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Machine Learning and Reinforcement Learning for Adaptive Exoskeleton Design Using Motion Capture Data

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Abstract: This study presents a novel framework that applies machine learning (ML) and reinforcement learning (RL) to the development of adaptive exoskeletons using motion capture data. Recurrent Neural Networks (RNNs) were employed to forecast joint marker trajectories with a low mean squared error of 0.0397, supporting accurate motion prediction. For activity recognition, Feedforward Neural Networks (FNNs) classified motion patterns such as walking and lifting with a high accuracy of 99.41%. Reinforcement learning, using the Proximal Policy Optimization (PPO) algorithm, was employed to improve actuator performance, resulting in smoother transitions and enhanced energy efficiency. The RL controller improved over training episodes, extending performance from 71 to 86 steps. These findings validate the feasibility of ML and RL in creating responsive and efficient exoskeleton systems for rehabilitation and industrial assistance.

Keywords: Motion Capture Data, Adaptive Exoskeleton, ML, RNN, FNN, RL

INTRODUCTION

Exoskeletons are increasingly used in rehabilitation and assistive technologies to help individuals with motor impairments such as those caused by stroke, spinal cord injury, or neuromuscular disorders. These wearable devices aim to improve functional mobility, alleviate muscular strain, and support motor learning. Yet, one of the key challenges lies in developing control systems that can adapt to the wide variability in user biomechanics and dynamic movement tasks. Recent progress in artificial intelligence (AI), particularly in machine learning (ML) and reinforcement learning (RL), has opened new possibilities for more responsive and intelligent control mechanisms [1–3].

ML and RL models have shown promise in predicting joint trajectories, fine-tuning actuator responses, and adapting assistance strategies based on individual user behavior in real time. Research has also extended into related domains, such as motion-guided training systems, where motion capture and robotic actuators have been combined to support motor skill acquisition [4].

In exoskeleton applications, data-driven reinforcement learning has enabled the fine-tuning of torque assistance to align more closely with a user's natural movement patterns, thereby lowering muscle effort [5]. Learning systems trained entirely in simulation have also shown success, eliminating the need for human trials during early controller development while still delivering measurable metabolic benefits [6]. Moreover, reinforcement learning controllers, particularly those using algorithms such as Twin Delayed Deep Deterministic Policy Gradient, have enhanced walking support by adjusting hip flexion-extension forces in real time [2]. Comparative analyses of temporal-difference learning methods have shown faster convergence rates and lower error values when predicting lower-limb sensor signals [3].

Researchers have explored various control strategies to enhance the adaptability of exoskeleton systems. For instance, trajectory optimization for ankle rehabilitation robots has leveraged reinforcement learning in combination with musculoskeletal models and real-time EMG feedback, improving motion tracking and user response [7].

Broader systematic reviews examining AI in robotic rehabilitation point to key limitations, particularly the lack of robust, scalable frameworks that integrate ML and RL across multiple domains [8]. Deep reinforcement learning, when paired with musculoskeletal modeling, has proven effective in stabilizing gait and improving user adaptability in lower-limb systems [9]. Other work has demonstrated the value of machine learning in handling uncertainty in knee exoskeleton control [10], while EMG-based upper-limb systems using LSTM networks have reached high accuracy in motion prediction, supporting real-time rehabilitation [1].

Innovative approaches, such as combining central pattern generators with RL, have enabled smoother lower-limb motion trajectories [11]. Evaluations of stroke rehabilitation programs using EMG metrics confirm that robotic gait training can support neural recovery [12]. Additionally, RL-based squat-assist controllers have been validated through hardware testing, showing promise for real-world deployment [13].

A recurring theme in recent reviews is the underuse of full-body motion capture data, despite its potential to significantly improve control algorithms. The article stressed the need for richer datasets to inform adaptive learning models [14]. Similarly, adaptive feedback regulators have been introduced to manage model uncertainty and offer personalized support in powered exoskeletons [15].

