Development of a method for analyzing muscle cooperation using neural networks for biomechanics and medical applications

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Summary

This publication presents a novel method for analyzing muscle cooperation using neural networks within the fields of biomechanics and medical applications. Various neural network architectures, including Echo State Networks (ESN), Long Short-Term Memory (LSTM), and recurrent neural networks, were applied to electromyographic (EMG), kinematic, and dynamic data. The goal was to determine individual muscle contributions to total muscle force generation. The methodology involved training and testing neural networks on datasets representing lower limb muscle activity, predicting force generation, and validating the results against biomechanical simulations in OpenSim. The outcomes demonstrated the potential of neural networks for precise muscle function modeling, with applications in rehabilitation or sports injury prevention. This interdisciplinary approach bridges advanced machine learning with biomechanics, opening new opportunities for research and practical implementation.

Introduction

The complexity of human movement arises from the intricate interactions between muscles, joints, and neural inputs. Understanding muscle cooperation is essential in fields like biomechanics, rehabilitation, and sports science. Traditional methods for modeling muscle behavior often rely on simplified mathematical models, such as Hill-based muscle models, which have limitations in accurately capturing nonlinear interactions [1]. This publication integrates neural network technology with biomechanical data to propose a novel approach to modeling muscle cooperation. By leveraging electromyography (EMG), kinematic, and dynamic data, this method seeks to predict individual muscle contributions to total muscle force generation.

Methods

The dataset originated from an open-access biomechanical repository [2] containing EMG signals, kinematic, and dynamic information from eight lower limb muscles was utilized. Data preprocessing involved filtering EMG signals, normalizing kinematic inputs, and dividing the dataset into training and testing sets. Five neural network architectures were tested: Echo State Networks (ESN), Long Short-Term Memory (LSTM), support vector machines (SVM), random forests, and regression models [3]. Model training and testing were conducted in MATLAB, with biomechanical simulations in OpenSim used for validation. Error analysis focused on absolute and relative differences between predicted and simulated forces. To evaluate generalizability, models were tested on movements not included in the training set, such as knee lifts and stair descents [4].

Results and Discussion

The neural networks exhibited varying levels of accuracy in predicting muscle forces. Recurrent and LSTM models achieved the highest accuracy, particularly in capturing the nonlinear relationships between EMG signals and muscle forces. SVM and random forest models performed adequately but showed limitations in generalizing to untrained movements. Error analysis revealed that recurrent models excelled in predicting complex movements, while LSTM offered computational efficiency for real-time applications. The results highlight the potential of neural networks to enhance biomechanical modeling by offering precise, non-invasive estimations of muscle activity. Limitations include dependence on high-quality input data and challenges in extrapolating findings to diverse populations.

Conclusions

This study demonstrates the feasibility of using neural networks for modeling muscle cooperation in biomechanics. The integration of EMG, kinematic, and dynamic data with machine learning provides a robust framework for analyzing muscle contributions to movement. The proposed method offers practical applications in rehabilitation, enabling personalized therapy plans, and in sports, optimizing training regimens and injury prevention strategies. Future work should focus on extending the dataset to include diverse subjects and movements, improving model robustness, and exploring real-time implementation.

References

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