Prediction of grasping force based on features of surface and intramuscular EMG

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Abstract

Myoelectric prosthetic devices can be controlled based on surface electromyography (sEMG). However, intramuscular EMG (iEMG) has been proposed as an alternative control signal, since it may provide more stable and selective recordings with several advantages such as electrode implantation. An earlier study quantified the relationship between iEMG and grasping force, however, this was solely based on one feature and force ranging from 0-50 N. The present study quantified the linear relationship between grasping force and 14 different EMG features using the entire force range from 0 to 100 % maximum voluntary contraction (MVC) and assessed their predictive capabilities. Single-channel iEMG and sEMG were recorded concurrently from the muscle flexor digitorum profundus (FDP) from 11 subjects who exerted four force profiles during power grasping. The predictive capability of all the features was assessed using $R^2$ with a 1st order polynomial and an Artificial Neural Network (ANN).

Wilson Amplitude ($WAMP$) showed the best results for both sEMG and iEMG in linear relationship and linear prediction ($\bar{R}^2 > 0.9$), with no significant difference between the two signals for linear prediction. For the ANN, constraint sample entropy ($CSE$) and $WAMP$ showed the best results for iEMG and sEMG, respectively ($\bar{R}^2 > 0.9$). No significant difference was found for the ANN between the two signals. Furthermore, there was no significant difference between linear prediction and ANN. Thus, the choice of prediction model (linear prediction or ANN) did not play a significant role. These results indicate that iEMG can be used for force prediction with a 1st order polynomial and thus in proportional control (0-100 % MVC) with same accuracy as for sEMG.

Keywords: Surface EMG, Intramuscular EMG, Grasping force, Power grip, Flexor digitorum profundus, Linear relationship, Artificial Neural Network, Prediction, Features

1. Introduction

The dominant causes for missing limbs in the upper-extremity are malformation, and amputation caused by trauma or surgery. For most of the patients with amputations, the only possibility for restoration of movement is through the use of prosthetic devices. The use of prosthetic devices has shown positive effect on the quality of life for amputees. To further improve the daily life of amputees, extensive research is being conducted in order to enhance the usability of prosthetic devices by finding advanced control schemes, and thereby make movements as intuitive as possible for the users.\[1\] It is well known that surface EMG (sEMG) is used for the control of myoelectric prosthetic devices, where the applied force is predicted proportionally to muscle activity.\[2,3,4\]

Several studies have shown that the exerted force can be predicted based on features extracted from EMG signals. These range from Integrated EMG, Variance (VAR), Zero-Crossing (ZC), Slope-Sign Changes (SSC), Waveform Length (WL) and Wilson Amplitude ($WAMP$) to a parametric autoregressive model (AR-model).\[5,6,7\] In these studies, $WL$, VAR and integrated EMG\[5\] showed the best performance. The relationship between these features and force has been shown to be monotonic, both linearly\[8,4\] and non-linearly.\[9,10\] Despite good results, the use of sEMG has the following disadvantages: is limited to a single Degree-of-Freedom (DoF), can only be measured from superficial muscles, is sensitive to crosstalk, and can cause irritation of the skin during repeated use.\[11,2\]

Use of intramuscular EMG (iEMG) for prosthetic devices has been proposed because iEMG may provide more stable and selective recordings than sEMG, and may be used for achieving effective control of multiple DoFs. Furthermore, it might be possible to implant iEMG electrodes chronically.\[2\]

Because of their high selectivity, iEMG electrodes may be less representative of the global muscle activity and thereby contain less information about the force produced by the entire muscle. However, only few studies on iEMG recordings for linear relationship have been published. Thus, only two features (global discharge rate, GDR, and Integrated EMG) have been investigated for iEMG.\[2,12\] Kamavuako et al.\[2\] has shown that there
is a high correlation (linear correlation coefficient of ~0.9) between the GDR feature of iEMG recordings and force. However, force was limited to 50 N and an indirect muscle was used to measure EMG. Onishi et al.\textsuperscript{[12]} showed a coefficient of determination ($R^2$) above 0.85 between the integrated EMG feature of iEMG recordings and force, though, this was done for knee extension.

