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Development of Artificial Muscle Control Algorithm for Pneumatic Soft Robot

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Abstract

Pneumatic artificial muscle (PAM), as a key driving component of soft robot, faces the difficulty of high precision control because of its strong nonlinear and hysteresis characteristics. This paper systematically reviews the evolution of PAM modeling and control strategies, from physical mechanism modeling to data-driven methods, from classical control to intelligent algorithms, and discusses the cutting-edge progress of multimodal perception and human-machine collaboration. On this basis, an integrated research framework of "multi-physical field modeling-reinforcement learning optimization-digital twin verification-myoelectric feature fusion" is proposed, focusing on dynamic modeling of filament winding angle, LSTM hysteresis compensation, DDPG adaptive control, etc. The core content is launched, and the system performance is verified through rehabilitation and space scenarios, aiming to provide systematic solutions and implementation paths for PAM intelligent control.

Subject Areas

Robotics

Keywords

Pneumatic Artificial Muscle, Nonlinear Control, Hysteresis Compensation, Deep Reinforcement Learning, Digital Twins, EMG Signal, Soft Robot

1. Research Background

Soft robot technology is a frontier branch of robotics, which is inspired by the excellent movement and adaptability of octopus, elephant trunk, worm and other creatures in nature. By using flexible materials and continuum structures, soft robots break through the limitations of traditional rigid robots in terms of degree of freedom, environmental adaptability, and human-computer interaction safety, and provide services for operations in unstructured, dynamically complex, and human-computer integration scenarios. A new solution is provided [1]. Among the many soft drives, the pneumatic artificial muscle represented by the McKibben type has become one of the most concerned and widely used drives because of its simple structure, high work-to-weight ratio, and safe and easy access to the driving medium (air) [2]. As shown in **Figure 1**, a typical McKibben-type PAM consists of an inner elastic bladder, a braided mesh shell, and two end fittings; when pressurized, the radial expansion of the bladder is constrained by the mesh, resulting in axial contraction and a tensile force. This structure enables efficient actuation with a high force-to-weight ratio, making it ideal for various soft robotic applications.

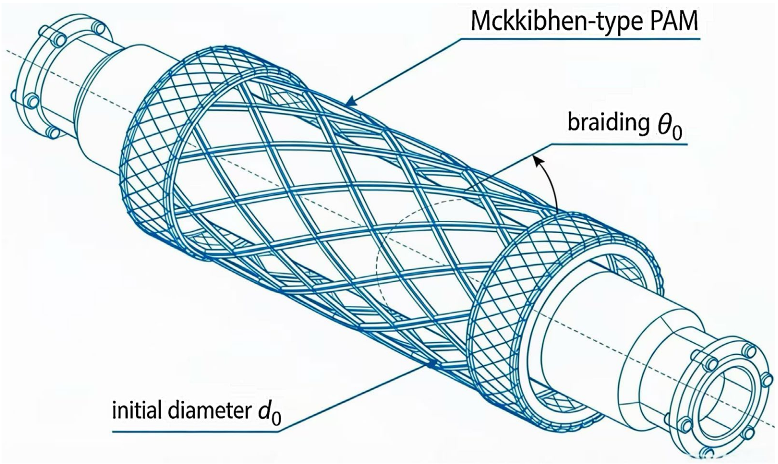

Figure 1. McKibben-type PAM structural diagram.

However, the wide application of PAM is always restricted by its complex dynamic characteristics. Its working principle determines that its behavior is the result of the coupling of thermodynamics, structural mechanics and materials science: the compressibility of gas brings dynamic nonlinearity, the hyperelasticity and viscoelasticity of rubber materials lead to complex hysteresis and creep of the force-displacement relationship, and the geometric constraints of the external fiber braided sleeve introduce strong structural nonlinearity [3]. These characteristics are intertwined, making PAM a complex system with strong nonlinear, time-varying and difficult to accurately model. Traditional control methods based on linearization assumption (such as PID) can still maintain basic functions under simple working conditions, but in the face of dynamic load changes, long-term operation or unknown disturbances, the control performance drops sharply, and the accuracy and stability cannot be guaranteed.

In recent years, emerging technologies represented by artificial intelligence, high-performance computing and advanced sensing have brought new opportunities to solve PAM control problems. Data-driven methods provide new tools for complex nonlinear modeling [4], deep reinforcement learning opens up a new path for finding optimal control strategies under unknown models [5], and digital twin technology builds a new platform for efficient training and security verification of algorithms. A new platform for virtual-real fusion. At the same time, the introduction of biological information such as myoelectric signals (sEMG) and even muscle fatigue states that reflect human motion intentions into the control closed loop is promoting the evolution of human-machine collaboration in a more natural and intelligent direction [5]. In this context, it is of vital significance to systematically sort out the development status of PAM control technology, clarify key challenges, and plan a breakthrough path integrating multidisciplinary cutting-edge technologies to promote the practicality and intelligence of soft robot technology.

