A COMPARISON STUDY OF EMG FEATURES FOR FORCE PREDICTION

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Abstract – Myoelectric prosthetic devices can be controlled by use of surface electromyography (sEMG). However, intramuscular EMG (iEMG) has been proposed as an alternative, since it may provide more stable and selective recordings with several advantages. The purpose of this study was to assess the predictive capabilities of 14 features of iEMG and sEMG for force ranging from 0 to 100 % maximum voluntary contraction (MVC). Intramuscular EMG and surface EMG were recorded concurrently from the muscle flexor digitorum profundus from 11 subjects who exerted four force profiles during power grasping. The predictive capability of each feature was assessed using the mean R^2-value with a 1st order polynomial (linear prediction). Wilson Amplitude showed the best results for both sEMG (R^2 = 0.952 ± 0.007) and iEMG (R^2 = 0.948 ± 0.008), with no significant difference (P = 0.658). Application of an advanced model based on artificial neural network did not improve the performance (P = 0.895). We have concluded that a linear model is sufficient for force prediction (0-100% MVC), and that iEMG is potentially suitable for proportional control in the same manner as when using a more global measure of intensity.

INTRODUCTION

For many amputees, the only possibility for restoration of movement is through the use of prosthetic devices. Surface EMG (sEMG) is already being used for the control of myoelectric prosthetic devices, where the applied force is estimated proportionally to features extracted from sEMG.[1,2,3] Despite good results, the use of sEMG has a number of disadvantages: (1) it is limited to one or two Degrees of Freedom (DoF), (2) it can only be measured from superficial muscles, (3) it is sensitive to crosstalk, and (4) it can cause irritation of the skin during repeated use.[1,4]

Use of intramuscular EMG (iEMG) for prosthetic devices has been proposed because iEMG may provide more stable and selective recordings compared to sEMG, and may allow effective control of multiple DoFs. Furthermore, iEMG electrodes may be chronically implanted.[1] Because of their high selectivity, iEMG may be less representative of the global muscle activity and thereby contain less information about the force produced by the entire muscle. To our best knowledge, very few features of iEMG have been explored in relation to force e.g. integrated EMG,[5] global discharge rate,[1] root mean absolute values and constraint sample entropy (CSE).[6] 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 assess the predictive capabilities of 14 EMG features for both iEMG and sEMG using the entire force range from 0 to 100 % MVC. This was based on a linear relationship and a relationship found by an Artificial Neural Network (ANN).

METHODS

Experiment

Subjects: The study included 11 right-handed healthy subjects (4 w/7 m) in the age of 22 to 26 years (mean 23.8 yrs). 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 and gave written consent prior to the experiment.

Procedure: The subjects performed power grasping on a force dynamometer (Noraxon) with their right hand, while seated in a chair with their arm placed in an armrest (Figure 1). The MVC force of each subject was recorded three times with a 3 min rest after each trial. The subjects were then asked to follow four different force profiles:

1. A *step* profile of 9 sec with force increasing in 6 steps.
2. A *double ramp* profile of 9 sec.
3. A *bell* profile of 9 sec.
4. A *free varying* profile of 9 sec where 100% MVC had to be reached at least once.

The order of the profiles was randomized. The *step*, *double ramp* and *bell* profile were recorded two times each 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 recordings.

Data recording

In order to measure grasping force a Jamar compatible handgrip dynamometer (Noraxon) with an adjustable grip size was used.

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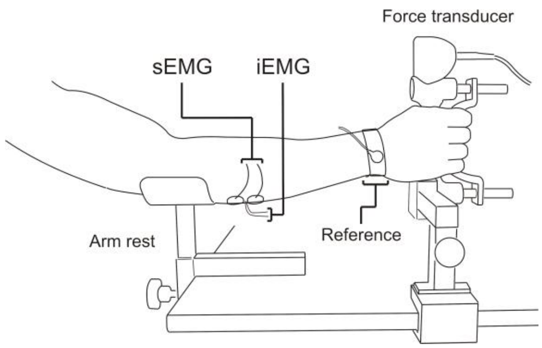

Figure 1: Sketch of the experimental setup.

The grip size for each subject was determined based on which setting resulted in maximum force whilst being comfortable for the subject. The iEMG electrodes (custom-made by use of hypodermic needles and Teflon coated wires (A-M Systems, Carlsberg, WA; diameter 50 μm)) were inserted in the muscle Flexor Digitorum Profundus (FDP) at the middle one-third of the forearm ventral to the ulnar shaft.[7] The electrodes were placed in a bipolar configuration. 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 (Ambu Neuroline 720) was recorded in a bipolar configuration 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.

