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A Model-Free Method-Based Shape Reconstruction for Cable-Driven Continuum Manipulator Using Artificial Neural Network

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***Abstract* – The robot-assisted natural orifice transluminal surgery (NOTES) typically involves applying the lengthy and slender continuum instruments/manipulators to get access to the target lesion sites, and then performs complex operations. However, due to the strong-nonlinearity of continuum robotic manipulators and the confined and tortuous anatomical paths, it's difficult to establish accurate inverse kinematics (IK) model to achieve precise motion control and real-time shape sensing for accurately modeling their shapes. To tackle such difficulties, a model-free method based on neural network have been proposed to solve the IK problem and reconstruct the shape of a continuum manipulator at the same time using the training results from the electromagnetic (EM) tracking approach. For the IK problem, the relationship between the tip position and the corresponding cable lengths can be learned and for the shape estimation problem, the mapping from the cable lengths to the shape of the continuum robot can be established. A dataset of 500 random continuum manipulator postures was used to train the neural network, with recorded EM sensors-tracked positions logged synchronously to the cable lengths. Experiment results show the proposed model-free method could achieve high accuracy and reliable inverse kinematics and shape reconstruction outcomes.**

Index Terms - Continuum robots, Shape reconstruction, Inverse kinematics, Neural networks.

I. INTRODUCTION

In recent years, the robot-assisted NOTES systems have played an important role in treating the gastrointestinal cancers, among which esophageal cancer, gastric cancer and colorectal cancer account for around 37% of the total cancer incidence and 40% of the associated deaths [1]. Due to the advantages of NOTES systems in terms of reduced blood loss, less trauma, fewer postoperative complications, and shorter hospital stay, the cure and survival rate of the early-stage cancer treatments have been greatly enhanced [2]. The NOTES treatment procedures typically involve applying flexible manipulators to get access to the target surgical sites along anatomical tortuous paths through the patient's natural orifices or small incisions to perform delicate operations with various both environmental and the instruments' mechanical constraints [3], as shown in Fig.1. Such requirements from these NOTES-associated treatment procedures put forward difficulties for the robot design in terms of operability, flexibility and patient comfort and safety [4].

To address these difficulties, continuum robots have been increasingly introduced for board applications in various NOTES treatment procedures. They not only provide curvilinear and flexible accessibility through small incisions or orifices, but are also capable of generating large forces at the distal ends to support surgical operations [5]. In particularly, the superior capacity of inherent structural flexibility makes it possible to approach lesion locations along the tortuous anatomic path in a confined and narrow environment and further perform complex and delicate surgical procedures. However, their inherent structural compliance design and the uncertainties caused by both accessible and operational interactions between them and human tissues, make it difficult to accurately model their shapes, resulting in increased risks of tissue damages [6]. To achieve precise and reliable motion control and further path-planning of continuum manipulators used in robot-assisted NOTES procedures, accurate and real-time shape reconstruction together with tip localization and accurate inverse kinematics model are needed.

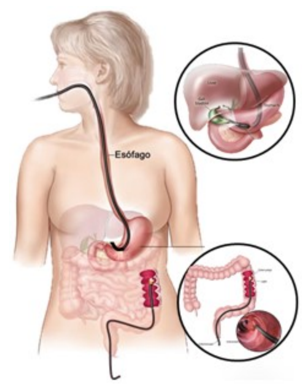

Fig. 1 The robot-assisted natural orifice transluminal surgery (NOTES)

To tackle the challenges in shape reconstruction of continuum robots, model-based, medical imaging-based and shape sensors-enabled methods have been proposed [7]. Model-based methods critically rely on kinematics and mechanics, and most of them are implemented based on the assumption of the piecewise constant curvature assumption [8]. However, the inherent deformable design of continuum robots and the unknown external payloads can lead to a high instability for identification of modeling parameters. Such limitation makes these methods inaccurate, thus could cause probable damages

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to human tissues [9]. The medical imaging modalities such as, CT, MRI, endoscopy and ultrasound, have also been tried to realize shape sensing of surgical continuum manipulators. However, they suffer from different limitations such as, offline detection, narrow views or limited accuracy, making it difficult to realize real-time shape estimation by standalone use of one imaging modality [7].

