Towards Modeling of Hysteresis in Robotic Catheters based on LSTM

D. Wu[1,2], M. Ourak[1], K. Niu[1], Y. Zhang[1], M. Ahmad[1], J. Dankelman[2], E. Vander Poorten[1]
[1]*KU Leuven, Department of Mechanical Engineering, Leuven, Belgium*
[2]*TU Delft, Department of Biomechanical Engineering, Delft, the Netherlands*
di.wu@kuleuven.be

INTRODUCTION

Coronary artery disease (CAD) is one of the leading causes of death worldwide. One-third of deaths in developing and developed countries in people over 35 years old were caused by CAD. This percentage even approached 50% in Western countries [1]. The clinical symptoms of CAD are breathing difficulties, chest pain, heart attack and even sudden death. Percutaneous Coronary Intervention (PCI) is a common procedure for treating CAD. In this procedure, a catheter is guided through the aorta until reaching left and right coronary arteries. Next, a microcatheter or a guidewire is steered to recanalize the occlusion. Due to the tortuosity of the aorta, the fragile and deformable nature of the vessels, and heartbeat, good maneuverability and controllability of the catheters are imperative [2].

Robotic catheters can be operated based on various working principles [3]. Cable-driven technology is one of the most popular driving principles for steerable catheters. The cables, which are routed over the entire length of the catheter, undergo quite some friction with their guiding tubes. Consequently, reaching a large bandwidth is generally difficult. Instead of using tendons, Pneumatic Artificial Muscle (PAM) could also be used to actuate catheters. PAMs have a few advantages e.g. large bandwidth, easy fabrication, lightweight, and low cost [4]. Overall, they show good promise for use in catheters. Therefore, this work investigates on the feasibility to actuate robotic catheters with embedded PAMs.

In practice, accurate control of catheters is difficult regardless of actuation technology. Amongst other factors, hysteresis is a major cause of imprecision. Hysteresis generates a complex non-linear multi-valued relationship between input commands and in this case, the response of the catheter distal tip. This multi-valued relation complicates navigation and results in inaccurate manipulation and positioning of the catheter tip. Moreover, inadequate positioning of the relatively acute tip could induce tissue damage or lead to complications. To overcome this problem, analytic models for modeling hysteresis have been explored in the past [5]. A disadvantage of analytic models is that they require a large number of parameters which leads to a complex identification process. Deep learning has already acquired increasing attention as it allows to avoid such intricate identification process and replaces this by an, admittedly not always straightforward, training process of an Artificial Neural Network (ANN). The deep learning technique applied in surgical robotics field has continuously grown, such as those presented in [6] - [9]. The performance of deep learning depends on the presence of sufficient and proper data [10]. So far, few works have attempted to use machine or deep learning for hysteresis modeling. Porto *et al.* [11] used

