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Optimization of Data Quality Related EMG Feature Extraction Parameters to Increase Hand Movement Classification Accuracy

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Abstract— **Many biomedical robotic interfaces (e.g., prostheses, exoskeletons) classify or estimate user movement intent based on features extracted from measured electromyograms (EMG). In most cases, the parameters of feature extraction are determined heuristically or assigned arbitrary values. We propose a more rigorous method, numerical optimization, to systematically identify parameters that maximize classification accuracy based on EMG signal characteristics. In this study, we used simulated annealing, a common global numerical optimization method, to find the optimal values of three feature extraction parameters based on the root mean square (*rms*) magnitude of the EMG signal. The EMG data, obtained from a public database, had been measured from 2 muscles (one hand flexor and one hand extensor) of 5 able-bodied participants performing 6 different movement tasks. Using optimization, we increased the offline movement classification accuracy by 3-5% for each participant and from 79.91% to 92.25% overall. The value of one optimized parameter (threshold of Wilson amplitude) was strongly correlated with the *rms* magnitude of the EMG signal (R^2=0.81). Other parameters were suspected to be related to signal noise, since no strong correlation with *rms* magnitude was observed. Future studies will refine the optimization approach and test its practicality and effectiveness for improving online classification accuracy with robotic interfaces.**

Clinical Relevance— **Parameter optimization can potentially make EMG-based control more accurate and reliable by automatically accounting for variations in EMG signal quality across channels or time without changing the data collection procedure.**

I. INTRODUCTION

Estimating movement intent is a critical component of providing users effective volitional control of robotic interfaces such as prostheses and exoskeletons [1, 2]. Electromyograms (EMG), electrical signals measured from muscles during contraction, are one of the most common bio-signals used for estimating movement intent. Various artificial intelligence (AI)-based classification algorithms (i.e. classifiers) have been used by researchers to estimate intended movements using features extracted from EMG signals [e.g., 3, 4]. The accuracy of movement classification depends on factors such as the classifier used, classifier parameters, types of features extracted, and correlation between features. Previous studies have reported the feature combinations and classifier parameters that tend to increase classification accuracy [5, 6].

A relatively understudied factor that affects classification accuracy is "values of feature extraction parameters". Feature extraction is performed using algorithms that compute a numerical value from a short (typically <500 ms) window of EMG data. Many feature extraction algorithms have parameters whose values are intended to be based on characteristics of the EMG signal. For example, commonly used EMG features like number of zero crossings (ZC) and Wilson amplitude (WAMP) have parameters whose values should be based on the EMG signal-to-noise ratio and magnitude, respectively.

Previous studies have shown that the extracted feature values and movement classification accuracy can be highly sensitive to the values of feature extraction parameters [7]. Therefore, it is critical to assign appropriate parameter values to maximize classification accuracy. Unfortunately, in most cases, the EMG signal characteristics and feature extraction algorithm parameter values are not determined rigorously; rather, the parameters are typically assigned constant values across all data collection channels based on previously defined "best practices". This is problematic because EMG signal characteristics can vary across users, channels, and time due to hard-to-control factors such as electrical noise from the device/environment, skin preparation, sensor location, and user anatomy (e.g., subcutaneous fat). Thus, there is a need for methods to determine optimal feature extraction parameter values that account for varying EMG signal characteristics each time the user dons the robotic interface.

Numerical optimization is one potentially effective approach to compute feature extraction parameter values that maximize movement classification accuracy. Numerical optimization has been used in countless applications; the authors previously used numerical optimization to define parameters for a musculoskeletal model-based prosthesis controller [8, 9]. Movement classification often requires several EMG channels and, thus, defining several feature extraction parameter values; in this case, global numerical optimization algorithms are needed to increase the chance that a set of parameter values achieves a global (not local) maximum classification accuracy.

In this study, our goal was to determine the extent to which movement classification accuracy could be improved by global numerical optimization of feature extraction parameters for each EMG channel, rather than applying the same generic parameters to all channels across all participants. Our analysis replicated that of a previous study on a publicly available dataset [3], except that we (1) computed feature extraction parameter values using simulated annealing, a common global optimization algorithm and (2) used a different classifier (rationale and description provided in Section II). We

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computed parameter values for two optimization scenarios that maximized movement classification accuracy either for each participant separately or across all participants. Finally, we performed correlation analyses to see how parameter values related to physiologic EMG signal characteristics.

