Surface versus Untargeted Intramuscular EMG Based Classification of Simultaneous and Dynamically Changing Movements

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Abstract

The pattern recognition based myoelectric control scheme is in the process of being implemented in clinical settings, but it has been mainly tested on sequential and steady state data. This paper investigates the ability of pattern recognition to resolve movements that are simultaneous and dynamically changing; and compares the use of surface and untargeted intramuscular EMG signals for this purpose. Ten able-bodied subjects participated in the study. Both EMG types were recorded concurrently from the right forearm. The subjects were instructed to track dynamic contraction profiles using single and combined degrees of freedom in three trials. During trials one and two, the amplitude and the frequency of the profile were kept constant (non-modulated data); and during trial three, the two parameters were modulated (modulated data). The results showed that the performance was up to 93% for non-modulated tasks, but highly depended on the nature of the data used. Surface and untargeted intramuscular EMG had equal performance for data of similar nature (non-modulated), but the performance of intramuscular EMG decreased, compared to surface, when tested on modulated data. However, the results of intramuscular recordings obtained in this study are promising for future use of implantable electrodes, because, besides the value added in terms of potential chronic implantation, the performance is theoretically the same as for surface EMG provided that enough information is captured in the recordings. Nevertheless, care should be taken when training the system since data obtained from selective recordings probably need more training data to generalize to new signals.

Index Terms—pattern recognition, simultaneous movement, intramuscular EMG, classifiers, dynamic movement

I. Introduction

Surface electromyography (EMG) is the golden standard technique for controlling currently available upper limb electric prostheses. Several methods have been proposed in the literature in order to improve the control systems [1] - [7]. The methods can be generalized and grouped into conventional methods and pattern recognition based methods [8].

In conventional methods, features of the EMG signal, such as mean absolute value (MAV), are used as a direct control source in order to drive a device. The first generation of these systems offered an ON/OFF control approach, where one channel of EMG signal is mapped to one prosthetic function or one control state [9]. If the amplitude exceeds a predefined threshold value, the corresponding function is activated at a constant speed. Multiple functions can be assigned to different channels when multiple signal sites are available. The second generation of conventional control included proportional control, in which the velocity of a selected prosthesis function is proportional to the level of the myoelectric activity [10]. Proportional control allows for more intuitive use, as the control sites can be selected so that each function corresponds to the physiologically appropriate muscle. However, this scheme needs at least two signal sites to implement one physiological degree of freedom (DoF). For example, one signal can be used to derive the velocity of hand opening, while a second signal is needed for hand closing. Therefore, current commercially available prosthetic devices only provide very few controllable DoFs. Pattern recognition is one way to increase the amount of information extracted from muscle signals and to eliminate the need for isolated EMG signals. These algorithms look for patterns of muscle activity across one or more muscle sites rather than relying on independent EMG signals [11].

In pattern recognition-based techniques, it is assumed that there exists a set of distinguishable and repeatable signal patterns in the EMG signal during different types of movements. These systems consist of a feature extraction module and a classifier module. Within classifiers, the two major categories are statistical classifiers and learning classifiers. The statistical classifiers establish the mapping rule by estimating statistical characteristics of the features. The learning classifiers determine a mapping rule using an iterative learning and some cost functions. Several feature extraction techniques have been proposed, including the MAV and the variance of the surface EMG [12] - [14], autoregressive coefficients [15]; the short time Fourier transform [16] and the wavelet transform [17],[18]. Although different choices of classifiers have also been explored, most classifiers, when tested on steady-state data, provided similar classification accuracy given proper data preprocessing and choice of feature sets [19].

Despite increased performance achieved by controllers based on pattern recognition, they are currently not used in the clinic [20]. Therefore, researchers are recently investigating the clinical usability of pattern recognition with studies related to the influence of proportional contraction, limb position [21], and electrode shift [22] on pattern recognition, just to mention some of the challenges that face this type of systems [11]. The current study focuses on the way in which pattern recognition resolves dynamic and simultaneous data, as a necessary step to assess its potential use and added value compared to the current clinical use of proportional control schemes. One of the problems associated to this myocontrol approach is indeed the fact that current classification techniques for EMG pattern recognition are mostly tested on sustained, steady-state contractions. This imposes sequential control, while the natural control of artificial limbs requires the simultaneous control of multiple DoFs during dynamically changing movements [23], [20]. Pattern recognition control has been attempted on transient scenarios alone [8] and in combined transient/steady state scenarios [24] with successful results. However, the dynamic characteristic of transient data resembles a ramp that lasts for only a few seconds while the remaining part is sustained during sequential movements. In this study, we investigate pattern recognition methods for movements that are entirely changing in intensity and switching over time, including simultaneously performed DoFs.