2. Research Significance

2.1. Theoretical Significance

Deepen the control theory of nonlinear systems: PAM is a typical strong nonlinear and hysteresis system. In-depth research on its control algorithm will enrich and develop the theoretical system of nonlinear control, adaptive control and intelligent control, and provide theoretical reference for solving a class of engineering control problems with similar characteristics [6].

Promoting the integration of "physical model-data-driven" model building: exploring a hybrid modeling method that deeply integrates first principles and machine learning will help establish a more accurate and efficient software driver model and provide complex system modeling methodological innovation.

Expanding the perception-control framework of human-machine collaboration: studying the deep fusion mechanism of EMG signals and fatigue characteristics and machine control will lay the foundation for the establishment of a new generation of intelligent human-computer interaction theory based on biofeedback.

2.2. Technical Implications

Overcome the core technology of PAM high-precision control: Through the development of new intelligent control algorithms and compensation strategies, break through the performance bottleneck of PAM under time delay, creep and disturbance, and achieve sub-millimeter positioning accuracy and millisecond dynamic response, reaching the international advanced level [6].

Build a research paradigm for digital twin empowerment: establish a set of "modeling-simulation-control-optimization" full-chain technical process based on digital twins, significantly improve the development efficiency and system reliability of control algorithms, and provide an efficient tool chain for the research and development of soft robots.

Realize low-cost, high-performance localized solutions: the research results are expected to replace expensive imported precision pneumatic actuators, greatly reduce the cost of rehabilitation exoskeletons, flexible production lines and other equipment, and promote the upgrading of related industries.

2.3. Application and Social Significance

Serving people's livelihood and health and national strategic needs: develop low-cost, high-performance rehabilitation assistive equipment, which can benefit tens of millions of patients with physical disabilities in my country; The space flexible operation technology developed can provide technical support for major national projects such as deep space exploration and on-orbit services.

Promote interdisciplinary and talent training: This research involves robotics, control theory, artificial intelligence, biomedical engineering and other disciplines. The implementation of the project will cultivate compound talents with interdisciplinary vision and innovative ability.

3. Research Status at Home and Abroad

3.1. Research Status of Modeling Methods

International research has developed from simple geometrical static models to dynamic high-fidelity models with coupling of multiple physical fields (**Figure 2** Development History of System Modeling Methods). The Massachusetts Institute of Technology (MIT) team proposed a multi-scale modeling framework for fiber-reinforced composite soft actuators in Science Robotics, which significantly improved the prediction accuracy of the model [7]. In terms of hysteresis modeling, parameterized models based on operators such as Prandtl-Ishlinskii and Bouc-Wen and data-driven models based on long-term and short-term memory networks (LSTM) have become mainstream [8]. Domestic modeling research has made rapid progress in recent years, but in terms of refinement, especially in the model considering the dynamic effect of filament winding and thermal-mechanical coupling, it still relies on empirical formulas, which is far behind the top level abroad. The development trend is the deep mixing of mechanism models and data-driven models [9], and the use of digital twins to realize online calibration and update of model parameters.

