A Path Toward Personalized Muscle Synergy-Based Rehabilitation

D-S. Komaris[1], K. Risvas[1], D. Tsaopoulos[1], S. Nikolopoulos[1], I. Kompatsiaris[1]

[1] Centre for Research & Technology Hellas, Information Technologies Institute, Thessaloniki, Greece.

Email: s.komaris@iti.gr

Summary

This study investigated whether EMG data simulated on OpenSim could accurately replicate muscle synergies from experimental EMG data. Results showed strong consistency between simulated and experimental data, with four distinct muscle synergies, and cross-correlation coefficients of the activation profiles ranging from 0.71 to 0.79. These findings support the potential for simulating rehabilitation interventions, such as functional electrical stimulation, to help design personalized, muscle-targeted rehabilitation strategies.

Introduction

Muscle synergy analysis offers a promising approach by examining neuromuscular coordination through EMG-based decomposition of muscle activation patterns into synergies and their temporal profiles [1]. This method has demonstrated sensitivity to motor deficits across conditions such as stroke [2]. Linking synergies to gait phases may enhance tailored rehabilitation strategies, improving functional recovery and quality of life. This study investigated whether EMG data from simulated walking trials can accurately generate muscle synergies compared to experimental EMG signals.

Methods

We used an open-access dataset of 138 able-bodied adults, with kinematic data recorded at 100 Hz using the PiG model and EMG data from 12 lower limb muscles recorded at 1000 Hz [3]. Sensors were placed bilaterally on rectus femoris (RF), vastus lateralis (VL), biceps femoris (BF), semitendinosus (ST), tibialis anterior (TA), and gastrocnemius (GAS). Kinematic data were treated with a 10 Hz Butterworth filter, and EMG signals were band-pass filtered (10-300 Hz), rectified, smoothed, and time-normalized to 1000 points.

We have additionally performed a computational biomechanical analysis on OpenSim, with musculoskeletal models featuring 23 degrees of freedom and 80 muscle-tendon actuators [4]. Initially, we extracted the marker trajectories and GRFs for each gait trial from the dataset. Then, we created multiple scaled versions based on the anthropometric data of each patient. Inverse dynamic analysis was used to compute joint angles and moments from a subset of 35 gait cycles, and static Optimization (SO) to estimate EMG data for each trial. Then, we extracted muscle synergies twice, once for the experimental and once for the simulated EMG data, using non-negative matrix factorization (NNMF) to generate spatial synergies (**W**) and temporal activation coefficients (**C**). NNMF analysed up to 14 synergies through 10 iterations, optimizing weights via gradient descent. The optimal number of synergies was determined by achieving a reconstruction quality (R^2) of 0.8.

Results and Discussion

Spatial synergies and activation coefficients were visualized as bar charts and time-series graphs to illustrate the conformity of the simulated signals with the experimental data. The number and structure of the extracted muscle synergies was consistent, with four muscle synergies (**W1**: hip flexors; **W2**: dorsal flexors; **W3**: plantar flexors/knee extensors; **W4**: hamstrings; **Figure 1**, left). The average temporal activation coefficients (**Figure 1**, right) also displayed comparable morphology, with cross-correlation coefficients (*r*) between 0.71 (**C4**) and 0.79 (**C2**).

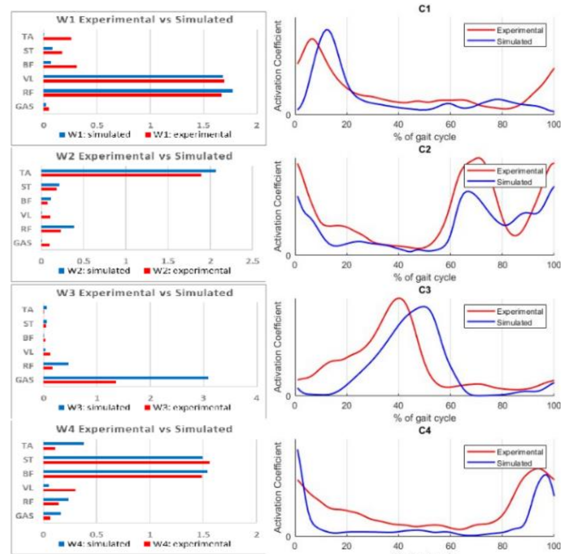

Figure 1 Muscle synergy weights (W) and activation coefficients (C)

Conclusions

This study demonstrated that EMG activity simulated on OpenSim generates muscle synergy results consistent with experimental data. This approach offers a valuable tool for evaluating the impact of clinical rehabilitation interventions such as Functional electrical stimulation (FES), enabling clinicians to design personalized rehabilitation strategies that can target specific muscles involved in abnormal synergies.

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