Another factor that has been pointed out as a drawback of myoelectric control is the lack of independent command sites due to the use of surface EMG that has limited selectivity. It has been suggested that both an increase in the number of DoFs and simultaneous control can be achieved by increasing the availability of independent command sources with suitable interfaces to the nerves or muscles [25].

Intramuscular EMG is recorded from inside a muscle as an alternative signal source for controlling prostheses that may help overcome some of the drawbacks associated with surface EMG [26]. The greater selectivity of intramuscular with respect to surface EMG may, on the other hand, be a disadvantage, since the signal may provide local, rather than global information. Nevertheless, it has been shown that surface EMG and intramuscular EMG have equal classification performance [19], [27]. Furthermore, there was no significant difference between surface, targeted and untargeted intramuscular EMG based classification of movements [27]. However, these previous comparisons were made on steady-state and sequential movements only. Thus, it is not known whether surface and intramuscular EMG will perform similarly during simultaneous and dynamically changing movements.

The aim of this study was to investigate the ability of pattern recognition techniques to provide a control scheme that includes simultaneous, dynamically changing movements and to compare the performance of surface and untargeted intramuscular EMG for this purpose.

II. METHODS

A. Subjects

The experiments were conducted on ten able-bodied subjects (6 men/4 women, age range: 23 - 26 yrs). The procedures were in accordance with the Declaration of Helsinki and approved by the Danish local ethical committee (approval no.: N-20080045). Subjects provided their written informed consent prior to the experimental procedures. The subjects had no history of upper extremity or other musculoskeletal disorders.

B. Experimental procedures

EMG signals and torque signals were collected during simultaneous, isometric, but dynamically changing tasks of the wrist. The experiment was carried out in three trials with a 5-min rest in between. Each trial included eight combinations of tasks separated by 2 min of rest to minimize the effect of fatigue. The performed tasks were categorised into individual and combined (simultaneous) DoFs in order to test the ability to classify movements in two DoFs simultaneously. The selected DoFs were wrist flexion / extension (first DoF) and wrist supination / pronation (second DoF). The eight tasks were paired: wrist flexion/wrist extension, supination/pronation, simultaneous flexion+pronation/ extension+supination and simultaneous extension+pronation/flexion+supination. All tasks were dynamically changing from one movement to the other within each DoF and pair of DoFs based on a sinusoidal profile lasting 30 s at moderate torque level. For example, the subject performed flexion followed by extension or simultaneous flexion with pronation followed by simultaneous extension with supination. The first and last three seconds of each profile consisted of rest to obtain data for a *no motion* class, so that the classification problem consisted of nine classes. We used sinusoidal profiles to include dynamic contractions, requiring constant changes in the force (and EMG intensity) level of the performed task. The subjects were seated in a chair with their right arm placed in an armrest (Figure 1). Subjects were asked to track one profile or two simultaneous profiles depending on whether it was a single DoF or two simultaneous DoFs, as shown in Figure 2A and 2B. The order of the eight tasks was randomized; and subjects received visual feedback as to how closely they tracked the profiles. The subjects had sufficient time to train and become familiar with the profiles. During trial 1 and 2, the amplitude and frequency (non-modulated data at 0.5 Hz) of the sinusoidal profile were kept constant, while in trial three these two parameters were modulated (modulated data with frequency range 0.1 – 0.5 Hz) as shown in Figure 2B.

Figure 1 and Figure 2 about here

C. Data collection

A custom-made hand support incorporating a commercially available dynamometer (Gamma FT-130-10, ATI Industries) was used to provide feedback to the subjects about the level of activation (torque) for each task. Two torque signals were recorded, corresponding to the two DoFs. Six pairs of surface EMG electrodes (Ambu Neuroline 720) were placed equidistantly around the forearm, starting a few centimeters lateral to the ulnar exposure at the point of largest circumference.

The intramuscular EMG was recorded using six bipolar wire electrodes, inserted to reside underneath each surface EMG electrode pair, providing an equidistant distribution around the forearm. Intramuscular wire electrodes were made of Teflon-coated stainless steel (A-M Systems, Carlsborg WA, diameter 50 μm) and were inserted into each muscle with a sterile 25-gauge hypodermic needle. The insulated wires were cut to expose only the cross section at the tip, providing high selectivity. The needle was inserted to a depth of a few millimeters below the muscle fascia and then removed to leave the wire electrodes inside the muscle. All signals were anti-alias filtered and amplified (AnEMG12, OTbioelletronica, Torino, Italy), A/D converted on 16 bits (NI-DAQ USB-6259), and sampled at 10 kHz. A reference electrode was placed around the wrist.

