Controlling of a Micropositioning Piezoelectric Actuator using an LSTM Network for Robotic Eye Surgery

Yao Zhang[1], Mouloud Ourak[1], Eric Verschooten[2], Kenan Niu[1], Di Wu[1], Gianni Borghesan[1,3], Philip X. Joris[2], Emmanuel Vander Poorten[1]

[1]*KU Leuven, Department of Mechanical Engineering, Leuven, Belgium*
[2]*KU Leuven, Laboratory of Auditory Neurophysiology, Leuven, Belgium*
[3]*Core Lab ROB, Flanders Make, Belgium*

INTRODUCTION

Retinal venous occlusion (RVO) is the second most common retinal vascular disease. In total, more than 16.4 million people suffer from it worldwide [1]. RVO can lead to severe vision-impairing damage due to neovascularisation, ischemia, and edema. Currently, retinal vein cannulation (RVC) provides a promising solution. However, it remains a challenging operation for surgeons. During the procedure, a clot-dissolving drug that can cannulate the clotted retinal vein is injected into an obstructed vein through a micro-scale cannulation needle [2]. However, due to the small scale of the retinal veins (30 to 400 µm), reliable manual injection is extremely challenging [3].

With advancements in robotic eye surgery [4], the feasibility of robot-assisted cannulation has been demonstrated recently [5]. However, precise control of the insertion depth remains a challenge. Too deep insertion means that the targeted vein could be pierced and the active agent could be injected below the vein into a highly sensitive region. In order to avoid this problem, this abstract investigates the use of piezoelectric actuation to produce precise insertion. However, piezoelectric actuator exhibits hysteresis between the applied input voltage and output displacement. To cope with the complex non-linear relationship generated by hysteresis, mathematical modeling approaches, such as the Rate-Dependent Prandtl-Ishlinskii (RDPI), e.g. used in [6], were proposed. These methods require careful identification of quite a number of parameters. Recently, deep learning (DL) has also shown good potential to learn complex hysteresis behaviour [7]. This work investigates accurate control of the micropositioning piezoelectric actuator for RVC using such DL-method.

MATERIALS AND METHODS

Hysteresis is typically described as time series data, because it is affected by both current and previous inputs. To cope with this type of data, a Long Short-Term Memory (LSTM) artificial neural network, which uses historical data as a starting point and applies this knowledge to predict future outputs, is proposed [8].

To collect training data and evaluate the performance of the LSTM, an experimental setup was developed (see Fig.

This work was supported by a grant from the Belgian FWO [SB/1S96922N], and an internal KU Leuven C3 project 3E200471.
Corresponding author: yao.zhang@kuleuven.be

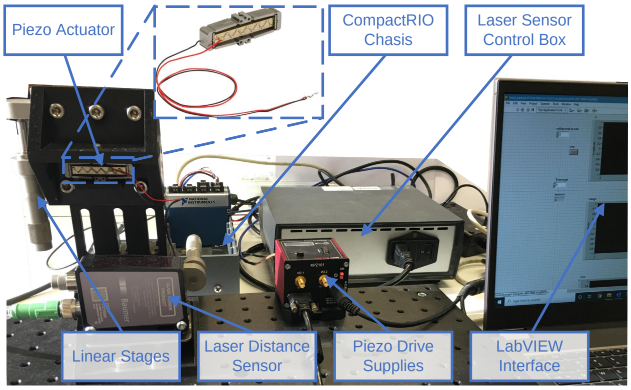

Fig. 1: Experimental setup, a piezo actuator realizes 1-dimensional motion, a laser distance sensor captures the achieved motion for evaluation purposes.

