Research on the inverse kinematics prediction of a soft actuator via BP neural network

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ABSTRACT

In this work we address the inverse kinetics problem of motion planning of the soft actuators driven by three chambers. Although the mathematical model describing inverse dynamics of this kind of actuator can be employed, this model is still a complex system. On the one hand, the differential equations are nonlinear, therefore, it is very difficult and time consuming to get the analytical solutions. Since the exact solutions of the mechanical model are not available, the elements of the Jacobian matrix cannot be calculated. On the other hand, material model is a complicated system with significant nonlinearity, non-stationarity, and uncertainty, making it challenging to develop an appropriate system model. To overcome these intrinsic problems, we propose a back-propagation (BP) neural network learning the inverse kinetics of the soft manipulator moving in three-dimensional space. After the training, the BP neural network model can represent the relation between the manipulator tip position and the pressures applied to the chambers. The proposed algorithm is very precise, and computationally efficient. The results show that a desired terminal position can be achieved with a degree of accuracy of 2.59% relative average error with respect to the total actuator length, demonstrate the ability of the model to realize inverse kinematic control.

Keywords: mechanism design, theoretical kinematics, soft robots, control

1 Introduction

There have been expanding interests and increasing advancements of soft robots in recent years. Compared with traditional rigid robots, soft robots have irreplaceable advantages due to their intrinsic softness, such as high flexibility, good environmental adaptability, and safe interactions with the surroundings, etc[1, 2]. They play an irreplaceable role in the development of society. Therefore, soft robots could make significant impact in many areas including industrial applications[3], medical rehabilitation training devices[4, 5], and bionic robots[6, 7].

Soft pneumatic actuators (SPAs) with internal fluidic channels are made of hyperelastic materials, which deform upon the pressurisation of the internal channels to generate moving[8, 9]. The motion response of SPAs is governed by its morphology, which is defined by the geometry of the internal fluidic channels and the material properties used in fabrication. During the fabrication of SPAs, carbon fibre reinforced plastic is added to constrain the motion posture and significantly improve their strength, resulting in bending motion similar to human fingers and arms[10]. Therefore, as SPAs are used as soft robotic arms and soft robotic fingers, different structure designs and drive pressures will produce multi-stance 2D and 3D movements.

Compared with rigid robotic actuators, it is difficult to accurately model and control the forward and inverse kinematics of SPAs due to both material and geometric nonlinearities. As for the research on modelling and characterization of SPAs, previous efforts on analytical modelling typically include simplifications and assumptions in their formulations[11]. Subsequently, in order to improve the prediction accuracy of the model, the kinematics in soft robots are mainly derived based on the piecewise constant curvature approximation[12]. Furthermore, many of the dynamics used either Euler/Lagrange or Lagrange formulation with quasi-static simplification [13-15]. For SPAs, the solution of the inverse kinematics problem is essential to generate paths in the task space in order to perform grasping or other tasks. It is a hard task to solve the inverse kinematics. The inverse kinematics algorithms for continuum SPAs can follow originally either an analytical or a numerical approach [16-18]. For continuum SPAs, just like for rigid robots, we can differentiate the direct kinematics model to find manipulator tip position kinematics model, i.e. the linear transformation of the tip position velocity into the actuation variables velocity. The linear transformation is realized by the Jacobian matrix. These models may not accurately capture the complex nonlinear dynamics of soft robots, in part, due to the simplicity of the models themselves and the computational hardness of Jacobian matrix[19]. In second place, an accurate material model is needed. When SPAs are made of different materials, designed for complex structure, or added embedded components, the theoretical model will become more complex[20]. A more complex model may solve these problems, but the process of deriving such models is tedious and brings some difficulty to the calculation[21, 22].

The aforementioned challenges can be tackled via machine learning approaches. Initial research into combining soft robotics with machine learning approaches can be traced back to Elgeneidy et al. [23] who apply a purely data-driven approach for modelling the bending of soft pneumatic actuators. In addition, Van Meerbeek et al[24] propose various machine-learning techniques to predict the type and magnitude of deformations in terms of twisting and bending
of soft optoelectronic sensory foams with proprioception. Apart from that, only a few literatures consider using a long short-term memory (LSTM) network as the kinematic and force model[8, 25, 26]. Nonetheless, these works did not address the issue of inverse dynamics of soft actuators, that is, the ability to estimate the input signal according to the moving state of actuator systems.

