Typifying power wheelchair joystick control using EMG feature and channel selection

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INTRODUCTION

Independent mobility plays a key role in the functional, social, psychological, and material dimensions of wellbeing [1–2]. Accordingly, people with mobility disabilities face multiple barriers to health-related quality of life. Power wheelchairs (PWCs) help mitigate those barriers for people with severe mobility disabilities. However, functional steering is extremely challenging for many PWC users [3] and is associated with both perceived and real safety risks [4]. Smart wheelchairs address those risks through computational assistance [5] but simultaneously risk imparting users with skill regressions, errant mental models, and attentional deficits [6]. Adaptive automation minimizes those residual effects by calibrating the level of assistance in real time based on contextual cues from the environment and the user.

In previous studies, we reported our work on contextualizing both components [7,8]. The user-based component [8] leveraged a vector autoregression model to classify electromyography (EMG) signals into PWC driving tasks. In that feasibility stage, classification was limited to one prediction per driving sequence rather than per time interval (e.g., every 125 ms) because the model was not exposed to real-time joystick movements. Furthermore, we used a fixed feature set without selecting or interpreting important features and channels.

In this study, we extended our previous EMG work via online classification, feature reduction, and feature assessment. The purpose was to typify PWC joystick control in terms of EMG activity. First, we brought real-time resolution to the EMG model by merging instantaneous joystick input and reimplementing the sequence-based classifier (based on minimum mean squared error) as a real-time classifier (based on regularized gradient boosting). Second, we quantified the most important features and channels per participant by using a redundance-relevance algorithm. Third, given the resultant feature rankings, we evaluated joystick control strategies via the directional class centroids within each participant's top-ranked feature spaces.

METHODS

Participants

Three members of the Rehabilitation Engineering Laboratory participated in this study. None presented with a physical disability.

Instrumentation

A microcontroller board (Mega 2560 R3, Arduino; Somerville, MA) was manually interfaced with the joystick microcontroller board of a front-wheel-drive PWC (C400, Permobil; Lebanon, TN) to intercept FORE_AFT and LEFT_RIGHT signals at 10 Hz. The EMG signals were sampled at 2,000 Hz using three-lead myoelectric amplifiers (EMG100C, Biopac; Goleta, CA) via bipolar surface electrodes (EL507, Biopac).

Procedure

Electrodes were placed over the cleaned and abraded motor points of five arm muscles: flexor carpi radialis (FCR), extensor carpi ulnaris (ECU), extensor carpi radialis (ECR), pronator teres (PT), and triceps brachii (TB). Based on tasks #8, #10, and #11 of the Wheelchair Skills Test for PWCs [9], four driving activities were assessed—forward: roll forward 10 m, rightward: turn right 90° while moving forward, backward: roll backward for 5 m, and leftward: turn left 90° while moving forward. Participants self-selected the most comfortable joystick grip: right-handed pinch grip for participant A and right-handed power grip for participants B and C. Each activity was repeated at least five times and up to eight times depending on participant availability. Activity segments were separated by brief resting periods.

Data Reduction

The joystick and EMG signals were synchronized using microsecond timestamps. The sparser joystick values were propagated forward to pad missing time points. The EMG signals were bandpass filtered using a recursive Butterworth design with low- and high-cutoffs of 20 Hz and 500 Hz, respectively.

A vector of 65 feature values was extracted from each 250 ms sliding window incremented by 125 ms, including 13 values per EMG channel: 6 autoregression (AR) coefficients, 1 mean absolute value (MAV), 2 mean absolute value slopes (MAVS), 1 root mean square (RMS), 1 slope sign change (SSC) count, 1 waveform length (WL), and 1 zero crossing (ZC) count.

Data Analysis

Classification was implemented using the extreme gradient boosting (XGBoost) algorithm, a modern tree boosting system with improvements over standard gradient boosters, including a regularized objective function to guard against overfitting. Joystick angles were partitioned into four polar bins to serve as classification labels. Joystick coordinates were only included if beyond a 20% radius of the neutral-to-maximum excursion distance. All classification was cross validated using a leave-one-trial-out policy.

Features were ranked using the minimal-redundance-maximal-relevance (mRMR) algorithm, a feature selection filter with a mutual information criterion for estimating the optimal compromise between feature-feature redundance and feature-target relevance. Liu et al. [10] used a similar approach to detect relevant features from 57 equally spaced EMG electrodes (i.e., not directly placed on motor points). The ranked features were successively combined as classifier inputs until diminishing returns were observed. With the resultant feature subset, the channels were then ranked by mRMR and successively combined as classifier inputs until diminishing returns were observed.