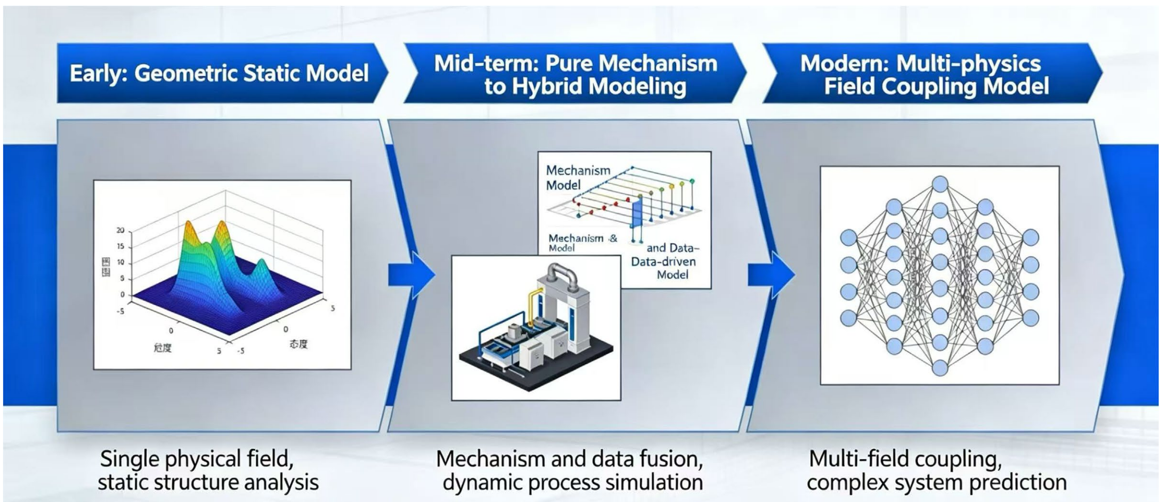

Figure 2. Development history of system modeling methods.

3.2. Research Status of Control Strategy

The control method has undergone the evolution from PID to modern robust/adaptive control, and then to intelligent control. The University of Tokyo in Japan took the lead in applying reinforcement learning to PAM control, realizing adaptive force control under unknown disturbances [10]. Fuzzy logic, neural networks (especially recurrent neural networks) are widely used for hysteresis feedforward compensation and direct inverse control. Domestic research is relatively mature in the improvement of traditional PID and the application of fuzzy control, but relatively weak in the original research and system integration of autonomous intelligent algorithms (such as deep reinforcement learning). The current frontiers focus on the combination of deep reinforcement learning and model predictive control, and the use of digital twins as "training grounds" to safely and efficiently optimize control strategies.

3.3. Research Status of Perception and Human-Computer Interaction

International research attaches great importance to multimodal perception and biological signal fusion. The development of flexible electronics has made distributed proprioception possible [11]. In terms of biological signal interaction, sEMG-based motion intention recognition is relatively mature, but how to process the impact of muscle fatigue on signals in real time is the key to improving the practicability of the system. The research of Yan Shijia *et al.* (2024) shows that the fusion of real-time muscle fatigue features can significantly improve the robustness of gesture recognition, which provides important enlightenment for the adaptive control of PAM rehabilitation system. China keeps up with the international pace in the application of flexible sensing and sEMG, but the systematic work in the deep fusion of multi-modal information and closed-loop control still needs to be strengthened. The future direction is to develop "smart materials" that integrate driving, sensing, and computing, and build a context-aware collaborative control system that can understand the user's physiological state (such as fatigue).

4. Project Research Content

This project aims to build a full-chain research system covering "theoretical modeling - algorithm development - system implementation - application verification". The following is a detailed research content plan.

4.1. Overall Technical Framework and Data

To ensure the reproducibility of the proposed framework integrating "multiphysics modeling, reinforcement learning optimization, digital twin verification, and sEMG feature fusion," this paper designs the following data and control flow:

Input Layer:

- Raw surface electromyography (sEMG) signals

- Desired displacement/force commands
- Pressure sensor feedback values

Processing Layer:

1) Multiphysics Modeling Module → Reinforcement Learning Module: Outputs the nonlinear dynamics model of the PAM (including Bouc-Wen hysteresis parameters and the dynamic equation of braid angle variation), which serves as the simulation environment for the DDPG agent.

2) Reinforcement Learning Module → Digital Twin Module: Outputs the trained control policy network (in.pt or.onnx format) along with hyperparameter configurations, which are imported into the digital twin platform (e.g., Simulink + Unity) for virtual validation.

3) Digital Twin Module → sEMG Fusion Module: Outputs the validated control parameters (e.g., assistive force ratio, impedance coefficients) and receives fatigue features (median frequency slope, root mean square value) as online adjustment signals.

Output Layer:

- Compensated desired pressure value → proportional valve drive voltage
- Closed-loop feedback of actual displacement/force
- Human-robot collaborative adaptive strategy (fatigue → decrease assistive force/increase impedance)

4.2. Multi-Physical Field Coupling Fine Modeling and Parameter Identification

Objective: To establish a high-fidelity dynamic model of PAM which can accurately reflect filament winding effect thermodynamic process and material nonlinearity.

Research Content:

1) Establishing the governing equations of integrated thermodynamics-mechanics:

Thermodynamic model: The PAM chamber is regarded as a variable capacitance adiabatic system, and the mass flow and energy exchange in and out of the gas are considered.

$$\frac{\mathrm{d}P}{\mathrm{d}t}=\frac{\gamma R}{V(L)}\left(\dot{m}_{in}T_{in}-\dot{m}_{out}T\right)-\frac{\gamma P}{V(L)}\frac{\mathrm{d}V}{\mathrm{d}L}\frac{\mathrm{d}L}{\mathrm{d}t}$$

Where P is the intracavity pressure, T is the temperature, $V(L)$ is the volume geometric function related to the muscle length L, γ is the specific heat capacity ratio of the gas, R is the gas constant, and $m_{in/out}$ is the inlet and outlet mass flow rate.

