Biomedical Signal Processing and Control 43 (2018) 1–8

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

# The effect of arm position on classification of hand gestures with intramuscular EMG

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ARTICLE INFO

*Article history:*
Received 26 September 2017
Received in revised form 20 January 2018
Accepted 18 February 2018
Available online 23 March 2018

*Keywords:*
Surface EMG
Intramuscular EMG
Prosthetics
Arm position
Upper extremity

ABSTRACT

The arm position affects discrimination between upper limb motion classes when using surface EMG (sEMG). In this study, the effect of arm position on motion class discrimination was investigated using intramuscular EMG (iEMG). Eight able-bodied subjects performed five motion classes (hand grasp, hand open, rest, wrist extension, wrist flexion) in four different arm positions (0, 45, 90, 135°). Three classification scenarios were evaluated using Hudgins' time domain features and a Bayes classifier; within position classification (WPC), across position classification (APC), and between position classification (BPC). The same analysis was performed using sEMG and with combined surface and iEMG. For WPC, similar classification accuracies were obtained using the different types of EMG (93–98%). The mean absolute value and waveform length were associated with the highest classification accuracies compared to zero crossing and slope sign changes for WPC. For APC, classification accuracies dropped to 85–95%, and for BPC, classification accuracies dropped to 69–83% with hand opening being the least discriminable motion class. The degree of decreased performance was computed as: 1) APC/WPC: 0.94 ± 0.03 (sEMG) and 0.92 ± 0.05 (iEMG), and 2) BPC/WPC: 0.81 ± 0.06 (sEMG) and 0.78 ± 0.12 (iEMG), indicating that arm position affects iEMG in a similar degree as sEMG, which is a practicality issue for the clinical application of pattern recognition based control schemes.



## 1. Introduction

Over the past two decades, the research within the area of prosthetic devices and control has advanced. It is possible to obtain high performance of prosthetic devices that have more than one degree of freedom (DoF) and can perform some of the basic tasks a human hand can do. Surface electromyography (sEMG) signals have been one of the major neural control sources of the electrically powered devices; and various control strategies have been used to extract the user's intended movement with EMG signals. Clinical development has gone from ON-OFF systems to direct and proportional control although with limited functionalities with regards to dexterous prostheses [1–4]. Advanced signal processing approaches such as pattern recognition [5] (PR) and regression algorithms [6] have shown to provide the ability to control multiple DOFs. In the PR scheme, a set of features containing temporal, spectral or spatial information about the acquired signals is extracted and used as input to a classifier; which determines the subject's intended motion. Many research studies have used myoelectric PR control strategies for upper limb prosthetics and reported high classification accuracies using various pre-processing, features extraction and classification algorithms [5,7,8] though with limited clinical usability. Recent studies have shown that performance of PR control schemes in real world conditions can significantly deteriorate as a result of electrode shift, variation in contraction force, muscle fatigue over time, and electrode orientations [9–13]. In these studies subjects were asked to perform several classes of hand or wrist motions in a specific positon. The most commonly used position is when the hand is upright naturally.

When subjects perform hand motions in different positions, the performance of the PR control scheme may be affected. This has been reported in a couple of studies where it was shown that the arm position increased the classification error when using training data from one position and testing in another position [7,9,14–16]. Often a number of tasks is performed in a seated position where movements are performed as uniformly as possible to obtain good discrimination of the training data; however, the performance under actual use or testing will often be reduced due to the more

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https://doi.org/10.1016/j.bspc.2018.02.013
1746-8094/

task oriented usage in these scenarios compared to the training data that are used for calibration [14]. This may account for some of the performance differences observed between offline studies and clinical use [7]. In the few previous studies that have investigated the effect of limb position, high intra-position (within position classification – WPC) classification accuracies can be obtained, but the inter-position (between position classification – BPC) classification accuracies were much lower. To overcome this a few solutions have been proposed such as integration of accelerometers, identification of position invariant features or simply calibrating the pattern recognition algorithms in different positions [7,9,14–16]; however, this prolongs the calibration time. The studies, where the effect of limb position has been investigated, have used sEMG. Intramuscular EMG (iEMG) has been thought to possess properties that may overcome some of the limitations associated with non-invasive systems [17]. For example, Kamavuako et al. [18] showed that the classification accuracy of a myoelectric control system with combined sEMG and iEMG was superior to sEMG alone. There is also a body of evidence comparing the individual performance of sEMG and iEMG for classification of hand and wrist movements, and generally a similar performance has been found [19–22].

Therefore, the aim of our study was to investigate how the effect of arm position affects the classification performance of different motor tasks using iEMG. Surface EMG were also recorded to validate previous findings and to be able to use a combination of surface and intramuscular EMG (cEMG). Lastly, it was investigated how the Hudgins' time domain features [2] are affected by arm position. This was evaluated using different classification scenarios to assess the intra- and inter-class classification accuracies.

## 2. Methods

### 2.1. Subjects

Eight male healthy subjects were recruited (31 ± 4 years old). All subjects gave their written informed consent prior to participation. All procedures were approved by the local ethical committee (N-20140014).