The same 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 output from force, iEMG and sEMG was sampled by use of a 16 bit AD converter (NI-DAQ USB-6259) with a sampling frequency of 20 kHz.

Signal processing

Digital filters: Apart from the analogue filtering, three digital 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 of 100-2500 Hz and 20-500 Hz, respectively. Furthermore, a 2nd order Butterworth filter with a cutoff frequency of 1 Hz was applied to the extracted features.

Extracted features: In total 14 features were chosen to represent the iEMG and sEMG signals. Windows of 200 ms with a step size of 50 ms were applied and features were computed for each window. The same window size was applied to the force signal where the mean was calculated for each window. Thresholds that were general for all subjects and profiles were found by visually inspecting the performance of the features. The extracted features were; *Waveform Length (WL), Zero Crossing (ZC), Slope Sign Changes (SSC), Wilson Amplitude (WAMP), Mean Absolute Value (MAV), Modified Mean Absolute Value (MMAV), Mean Absolute Value Slope (MAVSLP), Variance (VAR), Autoregressive model (AR-model), Histogram EMG (HEMG), EMG envelope energy (EMG_env_energy), EMG envelope (EMG_env), Constraint Sample Entropy (CSE) and Root mean square (RMS).* See Bøg et al.[8] For further description about implementation of the features.

Data analysis

Force was predicted using two different approaches:

Linear Prediction: For each feature a linear model was derived (with a 1st order polynomial) based on data for all combinations of the *bell*, *step* and *double ramp* profiles. This linear model was then used to predict the force produced during the *free varying* profile.

Artificial Neural Network (ANN): An ANN was used to find the association between each feature and force using data for all combinations of the *bell*, *step* and *double ramp* profile for training. In this study a three layer ANN architecture was applied. The transfer function for the hidden layer was a tan sigmoid and for the output layer a linear transfer function was used.[9] The Levenberg-Marquardt training method was used with the Mean Square Error (MSE) as the performance function. Weights and biases were set randomly at the beginning of the training.[9] 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 then used for testing the model.

Statistical analysis

The statistical analysis was done separately but in the same way for the linear prediction and for the ANN. Moreover the two models were compared. A one-way ANOVA (with factor features) was performed in order to find the feature with the highest mean R^2-value for both sEMG and iEMG. Furthermore, a paired t-test was performed in order to compare the two signals. The comparison of the two models was performed using a paired t-test.

RESULTS

Linear prediction

In Figure 2, the R^2-values for the different features for linear prediction are depicted. *WAMP* showed to have the highest mean R^2-value for both iEMG (R^2 = 0.948) and sEMG (R^2 = 0.952) with no significant difference between the signals (P = 0.658). For iEMG, *WAMP* was significantly different from *CSE* (P = 0.038) and from *MAVSLP*, *HEMG* and *AR-model* (P < 0.01). For sEMG, *WAMP* was significantly different from *ZC* (P = 0.041) and from *MAVSLP*, *HEMG*, and *AR-model* (P < 0.01).

