The Spatial and Temporal Resolution of Motor Intention in Multi-Target Prediction

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Abstract. Reaching, grasping, and object manipulation are essential motor functions in everyday life. This study predicts movement direction and target location from multichannel electromyography (EMG) signals, examining how spatially and temporally accurate intentions can be detected relative to movement onset. A computational pipeline combining data-driven temporal segmentation with Random Forest model is applied to EMG data across planning, execution, and contact phases of a reaching task.

Early prediction can improve device responsiveness and support motor recovery with up to 80% accuracy across classification of 25 spatial targets. Results further show that motor intentions can be reliably decoded with reduced data, highlighting the potential for efficient, anticipatory control in adaptive rehabilitation systems.

Keywords: Motor Control · Random Forest · HMI · EMG.

1 Introduction

Reaching, grasping, and manipulating objects are fundamental components of human daily activity. These motor functions rely critically on the upper limb, highlighting the importance of preserving arm function for independence and interaction with the environment. While the neural decision-making and motor control are complex [14], in this study, we focus specifically on intention prediction, the ability to infer the direction and target of a movement from the electromyography (EMG) signal.

A key question in this context is how precisely movement intentions can be decoded from EMG signals in both spatial and temporal resolution, that is, how accurately the intended target can be identified and how early it can be predicted relative to movement onset. Previous studies suggest that neural signals recorded via EEG may reflect a general "go" signal, but provide limited information about the specific movement direction. Previous work has demonstrated that measurable EMG activity emerges as early as approximately 50 ms prior to movement onset, indicating early activation of motor commands [3] (Fig. 1c). It remains an

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open question whether such pre-movement EMG activity also encodes spatial aspects of the upcoming movement, such as reach direction or endpoint position. Understanding these limits is essential not only for basic neuroscience, but also for practical applications in rehabilitation and human–machine interfaces (HMI), such as prosthetic control and assistive robotics. An early prediction of movement intention enables HMI to anticipate actions rather than react and can assist patients when they intend to move, encouraging active participation. This reduces delays and promotes more effective and intuitive motor recovery.

To demonstrate this, we use a delayed reaching task with 5×5 spatial targets distributed by 14° azimuth/altitude to investigate upper-limb movement. In this task, the spatial goal of the reach is revealed to the participant in advance, while the initiation of the movement is withheld until a go cue (Fig. 1e). This setup ensures that EMG activity observed before movement onset can be attributed to motor planning and preparatory processes rather than to actual movement execution. This allows us to examine if the preparatory phase contains sufficient information not only to predict the imminent onset of movement, but also to infer the intended movement direction or target location before execution begins.

We start with assessing the classification performance to determine how accurately EMG can resolve different movement directions based on the EMG signal. To achieve this, we employ a Random Forest (RF), suited for these tasks [10]. We then systematically evaluate channel selection and feature reduction, determining how the number of EMG channels and temporal features affects predictive performance. Furthermore, we analyze predictive accuracy across temporal windows, spanning pre-motion, early motion, late motion, and holding to determine how intention-related information evolves over time.

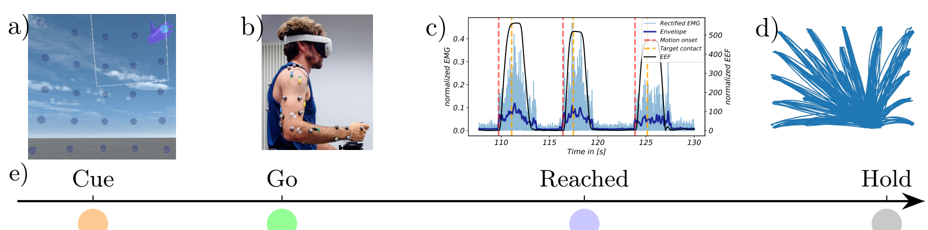

Fig. 1: Experimental setup and task: a) VR environment from the participant's perspective. b) placement of motion capture markers and EMG electrodes. c) EMG and End-EFfector trajectory, and task events. d) EEF trajectory. e) Task event timeline.

