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REGULAR PAPER

Learning-Based Discrete Hysteresis Classifier Using Wire Tension and Compensator for Flexible Endoscopic Surgery Robots

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Abstract

The tendon-sheath mechanism can be applied to a flexible endoscopic surgery robot because of its flexibility and power transmission. However, the hysteresis, which is the inherent problem with this mechanism, affects the precision of the control of the surgical robot. Despite several studies that are aimed at tackling hysteresis, only a few literatures consider a practical circumstance such as initial unknown hysteresis, proper surgical procedure, and camera illumination. In this study, we propose a novel framework to reduce the hysteresis of a flexible surgical robot using the learning-based hysteresis classification and a feed-forward compensation based on practical scenarios. We empirically discretize and divide the hysteresis class based on its size and show the correlation between hysteresis and time-series wire tension experimentally to study its potential for use in real surgical robots. The results indicate that the hysteresis can be classified by utilizing the time-series wire tension data. Moreover, the proposed compensator could enhance the performance of a real-size flexible endoscopic surgery robot based on actual surgical environment.

Keywords Flexible endoscopic surgery robot · Hysteresis · Deep neural network · Bouc–Wen model

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1 Introduction

Flexible endoscopic surgery robots are innovative platforms that can overcome the limitations of the rigid surgical robots owing to their dexterity and accessibility to lesion [1–5]. Such robots mainly use a tendon-sheath mechanism (TSM) and offer multiple advantages such as high flexibility, light weight, and dexterity. Although TSM facilitates flexible endoscopic surgery robots to execute continuous curvatures, and easily access clinical targets and lesions, it invariably causes hysteresis issues that can degrade the precision of the surgical instrument control due to various cable-related factors such as nonlinear friction, backlash, wire slack, wire elongation [6, 7].

Several promising approaches have been developed to compensate for the hysteresis of flexible endoscopic surgery robots. The on-line method, which compensates hysteresis during operation in real-time, has the potential to build a most-advanced control technology for surgical robots. Liu et al. measured the shape of a continuum manipulator using a fiber Bragg grating (FBG) sensor [8]. Omisore et al. proposed parameter estimation for hysteresis using an electromagnetic position sensor [9]. Moreover, image-based methods that use an endoscope camera have been proposed

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to reduce hysteresis. Reilink et al. compensated for the hysteresis of a three-degrees-of-freedom (DOF) surgical instrument by attaching a marker [10]. Baek et al. estimated the bending two-degrees-of-freedom (2DOF) of a surgical instrument with a learning-based method using images from a camera and simulations [11]. They further proposed a robust method for occlusion using both the image and the kinematic information [12]. In recent years, vision-based optimized feed-forward compensation scheme was also proposed [13]. However, the performance of these schemes possesses inherently limited performance depending on an endoscopic camera view. In the contrast of these approaches, our framework is not affected by the camera illumination because we utilize the wire-tension, which is measured by external sensors.

The off-line method hampers the hysteresis effect because of the use of prior knowledge (e.g., initial friction and backlash) before actual surgical operation. The analytic mathematical model or data-driven regression methods are widely used in this approach. Do et al. proposed a direct inverse model-based approach to reduce the hysteresis of TSMs [14]. Refael et al. proposed a positive inverse kinematic model-based method centered on offline learning, considering the hysteresis of a surgical instrument [15]. Hong et al. proposed a backlash model that considers the deformation of the tendon and sheath [16]. Do et al. also presented a nonlinear model that adapts to time-varying sheath configurations [17]. Lee et al. proposed a linear model to identify hysteresis using the motor current [18]. However, most offline-based methods do not consider the initial unknown hysteresis, which has changed randomly and unexpectedly in the target lesion. Although the method proposed in [17] is robust for time-varying sheath configurations, it is impractical because it requires an encoder at the distal end. Specifically, in the case of a flexible endoscopic surgery robot, initial hysteresis could vary considerably due to its flexible body.

To supplement the limitations of each method, we aim to develop a hysteresis compensation method that helps to reduce hysteresis of a flexible endoscopic surgery robot despite the lack of information regarding the initial hysteresis at the target lesion, several camera condition. Moreover, we study its feasibility for use in surgical robots. The usage of the predefined optimized parameters of Bouc–Wen hysteresis model could block the use of strange parameters that could potentially cause insecure motion, and only external sensors are used in our framework considering the sterilization. Our method can be applied quickly (less than 11 s) during the robot calibration, which is an essential requirement. Based on previous studies [7, 12, 13], we mainly address hysteresis in a bending angle of a surgical robot instrument rather than rotation or translation.

In this study, we propose a practical framework to compensate hysteresis of a flexible endoscopic surgery robot using learning-based discrete hysteresis classification, and we demonstrate its ability to compensate the hysteresis using Bouc-Wen model applied predefined optimized parameters. The class of hysteresis is discretely divided by considering the maximum and minimum hysteresis size for the instrument, and the optimized parameter for each case are acquired beforehand using a genetic algorithm. This algorithm shows the best performance in solving the global optimization problem. Our primary goal is to suggest a practical and efficient way to search the closest hysteresis class with unknown initial hysteresis after the robot accesses the lesion. Thus, a preliminary experiment was conducted to prove the existence of a correlation between hysteresis and time-series wire tension.

The primary contributions of this study are as follows. (1) Practical hysteresis compensation framework using learning-based hysteresis classification that utilizes wire-tension is proposed. (2) The correlation between wire tension and hysteresis is experimentally demonstrated, and the results show that hysteresis can be classified discretely through the wire tension. (3) The proposed method can be applied to real-size surgical robot and this approach substantially reduce hysteresis of a surgical instrument even in a shape that involves a real organ.

The remainder of this paper is organized as follows: Sect. 2 describes the design of the flexible endoscopic surgery robot testbed, preliminary tests for wire tension data and hysteresis, data collection procedures, hysteresis classification using neural networks, and hysteresis compensation using the Bouc-Wen model. Section 3 goes over the experiment and its results. Section 4 discusses the results of this study and provides the concluding remarks along with an outline of the future works.