D. Signal processing

Intramuscular and surface EMG signals were digitally band-pass filtered (4th order Butterworth filter) between 100 – 3000 Hz and 20 – 500 Hz, respectively. Each recording was segmented at the points of zero crossings of the torque signals, between the two movements of a particular movement pair in order to obtain data segments for each class. In case of simultaneous movements, we used the best trade-off between the crossings of the two simultaneous torque signals. Eight Time domain (TD) [8], [28], seven frequency domain (FD) [19] and eleven time-frequency domain (TFD) [17] features were extracted using a window of 150 ms and a step size of 50 ms for each channel. All features were combined resulting in a 156 dimensional feature space per EMG type.

Two dimensionality reduction methods were investigated and compared with "*no reduction*", namely principal component analysis (PCA) and an unreported method within myoelectric control known as separability and correlation (SEPCOR). Dimensionality reduction was assessed in order to test if the performance can be influenced by the number of features. PCA projects the feature space into uncorrelated variables orthogonal to the direction of maximal variance, such that the first variable describes the largest amount of variance. The number of stored variables depends on the desired minimum cumulative retained variance of the original feature space. SEPCOR is a feature selection technique that stores the features with highest discriminative power and discards features that are highly correlated to the stored features. Thus, features are selected based on maximal allowed correlation [29]. To assess the effect of the aforementioned parameters, PCA was used with minimum variance of 95% and 99% (PCA95 and PCA99); and SEPCOR with maximum correlation of 0.90 and 0.95 (SEP90 and SEP95).

The classification was performed using five commonly used classifiers and the percentage of correct classifications (PCC) was used as performance measure. The *Artificial Neural Network (ANN)* is an emulation of the biological system and consisted of one hidden layer with ten neurons with the hyperbolic tangent sigmoid functions as transfer functions in both the hidden and output layers. The training data were randomly divided so that 70 % was used in the training and 30% for validation in order to minimize overfitting. Each network was trained 50 times and the network with the highest PCC on the validation data was used on the test data. *K-Nearest Neighbor (kNN)* uses a distance measure (Euclidian in our case) to classify new observations based on the *k* nearest observations in the training set. The value of *k* was set to five. *Linear Discriminant Analysis (LDA)* is a statistical classifier that aims at finding combinations of features that optimally discriminate between classes. A *Support Vector Machine (SVM)* offers a more complex approach for separating between two classes. A linear kernel was used, where the optimal boundary was found by maximizing its distance to the nearest training observations on both sides. The first mode of SVM used the One Against All (OAA) approach, which separated each class with respect to all the others together, where the final decision was obtained by selecting the class maximizing the discriminant function. The second mode of SVM classifier used the One Against One (OAO) approach, which provided a decision for each pair of classes, where the final decision was obtained through a majority vote.

E. Data analysis

The analysis for the nine classes (flexion, extension, pronation, supination, simultaneous flexion +

supination, simultaneous extension + pronation, simultaneous flexion + pronation, simultaneous extension + supination and no motion) problem was carried out in two steps. First, we used a four-fold cross validation procedure using data from trial one and trial two (non-modulated). Each fold was comprised by assigning a half trial as testing data and the remaining one and half trial as training data. This is referred to as the *four-fold validation test*. Second, we used a similar approach where we included the modulated data (trial three). For this part, we performed two four-fold validations (1) between trial one and trial three, and (2) between trial two and trial three. The average result of these two is reported. This is referred to as the *four-fold modulation test*.

An extension of these analyses focused upon ignoring the transition part from one DoF to another. Recall that each profile was dynamically changing with around eleven transitions between movements (See Figure 2). This resulted in periods of transition that are assigned to the active classes instead of *no motion* where the applied torque is nearly zero with a corresponding lack of EMG activity. This imposes a contradictory situation to the classifiers. Thus, we examined how rejecting these periods (assign them to *no motion*, using a torque threshold) would affect the classification accuracy. We investigated ignoring zone periods corresponding to approximately 8 – 38 % of the targeted torque level. This resembles the clinical use of prosthesis where a threshold is used on the EMG signal in order to determine when the prosthesis is inactive. In this study the *no motion* threshold (referred to as rejection threshold) was varied from 8% to 38% in ten equal steps.

F. Statistical analysis

For each EMG signal type (surface and intramuscular), a two-way repeated measures analysis of variance (ANOVA) was used to compare PCC between the classifiers and different feature reduction methods. For each step of the analysis, a two-way repeated measure ANOVA (with factors EMG signals and thresholds) was also used to compare the performance of intramuscular and surface EMG and the gain of applying increased rejection thresholds. P-values less than 0.05 were considered significant. The Bonferroni–Dunn adjustment was used for multiple comparisons.