From our best knowledge, there is only one study on the iEMG recordings and force prediction. This study showed a $R^2$-value of ~0.8 between the Constraint Sample Entropy (CSE) feature of the iEMG recordings and force.\textsuperscript{[13]}

Furthermore, no studies have shown whether the used features proposed for sEMG can be applied for iEMG in the entire range of force from 0 to 100 % maximum voluntary contraction (MVC). Therefore, the aim of this study was to quantify the linear relation between grasping force and EMG features using the entire force range from 0 to 100 % MVC and to assess their predictive capabilities.

The extracted features in this study were: WL, ZC, SSC, WAMP, Mean Absolute Value (MAV), Modified Mean Absolute Value (MMAV), Mean Absolute Value Slope (MAVSLP), VAR, AR-model, Histogram of EMG (HEMG), EMG Envelope Energy (EMG\textunderscore env\textunderscore energy), EMG Envelope (EMG\textunderscore env), CSE and Root Mean Square (RMS). The investigation was carried out in three steps: First the best linear relationship was found for each feature, and then the force was predicted (with a 1st order polynomial) based on the results of the previous step. Finally, the Artificial Neural Network (ANN) was applied in order to determine whether there was a significantly better prediction accuracy than the linear.

2. Methods

2.1. Experiment

2.1.1. Subjects

The experiment included 11 healthy subjects (4 w/7 m) in the age of 22 to 26 years, with a mean of 23.8 years. The experiment was approved by the Danish local ethical committee (approval no.: N-20080045). All subjects received both written and oral information about the experiment in advance and gave written consent prior to the experiment.

2.1.2. Procedure

The subjects exerted force while seated in a chair with their right arm placed in an armrest (Figure 1). First, the subjects exerted their MVC force, which was recorded three times with a 3 min rest after each trial. Afterwards the subjects were asked to follow four different force profiles:

1. A step profile of 9 s with force increasing in 6 steps (Figure 2a).
2. A double ramp profile of 9 s (Figure 2b).
3. A bell profile of 9 s (Figure 2c).
4. A free varying profile of 9 s with the only constraint to reach the MVC force within this time.

The order of the profiles was randomized. The step, double ramp and bell profile was recorded two times and the level of force spanned from 0 to 100 % MVC. The free varying profile was only recorded once. The force was shown on an oscilloscope in order to provide the subject with visual feedback during each profile. Each trial was followed by a 3 min rest, and all subjects were provided with adequate time to practice matching the profile before the actual recording.

2.1.3. Data recording

In the experiment, a Jamar compatible handgrip dynamometer (Noraxon) with an adjustable grip size was used in order to measure the grasping force. The grip size was set according to the maximum force of each subject. The iEMG electrodes (custom-made by use of hypodermic needles and Teflon coated wires (A-M Systems, Carlsberg, WA; diameter 50 µm)) were placed in a bipolar configuration, in the muscle flexor digitorum profundus (FDP). This muscle was chosen since it has a good reliability and acts as a direct finger flexor during power grasp.\textsuperscript{[14]} The needle was placed in the middle one-third of the forearm ventral to the ulnar shaft.\textsuperscript{[15]} The analogue output from the iEMG electrodes was amplified with a factor of 1000 and filtered with a bandpass of 20-5000 Hz. Simultaneously, sEMG was recorded in a bipolar configuration (Ambu Neuroline 720) from the same muscle. The analogue output from the sEMG electrodes was amplified with a factor of 2000 and filtered with a bandpass of 20-500 Hz. An amplification and filtering device (EM001-01 SMI) was used for both iEMG and sEMG. A wristband was used as a common reference electrode. The analogue outputs of the force, iEMG and sEMG were sampled by use of a 16 bit AD converter (NI-DAQ USB-6259) with a sampling frequency of 20 kHz.
2.2. Signal processing

2.2.1. Digital filters

Three 4th order Butterworth filters were applied. The force was lowpass filtered with a cutoff frequency of 20 Hz. The iEMG and sEMG were bandpass filtered with frequencies 100-2500 Hz and 20-500 Hz, respectively. Furthermore, a 2nd order Butterworth filter with a cutoff frequency of 1 Hz was applied for the features.

