High-Dimensional Nonlinear Dynamics Based on LSTM Modeling for Accurate Manipulation of Soft Manipulators

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Abstract. The continuous soft manipulator is gradually regarded as a feasible alternative to the traditional rigid link robot because of its good flexibility. However, due to its obvious nonlinear and time-varying characteristics, actual modeling and control are still difficult. This paper focuses on the motion control method based on long short-term memory (LSTM), combs the basic theory of soft manipulator and LSTM. The existing work can be roughly divided into three categories: modeling and control of a single manipulator, multi-manipulator collaboration, and applications in complex environments. The LSTM method has certain advantages in dealing with time-varying and hysteresis characteristics, it still faces problems such as complex models, data dependence, and limited real-time performance. Combining physical models with data-driven methods and designing lighter control strategies may be a more practical direction. This paper provide some reference for the design of adaptive and intelligent control methods of soft robots.

Keywords: Soft robotic manipulators; LSTM; Model predictive control; Data-driven control

1 Introduction

The increasing demand for robots that can operate safely and adaptively in unstructured environments has also promoted the development of robotic arms from traditional rigid structures to flexible continuum structures. Soft manipulators composed of compliant materials usually have higher safety and adaptability, as well as continuous deformation ability, so they have great application potential in minimally invasive surgery, auxiliary robots, human-computer interaction and other scenarios [1]. Inspired by biological systems such as octopus arms, such manipulators can complete complex interactive tasks through their own characteristics, thus simplifying the control process to a certain extent [2]. In recent years, advances in materials and manufacturing technologies have made it possible to design structures that are more compact, more flexible, and have large bending capacity [3]. However, in practical applications, control problems are still a major limiting factor.

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In terms of control, traditional methods are usually based on certain simplified assumptions, such as the piecewise constant curvature (PCC) model, in order to obtain a tractable kinematic expression. Such methods perform well under quasi-static conditions, but they are often difficult to describe the nonlinear dynamics, hysteresis effects, and time-dependent characteristics that are common in soft robots, thus limiting the control accuracy and response speed of the system. On the other hand, it is also difficult to establish an accurate model from the first principle, so more and more research has begun to turn to data-driven methods. Existing work shows that neural networks have certain advantages in dealing with complex nonlinear problems. Among them, recurrent neural network (RNN), especially long-term and short-term memory (LSTM) network, performs well in describing time-related behaviors and hysteresis effects, and can be used to achieve more accurate dynamic prediction [4]. For example, the combination of RNN and model predictive control (MPC) can realize the closed-loop control of soft manipulator under unknown load conditions [5].These results also show that the learning-based method can make up for the shortcomings of traditional models to a certain extent.

Nevertheless, the application of LSTM and other learning methods in soft manipulators still faces some problems. Existing research often focuses on a certain type of modeling method or control strategy, and does not pay enough attention to the overall relationship between dynamic modeling, control framework and specific applications. At the same time, in complex or unstructured environments, the system is still affected by factors such as strong nonlinearity, lag effect, and high dependence on data. The generalization ability of the model also needs to be improved, which limits the actual deployment to a certain extent.

Based on the above background, this paper combs and analyzes the motion control method of soft manipulator based on LSTM, focusing on the theoretical basis, modeling method and control strategy, and tries to make a clear summary of the development process of related technologies. On this basis, the main problems existing at present are discussed, and the possible research directions in the future are also briefly analyzed, hoping to provide some reference for the design of subsequent control methods.

The structure of this paper is as follows : Section 2 introduces the related research of soft robot modeling and control ; in section 3, the motion control method based on LSTM is analyzed. Section 4 discusses typical applications and their performance characteristics ; section 5 summarizes the main problems and gives the future development direction ; section 6 summarizes the full text.

2 Kinematic theory of soft continuum manipulators and fundamentals of LSTM networks

2.1 Classification of soft continuum manipulators

Soft Continuum Manipulators (SCMs) is a kind of robot system characterized by continuous deformable structure. Different from the traditional manipulator composed of rigid joints, its motion mainly comes from the distributed elastic deformation of materials. Due to this structural feature, SCMs usually have higher flexibility, are easier to adapt to unstructured environments, and are more secure in human-computer interaction. In general, it can be classified from two perspectives: driving mode and modeling method.

(1) Classification by driving mode

Pneumatic and hydraulic soft manipulator produces bending deformation by adjusting the pressure difference of the internal cavity. The structure is light and can achieve a large bending range. However, in practical use, due to the lag of material, the coupling between pressure and the influence of external load, its behavior often shows strong nonlinear characteristics, and the modeling is difficult.