### 2.2. Recordings

#### 2.2.1. Surface EMG

Two sEMG electrodes (one channel, AMBU self-adhesive EMG electrodes) were placed on the extensor muscles on the forearm with 2 cm between them. Similarly, two electrodes (one channel) were placed on the flexor muscles on the forearm. A moist wrist band was used as reference. The sEMG was sampled with 10 kHz and a gain of 2000 (AnEMG12, OT bioelletronica, Torino, Italy).

#### 2.2.2. Intramuscular EMG

One pair of custom-made iEMG wire electrodes was inserted in the flexor and extensor muscle on the forearm between the two sEMG electrodes. 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 sterilized 25-gauge hypodermic needle. The insulated wires were cut to expose 3 mm of wire from the tip [18]. The needle was inserted to a depth of approximately 10–15 millimetres below the muscle fascia and then removed to leave the wire electrodes inside the muscle [18]. The same reference was used for sEMG and iEMG. The iEMG was sampled with 10 kHz and a gain of 1000.

### 2.3. Experimental setup

The electrodes were mounted on the subject's right arm, and the signal quality was checked. The subject was standing and facing a wall where different positions were marked (see Fig. 1). The subject was asked to perform five motion classes in four different positions. The four different positions were measured between the right arm and the torso in the sagittal plane and marked on the wall. The following positions were measured: 0°, 45°, 90° and 135°. 0° were not marked on the wall since the arm was hanging down the side of the subject. In each position five motion classes were performed four times lasting for four seconds each: 1) hand grasp (palmar grasp), 2) hand open, 3) rest, 4) wrist extension, and 5) wrist flexion. The order of the positions and the motion classes were randomized using MATLAB's random number generator.

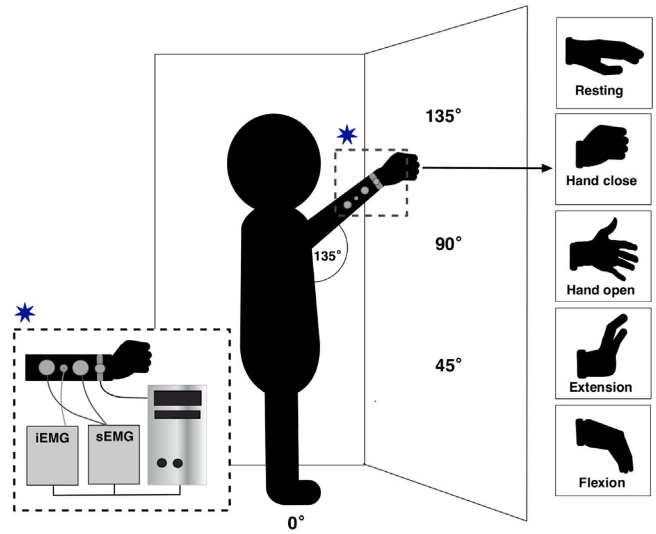


**Fig. 1.** Experimental setup showing the positions of the arm and the five motion classes to perform: 1) rest, 2) hand close, 3) hand open, 4) wrist extension and wrist flexion. Surface EMG and intramuscular EMG were recorded from flexor and extensor muscles. Here only the extensor side is shown.

### 2.4. Data analysis

#### 2.4.1. Pre-processing and feature extraction

Surface EMG was bandpass filtered from 20 to 500 Hz using a 2nd order zero-phase shift Butterworth filter, and iEMG was filtered from 60 to 2000 Hz. Moreover, signals were filtered with a notch filter to attenuate power line interferences. Following the filtering, four features were extracted from the sEMG and the iEMG: mean absolute value (MAV), waveform length (WL), zero crossings (ZC), and slope sign changes (SSC) [2]. These features were extracted from a 200 ms data window with 50 ms increment. An example of the filtered and rectified EMG is shown in Fig. 2.

#### 2.4.2. Classification

The features were classified with a naïve Bayes classifier [23]. Different classification analyses were performed: 1) Within position classification (WPC), 2) Across position classification (APC), and 3) Between position classification (BPC).

For WPC, the classification accuracies were calculated in the scenario where the training and test data belonged to the same position using a 4-fold cross-validation procedure. In each arm position, the four repetitions of each motion class were concatenated. The data from each motion class were randomly divided into four subsets; three for training and one for testing. The training and testing sets from the different motion classes were pooled into one training set and one testing set containing all five motion classes. The average classification accuracies (5-class problem) across the testing folds are reported.