The main contribution of this work is to overcome the current limitations to solve the inverse kinematics problem. We propose a BP neural network-based scheme. With sufficient data, efficient BP neural networks can be trained to implicitly account for the relation between the manipulator tip position and the input pressures applied to the chambers of a pneumatic-based soft actuator. Results demonstrate the ability of the model to reverse inverse kinematic control.

2 Actuator Design and Fabrication

Figure 1 shows the main structures of the soft actuator: 1) High elastic silicone driver matrix; 2) Three fibre-reinforced chambers; 3) Pneumatic connectors; 4) High hardness silicone moulded sealed cap; 5) A metal base connector; 6) Pneumatic hoses.

The soft actuator is composed entirely from soft materials. The three elastic chambers dispose at 120° apart, and three smaller internal passages disposed at 120° apart for weight loss. The radial restraint of the three chambers takes the form of left-right symmetrical double spiral fibre winding in this design, and the winding angle of the fibre is ±3°. In this way, the elastic fibre provides tension along the direction of itself to exert large circumferential stress. When filled with fluid, the elastic air chamber only extends axially. The three chambers connect to different air valves that provide pressurized fluid through a pneumatic hose inserted at the top of each chamber. Afterwards, the actuator deforms under the action of the three trigonally symmetrical pressurized chambers. When the pressures in chambers are equal, the chambers elongate to a same length, leading to an axial stretching of the whole actuator. When the pressures in chambers are not equal, the lengths of the chambers differ from each other, which allows the soft actuator to bend in any direction besides stretch in axial direction. The metal base connector can be used to match the rigid mounting plate on the experimental platform to ensure the stability of installation. Meanwhile, the connector is designed for expansibility. It can be further stuck to another soft actuator or other modules.

The procedure involved for fabricating the soft actuator can be summarised in the following steps as shown in Fig. 2:

I: The mould pressing of the elastic chamber. First, the chamber core and chamber casting mould are 3D printed with the ABS material, and the inner layer elastic air chamber with a thickness of 1.5mm is cast with low-hardness silicone. The silicone consists of parts A and B (1 A: 1B by weight). Before assembling the moulds, the release agent (LW-366, LONGWEI, China) is used to treat the surface of the moulds to reduce the adhesion between silicone and ABS moulds.

II: The fibre winding. Kevlar fibres are used to envelop elastic chambers and restrain their radial expansion.

III: The actuator matrix moulding. Insert the fibre-reinforced elastic chambers into the positioning hole of the ABS base plate, and cast the main part of the soft actuator with low hardness silicone. After curing, the joint sealed cap part is cast with high-hardness silicone.

IV: The actuator end seal encapsulation. Fix the metal base connector with silica gel adhesive to the actuator matrix after stripping, and finally connect the joint with pneumatic hoses.

3 Experiments Setup

To explore the relation between the pressures and manipulator tip position, and validate the inverse dynamic modelling based on BP networks, we have set up an experimental platform as shown in Fig. 3. The soft actuator is driven by a pneumatic driving device which could set pressure of the three chambers via proportional valves (ITV0030-2BL, SMC, Japan). The control algorithm of proportional valves is programmed in Arduino. The timing of the actuation and the effective pressure supply are implemented through an Arduino Mega board (UNO R3, Arduino, Italy). Three pressure sensors (ISE80H-02-R, SMC, Japan) are used to collect the real-time pressures of the fluid in three chambers. Coloured tape is attached to the ends of the soft actuator as marker to facilitate the coordinate recognition. Two high-definition cameras (MV-VD030SC, Microvision, China) are mounted on the two adjacent walls to collect the tip coordinates of the soft actuator. Finally, the coordinates of mark points could be measured by a motion analysis software Tracker.

In order to demonstrate the value of the proposed kinematic model, we apply the input pressures to three chambers in various combinations of 0 kPa to 200 kPa at intervals of 40 kPa and test the tip positions of the soft actuator. In total, 216 pairs of valid data (pressures and tip positions) are obtained.