II. METHODS

A. Electromyography data

We used the same data as Sapsanis, *et al.* [3], which included EMG data from 5 able-bodied participants. In their study, two bipolar EMG electrodes were placed on the skin, one over the flexor carpi ulnaris muscle and the other over the extensor capri radialis, longus and brevis muscles [10]. Each EMG signal was considered a "channel"; since there were 2 channels per participant and 5 participants, there were 10 total channels. EMG data were recorded using a desktop system (Bagnoli, Delsys, USA) with an analog-digital conversion card (USB-6009, National Instruments, USA) at 500Hz using Labview software (National Instruments, USA) [11]. Each participant performed 30 trials each of 6 different hand movements (30 trials x 6 movements = 180 total trials). Each trial was 6 s long. Like Sapsanis*, et al.* [3], before performing any procedures described below, the EMG data were filtered using a 4^{th} order high pass Butterworth filter with a cutoff frequency of 15 Hz and an IIR notch filter of 50 Hz.

B. Onset detection

Onset detection of an EMG signal directly depends on the amount of noise in the signal. Like Sapsanis*, et al.* [3], we used a 40-ms sliding window to detect the onset. Onset was assumed when the integrated EMG, $IEMG = \frac{1}{N}\sum_{k=1}^{N}|x_k|$ was greater than a threshold T1. x_k is the k^{th} data sample, and N is the number of data samples in a 40-ms window. Since there were 2 channels for each trial, the earlier onset time between the two channels was considered the onset time for that trial.

C. Data segmentation

From the onset detection until the end of the signal, the data were segmented into smaller windows and the movement was classified for each window. Like Sapsanis*, et al.* [3], we chose overlapping 300-ms segmentation windows that were displaced by 30 ms (i.e. consecutive windows overlapped each other by 270 ms). Overlapping windows are commonly used for EMG-based interfaces (e.g., prostheses, exoskeletons) because they make the interface's response to the user's movement intentions closer to real time.

D. EMG feature extraction

The same eight features as Sapsanis*, et al.* [3] were extracted from each window and each EMG signal for movement classification. These features were IEMG, zero crossing, variance, slope sign changes, waveform length, Wilson amplitude, kurtosis, and skewness. Out of these 8 features, two (zero crossing and Wilson amplitude) depend on the relative amplitudes of the EMG signal and noise. Zero crossing is calculated as:

$ZC = \sum f(x)$, where

$$f(x) = \begin{cases} 1, & ((x_k > 0 \; AND \; x_{k+1} < 0) OR (x_k < 0 \; AND \; x_{k+1} > 0)) \\ & AND \\ & (|(x_{k+1} - x_k| > T2) \\ 0, & otherwise \end{cases}$$

for $k = 1,2,3,$ … *N-1*

The optimal value for threshold T2 should be inversely proportional to the signal-to-noise ratio; if the noise amplitude is relatively high, then T2 should be increased to make sure that the ZC feature is independent of the noise.

Wilson amplitude is calculated as:

$$WAMP = \sum_{k=1}^{N-1} f(|x_{k+1} - x_k|)$$

$$f(x) = \begin{Bmatrix} 1 \;\; if \; x > T3 \\ 0 \; otherwise \end{Bmatrix}$$

for $k = 1,2,3,$ … *N-1*

The optimal value for threshold T3 should be directly proportional to the signal-to-noise ratio.

Since the optimal values of thresholds T1, T2 and T3 depend in part on the signal amplitude, the thresholds were computed as:

$T1 = r1 \; \times rms(signal)$

$T2 = r2 \; \times rms(signal)$

$T3 = r3 \; \times rms(signal)$

where, rms is the root mean square of the EMG signal calculated over the entire trial, and $r1$, $r2$, and $r3$ are scaling parameters. Initially, we defined the values of these r-parameters to be the same for all participants and all trials to represent the standard approach as described in Section I while best matching the thresholds used by Sapsanis *et al.* [3]: $r1 = 0.5, r2 = 0.05, r3 = 0.05$ (Figure 1). In subsequent steps, we used a numerical global optimization approach (Section II.F) to compute the *r*- parameter values.

E. Movement Classification

We used a support vector machine (SVM) algorithm for movement classification. SVM was used since it is more efficient than many other classification algorithms *[12]* and has been used to classify movement using EMG features *[13, 14]*. The participant-specific classification accuracy with SVM was 3-9% higher that with the simple linear classifier used by Sapsanis*, et al. [3]* (Table I). We used a gaussian kernel in the SVM implementation.

