Real-Time D4PG-Based Control Algorithm for Hip Exoskeleton Motion Assistance: Action Intention Detection During Fatigue

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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 Patterns, 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) for exoskeleton controlling. D4PG offers superior handling of complex tasks compared to other RL models[5, 6]. The Temporal Convolutional Network (TCN) acts as the actor, detecting user's action intentions during muscle fatigue, commanding the motor controller of the exoskeleton to aid walking. The Deep Q-Network (DQN) evaluates the actor's action from rewards. This data-driven approach (**Figure 1**) allows the user to optimize the model by walking at multiple speeds to interact 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 have compared integrated EMG (iEMG) *w.* and *w.o.* exoskeleton assistance.

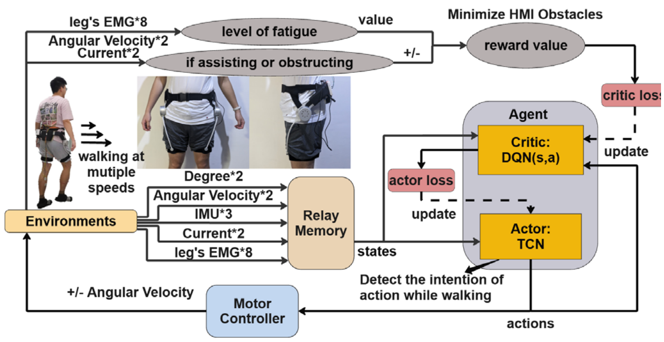

Figure 1. the block diagram of the algorithm. Data passes through the relay memory, providing state over a duration, and updating two models in the agent based on fatigue and assistance-evaluated rewards.

RESULTS AND DISCUSSION

Through iterative updates of the model weights, the TCN generates advantageous actions for user intended Gait Patterns under the rewards of varying muscle conditions. These rewards monitor discrepancies between the user's Gait Pattern and the exoskeleton's movements. **Figure 2** illustrates force utilization based on EMG with the aid of 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].

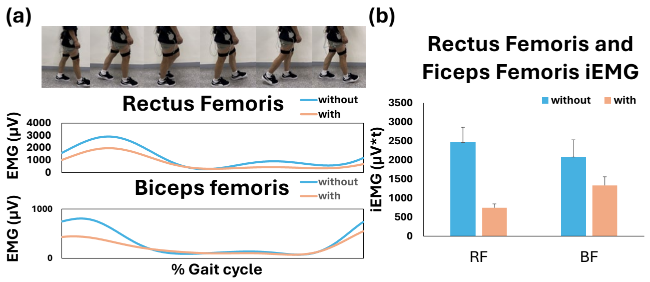

Figure 2. Rectus Femoris and Biceps Femoris EMG and iEMG. (a) EMG values of the Rectus Femoris and Biceps Femoris *w.* and *w.o.* exoskeleton assistance. **(b)** The iEMG values for the Rectus Femoris and Biceps Femoris muscles. The comparisons are made between conditions *w.* exoskeleton assistance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

CONCLUSIONS

Our system employs RL deployed on the exoskeleton to 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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