causing a bending moment. A laser sensor is used to measure the catheter tip displacement. A proportional pressure valve is employed to regulate the pressure applied to the PAM. The pressure and displacement data is collected at a sampling frequency of 250 Hz and visualized on LabVIEW®.

To fully excite the system, pressure signals as descending sine waves following:

$$p(t) = e^{-\tau t}(1.5 \times \sin(2\pi f t - \frac{\pi}{2}) + 1.5) \qquad \text{[bar]} \qquad (1)$$

were used to induce multi-loop hysteresis. The resulting catheter tip displacement - pressure data collected therefrom were then used to train the LSTM. In Eq. (1), the variable τ regulated the descending speed of the sine wave and it was set to -0.05. The variable f was the excitation frequency in Hz and it was switched among 0.2, 0.4, 0.6, 0.8. Consequently, there are four groups of data containing 34413 data points in total for training the LSTM.

To estimate the pressure for controling flexible catheters, the displacement data were used as input to the LSTM, while the predicted pressures are the output. The training of the LSTM was performed on a 4 GB NVIDIA CUDA-capable GPU. The LSTM was trained for 50 epochs, and the training time is around 20 to 30 minutes. For prediction, the average

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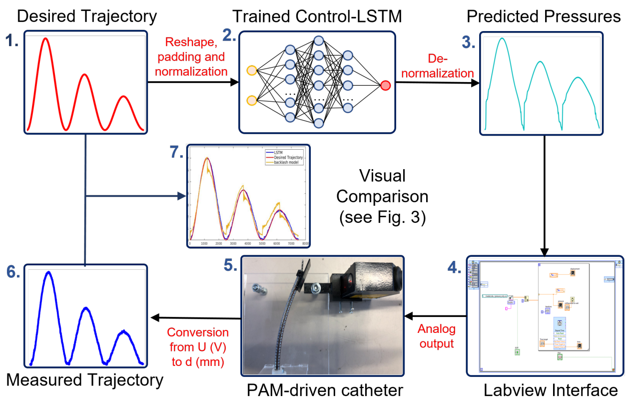

Fig. 2. The validation procedure for investigating the performance of the LSTM: 1) Creating a desired trajectory; 2) The desired trajectory is pre-processed and fed into the LSTM; 3) The LSTM predicts the corresponding pressures; 4) The predicted pressures are read by Labview and applied to the catheter as feedforward control; 5) The catheter tip motion is measured by a laser sensor; 6) Measured voltages are converted to catheter tip displacements; 7) Both measured and desired trajectories are visualized and compared.

inference time for a single point is 2.5 ms.

To evaluate the trained LSTM, an experimental procedure shown in Fig. 2 was conducted and illustrated as follows: 1) desired trajectory of the catheter tip is created by the users. In this work, a descending sinusoid trajectory following Eq. (2) is tested:

$$d(t) = e^{-0.05t}(4.5 \times \sin(0.2\pi t - \pi) + 4.5) \qquad [\text{mm}] \quad (2)$$

2) displacement data are reshaped into a window size of 120, containing previous 120 samples $d^{(t-119)}$,$d^{(t-118)}$, ... $d^{(t-1)}$ and $d^{(t)}$, and they are fed into the trained LSTM to predict $p^{(t)}$; 3) predicted pressure is produced by LSTM and saved into a spreadsheet; 4) Labview reads the pressures from the spreadsheet and sends this to the PAM-driven catheter through an analog output as a feedforward control. The pressure control frequency is 250 Hz; 5) a laser sensor measures the motion of the catheter tip as voltage signals; 6) the measured voltage signals are converted to catheter tip displacements; 7) both the desired trajectory and the measured trajectory are visualized and compared on the same plot. Root Mean Square Error (RMSE) and Maximum Absolute Error (MAE) are used to quantitatively evaluate the performance of hysteresis compensation.

A controller based on a backlash model introduced in [5] was established for comparison with the LSTM-based controller. The backlash model is a rate-independent model that has a non-continuous function describing the dead zone. Measured trajectories resulting from both controllers are visualized and compared.

RESULTS

The experiments on both the LSTM and backlash models were run ten times. One example of ten experimental results is visualized in Fig. 3. It can be observed that the LSTM-based controller is able to achieve effective hysteresis compensation, and the measured trajectory can precisely track the desired trajectory. One can see that the backlash model-based controller tries to compensate for the hysteresis by applying large pressure variations when approaching the

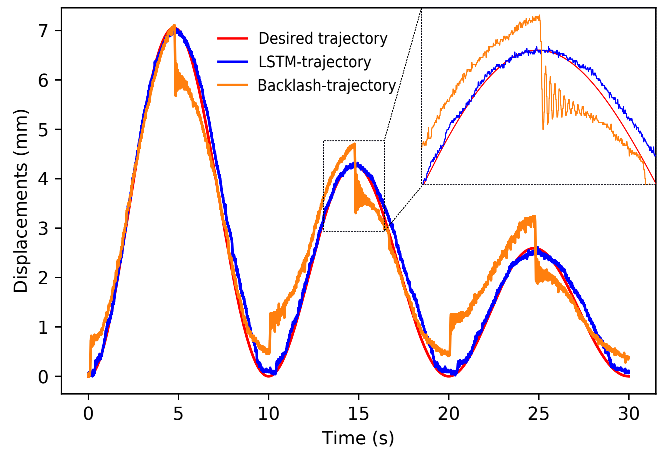

Fig. 3. Trajectories achieved by LSTM (blue) and backlash model (orange) compared to the desired trajectory (red).

TABLE I: MEAN AND STANDARD DEVIATION OF RMSE AND MAE OF 10 GROUPS OF EXPERIMENTS

Models	RMSE (mm)		MAE (mm)	
	Mean	STD	Mean	STD
LSTM	0.214	0.007	0.626	0.033
Backlash model	0.499	0.014	1.350	0.042

extrema points. However, this controller has difficulties in estimating the exact pressure-change that is needed, leading to significant over/under-shoots followed by some oscillations. The average mean and standard deviation over ten groups of the experiments (Table I) of the LSTM are 0.214 mm and 0.626 mm, respectively, which are less than half of the error achieved by the backlash model (RMSE = 0.499 mm and MAE=1.350 mm).

CONCLUSION AND DISCUSSION

This study proposes to compensate for the hysteresis in a flexible catheter using LSTM. The proposed LSTM was first trained based on four groups of descending sine waves, then the LSTM is utilized to predict the pressures based on a given trajectory. The performance of the LSTM was validated on a descending sine wave (RMSE = 0.214 mm, MAE = 0.626 mm). The results indicate that the LSTM is able to effectively compensate hysteresis in a PAM-driven catheter. The errors are less than half of those achieved by the backlash model. Future work focuses on validating the generalization ability of the LSTM on other trajectory patterns that are completely different from the training data, e.g. ascending sine waves, sine waves with time-varying frequency, triangle waves.

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