F. Global Optimization of Feature Extraction Parameters

We used a simulated annealing global optimization algorithm [15, 16] to compute the values of $r1, r2$ and $r3$ that maximized a cost function (the classification accuracy). Simulated annealing was chosen because it can handle a non-continuous cost function, making it more robust than some other global optimization algorithms.

The values of the r -parameters were optimized for each EMG channel in two steps (Figure 1). In **Step 1**, r-parameter values were computed in 5 separate optimizations to maximize the movement classification accuracy (Section II.G) for each participant; we used parameter values $r1 = 0.5, r2 = 0.05, r3 = 0.05$ for all channels as our initial guess. In **Step 2**, a single optimization was performed to compute r-parameter values that maximized movement classification accuracy across all participants (that is, the overall classification accuracy), using r-parameter values computed from Step 1 as our initial guess.

Since optimization is computationally expensive, we segmented the data into non-overlapping 300-ms windows during Steps 1 and 2 of the optimization process. After obtaining the optimal values of r-parameters from each optimization step, we classified movements using overlapping windows in the segmentation as described in Section II.D; this allowed us to compare classification accuracy between optimized and non-optimized r-parameter values.

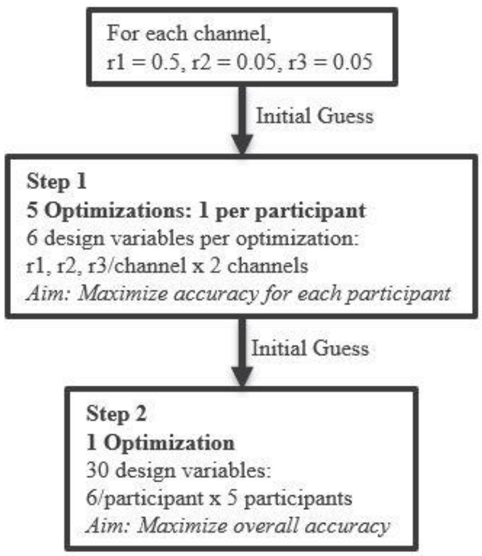

Figure 1. Flow diagram of the optimization process. Step 1 optimizes $r1, r2$ and $r3$ to maximize movement classification accuracy for that participant. Step 2 optimizes $r1, r2$ and $r3$ to maximize movement classification accuracy across all participants.

G. *Classification Accuracy*

We computed the movement classification accuracy for three different scenarios: (1) constant r -parameters, (2) r -parameters computed from optimization Step 1, and (3) r -parameters computed from optimization Step 2. For each scenario, one SVM model was trained and tested for each participant (5 participant specific SVM models) and one SVM model that was trained and tested using data from all participants. With the participant-specific SVM model, movement classification accuracy was calculated for each participant using a 5-fold cross validation approach. With the across-participant SVM model, the "overall" movement classification accuracy was calculated using a 10-fold cross validation approach, since there was more data when combined across participants. We included the classification accuracy results from Sapsanis, *et al.* [3] for reference.

III. Results

Table 1 displays the movement classification accuracy before and after optimization. The participant specific accuracy values achieved by Sapsanis, *et al.* [3] are listed for reference, though they failed to mention the values of T1, T2 and T3; hence the r-parameters for their study could not be computed. Changing from a simple linear classifier to SVM with constant r-parameter values ($r1 = 0.5, r2 = 0.05, r3 = 0.05$) increased the classification accuracy of each participant compared to results from Sapsanis, *et al.* [3]. Optimizing the r-parameters to maximize each participant's classification accuracy (optimization Step 1) increased each participant's movement classification accuracy by 3-5%. Overall accuracy also increased after optimization Step 1 from 79.91% to 89.24% even though the aim of this step was only to increase the accuracy of each participant independently. Step 2 of optimization further increased the overall accuracy to 92.25%, a 12.34% increase compared to the overall accuracy when the same $r1, r2$ and $r3$ values were used for all channels. Not surprisingly, since the aim of Step 2 was only to increase the overall accuracy, the classification accuracy of each participant decreased from Step 1 to Step 2 by up to 2% for some participants.