2.2.2. Extracted features

In total 14 features were chosen to represent the iEMG and sEMG signals. The features were all applied to windows of 200 ms with a step size of 50 ms. Furthermore, the same window size was applied on the force signal where the mean was calculated for each window. Thresholds were found by visually inspecting the performance of the features. These thresholds were general for all subjects and profiles. The extracted features were:

1) Waveform Length (WL): The WL feature is related to the fluctuations of a signal when the muscle is activated.[7] The feature was defined as in Phinyomark et al.[7]

2) Zero Crossing (ZC): The ZC feature is a measure of how many times the signal crosses zero on the amplitude axis. The effect of noise was minimized by using a threshold of 0.1 mV and 0.05 mV for iEMG and sEMG, respectively. The ZC feature was defined as in eq. 1:[5]

\[ ZC = \sum_{k=2}^{N} f[(x_k - \epsilon) \cdot (x_{k-1} - \epsilon)] \quad \text{for } i = 1, ..., I \quad (1) \]

\[ f(x) = \begin{cases} 1, & \text{if } x < 0, \\ 0, & \text{otherwise.} \end{cases} \]

where \( x_k \) is the k-th sample data of the signal, \( N \) is the total number of samples in the window, \( i \) is the current window, \( I \) is the total number of windows, and \( \epsilon \) is the applied threshold.

Each time there is a difference in the sign between two samples, the ZC will be incremented. Eq. 1 is a modified version of the equation proposed by Phinyomark et al.[7]

3) Slope Sign Changes (SSC): The SSC feature is related to ZC and is an expression for the number of times the sign changes in the slope of the signal.[16] The feature was defined as in Phinyomark et al.[16] To reduce the effect of noise, a threshold of 0.2 nV for sEMG and 0.01 mV for iEMG was implemented.

4) Wilson Amplitude (WAMP): The WAMP feature is similar to GDR[2], but here there is no compensation for amplitude. WAMP describes how many motor units are firing. To evaluate the number of firing motor units, it was counted how many times the amplitude of the signal exceeded a certain threshold.[5] The threshold was set to 0.005 mV for sEMG and 0.02 mV for iEMG. The feature was defined as in Huang and Chen.[5]

5) Mean Absolute Value (MAV): The MAV feature expresses the mean absolute value of the signal and is often used for applications recognizing hand movement and for proportional control of prostheses.[7] The feature was defined as in Phinyomark et al.[7]

6) Modified Mean Absolute Value (MMAV): The MMAV feature is an extension of MAV where a window is applied to the signal in order to improve the robustness of the feature.[7] The feature was defined as in Phinyomark et al.[7] However, instead of weighting the samples with a single fixed value as proposed by Phinyomark et al.[7] a Hanning window was applied.

7) Mean Absolute Value Slope (MAVSLP): The MAVSLP feature is an extension of MAV that describes the difference between sums in adjacent windows.[17] The proposed equation was modified by taking the absolute value of MAV_{i+1} - MAV_{i}.

\[ \text{MAVSLP} = \sum_{i=1}^{I} \sum_{k=2}^{N} |(x_k - \epsilon) \cdot (x_{k-1} - \epsilon)| \quad \text{for } i = 1, ..., I \quad (2) \]

\[ f(x) = \begin{cases} 1, & \text{if } x < 0, \\ 0, & \text{otherwise.} \end{cases} \]

where \( x_k \) is the k-th sample data of the signal, \( N \) is the total number of samples in the window, \( i \) is the current window, \( I \) is the total number of windows, and \( \epsilon \) is the applied threshold.

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7) Mean Absolute Value Slope (MAVSLP): The MAVSLP feature is an extension of MAV that describes the difference between sums in adjacent windows.[17] The proposed equation was modified by taking the absolute value of MAV_{i+1} - MAV_{i}.
8) **Variance (VAR):** The VAR feature is a measure of the power of the signal. The feature can be used to increase the difference between high and low amplitudes in order to detect muscle activity.[7]

The feature was defined as in Phinyomark et al.[7]

9) **Autoregressive model (AR-model):** The AR-model feature describes each sample of the EMG as a linear combination of previous samples plus an independent error term. This model can be used since the signal can be considered as a Gaussian process for short periods of time.[18]

The AR-coefficients were predicted using the Yule-Walker approach and the RMS of the AR-coefficients was used as a representation of the signal within a given window.

