Hip Exoskeleton Motion Assistance

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INTRODUCTION

Prolonged physical activities lead to muscle fatigue, posing safety and health risks. Our system aims to reduce the intensity of specific muscle usage and extend the duration of strenuous activities, especially for duty officers in disaster relief sites where heavy lifting is required, and muscle fatigue is a significant threat to their safety[1]. Traditional models require precise motion assumptions, which often necessitate the simplification of passive joints and consideration of the mechanical system of the motors to achieve system accuracy[2, 3]. In contrast, the architecture of Reinforcement Learning (RL) automates the process of guiding the model. The introduction of deep learning allows RL to maintain flexibility in its structure without the need for explicit formulas[4]. In this study, we integrated multiple Electromyography (EMG) patches with the exoskeleton, monitoring joint angles, Inertial measurement unit (IMU). A deep RL model is used to adapt to the user's gait, aiming to alleviate the burden on specific muscles [5].

METHODS

We employ the Distributed Deep Deterministic Policy Gradient (D4PG) strategy to detect action intentions and enhance Human-Machine Interaction (HMI). The introduction of D4PG allows for better handling of complex data and tasks[5, 6]. The Temporal Convolutional Network (TCN) acts as the actor, identifying time series and understanding user action intentions during muscle fatigue, subsequently commanding the motor controller. The Deep Q-Network (DQN) optimizes the actor's performance. This data-driven approach simplifies the training process by allowing the user to walk at multiple speeds while interacting with the environment. To test our hypothesis that the system provides precise control to reduce the burden on the Rectus Femoris and Biceps Femoris muscles during walking, we conducted experiments comparing integrated EMG (iEMG) with and without assistance (**Figure 1**).

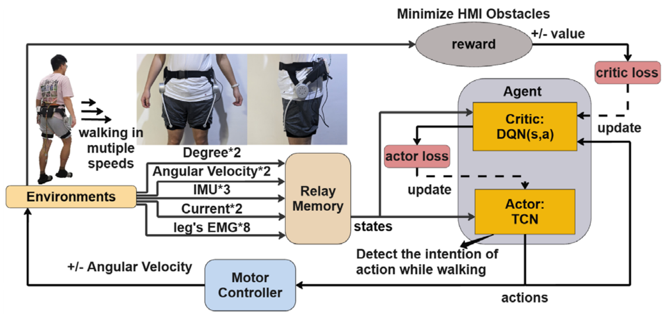

Figure 1. the block diagram of the algorithm. Data from the environment passes through the relay memory, providing state information over a duration, and updating two models in the agent based on rewards.

RESULTS AND DISCUSSION

Through iterative updates of the DL model weights, the TCN generates advantageous actions for Gait Patterns under the guidance of personalized reward functions. These reward functions monitor discrepancies in the user's specific gait pattern templates and detect fatigue levels. **Figure 2** illustrates model training results while the user is walking with the exoskeleton. The exoskeleton effectively reduces the intensity of specific muscle activities by predicting the next gait patterns for subsequent movements. This training process highlights the system's adaptability, allowing for optimization by acquiring new weight sets by interacting with the exoskeleton without necessitating mathematical modifications to the existing models [2, 3].

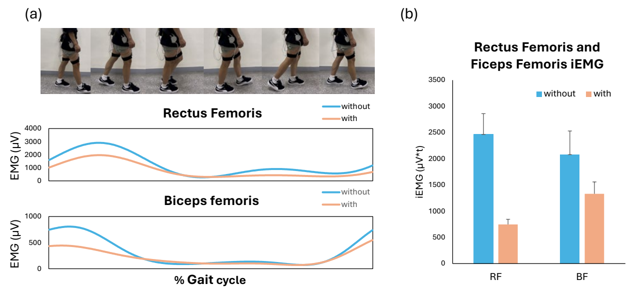

Figure 2. Rectus Femoris and Biceps Femoris EMG and iEMG. (a) EMG values of the Rectus Femoris and Biceps Femoris w. and w.o. exoskeleton assistance. **(b)** The iEMG values for the Rectus Femoris and Biceps Femoris muscles. The comparisons are made between conditions w. exoskeleton assistance (orange bars) and w.o. exoskeleton assistance (blue bars).

CONCLUSIONS

Our system employed RL to optimize gait and reduce muscle fatigue, specifically targeting disaster relief workers. This approach enhances flexibility and effectiveness compared to traditional exoskeletons, extending the duration of physical activity and mitigating associated health risks.

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