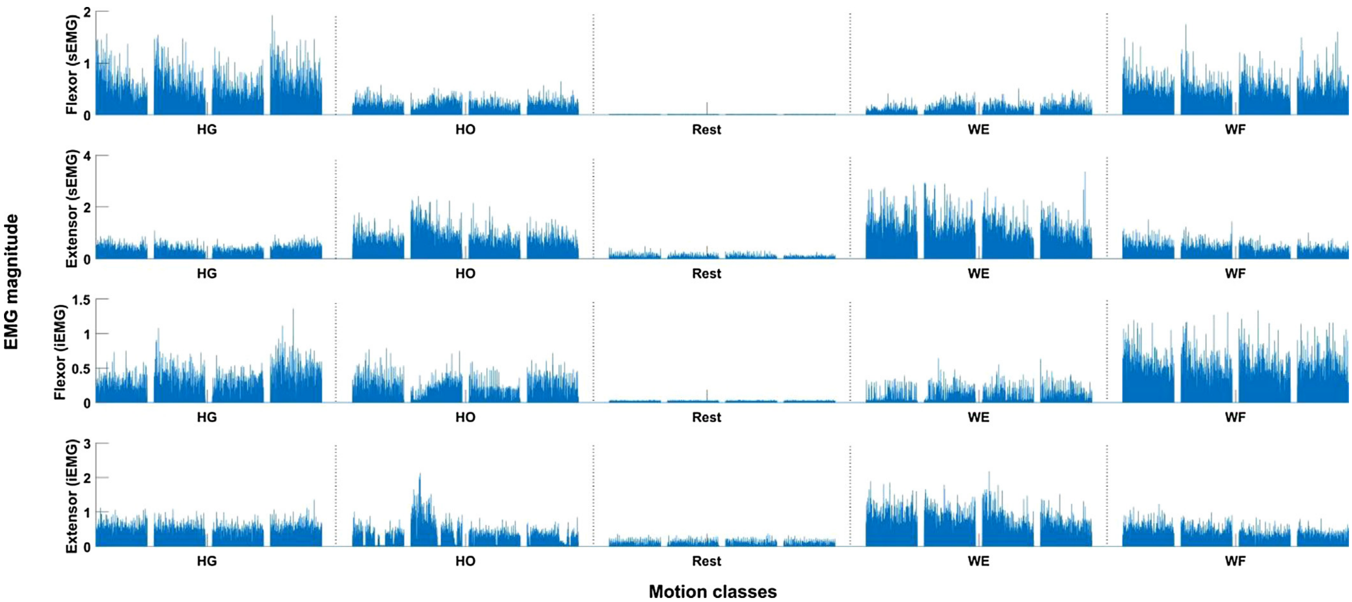


**Fig. 2.** Rectified and bandpass filtered surface EMG (sEMG) and intramuscular EMG (iEMG) for a single subject. The four repetitions in the 0° position is shown for each of the five motion classes. 'HG': hand grasp, 'HO': hand open, 'WE': wrist extension, and 'WF': wrist flexion.

Using the same 4-fold cross-validation procedure, the APC was calculated. In this scenario, the classifier was trained on data containing information from all of the four arm positions, and the testing data also consisted of data from all positions. Again, the average classification accuracies (5-class problem) across the testing folds are reported.

The effect of training the classifier on data from one position and testing on another (e.g. training on 0° and testing on 45°) was tested in the BPC scenario. Here all pairwise comparisons were tested. For each comparison, the 5-class classification accuracy was calculated. All of the data from position 1 were used to train the classifier, and all of the data from position 2 were used for testing. The average classification accuracies across the position pairs are reported. Moreover, it was investigated which motion classes that mostly affected the classification accuracies. The confusion matrices were calculated for all pairwise comparisons, as described before, and the average was calculated. Moreover, the classification was performed for the different paradigms with linear discriminant analysis (LDA) [23] to make a comparison with the Bayes classifier to investigate if a potential arm position-classification accuracy dependency was due to the classification method. The analysis was performed on the same folds for the two classifiers to make a fair comparison.

Data analysis was carried out using all Hudgins' time domain features combined, but also using each feature type individually. The pre-processing, feature extraction was performed using MATLAB.

### 2.5. Statistics

For the WPC and APC calibration paradigm, two (sEMG and iEMG) 1-way repeated measures analysis of variance (rmANOVA) tests were used to investigate the effect of 'Feature type' (four levels: MAV, WL, ZC, and SSC) on classification accuracies (average across positions for WPC).

To investigate the effect of training position in the BPC paradigm, the mean was taken across the test positions (e.g. training in position 1 and testing in 2–4). This was followed by a 1-way rmANOVA test with 'Arm position' (four levels: 0, 45, 90, and 135°) as the factor for sEMG, iEMG, and cEMG. Similarly, three 1-way rmANOVA tests were performed to investigate the effect of 'Motion class' (five levels: HG, HO, rest, WE, and WF).

The ratios between APC/WPC and BPC/WPC for each subject were calculated and compared with a 2-way rmANOVA with the factors 'EMG modality' and 'Ratio' (two levels: APC/WPC, and BPC/WPC) to investigate if the calibration paradigm and EMG modality affected the classification accuracies when using all features. Lastly, a 3-way rmANOVA was performed to investigate if similar tendencies were observed in classification accuracies when using two different classifiers. The factors were "EMG modality", "Ratio" and "Classifier" (two levels: "Bayes", and "LDA").

Significant tests were followed up with Bonferroni's post hoc test. The Greenhouse-Geisser correction was used if the assumption of sphericity was violated. Significant test statistics were assumed when $P < 0.05$. The effect size is also reported using partial eta squared ($\eta^2$). The statistical analyses were performed in the IBM SPSS Software.

## 3. Results

### 3.1. WPC

In Table 1, the results are summarized when the classifier is trained and tested on data collected from the same position, and the effect of the "Feature type" when using them individually for classification is shown as well. High classification accuracies are obtained when using all features for both sEMG and iEMG with almost similar classification accuracies. When the two types of EMG are combined the classification accuracies increases with ~3 percentage points.

For the individual features, the statistics revealed a significant effect of 'Feature type' ($F_{(3,21)} = 11.1$; $P < 0.001$; $\eta^2 = 0.6$) for sEMG. The post hoc tests revealed higher classification accuracies for WL and MAV compared to ZC. Also, a significant effect of 'Feature type' ($F_{(3,21)} = 4.2$; $P = .02$; $\eta^2 = 0.4$) was found for iEMG with higher classification accuracies for MAV compared to WL.