For each participant's top-ranked channel pair, feature centroids per joystick direction were generated for the top-ranked feature set.

All analysis was performed in Python 3.

RESULTS

During feature selection, cross validation plateaued after three, two, and three features for participants A, B, and C, respectively (Figure 1). For all three participants, the SSC feature was ranked highest and was also the only feature to be selected across all participants. The AR coefficients were ranked lowest across all participants.

During channel reduction, cross validation plateaued after three, two, and three channels, respectively (Figure 2). The top-ranked channel was different for each participant—ECU, TB, and ECR, respectively. The ECU channel was the only channel to be selected across all participants and was used as a reference axis for visualizing joystick directional classes across all feature spaces (Figures 3–5).

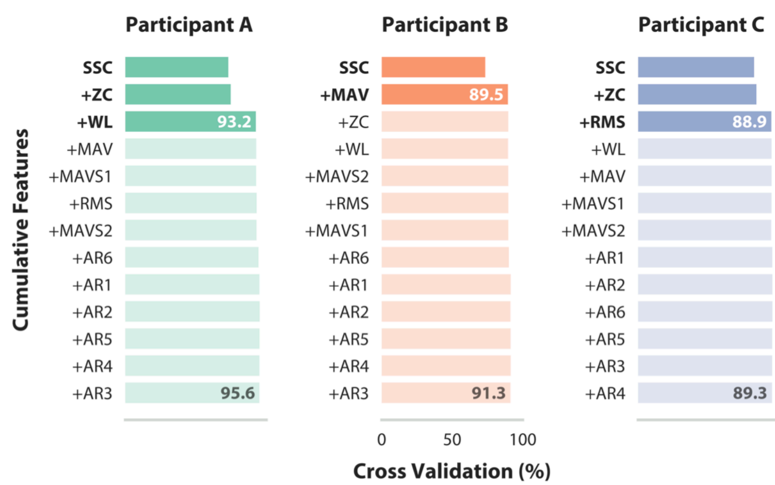

Figure 1. Reduced feature sets selected by successively combining each participant's ranked features to the point of diminishing returns in cross validation

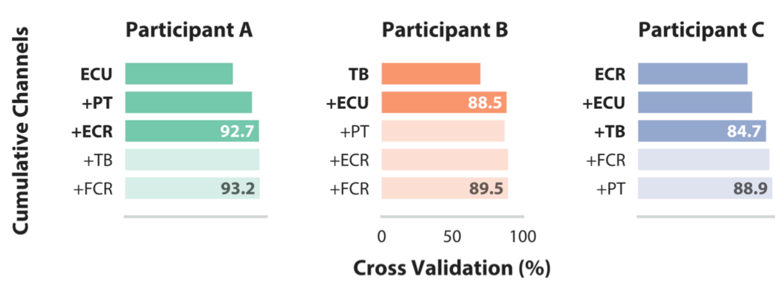

Figure 2. Reduced channel sets selected by successively combining each participant's ranked channels to the point of diminishing returns in cross validation

DISCUSSION

Our results are valuable both for development and assessment. By minimizing input dimensionality (i.e., -85.0%, -93.3%, and -85.0% per participant), we reduce computational load at a negligible cost to classification accuracy (i.e., -3.1%, -3.0%, and -4.6% per participant). By minimizing channel count, we reduce the number of sensors to be worn. For a smart wheelchair user, this can mean the difference between wearing five sensors versus two. Beyond smart wheelchair considerations, the filtering pipeline also reveals relevant features and channels for visual interpretation. In each reduced feature set, we have a basis to evaluate PWC joystick control with respect to frequency and amplitude. The SSC and ZC features are frequency surrogates that use time domain information to encapsulate frequency content indirectly. The MAV and RMS features are amplitude measures that encapsulate signal energy while WL encapsulates signal complexity.

Participant A's control strategy (Figure 3) can be summarized by extensor activity for left-right movements and pronator activity for fore-aft movements. The amplitude space also reveals extension-pronation interaction—PT and ECU amplitudes are correlated positively for fore-aft movements and negatively for left-right movements.

Participant B's control strategy (Figure 4) is unique in the high utilization of the upper arm, possibly related to using a power grip. In the fore-aft axis, TB amplitudes are higher and lower for forward and backward movements, respectively. In the left-right axis, TB amplitudes are higher and lower for rightward and leftward movements, respectively. The strategy is also unique in its extensor utilization. We see rightward movements yielding high ECU energy but low ECU frequency. Fatigue is a possibility given abnormal frequency content but unlikely here given experimental context. Since joystick control with resting periods seems unlikely to induce fatigue, there may have been other physiological factors or hardware interference involved. Also of note is the overlap between forward and leftward movements in both feature spaces. This class similarity may explain the lower classification accuracy compared to participant A.

