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Comparison of surface and intramuscular EMG pattern recognition for simultaneous wrist/hand motion classification

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Abstract

The simultaneous control of multiple degrees of freedom (DOFs) is important for the intuitive, life-like control of artificial limbs. The objective of this study was to determine whether the use of intramuscular electromyogram (EMG) improved pattern classification of simultaneous wrist/hand movements compared to surface EMG. Two pattern classification methods were used in this analysis, and were trained to predict 1-DOF and 2-DOF movements involving wrist rotation, wrist flexion/extension, and hand open/close. The classification methods used were (1) a single pattern classifier discriminating between 1-DOF and 2-DOF motion classes, and (2) a parallel set of three classifiers to predict the activity of each of the 3 DOFs. We demonstrate that in this combined wrist/hand classification task, the use of intramuscular EMG significantly decreases classification error compared to surface EMG for the parallel configuration ($p<0.01$), but not for the single classifier. We also show that the use of intramuscular EMG mitigates the increase in errors produced when the parallel classifier method is trained without 2-DOF motion class data.

I. Introduction

Myoelectric prostheses have traditionally used the surface electromyogram (sEMG) to provide control signals. Much of the current myoelectric control literature has continued to use surface signals, as they are convenient and noninvasive. Intramuscular recordings provide an alternative source of EMG signals and address some of the difficulties associated with sEMG-based control, such as maintaining robust electrode contact with the skin. Intramuscular EMG (imEMG) also provides addition benefits, such as the ability to record from deep muscles with little EMG crosstalk. ImEMG has been clinically infeasible, as it requires the use of percutaneous wire/needle electrodes to transmit signals to the prosthesis. However, the development of wireless implantable recording devices [1] may soon make imEMG a viable signal source for myoelectric prostheses. Therefore, investigations regarding the potential of imEMG for myoelectric prosthesis control are necessary.

Pattern recognition using EMG has provided a successful approach for classifying single degree of freedom (DOF) motions in a sequential manner [2–5]. The use of both sEMG and imEMG has been previously evaluated. Both signal sources have shown equivalent classification accuracy of wrist movements and hand grasps when intramuscular electrodes are targeted to muscles corresponding to intended movements [4, 5]. Few previous studies have investigated simultaneous finger control using imEMG pattern classification [6–8];

most studies using pattern recognition to simultaneously control two DOFs have used sEMG [9–13].

One straight-forward approach for simultaneous multi- DOF control using pattern recognition is to simply include 2- DOF movements, labeled as distinct motion classes, in the training of a single pattern classifier (e.g. the classifier discriminates between motion classes that include supination, hand closed, and supination/hand closed) [9, 11–13]. A second straight-forward approach uses a "parallel" architecture of pattern classifiers [6, 10, 11, 13], where multiple classifiers are used in parallel to independently classify different DOFs simultaneously. The parallel strategy is an attractive approach for simultaneous multi-DOF pattern recognition control, because it may be trained with only 1- DOF motion exemplars (whereas the single-classifier approach requires exemplars for all possible DOF combinations); however, providing combined movement exemplars does result in lower classification errors when using sEMG [13]. Furthermore, the parallel architecture may provide a straightforward avenue for simultaneous proportional control, by applying algorithms currently used to provide proportional control estimates for sequential pattern recognition [14].

The objective of this study was to compare the offline classification accuracy of combined wrist/hand movements using both sEMG and imEMG pattern recognition. This was evaluated using both a single classifier and a parallel classifier approach.

