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The Closed-Loop Construction of Soft Robot Perception, Decision-Making, and Control Under the Cyber-Physical Systems (CPS) Framework

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Abstract

This paper aims to explore the "Sense-Plan-Act" closed-loop construction of soft robot within the Cyber-Physical System (CPS) framework. The soft robot is deconstructed into the perception layer, decision layer, and control layer, and the organic combination of these three layers to form an effective closed-loop system is elaborated. Initially, within the perception layer, key challenges and advanced technologies for soft robot state acquisition are discussed, including the integration of multi-modal sensors and data fusion methods. Furthermore, the application of soft sensors to address the perception challenges arising from complex deformations is examined. Subsequently, within the decision layer, the architectures and algorithms for information processing, state estimation, and intelligent decision-making are analyzed, with a particular focus on leveraging artificial intelligence (AI) and machine learning (ML) technologies to extract meaningful information from noisy data and enable robust decision-making. Finally, in the control layer, the actuation system and the challenges and progress of its practical implementation will be explored. This includes adaptive control strategy and human-robot collaboration methods, which are crucial for ensuring the precise and safe operation of the soft robot in complex environments. Through the establishment of this framework, this review aims to provide comprehensive theoretical support and guidance for the research and application of soft robot within a CPS context.

Keywords

cyber-physical system (CPS), soft robot, machine learning, human-robot collaboration

1. Introduction

As an emerging technology in the robotics realm, soft robot exhibits unique advantages that traditional rigid robots struggle to match in many application scenes due to its inherent high compliance and intrinsic safety. Its biomimetic design enables it to better adapt to complex and changing environments, such as conducting minimally invasive surgery in the medical realm, exploring in unknown environments, and affording a safer contact experience in human-computer interaction, etc. [1]. Soft robots are mainly made of soft materials and are designed to develop multifunctional systems similar to natural organisms, endowing robots with strong environmental adaptability, excellent motion flexibility, and efficient and safe human-computer interaction competency [2].

This flexibility attribute enables soft robot to navigate in confined spaces and safely interact with fragile objects, thereby greatly expanding its potential application boundary [3, 4].

The nonlinear characteristics of flexible materials, drive hysteresis, and the complexity of difficult modeling make the perception, modeling, and control of soft robots exceptionally challenging. Current soft robot research often exhibits fragmented characteristics. For example, sensing, control, and actuation mechanisms tend to develop independently, lacking a unified framework to integrate these disparate technologies to achieve efficient Integrity. This lack of systematic integration limits the application of soft robots in complex tasks and uncertain environments.

To effectively address the above challenges, the concept of Cyber-Physical Systems (CPS) provides an innovative solution [5, 6]. CPS is a complex distributed system that tightly integrates computation, communication, and physical processes [7, 8]. Its core idea lies in achieving real-time interaction and intelligent decision-making between physical entities and virtual information through the "Sense-Connect-Comprehend-Control" closed-loop mechanism [9, 10]. Soft Robot is a typical CPS, and its efficient operation and intelligent development largely depend on the deep interaction and gapless integration between the information domain and the physical domain. Through the sensor, data from the physical world is acquired in real time, processed, analyzed, and decided upon in the Information Domain, and finally acted upon the physical world through the Actuator, forming a continuous feedback control circuit.

CPS enables the system to monitor physical process in real time, analyze analytical data, make Intelligent decision-making, and precisely control physical behavior by integration perception, communication, computing, and control technology. For soft robot, this means taking advantage of advanced sensing technology(such as embedded soft sensors or vision and lidar fusion perception) to grab its complex deformation state and environmental information; achieving express transfer and processing of data through cloud computing platform or edge computing; using machine learning and deep learning algorithms to conduct state estimation, behavior prediction, and decision optimization; and ultimately achieving the desired deformation and task execution by precisely controlling drivers(such as pneumatic, hydraulic, or shape memory alloy actuators).

This closed-loop perception-decision-control framework can effectively cope with the uncertainty brought by the soft robot's physical characteristics, and integrate fragmented research to achieve the boost of overall system performance.