### 3.2. APC

When data from all positions are used in the training of the classifier and it is tested on data from all positions, the classification

**Table 1**
Classification accuracies when training and testing in the same position. The results are reported as mean ± standard deviation (across the subjects) for surface EMG (s) and intramuscular EMG (i). 'c' is the combined surface and intramuscular EMG. 'MAV': Mean absolute value, 'WL': waveform length, 'ZC': zero crossing, and 'SSC': slope sign changes.

| PositionFeature type | All (%) [s/i/c] | MAV (%) [s/i] | WL (%) [s/i] | ZC (%) [s/i] | SSC (%) [s/i] |
|---|---|---|---|---|---|
| 0° | 95 ± 4/95 ± 4/98 ± 3 | 79 ± 9/72 ± 10 | 80 ± 12/62 ± 12 | 59 ± 9/62 ± 10 | 61 ± 7/59 ± 10 |
| 45° | 95 ± 6/95 ± 6/98 ± 4 | 82 ± 6/72 ± 6 | 87 ± 7/58 ± 13 | 63 ± 11/58 ± 11 | 69 ± 12/64 ± 10 |
| 90° | 93 ± 6/96 ± 3/97 ± 4 | 77 ± 6/73 ± 4 | 79 ± 6/56 ± 5 | 62 ± 14/57 ± 10 | 76 ± 8/67 ± 12 |
| 135° | 95 ± 4/95 ± 3/98 ± 2 | 77 ± 8/73 ± 7 | 78 ± 9/51 ± 11 | 65 ± 14/59 ± 11 | 67 ± 7/59 ± 11 |

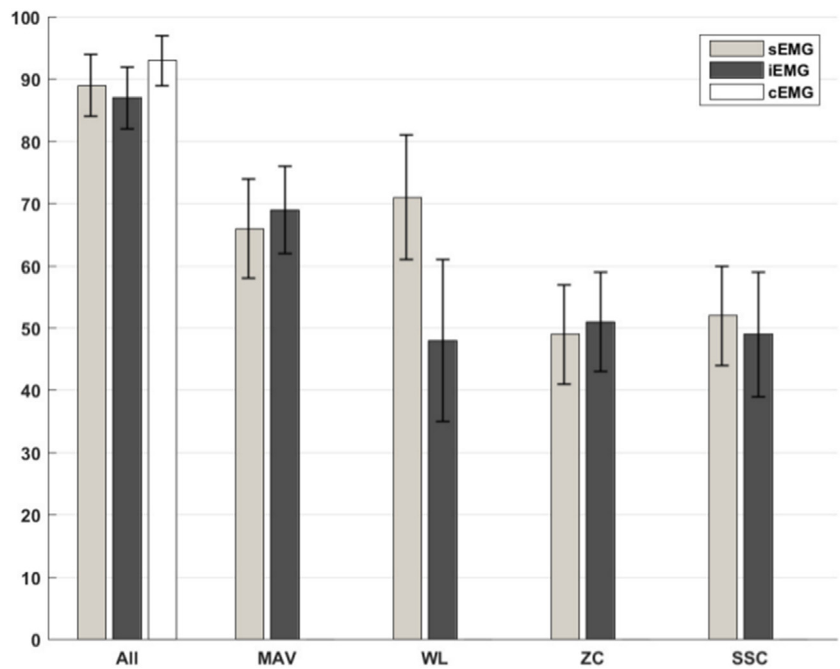


**Fig. 3.** Classification accuracies (%) when training and testing in all positions. The results are reported as mean ± standard deviation (across the subjects) for surface EMG (sEMG), intramuscular EMG (iEMG), and combined surface and intramuscular EMG (cEMG). 'MAV': Mean absolute value, 'WL': waveform length, 'ZC': zero crossing, and 'SSC': slope sign changes.

accuracies decrease (see Fig. 3) compared to those obtained when training and testing in a single position (Table 1). Again, the classification accuracies are higher when sEMG and iEMG are combined and all features are used.

The statistics revealed a significant effect of 'Feature type' ($F_{(3,21)} = 11.3$; $P < 0.001$; $\eta^2 = 0.6$) for sEMG. The classification accuracies were higher for MAV and WL compared to ZC. A significant effect of 'Feature type' (($F_{(3,21)} = 6.0$; $P = .006$; $\eta^2 = 0.5$) was also found for iEMG with higher classification accuracies for MAV compared to WL and ZC.

### 3.3. Feature type visualization

In Fig. 4 (sEMG) and 5 (iEMG) the feature distributions (mean and standard deviation) of the different motion classes is shown for each position for each feature type. The x-axis and y-axis show the flexor and extensor, respectively. From Fig. 4 it can be seen that the distributions are close to each other or overlapping and that the variability increases when the arm position changes from 0°; moreover, there is a shift in the mean value for some of the motion classes when the position of the arm is changed, especially for HO. In general, for the iEMG (Fig. 5) it can be seen that the distributions are overlapping for all feature types. The MAV is less affected by the changes in arm position, while the 'rest' motion class moves for WL when the arm position changes. For ZC, the variability was large in the WF motion class, and it was affected by the arm position. For SSC the HO motion class was affected the most by arm position.