Despite these advances, several challenges persist. Many existing solutions are limited to specific users or narrow movement tasks, reducing their ability to generalize across real-world scenarios. High-resolution motion capture data remains underutilized in training movement prediction models, and most systems rely heavily on EMG inputs, which can be inconsistent across sessions. Modular, scalable learning-based architectures that adapt in real time to both the task and the user are still rare. To address these issues, the present study proposes an adaptive exoskeleton control framework that combines supervised learning and reinforcement learning, trained on real motion capture data. It employs Recurrent Neural Networks (RNNs) for forecasting joint trajectories, Feedforward Neural Networks (FNNs) for recognizing specific activities, and Proximal Policy Optimization (PPO) to refine actuator commands for smoother and more energy-efficient motion.

METHODOLOGY

The methodology for this study consists of four main components: data extraction, preprocessing, machine learning model implementation, and reinforcement learning agent development. Motion capture data were extracted from trials **86_06.c3d** and **86_03.c3d** of the CMU Motion Capture dataset [16], which includes the 3D positions of markers placed on key joints (e.g., wrist, elbow, and shoulder) across thousands of frames. A schematic diagram of marker placement on the exoskeleton is shown in **Fig. 1**. Using the **ezc3d** library, marker positions were processed to create a structured dataset of X, Y, and Z coordinates for further analysis.

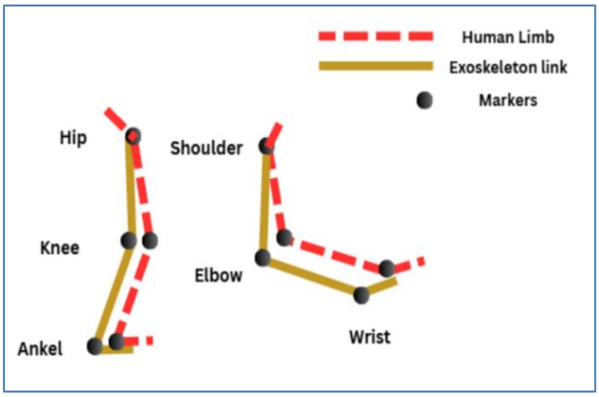

Fig. 1. Schematic of Exoskeleton with Marker Placement

Preprocessing involved normalizing marker positions to scale values to the range **[0, 1]**, ensuring consistency across trials. In order to capture the dynamic behavior of joint movement, both velocity and acceleration parameters were computed from the marker data. Velocity was estimated as the positional change over time, while acceleration was determined as the change in velocity across consecutive frames. These dynamic features provided essential context for analyzing motion patterns.

The machine learning component of the study addressed two primary goals. The first involved the use of a Recurrent Neural Network (RNN) to predict the future positions of motion capture markers. This model took as input the normalized three-dimensional coordinates (X, Y, Z) from the preceding 10 frames and generated the expected marker location for the next time step. This approach allowed for real-time anticipation of joint motion. The second objective focused on activity classification. A Feedforward Neural Network (FNN) was trained using computed velocities and accelerations as inputs to identify specific motion types, such as walking or lifting. The classification output enabled adaptive adjustments in the exoskeleton's assistance strategy, tailored to the detected activity.

For actuator control, the study employed reinforcement learning via the Proximal Policy Optimization (PPO) algorithm. A custom simulation environment was constructed to model exoskeleton dynamics, where each state was defined by the marker's spatial coordinates and velocities. The corresponding actions controlled simulated actuator forces and torques. A reward function was formulated to discourage sudden, jerky movements and to promote smooth, energy-efficient transitions. Through repeated interactions with the environment, the PPO agent progressively optimized its control policy across multiple training episodes.