2 Experiment for Demonstrating Correlation of Hysteresis and Wire Tension Data

2.1 Flexible Endoscopic Surgery Robot System

A flexible endoscopic surgery robot testbed was utilized for conducting all experiments (see Fig. 1). This testbed was designed to be developed with the same size of actual surgical robot system [1]. The testbed consists of a surgical instrument and driving part. The surgical instrument is driven by tendon-wire mechanism and a rolling-contact joint is used [19]. Two tendon-wires are controlled by a servo motor (XM-430, ROBOTIS, Korea). Four load cells (333FDX-KTOYO) are attached to the driving part to measure the wire tension of the surgical instrument. An Aurora sensor (Northern Digital Inc., Canada) was attached to the surgical instrument for measuring the actual bending joint

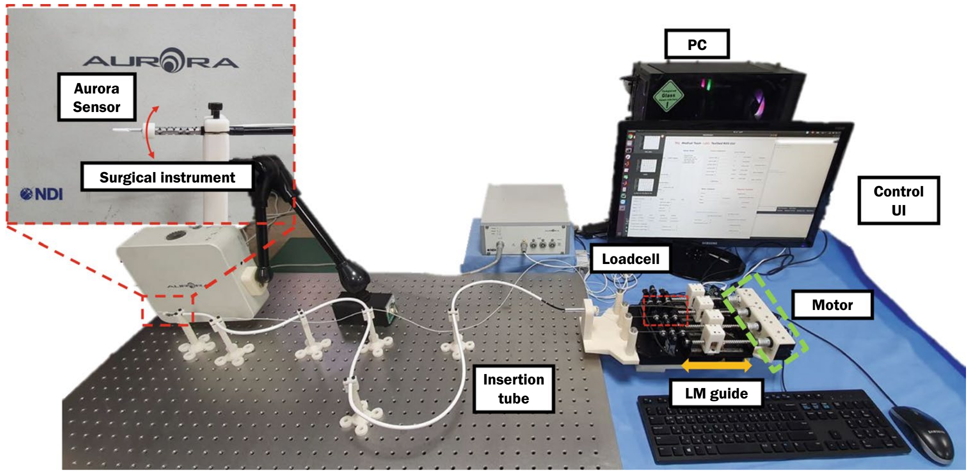

Fig. 1 Flexible endoscopic surgery robot test bed

angle of the surgical instrument. Note that the length of an insertion tube is long enough to represent the winding environment inside the colon.

2.2 Design and Result of Preliminary Experiment

We conducted a preliminary experiment to demonstrate the correlation between the time-series wire tension data to show the potential of usage of wire tension as a key feature distinguish hysteresis discretely. It is well-known that there are multiple coupled-factors (e.g., wire elongation, change configuration of insertion tube, friction, and backlash) that affect hysteresis and these factors are not independently. Figure 2 shows how we build a data-set including hysteresis and wire tension data. To minimize the influence of initial wire elongation and slack that occurs naturally through the use of the instrument, the pretension (5N) is applied to each wire as the first step. This enables to keep the initial wire tension every calibration step as similar as possible despite the effecting of other factors. Afterwards, a sinusoidal signal ($90\sin(\omega t), 0.159Hz$) was given and the time-series wire tension data is acquired from load cells. To obtain actual hysteresis, we measured the actual joint angle of a surgical instrument via the Aurora sensor. Note that the signal used in this experiment can be replaceable with other signals. We changed the configuration of insertion tube of the flexible endoscopic surgery robot randomly to get a number of hysteresis cases as shown in Figs. 3 and 4. We noticed that the change of configuration of insertion tube (sheath) critically affect the size of hysteresis. Through using different sheath configuration indicating the similar hysteresis, we emphasize that the time-series wire tension data has a higher correlation with hysteresis regardless of varying sheath configuration. To separate hysteresis discretely, we defined hysteresis class based on its backlash size gained using “*boundary*” function of MATLAB as shown in Fig. 2.

To determine the quantity of similarity between the time-series wire tension data and hysteresis, we used a root mean square error (RMSE) between the standard data obtained in the configuration 1 and another data obtained in other shapes. The size of backlash that highly affects the performance of surgical robot [7] is considered as the representative feature to represent hysteresis.

Table 1 summarizes the result of RMSE of wire tension and backlash size for all shapes in three cases. The result shows that both RMSE of wire tension and backlash size are similar among different shapes, which means that hysteresis is similar if time-series wire tension is similar. Also, we note that discrepancy of backlash size is significantly large among three different cases. Based on the result of the preliminary experiment, we propose the learning-based hysteresis classification using the time-series wire tension to segregate hysteresis discretely.

3 Method

The overall process of the proposed method is exhibited step by step in Fig. 5. To consider the actual surgical procedure, our method starts to be applied to the robot in the calibration phase that is conducted after a flexible surgical robot accesses the target lesion. Note that calibration phase is necessary for almost every robots before they are operated and our calibration process takes less than 11 s. For the calibration, the sinusoidal signal utilized in collecting a pre-built dataset is given to the robot and the time-series wire tension data is acquired by using load cells. Then, the pre-trained 1D-Convolutional Neural Network (CNN) model can search the closest hysteresis class in the pre-built dataset.

