Feature Selection for Muscle Fatigue Classification During Functional Electrical Stimulation (FES)

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Summary

Muscle fatigue during FES is a persistent problem. This study investigates feature extraction and selection for muscle fatigue classification in FES, focusing on force and motion data. Reducing features from 72 to 16 illustrates the potential for simplifying models while maintaining stable predictions.

Introduction

Muscle fatigue poses a challenge in FES applications, affecting rehabilitation outcomes [1]. Despite efforts to reduce fatigue through optimized stimulation parameters [2], fatigue classification remains crucial for adaptive systems that mitigate its effects further [3]. This study aims to identify features for the classification of muscle fatigue using force and motion data from isometric and isotonic contractions.

Methods

The force or movement data of the fingers II-V of 9 healthy participants (8M, 1F) were recorded during FES-induced isometric and isotonic muscle contractions. Each participant took part in a total of 16 stimulation sessions, each lasting 20 minutes. For each session, the stimulated muscle or stimulation setting was altered. For the initial classification of fatigue states, the Fatigue Index $FI_n = Area_n / Area_{init}$ was calculated based on the area under the data-time curve for every stimulation cycle and grouped into 3 classes (no, medium, and high fatigue). To eliminate the influence of maximum amplitude, every stimulation cycle was min-max normalized. In addition, the first *(D1)* and second *(D2)* derivatives of the force and motion data were calculated. A total of 72 features were extracted, including distance metrics (e.g., force or movement relative to the energy introduced by the FES system), statistical metrics, and domain-specific features. A correlation analysis (corr.) was performed to remove highly correlated features. The performance of the model in relation to the number and type of features was then evaluated using recursive feature elimination (rfe) to determine the number of features above which no increase in model performance could be achieved. We used a multi-criteria hyperparameter optimization with a dropout mechanism to reduce overfitting and increase classification quality. For the performance evaluation and optimization of the model, we were using the f1-score, the difference between training and test loss, and a 5-fold cross-validation.

Results and Discussion

We were able to reduce the number of features from 72 to 16, with only a 0.9% decrease in prediction accuracy, demonstrating minimal impact on training and classification performance (Table 1). The SHAP Beeswarm plot (Figure 1) for the class *high fatigue* shows, as an example, that the distance metrics (dist.) have high feature values in the positive SHAP region, indicating that higher values support the classification of *high fatigue*. This aligns with the physiological relationship between introduced energy and movement or force output, where low deviations indicate no or medium fatigue, while increasing deviations with advancing fatigue lower these feature values. This suggests that the model effectively captures changes in neuromuscular efficiency for fatigue classification.

Table 1: Model Performance across feature reduction stages

Number Features	Accuracy	Precision	Recall	Train loss	Test loss
72 *(orig.)*	0.702	0.702	0.705	0.909	1.014
36 *(corr.)*	0.695	0.695	0.698	0.952	1.022
16 *(rfe)*	0.693	0.693	0.696	0.956	1.023

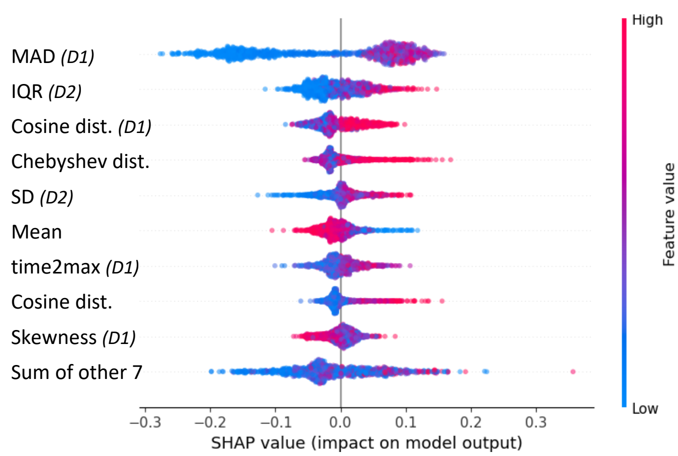

Figure 1: SHAP-Beeswarm plot for the class *high fatigue*

This process resulted in a moderately accurate classifier for detecting muscle fatigue during FES with a minimum of 16 features. Distance metrics, for example, have proven to be particularly important features that can map changes in force and movement dynamics. Refining the initial labelling is critical, as unclear fatigue boundaries are likely to have caused mislabeling, negatively impacting model performance and the ability to further reduce the number of features.

Conclusions

This study highlights the potential of fatigue classification models during FES by maintaining prediction stability despite feature reduction.

References

[1] Schmoll et al. (2021). *NeuroEngineering Rehabil*, ***18***
[2] Barrs et al. (2018). *Arch Phys Med Rehabil*, **4:** 779-791.
[3] Zhang et al. (2022). *MDPI Sensors*, **1**: 335.