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RESULTS AND DISCUSSION

This study demonstrates the effectiveness of machine learning and reinforcement learning techniques in improving adaptive exoskeleton systems. Key components of the framework—motion prediction, activity classification, and actuator control optimization—were evaluated using motion capture data from the CMU Motion Capture dataset. The results showcase advancements in accurately predicting motion trajectories, classifying activities based on marker dynamics, and refining actuator control strategies to achieve smoother transitions and improved energy efficiency. The following sections detail the performance of each model, supported by graphical analyses that validate the outcomes.

Motion Prediction

Motion prediction was achieved using a Recurrent Neural Network (RNN) trained on normalized marker positions (X, Y, Z) from selected markers such as the wrist, elbow, and shoulder. The model demonstrated a strong ability to predict marker trajectories, achieving a Mean Squared Error (MSE) of **0.0397** on the testing data. This low error reflects the precision of the RNN in forecasting future positions based on temporal dependencies in motion capture data.

Fig. 2 illustrates the predicted versus actual X positions for Marker 0 across a subset of testing frames. The close alignment between the predicted and actual trajectories validates the model's accuracy and robustness. The smooth transitions observed in the predicted positions further highlight the RNN's capability to capture motion dynamics effectively, enabling real-time actuation for exoskeleton systems. These results emphasize the RNN's applicability in real-world scenarios where precise motion prediction is critical for replicating natural joint movements. By integrating this model into exoskeleton control systems, it is possible to achieve adaptive actuation that aligns closely with user motion patterns.

Activity Classification

Activity classification was addressed using a Feedforward Neural Network (FNN) trained on marker velocities and accelerations as input features. The model achieved an accuracy of **99.41%**, effectively distinguishing between motion types such as walking and lifting. **Fig. 3** presents the confusion matrix generated during testing, demonstrating near-perfect predictions for both activity types. The high classification accuracy highlights the FNN's ability to adapt exoskeleton settings dynamically based on user activity. For instance, the exoskeleton can adjust actuator behavior to provide greater assistance during walking or more targeted support during lifting tasks. This dynamic adaptability enhances both user comfort and performance, making the FNN a valuable component of the integrated framework.