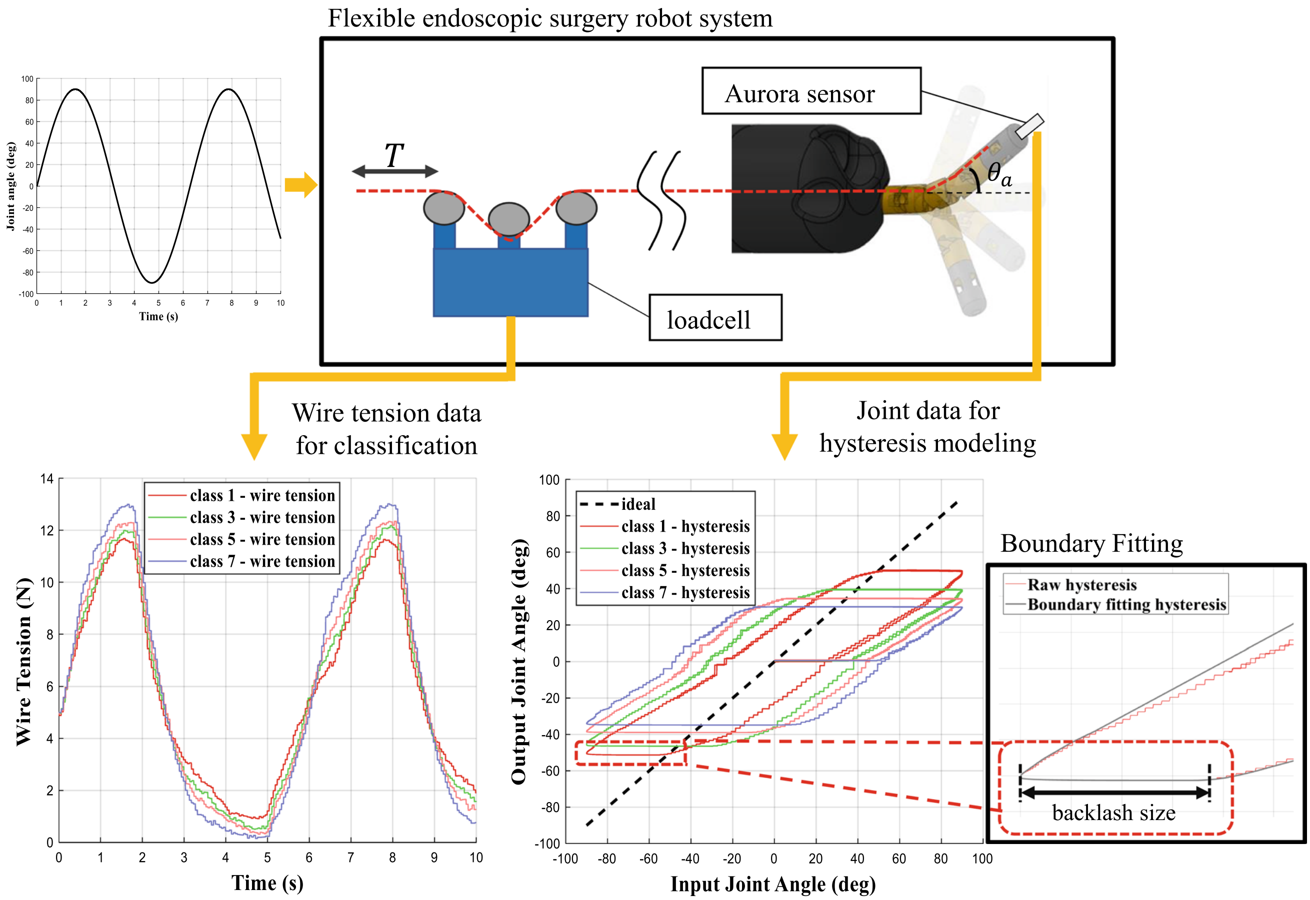

Fig. 2 Procedure of data collection for the time-series wire tension and hysteresis

3.1 Database Construction

This section describes how we construct the pre-build dataset $\mathcal{D}$ containing hysteresis and the time-series wire tension data $T^{(i)}$. Based on the minimum (40°) and maximum (100°) size of backlash hysteresis in our platform, we divided the hysteresis class q to seven classes which have 10° interval. This interval size is not optimal but we noticed that this is quite enough in terms of reducing hysteresis with a feed-forward compensation. The dataset is constructed as follows:

$$\mathcal{D} = \{D_1, \ldots, D_7\}, D \in \mathcal{D}, D = \{S_1, \ldots, S_t\}_{t=1}^{N}, N = 9000 \tag{1}$$

$$S_i = \left\{ T^{(i)}, \theta_d^{(i)}, \dot{\theta}_d^{(i)}, \theta_a^{(i)} \right\} \tag{2}$$

where D denotes the time-series data collected in 9 s (1000 per second) and the paired data S includes the wire tension $T^{(i)}$, desired joint angle $\theta_d^{(i)}$, desired angular velocity $\dot{\theta}_d^{(i)}$, and actual joint angle of the surgical instrument $\theta_a^{(i)}$. Here, i represents the time. 30 time-series data D were gathered for each class to include more variance of hysteresis (total number of $\mathcal{D}$ is 210). These data are obtained during the calibration phase and we paired up the D_i, q^i to train 1D-CNN. Here, q^i denotes the hysteresis class (e.g., 1, 2, $\cdots$, 7).

3.2 Hysteresis Classification Using 1D-Convolutional Neural Network

In this section, we describe the proposed learning-based hysteresis classification method using the time-series wire tension data. Based on results of our preliminary experiment, the primary aim of our classifier is to identify the most similar hysteresis in the prebuilt dataset $\mathcal{D}$ using the pretrained 1D-CNN model that uses the time-series tension data as an input. In the previous research, deep learning could improve the classification performance [20], and it is well-known that deep learning can bode well with various uncertainties and noises. To maximize these benefits into our method considering a high variance of the time-series tension data, we utilized a 1D-Convolutional Neural network (1D-CNN), which is known for its effectiveness for extracting feature from the time-series data.