Besides the model-based and imaging-based approaches, other emerging and alternative techniques based on sensing elements have been recently reported. Fiber Bragg grating (FBG) sensors have been applied to realize shape sensing for flexible instruments [10]. They have excellent properties in terms of multiple-point strain detection, biocompatibility, inertness to chemical corrosions, making them outstanding candidates for various medical applications. Roesthuis et al. applied a set of three fibers to achieve the shape estimation of surgical needle with an accuracy of 0.74mm for tip tracking. This group also integrated a triplet fiber configuration on a cable-driven continuum robot to support closed-loop control [11]. However, the FBG-enabled shape sensing accuracy of continuum robots with low stiffness and lengthy structures is limited and the costs of the optical system are relatively high. In addition, the EM tracking approach has also been widely investigated to realize both tip localization and shape reconstruction with multiple EM sensors attached along the continuum robots [12,13]. Song et al. proposed a real-time shape reconstruction algorithm by fitting multiple quadratic Bezier curves based on the pose information captured for the EM trackers and the prior curve length information. This implementation achieved a mean position error of 1.7mm [14]. However, the EM tracking system's workspace is limited and they are prone to produce relatively large measurement errors due to the EM interferences inside the operating theatre.

To solve the existing problems in above-mentioned methods such as, low accuracy, high computation cost and critical dependence on specific shape sensors, a model-free method based on artificial neural networks (ANN) have been proposed to solve the inverse kinematics problem and estimate the whole shape of the continuum robot. Two ANN models have been proposed to learn the mapping from tip position to cable length, and from the cable length to the whole shape, respectively. Several EM sensors were placed on the backbone of the designed continuum robot to collect position data together with the cable lengths for training the ANN model to learn the proposed mapping. When the model training is done, tip position is the only needed parameter to reconstruct the shape of the manipulator. Unlike the traditional methods, the proposed method is data-driven, therefore analytical models based on kinematics or dynamics is not needed. It can compensate for the robot's fabrication errors without precise/prior knowledge of the EM sensors' accurate locations during the training procedure. Experiment results on a physical platform show the proposed model-free methods can achieve high accuracy and reliable inverse kinematics and shape estimation outcomes.

II. The Proposed Model-Free Method for Inverse Kinematics and Shape Reconstruction Based on ANN

The overall workflow of the proposed model-free method for shape reconstruction is illustrated in Fig.2. The ANN has been introduced to learn and model different mappings for the continuum robot to form the model-free method, due to its excellent approximation capabilities for nonlinear functions. For the model-free inverse kinematics model, the mapping from the tip position to the cable length can be directly established after learning. Once the desired tip position information is given, the corresponding cable lengths could be determined without any specific kinematics or mechanical model. For the model-free shape estimation method, the mapping from the cable lengths to the whole shape of the continuum robot is investigated. When the model training is done, tip position is the only needed parameter to reconstruct the shape.

