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Evaluating task characteristics as predictors of continuous hand motion decoding performance

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Abstract: Prosthetic hand control using biosignals requires robust decoding across diverse real-world conditions. We systematically evaluated how task characteristics influence muscular activity-based continuous hand motion decoding performance using the MyoKi database. Multiple linear regression with forward selection revealed that muscle fatigue modestly predicted task-wise decoding accuracy. Categorical task characteristics, such as grasp type, vertical task location, and force level, showed no significant effects on within-participant decoding performance in repeated measures ANOVAs, which demonstrates that the decoder maintains stable performance across diverse task characteristics. This is promising for prosthetic applications requiring robust performance across daily activities.

I. Introduction

Machine learning approaches for biosignal-based control of prosthetic and robotic hands have focused predominantly on maximizing decoding accuracy through algorithmic refinement [1]. However, understanding how experimental conditions influence signal decodability remains under-explored [2], highlighting a gap to optimize data acquisition protocols to train intelligent robotic hands and prostheses for optimal performance in real-world applications.

The present study leverages our recently published multimodal MyoKi database [3] (first participant subset with P01 to P25), which combines surface electromyography (sEMG), inertial measurement units (IMUs), and hand kinematics, including 74 naturalistic daily-life tasks performed with variable arm positions, object locations, and whole-body movements, to systematically assess continuous hand and wrist joint angle prediction. We examine how task characteristics (e.g., grasp type, required force, muscle fatigue, and task duration) influence decoding accuracy, providing insights for optimizing data acquisition protocols and prosthetic control strategies to improve prosthetic functionality and user acceptance.

II. Material and methods

In the MyoKi database, biosignals were recorded from participants' right arms using 12 sEMG electrodes and 9 IMUs (containing 3-axis accelerometers and gyroscopes). Six sEMG sensors were positioned on the upper forearm using the multimodal bracelet from Andreas et al. [4], with additional sensors placed on the mid- and lower forearm, as well as the upper arm and shoulder muscles. Hand motion was measured using an 18-channel sensor glove capturing finger and wrist joint angles. We used the LSTM model from the MyoKi database descriptor [3] with the same feature set to decode multimodal biosignals into continuous hand kinematics, with performance quantified using the coefficient of determination (R^2). A repetition-based 6-fold cross-validation approach was implemented, where each of the six task repetitions served once as the test set, with one other repetition for validation and the remaining four for training. R^2 scores were averaged across folds (after outlier removal) for each task-participant combination.

Specific subsets of tasks were selected to allow systematic variation of individual task characteristics while keeping other task properties as constant as possible. These subsets were defined a priori to isolate four categorical task factors: grasp type (cylindrical, spherical, hook, tripod, pinch, lumbrical; tasks 1–45), horizontal movement distance (short, medium, long; tasks 1–6, 16–27), vertical task location (below, at, and above table height; tasks 28–39, 46–48), and required force level (low, medium, high; tasks 9–14, 40–45, 49–51). To test whether these predefined within-participant task factors influenced decoding performance, separate repeated-measures ANOVAs were conducted with R^2 as the dependent variable. Before analysis, normality of within-participant differences was assessed using Shapiro–Wilk tests. For each factor, R^2 values were averaged across tasks within each factor level for each participant, yielding one value per participant per condition for statistical analysis.

To complement the categorical analyses, we examined task duration and median frequency (MDF) of EMG (an indicator of muscle fatigue [5]) as continuous predictors. Therefore, we averaged the data across all 25 participants to yield a single R^2 value per task. Following collinearity assessment of predictors (z-score normalized), these task-level R^2 scores served as the response variable in multiple linear regression (MLR) analyses using forward selection based on Akaike Information Criterion (AIC) to identify factors influencing task-wise decoding performance.