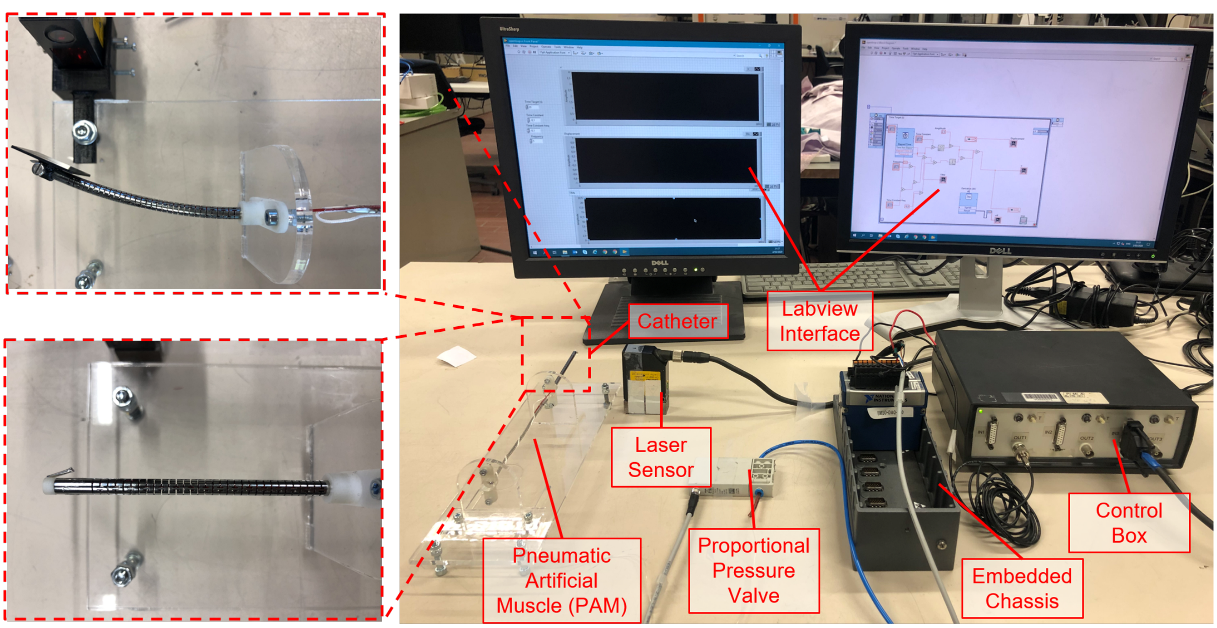

Fig. 1. An experimental setup for hysteresis data collection. The catheter distal segment is actuated by an embeded Pneumatic Artificial Muscle (PAM). The PAM is attached off-center to the catheter tip and thus applies torque to the tip when increasing the pressure. The resulting catheter tip displacement is measured by a laser sensor. A Graphical User Interface (GUI) is created based on Labview for pressure control and data collection. A close-up left up and left down show respectively the bending and straight configuration of the catheter segment.

machine learning to produce position control of a flexible surgical robot. Xu *et al.* [12] employed regression methods to learn the inverse kinematics model of a serpentine surgical manipulator. Both of them worked on tendon-driven robots and adopted traditional machine learning methods and not deep learning.

This study proposes to use deep learning and more specifically a Long Short-Term Memory (LSTM) network to model the hysteresis. The proposed LSTM network was first tested on simulated data and then further validated on hysteresis data collected from an experimental setup (see Fig. 1). The setup contains a one-DOF PAM-driven catheter segment as well as a laser distance sensor to measure the displacement of the catheter segment.

METHODS

A system is said to exhibit hysteresis if it has a sort of memory. This means that the output at a certain moment is not only determined by the corresponding input but also by the past inputs [13]. LSTM is an effective tool for processing sequential information since it takes historical information into account and utilize this knowledge to predict behavior at future time steps [14]. Therefore it is only but logical to explore the feasibility to model hysteresis with LSTM as is being proposed in this work.

The feasibility of using LSTM for modeling hysteresis was investigated first in simulation and then experimentally. In order to excite the system and provide the LSTM with abundant training data, descending sine waves following (1) were used as input data. A random noise between 0 and 0.1 using the Matlab® (The MathWorks, Inc., US) function *rand* was added to the excitation signals to simulate hysteresis in real applications.

$$p(t) = Ae^{-\tau t}(\sin(2\pi f t - \frac{\pi}{2}) + 1) + rand(0, 0.1) \tag{1}$$

In simulation, the amplitude A in (1) was set to 1. The time constant τ regulated the descending speed of the excitation signals. The time constant was set to 0.01, 0.02, 0.05, 0.1, 0.15, 0.2. Variable f was the excitation frequency in Hz. The frequency f was taken to be 0.2, 0.4, 0.6, 0.8. Combining various f and τ values resulted in 24 groups of data in total. In each group, 1000 data points were evenly distributed over a time interval of 20 s. All the above sine waves were input into a classical Prandtl-Ishlinskii (PI) model that was developed to simulate multi-loop hysteresis [15]. In the simulation, this PI model served as the ground truth model, which the LSTM should try to ‘learn”. The basic component of the PI hysteresis model is the backlash operator $H_r(p, t)$.

$$\begin{aligned} H_r(p,t) &= \max\{p(t) - r, min\{p(t) + r, H_r(t-T)\}\} \\ H_r(p,0) &= \max\{p(0) - r, min\{p(0) + r, 0\}\} \end{aligned} \tag{2}$$

where $p(t)$ denotes the input and, in this case, the input pressure, r is the threshold of a backlash operator. Time t is the current time and T represents the sampling period. The PI model is formed as a weighted superposition of n backlash operators:

$$\begin{aligned} d(t) &= [w_1, w_2, ..., w_n] \cdot [H_{r1}(p,t), H_{r2}(p,t), ..., H_{rn}(p,t)]^T \\ &= \mathbf{w}^T \cdot \mathbf{H_r}(p,t) \end{aligned} \tag{3}$$

with $d(t)$ the output of the PI model and in this case, the catheter tip displacement, n denotes the number of backlash operators, $\mathbf{w}$ is a vector of weights. The PI model in this work consists of 5 backlash operators. The weights $\mathbf{w}$ of PI model were tuned such as to produce a behaviour comparable to the hysteresis visible in a real application. Seventy percent of the above data was used as training subset and the remaining 30% of the data was employed as validation set. Apart from these data, four groups of test sets were prepared to verify the generalizability of the LSTM: a) a descending sine wave; b) a descending triangle wave; c) an ascending sine wave; d) an ascending sine wave with altering frequency. The time series data were segmented into a window size of 50, which means the pressure $p^{(t-49)}$,$p^{(t-48)}$,...$p^{(t)}$ are used to predict the simulated displacement $d^{(t)}$. The hyperparameters of the LSTM used in simulation was shown in Table I.