4 Modelling

4.1 Modelling based on BP neural networks. BP neural network is a kind of multilayer feed-forward with forward information propagation and error back-propagation. Compared with the traditional curvature approximation method, the BP neural network method is more suitable for processing non-linear and complex system problems preferably due to its complex self-learning and adaptive capabilities, which can greatly increase the fitting accuracy.
And it does not need to filter and denoise the experimental data. Thus, we propose a BP neural network architecture based on finite experimental data of tip coordinates of the soft actuator. This architecture could efficiently implement the prediction of the soft actuator motion. The BP neural network is a three-layer network, which utilizes the connection weight to store information and fit function. The layers contain input layer, hidden layer and output layer. And each layer has a series of nodes. The structure diagram of the BP neural network is presented in Fig. 4. The connection weights are expressed as \(\omega_{ij}\) and \(\omega_{jk}\), which denote the weight from input node \(i\) to hidden node \(j\) and hidden node \(j\) to output node \(k\), respectively. In the error reverse propagation algorithm, the BP neural network adjusts the weights and thresholds continuously to approximate an arbitrary nonlinear function until obtain the satisfactory output. Assume that the input value is \(x_i\), \(i = 1, 2, \ldots, n\), the outputs of hidden layer are calculated at first[27],

\[
y_j = f_1\left(\sum_{i=1}^{n} \omega_{ij} x_i + b_j\right) \quad j = 1, 2, \ldots, m
\]

where \(y_j\) denotes the output of hidden node \(j\), \(b_j\) represents the bias of hidden node \(j\), \(m\) stands for the number of hidden nodes and \(f_1\) is the activation function of hidden layer. Then the output value is computed as follows,

\[
P_k = f_2\left(\sum_{j=1}^{m} \omega_{jk} y_j + \beta_k\right) \quad k = 1, 2, \ldots, p
\]

where \(P_k\) represents the output of output node \(k\), \(\beta_k\) represents the bias of output node \(k\), \(p\) stands for the number of output nodes and \(f_2\) is the activation function of output layer.

The global prediction error \(E\) is trained to achieve the minimum value via the back propagation.

\[
E = \frac{1}{2} \sum (P_k - R_k)^2 \quad k = 1, 2, \ldots, p
\]

where \(R_k\) is real output data.

In the current study, sigmoid function is used for non-linear relationships and represents an activation function for the respective neural layer. It has the advantages of being smooth, continuous and differentiable and is more accurate than the linear function. In addition, the sigmoid function is not sensitive to the noise generated in learning, which can reflect the mainstream direction of a large number of data samples. By using sigmoid hidden neurons, nonlinear mapping from the tip coordinates \((x, y, z)\) of the soft actuator to input pressures is established, that is,

\[
(P_1, P_2, P_3) = f(x, y, z)
\]

The number of nodes of the input layer is the number of the tip coordinates \((x, y, z)\), and therefore, the number of input nodes is 3. We predicted the input pressures \((P_1, P_2, P_3)\) of three chambers at the same time, and therefore, the number of output nodes is 3.

The node number of the hidden layer affects the capacity of the BP network a lot: if the number of nodes is too small, it is less likely to produce the network with low precision; on the contrary, it is prone to oscillation and local minimum phenomenon may appear. In this paper, we use the empirical formula to calculate the number of the hidden layer neurons in the first training process, trained and compared the different numbers of neurons, and thus derived the optimal neuron number of the hidden layer[28].

\[
N_{hid} = \sqrt{N_{in} + N_{out}} + \alpha
\]

where, \(N_{hid}\) is the number of hidden layer neurons; \(N_{in}\) and \(N_{out}\) are the input node number and the output node number, respectively. \(\alpha\) is a constant between 1-10.

Since BP neural network models is 3-input 3-output model, the number of hidden layer neurons ranges from 3 to 13. Even if a same number of hidden layer neurons are trained by using same data, the output results may be different for its uncertainty and complexity. Therefore, the optimum neurons in hidden layer of the network was determined by method of trial and error this study. Regression-coefficient \((R)\) is frequently used measure of the differences between the values predicted by a model or an estimator. If a good model is expected, \(R^2\) must be close to 1.

In order to avoid over fitting and falling into local minimum, the structure of BP neural network is: training times as 500, training precision as \(10^{-3}\), learning ratio as 0.01.