10) **Histogram EMG (HEMG):** The HEMG feature gives information about the different amplitude levels in a specified time segment. It is considered as an extension of the ZC and WAMP. The HEMG is suitable when detecting and classifying hand motion.[19] A normalized histogram was used and the distribution of a segment was represented by the amplitude level \( i \) for the median of the distribution.

11) **EMG envelope energy (EMG_env_energy):** The EMG_env_energy feature is a sum of the samples that exceeds a certain threshold.[5] This threshold was set to 0.5 \( \mu \text{V} \) for sEMG and 20 \( \mu \text{V} \) for iEMG in order to minimize the noise. The feature was defined as in Du et al.[6]

12) **EMG envelope:** The EMG envelope feature is a combination of WL and the SSC.[6] To avoid the effect of noise, a threshold of 0.025 mV was used for sEMG and 0.01 mV for iEMG. The feature was defined as in Du et al.[6] However, the proposed equation was modified by taking the absolute value of \( x \).

13) **Constraint Sample Entropy (CSE):** The sample entropy is an expression for the complexity of the EMG signal. It computes the likelihood that similar patterns of data will stay similar within a longer pattern. Two vectors are said to match one another if the distance between them is within a predefined tolerance level \( r \).[13]

CSE was defined as in Kamavuako[13], with \( r \) being 0.2 times the standard deviation in the EMG signals during the MVC profiles.

14) **Root mean square (RMS):** The RMS is a well know feature and will thus not be described further. RMS is especially suited for signals with both positive and negative values.[7]

### 2.3. Data analysis

The analysis was done in two phases; first, the linear relationship between grasping force and signal features was assessed and secondly the predictive capability of these features was assessed.

#### 2.3.1. Phase 1: Linear relationship

The linear relationship was performed between grasping force and the extracted features using seven different profile combinations: Single profiles (step, bell and double ramp), combination of two profiles (step+bell, step+ramp, bell+double ramp) and combination of all profiles (step+bell+double ramp).

The performance measure for each relationship was the R\(^2\)-value.

#### 2.3.2. Phase 2: Force prediction

Force was predicted using two different models; linear prediction and ANN as described below:

**Linear Prediction:** For each feature, the combination of profiles described above was used to derive the linear prediction model (with a 1st order polynomial) in order to predict the force produced during the free varying profile.

**Artificial Neural Network (ANN):** The ANN was used to find the association between each feature and force using the same combination of profiles. In this study a three layer ANN architecture was applied. The transfer function for the hidden layers was a tan sigmoid and for the output layer the linear transfer function was used.[20]

The input data was divided into two contiguous blocks of equal size and the Levenberg-Marquardt training method was used with the mean square error (MSE) as a performance measure. Weights and biases were set randomly at the beginning of the training.[20] The training of the network was done 50 times and the network with the best R\(^2\)-value was chosen. The free varying profile was used for testing the model.

### 2.4. Statistical analysis

Analysis of Variance (ANOVA) and paired t-test were performed in SPSS 18.0 software and P-values less than 0.05 were considered significant. When performing ANOVA, the Bonferroni–Dunn test was used for pair-wise comparisons if the ANOVA was significant. A sphericity test was done for each ANOVA. If this test showed significant results the Huynh-Feldt test was used.

#### 2.4.1. Linear relationship

For each signal type (iEMG or sEMG) two-way ANOVA (with factor features and profiles) was performed in order to compare the features and associated profile combinations. The feature with the highest mean R\(^2\)-value (\( \bar{R}^2 \)) was selected for each signal and one-way ANOVA (with factor profiles) was performed for each signal in order to compare the profiles for the specific feature. Additionally, two-way ANOVA (with factors signals and features) were performed in order to compare the features with the highest \( \bar{R}^2 \)-value between sEMG and iEMG.
2.4.2. Force prediction

**Linear prediction:** Profiles were not taken into consideration for the linear prediction since a linear relationship causes the $R^2$-value of one feature to be the same for all profiles. Therefore, a one-way ANOVA (with factor features) was performed in order to find the feature with the highest $R^2$-value for both sEMG and iEMG. Furthermore, a paired t-test was performed in order to compare the signals.