Participant C's control strategy (Figure 5) is unique in its heavy reliance on both extensors. This homogenous strategy may explain the consistently lower scores in cross validation. In general, we see ECU activity explaining left-right movements and ECR activity explaining fore-aft movements. The TB feature also ranks highly for this participant although not plotted as a feature space. Given that the TB feature only appears for the power grip participants, triceps activity may be distinct to the grip type. Furthermore, power grips may yield reduced discrimination between certain class pairs. We see limited class separation between forward and leftward classes across all feature spaces of both participants B and C, as well as limited separation between backward and rightward movements for participant C.

These class similarities may indicate the absence of key features or channels needed to fully characterize joystick power grips. Our original set of features and channels may encapsulate sufficient information for PWC joystick pinch grips but not power grips. Alternatively, the mRMR algorithm may be overlooking the most discriminating features due to its classification-agnostic nature. In our results, we see frequency surrogates consistently outranking amplitude measures despite yielding apparently

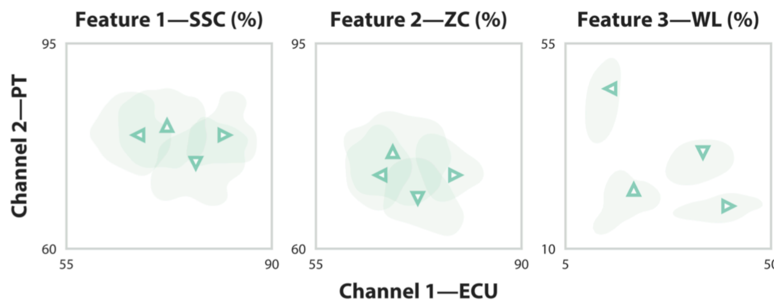

Figure 3. Joystick directional classes (contours) and centroids (arrowheads) in participant A's top-ranked feature spaces

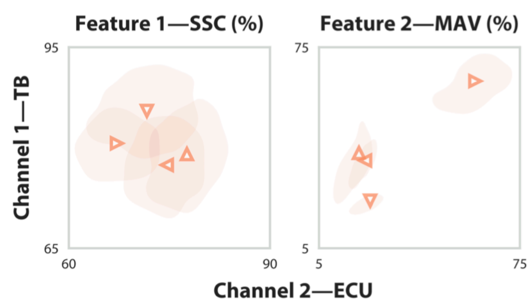

Figure 4. Joystick directional classes (contours) and centroids (arrowheads) in participant B's top-ranked feature spaces

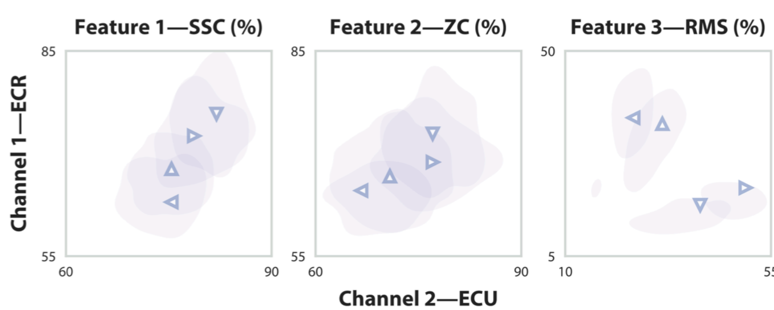

Figure 5. Joystick directional classes (contours) and centroids (arrowheads) in participant C's top-ranked feature spaces

lower discriminability. Feature filters as a whole only consider intrinsic statistical properties—e.g., correlation, entropy, mutual information, etc.—without explicitly considering class discriminability. Classification-aware reducers maximize class separability but at a high computational cost. A hybrid feature reduction pipeline could initially use mRMR to select candidate features and subsequently rank those candidates with a classification-aware wrapper.

In future work, we will explore features, channels, and algorithms to better characterize PWC joystick power grips. More participants, including people with disabilities, will be recruited. With online functionality now implemented in both the environment- and user-based components, we will continue working toward a context-aware smart wheelchair with adaptive automation. Given risk levels reported by our environment-based component and congruence levels reported by our user-based component, the level of automation would be adjusted accordingly in real time.

CONCLUSIONS

This study identified the ulnar extensor as a commonality in PWC joystick control across all participants and grips. Feature space analysis further suggested that PWC users with pinch and power grips relied on pronator- and triceps-based tuning strategies, respectively. This preliminary finding on grip-based control strategies may be useful for PWC prescription and training. The finding also informs EMG-based PWC aids by identifying key features and muscles for real-time joystick classification.

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