### 3.4. BPC

#### 3.4.1. Position

The classification accuracies when training on data from one position and testing in another position are presented in Table 2 when all features were used together. The classification accuracies on the diagonal have been presented in Table 1. Compared to the APC paradigm in Fig. 3, the classification accuracies decrease even further. In general, the lowest classification accuracies were obtained when training in the 0° position and testing in the 135° position.

The statistics revealed no difference ($F_{(3,21)} = 1.4$; $P = .3$; $\eta^2 = 0.2$) between 'Arm position' for sEMG. For iEMG a significant difference was observed ($F_{(3,21)} = 7.4$; $P = .001$; $\eta^2 = 0.5$) with lower classification accuracies when training in the 0° position compared to the 90 and 135° positions. There was also a significant difference for cEMG ($F_{(3,21)} = 4.3$; $P = .02$; $\eta^2 = 0.4$). Again the classification accuracies were lower when training in the 0° position compared to training in the 135° position.

To see the effect on the motion classes in the worst scenario (training in 0° and testing in 135°), the confusion matrix was calculated. This showed the following values on the diagonal for cEMG: 91% (HG), 60% (HO), 54% (Rest), 79% (WE), and 61% (WF).

#### 3.4.2. Motion class

The highest classification accuracies are observed on the diagonal in the confusion matrices (Tables 3–5). The classification accuracies are lower when the classifier is trained in one position

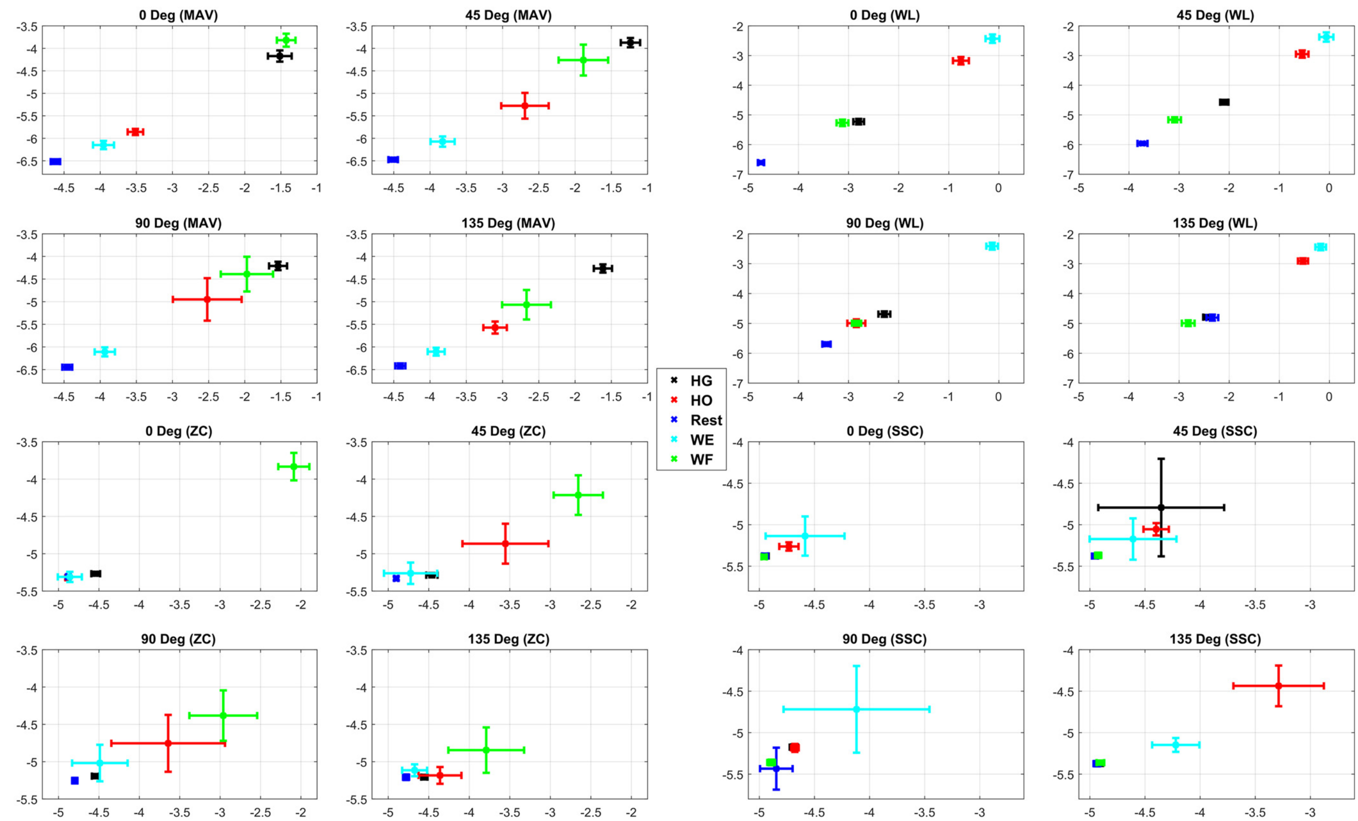


**Fig. 4.** Feature distribution (mean and standard deviation) of surface EMG (subject 1). The scaling is the same for each feature type. The x-axis is the flexor EMG, and the y-axis is the extensor EMG. 'MAV': Mean absolute value, 'WL': waveform length, 'ZC': zero crossing, 'SSC': slope sign changes, 'HG': hand grasp (black), 'HO': hand open (red), 'WE': wrist extension (cyan), and 'WF': wrist flexion (green). 'Rest' is marked with a blue cross. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 2**
Classification accuracies when training in one position and testing in another position. The average values are reported across all motion classes and across subjects. All features were used for the classification. Example: Training in 45° and testing in position 0° lead to 83% classification accuracy for surface EMG. 'sEMG': surface EMG, 'iEMG': intramuscular EMG, and 'cEMG': combined surface and intramuscular EMG.