IV. Discussion

We have shown that numerical optimization of select feature extraction parameters can be an effective way to address the problem of inconsistent signal-to-noise ratio across EMG channels. In clinical applications, optimization could be performed as a calibration step at the time a patient is fitted with an exoskeleton or prostheses. Optimization automatically overcomes issues related to data quality without changing the data collection process, reducing demands for data collection expertise and precision on practitioners. In this way, optimization could lower barriers to commercialization and clinical translation of EMG-driven robotic interfaces.

To understand the relationship between EMG data characteristics and the optimized values of $r1, r2$ and $r3$, we assessed the linear correlation between the thresholds (T1, T2, T3) post optimization step 2 and mean rms values of the

TABLE I. MOVEMENT CLASSIFICATION ACCURACY (%)

Classification accuracy	**Sapsanis, *et al.* [3] (*r* - parameters unknown)**	***r*1 = 0.5, *r*2 = 0.05, *r*3=0.05**	**Step 1: *r* -parameters optimized per participant**	**Step 2: *r* -parameters optimized for all channels and all participants**
Participant 1	85.24	91.52	95.74	95.84
Participant 2	83.88	92.2	97.39	95.81
Participant 3	84.82	89.05	93.40	93.70
Participant 4	86.92	90.44	93.82	93.12
Participant 5	92.38	95.9	98.09	97.65
"Overall" (across all participants)	Not reported	79.91	89.24	92.25

channels. Linear correlation was quantified as the coefficient of determination, R^2. Fig. 2 shows a strong correlation (R^2 = 0.81) between the optimal thresholds of WAMP (T3) and the mean rms value of the channels. This observation is consistent with our expectation that an optimal T3 value should be directly proportional to the signal-to-noise ratio. The observation is physiologically reasonable since WAMP depends on the absolute difference between consecutive data points of the signal, and a signal with a higher signal amplitude can afford to have a higher WAMP threshold.

The correlations of post-optimization thresholds T1 and T2 with mean rms value of each channel were weak, with R^2 values of only 0.48 and 0.41, respectively. This was likely because both thresholds are more dependent on the noise amplitude rather than the signal amplitude. In this case, optimizing T1 and T2 based on a different signal characteristic than rms may further improve classification accuracy and elucidate how the thresholds relate to signal characteristics. Additionally, changing threshold T1 affects the onset of the signal, the data points that compose each window, and, thus, the values of all the extracted features; determining how the threshold T1 affects the classification accuracy requires a more in-depth analysis that was beyond the scope of our study.

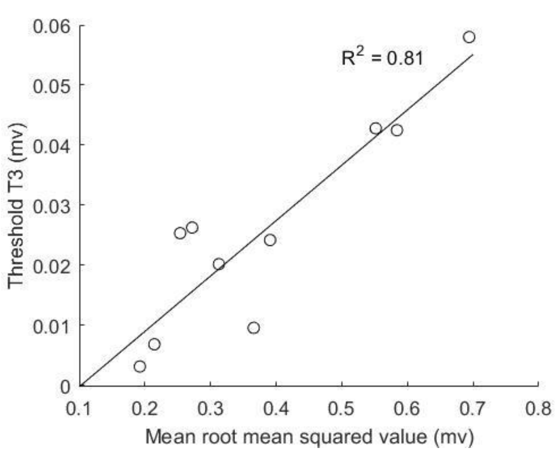

Figure 2. Wilson amplitude threshold vs mean RMS values of all channels. The positve correlation indecates that signals with higher strength can afford to have a higher threshold for Wilson Amplitude.

Although we were able to increase classification accuracy, our study had certain limitations. First, optimization is computationally expensive, and the calibration process using optimization to increase accuracy can take hours to converge. Optimization time, though, can be reduced by using techniques such as parallel processing. Second, we used one optimization algorithm (simulated annealing), one classification algorithm (SVM), and only 8 EMG features. It is possible that other optimization algorithms, classification algorithms, and features might generate better classification accuracy and should be explored in future studies. The aim of this study, however, was only to test our hypothesis that optimization of select parameters in the feature extraction process can increase classification accuracy, not to generate the highest possible accuracy.

V. Conclusion

We developed and tested a global numerical optimization framework that can address the problem of EMG data quality at the feature extraction stage, without changing the data collection process itself. Optimization increased movement classification accuracy by 3-5% for each participant and by 12% overall. We expect that optimization would be simple and inexpensive to implement as a calibration step for EMG driven robotic interfaces to improve performance and user satisfaction. Future studies should also (1) investigate the relationship between optimized parameters and signal characteristics, and (2) test other optimization approaches to maximize movement classification accuracy.

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