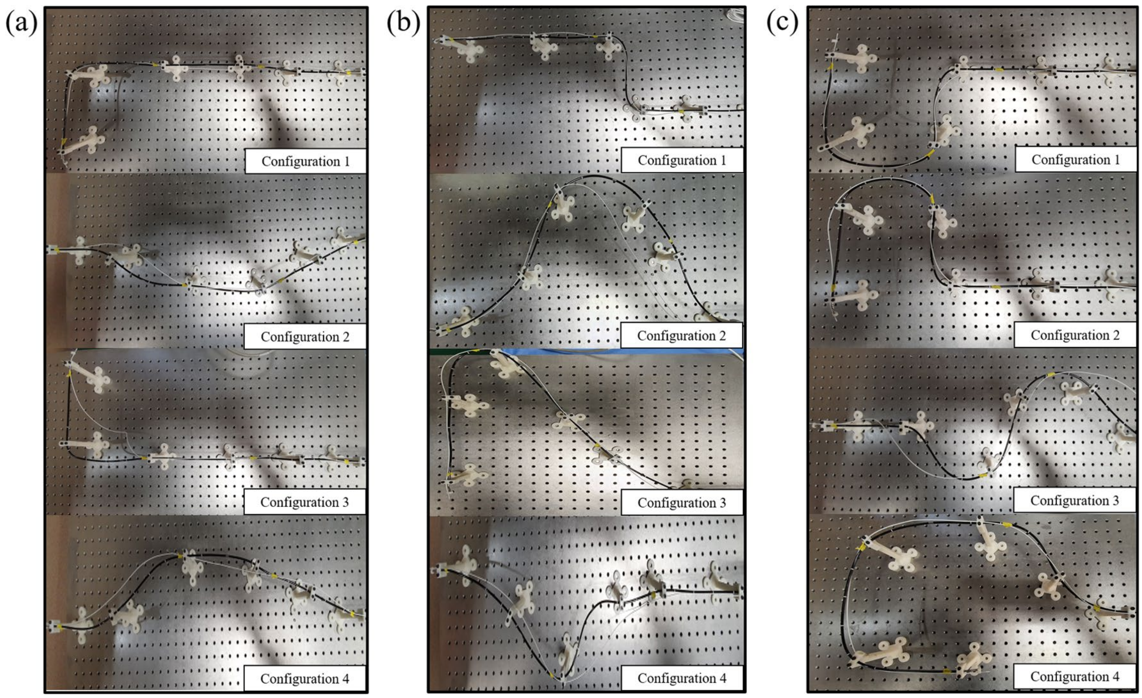

Fig. 3 Random configurations of the insertion tube to obtain various hysteresis for constructing the data-set and conduct the preliminary experiment. Four different configurations in each case show similar hysteresis but possess plainly variant shapes

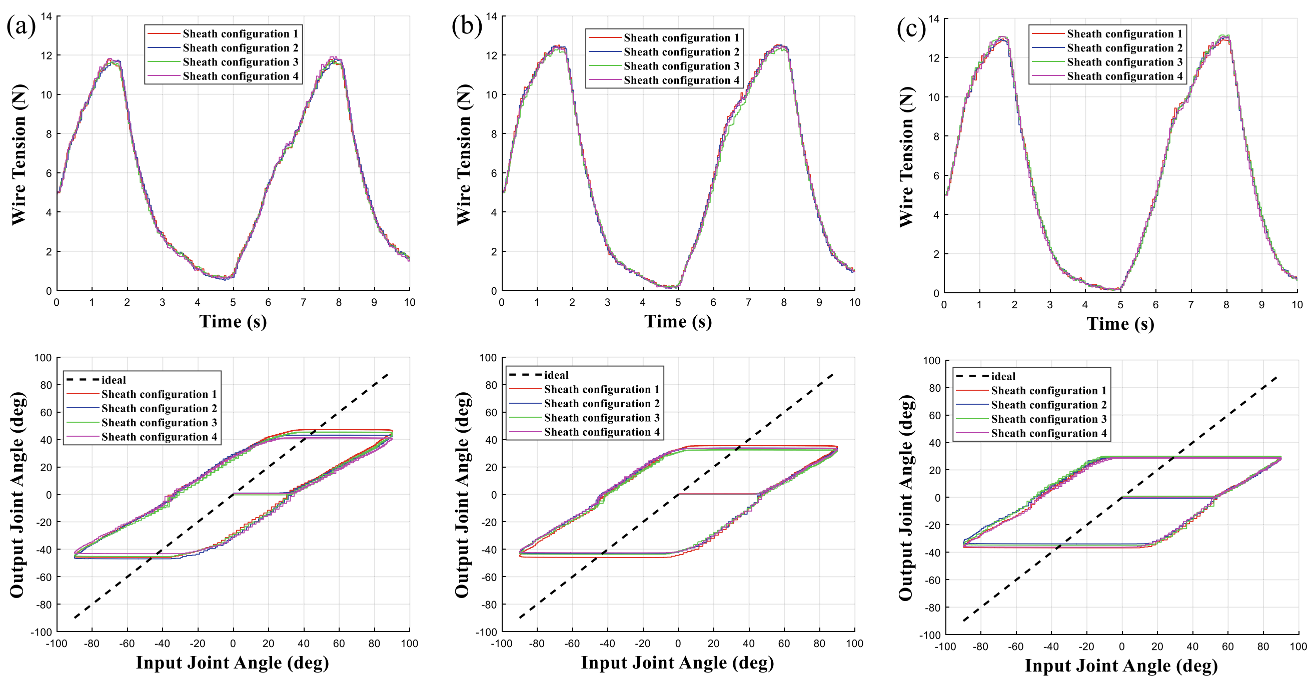

Fig. 4 Results of preliminary test. Each cases **a**–**c** correspond to the cases in Fig. 3, respectively

Table 2 shows the structure of the 1D-CNN used in this work. The learning algorithm was implemented using the PyTorch. To train the network, the batch size was set to 100 and the number of epochs was set to 100. The Adam optimizer is chosen for the optimization, and we set the learning rate and learning rate decay to 0.0005 and 0.96, respectively.

