Dynamic Gait Adaptive Control Strategy for Modular Exoskeletons Based on Human-Cooperative Reinforcement Learning

Dexi Meng
Shandong Experimental High School, Jinan, Shandong, China

Abstract: Exoskeleton technology demonstrates significant potential in medical rehabilitation, military enhancement, and industrial assistance by augmenting human mobility. However, adaptive control of dynamic gait remains a core challenge. This paper systematically reviews modular exoskeleton control strategies based on Human-Cooperative Reinforcement Learning (HCRL), integrating biomechanical modeling, reinforcement learning algorithms, and modular design methodologies. Research demonstrates that HCRL optimizes human-machine synergy efficiency through real-time interaction, significantly improving gait adaptability (with energy consumption reduced by 15%–20%). The modular architecture enables rapid adaptation to diverse user needs (configuration time shortened by 50%). Future studies must address real-time constraints, multi-objective optimization conflicts, and robustness in user intent recognition to advance exoskeleton technology toward intelligent and personalized development.

Keywords: Human-Cooperative Reinforcement Learning (HCRL); Modular Exoskeletons; Dynamic Gait; Adaptive Control; Biomechanics

1. Introduction

Exoskeleton technology is a revolutionary innovation that cleverly combines mechanical structures with human movement, providing powerful support for patients with motor dysfunction and workers in need of enhanced physical strength. This technology simulates natural human movement, helping patients regain walking ability and reducing the physical burden on workers, significantly improving their lives and work efficiency. However, traditional control strategies, such as pre-programmed gaits, fall short when faced with complex and ever-changing environments and individual differences. These strategies often fail to adjust according to users' real-time needs and physical conditions, resulting in excessive energy consumption and poor user experience (Herr, 2009) [1]. This not only limits the widespread application of exoskeleton technology but also hinders its in-depth development in medical and industrial fields. To overcome this bottleneck, Human-Computer Collaborative Reinforcement Learning (HCRL) has emerged. HCRL continuously optimizes control strategies through real-time interaction, making them more aligned with users' actual needs. At the same time, combined with modular design, HCRL achieves flexible hardware configuration, providing possibilities for personalized customization of exoskeleton technology. This innovation not only improves the adaptability and flexibility of exoskeleton technology but also lays a solid foundation for its application in a wider range of fields (Tucker et al., 2015) [15]. This research has far-reaching theoretical and practical value. At the theoretical level, we have constructed a "biomechanics-reinforcement learning-modular design" trinity control framework, providing new ideas for the intelligent development of exoskeleton technology [3]. At the application level, this technology provides adaptive and high-efficiency solutions for gait reconstruction in the field of rehabilitation medicine and logistics handling assistance with industrial exoskeletons, which is expected to drive the intelligent transformation of healthcare and industry in the future. In summary, the integration of Human-Computer Collaborative Reinforcement Learning and modular design has not only promoted the innovation and development of exoskeleton technology but also injected new vitality into the intelligent transformation of rehabilitation medicine and industry. In the future, as the technology continues to mature and application scenarios continue to expand, exoskeleton technology is expected to play an important role in more fields, contributing more to the development of human society.

2. Theoretical Basis

2.1 Human-Computer Collaborative Reinforcement Learning (HCRL)

Human-Computer Collaborative Reinforcement Learning (HCRL) is a cutting-edge method for optimizing control strategies, particularly suitable for complex human-machine interaction systems such as exoskeleton technology. The core of HCRL lies in quantifying the effectiveness of human-machine collaboration through carefully designed reward functions, which may include multiple dimensions such as gait stability, energy efficiency, and user comfort. In practical applications, HCRL utilizes deep reinforcement learning algorithms, such as Deep Deterministic Policy Gradient (DDPG) or Proximal Policy Optimization (PPO), to dynamically adjust control strategies based on these reward signals, thereby achieving optimal human-machine collaboration. Chen et al. (2020) proposed a bidirectional reward mechanism based on muscle synergy signals in their research [4]. This mechanism, by capturing and analyzing users' muscle activity patterns, can more accurately identify users' intentions and adjust the control strategy of the exoskeleton accordingly. Experimental results show that this bidirectional reward mechanism effectively reduces user intention recognition errors by 30%, significantly improving the efficiency of human-machine collaboration and user experience.

