Deep Learning Methods for Soft Robot Control: Data-Driven Modeling, Policy Learning, and Dynamic Prediction

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Abstract. Soft robots, relying on compliant materials, exhibit inherent safety and environmental adaptability in complex environments, but their strong nonlinear characteristics make modeling and control particularly challenging. This paper employs a literature review and comparative analysis approach to summarize research on deep learning-based control of soft robots, focusing on data-driven modeling, policy learning, and dynamic prediction. The results show that deep networks can serve as surrogates for numerical models, reinforcement learning facilitates the learning of complex control strategies, and time-series models improve dynamic prediction capabilities. The integration of physical priors with deep learning, as well as learning mechanisms focused on safety and few-shot learning, will be important directions for promoting the practical application of soft robots.

Keywords: Deep Learning; Soft Robot Control; Dynamic Prediction

1. Introduction

Soft robots are an emerging category of robots, and they generally move by bending, stretching and contracting. Compared with robots with traditional structures, they are more flexible, adaptable and compliant, and are especially suitable for interactive tasks related to complex environments. They provide new solutions for problems in fields such as medical care, rescue and environmental monitoring. Because soft robots have highly nonlinear dynamic characteristics, modeling and controlling them is often complex and accurate prediction is difficult [1].

Deep learning has been proven to have special capabilities in dealing with nonlinear and real-time control systems, and has become common in robotics. Indicatively, the deep learning approach allows machines to understand how mechanical systems work based on data, so that they can control themselves with intelligence optimizing their control approaches, which takes up less effort on the part of an engineer when writing control schemes.

Since the soft robots are flexible and can perform various driving actions, the conventional soft robot control solutions offered by methodologies that rely on physical concepts generally experience complex problems with real-time operation and adaptive control [2]. The control model calculation and control optimization appear to be the solution to this issue. On conventional physical models, deep learning has the potential to improve the accuracy levels of

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the control schemes. By training on a significant volume of sensor information, deep learning based systems can recognize the possible trends of the robot behavior, and subsequently construct really responsive control models. These models are also more comfortable and quicker to work with than the traditional physical models [3]. On control, policy learning, specifically the reinforcement and the deep reinforcement learning exists. Such approaches give the robots the capability to ever optimize decision-making policies with the environment, such that they can be able to learn on their own in addition to performing actions in complicated and unclear conditions [4]. The other method of maximizing control is applying a dynamic prediction model, particularly an RNN-based and an LSTM-based model, which allows the robot to anticipate the next state and modify the control actions in real time based on the prediction outcomes, and in this way improve the performance of the robot in dynamic settings [5].

The objective of the paper is to critically review the approaches of deep learning in the control of soft robots with the emphasis on the data-driven modeling, policy learning, and dynamic prediction. It constitutes the progress and the challenges of applying deep learning to the sphere of soft robots and looks to the future research directions, particularly, the opportunities it has to improve the accuracy of the real-time control of soft robots, handle changing environmental conditions, and complete multi-task tasks.

2. Challenges and existing methods in soft robot control

Soft robots rely on compliant materials and continuous deformation to achieve movement and operation, and have outstanding advantages in medical, rescue, and underwater exploration scenarios. This compliance also makes modeling and control much more difficult than rigid robots: the system exhibits strong nonlinearity, high dimension, time-varying and closely coupled with the environment, and traditional control theories often cannot be directly applied [2], which is one of the core problems in the research.

From a modeling perspective, soft robots face three main challenges. First, the dynamics exhibit high nonlinearity and uncertainty. When modeling, it is necessary to consider the large deformation, hysteresis, and friction effects of flexible materials, making analytical modeling extremely troublesome. In addition, changes in external contact and load constantly introduce disturbances and uncertainties [6]. Second, there are many degrees of freedom and high dimensionality of state space. The soft structure is essentially an infinite-dimensional continuum. When modeling, it is necessary to consider not only the end pose but also the overall shape, stiffness distribution, and contact with the environment [4]. Third, there is the pressure of real-time control and system integration. Soft robots generally integrate multi-path drive and multi-modal sensing. The controller must process a large amount of sensor data in real time and provide control input within the framework of limited computing power. High-fidelity numerical models (such as FEM) are often difficult to implement directly in this scenario [7].