This paper will conduct a review of the perception, decision-making, and control of soft robots from the perspectives of the CPS framework, and clarify how to build a closed loop among the three. Specifically, this paper deconstructs soft robots into a perception layer(state acquisition), a decision-making layer(information processing), and a control layer(command execution), and is focused on elaborating how the three work together to form an adaptive, high robustness closed-loop system.

2. Core Technology

2.1 CPS Framework's Perception Tier: State Acquisition and Information Fusion

2.1.1 The Sensing Layer's CPS Role

Under the CPS framework, the sensing layer connects the physical world with the information world.Its core task is to reliably and precisely acquire the soft robot's physical state(e.g., shape, curvature, force) and environmental information. These raw data serve as the foundation for the decision-making layer to perform intelligent judgment and planning [11].

2.1.2 Flexibility Sensing Technology (The Physical Basis)

Flexibility sensing technology is the physical basis for realizing soft robot perception. Common flexibility sensors include: resistive sensors that sense force or deformation by measuring changes in resistance caused by material deformation. For example, conductive hydrogel sensors have been used to measure the bending angle and motion control of soft robots [12]. There are also capacitive sensors that sense changes in capacitance caused by deformation, which are often used for haptic and pressure sensing. In addition, there are fiber optics sensors, which measure strain, temperature and other arguments by using the change of light transmission attributes in the fiber optics, and have the advantage of anti-electromagnetic interference. Finally, there are liquid metal sensors, which use the resistance change caused by the deformation of liquid metal in the flexible substrate to achieve high-sensitivity deformation perception.

To overcome the limitations of single sensor, Ma et al. proposed a multi-sensor fusion method, which improves the state estimation's robustness and accuracy by combining data from multiple sensors (such as a resistive flexibility sensor) [13].

2.1.3 Information Processing and Fusion (Information Domain Core)

Raw Sensor data is often characterized by nonlinearity, multi-modality, and high noise, making it difficult to use directly for decision-making. Therefore, information processing and fusion are key to improving the quality of perception and are a core component of the perception layer of CPS. In recent years, machine learning and deep learning methods have demonstrated powerful competency in processing such data. For example, by taking advantage of neural network models to learn complex deformation patterns of soft robots from sensor data, accurate state estimation and three-dimensional shape reconstruction can be achieved [13]. In the realm of haptic recognition, deep learning models are capable of processing the massive amounts of data generated by haptic sensor arrays to recognize contact forces, texture, and even object shapes [14].

Also, in terms of data fusion algorithms, deep learning models can develop advanced algorithms, such as gradient descent policies, to fuse measurements from different sensors (such as proprioceptive sensors) to determine the bending angle of soft robots and overcome the matchmaking between sensors and robot size [13]. In addition, deep learning models can also take advantage of 3D digital video cameras to acquire depth images, processing them through convolutional neural network (CNN) models to estimate the deformation state of soft materials, thereby providing guidance for robots to perceive the external environment and conduct collaborative actions [15].

2.2 The Decision-making Tier of the CPS Framework: Intelligence Planning and Model Building

2.2.1 The Decision-making Layer's CPS Role

The decision-making layer is one of the most important parts of the Information domain, and its task is to generate valid control policies or motion planning in uncertain environments, based on the information provided by the perception layer and predefined task goals. This includes the prediction of future states, the optimization of current behaviors, and the handling of contingencies [16].

2.2.2 Model-driven Decisions

Traditional soft robot decision-making methods typically rely on precise physical models, such as the Cosserat rod model, to describe the continuum deformation of the robot. However, due to the nonlinearity, high compliance, and infinite-dimensional degrees of freedom of soft material, establishing accurate and computation-efficient analytical models is extremely challenging. This limits the applicability of model-driven control methods when dealing with complex tasks and unmodeled dynamics [17].

2.2.3 Data-driven Decisions

To overcome the model uncertainty problem, data-driven methods, especially reinforcement learning(RL), have become powerful tools for addressing the decision-making challenges of soft robots. RL autonomously learns the optimal control strategy through trial and error interaction with the environment, without the need for precise physical models. There are many applications of RL in the realm of soft robots. For example, RL algorithms can learn how to remedy attributes drift in soft robots caused by material aging or environmental changes, achieving adaptive control [17]. In addition, RL can plan complex motion trajectories for soft robots to complete quests such as scrape, actions, etc., without explicit mathematical models.