Figure 5 shows the training and verification results of a different number of neurons in hidden layers, it is found that the training error is the smallest when the hidden layer has 13 neurons. The mean value and median level under this number of neurons in hidden layer are also highest, representing that the network under this hidden neuron number is more stable. Then the network structure of the model is determined to be 3-13-3.

After determining the number of hidden layer neurons, the data set is divided in training set and testing set. The data under the chamber 1 pressure of 0 MPa, 0.8 MPa, and 1.6 MPa serves as the training set. The data under the chamber 1 pressure of 0.4 MPa, 1.2 MPa and 2.0 MPa serves as the testing set. The training set is used during learning phase, whereas the testing set is only employed to evaluate the performance of the BP neural network model.

4.2 Model error analysis. The training set is used to train the BP neural network model with 3–13–3 structure. At the same time, the testing set is used to verify the identification accuracy, as shown in Fig. 6. To evaluate the performance of the model, mean absolute percentage error (MAPE) are applied. And this metric is defined as follows,

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{F_i - T_i}{T_i} \right| \times 100\%
\]

where, \(F_i\) is the predicted output and \(T_i\) is the true output. The training process is considered to be completed when the error between the training set and testing set is minimal.
where $N$ is the number of test data, $F_i$ is the $i$ th forecast value and $T_i$ is the $i$ th actual value.

The results show that under different tip positions of the soft actuator, the maximum absolute percentage error between test values and prediction values is less than 6%. The MAPE by this model is less than 5%. The $R^2$ of the prediction model reaches to 0.9767, which indicates that the predicted values are in good agreement with the actual values and could meet the prediction requirements of the inverse kinematics and the control demands of soft actuators.

5 Model Application

To prove the practical value of the BP networks model, we conduct the model-based open loop control of tip positions of the soft robotic arm and carry out a path following experiment. The target path is an 8-shaped spatial curve at the projection onto XOY plane. We choose 41 waypoints from it. According to the BP networks prediction model, we can calculate the corresponding input pressure vector. In Fig. 7, the input signals of three chamber pressures used to complete the path are given. Figure 8 shows the target path at the tip of the soft robotic arm, the target route point selected to calculate the required pressure and the actual route point in the top view and the side view, respectively.

The position error while following the path is shown in Fig. 9. For the 41 waypoints, the average position error is 5.45 mm, the standard deviation is 0.42 mm and the maximum value is 12.128 mm. The experimental results demonstrate that the developed model has acceptable accuracy.

The performance of the model in the path following experiment is not perfect. The reasons of measurement error are analyzed. On the one hand, an open loop static controller is not suitable enough for continuously moving control; on the other hand, the hysteresis of soft materials and the pulse shock signal of proportional valves lead to errors.

6 Conclusion

In this study, we demonstrate a three-chamber pneumatic soft actuator which has a modular structure and present its design and fabrication. Although some kinematic model studies have been carried out on the three-chamber soft actuator, few people combine the neural network with the kinematic model. Thus, this article puts forward a scheme aided by BP neural network modelling to realize nonlinear prediction and mapping from the tip coordinates $(x, y, z)$ to the input pressures, using finite experimental data.

The feasibility of the prediction model based on BP neural network has been tested on the real soft robotic arm. The prediction model shows accurate and fast performance, because the mean position error is 5.45 mm and the standard deviation is 0.42 mm. The mean relative error relative to the total arm length is 2.59%. In future, in order to explore the universality of this method, it will be validated with more complex soft actuators.

The performance results of the model in the model application section is not perfect. The current problem is that this BP neural network model is an open loop static controller, which is not suitable enough for continuous control. In addition, the manufacturing error and environmental change greatly affect the motion results of the soft robotic arm. For future work, the combination of feedback control and damping is expected to achieve more precise control of the complex motion.

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**Fig. 1** Schematic of the soft robotic arm

**Fig. 2** Schematic of the fabrication of the soft actuator

**Fig. 3** Overview of the soft actuator experiments setup.

**Fig. 4** The structure diagram of a BP neural network

**Fig. 5** The $R^2$ values of different neurons numbers in the hidden layer.

**Fig. 6** The MAPE of BP neural network model
Fig. 7 Pressure inputs to the three chambers.

Fig. 8 Path of the tip of the soft actuator. (a) Side view. (b) Top view.

Fig. 9 Position error in path following experiment.