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Machine Learning-Enhanced Biomechanical Analysis for Robotic Rehabilitation

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1. Introduction

Exoskeletons for the upper limbs have been developed to support people who are limited in their mobility due to diseases such as cerebral palsy. These exoskeletons come in various configurations, from simple mechanical designs to sophisticated robotic technologies (Charafeddine et al., 2021). The advent of machine learning promises to have a transformative impact on robotic assistance by providing more natural and flexible control mechanisms. The main objective of this study is to utilize these machine learning techniques to improve the control mechanisms of upper limb exoskeletons, with a particular focus on the application of the neuro-motor index (NMI). The NMI was derived from the co-contraction index — a quantifiable metric of muscle activity during movement — and serves as a critical variable in the development of a machine learning-based approach to optimize exoskeleton functionality and user interaction (Charafeddine et al., 2019). By integrating NMI into our models, we aim to improve the predictive accuracy and responsiveness of these aids, thereby increasing user autonomy and mobility.

2. Methods

The data set of Granados et al. (2017) contains surface EMG readings from five patients structured in three columns: two for EMG signals of the right arm and one for flexion and extension angles of the right elbow. Customized data manipulation processes facilitated

precise management and analysis tailored to the specific needs of the study.

2.1 Data Pre-processing

In this section, the methodology mirrors that in reference (C. Jiangcheng et al., 2018), focusing on reducing high and low-frequency noise. Band-pass filtering was applied to keep frequencies between 20 and 450 Hz, determined as the optimal range for EMG signal clarity through empirical research and experimentation. However, some noise remained, complicating analysis. Power spectral density plots were used to find the effective filtering interval, with a notch filter targeting the 57 to 63 Hz range to reduce interference while preserving core signal frequencies. The analysis showed segregating the signal into positive and negative components did not aid analysis and could obscure data interpretation. Thus, the process also involved eliminating abrupt data shifts. Due to the large dataset size, which challenged timely model training, a resampling strategy, selecting every 250th data point, was adopted to streamline the dataset for efficient analysis.

2.1 Machine Learning application

The aim of this study is to develop a regression model for controlling upper limb exoskeletons using the neuro-motor index (NMI) based on co-contraction indices (J. Charafeddine et al., 2020).

$$INM = A(t) \left[\frac{1}{B(t)} + \frac{Rx(t)}{C(t)} \right] (1)$$

Here, $A(t)$, $B(t)$ and $C(t)$ are integrals of electromyography (EMG) signals representing muscle co-contraction and overall muscle activity during four consecutive flexion/extension movements. $R_x(t)$, a non-linear regression model based on a Hermitian polynomial, captures the complex interactions between muscle co-contractions and joint angles. This model facilitates the calculation of the neuromotor index by analysing the variations in joint angles to determine the antagonistic muscles for each movement. A decrease in angle indicates a flexion associated with the triceps, an increase indicates an extension associated with the biceps, and no change indicates a repetition of the previous movement. This index is crucial for the development of a machine learning model to control upper limb exoskeletons. It provides detailed insights into muscle activation during movements and enables precise prediction of joint angles. The model uses the K-nearest neighbors (KNN) algorithm, which uses a user-defined distance metric to measure the proximity of the test data to the training data, enabling accurate angle prediction. The data is split, with 80% used to train the KNN model and the remaining 20% used for validation. Angle prediction is done by calculating the distances between a test point and the corresponding training points, where the predicted angle is the average of the 'K' closest training data points.

3. Results

The results of this study show that the error rates during the training and validation phases are consistent with the optimal mean squared error (MSE) for the best choice of neighbors (K). As shown in Table 1, the MSE for training and validation decreases as the number of training examples increases. By applying the K-nearest neighbor (KNN) algorithm with this optimally chosen K value to the test data set, the performance of the model was evaluated using the MSE and the coefficient of determination (R^2). With a K value of 5, the model recorded an MSE of 342.663 and an R^2 value of 80.94%, confirming its high predictive accuracy.

Table 1. MSE of Training and Validation

Examples	Train - MSE	Val - MSE
20	3,500	2700
40	1,600	1,450
60	800	750
80	600	580
100	500	490
120	450	430

An in-depth analysis of the model's precision was performed using a scatter plot comparing the actual and predicted joint angles, with the neuromotor index as a predictor. This analytical approach, supported by the results shown in Table 1, underlines the accuracy of the model in simulating real movements.

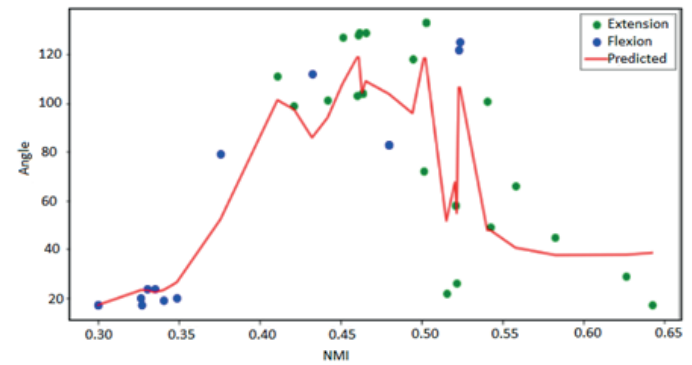


Figure 1. Predicted vs Actual Angle Values

This illustration (Fig. 1), which was categorized by the type of movement (flexion versus extension) and featured a line for predicted values, demonstrated a significant correlation between the predicted and actual values, highlighting the model's accuracy in simulating real world movements.

4. Discussion and perspective

This study establishes the neuromotor index as a reliable predictor of joint angles in upper limb exoskeletons and emphasizes the crucial role of signal processing techniques such as notch filtering to eliminate electrical noise and improve data quality. Integrating the neuromotor index into exoskeleton control systems significantly improves precision and offers a promising method to increase the accuracy and efficiency of these devices. However, the study highlights a limitation in that EMG activity from key muscles such as the brachialis and brachioradialis, which are important for elbow flexion, were not included. This omission could affect the completeness of the results and the overall effectiveness of the neuromotor index. Future research should include these muscles to gain a more comprehensive understanding of muscle activity and thus improve the accuracy and practical applicability of the index. In addition, it is proposed to extend the study to different patient groups and evaluate the effectiveness of the prediction model in controlling experimental

exoskeletons. This could lead to significant advances in exoskeleton technology, especially for patients with various conditions.

5. Conclusions

The aim of this study was to develop a machine learning method for the control of upper limb exoskeletons using surface electromyography signals. An investigation of both signal pre-processing and machine learning strategies confirmed the potential of these models to accurately predict upper limb movements. This research is a contribution to the burgeoning field of machine learning for exoskeleton guidance and control. It highlights the importance of biomechanical knowledge of the upper limbs in formulating effective control mechanisms to assist people with upper limb problems.

Conflict of Interest Statement

The authors confirm that there are no commercial or financial relationships that could be considered potential conflicts of interest influencing this research.

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