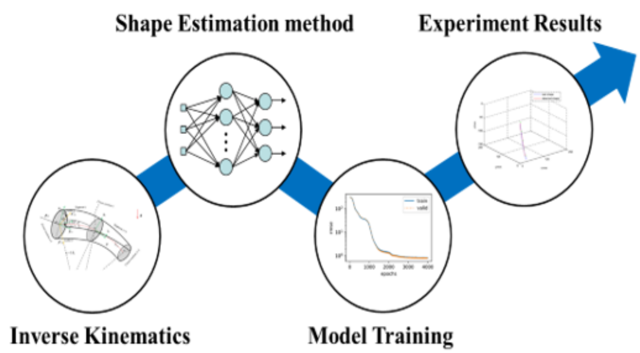

Fig. 2 The workflow of the proposed model-free method

A. *Model-Free Inverse Kinematic Solver*

The inverse kinematic modeling for continuum manipulators requires essential performances in terms of high accuracy and less computational time to tackle the closed-loop control and path planning problems in NOTES. Traditional model-based inverse kinematics for continuum manipulators follow an analytical or numerical approach. The analytical model is typically split into two mappings, one from the task space to configuration space and the other from the configuration space to actuation space. For continuum robots, the actuator space can be expressed as a set of actuation variables such as, the lengths of cables, and the task space is described as the position and orientation of the robot distal tip. An intermediate description between these two spaces is the configuration space, which is described by the position and orientation of an orthonormal local frame [15], as shown in Fig.3. These methods are mainly based on some geometric assumptions such as, the piecewise constant curvature assumption, resulting in low accuracy. When the inverse kinematics problem cannot be solved analytically, numerical methods based on Jacobian could be implemented instead [16]. Although this method avoids the slack problems that are closely associated with the cable-driven methods, it is an iterative algorithm, therefore causes a high computational cost, making it less attractive for real-time applications.

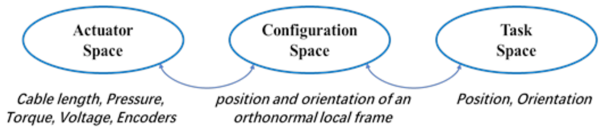

Fig. 3 The relationship between the continuum robot's workspace.

To improve the accuracy of the inverse kinematics and reduce the computational cost, model-free methods have been proposed. These methods are data-driven, and datasets of cable lengths and tip position are implemented to train the model, making it possible to directly learn the mapping from the task space to actuator space. They don't rely on any specific kinematics or dynamics model, making it relatively easy to establish the IK model. For non-redundant continuum manipulator, the inverse kinematic problem could be solved by adopting a simple ANN model. This approach could offer a faster and more adaptable solution, compared with model-based and iterative methods such as Jacobian method. The general idea to achieve tip localization is to learn the inverse model $l = \psi(x_L)$ that provides the cable lengths $l = (l_1, l_2)$ to reach the desired tip position $x_L = (x_x, x_y)$. The function ψ represents the IK of a continuum manipulator, and it can be learned by collecting data (l, x_L) from the manipulator and exploiting the outstanding nonlinear function approximation capability of ANN. Specifically, a fully connected ANN has been implemented and with an activation function $(a(x) = relu(x))$. After the training process is done, the detailed ANN parameters can be determined. Once the input of the desired tip position x_L is provided, the corresponding output of cable lengths $l^* = (l_1^*, l_2^*)$ can be calculated based the derived ANN model, as shown in Fig. 4.

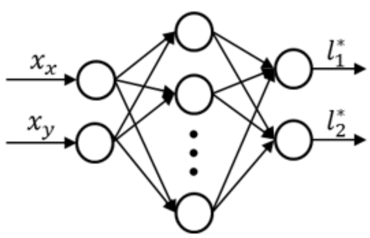

Fig. 4 ANN structure for inverse kinematic. The FNN is fed by the desired tip position and provides the approximated cable lengths.

B. Model-Free Shape Reconstruction with ANN

To reconstruct the whole shape of the continuum robot by cable length information, the uniqueness of the mapping from the cable length to the whole shape needs to be validated. For non-redundant cable-driven continuum manipulators, the direct kinematics model could develop a unique mapping from the input cable lengths to the distal tip position of the manipulator. For continuum manipulator, there exists a single unique shape for each tip position, unlike the case of rigid robots that can have multiple shapes [17]. Thus, the uniqueness of the proposed mapping can be proved to be unique. Once given specific cable lengths, there exists a unique shape of the continuum manipulator.