2.2 Principles of Modular Exoskeleton Design

Modular exoskeleton design is an innovative design concept that emphasizes the rapid combination and flexible configuration of components such as joints, sensors, and actuators through standardized interfaces. This design not only improves the adaptability and scalability of exoskeletons but also greatly reduces production and maintenance costs. The core advantages of modular design are mainly reflected in two aspects: flexibility and maintainability. In terms of flexibility, the modular architecture allows for personalized customization according to different users' body characteristics, movement needs, and application scenarios. For example, the hip joint module can be independently adjusted to adapt to different users' gait characteristics. This flexibility enables exoskeletons to be more widely used in different populations and scenarios (Vallery et al., 2013) [5]. In terms of maintainability, modular design ensures that local failures do not have a severe impact on the entire system. When a module fails, it only needs to be replaced or repaired, without the need to dismantle and rebuild the entire system. This not only improves the reliability and stability of the system but also reduces maintenance costs and downtime. Furthermore, modular design facilitates system upgrades and expansions, reserving space for future technological innovations (Ronsse et al., 2011) [6].

3.Dynamic Gait Generation and Adaptive Control Methods

3.1 Gait Optimization Based on Reinforcement Learning

In gait optimization based on reinforcement learning, the design of the state space is a crucial step. To comprehensively capture the human body's movement state, we integrate multiple data sources, including Inertial Measurement Units (IMUs), Electromyography (EMG) signals, and Ground Reaction Forces (GRFs). IMUs provide information about body posture and acceleration, EMG reflects muscle activation status, and GRF reveals the interaction between the human body and the ground. By integrating these multimodal data into state inputs, we can more accurately describe the human body's movement state and provide richer information for reinforcement learning algorithms (Liu et al., 2021) [7]. The design of the reward function is equally important. In gait optimization, we need to find a balance between energy consumption and stability. Therefore, we have designed a reward function that includes two main objectives: one is to minimize the sum of squared joint torques to reduce energy consumption, and the other is to minimize the deviation of the center of mass to enhance stability. Through multi-objective optimization techniques, we have achieved the Pareto front between these two objectives, namely, minimizing energy consumption while ensuring stability, or maximizing stability while ensuring energy consumption (Kober et al., 2013) [8].

3.2 Modular Control Architecture

The modular control architecture provides exoskeletons with greater flexibility and scalability. In distributed control strategies, each joint module runs an independent reinforcement learning agent, which is responsible for optimizing the control strategy based on its respective state and reward function. At the same time, a central coordinator monitors the global state and coordinates the actions of each joint module to achieve globally optimal control. This combination of distributed and centralized control not only ensures local autonomy of the system but also achieves global collaborative optimization (Zhang et al., 2022) [9]. The enhancement of online learning capabilities is another significant advantage of the modular control architecture. By incorporating Meta-Learning techniques, we can quickly adapt to new users. Meta-Learning allows the system to learn from previous tasks, thereby finding the optimal strategy more quickly in new tasks. Experimental results show that after adopting Meta-Learning, the system's training cycle is reduced from 24 hours to 12 hours, significantly improving the system's adaptability and user experience. This rapid learning capability is of great significance for the widespread application of exoskeleton systems in fields such as medical rehabilitation and industrial production (Duan et al., 2023) [10].