III. RESULTS

A. *Four fold validation test*

1) *Without rejection threshold*

For both surface and intramuscular EMG, there was a significant difference between classifiers ($p < 0.001$) with KNN performing worse than the other four classifiers (ANN, LDA, SVMOAA and SVMOAO). When comparing the effect of dimensionality reduction, there was also a significant difference ($p < 0.001$), with PCA95 having the worst performance for both types of EMG signals. *No reduction* provided the best global result followed by SEP99 and PCA99 as illustrated in Figure 3. However, a significant interaction was found, meaning that different classifiers were affected differently by the choice of reduction method as depicted in Figure 4. Thus, for the remaining of the analysis, only three classifiers were tested (ANN, LDA and SVMOAO) with *no reduction* in the feature space.

2) *With rejection threshold*

As expected, two-way ANOVA revealed a significant difference ($p < 0.001$) between rejection thresholds up to step five corresponding to 21% of the targeted torque level. No significant difference was found between surface (92.5 ± 3.5%) and untargeted intramuscular (90.3 ± 4.7) EMG ($p = 0.13$). No difference was found between the classifiers for both types of EMG, thus Figure 5 only presents data from the LDA classifier.

Figure 3 and Figure 4 about here

B. *Four-fold modulation test*

As for the previous case, a significant difference was observed between the thresholds. However, there was also a significant difference between surface (93.9 ± 2.5%) and intramuscular EMG (88.7 ± 3.5%) when involving modulated data (Figure 5), with sEMG performing better ($p = 0.005$). A significant interaction was also observed, indicating that the difference depended on the threshold value. In fact when trained with modulated data, surface EMG increased in performance while intramuscular decreased in performance. A possible explanation is presented in Figure 6, which depicts the classification accuracy of each fold in the three tests. We can note a decrease in performance, consistent for all subjects, at two spots corresponding to the classification of the second half of trial three.

Figure 5 and Figure 6 about here

IV. DISCUSSION

This study analysed the effectiveness of using pattern recognition techniques for resolving simultaneous and dynamic movements; and the comparison between surface and untargeted intramuscular EMG. The investigation revealed that pattern recognition can resolve simultaneous movements with considerable accuracy (up to 93%). Moreover, when tested on data that are similar in nature (non-modulated data), surface and untargeted intramuscular EMG resulted in statistically the same performance. However, when tested on more complex data (with modulation), surface EMG outperformed intramuscular EMG. The performance of surface EMG increased when training with more complex data (modulated) as this type of data adds more information into the system, as previously shown [11], [24]. However, contrary to the observation based on surface EMG, the performance of intramuscular EMG on modulated data was poorer than on non-modulated signals. In this case, the most prominent error occurred when training with part one of trial 1 and testing on part two of trial 3. This is most likely related to the nature of the modulation, as the modulation begins with low amplitude and low frequency and ends with higher amplitude and frequency. Surface EMG measures the global information about a contraction, while intramuscular is more selective and with the type of electrodes used in this study (wires exposed only at the tip) the recording was very selective. Thus, as intramuscular recordings rely on the recruitment of motor units, it could be that not enough information was captured at low amplitude/frequency. This is further supported by the fact that adding the first half of trial 3 to the training set did not add the necessary information needed for classification of the more rapid changes in frequency and higher amplitude (second half of trial 3, see Figure 6). However, the results with intramuscular recordings obtained in this study are still promising for future use of implantable electrodes, because, besides the value added in terms of potential chronic implantation, the performance is theoretically unchanged for data of similar nature (non-modulated data). Still, more care should be taken when applying intramuscular EMG compared to surface EMG in the training phase. For example, in our case the modulated data should have contained repeated cycles of low and high amplitude / frequency in order to get a more representative training data set.

It is difficult to compare the results of this study with others, because to our best knowledge no other studies have used data as challenging in nature as the current, which were both dynamic with transitions directly between movements, and, moreover, contained simultaneously performed DoFs. All previous studies have used steady-state data in sequential movements. Nevertheless, Lorrain *et al.* [24] has reported a decrease in classification performance when classifying data that were semi-dynamic (a ramp followed by static contraction).

Results also showed that the rejection threshold had a significant influence on the performance up to level five, corresponding to 20 % of the targeted torque level. This is reasonable as at this level the influence of background noise is less pronounced and EMG signals are easy to differentiate from noise. Nearly all commercially available prosthetic devices use a kind of threshold on the EMG activity in order to differentiate the active state from rest. The difference between surface and intramuscular EMG was not prominent when trained with a fold validation technique on non-modulated data mainly due to the involvement of the properties of the test data in the training set, as explained above. The results with fold validation agree with previous reports [19], [27] that compared surface and intramuscular EMG. We found a significant difference on modulated trial; which was not included in previous comparisons. These authors only used steady-state EMG, where the signal is more or less stationary and thus less challenging for the classifier. Moreover, the classified movements were not performed simultaneously as in this study.

