sEMG Prediction Using Gait Kinematics and Machine Learning

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Summary

This study proposes a novel model for predicting lower limb muscle sEMG signals from gait kinematics and demonstrates that incorporating dynamic information significantly enhances model performance. These findings suggest that domain knowledge based on dynamics plays a crucial role in sEMG prediction models.

Introduction

Surface electromyography (sEMG) signals provide valuable insights into muscle activity; however, their high acquisition cost limits widespread applications [1]. Therefore, this study proposes a predictive model that utilizes gait kinematics information, which offers greater accessibility, to estimate sEMG signals. Since kinematic data shows a weak correlation to muscle activation, sEMG signal prediction based solely on kinematics requires complex models. However, publicly available sEMG datasets are limited [1]. To address these challenges, this study introduces an approach that leverages dynamic information that exhibits strong correlations with both kinematic and sEMG data to reduce model learning complexity and enhance prediction accuracy.

Methods

To predict lower limb muscle sEMG signals during gait, this study constructs a multi-layer perceptron (MLP) model. The model is trained using gait kinematics-sEMG data collected from 22 participants [2]. First, a model is developed to estimate joint torques in the sagittal, frontal, and transverse planes using input kinematic data, specifically the sagittal flexion angles of the hip, knee, and ankle joints. Subsequently, an additional hidden layer with 15,200 parameters is incorporated into the torque estimation model, and fine-tuning is performed using kinematics-sEMG data. As a result, a torque-based sEMG prediction model is constructed, predicting sEMG signals for seven lower limb muscles. The performance of the proposed model is compared against a baseline MLP model, which is directly trained on kinematics-sEMG data with 15,575 parameters.

Results and Discussion

Table 1 demonstrates that the torque-based model outperforms the baseline model in predicting sEMG signals.

This result highlights the effectiveness of incorporating dynamic information as an intermediate variable when predicting sEMG signals from gait kinematics. Furthermore, it suggests that in scenarios where training highly complex models for sEMG prediction is impractical, leveraging domain knowledge based on gait dynamics plays a critical role in improving model performance.

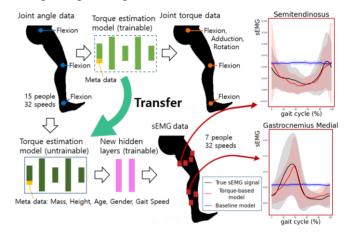


Figure 1: Training process of a torque-based model (left) and graphs of ensemble averages of estimated sEMG signals (right).

Conclusions

Utilizing dynamic information enhances the accuracy of sEMG prediction models based on gait kinematics. This suggests that dynamics-based domain knowledge can be significantly utilized in sEMG prediction models.

Acknowledgments

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References

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Table 1: R² values of ensemble averages of true and estimated sEMG signals for lower limb muscles during gait.

| Muscle | Tibialis Anterior | Gastrocnemi us Medial | Vastus Lateralis | Rectus Femoris | Biceps Femoris | Semitendino sus | Soleus |
|--------------------|----------------------|--------------------------|---------------------|-------------------|-------------------|--------------------|---------|
| Torque-based model | 0.737 | 0.877 | 0.687 | 0.470 | 0.573 | 0.808 | 0.824 |
| Baseline model | -1.14 | -0.0516 | -26.9 | -73.8 | -2.02 | -4.24 | 0.00343 |