For example, deep reinforcement learning has been used to optimize actuator network security strategy in industrial control systems [18]. In the backdrop of Industry 4.0 and smart manufacturing, digital twins technology based on deep reinforcement learning can also be used for manufacturing process tuning, optimizing production quality and efficiency through learning and inferencing [19].

2.2.4 Digital Twin

Digital Twin (DT) technology plays an increasingly important role in the decision-making tier under the CPS framework. It achieves real-time mapping of physical entities by creating virtual models of soft robots in the information spatial realm [20]. This virtual model can be used for emulation and prediction, to facilitate decision-making and tuning, and for human-computer collaboration. For example, high-fidelity emulation of soft robot behaviors can be conducted without affecting physical entities, and their responses under different operating conditions can be predicted; Digital Twins can also be combined with machine learning model to test and optimize control policies in a virtual environment, and then deploy the optimized policies to physical robots [21].

For example, Digital Twins can be used to monitor and optimize clarification steps in biopharmaceutical continuous production processes [20].

In addition, digital twins can also enable human-robot collaboration, for example, in the manufacturing process by transferring human poses from a human digital twin to a collaborative robot digital twin to achieve teleoperation for imitation learning [22].

2.3 The Control Layer of CPS Framework: Instruction Issuance and Closed-loop Implementation

2.3.1 The Control Layer's CPS Role

The control layer is a critical component for achieving deep fusion of the info space and the physical process, and its core functionality is to transform the abstract directives generated by the decision-making layer into specific physical driving signals, thereby changing the physical state of the soft robot. This layer is responsible for ensuring that decision-making can accurately and promptly act on the physical system [11].

2.3.2 Actuation Technology (Physical Domain Foundation)

There are various actuation technologies for soft robots, which are the basis for realizing robot motion and function. Common actuation methods include pneumatic actuation—using changes in air pressure to drive the deformation of soft structures, which has the advantages of fast response and large force. There are also shape memory alloys (SMAs) that generate reversible deformation by heating to cause a material phase transition, which are suitable for scenarios requiring compact actuation [23]. In addition, tendon actuation is also one of the very classic actuation methods. It generates bending or contraction by pulling tendons (cables) integrated into the soft structure, similar to the movement of biological muscles. For example, rope-driven soft machines face state estimation challenges due to their complex deformations.

2.3.3 Closed-loop Control

Closed-loop control is the key to the efficient operation of soft robot CPS. It delivers the feedback information of the perception tier to the decision-making tier in real time, and the decision-making tier adjusts the policy and issues new control directives accordingly, so as to realize the adaptive and anti-interference competency of the system [24]. It includes three parts. The first is the feedback mechanism. The perception tier (such as flexibility sensor or vision system) continuously monitors the presence status of the soft robot and the environmental information. These real-time data are transferred to the decision-making tier.

The second is decision-making tweak. The decision-making tier take advantage of these feedback information, combined with the current task targeting and Learned control policy, to conduct remediation or tuning of the directives in the next control cycle. For example, recursion neural networks (RNN) can be used to construct adaptive mock-ups to realize closed-loop control of continuum robots. Finally, it is command execution, the new control commands are transformed into physical actions through driving technologies (such as pneumatic gates, motors, etc.) and act on the soft robot, forming a complete “Sense-Plan-Act” closed-loop [24].

2.3.4 Instance Application

Nicola et al. proposed a data-driven method to estimate material deformation in images. By acquiring depth images with an RGB-D camera installed on the robot end cap actuator, and taking advantage of a pre-trained DenseNet-121 convolutional neural network, the amount of material deformation relative to a preset state is estimated. This method solves the problem that it is difficult to accurately perceive the material deformation state through traditional force sensor during the human-robot collaborative handling of soft materials, and achieves a deformation perception method without relying on human skeleton tracing, and enhances the robustness of the system.

Güler et al. proposed a real-time taxonomy supervision learn method for subtask based on artificial neural network. By collecting sensor data such as robot end cap velocity, interaction force, and human power, accurate recognition of three types of subtasks, namely free, bootstrap, and contact, is achieved, and the damping and fractional order argument of the admittance director are adaptive adjusted accordingly. This method solves the problem that in rigid environment contact human-robot collaboration tasks, the pinning argument director is difficult to balance the transparency of the bootstrap stage and the stability of the contact stage, and constructs a adaptive admittance control schema based on learn-based subtask recognition, which significantly reduces the human burden and improves the dynamic performance and stability of the system in collaborative drilling and other tasks [25].