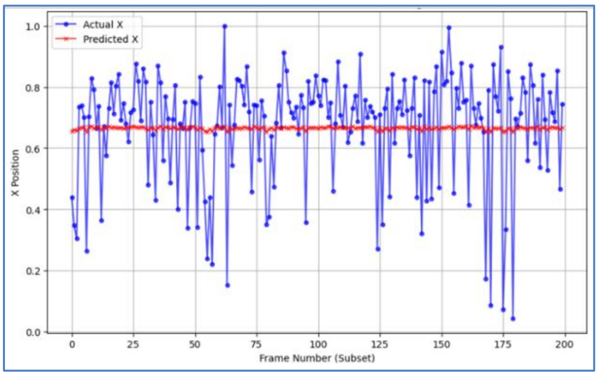

Fig. 2. Predicted vs. Actual X Positions on Testing Data

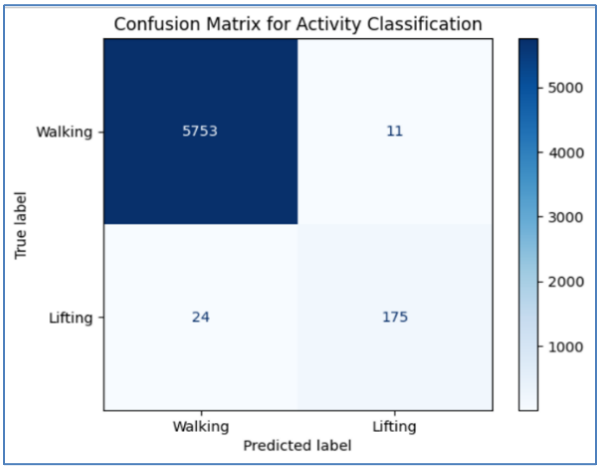

Fig. 3. Confusion Matrix for Activity Classification

Reinforcement Learning for Actuator Control Optimization

Proximal Policy Optimization (PPO) was employed to optimize actuator forces and torques for smooth motion transitions. The RL agent interacted with a simulated environment to refine its policy, achieving measurable improvements across multiple iterations. Episode lengths increased from 71 steps in early iterations to 86 steps in later testing, indicating progress in policy optimization. Similarly, total rewards improved from -87.08 to -97.42, highlighting the agent's ability to adapt to dynamic state-action spaces. **Fig. 4** illustrates the force and torque values generated by the RL agent during testing. The results indicate a progressive refinement in motion control, with smoother transitions between successive actions. This trend contributes to improved energy efficiency and

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minimizes penalties associated with abrupt movements.

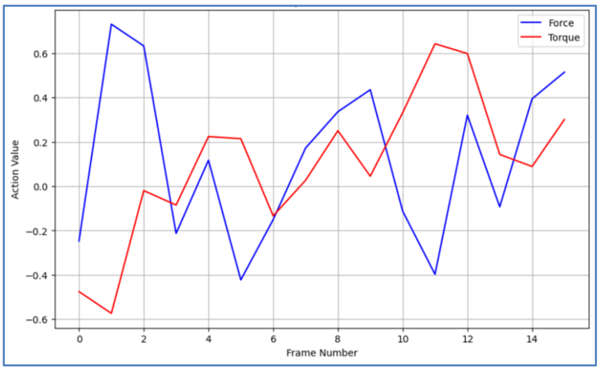

Fig. 4. Force and Torque Values over Frames

These results validate the feasibility of reinforcement learning for actuator control in exoskeleton systems. By processing dynamic marker inputs and producing continuous actions, the PPO agent establishes a baseline for RL-based control frameworks. While the rewards remain negative, they demonstrate the agent's capability to interact effectively with the environment and refine its policy to balance smoothness and efficiency.

ntegrated Framework and Implications

The integration of RNN-based motion prediction, FNN-based activity classification, and PPO-based reinforcement learning provides a unified framework for adaptive exoskeleton systems. The RNN enables precise real-time actuation by forecasting marker trajectories, while the FNN ensures dynamic adaptability by classifying motion types with high accuracy. Reinforcement learning further refines actuator control, optimizing force and torque values for smoother transitions and improved energy efficiency. By leveraging motion capture data and advanced algorithms, the study highlights the potential of AI-driven approaches to enhance rehabilitation outcomes, reduce therapist workload, and enable scalable solutions for motion assistance. The results provide insights into the design of energy-efficient and responsive exoskeleton systems, paving the way for advancements in medical and industrial applications.

CONCLUSION

This study highlights the successful application of machine learning and reinforcement learning techniques to enhance adaptive exoskeleton systems. Leveraging motion capture data from the CMU Motion Capture dataset, the framework addressed critical challenges in motion prediction, activity classification, and actuator control. The models demonstrated real-time adaptability and dynamic adjustments tailored to user-specific motion patterns, while reinforcement learning facilitated optimized actuator control, achieving smoother transitions and improved energy efficiency.

The outcomes of the ML model include:

- The Recurrent Neural Network (RNN) achieved a Mean Squared Error (MSE) of 0.0397, accurately forecasting marker positions and validating its capability to replicate natural joint movements for real-time actuation.
- The Feedforward Neural Network (FNN) demonstrated a classification accuracy of 99.41%, effectively distinguishing motion types such as walking and lifting. This adaptability ensures dynamic adjustment of exoskeleton settings to meet activity-specific demands.
- The Proximal Policy Optimization (PPO) agent refined actuator control strategies, improving episode length from 71 steps in early iterations to 86 steps during testing. The progress observed in force and torque transitions highlights the potential of reinforcement learning for dynamic optimization in complex environments.
- The results underscore the feasibility of integrating advanced AI-driven approaches into exoskeleton design, paving the way for scalable solutions in rehabilitation and industrial applications.

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