III. Results and discussion

Shapiro-Wilk tests on pairwise differences showed that most comparisons satisfied normality assumptions (grasp: 13/15, distance: 3/3, vertical location: 3/3, force: 2/3). Repeated measures ANOVAs revealed no significant main effects for any tested task characteristic on decoding performance: grasp type ($F(5,120) = 1.93$, $p = 0.094$), horizontal distance ($F(2,48) = 0.39$, $p = 0.679$), vertical task location ($F(2,48) = 0.02$, $p = 0.978$), and force level ($F(2,48) = 0.91$, $p = 0.409$) indicating that decoding performance remains stable across diverse task characteristics at the participant level.

While the tasks in the MyoKi database were designed to reflect naturalistic activities, this goes along with ecological confounding between certain factors (e.g., hook grasp and below-table vertical location, $r = 0.71$). This confounding limits the ability to isolate individual effects of grasp type versus vertical location. However, the absence of significant main effects for any categorical task characteristic suggests that the decoder maintains stable performance across the tested task space, despite these design limitations. Further limitations of the MyoKi database include that even high-force tasks involved only moderate weights (e.g., manipulating a 1 kg bottle, lifting a 3 kg bag), which may explain the absence of force-related effects on decoding performance. With heavier weights, two competing mechanisms could emerge: increased muscle fatigue may degrade signal quality, while stronger muscle activations may improve signal-to-noise ratios. Whether these effects cancel out or result in net performance changes under higher load conditions requires further investigation.

Collinearity analysis of continuous predictors revealed that MDF and task duration were independent ($r = 0.20$), indicating that fatigue is primarily task-dependent rather than duration-dependent. MLR with forward selection identified MDF as the sole significant predictor of task-level decoding performance (AIC = -464.10, Adjusted R^2 = 0.16). Recording Time was not selected by the AIC-based forward selection algorithm, indicating it does not improve model fit beyond what MDF already explains.

Table 1: Multiple linear regression (MLR) using forward selection for task-wise R^2 scores showing coefficient (β), standard error (SE), and p-value for each predictor.

Step	Predictor	β	SE	p
0	Const	0.6888	0.0013	<0.001
1	MDF	0.0049	0.0013	<0.001

Table 1 shows that higher MDF values (indicating less muscle fatigue) were associated with significantly better decoding accuracy. This finding aligns with the established understanding of fatigue-induced changes in EMG: as muscles fatigue, the power spectrum shifts toward lower frequencies due to reduced muscle fiber conduction velocity and altered motor unit recruitment patterns. This degradation in signal quality directly impacts decoder performance, confirming that maintaining fresh muscle state would be ideal for robust prosthetic control, which is in line with previous studies [5]. However, MDF only shows a medium effect size (Cohen's $f^2 = 0.21$). A 1 SD increase in MDF corresponds to a 0.0049 increase in R^2, which is 41.5% of the typical task-to-task variability (SD = 0.0118). In absolute terms, this change represents a small shift on the R^2 scale, indicating that although the relationship is statistically reliable, its practical impact is limited, and decoder performance remains relatively stable even under moderate fatigue.

This is a positive finding for practical usability and suggests that muscle fatigue barely impacts robust muscular activity-based hand motion decoding. To even mitigate the small negative effect, adaptive recalibration algorithms could monitor MDF in real-time and trigger decoder updates when fatigue is detected.

IV. Conclusions

This study systematically evaluated how task characteristics influence muscular activity-based continuous hand motion decoding. Muscle fatigue (indicated by MDF) was observed to have the largest influence on decoding performance, although the effect remained modest. All other investigated task characteristics (grasp type, horizontal distance, vertical task location, force level, and task duration) did not explain variations in task-wise R^2 scores. These findings indicate that decoding performance remains largely independent of task characteristics, with the decoder maintaining consistent accuracy across diverse movements. This robustness is particularly promising for prosthetic applications, where users face countless task variations during daily life, suggesting that comprehensive sensor coverage can enable task-independent motor control. Future databases using fully orthogonal factorial designs could provide more definitive evidence regarding individual factor effects and thus clarify the roles of grasp type and force level on task-wise decoding performance.

AUTHOR'S STATEMENT

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