| All Features | | **Test (sEMG)** | | | | **Test (iEMG)** | | | | **Test (cEMG)** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0 | 45 | 90 | 135 | 0 | 45 | 90 | 135 | 0 | 45 | 90 | 135 |
| Training position (degrees) | 0 | | 81 | 69 | 73 | | 67 | 67 | 65 | | 79 | 73 | 69 |
| | 45 | 83 | | 74 | 83 | 77 | | 80 | 70 | 86 | | 81 | 81 |
| | 90 | 79 | 71 | | 75 | 77 | 81 | | 74 | 82 | 80 | | 77 |
| | 135 | 76 | 79 | 74 | | 77 | 76 | 81 | | 81 | 86 | 81 | |

**Table 3**
Confusion matrix for surface EMG when using all features. The average values are reported across all possible position pairs and across subjects. 'HG': hand grasp, 'HO': hand open, 'WE': wrist extension, and 'WF': wrist flexion.

| | | Predicted label | | | | |
|---|---|---|---|---|---|---|
| **True label** | | HG | HO | Rest | WE | WF |
| | HG | 70 | 8 | 10 | 6 | 6 |
| | HO | 10 | 67 | 5 | 17 | 2 |
| | Rest | 5 | 4 | 91 | 0 | 0 |
| | WE | 2 | 17 | 0 | 81 | 0 |
| | WF | 19 | 3 | 5 | 0 | 73 |

**Table 4**
Confusion matrix for intramuscular EMG when using all features. The average values are reported across all possible position pairs and across subjects. 'HG': hand grasp, 'HO': hand open, 'WE': wrist extension, and 'WF': wrist flexion.

| | | Predicted label | | | | |
|---|---|---|---|---|---|---|
| **True label** | | HG | HO | Rest | WE | WF |
| | HG | 85 | 6 | 2 | 4 | 3 |
| | HO | 13 | 53 | 1 | 22 | 11 |
| | Rest | 12 | 6 | 77 | 5 | 0 |
| | WE | 5 | 13 | 2 | 78 | 2 |
| | WF | 9 | 9 | 1 | 2 | 80 |

and tested in another position when compared to the classification accuracies in Tables 1 and 2. The overall classification accuracies on the diagonal are similar for sEMG and iEMG, but the classification accuracies for HG and HO are a bit different when comparing the two types of EMG; 15 and 14 percentage points, respectively. As for the other classification scenarios, the cEMG increases the classification accuracies compared to each type of EMG individually. The motion class HO was consistently lower compared to the other motion classes and often predicted as WE.

The statistics revealed no significant effect of 'Motion class' for sEMG ($F_{(4,28)} = 2.0$; $P = .1$; $\eta^2 = 0.2$), iEMG ($F_{(1.9,13.1)} = 3.3$; $P = .07$; $\eta^2 = 0.3$), or cEMG ($F_{(4,28)} = 1.0$; $P = .4$; $\eta^2 = 0.1$).

### 3.5. Ratios

The APC/WPC and BPC/WPC ratios were calculated for sEMG and iEMG to investigate if there were differences in the classification paradigms for sEMG and iEMG. The ratios for BPC/WPC were

