# FEASIBILITY OF SPATIO-TEMPORAL LINEAR FEATURE LEARNING FOR MYOELECTRIC CONTROL: A SMALL WINDOW SIZE APPROACH

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## ABSTRACT

Numerous research papers have delved into spatio-temporal analysis for myoelectric control, yielding meaningful outcomes, often employing window sizes ranging from 100 to 300 milliseconds. However, the industry is interested in achieving robust performance within smaller window sizes, more applicable to real-world scenarios. This study introduces a novel approach, Spatio-Temporal Linear Feature Learning (STLFL), with a robust trade-off between high performance and compact window size. Our investigation primarily focused on five classes within the state-of-the-art DB5 dataset—rest, abduction of all fingers, pointing index, power sphere grasp, and prismatic pinch grasp. Comparative analyses with two established methods, namely support vector machine (SVM) and convolutional neural network (CNN), revealed that STLFL consistently outperformed, achieving an impressive average accuracy of 84.6±3.9% across 10 subjects within an 80-millisecond window in a 16-channel electromyography signal. These results highlight the efficiency of STLFL in achieving myoelectric control within a limited timeframe, demonstrating promising outcomes for multiclass applications in both future contexts and real-world scenarios.

## INTRODUCTION

Spatio-temporal analysis is extensively utilised in recent electromyography (EMG)-based literatures due to its capacity to leverage optimal features in both spatial and temporal domains [1-3]. This preference stems from recognised limitations in traditional EMG feature extraction methods, which encounter challenges such as the inability to extract inter-temporal dependencies between feature extraction windows and a limitation in capturing synergistic and spatial muscle patterns [1]. Advanced approaches such as spatio-temporal-based techniques are thus warranted to address these shortcomings. However, in many cases, there is a critical aspect that is often overlooked, and that pertains to the window size.

Various studies indicate that the choice of window size significantly influences classification accuracy and control delay in real-world scenarios [4]. Many research papers have explored window sizes ranging from 100 to 300 milliseconds, although this may lead to increased computational time [5, 6]. In contrast, recent literature [4] has shown promising outcomes with smaller window sizes for the first time, demonstrating accelerated processing in high-dimensionality EMG decoding systems. In light of this, we are inspired to adopt a smaller window size (below 100 milliseconds) for our spatio -temporal linear feature learning approach, focusing specifically on a 16-channel EMG signal. The primary objective of our work is as follows:

- Presenting a new version of the spatio-temporal linear analysis in multi classes objective, yielding promising outcomes when applied to raw state-of-the-art EMG signals.
- Adopting a small window size with the objective of reducing delay in controlling myoelectric signals for future real-world scenarios.

## METHODS

### Dataset

To assess the effectiveness of our proposed method, we utilised a widely recognised EMG dataset obtained from the Ninapro website (DB5) [7]. The dataset captures the EMG activity of ten healthy participants' hands, recorded through 16 surface electrodes (utilizing two Thalmic Myo Armbands). Participants performed 53 distinct hand gestures, which included periods of rest. Each hand gesture was repeated six times, with each repetition lasting approximately 5 seconds, followed by a 3-second rest interval. The sampling frequency of the recorded EMG signals was set at 200 Hz. In our study, we focused on five classes: rest, abduction of all fingers, pointing index, power sphere grasp, and prismatic pinch grasp. These classes were chosen for our primary investigation into the application of the proposed spatio-temporal linear method in myoelectric control.

### Pre-processing

Prior to initiating the classification process, we employed a 6th-order high-pass Butterworth filter with a cutoff frequency set at 10 Hz. For extracting input, we adopted an overlapped segmentation approach with a window length of 80 ms and a 10 ms incremental step. In our approach, we opted to utilise raw EMG data rather than extracting predefined feature sets. This decision guided us to represent the input as overlapped windows of 2D arrays (time-by-channel) in the format of $R^{16\times16}$ for our proposed method.