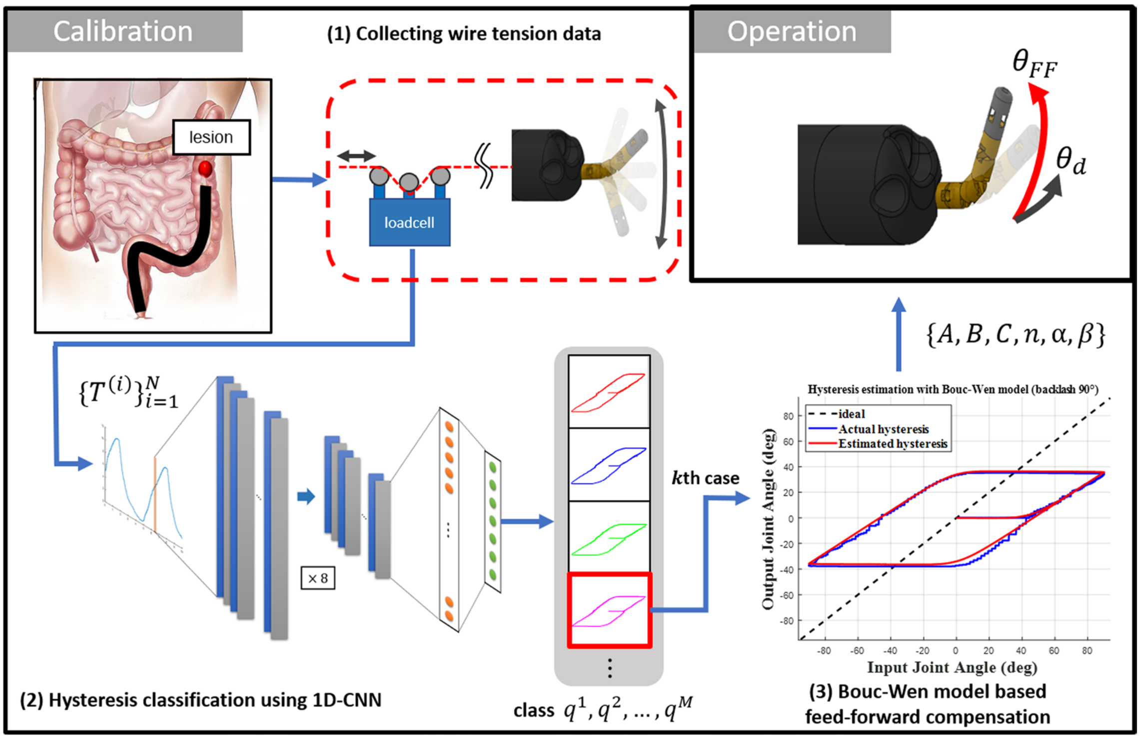

Fig. 5 Overall flow of hysteresis classification and compensation for flexible endoscopic surgery robot

Table 1 Results of RMSE of time-series wire tension and backlash size in each case

		Shape 1	Shape 2	Shape 3	Shape 4
Case 1	RMSE of wire tension (N)	–	0.21 ± 0.02	0.21 ± 0.09	0.21 ± 0.02
	Backlash size (°)	53.97 ± 0.67	54.74 ± 0.16	54.1 ± 0.65	54.74 ± 0.39
Case 2	RMSE of wire tension (N)	–	0.22 ± 0.03	0.22 ± 0.05	0.16 ± 0.13
	Backlash size (°)	85.50 ± 0.56	85.88 ± 0.55	84.95 ± 1.15	86.15 ± 0.39
Case 3	RMSE of wire tension (N)	–	0.18 ± 0.02	0.25 ± 0.04	0.23 ± 0.03
	Backlash size (°)	105.95 ± 0.73	104.40 ± 0.68	105.32 ± 0.44	104.26 ± 0.72

Table 2 Structure of 1D-CNN

Layer	Type	Kernel	Strides	Batch Normalization	Activation
1 ~ 8	Convolution	3	3	Yes	ReLU
9	Dense	–	–	No	Softmax

3.3 Designing Feed-Forward Controller Based on the Bouc–Wen Model

After finding the most similar hysteresis in pre-built dataset using the learning-based classifier, the selected optimized parameters are applied to a feed-forward controller. We use the inverse Bouc-Wen hysteresis model to com-pensate for the hysteresis because this model has the ability to describe the non-linearity of hysteresis including backlash and friction [21]. The Bouc-Wen model consists of a first-order nonlinear differential equation that contains a few parameters to approximate the behavior of a given hysteresis. A total of six hyperparameters are used in this model, and they should be optimized before being applied to a controller. The symmetric Bouc–Wen and direct inverse models can be expressed as follows:

$$\hat{\theta}_a = \alpha\theta_d + \beta h \tag{3}$$

$$\dot{h} = A\dot{\theta}_d - B|\dot{\theta}_d||h|^{n-1}h - C\dot{\theta}_d|h|^n \tag{4}$$

$$\theta_{FF} = \frac{1}{\alpha}(\theta_d - \beta h) \tag{5}$$

where $\hat{\theta}_a$ is the actual joint angle measured from Aurora sensor and θ_d is the desired joint angle. The solution of Eq. (4) represents the internal state h. The dimensionless parameters

A, B, C, and n adjust the shape and size of the hysteresis profile, and α and β are factors that control the ratio of $\hat{\theta}_a$, θ_d and h. Based on the hysteresis corresponding to the joint angle, the inverse model is directly transformed from the model given by Eq. (3) and (4). A new control input θ_{FF} is applied to the controller. To identify the hyperparameters of Bouc–Wen model, we used the interior-point algorithm of the "*fmincon*" solver from the MATLAB Global Optimization Toolbox.

4 Experiment and Result

The primary objective of this experiment is to study the performance of the proposed learning-based classifier and the feed-forward compensator using Bouc–Wen model. We aimed at expressing the actual colon shapes (descending colon and transverse colon) using a flexible endoscopic surgery robot testbed, as shown in Fig. 6. To train the learning-based classifier, we built a new dataset, which has the same configuration as that described in the Sects. 2.1 and 2.2. Figures 6 and 7. shows each colon shape and the length of each part [22].