To address the aforementioned challenges, existing research has proposed several representative control methods. Model-based control methods use Cosserat lever models, simplified continuum models, or finite element models to describe the dynamics of soft robots, and on this basis, design strategies such as PID control, feedforward compensation, or model predictive control (MPC) [2]. These methods have clear physical meaning and strong interpretability, but the cost of model construction and numerical solution is high, and the cost of model maintenance increases once the structure or working conditions change. Optimization-based control methods obtain control input by solving optimization problems online. A typical example is MPC, which can plan shape and trajectory while considering constraints, thus improving control accuracy and robustness to a certain extent. However, in high-dimensional soft systems, real-time solution still faces significant computational pressure [8]. In addition, some works have introduced adaptive and robust control ideas, and alleviated the influence of modeling errors and external disturbances by adjusting control parameters online or introducing uncertainty boundaries [9]. However, in scenarios with strong nonlinearity and strong coupling, they still face the problems of complex design and difficult parameter adjustment.

Traditional solutions offer greater interpretability, but when faced with the demands of achieving real-time performance and accuracy for soft robots under complex, nonlinear, high-dimensional, and highly uncertain conditions, they suffer from high solution and maintenance costs and difficulties in model debugging.

3. Deep learning-based control strategies for soft robots

The data-driven approach is currently a fundamental technology used to deal with the solution to the soft robot control problem due to the rapid advancement in the deep learning field. Control strategies Profits from deep learning can be trained using vast data volumes, automatically learn the control strategy and optimize it, enhancing the control precision and stability of soft robots. This section shall dwell on deep learning application to soft robot control, technological advancements of data-driven model, policy learning and dynamic prediction.

3.1 Data-driven modeling

In a deep learning-based soft robot control system, data-driven modeling expects to learn the mapping relationship between the state and control inputs of the soft robot by directly applying experimental or simulation data into the learning process, which is the basis of any future policy learning and dynamic prediction. In comparison with conventional approaches which use specific physical models, this one puts more focus on relying on the data provided by massive sensor to represent the multifaceted nonlinear nature of the dynamics with the environment.

With the help of a model like deep neural networks (DNN) and convolutional neural networks (CNN), machines are able to automatically identify features in sensor data and train to learn the possible patterns of different behaviors. The data-based modeling can prevent the intricate computations that might be faced in the process of correct modeling, and enhance the flexibility of dealing with uncertainty as well as dynamic surroundings. An illustrative example is that deep learning is capable of training deformation and motion patterns of soft robots by processing a large quantity of sensor data, [3] therefore, creating an approximate dynamic model that enables the attainment of efficient control.

Deep neural networks which have been applied in controlling soft robots, where physical models are not necessarily applied, can precisely predict the state of a robot, making the process of controlling it better by learning the interaction mode of the environment [7]. The benefit of such approach is that it can dynamically change the control scheme in different operating conditions which are appropriate when soft robots have to deal with tasks within dynamical and uncertain environment.

Policy Learning. Policy learning in contrast to control design on the basis of dynamic equations tends to employ the reward signal of the task as a way of adjusting the control law to an interaction with the environment thus achieving a superior behavioral policy in complex and changing situations [10]. The policy learning scheme used to enable the machine to learn directly the mapping $\pi(s)$ between the state and the control input in the control process, thus avoiding the accurate analytical model. The method is certainly a good alternative when it comes to soft structures which have complicated deformation modes and a modelling error that cannot be avoided.

Deep reinforcement learning finds extensive application in solving continuous control problems in real-life practice, including adaptive grasping, trajectory tracking, and obstacle avoidance. As an example, Wang, et al. applied deep learning to reconstruct controls of an underwater soft manipulator by implying stable control, whereas Centurelli, et al. applied deep reinforcement learning to learn closed-loop dynamic control of a soft manipulator and reach high control accuracy without an explicit dynamic model [4, 11]. These types of methods are naturally capable of dealing with high dimensional sensory inputs and continuous motion spaces and can use engineering constraints like safety limits, power usage or stability to guide the control goal by designing rewards.