### Spatio-Temporal Linear Feature Learning (STLFL)

The STLFL was introduced in our prior work on binary classification [8]. Here, we extended the method to accommodate multiple classes using a one-vs-one approach and implemented it on the raw EMG signal. The primary objective of this algorithm is to identify the most relevant spatial and temporal features from raw data. To achieve this, the algorithm adjusts two weights associated with the spatial and temporal dimensions of the raw dataset. This adjustment aims to enhance the between-class distribution while minimizing the within-class distribution.

The optimization process is iterative and continues until the error, defined as the minimum difference between the weights in the current iteration and the preceding iteration, reaches a threshold of 0.0001. In our present study, the number of final features is determined by the smaller value between the number of channels and temporal features. Subsequently, the more informative features are inputted into Linear Discriminant Analysis for the purpose of classification.

### Convolutional Neural Network (CNN)

In our research, we employed a CNN to compare with STLFL, the parameters of which were chosen through heuristic methods for optimal performance. The model comprises six layers: batch normalization, two convolutional layers, another batch normalization, fully connected, and a final softmax layer for classification. ReLU is used as the activation function throughout and the learning rate for our model is set to 0.001.

For the convolutional operation, three crucial parameters—size, number of kernels, and stride—are considered. Our approach used a convolutional layer with 20 kernels of size [Ch × 1], where Ch is the number of channels (16), and a stride of 1 was applied. Furthermore, we applied a second convolutional layer with 20 kernels of size [1 × 2] and a stride of 1 subsequent to the initial convolutional layer.