2 Method

The delayed reaching task is implemented in Unity and presented via an Oculus Quest 2 headset. Participants reach toward targets arranged in a 5×5 spherical grid (14° spacing) with a radius adapted to individual arm length (500–650

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mm), enabling reaching without trunk movement (Fig. 1a,d). The experiment consists of 3 sessions with 6 repetitions each; target order is randomized, resulting in 18 reaches per target. The study is approved by the Ethics Committee of Ruhr-University Bochum, and all participants provided written informed consent. EMG and positional data are recorded simultaneously. EMG is acquired at 2000 Hz using a Delsys Trigno system with 10 electrodes placed (triceps and biceps brachii, wrist and extensor, deltoid posterior/lateral/anterior, pectoralis, trapezius, latissimus dorsi), and processing is according to SENIAM [9]. Motion capture is performed at 100 Hz using a Vicon system with 6 cameras and 20 markers based on a modified Southampton Upper Limb model [16] (Fig. 1b,d).

3 Results

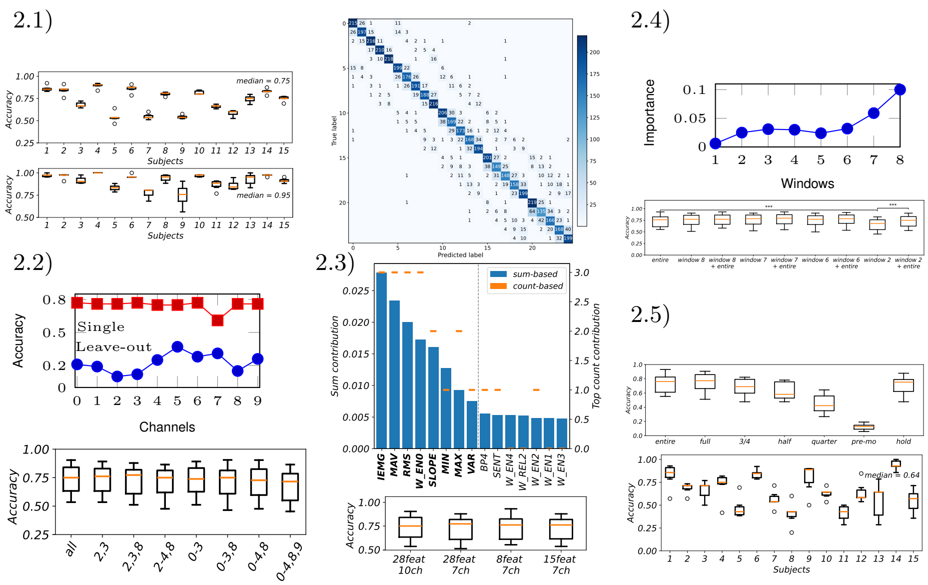

Fig. 2: Comprehensive Random Forest analysis combining baseline classification performance (2.1), channel importance (2.2), feature importance (2.3), temporal segmentation (2.4), and early intention decoding (2.5).

3.1 Spatial resolution Baseline Classification

Random Forest (RF) is commonly used as a baseline model due to its strong performance on high-dimensional, heterogeneous data and robustness to noise [6]. EMG features often exhibit correlation and redundancy due to muscle synergies and co-contraction patterns, which RF handles effectively through feature

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subsampling and ensemble averaging, reducing overfitting while preserving discriminative power.

To optimize model performance, hyperparameters are tuned using Optuna with a Tree-structured Parzen Estimator sampler. The optimized hyperparameters include 500 estimators, a maximum tree depth of 10, a minimum of 2 samples for splitting, 3 samples per leaf, and a maximum feature selection of the square root of number of features.

We evaluate the RF classifier using 5-fold cross-validation with an 80/20 train–test split in each fold. To account for inter-subject variability, separate models are trained for each participant. As an initial benchmark, a baseline configuration is assessed to provide an overall measure of classification performance. This baseline uses all available EMG channels, a single temporal window covering the entire reaching movement, and the full set of 28 extracted features. Under this configuration, the median classification accuracy across subjects was 75%, corresponding to a spatial resolution of up to 14°. Individual subject accuracies range from 50% to 90% (Fig. 2.1), with lower-performing subjects (50% − 60%: subjects 5, 7, 9, 11, and 12) showing similar trends across other classification approaches.