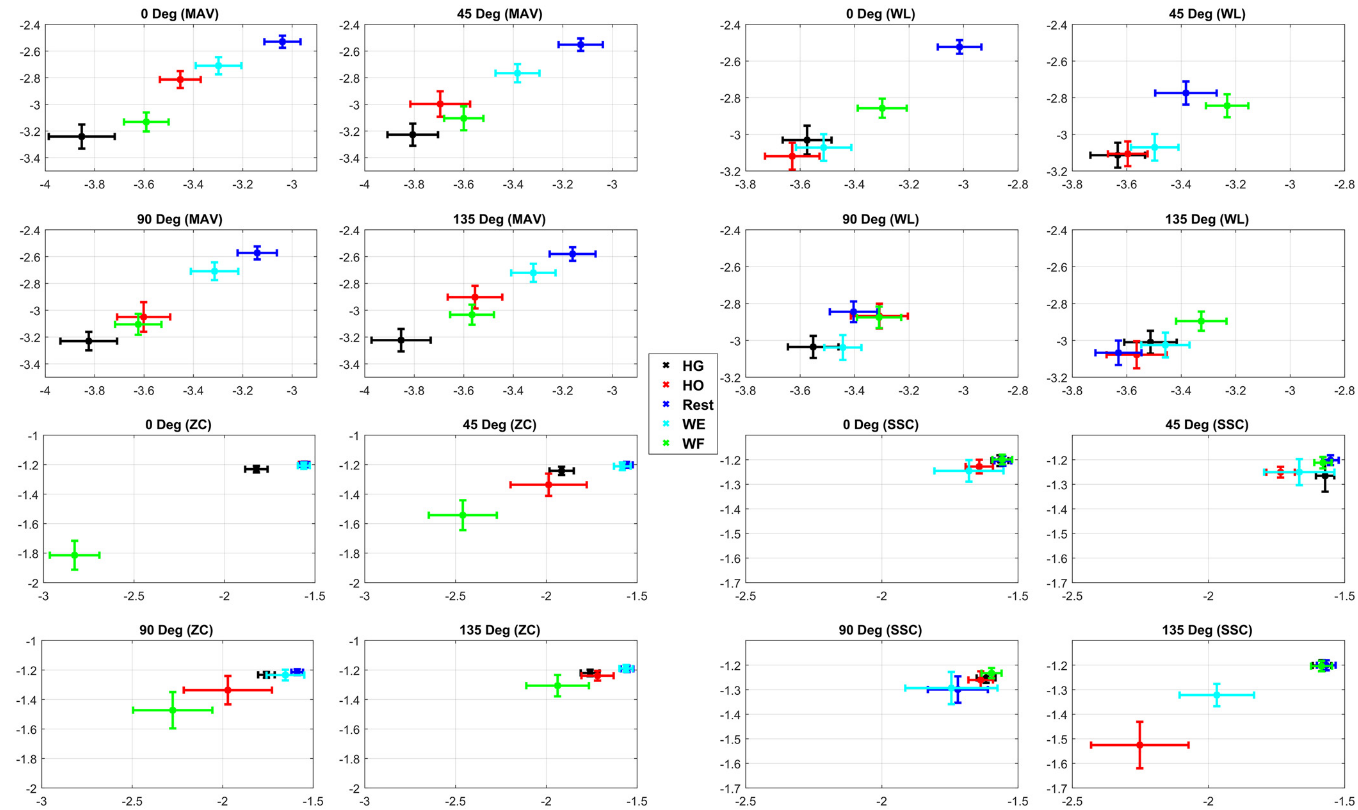

**Fig. 5.** Feature distribution (mean and standard deviation) of intramuscular EMG (subject 1). The scaling is the same for each feature type. The x-axis is the flexor EMG, and the y-axis is the extensor EMG. 'MAV': Mean absolute value, 'WL': waveform length, 'ZC': zero crossing, 'SSC': slope sign changes, 'HG': hand grasp (black), 'HO': hand open (red), 'WE': wrist extension (cyan), and 'WF': wrist flexion (green). 'Rest' is marked with a blue cross. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 5**
Confusion matrix for combined surface and intramuscular EMG when using all features. The average values are reported across all possible position pairs and across subjects. 'HG': hand grasp, 'HO': hand open, 'WE': wrist extension, and 'WF': wrist flexion.

| | | Predicted label | | | | |
|---|---|---|---|---|---|---|
| **True label** | | HG | HO | Rest | WE | WF |
| | HG | 83 | 6 | 3 | 5 | 3 |
| | HO | 9 | 67 | 2 | 18 | 4 |
| | Rest | 10 | 6 | 83 | 0 | 0 |
| | WE | 3 | 14 | 0 | 83 | 0 |
| | WF | 12 | 4 | 2 | 0 | 82 |

$0.81 \pm 0.06$ and $0.78 \pm 0.12$ for sEMG and iEMG, respectively. The ratios for APC/WPC were $0.94 \pm 0.03$ and $0.92 \pm 0.05$ for sEMG and iEMG, respectively. There was no significant interaction between 'EMG modality' and 'Ratio' ($F_{(1,7)} = 0.01$; $P = .9$; $\eta^2 < 0.001$). The APC/WPC ratio was significantly higher than BPC/WPC ($F_{(1,7)} = 86.7$; $P < 0.001$; $\eta^2 = 0.9$), but there was no difference between the two EMG modalities ($F_{(1,7)} = 0.6$; $P = .5$; $\eta^2 = 0.08$).

### 3.6. Classifier comparison

The results from the classifier comparison are summarized in Fig. 6. Similar tendencies are observed when using the two different classifiers, the APC/WPC ratio was higher than BPC/WPC for all three modalities. It changed whether the LDA or Bayes achieved higher classification accuracies. There was no interaction between all three factors ($F_{(2,14)} = 2.7$; $P = .1$; $\eta^2 = 0.3$), but there was a significant 2-way interaction between classifiers and ratio ($F_{(1,7)} = 7.3$; $P = .03$; $\eta^2 = 0.5$), and there was a significant effect of ratio as shown in the previous section. The post hoc analyses showed that the APC/WPC ratio was higher than the BPC/WPC ratio for the three EMG modalities and for the two classifiers.

## 4. Discussion

In this study it was found that the intra-class (WPC) classification accuracies of five motion classes were high. However, these classification accuracies decreased when more positions of the arm were included in the training set (APC), and the lowest classification accuracies were obtained when the classifier was trained on data from one position and tested in a different position (BPC). All feature types were affected by the change in arm position, but the least position affected feature was MAV. The motion class that was affected the most by the change in arm position was HO. The same tendencies were seen with either a Bayes or LDA classifier.