In tendon-driven continuum robots (TDCRs) system, multiple tendons are arranged along the backbone of the manipulator, and the bending is realized by adjusting the tension difference. Compared with pneumatic drive, such robots are usually easier to control and have higher load capacity. Its modeling is mostly based on the Cosserat rod theory, which is used to describe the coupling deformation of bending, torsion, shear and tension.

Concentric tube continuum robots (CTCRs) is composed of multiple pre-bending elastic tubes, which can form complex spatial shapes through relative rotation and translation. In practical applications, CTCRs are common in scenarios such as minimally invasive surgery, mainly due to their compact structure and good flexibility.

(2) Classification by modeling assumptions

From the perspective of modeling, SCMs can usually be divided into PCC model, variable curvature model and continuous Cosserat rod model. Among them, the PCC model is still the most widely used approximation method due to its simple form and low computational complexity.

Under the unified representation, different forms of PCC models are essentially equivalent, and their mapping relationships can usually be divided into two parts: one is a geometric transformation unrelated to a specific robot, and the other is related to the driving mode.

It should be noted that the traditional bending angle parameterization is prone to singularity problems when approaching a straight-line configuration. In view of this, some improved parameterization methods have been proposed to eliminate discontinuities and improve the stability of numerical calculations [6].

2.2 Dynamics modeling of soft continuum manipulator

The dynamic behavior of SCMs is mainly determined by the distributed elasticity and geometric nonlinearity of materials. Different from the rigid manipulator, its configuration changes continuously along the arc length, so it is usually necessary to use partial differential equations to describe its dynamic characteristics, which also increases the complexity of modeling and solving.

2.2.1 Piecewise constant curvature approximation

Under the PCC assumption, the manipulator is divided into several segments, each of which is approximately an arc with constant curvature, and its curvature is denoted as κ:

$$\kappa = \frac{\theta}{L} \tag{1}$$

where θ is the bending angle and L is the segment length. The homogeneous transformation along arc length s can be expressed as:

$$T(s) = \begin{bmatrix} R(s) & p(s) \\ 0 & 1 \end{bmatrix} \tag{2}$$

where $R(s)$ is the rotation matrix and $p(s)$ is the position vector. Although PCC models are computationally efficient and suitable for real-time control, they neglect shear and extension effects and may suffer from reduced accuracy under external loads.

2.2.2 Dynamic model based on cosserat rod model

For high-fidelity modeling, the manipulator skeleton can be described using the cosserat rod model theory [7]. The force balance equation along the arc length s is:

$$\frac{\partial \mathbf{n}}{\partial s} + \mathbf{f} = \rho A \frac{\partial^2 \mathbf{r}}{\partial t^2} \tag{3}$$

Where n is the internal force, f is the distributed external force, ρ is density, A is cross-sectional area, r is position vector. The moment balance equation is:

$$\frac{\partial \boldsymbol{m}}{\partial s} + \boldsymbol{r}_s \times \boldsymbol{n} + \boldsymbol{l} = \rho \boldsymbol{I} \frac{\partial \omega}{\partial t} \tag{4}$$

Where m is internal moment, l is distributed external moment, I is the area moment of inertia, ω is angular velocity. The constitutive relationship for a linear elastic rod is:

$$\boldsymbol{m} = K_b(\kappa - \kappa_0) \tag{5}$$

where K_b is the bending stiffness matrix and κ_0 is intrinsic curvature. These coupled PDEs describe bending, torsion, shear, and axial extension simultaneously. Numerical discretization transforms them into boundary value problems solvable in real time.

2.3 The basis of Lstm network architecture

The soft continuous manipulator exhibits hysteresis, viscoelasticity and time-dependent coupling between drive and deformation. Therefore, data-driven methods such as LSTM networks are used to model nonlinear temporal dynamics. An LSTM unit consists of a cell state C_t and a hidden state h_t. The unit state stores long-term information, and the hidden state represents the output of the unit at the time step t. The Gate of Forgetting can be expressed as:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{6}$$

This gate determines how much previous memory is retained. The input Gate can be express as:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{7}$$

With the memory effect, the output of LSTM can be express:

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{8}$$

where σ denotes the sigmoid activation function and ⊙ represents element-wise multiplication.

The soft continuous manipulator usually has obvious hysteresis, viscoelasticity and time coupling effect between actuation and deformation, which makes it difficult to describe the system simply by physical model. On the one hand, such models often have a large amount of calculation, and some material parameters that are difficult to obtain accurately are also needed.

In this case, the LSTM network provides a more realistic way of modeling. It can directly learn complex nonlinear input-output relationships from experimental data, thereby reducing dependence on explicit analytical models. At the same time, due to its memory structure, it can better describe hysteresis and time-related behavior, which is particularly important for software systems.