The confusion matrix (Fig. 2.1) illustrates the relationship between predicted and true class labels. As expected, given the high overall accuracy, the diagonal elements dominate, indicating a high rate of correct predictions. Misclassifications primarily occur between spatially adjacent targets left, right, above, or below the true location suggesting that errors are confined to nearby classes and reflecting a graded spatial encoding of movement direction in the EMG signals.

To explore the impact of task difficulty, we compare the full 5×5 target grid (each target 14° apart with 75% accuracy) with a reduced number of targets (every second target omitted, leaving 12 or 13 classes). Classification accuracy substantially improves, with median accuracy across participants reaching 95% (Fig. 2.1). Most subjects even approach 100% accuracy, though lower-performing subjects remain below this ceiling. Misclassifications continues to occur primarily between neighboring classes.

These results highlight that baseline performance is robust, while classification errors are localized to nearby targets. The next step is to systematically reduce data dimensionality to identify the most informative EMG channels and feature subsets for movement prediction.

3.2 EMG channel importance

EMG signals are recorded from ten muscles involved in reaching movements. Some muscles may carry redundant information due to co-contraction or antagonistic patterns. To assess their contribution, we evaluate each muscle individually and via a leave-one-out approach (Fig. 2.2).

This analysis identifies the wrist flexor, wrist extensor, and trapezius as the least informative channels. Excluding these three, the RF model maintains a median accuracy of 75% (Fig. 2.2). Further channel reduction leads to decreased

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accuracy, indicating that most recorded muscles provide relevant information for the prediction task, despite limited redundancy.

3.3 Feature importance

To characterize EMG signals for upper-limb intention decoding, we extract features from the time, frequency, and time–frequency domains [12], [2].

Time-domain features include mean absolute value, root mean square, waveform length, variance, integrated EMG, slope, as well as minimum and maximum values. Frequency-domain features comprise mean frequency, median frequency, peak frequency, spectral entropy, total power, and relative band power. Time–frequency features are obtained using a discrete wavelet transform, from which wavelet energy, relative energy, and wavelet entropy are computed.

All features are calculated independently for each EMG channel and concatenated into a single feature vector, yielding 28 features in total. While many time-domain features are highly correlated, RF classifiers are robust to such redundancy. To refine the feature set, we analyze each feature's contribution to prediction accuracy (Fig. 2.3) and select 8 features that preserve maximal performance. This subset retains all time-domain features except waveform length, includes wavelet entropy, and excludes most frequency- and time–frequency features. Using this reduced feature set and fewer channels, the median classification accuracy slightly improves to 76%, with a substantial reduction in data dimensionality from 280 to 56.

3.4 Temporal resolution

So far, all features are computed over the entire movement from go cue to target contact. To identify which temporal segments contribute most to classification, the reach is divided into eight non-overlapping windows of ~ 200 ms each, recommended by [8], with 8 features computed for 7 channels per window. This preserves the chronological structure of muscle activation patterns. Window-wise permutation importance (Fig. 2.4) reveals that late segments dominate, with windows 7 and 8 (final ~ 400 ms before target contact) contributing most to classification. Evaluating accuracy across different window selections (Fig. 2.4) shows peak performance when excluding only the first window and further improves when the full-movement window is included, reaching 80%. Removing additional windows reduces accuracy, indicating that while late segments are most informative, early windows provide complementary cues. Overall, these results demonstrate that discriminative information is temporally concentrated toward the end of the reach, but that aggregating information across multiple time scales, including an entire window, yields the most robust classification.