Structural Mechanics Models: Fusion of Hyperelastic Constitutive and Fiber Constraints.

$$F=P\frac{\mathrm{d}V}{\mathrm{d}L}-\frac{\pi d_0^2 P}{4\tan^2\theta_0}\left(3\cos^2\theta_0-1\right)+F_{elastic}\left(L,\dot{L}\right)$$

where d_0 、 θ_0 is the initial diameter and braiding angle, and $F_{elastic}$ is the elastic force term of the rubber liner described based on the Mooney-Rivlin model:

$$F_{elastic} = \pi r_0^2 \cdot 4\left(C_{10} + C_{01}\right)\left(\lambda - \frac{1}{\lambda^5}\right)$$

2) Modeling the dynamic effect of filament winding angle: study the dynamic change (unconstant) of braiding angle θ in actual deformation, establish the relationship model between θ and axial strain ϵ, and substitute it into the above mechanical model to more accurately predict the stiffness and output of different deformation stages [12].

3) Global identification of parameters based on Bayesian optimization: Quasi-static and dynamic tensile tests at different strain rates (10%, 20%, 30%) are carried out on Instron material testing machine to obtain force-displacement data. Construct an optimization problem including model parameters, Bouc-Wen parameters, take experimental data as observations, use Markov chain Monte Carlo method for Bayesian inference, obtain a posterior probability distribution of parameters, and give 95% confidence interval, quantify model uncertainty [13].

4.3. Intelligent Control Algorithm Design and Deep Optimization

Objective: To develop an intelligent control algorithm that can effectively compensate for nonlinearity and hysteresis, and can adapt to environmental changes online.

Research Content:

1) Double Closed-Loop Controller Architecture Design

Inner ring (pressure fast tracking ring): A high-order sliding mode observer is used to design the pressure controller [14].

$$s_1 = P_{des} - P$$
$$\dot{\hat{P}} = v_1 + \alpha_1 \left|s_1\right|^{1/2} \operatorname{sign}\left(s_1\right)$$
$$v_1 = \beta_1 \operatorname{sign}\left(s_1\right)$$

where P_{des} is the expected pressure, the observer can converge in a finite time and estimate the disturbance, and the controller is designed based on the output of the observer to achieve a chattering suppression rate of >90%.

Outer loop (displacement/force control loop): A controller based on adaptive neuro-fuzzy inference system (ANFIS) is designed. The ANFIS structure combines the interpretability of fuzzy logic and the learning ability of neural networks, and its rule 1 output is:

$$R^l : \text{IF } x_1 \text{ is } A_1^l \text{ AND } x_2 \text{ is } A_2^l, \text{THEN } y^l = p_0^l + p_1^l x_1 + p_2^l x_2$$

2) LSTM-Based Hysteresis Feedforward Compensator

Construct an LSTM network whose inputs are the barometric pressure sequence $\left\{P_{t-N}, \cdots, P_{t-1}\right\}$ and the current expected displacement $d_{des}(t)$ at the last N moments, and whose outputs are the hysteresis compensated displacement

$$\begin{cases} \boldsymbol{h}_t, \boldsymbol{c}_t = \mathrm{LSTM}\left(\left[P_{t-1}, d_{des}(t)\right], \boldsymbol{h}_{t-1}, \boldsymbol{c}_{t-1}; W\right) \\ \Delta d_{comp}(t) = \boldsymbol{W}_o \boldsymbol{h}_t + b_o \end{cases}$$

4.4. X Training and Generalization Specifications for the LSTM Hysteresis Compensator

To ensure the reproducibility and robustness of the proposed LSTM compensator, the minimum training specifications are supplemented as follows:

1) Training Data Acquisition Protocol

Excitation Signals: A composite sinusoidal sweep signal (0.5 - 5 Hz) and a multi-amplitude pseudo-random binary sequence (PRBS) are adopted as the desired displacement inputs to sufficiently excite the nonlinearity and hysteresis characteristics of the PAM. Each signal lasts for 60 seconds with a sampling frequency of 1 kHz.

Loading Conditions: Data are collected under three static loading conditions: no load (0 N), low load (20 N), and high load (50 N). Additionally, dynamic transition data are collected during sudden load changes (20 N ↔ 50 N step).

Data Partitioning: 70% of the data is used for training, 15% for validation, and 15% for testing.