4.1 Comparison Classification Performance of the Proposed Learning-Based Classifier

The goal of the first experiment is to evaluate the performance of the learning-based classifier. For the benchmark test, we choose a MLP [23] that is most widely used in classification problem and another learning-based method that uses Recurrence plot (RP) and CNN [24]. To train each algorithm, we utilized the dataset described in the Sect. 2.1 and 2.2. In order to consider the overfitting caused by using a small number of dataset, we use k-fold cross-validation to evaluate the performance of the three networks.

For the benchmark test, we set k to five for getting the average test accuracy value and the result of k-fold cross-validation is summarized in Table 3. Notably, the accuracy of the 1D-CNN is 98.47%, which achieves the highest performance compared to other methods.

To verify the effectiveness of the proposed learning-based classifier, two different colon shapes that have the similar size to actual organ was considered for the experiment. The root mean square error (RMSE) was calculated as the evaluated index that indicates the discrepancy between predefined backlash sizes from 40° to 100° and backlash sizes of descending colon and transverse colon.

Table 4 shows the prediction results of the classifier where in the two colon shapes. If the classifier can find the most similar hysteresis in the pre-built dataset, this should spit out the most closest value. Because the backlash size of the descending colon is 94°, the class that has 90° size shows the lowest RMSE value. In the case of the

Table 3 Test accuracy results using k-cross validation of three neural networks

	Neural network		
	MLP	Recurrence Plot + CNN	1D-CNN
Test accuracy (%)	80	92	**98**

The bold text emphasizes that the 1D-CNN accuracy value of the proposed method was the highest

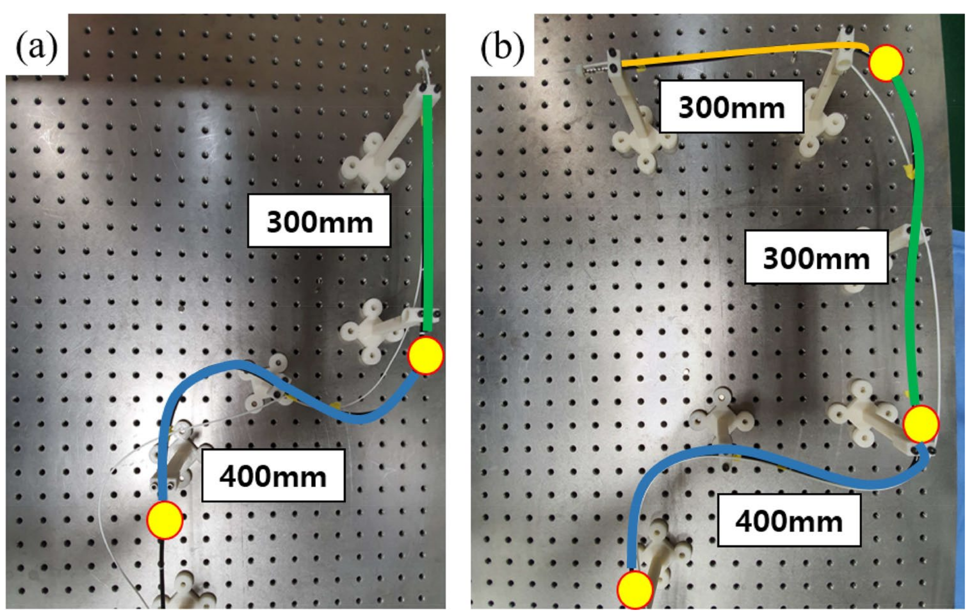

Fig. 6 Configurations of insertion tube of two colon shapes **a** descending colon, **b** transverse colon

Table 4 Classification results for hysteresis of two colon shapes

Hysteresis		Descending colon	Transverse colon
Backlash size (°)		94	102
Class prediction (°)		90	100
RMSE (°)	40°	15.76 ± 0.98	19.76 ± 0.94
	50°	12.40 ± 0.14	17.14 ± 0.16
	60°	7.61 ± 0.71	11.55 ± 0.39
	70°	7.20 ± 0.45	12.60 ± 0.42
	80°	2.52 ± 0.48	7.24 ± 0.12
	90°	**1.79 ± 0.05**	6.00 ± 0.82
	100°	4.06 ± 0.46	**4.86 ± 0.20**

The bold text emphasizes that the nearest hysteresis was predicted from the results performed on two colon shapes using the proposed classification method

transverse, the hysteresis also matches to the closest value among seven different classes. This results show that the proposed learning-based classifier is able to find the most similar hysteresis class.

4.2 Evaluating the Performance of Hysteresis Compensator

To validate the feasibility of the proposed approach, hysteresis compensation for two colon shapes was evaluated using the Bouc-Wen model-based feed-forward controller corresponding to each backlash size using the results of hysteresis classification presented in Sect. 4.1. The evaluation factors were selected as RMSE, and the backlash size between input and output of joint angle. In addition, hysteresis compensation was evaluated using periodic and non-periodic signals. The periodic signal was set as $60\sin(\omega t)$ and the frequency was set as 0.159Hz. Further, the non-periodic signal was set as $30\sin(\omega t) + 30\sin(\sqrt{3}\omega t)$. We evaluate its performance by comparing the case with and without using the compensator. The comparison consisted of two parts. (1) none, and (2) the proposed method. Here, the proposed method evaluated the hysteresis compensation by applying the class with the lowest RMSE to each colon shape and by reflecting the class prediction results in Sect. 4.2. The hysteresis compensation results were shown in Figs. 7. and 8. The results were listed in Table 5. Owing to hysteresis compensation using Bouc-Wen model corresponding to class prediction, the