3.5 Early Intention Decoding

We have demonstrated that 25 different movement classes can be reliably predicted from EMG signals. Beyond identifying configurations that maximize classification performance, it is also clinically relevant to determine how early in time

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the intended movement direction can be inferred and what trade-offs in accuracy arise when predictions are made from partial temporal information. To this end, we systematically evaluate classification performance using progressively longer temporal segments, including the first quarter, first half, first three quarters, and full reach duration, as well as the post-contact hold phase. Additionally, we analyze pre-motion conditions in which the target is known, but actual movement is constrained (Fig. 2.5).

Prediction performance decreases systematically when the analysis is restricted to earlier temporal segments. Using only the first quarter of the reach results in an accuracy of 42%, reflecting lower discriminative information during early movement execution. Notably, the median classification accuracy during the pre-motion interval is 13% across participants, despite the absence of observable movement, which is still three times better than a random selection of 4 options.

We further aim to determine the resolution limit of our approach, specifically the minimum number of classes to which the problem must be reduced in order to achieve reliable classification performance. By reducing the number of classes to 4, i.e. only considering the corner targets, the median classification accuracy across subjects in the pre-motion interval increases to 64% (Fig. 2.4). However, substantial inter-subject variability persisted, with some participants achieving considerably higher performance than others. This finding suggests that preparatory muscle activation already encodes information about the intended target before movement onset, which has important implications for rehabilitation, as it enables anticipatory, intention-driven assistance rather than purely reactive control, thereby supporting more natural and effective motor recovery and daily-life interaction.

4 Discussion

Classification performance exhibits substantial inter-subject variability. While several participants achieve high accuracies, others show reduced performance. This high variability of EMG signal derives from differences in anatomy, electrode placement, and subcutaneous tissue properties [15], [5], [1], [11], [7], [4], [13]. Also, the trajectory of the arm movement varies more. Such inter-subject differences are well known in EMG-based classification studies and highlight the challenges of developing subject-independent and universally robust decoding models.

Channel selection reveals physiologically meaningful patterns: proximal muscles dominate target discrimination, while wrist muscles and trapezius contribute little. In contrast, biceps, triceps, anterior deltoid, and pectoralis major are most informative, consistent with their role in arm transport. This aligns with the biomechanics of reaching movements performed in front of the body. Overall selecting 7 of 10 channels provides strong discriminative power.

The feature selection results are consistent with previous EMG classification studies [12], [2]. Time-domain features exhibit high discriminative power, reflecting their sensitivity to muscle activation amplitude and temporal structure. In

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addition, wavelet entropy emerge as a highly informative feature, capturing the complexity and non-stationary characteristics of EMG signals.

Optimizing the number of channels, features, and temporal windows results in a substantial reduction of the input data dimensionality while maintaining classification performance. The best-performing configuration consists of seven EMG channels, eight features, and a combination of seven temporal windows plus an entire window spanning the whole reach, achieving a median accuracy of 80%. Which is high compared to other reaching predictions [8] for 8 targets with around 70%.

Furthermore, we investigate the earliest point in time at which movement intention can be reliably decoded. As expected, prediction performance is highest when using the full reach. However, meaningful classification is already possible before initial target contact. During the pre-motion interval, when the target is known but movement execution has not yet started, classification accuracy reaches 13%, averaged for all 25 targets, and 64% in the simplified four-class scenario. This finding indicates that preparatory muscle activity encodes target-specific information well before actual movement begins. The ability to decode movement intention during pre-motion and early execution phases is particularly relevant for assistive robotics, exoskeleton control, and neurorehabilitation. Early intention detection could enable more responsive and anticipatory assistance, improving user comfort and task performance. Moreover, the demonstrated reduction in required sensors and features supports the feasibility of deploying such systems in practical, wearable settings.

5 Conclusion

This study shows that intended reaching targets can be reliably decoded from upper-limb EMG using a compact and physiologically meaningful representation. A reduced setup of 7 channels, 8 features, and several temporal windows achieves up to 80% accuracy with minimal loss in performance. Proximal muscles dominate target discrimination, while wrist muscles contribute little, and time-domain and wavelet features are most informative. Importantly, movement intention can be predicted also before movement onset, with performance well above chance in the pre-motion phase. This highlights the potential of EMG-based decoding for anticipatory control in assistive and rehabilitation systems.

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