II. Methods

A. Experimental Protocol

Four able-bodied control subjects participated in the following experiment, which was approved by the Northwestern University Institutional Review Board. EMG was recorded using either intramuscular or surface electrodes during two separate sessions. ImEMG signals were collected using percutaneous fine-wire electrodes (CareFusion, San Diego, CA) that were inserted using 25 ga hypodermic needles. Bipolar electrodes were inserted into six forearm muscles: pronator teres, supinator, flexor carpi radialis, extensor carpi radialis longus, flexor digitorum profundus, and extensor digitorum. Insertion locations were identified by palpation and confirmed by observing EMG channel activity during corresponding test contractions. A sEMG electrode on the olecranon was used for ground. Signals were collected using a Motion Lab Systems MA300 EMG system connected to a National Instruments DAQ (NI-USB 6218). Signals were amplified, bandpass filtered between 10–2000 Hz, and sampled at 5 kHz. sEMG signals were collected using 6 bipolar surface electrodes along the circumference of the proximal forearm, approximately 2 cm distal to the elbow. One electrode was placed on the main wrist flexor muscle group and one was placed on the main wrist extensor muscle group. Two additional electrodes were each placed on the anterior and posterior forearm, distributed equally between the main flexor and extensor bundle electrodes. Electrodes were not targeted to specific muscles, as previous literature has shown that targeted placement of surface electrodes has little effect on classification [5]. A ground electrode was placed on the olecranon. Signals were collected using a Delsys Bagnoli-16 Amplifier connected to a National Instruments DAQ (NI-USB 6218). Signals were amplified, bandpass filtered between 20–450 Hz, and sampled at 1 kHz.

After the electrode placement (either intramuscular insertion or surface adhesion), subjects were restrained in a neutral posture by a custom brace that restricted forearm rotation, and wrist and hand movement. Subjects were instructed by visual and audial prompt to produce isometric contractions of both discrete 1-DOF wrist/hand motions or simultaneous 2-DOF wrist/hand motions. EMG signals for fifteen motion classes were collected in total: 1 no motion/relaxation class, 6 single-DOF motions (pronation/supination, wrist flexion/

extension, and hand open/close), and 8 combined wrist/hand motion (pronation/supination with hand open/close and wrist flexion/extension with hand open/close). Subjects were provided a practice period to become accustomed to making contractions in the brace. Four repetitions of contractions were then collected. Subjects were instructed to produce comfortable, moderate level contractions for 3 s each, providing 12 s of signal in total for each motion. Analysis of classification performance was then completed offline.

B. EMG Data Processing

The presence of crosstalk in both the sEMG and imEMG signals was evaluated by calculating correlation coefficients between individual channels.

EMG features were extracted from 250 ms non-overlapping windows [15] of the collected signals. Both time domain [16] and autoregressive features [17] were calculated for each window to train the pattern classifiers.

C. Classifier Configurations

All classifier configurations used linear discriminant analysis (LDA) classifiers. Preliminary analysis comparing LDA classifiers and support vector machines showed no difference in performance for linear, third-order polynomial and Gaussian kernels. LDA classifiers were therefore used for ease of implementation.

The *single classifier* approach used one LDA classifier. This classifier was trained to discriminate between the fifteen motion classes collected: 1 no motion/rest motion class, 6 single-DOF motion classes and 8 combined wrist/hand motion classes, as previously described.

The *parallel classifier* approach used three LDA classifiers: one for each DOF (wrist rotation, wrist flexion/extension, and hand open/close) (Figure 1). Each LDA classifier distinguished between the two opposing motion classes for the DOF (e.g. supination and pronation for wrist rotation) and a no motion class. The overall commanded movement was the combination of the outputs from each classifier. The parallel classifiers were trained with and without 2-DOF motion class data. The 'no motion' class for all classifiers was trained using any exemplar where the DOF of interest was not active (e.g. the no motion class in the hand classifier was trained with true no motion, wrist flexion/extension, and supination/pronation exemplars, etc.).

D. Classifier Evaluation

Four classifiers were evaluated for each subject: (1) a single classifier using imEMG, (2) a single classifier using sEMG, (3) parallel classifiers using imEMG, and (4) parallel classifiers using sEMG. Classifiers were trained on the extracted features described above. For initial comparisons, both parallel classifiers were trained using both 1- and 2- DOF motion class data.

Classification error was calculated using random subsampling validation [18]: error was averaged over twenty repetitions, where a random sample of 90% of windows of each motion class was used for training, and the remaining data was used for testing. Overall classification error represented an equally weighted average of each of the fifteen motion classes collected. Classification error was also grouped and averaged for all 1-DOF intended movements and for 2-DOF intended movements.