3. Problems and Challenges

Although the CPS framework brings great potential to soft robots, it still faces many system-level challenges.

First, there are time delays in data transfer, processing, and execution in the sense-plan-act loop. This latency may affect the stability and live response of the system, especially in high-speed or high-precision tasks. Ensuring real-time performance is an important problem in robot control system. Second, complex AI algorithms require significant computation resource and energy. Deploying these algorithms on resource-constrained embed soft robot platform or mobile device faces severe challenges in power consumption and computation efficiency. In addition, soft robot systems typically containment multiple heterogeneous sensor, actuator, and computation apartment.

The lack of modular, standardized interfaces and communications protocol leads to a complex and time-consuming system integration process. This limits the interoperability between different components and the extensibility of the system. Finally, as AI plays an increasingly important role in CPS, how to warrant the cybersecurity, explainability, and overall robustness of AI decision-making becomes a critical Problem. In addition, cybersecurity holes may also lead to impaired system features or sensitive data leak.

4. Future Perspectives

4.1 Edge-Edge-Cloud Collaborative Computation

To address Computation challenges and power consumption issues, future soft CPS robots will increasingly adopt an edge-edge-cloud collaborative computation architecture. This will enable computation tasks to be rationally distributed among terminal appliances (edge), local servers (edge), and remote data factories (cloud) based on real-time performance, privacy, and Resources availability, thereby improving system efficiency and response velocity.

4.2 Design Automation for Driving

Currently, the physical structure design and control system development of soft robots are usually conducted independently. The future trends is to take advantage of AI to automate design, and simultaneously design the physical structure of the robot and the matchmaking control system through generative AI and tuning algorithm. This will accelerate the research and development cycle of soft robots and spawn more optimized performance.

4.3 More Advanced Embodied Intelligence

Soft robots, with their unique compliance and ability to physically interact with the environment, are considered an ideal carrier for realizing "embodied intelligence." Future research will explore how to enable soft robots to better understand the environment, learn quests, and exhibit higher levels of autonomy and intelligent behavior through deeper physical interaction.

4.4 Canonicalization and Open Source Framework

To address integration challenges and promote the development of the soft robot realm, it is crucial to establish unified development specifications and open source frameworks. This will include specifications for soft robot modeling, emulation, perception data processing, control interfaces, etc., thereby reducing development barriers and promoting collaboration and innovation between academia and industrial sectors.

5. Conclusion

Soft robots, due to their high compliance and inherent network security, exhibit unique advantages in realms such as medical, explore, and Human-computer interaction, but their non-linearity, drive hysteresis, and difficulty in precise modeling bring about the challenge of "physical world uncertainty." To address this challenge, this paper proposes placing soft robots within the Cyber-Physical Systems (CPS) framework, and achieving a deep integration of physical entity and the phantom information world through the "Sense-Connect-Comprehend-Control" closed-loop mechanism.

This paper deconstructs soft robots into a sensing layer, a decision-making layer, and a control layer. The sensing layer utilizes flexibility sensing technology such as resistance, capacitance, fiber optics, and liquid metal, combined with multi-sensor fusion to improve the accuracy of state estimation.

The decision-making layer adopts data-driven methods, especially reinforcement learning, to overcome the limitations of traditional physical models in processing the complex attributes of soft robots, achieving adaptive control and motion planning. The control layer is then implemented through directive issuance and closed-loop.

Despite the great potential of the CPS framework, its application in soft robots still faces challenges such as time defer, computation energy consumption, system integration, and the security and explainability of AI decision-making. The significance of this research lies in providing a unified theoretical framework that effectively enhances the adaptive and intelligence level of soft robots in uncertain environments by integrating perception, decision-making, and control.

The deep fusion of soft robots and CPS will promote their application in realms such as medical and industrial, especially in scenes requiring high security and precise actions. The industry will spotlight on addressing challenges such as real-time performance, computation efficiency, and system canonicalization to build more intelligence, robust soft robot systems and accelerate their business process.

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