To estimate the robot's shape from the cable lengths, a model-free model which could map from the cable-length data to the whole shape of the continuum robot has been proposed. The whole shape of the robot could be closely approximated by interpolating some reference nodes on the shape curve. Thus, the model-free method could be presented as the mapping from the cable lengths to the position information of the selected reference nodes. By attaching EM sensors on the backbone of the continuum manipulator, the reference nodes position information could be obtained. To deal with the model uncertainties that are either caused by fabrication and assembly of the continuum robot or when the EM sensors positions are not precisely known, this method should be capable of compensation to improve its robustness.

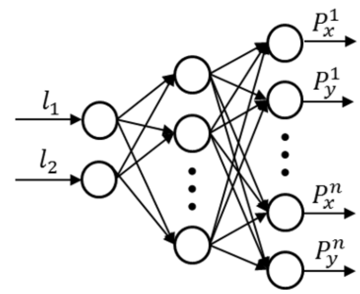

Fig. 5 ANN structure for shape estimation. The ANN is fed by the cable lengths and provides the corresponding shape reconstruction.

For this reason, a fully connected ANN model with an activation function $(a(x) = relu(x))$ is applied to learn the unique mapping from the cable lengths data to the discrete points position data which could be expressed as $P^n = \varphi(L)$. The inputs to the ANN model are the cable lengths (L_1, L_2) and outputs are several reference nodes position information along the backbone of the continuum manipulator $(P_x^1, P_y^1, \ldots P_x^n, P_y^n)$ which could be collected by EM sensors. After the mapping has been established, the reference nodes position information along the continuum manipulator can be determined with the input cable lengths, then cubic spline interpolation on these discrete nodes is followed to realize the whole shape reconstruction.

C. Hyper-Parameters Optimization and Cross-Validation

To achieve better model performance, a set of hyper-parameters of the ANN model need to be optimized. These hyper-parameters mainly include the maximum number of epochs N_{epoch}, the learning rate η, the batch size of the data for each epoch S and the ANN architecture that includes the number of hidden layers L and the corresponding number of neurons on each layer L_n. The values of the hyper-parameters are determined by the performance of the corresponding ANN model. For the case of model-free inverse kinematics, the performance refers to the mean absolute error between the cable length determined by the ANN model and the recorded ground truth. For the model-free shape reconstruction method, the values of the hyper-parameters are determined from the average value of the mean-squared-error (MSE) between the four nodes positions calculated from the ANN model and ground truth detected from EM sensors by trails and errors.

To assess how well the proposed ANN models could perform on new datasets, k-fold cross validation needs to be implemented. Cross-validation is typically used to estimate the model performance on unobserved data by splitting the obtained data into several subsets for training and evaluation purposes. In k-fold cross-validation, the obtained data are randomly divided into k evenly sized subsets. One subset is reserved for evaluation and the remaining k -1 subsets are used for training the model. This process is repeated k times for each subset, so that k models could be trained and evaluated.

III. Experiments and Results

In order to investigate the performance of the proposed model-free method, an experimental platform has been built for both distal tip and whole shape estimation. As shown in Fig.6, the designed hardware platform includes a cable-driven continuum manipulator, a microcontroller and four drivers, four stepping motors and an electromagnetic tracking (NDI Aurora, CA) unit.

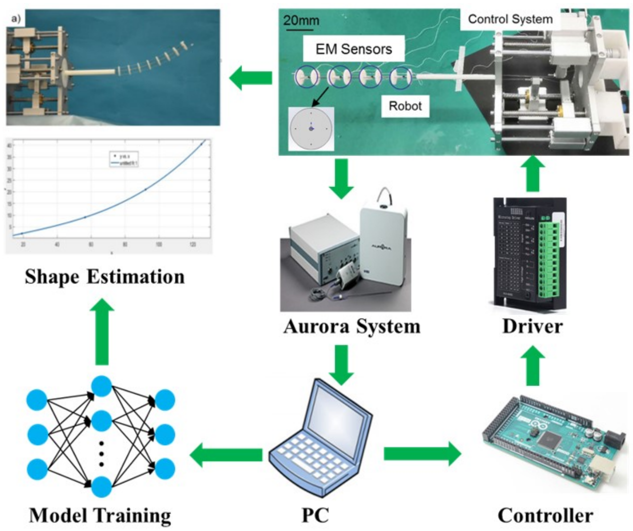

Fig. 6 Hardware configuration of the proposed system.