We also evaluated the classification error when parallel classifiers were trained with only 1-DOF motion class training data.

E. Statistical Analysis

Repeated measures analysis of variance (ANOVA) with post-hoc comparisons using the Tukey method was used to compare overall, no motion, 1-DOF, and 2-DOF classification error between the four classifier/signal source configurations.

For both imEMG and sEMG parallel classifiers, the effect of removing 2-DOF motion class training on 1-DOF and 2-DOF motion classification error was evaluated using paired t-tests.

Significance was evaluated with $\alpha = 0.05$. Residuals were confirmed to be normally distributed.

III. Results

Table I shows the correlation between channels for both intramuscular and surface raw EMG for one representative subject. Correlation coefficients with magnitudes greater than 0.5 are highlighted. There is almost no correlation between channels in the intramuscular signals, but substantial correlation between channels in the surface signals.

The overall, 1-DOF, and 2-DOF classification errors were significantly influenced by the combinations of classifier configuration and signal source ($p<0.01$) (Figure 2). There was no difference in no motion classification between the classifier configurations or signal sources.

Post-hoc comparisons revealed that a parallel classifier using imEMG produced significantly less overall, 1-DOF, and 2-DOF error compared to a parallel classifier using sEMG ($p<0.01$). A single classifier using imEMG produced a consistent but non-significant decrease in error when compared to a single classifier using sEMG.

Post-hoc comparisons also revealed that when using imEMG, the error of the single classifier was no different than the parallel configuration. However, when using sEMG, the single classifier produced significantly less overall, 1-DOF and 2-DOF error than the parallel classifier ($p<0.05$).

For both the sEMG parallel classifier and the imEMG parallel classifier, the removal of 2-DOF motion classes from the training data set caused large significant increases in 2-DOF motion classification error ($p<0.05$) (Figure 3). When no 2-DOF motion class training data was used, both the sEMG parallel classifier and the imEMG parallel classifier had very large 2-DOF motion classification errors (49% and 76%, respectively). For the sEMG parallel classifier, there was also a small significant decrease in 1-DOF motion classification error ($p<0.01$).

IV. Discussion

This preliminary study demonstrates the effects of using imEMG on the classification error of simultaneous wrist/hand movements using two pattern recognition strategies previously described in the literature (a single-classifier and a set of parallel classifiers) [6, 9–13]. Similar to [4, 5], using imEMG signals produced no significant reductions in error from sEMG for a single classifier approach (Figure 2). However, we show that the use of imEMG produced a significant decrease in classification error for parallel classifiers. Therefore, while a single classifier significantly outperformed a parallel classifier using sEMG (as was previously shown in [11, 13]), the use of imEMG decreased the parallel classifier's error to nearly that of the single classifier. The use of imEMG makes the parallel configuration a more promising approach for simultaneous control than had been previously suggested in sEMG studies.

The use of imEMG also improved error when attempting to train a parallel classifier without 2-DOF motion training data (Figure 3). One theoretical benefit of the parallel-classifier architecture that distinguishes it from the single-classifier approach is the possibility of training the classifiers without the use of simultaneous multi-DOF data. This is an attractive property of the parallel configuration, because the number of motion classes required to train a single-classifier for simultaneous multi-DOF control becomes burdensome as more DOFs are included. Neither imEMG nor sEMG provided useable levels of error when only 1-DOF motion classes were used to train the parallel classifiers. However, the use of imEMG mitigated this error (49% vs. 76% 2-DOF error for imEMG vs. sEMG, respectively).