2) Cross-Condition Generalization Capability Validation

Three methods are used to check generalization capability:

Load Generalization: Tests are performed under intermediate loads not seen during training (10 N, 35 N). The relative increase in the root mean square error (RMSE) of displacement tracking is calculated, and the increase is required to be ≤20%.

Frequency Generalization: Sinusoidal tracking at constant frequencies outside the training range (0.2 Hz, 6 Hz) is performed to evaluate phase lag and amplitude attenuation.

Long-Term Drift Test: A continuous 10-minute run (3000 control cycles) is conducted. The mean and standard deviation of the post-compensation displacement error are monitored for any monotonic increasing trend (linear fit slope < 0.01 mm/s).

4.5. Hardware System Integration and Multi-Scenario Verification

Objective: Build a high-performance real-time control experimental platform, and verify the effectiveness of the algorithm in typical application scenarios.

Research Content:

1) Hardware Platform Development

Drive and sensing: The drive unit is built with Festo MPVE proportional valve and custom silicone muscle. Integrated laser displacement sensor and micro pressure sensor, and through the NI cRIO-9068 real-time controller to synchronously collect all sensor data and execute control algorithms in a 1 ms cycle.

Real-time software architecture: Implement deterministic real-time loops in

LabVIEW RT. The TensorRT-accelerated LSTM and DDPG policy network inference engine is integrated internally to ensure that the forward propagation time of the neural network is less than 0.5 ms.

2) Adaptive Human-Machine Interface Fusing Myoelectric Fatigue Features (Innovative Application Verification) [15]

sEMG signal processing and fatigue feature extraction: Referring to the method of Yan Shijia *et al.* (2024), the median frequency (MDF) slope and root mean square (RMS) value are extracted in real time from the collected forearm sEMG signal as the estimation of muscle fatigue F_{level}.

$$F_{level}(t) = \alpha \cdot \left(-\frac{\mathrm{dMDF}(t)}{\mathrm{d}t}\right) + \beta \cdot \mathrm{RMS}(t)$$

Adaptive adjustment of the control law: the F_{level} as an additional state input to the DRL agent or a direct design of the fuzzy regulator. When the user's fatigue degree is detected to increase, the system automatically adjusts the auxiliary force ratio of the exoskeleton or the impedance parameter of the controller to provide more supportive assistance and realize the "people-oriented" adaptive collaborative control.

3) Systematic Performance Verification Experiment

Benchmark performance test: Step response, sinusoidal tracking (1 - 5 Hz), load mutation (0 - 50N) experiments, quantization positioning accuracy (target ± 0. 8 mm), response time (target ≤ 0. 3 s) and force control error (target < 2%).

Application scenario validation:

Rehabilitation glove scenario: Subjects wear soft gloves with integrated PAM drivers and perform grip-release tasks. Before and after the introduction of EMG fatigue feature adaptive adjustment, the changes of muscle activation degree and subjective fatigue feeling of users during long-term training were compared.

Microgravity simulation scene: Cooperate with the Space Environment Simulation Center of the Chinese Academy of Sciences to test the ability of the PAM manipulator to grasp and control floating targets under the microgravity conditions of hanging wire counterweight or parabolic flight simulation, and verify its robustness in extreme environments sex.

5. Summary

This paper comprehensively reviews the development process of pneumatic artificial muscle control technology. From the early control based on simplified physical models to the intelligent control integrating data-driven, artificial intelligence and advanced perception, this field is undergoing profound paradigm changes. Studies have shown that it is difficult for a single technology path to overcome the complex and non-linear challenges inherent in PAM, and future breakthroughs will inevitably rely on the deep integration of multidisciplinary methods and technologies.

The research scheme proposed in this paper is a positive response to this trend.

The solution takes "multi-physical field coupling refined modeling" as the cornerstone, "deep reinforcement learning and digital twin collaborative optimization" as the core engine, and "multi-modal perception (especially myoelectric fatigue) Features fusion" as a characteristic extension, and built a research system with clear levels, complete content, innovation and feasibility. This scheme not only plans the detailed technical route from theoretical formula derivation to specific algorithm implementation (such as LSTM compensator, DDPG optimizer), but also clarifies the system integration based on high-performance hardware and the two frontier areas of rehabilitation and space. Verification goals.

Through the implementation of this project, it is expected that substantial progress will be made in the three aspects of high-fidelity modeling of PAM, intelligent adaptive control and natural-machine coordination, and the core technology with independent intellectual property rights will be formed, which will provide key support for the development of high-performance and low-cost domestically produced soft robot drive systems, and ultimately promote it to play an important role in improving people's lives and health and serving the country's major strategic needs.

Conflicts of Interest

The authors declare no conflicts of interest.

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