Another challenge is the classification of supination/pronation which has been reported as a difficult DoF to estimate when not recording from the primary muscles (supinator and pronator, respectively) [31], [32]. This has been confirmed by a recent study [23] on force estimation using targeted intramuscular EMG with indwelling electrodes placed in the supinator m. and pronator teres m. The study showed that with this configuration, force during pronation had the highest accuracy compared to the other movements and their combinations. Although untargeted intramuscular EMG can save time on locating targeted muscle and placing electrodes in them, we believe that targeting muscles is a necessary step to take. The modulation issue discussed above might have been avoided with targeted intramuscular EMG that could capture low activities from the supinator and pronator muscles.

We compared the performance of different classifiers and found that only KNN performed significantly worse than the other four classifiers. This result extends those of previous studies [19], [33] that showed on a less complex data set that the classifier did not have a large impact on the myocontrol accuracy. Finally, we compared the effect of applying PCA and SEPCOR with different degree of feature retention. PCA95 performed significantly worse than the other approaches. Similar performance was seen between PCA99 and SEP99, but the advantage of PCA99 (on average 21 features) is that the number of retained features was less than SEP99 (on average 48 features). It should be noted that the classifiers were affected differently by the reduction techniques. Nevertheless, there was no advantage in reducing the feature space since using the *no reduction* technique consistently provided the highest performance in terms of absolute value across classifiers. On the other hand, SEPCOR has the advantage of being a feature selection technique rather than a feature projection technique, such as PCA. Thus, even though PCA99 only uses 21 features, these are obtained by transformation of all the original features, whereas SEPCOR simply removes features from the original feature space. The latter approach can thus save computational time.

V. Conclusion

The novelty of this study lies in testing the ability of pattern recognition to resolve movements that were both dynamic and simultaneous and showed that the performance was acceptable, but depended on the nature of the data used. Surface and untargeted intramuscular EMG had equal performance for data of similar nature, but the performance of intramuscular EMG worsened substantially for modulated data.

This study provides a theoretical assessment on how pattern recognition may resolve simultaneous and dynamic movements. We applied a four-fold validation technique to assess the performance. This type of training modality symbolizes the ideal situation with the aim (1) to reduce the variance of the accuracy estimate, and (2) to provide more training data per estimate. However, this training strategy is just a theoretical expression on how the scheme might work in practice, and should be tested in real application with potential users.

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Figure captions

Figure 1: Experimental setup showing the fixation of the arm.

Figure 2: Movement profiles followed by the subjects. (a) Profiles used in trial 1 and 2 for single DoF (upper plot) and simultaneous DoFs (lower plot). (b) Modulated profiles used in trial 3 for single and simultaneous DoFs (Frequency range 0.1 – 0.5 Hz) the bottom plot in (b) also contains a second sinus in grey. Dark line corresponds to one DoF and grey line to the second DoF.

Figure 3: Results of the four fold validation test per signal type comparing (a) the performance between different classifiers and (b) between different feature space reduction techniques. ** indicates cases where the performance is significantly worse ($p < 0.001$) than the remaining factors.

Figure 4: Interactions between the choice of classifier versus choice of reduction method for (a) intramuscular EMG and (b) surface EMG.

Figure 5: Results of (a) the four fold validation test, (b) single trial test and (c) modulation test data plotted for both surface and intramuscular EMG at different rejection threshold spanning from 0 to 38% of the desire force.

Figure 6: Results from each fold from all four-fold validation tests shown for all subjects using (a) intramuscular EMG and (b) surface EMG. (a) We notice a decrease when training with part one of trial 3 and test on part two of the same trial as indicated with the rectangular. T**x**P**y** stands for testing on Trial **x** (1 to 3) and Part **y** (1 or 2).