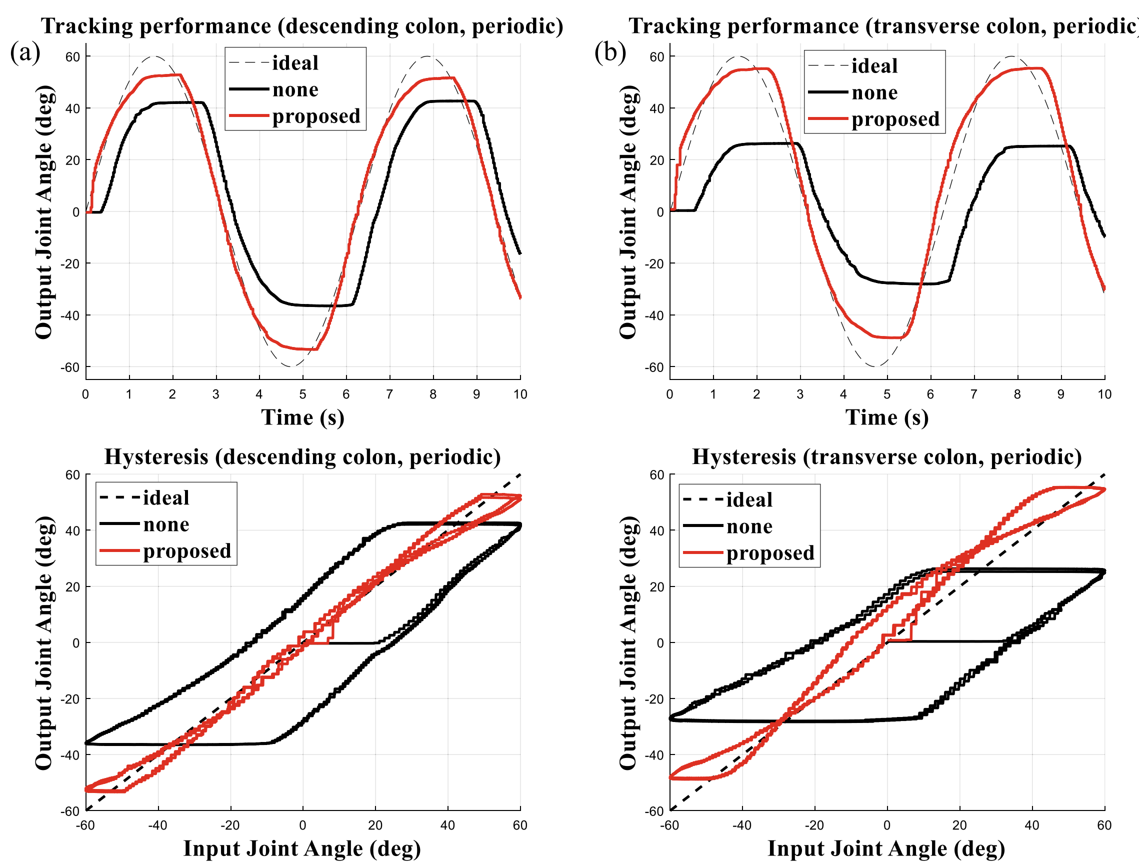

Fig. 7 Hysteresis compensation results of two colon shapes in periodic signal **a** Tracking performance and hysteresis compensation at descending colon shape, **b** Tracking performance and hysteresis compensation at transverse colon shape