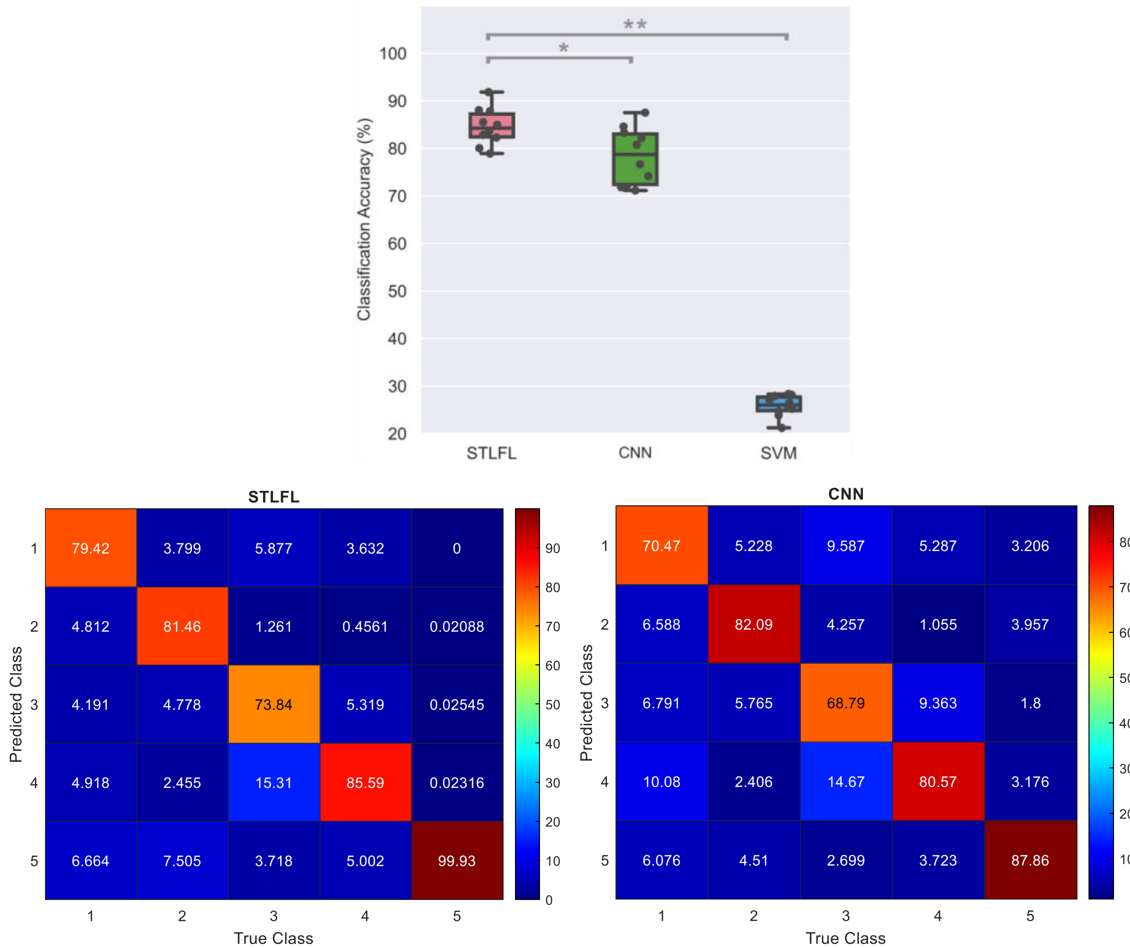
## RESULTS

In this research, we assessed the effectiveness of our proposed STLFL model in comparison to two other methods: CNN, a conventional deep learning model, and support vector machine (SVM), a traditional machine learning algorithm. We used classification accuracy as our evaluation criterion, maintaining a uniform preprocessing approach across all methods.

For statistical validation of the accuracy values, we employed a Wilcoxon sign-rank test with Bonferroni correction using MATLAB software, considering p-values less than 0.05 as indicative of significant differences. This nonparametric test enabled us to assess paired data (classification accuracy of the STLFL versus the SVM and the CNN), thereby enhancing the robustness of our research findings.

Figure 1 presents a box-plot depicting average accuracy values across all subjects for STLFL, CNN, and SVM. Notably, STLFL and CNN exhibit a significant performance advantage over SVM, with average accuracy values of approximately 84.6±3.9% and 78.3.30±6.0%, respectively. This visual representation underscores the superior performance of the STLFL compared to other methods.

Furthermore, in the comparison between STLFL and CNN, a substantial improvement of approximately 6% is evident in favour of STLFL. Our introduced STLFL model not only outperforms CNN but also demonstrates a statistically significant enhancement in accuracy (p-value = 0.002) when compared to the conventional CNN model.




(a) (b)

Figure 1: Box-plot depicts average classification accuracy values across 10 participants using different methods including STLFL, CNN, and SVM models and represent their individual accuracy by grey point. Significant differences are denoted with stars (* for $p$ <0.005 and ** for $p$ <0.001). Figures (a) and (b) display the average confusion matrix for STLFL and CNN, respectively.

## DISCUSSION

This paper introduces an innovative spatio-temporal linear feature learning approach for myoelectric control. Our method is intentionally designed with a minimal number of parameters, ensuring its practical suitability for real-world applications. The simplicity of our approach is particularly advantageous, especially in comparison to more intricate analyses such as deep learning techniques.

Upon evaluating our method alongside existing methodologies, including deep learning models like CNN, we have observed superior performance under similar conditions. These results underscore the potential effectiveness of linear approaches in myoelectric applications, highlighting the practical advantages in real-world implementation.

Our study also contributes significantly to the exploration of raw EMG signals in small window sizes, opening way for further investigations in this field. However, it is recognised that specific spatio-temporal convolutional neural networks (STCNN) [9] have achieved favourable results in real-world scenarios. By clarifying the approaches employed in both current proposed STLFL and other relevant STCNN models, and outlining their respective contributions, we aspire to obtain more thorough and informative results. This effort is anticipated to significantly advance our comprehension of the dynamics inherent in myoelectric control.

Moreover, the outcomes, particularly in small window lengths (less than 100 milliseconds), reveal promising advancements for EMG-driven systems, emphasizing enhanced system speed. Previous literature exploring small window lengths often concentrated on high-dimensional signals across numerous channels. In contrast, our study demonstrates these positive results using only a 16-electrode recorded EMG signal. Looking ahead, our method should be implemented in a real-time scenario, and efforts should be directed towards to increasing performance by developing the model.

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