Figure 1

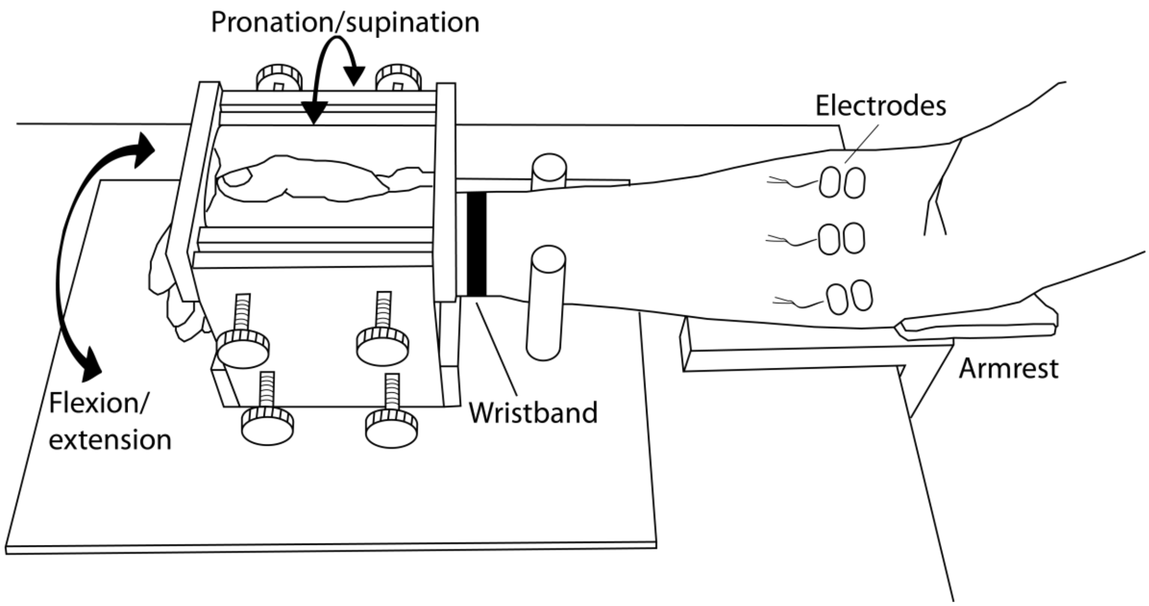

Pronation/supination
Electrodes
Flexion/
extension
Wristband
Armrest

Figure 2

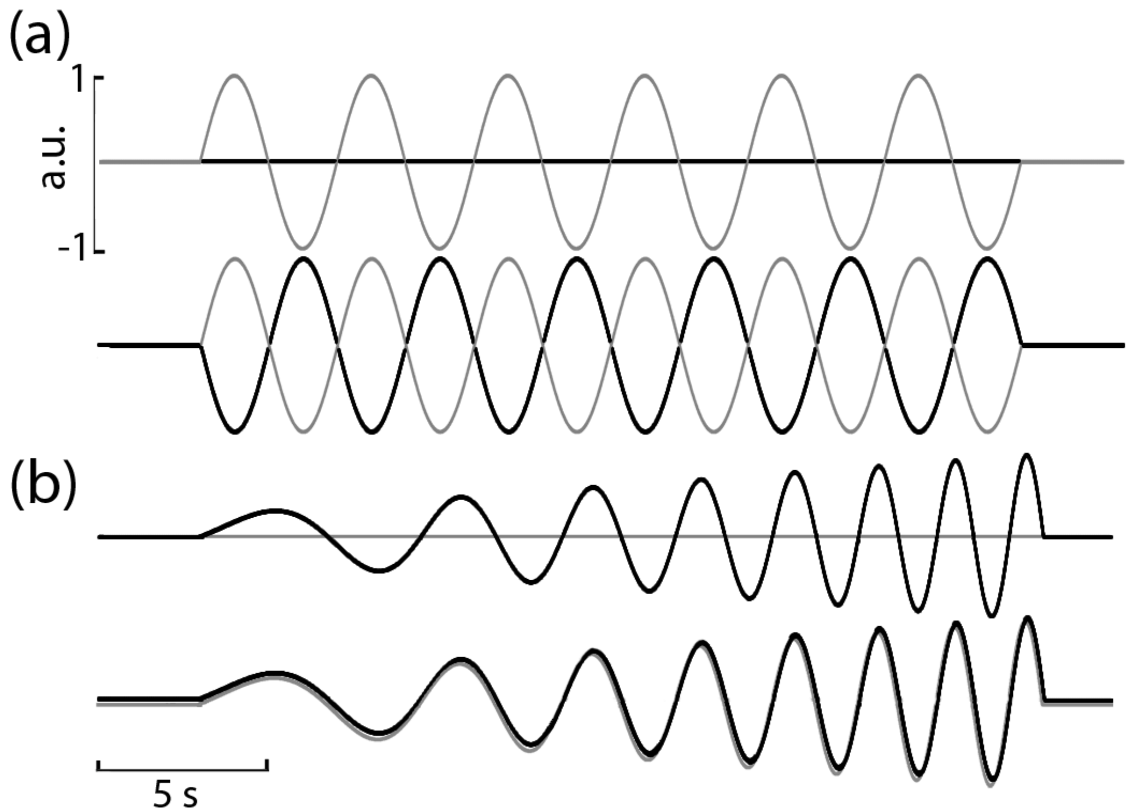


Figure 3

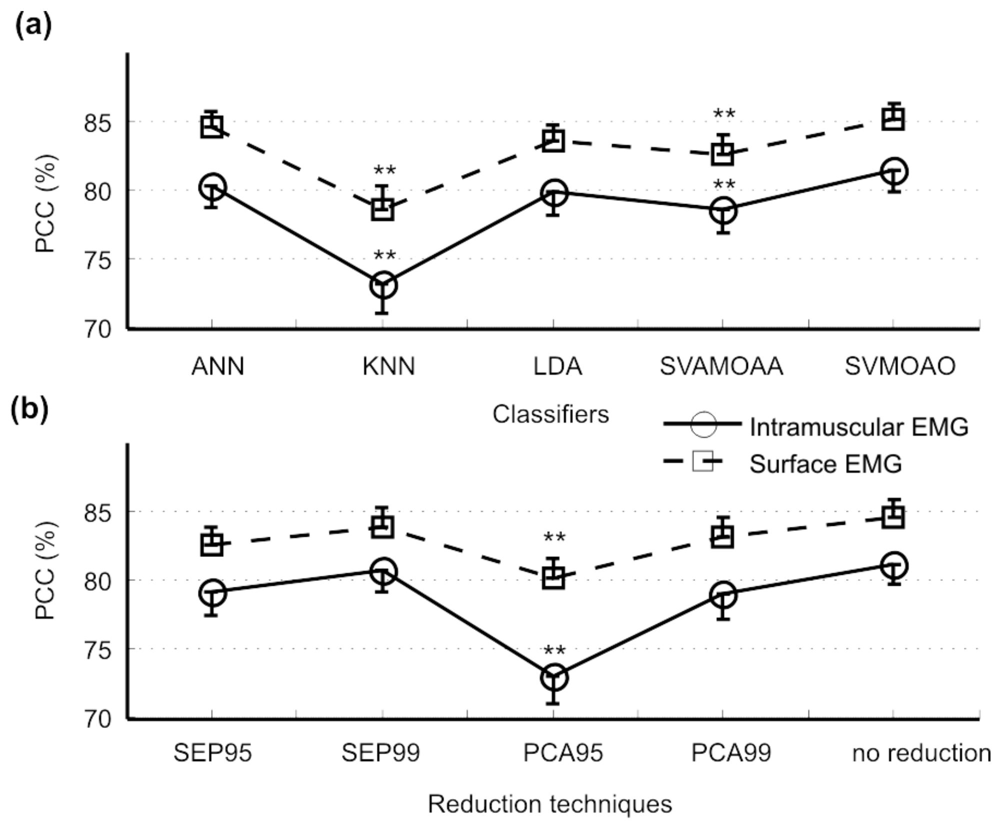

(a)
85
80
75
70
PCC (%)
**
**
**
**
ANN
KNN
LDA
SVAMOAA
SVMOAO