The continuum manipulator consists of a flexible nitinol backbone on which a series of plastic spacers have been attached and equally distributed. Each spacer has been made with four holes, and they are distributed with a uniform angle interval of 90°. Four stepping motors are utilized to drive the four independent cables to achieve 2-DOF rotation. The microcontroller of Arduino MEGA 2560 is employed to read control signals from the PC and command these motors. EM tracking techniques have been increasingly utilized to track and localize surgical continuum robots and intravascular flexible instruments in MIS, due to their superior attributes of miniature sensor sizes and freedom of line-of-sight constraints. The Aurora brand has been selected to perform EM tracking, and it can provide position and orientation information in 6 DoFs for the EM trackers placed inside the tracking volume.

As illustrated in Fig.6, four EM sensors have been attached along the continuum manipulator as reference nodes to reconstruct the shape of the continuum manipulator. Before the data collecting procedure, one extra EM sensor is attached on the manipulator base serving as a reference to provide coordinate transformation between EMT coordinate system and robot's coordinate system. After transformation, four sensors are mounted along the backbone of the continuum manipulator to serve as working sensors, with one mounted at the distal end of the manipulator. Their position and orientation information are used to perform the tip position tracking and shape reconstruction. The sensors' position information also serves as the ground truth of the reference nodes for evaluating the performance of the model-free inverse kinematic model and the shape reconstruction method. The coordinate transform method is shown in the following part.

The notations of R, E, B, W are employed to represent the coordinate systems of the continuum manipulator, EMT system, base reference sensor and working reference sensors. Therefore, the position of working sensor in manipulator coordinate system is

$$\begin{pmatrix} x_W & m_W \\ y_W & n_W \\ z_W & p_W \\ 1 & 0 \end{pmatrix} = (T_E^B)^{-1} T_E^W \begin{pmatrix} 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \end{pmatrix}$$

where, $(x_W, y_W, z_W)^T$ denotes the position and $(m_W, n_W, p_W)^T$ is the unit direction vector of X-axis of the working sensors in the manipulator coordinate system. T_E^B expresses the transformation matrix between the EMT system and base sensor; T_E^W is the transformation matrix between the EMT system and working sensors.

$$T_E^B = \begin{pmatrix} R_E^B & t_E^B \\ 0 & 1 \end{pmatrix}$$

$$T_E^W = \begin{pmatrix} R_E^W & t_E^W \\ 0 & 1 \end{pmatrix}$$

where, $t_E^B = (x_B, y_B, z_B)^T$ represents the position information reading from the base sensor, $t_E^W = (x_W, y_W, z_W)^T$ is the position information reading from the working sensors. R_E^B and R_E^W are decided by the azimuth, elevation and roll values from these two sensors. The working sensors position information in the manipulator coordinate system could be determined based on these formulas.

The datasets have been collected using the experimental platform illustrated in Fig.6. Within a predefined variation range, the input cable length values were generated randomly to actuate the continuum robot. The cable length values and the resulting position and orientation information from the EM sensors were recorded. A serial data set of 500 have been acquired for training and testing the proposed ANN models. The datasets have been grouped into three categories of a training set (60%), a test set (20%) and a validation set (20%). These datasets have been pre-processed by normalization to depress their redundancy and noises. This normalization is performed based on subtraction from the mean value and then divided by the standard deviation. The training set provides ground truth data to train the ANN model to automatically determine its detailed parameters including weights and bias for the neurons. The ANN model training procedure is realized by using the adaptive moment estimation (Adam) optimization algorithm. This algorithm implements the gradient descent method while automatically updating the learning rate to improve the robustness of the training procedure. The test set is employed to evaluate the ANN model's performance, while the validation set is utilized during the training process to avoid the probable over-fitting issue. Based on the above-mentioned method, the accuracy values for inverse kinematics model and the whole shape reconstruction model are experimentally determined, as described below.