**Artificial Neural Network (ANN):** The statistical analysis of the ANN was performed in the same way as for the linear relationship. In addition, a paired t-test was performed in order to compare linear prediction and ANN for the combination of the feature with the highest $R^2$-value and its corresponding profile with the highest $R^2$-value.
Table 1: Results from the linear relationship (LR) for each EMG-signal with standard error (SE) and confidence interval (CI). The P-value (P) is given for the difference between the signals regarding the chosen features. Only the feature with the highest $\bar{R}^2$-value and the corresponding profile with the highest $\bar{R}^2$-value are listed.

<table>
<thead>
<tr>
<th>Feature/profile with highest $\bar{R}^2$</th>
<th>$\bar{R}^2$</th>
<th>SE</th>
<th>CI</th>
<th>P</th>
</tr>
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<tbody>
<tr>
<td>Feature for:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>iEMG</td>
<td>WAMP</td>
<td>0.921</td>
<td>0.010</td>
<td>[0.898 , 0.944]</td>
</tr>
<tr>
<td>sEMG</td>
<td>WAMP</td>
<td>0.949</td>
<td>0.004</td>
<td>[0.940 , 0.959]</td>
</tr>
<tr>
<td>Profile for:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>iEMG</td>
<td>Bell</td>
<td>0.946</td>
<td>0.009</td>
<td>[0.927 , 0.965]</td>
</tr>
<tr>
<td>sEMG</td>
<td>Bell</td>
<td>0.966</td>
<td>0.004</td>
<td>[0.957 , 0.975]</td>
</tr>
</tbody>
</table>

Table 2: Results from the linear prediction (LP) for each EMG-signal with standard error (SE) and confidence interval (CI). The P-value (P) is given for the difference between the signals regarding the chosen features. Only the feature with the highest $\bar{R}^2$-value is listed.

<table>
<thead>
<tr>
<th>Feature with highest $\bar{R}^2$</th>
<th>$\bar{R}^2$</th>
<th>SE</th>
<th>CI</th>
<th>P</th>
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<td>Feature for:</td>
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<td></td>
</tr>
<tr>
<td>iEMG</td>
<td>WAMP</td>
<td>0.948</td>
<td>0.008</td>
<td>[0.929 , 0.966]</td>
</tr>
<tr>
<td>sEMG</td>
<td>WAMP</td>
<td>0.952</td>
<td>0.007</td>
<td>[0.937 , 0.967]</td>
</tr>
</tbody>
</table>

3. Results

Figure 3 shows examples of all four profile recordings from one subject. The overall mean of the maximum grasping force (MGF) was $511.1 \pm 146$ N for the recorded MVCs. Figures 4a and 4b depict an example of the raw sEMG and iEMG signals from a bell profile, respectively, while Figures 4c and 4d show the corresponding five features with the highest $\bar{R}^2$-values.

3.1. Linear relationship

In Table 1 the results are summarized for the feature with the highest $\bar{R}^2$-value for each signal along with the profile with the highest $\bar{R}^2$-value for this feature. In Figure 5 the $\bar{R}^2$-values for the different features are depicted.

WAMP showed the highest $\bar{R}^2$-value for both iEMG and sEMG. The two-way ANOVA (with factors signals and feature) showed that WAMP for sEMG had a significantly higher $\bar{R}^2$-value than WAMP for iEMG ($P = 0.044$).

For iEMG, WAMP was significantly different from MAVSLP, VAR, HEMG and AR-model ($P \leq 0.001$). For sEMG, WAMP was significantly different from SSC, VAR and EMG_Env ($P < 0.04$), and MAVSLP, ZC, HEMG and AR-model ($P < 0.001$).

When comparing the profiles for WAMP with the one-way ANOVA (with factor profiles) for each signal, bell showed the highest $\bar{R}^2$-value for both sEMG and iEMG. However, bell was not significantly different from the other profiles for iEMG and only significantly different from the bell-step profile for sEMG ($P = 0.039$).