Deep reinforcement learning is sensitive to the amount of interactive data, while real robotic platforms have high trial and error costs and wear and tear, and usually require high-fidelity simulation and sim-to-real transfer; at the same time, the learned policies are mostly in black box form, and their stability and security analysis is still insufficient, making it difficult to apply them directly in high-risk scenarios such as medical care and human-computer collaboration [12]. How to improve the sample efficiency, transferability and verifiability of policy learning is an urgent problem to be solved in subsequent research. Hybrid control that combines policy model driving and physical prior is an optional solution.

3.2 Dynamic Prediction

Soft robots need to respond quickly in a constantly changing environment, i.e., real-time control. Dynamic prediction technology is a key link to achieve this goal. Dynamic prediction allows soft robots to make better decisions in advance based on predictions of the environment and their own state, effectively avoiding potential errors.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs) are common deep learning models used for dynamic prediction. They are suitable for processing time series data, can learn from historical data, and then predict future dynamic performance. During the control of soft robots, these methods predict future actions based on the current state of the robot and environmental conditions, and adjust the control strategy accordingly. Wei et al. proposed to use LSTM-based prediction models for the dynamic control of soft robots. This model can predict the robot's motion trajectory in real time, and then optimize the control input to improve the stability and accuracy of the robot in complex environments [5].

By using dynamic prediction, robots can respond in advance and optimize control strategies when faced with uncertain environmental conditions, which makes soft robots more stable and efficient in practical applications, especially under dynamic environmental conditions [8].

3.3 Deep Learning-Integrated Control Framework

By combining data-driven modeling, policy learning, and dynamic prediction, soft robots can achieve more efficient and accurate control in complex and uncertain environments. Deep neural networks are used to complete data-driven modeling, which is combined with deep reinforcement learning to achieve policy optimization. Then, the control policy is corrected in real time according to dynamic prediction, creating a complete control framework. This control framework with the help of deep learning can not only solve the challenges that soft robots cannot cope with under traditional control methods, but also significantly improve the execution efficiency and accuracy of robots in multi-tasking situations.

4. Application Examples and Future Development Directions of Soft Robots Based on Deep Learning

The deep learning is able to learn with large volumes of data and in particular with real-time observation and feedback regulation, which offers effective solutions as compared to the conventional control tasks. Real-time control and dynamic prediction is an essential bind of the soft robots to perform tasks in complex and uncertain settings with high stability, and deep learning provides novel ideas and tools to optimize these tasks. The section will cover the applications of the deep learning in the realization of the dynamic prediction and real time control of the soft robots.

4.1 Significance of Dynamic Prediction

Dynamic prediction itself involves forecasting the state of a system at a later time given information about the previous states of the system. In the case of soft robots, dynamic prediction will not only assist in enhancing the precision and effectiveness of performing their tasks, but also enable them to be proactive and control all decisions based on uncertain environmental factors. The dynamics of the soft robots are generally very nonlinear, and there is a complex interaction between their behavior and the environment, material properties, and control inputs. Deep learning models (particularly RNNs and LSTMs) can be trained to discover such complicated connections with large volumes of past data and make predictions about future actions.

The proposed prediction uncertainty estimation approach with the help of deep learning by Ding et al. is expected to enhance the capability of the robots to sustain stability and accuracy in new environments that are multimodal perception by predicting the dynamic behavior of soft robots in the new environments. With their great time series prediction performance, LSTM and RNN networks are extensively applied in predicting the dynamic behaviour of soft robots, particularly, in the real-time control practice that is capable of producing more realistic prediction outcomes in control system and optimization control schemes [8].

4.2 Challenges in Real-Time Control and Deep Learning Solutions

When doing tasks, soft robots have to work with rather irregular and dynamic environments and the need to control feedback using real-time feedback control is increasing. Conventional control schemes (including PID control and fuzzy control) do not have capability of flexibly responding and adapting to complicated and dynamic behavior of soft robots, and are hard to manage when high-dimensional inputs and nonlinear systems are considered. On the other hand, deep learning is a learning mode that is based on the automated acquisition of the relationship between the robot and its environment, which offers an innovative means of controlling in real-time.

Real-time control of soft robots is achieved with Deep neural networks in particular convolutional neural networks and deep reinforcement learning. CNNs typically solve image processing and visual perception tasks, which are capable of extracting features of images and sensor inputs and modify the behavior of the robot in real time. DRLs assist robots to enhance their control strategies and it can then carry out tasks in situations where there is uncertainty and dynamism of the environment.