A. *Model-free Inverse Kinematic Solver Performance*

The above-described pre-processing and 5-fold cross-validation methods are employed to determine the hyper-parameters for the inverse kinematics ANN model. The optimized ANN architecture is shown in Fig.7. The parameters are determined as the following values to achieve the minimum absolute error:

1) k=5. 2) N_{epoch} = 6000 3) η = 0.00001. 4) S = 64. 5) L_1=70. L_2=50. L_3=30.

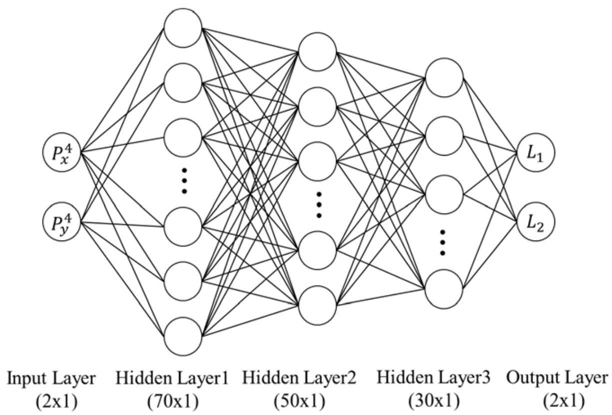

Fig. 7 Optimized ANN model architecture for model-free inverse kinematics.

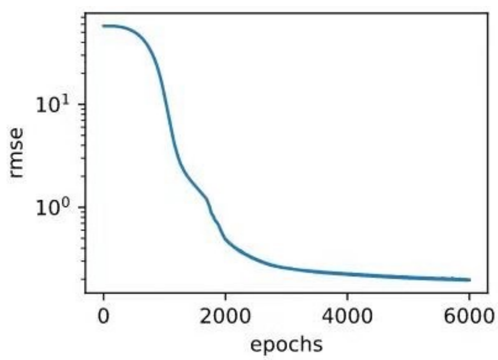

Fig. 8 ANN model for inverse kinematics training curves.

Using the defined parameters, the ANN model is trained. As for the inverse kinematics model, the ANN model performance is evaluated on the test set by calculating the absolute error between the ANN cable lengths and the test set cable lengths associated to the desired tip position. The error value decreases with the increase of the training epochs, and the error curves reach a value around 0.47 mm after 6000 epochs, that is 115.34s after the start of training on an Intel Core i5-6500. The ANN model took 0.454 ms to calculate the input cable lengths that correspond to the desired tip position. These results indicate that the proposed model-free inverse kinematic model could achieve high accuracy and suitable for real-time motion control of the continuum manipulator.

B. *Model-free Shape Reconstruction Results*

The ANN model architecture for shape reconstruction has be optimized and the ANN architecture is shown in Fig 9. The optimized architecture has two hidden layers. The values of optimized hyper-parameters are determined by 5-fold cross-validation:

1) k=5. 2) N_{epoch} = 5000. 3) η = 0.0001. 4) S = 64. 5) L_1=50. L_2=30.

The ANN model was trained which took around 95.68s on an Intel Core i5-6500 and the trends of the MSE during training procedure is shown in Fig.10. As for the shape estimation model, the ANN model performance is evaluated on the test set and calculating the average position errors generated at the four reference nodes. The MSE reached a value around 2.14 mm for each reconstructed point after 5000 epochs. After the training procedure, the ANN model took 0.397 ms to calculate the four nodes' position associated with the given cable lengths and then cubic spline interpolation is followed to get the whole shape of the continuum manipulator, which indicates that the proposed model-free method is suitable for real-time shape reconstruction.