3.2. Linear prediction

In Table 2 the results are summarized for the features with the highest $\bar{R}^2$-value for each signal. In Figure 6 the $\bar{R}^2$-values for the different features are depicted.

WAMP showed to have the highest $\bar{R}^2$-value for both iEMG and sEMG. The paired t-test when comparing WAMP for iEMG and sEMG showed no significant difference between iEMG and sEMG ($P = 0.658$). For iEMG, WAMP was significantly different from CSE ($P = 0.038$) and MAVSLP, HEMG and AR-model ($P < 0.01$). For sEMG, WAMP was significantly different from ZC ($P = 0.041$) and MAVSLP, HEMG, and AR-model ($P < 0.01$).
### 3.3. Artificial Neural Network (ANN)

In Table 3 the results are summarized for the feature with the highest $R^2$-value for each signal along with the profile with the highest $R^2$-value for this feature. In Figure 7 the $R^2$-values for the different features are depicted.

The feature with the highest $R^2$-value was CSE for iEMG and WAMP for sEMG. The two-way ANOVA (with factors signals and features) showed that the $R^2$-value for CSE for iEMG was not significantly higher than WAMP for sEMG ($P = 0.365$). For iEMG, CSE was significantly different from VAR ($P = 0.024$), and MAVLSP, HEMG and AR-model ($P \leq 0.001$). For sEMG, WAMP was significantly different from ZC ($P = 0.015$), and MAVLSP, HEMG and AR-model ($P < 0.001$).

When comparing the profiles for the best features (CSE and WAMP) with the one-way ANOVA (with factor profiles) for each signal, the profile with the highest $R^2$-value was double ramp and bell for iEMG and sEMG, respectively. However, they were not significantly different from other profiles except that bell was significantly different from step for sEMG ($P=0.01$).

### 3.4. Comparing linear prediction and ANN

The paired t-test showed that iEMG had higher $R^2$-values for the ANN (CSE and double ramp ($R^2 = 0.949$)) than for the linear prediction (WAMP and bell-step-double ramp ($R^2 = 0.948$)). However, the difference between the linear prediction and the ANN was not significant ($P = 0.895$). The paired t-test showed that sEMG had higher $R^2$-values for the linear prediction (WAMP and bell-step-double ramp ($R^2 = 0.952$)) than for the ANN (WAMP and bell ($R^2 = 0.948$)). As for iEMG, the difference between the linear prediction and the ANN was not significant ($P = 0.584$).

### 4. Discussion

The results showed that it is possible to predict force based on a linear relationship between force and features extracted from either sEMG or iEMG. The relationship and the prediction performance were dependent on the type of feature. Furthermore,
the results for sEMG and iEMG were similar for both the linear prediction and ANN.

4.1. Linear relationship

For the linear relationship WAMP showed to have the highest $R^2$-value for both sEMG and iEMG with sEMG significantly higher than iEMG. However, Kamavuako et al.\cite{2} showed no difference between iEMG and sEMG for the linear relationship, which might be caused by the difference in the used force range and in the choice of feature. Nevertheless, Kamavuako et al.\cite{2} found a correlation in the range of 0.82 to 0.94 (Pearson coefficient) between force and one feature for sEMG and iEMG respectively (for a window of 160 ms). To some degree this confirms the results obtained in the present study. However, we found the linear relationship for the entire range of force and for 14 different features.

When using WAMP, bell showed the best results for both sEMG and iEMG. This might be due to fact that the bell profile includes constant changes in the slope of the force making it non-linear. The non-linearity of the bell provides a dynamic quality to the model that cannot be obtained from the remaining profiles. Based on this, bell should be considered for training the association between grasping force and features of EMG.

However, bell was not significantly different from other profiles for iEMG and only significantly different from bell-step for sEMG.

4.2. Force prediction

Whether the linear relationship can be used in prosthetic devices or not, should be based on the performance of the prediction and not solely on the linear relationship.

For linear prediction WAMP showed the best performance for both sEMG and iEMG. In spite of the results from the linear relationship, the performance of the two signals for linear prediction was not significantly different. Based on these results both iEMG and sEMG can be used for linear prediction. The type of profile did not have an effect either.