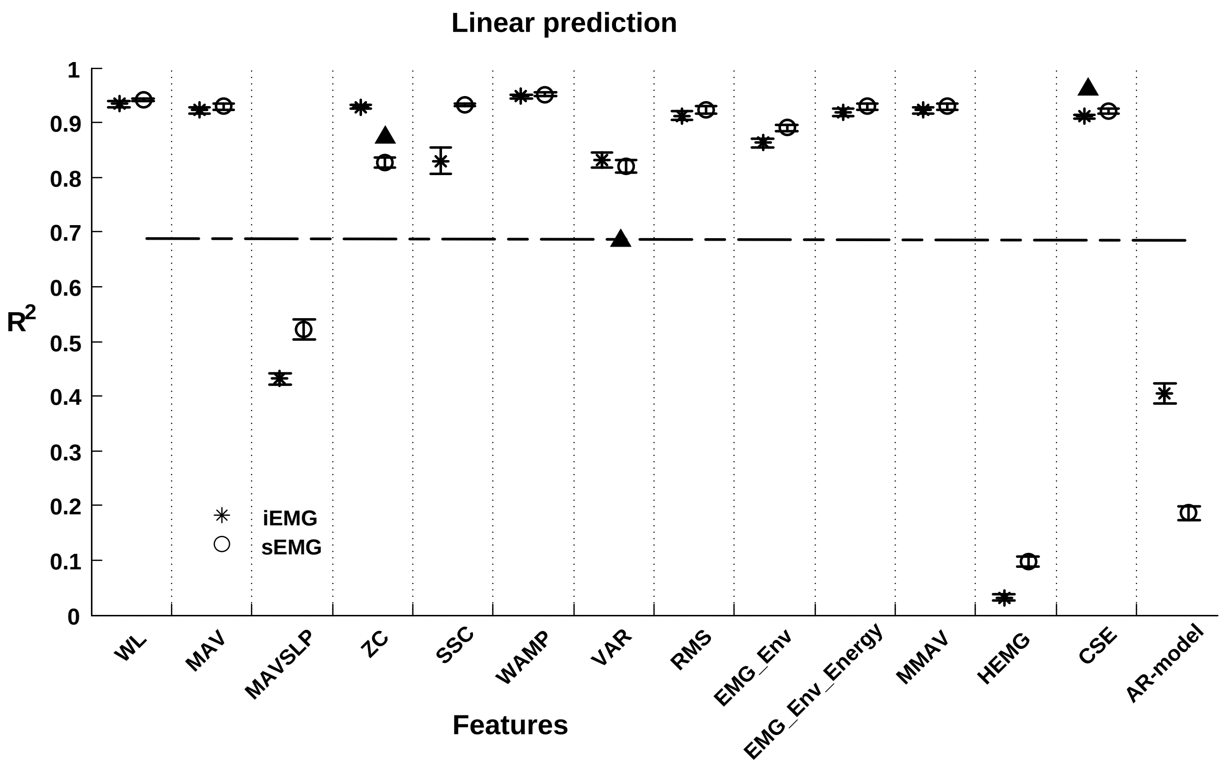

Figure 2: Performance of all features from linear prediction for all profiles for iEMG and sEMG. The x-axis represents the 14 features. The y-axis represents the R^2-values with the standard error (SE). The circles and stars represent sEMG and iEMG, respectively. All features below a filled triangle and below the dashed line are significantly worse than *WAMP* feature.

ANN

The feature with the highest mean R^2-value was *CSE* for iEMG (R^2 = 0.937) and *WAMP* for sEMG (R^2 = 0.927) with no significant difference between the signals (P = 0.365). For iEMG, *CSE* was significantly different from *VAR* (P = 0.024), and from *MAVLSP*, *HEMG* and *AR-model* (P ≤ 0.001). For sEMG, *WAMP* was significantly different from *ZC* (P = 0.015), and from *MAVSLP*, *HEMG* and *AR-model* (P < 0.001).

Comparing linear prediction and ANN

The paired t-test showed that iEMG had similar mean R^2-values for ANN (*CSE* with *double ramp*, R^2 = 0.949) and linear prediction (*WAMP* with *bell-step-double ramp*, R^2 = 0.948, P = 0.895). The same result was observed for sEMG.

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. Further, results for sEMG and iEMG were similar for both the linear prediction and ANN with R^2 > 0.9.

Force prediction

In a study by Phinyomark et al.[10] the *WL* feature showed the best performance for classification of hand movements; however, WAMP also had a good performance. This is similar to the results from the present study, which showed that *WL* had a good performance for force prediction, not significantly different from the best feature for both iEMG and sEMG (*WAMP*). This shows that the WL and WAMP features have an overall good performance and provide a good representation of the muscle activation, regardless of their application. Furthermore, Phinyomark et al.[10] showed that MAVSLP had the worst performance compared to other features, which is also valid for the present study, and therefore the MAVSLP in general provides an insufficient representation of the muscle activation. However, it should be noted, that Phinyomark et al.[10] only evaluated features extracted from sEMG, where the present study investigated both iEMG and sEMG.

In order to clarify whether there exist a better prediction model than the linear, an ANN was used. 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.[6] Thus, the choice of model (linear prediction or ANN) does not play a significant role when the best feature is selected. 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.

Model selection

Even though the linear prediction in general showed good performance it was not taken into consideration that there might be a difference in the properties of the EMG signals for increasing and decreasing force. Thus, the model was based on only one linear relationship instead of a relationship for increasing force and for decreasing force, respectively. 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.

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