ImEMG signal properties and the difference between the parallel and single classifier configurations may explain the error reductions seen with the parallel configuration. Perfect performance of the single classifier requires that motion classes are linearly separable. (While this study's error rates indicate that the classes are not completely separable, the low error suggest that classes are mostly separable, and subjects could potentially improve the separability of motion class features given real-time feedback.) In addition to this requirement, the parallel classifier also requires motion classes sharing at least one active DOF motion (e.g. supination, supination/hand open and supination/hand closed) to be grouped in feature space and separable from motion classes sharing the opposite motion. ImEMG may be a better signal source for such a configuration, because it provides signals with substantially less crosstalk, as is demonstrated by the decrease in inter-channel correlation when compared to sEMG signals (Table I). The decreased crosstalk results in more independently distributed EMG features, which may aid in the separability of the grouped feature distributions. In contrast, a single classifier, which does not use such groupings, may not benefit as much from this property of imEMG. Such findings are consistent with [4, 5], which showed no difference between imEMG and sEMG with a single classifier for 1-DOF motions.

The presented work focuses on the offline classification accuracy of two pattern classification approaches for simultaneous wrist/hand control using imEMG and sEMG. Future work should investigate whether pre-processing with source separation algorithms (e.g. principal component analysis, independent component analysis, or non-negative matrix factorization) could improve classification of 2-DOF motions by identifying similarities with the features of each 1-DOF motion class. This work is limited to a comparison between pattern recognition using imEMG targeted to muscles of interest and untargeted sEMG. Though previous work [5] has demonstrated no difference between targeted and untargeted sEMG for a single classifier configuration, this has not been demonstrated for the parallel configuration, and should be investigated in future studies. Future work should also focus on the development of proportional control algorithms and the real-time evaluation of prosthesis control using these classifiers. ImEMG has the potential to be a useful signal source for proportional control, as one can evaluate the EMG amplitude (and estimate intended contraction strength) of specific muscles that control the DOF of interest. This work is also limited to the use of able-bodied control subjects. Future studies will extend this evaluation to persons with amputations, who may produce different patterns of muscle activation / co-contraction than subjects without amputations.

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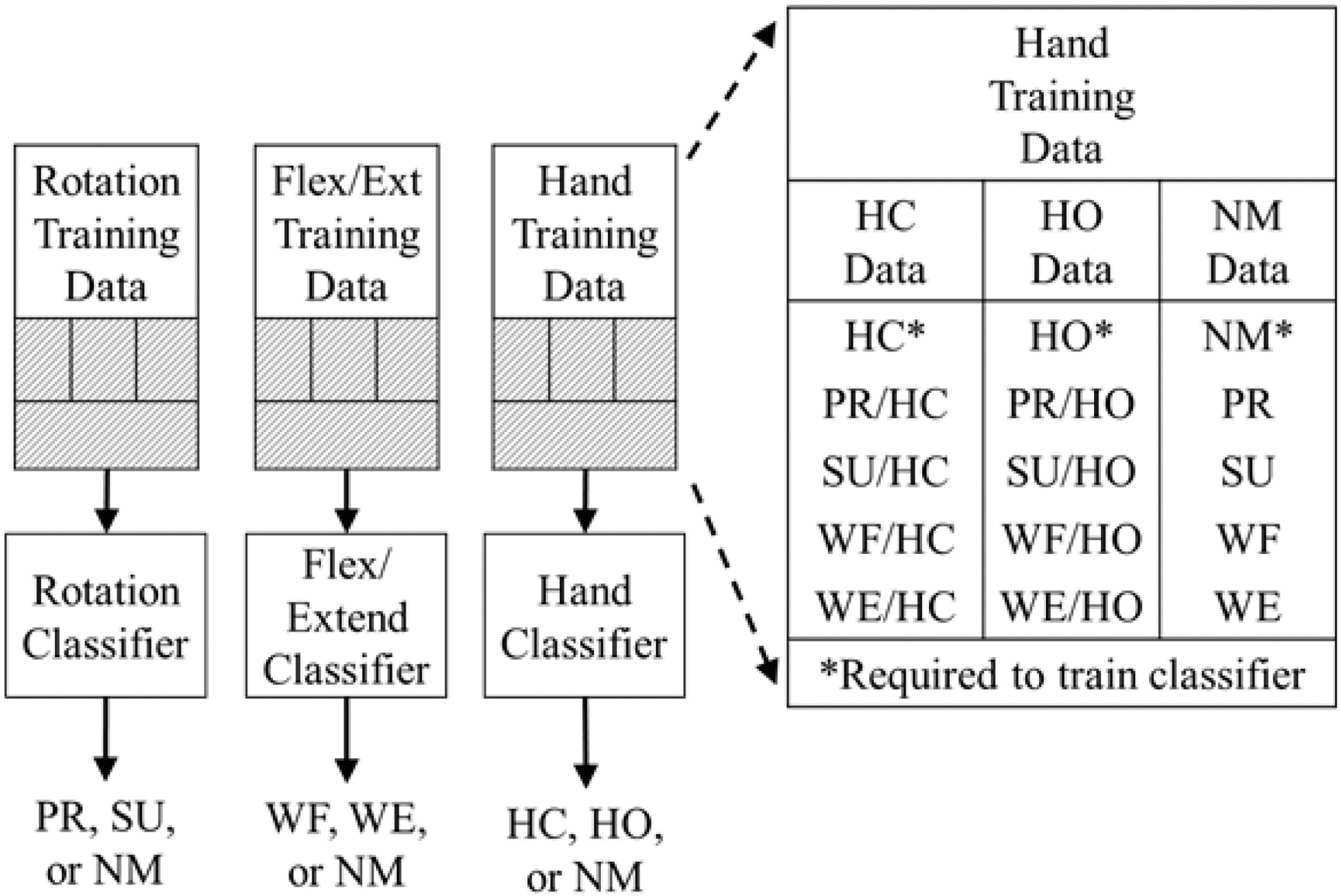