1). A micropositioning piezoelectric actuator (APF503, Thorlabs) is used to generate motion with amplitude up to 390µm. The piezoelectric actuator is actuated by piezoelectric drive supplies (KPZ101, Thorlabs) up to 150V. The piezoceramic is a smart material that expands or contracts when an electrical voltage is applied. The expansion or contraction of the piezoceramic is amplified into a larger linear movement through a flexure mounted on the actuator (visible in the insert of Fig. 1). The setup also contains a high-resolution (0.7µm) laser distance sensor (OM70-11216505, Baumer Group, Switzerland) that captures the motion of the piezoelectric actuator. The applied electrical voltage and resulting displacement is collected through LabVIEW®. Electrical voltages as descending sinusoidal waves following:

$$v(t) = Ae^{-\tau t}(\sin(2\pi f t - \frac{\pi}{2}) + 1) \qquad [\mathrm{V}] \qquad (1)$$

were used to drive the piezoelectric actuator and generate multi-loop hysteresis training data. The resulting displacement and collected electrical voltage was used as input and label to train the LSTM, respectively. The LSTM network contains 4 stacked layers. Each LSTM cell is made up of 64 neurons. Because of the small scale of the retinal veins, the amplitude A was set to $7.5V$ to ensure the peak value of the resulting motion would stay below 30µm. To enrich the training data, the descending constant τ was set to -0.08 and -0.12, the frequency f was set to 0.4Hz, 0.8Hz, 1.2Hz, and 1.6Hz. As a result, eight

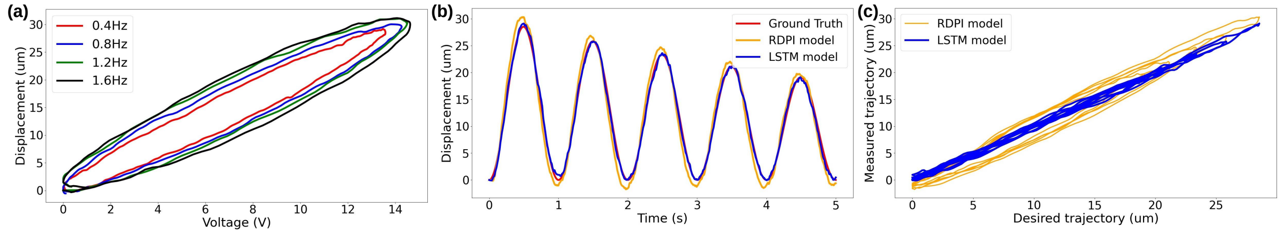

Fig. 2: (a): Rate-dependant hysteresis. (b): Desired trajectory (red) and measured trajectory achieved by RDPI (orange) and LSTM (blue). (c): Relation between desired trajectory and measured trajectory.

groups containing 19216 data points were used to train the LSTM. Figure 2(a) shows the major hysteresis loops of each frequency. The width of the hysteresis loops increases as the excitation frequency increases. This behavior is known as rate-dependent hysteresis. The whole training process takes around 25 to 30 minutes with 200 epochs on a 6 GB CUDA-capable GPU. To test the performance of the trained LSTM, the desired trajectory data were used as input, while needed control voltage was predicted as output. The following trajectory:

$$d(t) = 15e^{-0.1t}(\sin(2\pi t - \frac{\pi}{2}) + 1) \qquad [\mu m] \qquad (2)$$

was used to test the trained LSTM model. The amplitude was set to 15µm keeping the peak value of the test trajectory below 30µm. The test trajectory data were reshaped into a window size of 50. Each group acts like $d^{(t-49)}$, $d^{(t-48)}$, ... $d^{(t)}$, and was used to predict $v^{(t)}$. Afterwards, the reshaped trajectory data were fed into the trained LSTM model. The average prediction time of each Δ_{point} in LSTM is 4.5 ms. The output of the LSTM was read as control signal and sent to the piezo drive to generate the corresponding voltage. The measurements from the laser distance sensor served as ground truth to calculate the three types errors in Table I. To assess the quality of the LSTM-based controller, a state-of-the-art RDPI-based controller, introduced in [6], was set up as well. To quantitatively evaluate the performance of both controllers, three metrics are used, namely Maximum Absolute Error (MAE), Root Mean Square Error (RMSE), and Normalized Root Mean Square Error (NRMSE).