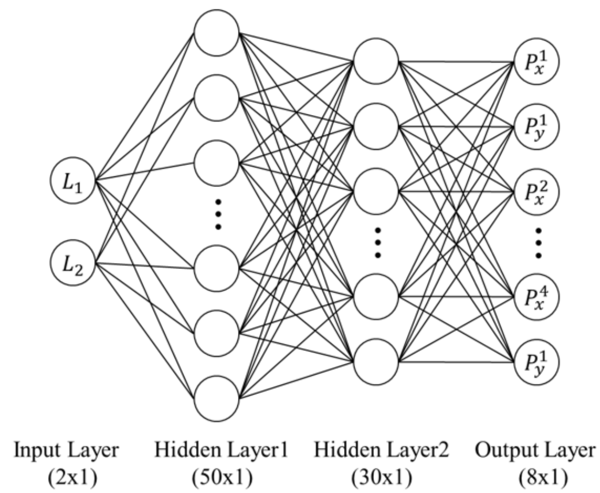

Fig. 9 Optimized ANN model architecture for model-free shape reconstruction.

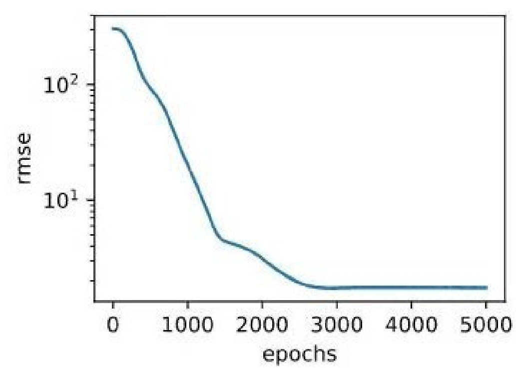

Fig. 10 ANN model for shape reconstruction training curves.

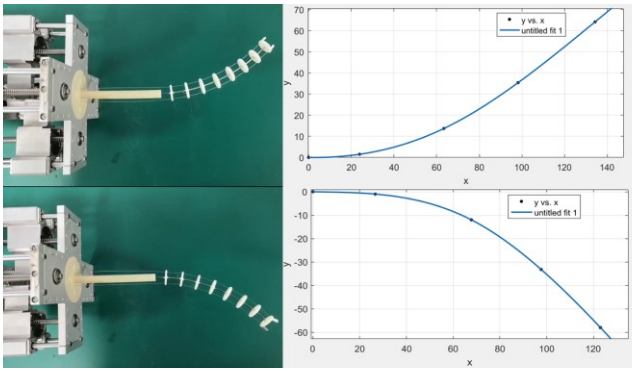

Fig. 11 The shape estimation results of the proposed method on the physical platform.

To validate the effectiveness of the shape reconstruction method, two sets of cable lengths have been applied on the physical platform and also given to the trained ANN as input data. The ground-truth shape of the continuum manipulator and the reconstructed shape from the cable lengths are shown in Fig.11. The experiment results show the proposed method could achieve reliable shape reconstruction of the continuum manipulator.

IV. Conclusion

In this paper, a model-free method which could achieve high accuracy inverse kinematics and shape estimation of a surgical continuum manipulator had been proposed. ANN models for learning the desired mapping had been established and trained by the data collected from the EM tracking system. Fundamental experiments for 2-D inverse kinematic and shape reconstruction were carried to validate the methods' effectiveness and accuracy. Although model-free methods based on ANN introduce a dependence on the obtained training data, the approach can compensate for fabrication errors while eliminating the need for complex modeling. It can be also extended and applied to other specific robots and applications. This proposed method could be applied to achieve motion control and reconstruct the whole shape of the continuum manipulator at the same time. Future efforts will be extended to achieve 3-D shape estimation of the flexible manipulator with higher accuracy and in real-time. Future work involves applying FBG-based force sensing techniques [18,19] to provide additional force inputs to form a multi-input system and generate more accurate shape estimation outcomes for continuum robots.

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