Classifiers
(b)
Intramuscular EMG
Surface EMG
85
80
75
70
PCC (%)
**
**
SEP95
SEP99
PCA95
PCA99
no reduction
Reduction techniques

Figure 4

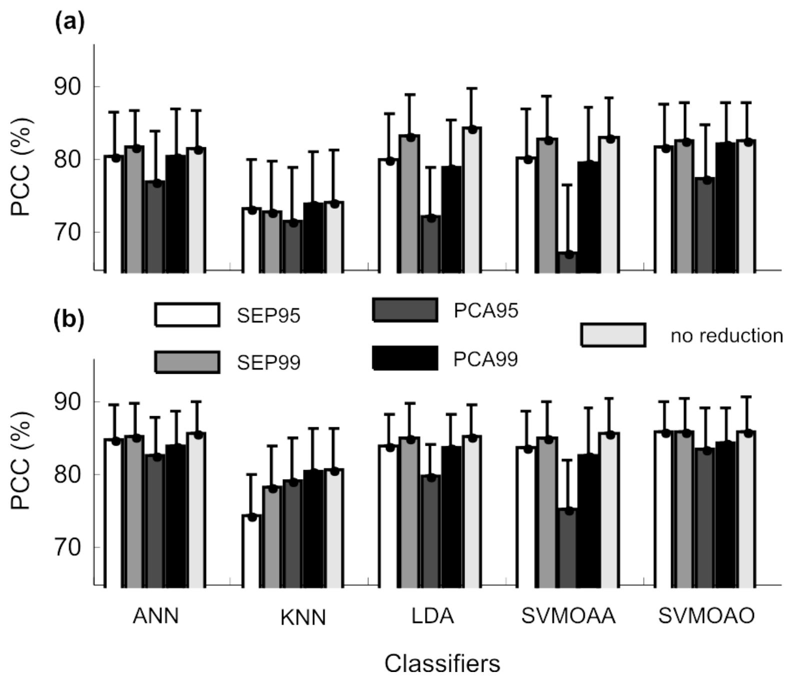

(a)
PCC (%)
90
80
70
(b)
SEP95
SEP99
PCA95
PCA99
no reduction
PCC (%)
90
80
70
ANN
KNN
LDA
SVMOAA
SVMOAO
Classifiers