In addition, LSTM can also compensate for model uncertainty and unmodeled dynamics to a certain extent, thereby improving the prediction accuracy of end motion. In practical applications, such methods are often combined with physical models to construct a hybrid modeling framework to achieve a better balance between accuracy and adaptability.

Compared with traditional feedforward neural networks, LSTM usually has more advantages in dealing with time series and dynamic characteristics, so it is more suitable for modeling and control of soft continuous manipulators

3 LSTM-based motion control methods for soft robotic manipulators

Due to the use of compliant materials and distributed drive, the soft manipulator usually exhibits obvious nonlinearity, time correlation and hysteresis effect, which makes it difficult to accurately model and control only by traditional analysis methods.

In recent years, LSTM and other RNNs have been gradually used to deal with such problems, and have performed well in describing time dependence and complex dynamics. According to the existing research, the motion control methods based on LSTM can be roughly divided into three categories: modeling and controlling of single manipulator, cooperative controlling of multiple manipulators, and application in complex environments.

3.1 LSTM-based controlling for single soft manipulators

For a single soft manipulator, the difficulty mainly lies in how to accurately describe its nonlinear dynamics and hysteresis effect. Traditional modeling methods, such as PCC model or cosserat rod theory, usually require certain simplification assumptions or rely on more accurate parameter identification, so they are often not ideal in dynamic situations. In contrast, LSTM can learn the relationship between input and output directly from the data, and use its time memory characteristics to describe the dynamic changes of the system.

Recent studies have shown that LSTM performs well in dynamic response prediction and kinematics modeling. For example, there is a work to apply LSTM to hydraulically driven soft manipulators to predict dynamic responses under different input conditions, and high accuracy can be obtained without relying on explicit physical models [8]. Similarly, in the tendon-driven flexible surgical robot, the LSTM-based modeling method can also achieve better results in the trajectory tracking task, which is better than the traditional analytical model [9].

Hysteresis modeling is also a typical application scenario. In soft actuators such as shape memory alloys (SMA), the system behavior is often closely related to the historical state. Ordinary feedforward neural networks have limited performance in this regard, while LSTM can better describe this dependence by introducing historical information, thereby improving prediction accuracy [10].

In addition to the standard LSTM method, some RNN variants are also used for model-free control. For example, variable parameter RNN (VP-RNN) is used to solve the inverse kinematics and Jacobian estimation problems of continuum robots. It can achieve more stable results without prior model parameters, showing good adaptability [11].

From the existing research, this kind of method mainly focuses on dealing with the problems of nonlinearity, time correlation and hysteresis, which provides a more flexible alternative for the traditional model method.

3.2 Learning-based coordination for multi-arm soft robotic systems

Compared with single manipulator, the complexity of multi-manipulator system is obviously higher, which is mainly reflected in the increase of state space dimension, the stronger coupling between manipulators, and the need to consider collision constraints at the same time. Therefore, the coordinated control not only depends on the modeling accuracy of a single manipulator, but also needs to reasonably deal with the interaction between them.

In response to these problems, there have been many attempts in recent years to combine LSTM with DRL. In multi-manipulator motion planning, LSTM is usually used to predict the future position of dynamic obstacles, while reinforcement learning algorithms, such as Soft Actor-Critic (SAC), are responsible for generating control strategies. This combination makes the system more stable in an environment containing static and dynamic obstacles.

Similar methods have also been applied to the dual-manipulator system, by training a distributed neural network controller to achieve collision-free motion while satisfying kinematic constraints [12]. Although these methods may not be directly controlled by LSTM, from the results, the learning method has obvious advantages in dealing with high-dimensional coordination problems.

In addition, for the multi-manipulator system with physical coupling, there are also studies using a neural network-based cooperative control strategy, which realizes synchronous motion through adaptive learning, and shows good convergence characteristics in cooperative tasks [13].

On the whole, in the multi-manipulator scenario, LSTM is more responsible for time prediction, especially in the dynamic environment, while reinforcement learning is mainly used for decision-making and control optimization. The combination of the two can improve the overall performance of the system to a certain extent.

3.3 LSTM-based controlling in complex and unstructured environments

Soft manipulators are usually used in complex scenarios such as minimally invasive surgery, underwater exploration, and human-computer interaction. These environments are often accompanied by strong uncertainties, external disturbances, and higher performance requirements, thus posing more stringent challenges to control methods.

In medical robots, tendon-driven flexible manipulators are susceptible to nonlinear transmission and modeling errors. Relevant research shows that LSTM-based kinematic modeling can improve control accuracy by learning task-related data, thereby achieving more stable trajectory tracking in a confined space [9].