Wei et al. suggested a predictive (dynamic) and real-time control model, which relies on LSTM. When the path planning and grasping part of the work are carried out with the help of the soft robot, and this part can anticipate the future situation, it is possible to enhance the efficiency of the way the task will be performed as the control input should be optimized. The deep learning model in this context would be able to provide the real-time feedback as well as the prediction and adjustment of the robot behavior, so that it may successfully accomplish the required task in complex settings and that too, with high accuracy [5].

4.3 Physics-Guided Deep Learning (PGDL)

Deep learning is useful in data-driven modeling and control, but the excessive dependence on data can lead to such issues as huge data demand and weak generalization capability. Physics-guided deep learning (PGDL) is also starting to appear, which integrates the strengths of both traditional physics models and deep learning through incorporating physical constraints into deep learning models. PGDL does have the potential to deal with the problem of overfitting that all-data-driven methods must directly deal with and enhance the accuracy of the model in practical conditions.

Beaber et al. presented a safety-based soft robots modeling and control system based on a combination of physical and deep learning, which generates better control outcomes of soft robots in terms of accuracy and ability to generalize the control process. In this way, not only the data allows the robot to learn the control strategies, but also the models of the physical robot can be used to predict its behavior and optimise the control actions depending on the prediction outcomes. This combination technique offers an alternative solution to the real-time control of soft robots operating in complicated dynamic environments [7].

4.4 Integration of Multimodal Sensors and Deep Learning

Multiple sensors (usually pressure sensors, tactile sensors, and visual sensors) are usually employed by the soft robots to sense the environment around them. Deep learning models with the help of multimodal sensor data could render useful data out of different data sources to obtain a more precise and all-encompassing environmental recognition. Multimodal sensors combined with deep learning increase the perception, as well as the precision of control of soft robots dramatically.

Thurusel and Iida have suggested a multimodal sensor fusion system which combines information measured by vision, a touch and pressure sensor, learns an expressive environmental comprehensive model through a deep learning model, and modifies the control approach depending on the multimodal data. This approach can greatly enhance the flexibility of soft robots in difficult settings particularly in high precision grasping and battery tasks [13].

5. Application Examples and Future Directions of Deep Learning in Soft Robotics

With the deeper research of soft robots by scholars, additional applications of soft robots are implemented each day, mainly in medicine, industry and even with exploration. In this regard, deep learning does not only help soft robots to operate in complex environments; it plays the role of improving precision and intelligence in robot control as well. Here, typical applications of deep learning-based soft robots will be discussed in practice, and the future of soft robots will be extrapolated.

5.1 Deep Learning in the Medical Field

The soft robots in the medical sector are flexible and adaptable and they are therefore applicable in the most delicate operation of minimally invasive surgery with the aim of minimizing the destruction of the nearby healthy tissues. Simultaneously, deep learning algorithms increase the perception of the robot and improve the precision of control, which, to a great extent, enhances the efficiency and safety of the surgery.

Wang et al. used deep learning to reconstruct the three-dimensional posture of the underwater soft robot hand, which has achieved remarkable results in underwater manipulation tasks. By using deep neural networks (DNN) to conduct sensor data analysis, the robot can be accurately positioned and then perform complex surgical tasks. The soft robot can be grasped and precisely operated by using a strategy learning method based on deep reinforcement learning (DRL), especially in the areas of patient rehabilitation training and tissue repair, customized operation strategies can be given [4].

As scholars further advance their research on deep learning technology applied to soft robots, soft robots are expected to play a more significant role in fields such as minimally invasive surgery, telemedicine, and rehabilitation aids. Robots like Octobot, which are made of soft materials and driven by fluid dynamics, can perform complex biomedical delicate tasks that require safe interaction with the environment.

5.2 Applications of Deep Learning in Industrial and Rescue Fields

The application of soft robots in industry and rescue is developing extremely rapidly. In rescue operations, their flexibility and high adaptability give them unique advantages when performing dangerous and complex tasks. During rescue work, soft robots can navigate confined spaces and perform tasks such as object handling and environmental monitoring. In industrial applications, soft robots are used in automated production lines for material handling, assembly, and inspection.