Additionally, an experimental setup (see Fig. 1) containing a single-DOF PAM-driven catheter segment was developed to collect real hysteresis data. The same excitation signals as described above were used to genrate pressure commands for actuating the catheter. For the experiments, A = 1.5 (bar) was used and the random noise in (1) was omitted. The displacements of the catheter tip were measured by a laser photoelectric sensor. Another LSTM network was trained based on real data. The hyperparameters of this LSTM remain the same as in simulation (see Table I).

The training of both LSTM was performed on a 2 GB NVIDIA CUDA-capable GPU. The training time is around 30 to 40 minutes. For prediction, the average inference time for a single point is 2.23 ms.

TABLE I: HYPERPARAMETERS FOR THE LSTM USED BOTH IN SIMULATION AND REAL DATA

	Number of hidden layers	Number of nodes (units) per hidden layer	Activation functions	Optimizer	Loss function	Training-subset /Validation ratio	Batch size
LSTM	2	64, 64	Relu	Adam	L2 Loss	70%/30%	16

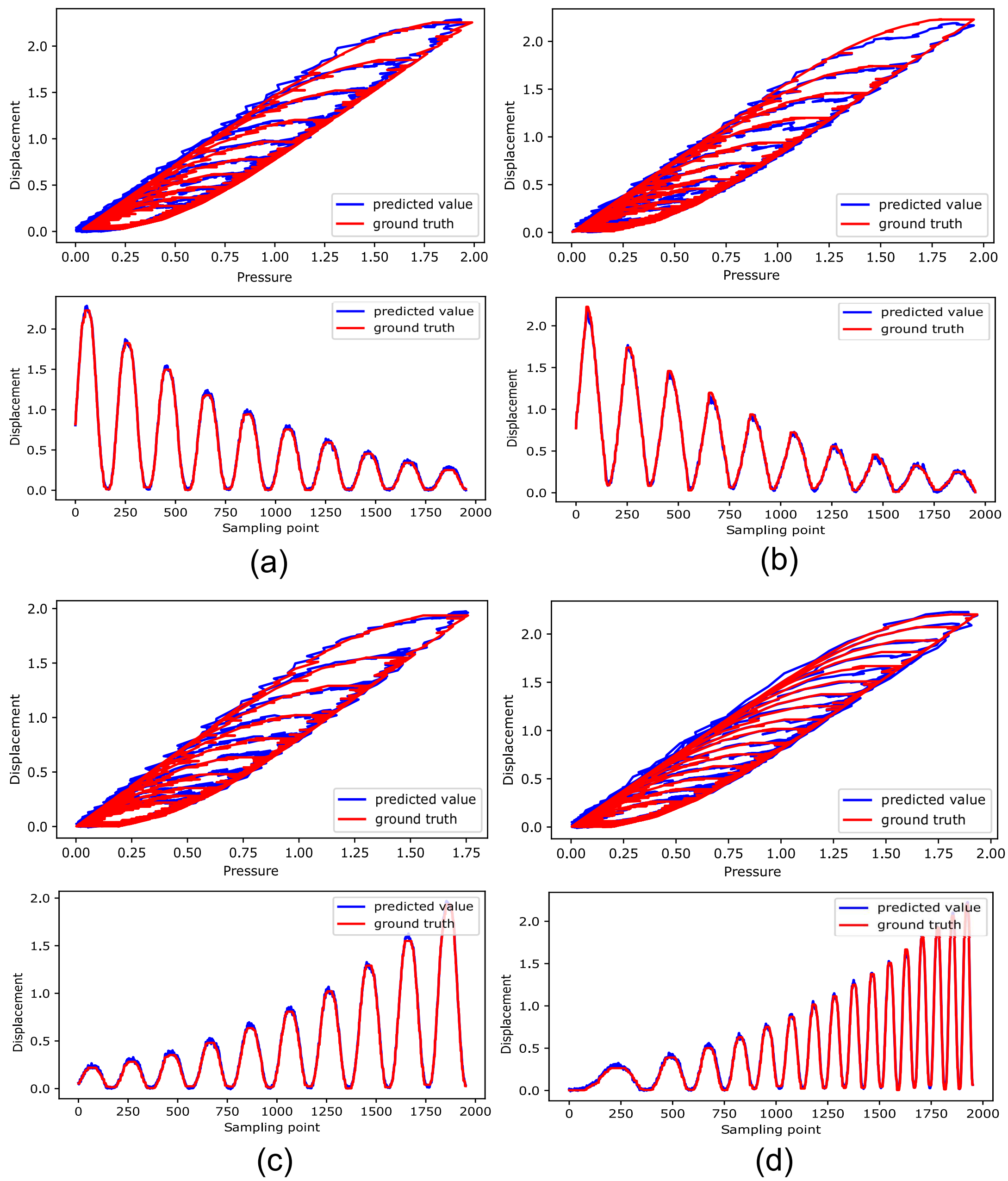

Fig. 2. The modeling performance of the LSTM on various kinds of test simulated signals: (a) a descending sine wave, whose f and τ are different from those in the training set; (b) a descending triangle wave; (c) an ascending sine wave; (d) an ascending sine wave with altering frequency.

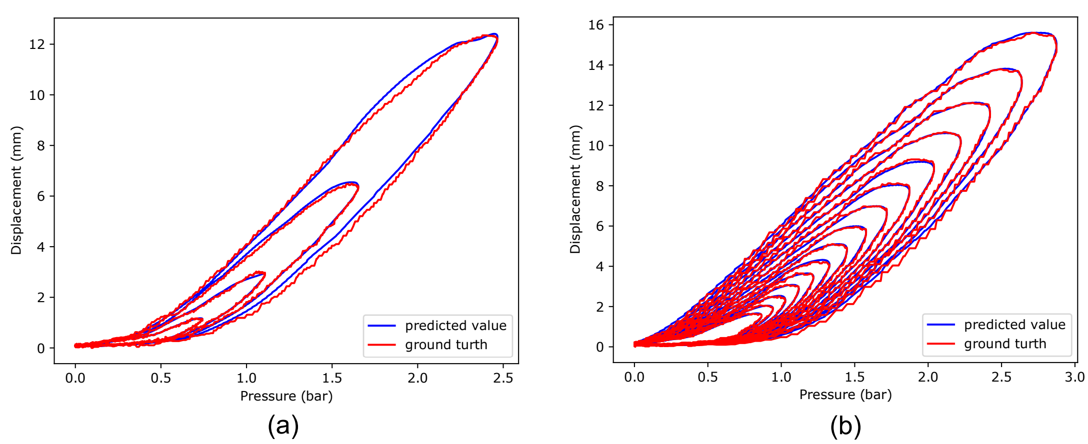

Fig. 3. The modeling performance of the LSTM on real data: (a) low frequency example with f=0.3, τ = -0.12; (b) higher frequency example with f=0.7, τ = -0.06.

RESULTS

The root mean square error (RMSE) between predicted output value and simulated and/or measured output value is used to quantify the modeling performance, which is visualised in Fig. 2. The RMSE of the four types of test signals are 0.023 (Fig. 2a), 0.025 (Fig. 2b), 0.022 (Fig. 2c), 0.024 (Fig. 2d), respectively. As shown in Fig. 2b, Fig. 2c, Fig. 2d, the LSTM demonstrates a promising transfer learning ability on various signal patterns that are different from the training data.