In the study by Phinyomark et al.\cite{7} the WL feature showed the best performance, however WAMP also had a good performance. This is similar to our results since we also showed that WL had a good performance which was not significantly different from the best feature (WAMP). Furthermore, the results obtained by Phinyomark et al.\cite{7} showed that MAVSLP had the worst performance compared to other features. This also applies for our results. It should, however, be considered that Phinyomark et al.\cite{7} only evaluated features extracted from sEMG where the present study investigated both iEMG and sEMG.

The present study showed that MAVSLP, HEMG and AR-model performed bad. However, this should be investigated further in order to confirm that these features are not suited for prosthetic devices.

To clarify whether there exists a better relationship than the linear, force was also predicted based on relationships found by ANN. The ANN prediction showed results similar to linear prediction for both sEMG and iEMG with no significant difference between the two prediction models. The same conclusion was obtained by Kamavuako\cite{13}. Thus, the choice of model (linear prediction or ANN) does not play a significant role. However, for our study the performance of the ANN in general seemed to vary, which implies that the possibility of other relationships performing better should be investigated further.

4.3. Use in prosthetic devices

Kamavuako et al.\cite{2} showed that iEMG has the same potential as sEMG for myoelectric control for force in the range of 0-50 N for a linear relationship. The present study obtained similar results for the entire force range for linear prediction.

For both sEMG and iEMG WAMP showed the best potential for myoelectric control when using linear prediction. However, if the signal-to-noise ratio decreases, the difference between two successive samples will be smaller and the amplitude threshold will possibly not be exceeded. Thus, it will not be registered when a new action potential arrives. The same issue can occur if the electrodes shift, since this may change the amplitude of the recorded signals. Therefore, the conditions for using WAMP for myoelectric control needs to be investigated further and other features should be considered as well.

4.4. Methodological aspects

4.4.1. The selected muscle, FDP

The area of insertion for the FDP muscle mostly controls the fingers digitus medicialis and digitus minimus.\cite{15} This might result in incorrect force recordings, if the subject does not use these fingers when grasping. However, in the present study the recordings from the FDP muscle showed high correlation with force and it is therefore considered to be a good muscle when used for force prediction during grasping. Furthermore, the placement of the iEMG electrodes can be optimized during the chronic implementation.

4.4.2. Model selection

Even though the linear prediction in general showed good performance it was not taken into considerations that there might be a difference in the properties of the EMG signals for the increasing and decreasing force. Thus, the model was based on only one linear relationship instead of one relationship for
increasing force and one for decreasing force. Both of these relationships could for example be implemented in a model containing hysteresis.

Future work should investigate if there is a difference in the increasing and decreasing EMG-signals, and if necessary, a new model should be defined in order to provide better force predictions.

4.4.3. Feature filtering

The extracted features from iEMG and sEMG were filtered in order to smoothen the result and thereby keep the frequency content similar to the fluctuations in the force profile. When used in prosthetic devices this would possibly slow the signal processing and thereby the movement. Nevertheless, filtering the features could possibly provide more precise force predictions. Though, this has to be investigated further.

4.4.4. Feature thresholds

The thresholds used for the features were estimated by adapting the threshold for one subject so the best possible result was achieved. However, the thresholds were used for all subjects and profiles and thus, were not specifically determined for each subject and for each profile. This might influence the results since the amplitude of the signals varies depending on needle placement. Therefore, the thresholds should be adapted for each subject or the use of features without thresholds should be considered. In this way the effect of a change in electrode position and signal-to-noise ratio might be avoided.

5. Conclusion

The capability of force prediction has been investigated for 14 features based on a linear relationship and an ANN. The results implied that WAMP was the best feature for both linear prediction (sEMG and iEMG) and ANN (sEMG). Force during power grasping can be predicted with the use of features extracted from sEMG and iEMG. The choice of prediction model did not play a significant role since there was no difference between the linear prediction and ANN. Furthermore, no significant difference was found between sEMG and iEMG in relation to force prediction. Thus, both can be used for proportional myoelectric control in prosthetic devices.

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References