Optimizing the path planning and grasping strategy of soft robots by using deep learning can greatly improve their efficiency in performing tasks in irregular and uncertain environments.

The multimodal sensor fusion approach proposed by Thuruthal and Iida gives soft robots a more comprehensive environmental perception effect, enabling them to interact efficiently and perform tasks in complex environments. During rescue missions, these robots can obtain real-time information about the surrounding environment with the help of sensors and optimize the motion path and grasping strategy with the help of deep learning models [13].

5.3 Applications in exploration and environmental monitoring

In the field of exploration and environmental monitoring, soft robots, with their flexibility and adaptability, can easily cope with complex terrains and environments, especially extreme environments in the ocean and outer space. Soft robots can be deployed in tasks such as seabed exploration, deep-sea sampling, and outer space exploration. By using deep learning algorithms, they can perform tasks efficiently and make decisions in real time based on sensor data.

Underwater soft robots achieve three-dimensional positioning and attitude estimation with the help of deep learning, and can carry out tasks such as grasping, sampling and data collection in complex underwater environments. Deep learning provides soft robots with efficient path planning and task execution strategies, improving their adaptability to uncertain underwater environments [4]. It seems that soft robots will show more potential in marine resource exploration, ecological monitoring and space missions.

5.4 Future Development Directions

Despite significant progress in deep learning-based soft robotics, a series of challenges remain. Training deep learning models typically requires a large amount of labeled data, and in the field of soft robotics, data collection and labeling costs are high. How to cope with limited data and improve the generalization ability of models is one of the important directions for future research.

In real-world environments, soft robots require higher real-time performance and robustness. Current deep learning models perform well in experimental environments, but still face challenges in dynamic environments. The "Physically Guided Deep Learning" (PGDL) method, which integrates deep learning with physical models, may enhance model accuracy while optimizing its resilience and real-time capabilities [7].

The application of deep reinforcement learning (DRL) in the field of soft robot control will continue to expand, especially in the implementation of complex tasks and environmental adaptation. Future research can combine multimodal sensing technology, advanced control algorithms and robot cooperation strategies to further enhance the intelligence level of soft robots.

Deep learning-based soft robots have demonstrated unique advantages in multiple fields, including medicine, industry, rescue, and exploration. Through data-driven modeling, policy learning, and dynamic prediction, soft robots can perform tasks in complex and uncertain environments and optimize control strategies in real time. Although they still face some challenges, with the increasing advancements in technologies such as deep learning, sensor fusion, and physical guided deep learning (PGDL), soft robots will have broader application potential.

6. Conclusion

Deep neural networks used to model the dynamics of soft robots are known as data-driven which show a major benefit in terms of interpreting more challenging-to-model dynamics including nonlinearity and hysteresis. It may be used as a replacement to the high-fidelity numerical models, and as a base to fast prediction in real-time control. Deep reinforcement learning, in relation to policy learning, can directly learn state-control policies in case of absence of precise analytical models. Its flexibility and adaptability in tasks like flexible grasping and tracking of a path are improved over traditional control in tasks like these. Nevertheless, it also brings to light such issues as the sensitivity to the data volume and inability to transfer simulation to reality. Currently, time series models like RNNs and LSTMs are used to compute the future form and end-effector trajectory of soft robots in dynamic prediction measurements to offer new feedforward compensation and predictive control frameworks to soft robots using learning models. Nevertheless, its closed-loop stability and robustness analysis is yet to improve. Deep learning applications are largely promising to enhance the modeling accuracy, control performance, and multimodal fusion of perception capabilities in soft robots, yet they currently lack much in the data efficiency and interpretability, as well as in real-world engineering application.

The further directions of use that can be taken by future research include full integration of physical models and deep learning, the creation of hybrid control architecture that will balance between interpretability and real-time performance, investigation of such aspects as few-shot learning and safety-constrained reinforcement learning, and the reduction in the number of costs associated with data and trial-and-error. Since these issues will be resolved gradually, deep learning-based soft robot control solutions will become increasingly important in some of the most important tasks, including medical assistance, service robots, and tasks in a complex environment, and facilitated the transition of soft robots out of the laboratory and into the practical application stage.

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