Figure 1.
Organization of parallel classifier tested. The configuration used three parallel classifiers: one for each DOF evaluated. Each classifier output one of two active motion classes or no motion. The overall commanded movement was the combination of the output from each classifier. An example of the training data used for the hand classifier is shown. Here, all 2-DOF motion classes containing hand closed are relabeled to hand closed, etc. It is not required to use 2-DOF motion classes to train the classifier. PR = pronation, SU = supination, WF = wrist flexion, WE = wrist extension, HC = hand closed, HO = hand open, NM = no movement.

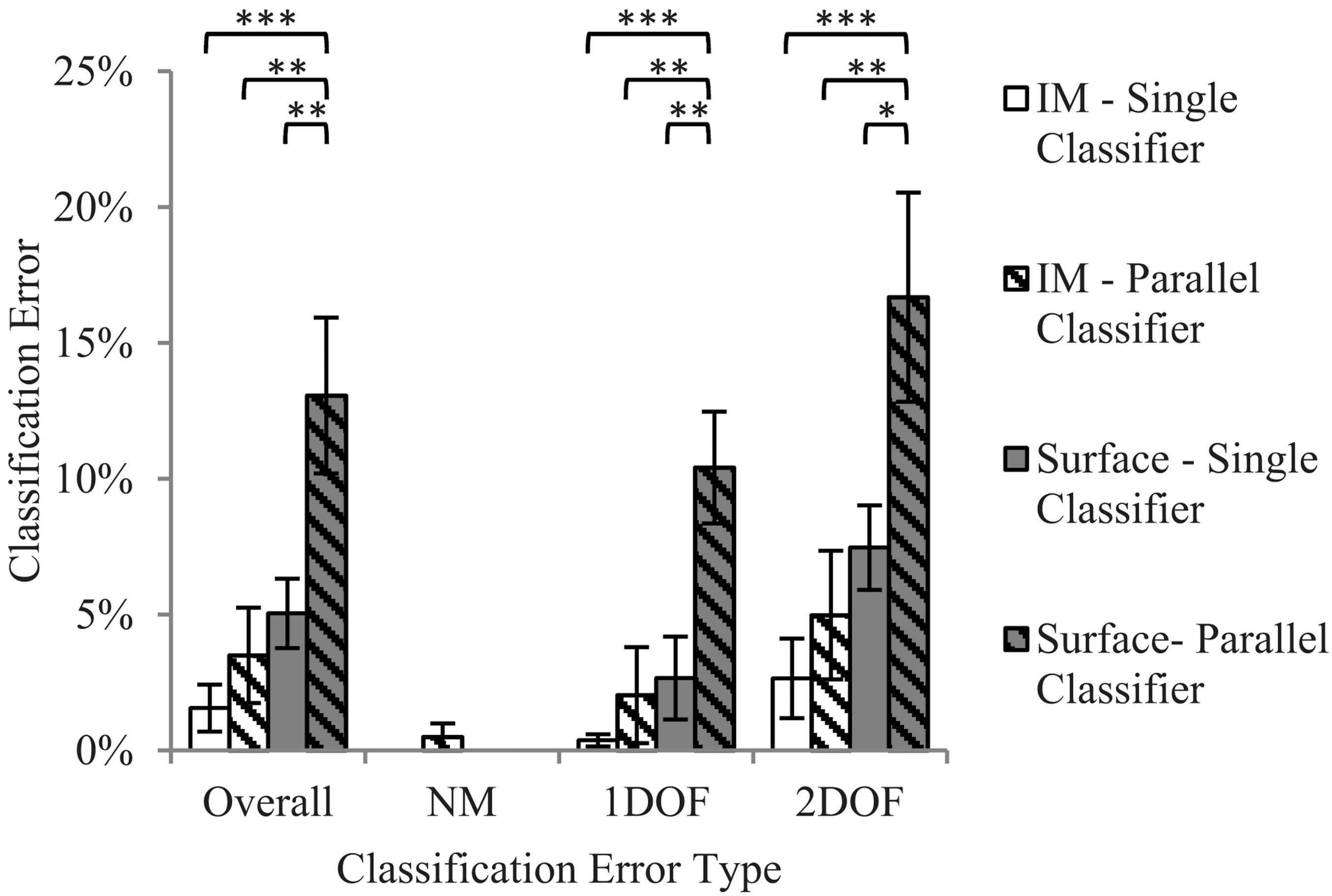

Figure 2.

Classification error for each classifier type, trained with either surface or intramuscular EMG. Parallel classifiers are trained with both 1-DOF and 2-DOF motion training data. Error is presented as an overall error, and broken into error for classification of no motion, 1-DOF intended motions and 2-DOF intended motions. For the parallel classifiers, the use of imEMG provided significant improvement in classification error when compared to sEMG. Results are an average of four subjects. * p<0.05, ** p<0.01, *** p<0.001. Error bars show +/− 1 SEM. (IM = intramuscular, NM = no motion)