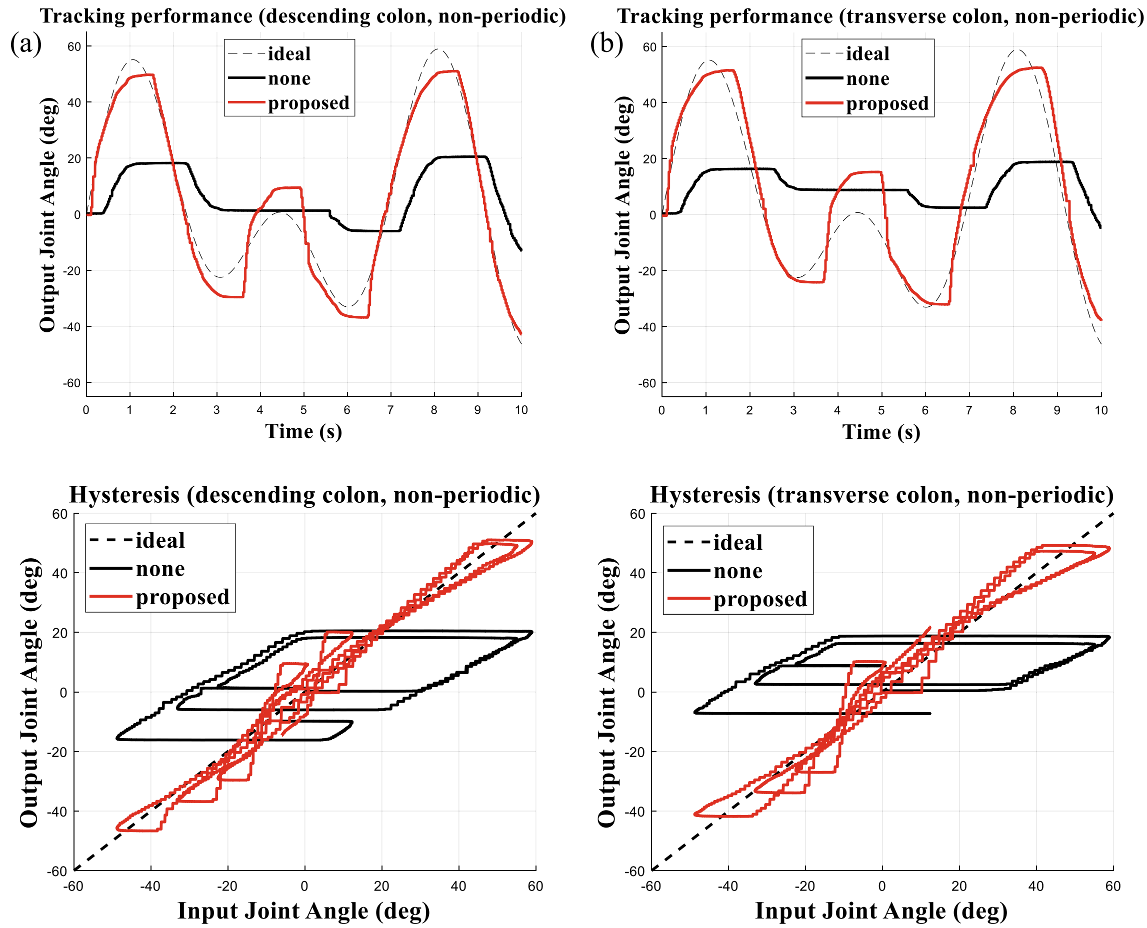

Fig. 8 Hysteresis compensation results of two colon shapes in non-periodic signal **a** Tracking performance and hysteresis compensation at descending colon, **b** Tracking performance and hysteresis compensation at transverse colon

Table 5 Hysteresis compensation results of two colon shapes in periodic signal and non-periodic signal

Hysteresis		Descending colon		Transverse colon	
Signal		Periodic	Non-periodic	Periodic	Non-periodic
RMSE (°)	None	18.08 ± 0.35	23.64 ± 0.08	25.95 ± 0.60	26.78 ± 0.13
	Proposed	**4.65 ± 0.13**	**6.34 ± 0.18**	**6.99 ± 0.65**	**6.33 ± 0.18**
Backsize size (°)	None	50.02 ± 1.16	56.88 ± 1.26	68.48 ± 0.77	70.55 ± 0.51
	Proposed	**10.77 ± 0.48**	**11.47 ± 0.71**	**17.05 ± 0.16**	**17.68 ± 0.10**

The bold text emphasizes the hysteresis compensation performance using the proposed method

maximum decrease in the RMSE when using the periodic signal reached 75% relative to none, and the backlash size was decreased to 13° or less. When using the non-periodic signal, the RMSE decreased by up to 76% relative to none, and the backlash size decreased to 17° or less.

Notably, we indirectly evaluate the hysteresis reducing performance of our method with our previous work [13] by comparing the improvement ratio of RMSE. In our previous work, the same testbed was utilized for the experiment so most physical characteristics (e.g., size, driving mechanism, etc) are identical. We chose case one for the comparison since its initial hysteresis is similar. This is important because the size of the initial hysteresis can influence the difficulty of the task in terms of reducing hysteresis. The previous work achieved 71% performance improvement and ours showed about 74% performance improvement. When non-periodic was given, previous work presented about 68% performance improvement and ours achieved 73%. Although our method is based on the discrete classifier, the results showed that our method could match the performance of the previous work which is one of state-of-the-art.

5 Discussion

In this paper, we propose the practical way to reduce hysteresis through learning-based hysteresis classifier and an optimized feed-forward controller using Bouc–Wen model. To be robust against unexpected visual disturbance as well as consider sterilization issue, we utilized the-time series wire tension data that can be obtained from an external sensor instead of using an endoscopic camera. We focus on decreasing initial unknown hysteresis after a robot approach to the target lesion. This is a critical point for a flexible surgical robot because there is no practical way to figure out the current shape of a robot due to its flexibility and uncertain organ shape and change of the shape considerably affects the size of hysteresis.

The results show that our proposed method can enhance the control performance of a flexible surgical robot even in two colon shapes that have the same configuration of an actual organ, which means that our method can potentially present the similar performance in real surgery. Moreover, the comparison result with the previous work suggests that the discrete classifier could achieve the matched performance of the regression-based method. We expected that the feedback compensator is required to further improve the performance rather than using only the feed-forward compensator. Our method can be applied to any-type flexible surgical robot which can measure their wire tension during its calibration phase before actual surgical operation.

Despite some advantages of our method, in order to implement the proposed method to another surgical robot, they need to measure their hysteresis and build their own dataset. Since inherent hysteresis can be different depend on a type of surgical robot, type of instrument, and even manufacturing condition, most data-driven methods have this limitation.

An external load on the surgical instrument might degrade the performance of our work. This usually requires a higher force in surgical instrument compared with normal condition. If our calibration process is conducted considering the external load in the surgical instrument, the discrete classifier may choose the predefined model with a larger size of backlash. However, in the actual surgical process, the calibration should be performed before starting the robotic surgery, which means that calibration with the external load is not the proper way. This is one of the limitations in the usage of feed-forward and we guess this can be alleviated via the incorporation of the feedback and the feed-forward compensator.

Although hysteresis can be significantly reduced by using the proposed framework, the residual errors still exist in tracking performance. This is because the predefined hysteresis is not perfectly identical with the actual hysteresis. In addition, using only a feed-forward controller is not able to reduce hysteresis completely. To improve the performance of the proposed method, data-driven regression approach that can predict the actual hysteresis more precisely is needed. Also, combination of using a feed-forward and feedback controller is able to achieve better performance. During operation, if the overtube of the system changes, the performance of the proposed method can be degraded, but this doesn't happen very often, at least in gastroenterology surgery. In addition, We expect that the proposed method can be used to overcome these limitations by merging online parameter estimation, such as recursive least-squares online identification [25]. Although we verified its performance by using one single bending joint, expanding our method to two joints are not difficult if we acquire more data before applying it.

6 Conclusion

In this study, we proposed the practical framework for compensating hysteresis using the learning-based hysteresis classifier. We presented that hysteresis could be divided discretely using the time-series wire tension data by conducting the preliminary experiments. The results demonstrated that the proposed learning-based classifier can find the optimal hysteresis class, and it outperforms the existed classifier. By using a feed-forward controller with the optimized Bouc–Wen model parameters, our method could significantly reduce the initial unknown hysteresis before starting actual operation.

In the future work, we will optimize the discrete number of maximum and minimum hysteresis of flexible endoscopic surgery robot and extend the another DOF of bending joint. Further, we will apply a more effective feed-forward method of describing hysteresis.

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