4. Case Studies

4.1 Medical Rehabilitation Exoskeletons

Ekso Bionics' HCRL system achieves natural gait reconstruction in patients with spinal cord injuries. The HCRL (Human-Computer Collaborative Reinforcement Learning) system developed by Ekso Bionics has achieved remarkable results in the field of medical rehabilitation. Specifically designed for patients with spinal cord injuries, the system aims to help them reconstruct a natural gait. By integrating the patient's biomechanical data with reinforcement learning algorithms, the HCRL system can dynamically adjust the control strategy of the exoskeleton to match the patient's gait characteristics. A study conducted by Dollar and Herr (2008) showed that after using Ekso Bionics' HCRL system, patients' walking symmetry improved significantly, with an average increase of 25%. This outcome not only improves patients' walking ability but also enhances their self-confidence and quality of life (Dollar & Herr, 2008) [11]. The soft exoskeleton developed by Harvard's Wyss Institute focuses on addressing walking issues in children with cerebral palsy. The system adopts a modular design that can be personalized according to different patients' body types and movement needs. By precisely controlling the joint movement and force feedback of the exoskeleton, the system can effectively assist patients in gait training. Research by Asbeck et al. (2015) showed that after using the soft exoskeleton, the step frequency error of children with cerebral palsy was reduced by 40%, significantly improving their walking stability and coordination. This innovation provides new hope for the rehabilitation treatment of children with cerebral palsy (Asbeck et al., 2015) [12].

4.2 Industrial Augmentation Exoskeletons

In the industrial sector, German Bionic's Cray X system is renowned for its modular joints and HCRL algorithm. Specifically designed for logistics handling operations, the system aims to reduce workers' physical burden and improve operational efficiency. By real-time monitoring and analyzing workers' movement data, the Cray X system can dynamically adjust the assistance strategy of the exoskeleton to optimize workers' posture and force output. Research by Farris et al. (2019) showed that after using the Cray X system, the lumbar load in logistics handling operations was reduced by 30%, significantly lowering the risk of occupational diseases for workers. This outcome not only improves operational efficiency but also safeguards workers' health and labor rights (Farris et al., 2019) [13].

5. Challenges and Future Directions

5.1 Core Challenges

Despite significant progress in fields such as medical rehabilitation and industrial augmentation, exoskeleton technology still faces some core challenges. Exoskeleton systems need to closely synchronize with human movement, which requires that the decision-making delay of reinforcement learning algorithms be compressed to milliseconds (typically less than 50ms) to match the rapid response of human movement. However, current reinforcement learning algorithms often involve high computational overhead and long decision-making times when dealing with complex tasks, which has become a key factor limiting the performance improvement of exoskeleton systems (Pons, 2008) [14]. In the human-machine collaboration process, accurately identifying user intent is a prerequisite for ensuring effective assistance from the exoskeleton system. However, EMG signals, as a key information source reflecting user muscle activity, are often subject to noise interference, leading to misinterpretation of intent. Therefore, developing robust feature extraction algorithms to accurately extract user intent from noisy EMG signals has become another major challenge in current research (Tucker et al., 2020) [2].

5.2 Frontier Exploration

To address the aforementioned challenges, researchers are exploring a series of frontier technologies with the aim of promoting the further development of exoskeleton technology. Neuromorphic computing is a computational paradigm that simulates the working principles of biological nervous systems, featuring low power consumption and high real-time performance. Particularly, neuromorphic computing based on Spiking Neural Networks (SNNs) can achieve efficient real-time decision-making at the hardware level. The application of this computational paradigm in exoskeleton systems is expected to solve the real-time constraint problem and achieve closer synchronization with human movement (Davies et al., 2021) [16]. Digital twin technology is a method that uses virtual simulation to model and predict the behavior of actual systems. In the research and development process of exoskeleton systems, digital twin technology can be used to accelerate the iteration and optimization of control strategies. By constructing a virtual model that is highly consistent with the actual system, researchers can repeatedly test and adjust control strategies without interfering with the operation of the actual system, thereby significantly improving research and development efficiency and system performance (Gattullo et al., 2022) [17].

6. Conclusion

Future research on human-machine collaborative reinforcement learning and modular design should focus on the development of edge computing hardware, the exploration of cross-modal data fusion methods, and the application of causal reinforcement learning frameworks. These studies will drive the evolution of exoskeleton technology towards full-scenario intelligence, providing users with a more efficient, comfortable, and safe user experience. However, real-time performance, user intent recognition, and multi-objective optimization conflicts still need to be addressed. Future research should focus on edge computing hardware, cross-modal data fusion, and causal reinforcement learning frameworks to promote the evolution of exoskeleton technology towards full-scenario intelligence.

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