TABLE I: Results, over 5 groups of experiments

Model	**RMSE** (µm)		**MAE** (µm)		**NRMSE** (%)	
	Mean	STD	Mean	STD	Mean	STD
RDPI	1.76	0.08	3.66	0.25	6.17	0.01
LSTM	0.56	0.08	1.48	0.23	1.95	0.01

RESULTS

The experiments were repeated five times. Figure 2(b) shows one example of the five experiments. One can observe that the LSTM-based model can accurately control the piezoelectric actuator, allowing it to follow precisely the desired trajectory. The three metrics and standard deviation over five groups of experiments are shown in Table I. The average RMSE, MAE, and NRMSE of the LSTM are respectively 0.56µm, 1.48µm, and 1.95%. Compared to the RDPI model, the LSTM model improves performance by 68%, 60%, and 69%, respectively. offering a lower standard deviation over the three metrics, the LSTM-based controller shows good repeatable performance. The compensated input-output relationship is shown in the Fig. 2(c) by comparing the measured and desired trajectories. Compared to the RDPI model, the LSTM-based controller establishes a more linear relationship. This 1-to-1 response shows that the hysteresis is adequately compensated by the controller.

CONCLUSIONS AND DISCUSSION

An LSTM-based controller was introduced to precisely control the piezoelectric actuator in this abstract. The proposed LSTM model was first trained under eight groups of descending sinusoidal waves. Following that, the trained LSTM model was tested with the desired trajectory under different frequencies f and descending constant τ. The performance of the LSTM model was evaluated with RMSE (0.56µm), MAE (1.48µm), and NRMSE (1.95%). The errors are less than half of those achieved by the RDPI model. The good linearity shown in Fig. 2(c) demonstrates the feasibility of the proposed LSTM model in compensating for hysteresis under micrometer scale in a micropositioning piezoelectric actuator, which offers an alternative control scheme for minimally invasive eye surgery.

Future work will focus on investigating generalization ability of the LSTM-based controller over different test trajectories. We also aim to move to a realistic pre-clinical phantom.

REFERENCES

[1] S. Rogers *et al.*, "The prevalence of retinal vein occlusion: pooled data from population studies from the United States, Europe, Asia, and Australia", *Ophthalmology*, Vol. 117, pp. 313-319, 2010.

[2] WM. Tang, *et al.*, "A study of surgical approaches to retinal vascular occlusions", *Archives of Ophthalmology*, Vol. 118, pp. 138-143, 2000.

[3] M. Ourak, *et al.*, "Combined oct distance and fbg force sensing cannulation needle for retinal vein cannulation: in vivo animal validation", *International journal of computer assisted radiology and surgery*, Vol. 14, pp. 301-309, 2019.

[4] E. Vander Poorten, *et al.*, "Robotic retinal surgery", *In Handbook of Robotic and Image-Guided Surgery, Elsevier*, pp.627-672, 2020.

[5] A. Gijbels, *et al.*, "In-human robot-assisted retinal vein cannulation, a world first", *Annu. of Biomed. Eng.*, Vol. 46, pp. 1676-1685, 2018.

[6] S. Shakiba, *et al.*, "Tracking control of an SMA-driven actuator with rate-dependent behavior using an inverse model of hysteresis", *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, Vol. 42, No. 8, pp. 1-15, 2020

[7] D. Wu, *et al.*, "Hysteresis Modeling of Robotic Catheters Based on Long Short-Term Memory Network for Improved Environment Reconstruction", *IEEE Robotics and Automation Letters*, Vol. 6, pp. 2106-2113, 2021.

[8] S. Hochreiter, *et al.*, "Long short-term memory", *Neural computation*, Vol. 9, pp. 1735-1780, 1997.