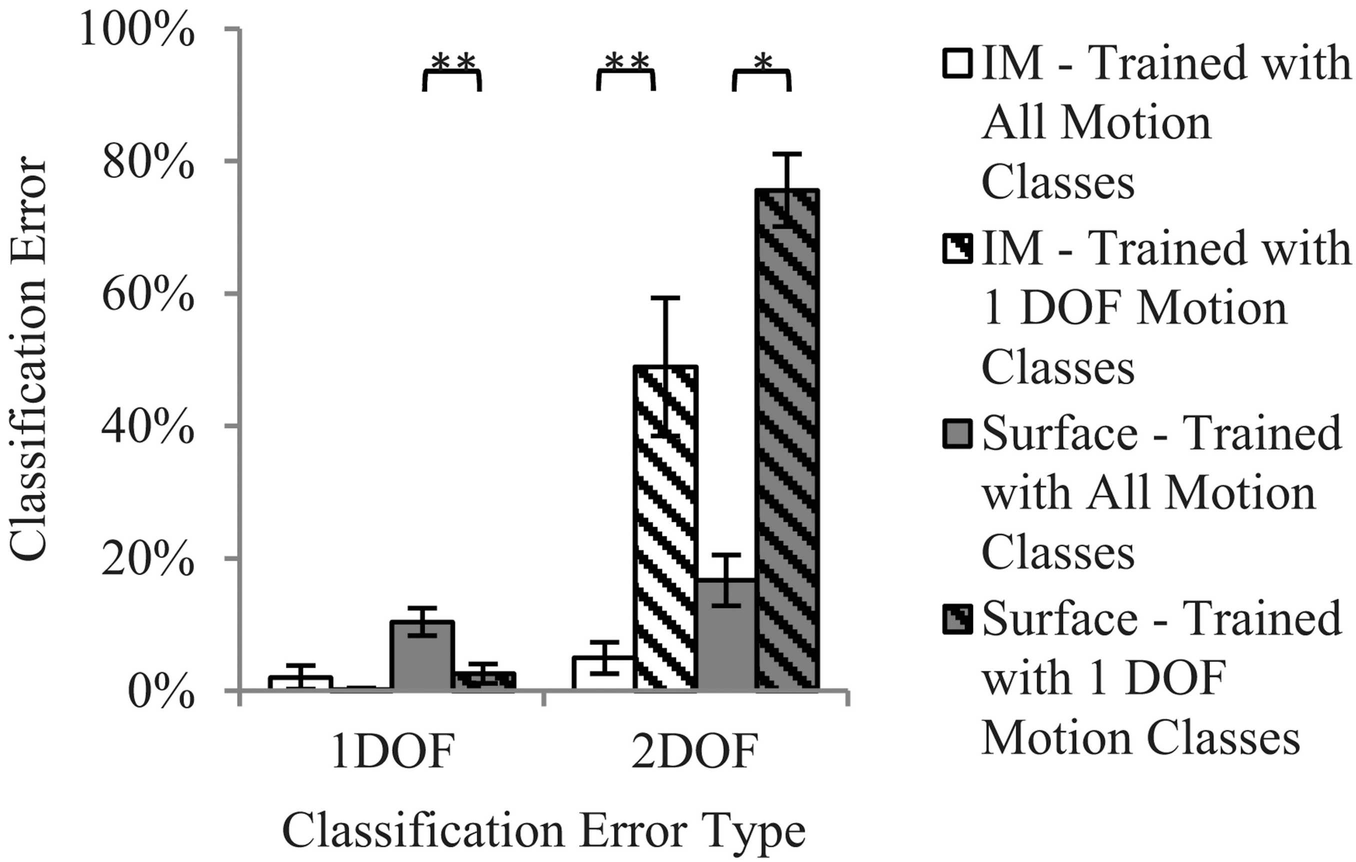

Figure 3.
Classification error of parallel classifiers when trained with and without 2-DOF motion class data. Error is partitioned into error for 1-DOF intended motions and 2-DOF intended motions. Training with only 1-DOF motion class data resulted in significant increases in error for both intramuscular and surface signal sources. Results are an average of four subjects. * $p<0.05$, ** $p<0.01$. Error bars show +/− 1 SEM. (IM = intramuscular)

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TABLE I

Correlation coefficients between EMG Channels in representative subject

Intramuscular EMG						
	Chan1	**Chan2**	**Chan3**	**Chan4**	**Chan5**	**Chan6**
Chan1	1.00	0.01	0.00	0.00	0.00	0.00
Chan2	0.01	1.00	0.00	−0.01	0.00	−0.01
Chan3	0.00	0.00	1.00	0.00	−0.01	0.00
Chan4	0.00	−0.01	0.00	1.00	0.00	0.00
Chan5	0.00	0.00	−0.01	0.00	1.00	0.00
Chan6	0.00	−0.01	0.00	0.00	0.00	1.00
Surface EMG						
Chan1	1.00	0.18	0.21	−0.50	−0.82	−0.21
Chan2	0.18	1.00	0.73	−0.41	−0.23	−0.54
Chan3	0.21	0.73	1.00	−0.49	−0.29	−0.38
Chan4	−0.50	−0.41	−0.49	1.00	0.72	0.37
Chan5	−0.82	−0.23	−0.29	0.72	1.00	0.24
Chan6	−0.21	−0.54	−0.38	0.37	0.24	1.00