Figure 5

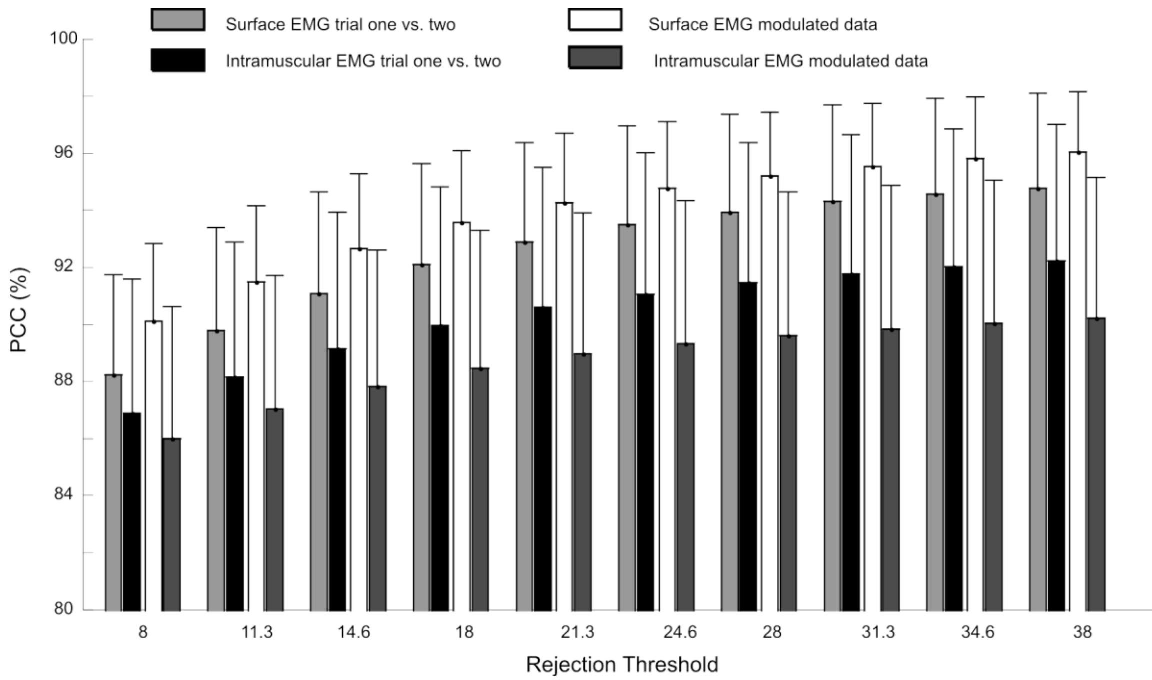
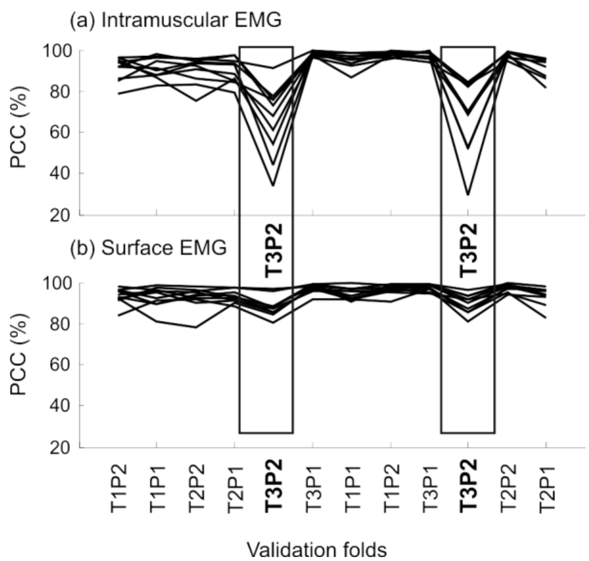

Surface EMG trial one vs. two
Surface EMG modulated data
Intramuscular EMG trial one vs. two
Intramuscular EMG modulated data
100
96
92
88
84
80
PCC (%)
8
11.3
14.6
18
21.3
24.6
28
31.3
34.6
38
Rejection Threshold

Figure 6



(a) Intramuscular EMG
PCC (%)
100
80
60
40
20
T3P2
T3P2
(b) Surface EMG
PCC (%)
100
80
60
40
20
T1P2
T1P1
T2P2
T2P1
T3P2
T3P1
T1P1
T1P2
T3P1
T3P2
T2P2
T2P1
Validation folds

2013

Surface Versus Untargeted Intramuscular EMG Based Classification of Simultaneous and Dynamically Changing Movements

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