The modeling performance on real hysteresis data is displayed in Fig. 3. The RMSE of a low frequency group (f = 0.3) and a high frequency group (f = 0.7) are 0.095 mm and 0.074 mm, respectively. The RMSE of the real data is slightly larger than those of the simulated data since the real data included measurement noise as well as the non-linearities that originate elsewhere but not PAMs e.g. friction between the air and tubes. Nevertheless, the RMSE of the real data i.e. 0.095 mm and 0.074 mm correspond to 0.77% and 0.47% of the overall excitation amplitude and is deemed promising for CAD applications where human accuracy is in order of 1 mm. The performance on both simulated data and real data reveals that the LSTM is able to learn the temporal structure between observations and shows good performance in hysteresis modeling.

CONCLUSION AND DISCUSSION

This abstract proposes to model and characterize the hysteresis in a robotic catheter using LSTM. The proposed LSTM was first validated on simulated data that was generated from a PI-model that consisted of five backlash operators. The LSTM was trained based on 24 groups of descending sine waves. The results reveal that the LSTM has good generalization ability on signals that have patterns differing from the training data. The LSTM was further investigated using real hysteresis data collected from a PAM-drive catheter. The RMSE of the modeling performance in a low frequency data group and a high frequency data group are 0.095 mm, 0.074 mm. Future work will focus on embedding LSTM network in controllers that actually compensate for the hysteresis on the PAM-driven catheters [16]. Moreover, the proposed LSTM is a generic method and its generalization ability on other systems suffering from hysteresis will also be investigated.

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