For underwater applications, the interaction between fluid and structure will bring great uncertainty. To solve this problem, some control methods based on deep learning are proposed. For example, DRL can enable soft robots to maintain stable motion in disturbed waters, showing good adaptability [14]. Although LSTM is not always directly involved in control, similar sequence modeling methods are still important when describing time-varying processes.

In human-computer interaction scenarios, such as wearable soft robots for rehabilitation, due to the strong uncertainty of human motion and interaction force, adaptive control methods combined with online learning are usually needed to improve the stability of the system. This kind of research also shows that combining data-driven models with physical systems is an effective way to achieve reliable control.

From the application point of view, in complex environments, such methods are mainly used to describe dynamic processes, compensate for uncertainties, and improve system adaptability. They are usually used in conjunction with reinforcement learning or hybrid control strategies.

4 Challenges and future directions

Although learning-based control methods (including LSTM) have developed rapidly in recent years, the soft manipulator still faces some key problems in practical applications, which limits its promotion to a certain extent. In general, these problems mainly come from three aspects: the characteristics of soft materials, the complexity of continuum dynamics, and the limitations of data-driven methods.

4.1 Complexity of modeling and controlling

One of the core problems is the complexity of modeling and control itself. Different from rigid robots, soft manipulators have approximately infinite degrees of freedom in theory, accompanied by obvious nonlinear and distributed dynamic characteristics, which makes the problem more difficult. Traditional methods such as PCC model or cosserat rod theory, although they can describe system behavior to a certain extent, usually require more simplified assumptions or have a large computational overhead, so their application in dynamic environments is limited. It has been pointed out that how to achieve a balance between accuracy and computational complexity is still a difficult point in soft robot control.

In order to solve these problems, researchers began to introduce data-driven methods, such as LSTM networks, to approximate the dynamic behavior of the system. However, this kind of method itself has some limitations. A more practical problem is that the dependence on data is strong, and the acquisition of high-quality training data is often costly, especially in software systems. In addition, the performance of such models outside the training conditions is usually not stable enough. When the environment or system parameters change, it is prone to performance degradation.

From the practical application point of view, these factors will affect the robustness and scalability of the pure data-driven method, and also show that there is still a need to find a more suitable combination between the model method and the data-driven method.

4.2 Real-time implementation

Another key issue is real-time implementation. Deep learning models such as LSTM have a large amount of calculation. If they are combined with methods such as MPC, the overall overhead will increase further. This makes it difficult to deploy on embedded platforms with limited computing resources, which affects its application in actual real-time control.

From the perspective of development trends, future research may focus more on hybrid modeling methods, such as combining physical models with data-driven methods, such as neural networks with physical constraints. This can not only improve the accuracy of the model to a certain extent, but also retain a certain physical interpretability, while reducing the dependence on a large amount of data.

In addition, combining learning methods with frameworks such as reinforcement learning or model predictive control also helps to improve the adaptability and overall performance of the system, which may be more advantageous in complex tasks.

4.3 Structural design

In addition, the performance of soft robot systems is largely affected by material properties and structural design. Due to nonlinear elasticity, hysteresis and variable stiffness, there is often a strong coupling relationship between the physical structure and the control strategy. Previous studies have also pointed out that it is still difficult to achieve high control accuracy while ensuring compliance, especially when external forces or interactive tasks are involved.

In view of these problems, future research may pay more attention to the collaborative design of materials, structures and control methods. For example, the introduction of smart materials with adjustable stiffness and low hysteresis characteristics helps to improve the controllability of the system while maintaining flexibility. At the same time, combining structural optimization with learning-based control methods, such as LSTM or reinforcement learning, is also expected to further improve the adaptability and overall performance of the system.

In addition, the multi-functional structure with embedded sensing and driving capabilities is also a noteworthy direction. Such design can make the connection between sensing, controlling and execution closer. From the perspective of application, these ideas are helpful to improve the stability and accuracy of soft robots in complex environments.

5 Conclusion

In conclusion, the motion control method of soft manipulator based on LSTM is sorted out. Starting from the basic problems of kinematics and dynamics modeling, combined with related research, the role of LSTM in describing nonlinear, hysteresis and time-related behaviors is analyzed. Combined with the existing work, the related research can be roughly divided into three categories : modeling and control of single manipulator, cooperative control of multiple manipulators, and application in complex environment. These studies have shown that data-driven methods can make up for the shortcomings of traditional model methods to a certain extent, especially when combined with methods such as model predictive control and reinforcement learning, showing better flexibility. However, from the practical application point of view, such methods are still limited by factors such as computational overhead, data dependence and generalization ability. Focusing on these issues, future research may pay more attention to hybrid modeling methods, lightweight algorithm design, and collaborative optimization of materials, structures, and control strategies. On the whole, the learning-based control method provides a new idea for soft robots, but there is still room for further improvement in engineering landing.

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