The results obtained for the sEMG when investigating the effect of arm position validate the previous findings as reported in [9,14,16], where similar classification accuracies/errors have been reported. Despite differences in the methodology, HO has also been associated with the lowest classification accuracy out of the motion classes that were similar to those in our study [14]. This suggests that if only one degree of freedom needs to be controlled it should be designed, so WE and WF are used. Similar to the findings in [18] the classification accuracies increase when sEMG and iEMG are combined. For the inter-class scenarios (APC and BPC), the classification accuracies are similar for the two types of EMG, which is reflected in the ratios that were calculated with respect to the intra-class scenario (WPC). For the individual features, the best features were MAV and WL. For iEMG, MAV was the best feature type leading to classification accuracies much higher than those obtained for the other features. The best features for sEMG were WL and MAV

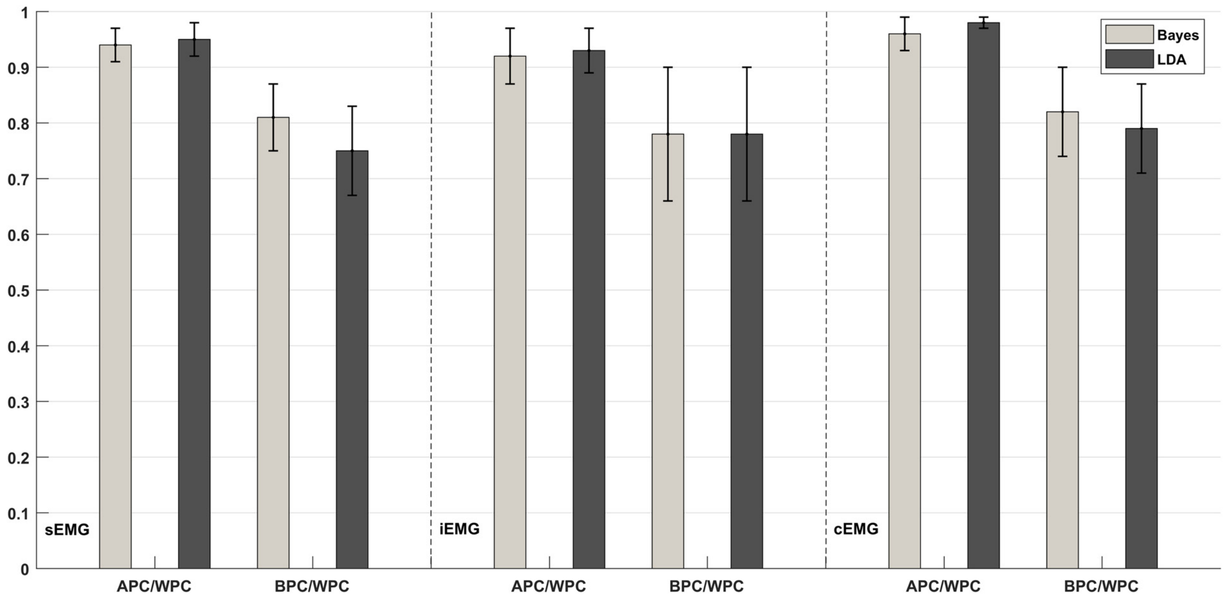


**Fig. 6.** Classification accuracies across subjects when comparing the Bayes and LDA classifiers for the two ratios. The results are reported as mean ± standard deviation (across the subjects) for surface EMG (sEMG), intramuscular EMG (iEMG), and combined surface and intramuscular EMG (cEMG).'APC': across position classification, 'WPC': within position classification, 'BPC': between position classification, and 'LDA': linear discriminant analysis.

which were associated with higher classification accuracies. As can be seen in Fig. 4, the distributions of some of the motion classes are moving which also explain the drop in classification accuracies. This may be due to a number of factors. One of the factors is variations in muscle recruitment due to gravitational forces, which fit well with our findings where the 'rest' class shows the lowest classification accuracy when calibrating the classifier on training data from the 0° position and testing it on data from the 135° position. Other factors include electrode shifts due to skin displacement. However, as iEMG is also affected, electrode displacement is unlikely to be the main contributing factor. Moreover, motor variability [24] could also affect the classification accuracy due to change in arm position during active motions. We believe that the subject's ability to produce motions of similar characteristics in terms of kinematics and kinetics is reduced with changes in position.

To overcome the effect of the limb position different approaches have been proposed such as integration of accelerometers to indicate the position of the arm [14], identification of position independent features [16], or simply calibrating the system in multiple positions [14]. By using the latter approach it is possible to expand the boundaries of each motion class to capture some of the variability that the arm position induces.

## 5. Conclusion

The results showed that the inter-class classification accuracy of five motion classes is affected by the arm position. It is possible to obtain relatively high classification accuracies when including training data from all positions in the calibration of the classifier, and when combining sEMG and iEMG. Among the four typical time domain features, MAV showed to be the least affected by arm position followed by WL. The same tendency for the effect of arm position was seen when using different classifiers implying that changes in the feature space due to changes in EMG characteristics are the primary contributing factors to position dependent performance. In future studies, amputees should be included in online classification to provide more clinically relevant evidence, and perform online testing of the three classification paradigms. Moreover, it would be relevant to do a thorough feature investigation study to try to identify position invariant features for optimizing the classification of hand gestures.

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