MEC '11
Raising the Standard

Resolving the Limb Position Effect

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Introduction

Aims of our study:

- **Investigate the effects of changes in limb position on pattern recognition based myoelectric control.**
- **Consider strategies to mitigate its effects.**

Variations in limb position can have a substantial impact on the robustness of myoelectric pattern recognition [1,2]. Hereafter this problem will be referred to as the *limb position effect*.

Proposed solutions:

1) Train the classifier in multiple limb positions

2) Measure the limb position with accelerometers

Questions to answer:

- In order to reduce the training time for the end users: In how many limb positions do we need to train the classifier?
- Accelerometers are relatively cheap, small, robust to noise and easy to integrate in a prosthetic socket. How useful is the accelerometer compared to adding expensive and space-consuming EMG electrodes?

Methods

17 normally limbed subjects:

- 10 male, 7 female
- 18 to 34 years

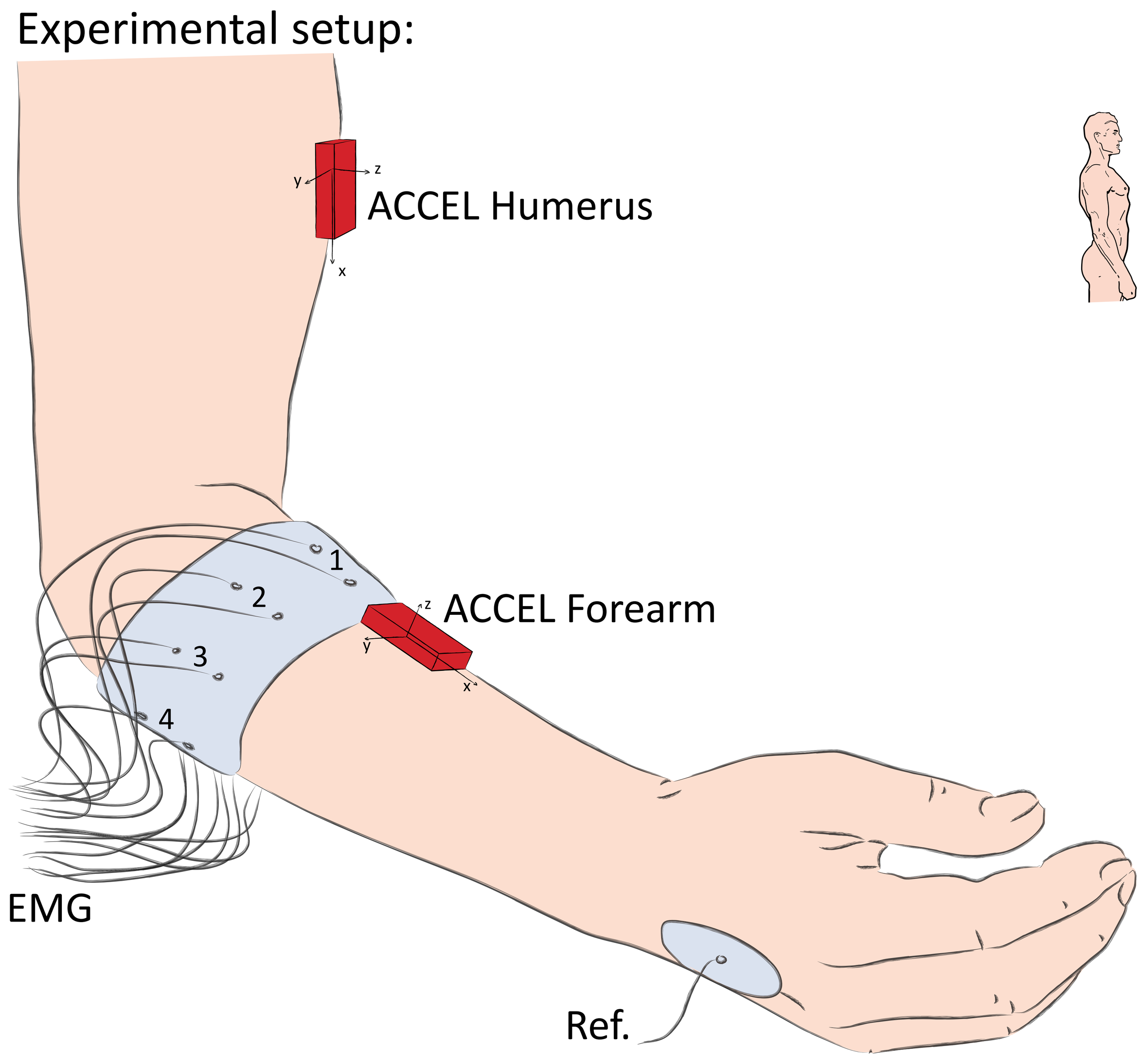
8 EMG channels:

- Stainless steel electrodes
- LTI differential amplifiers

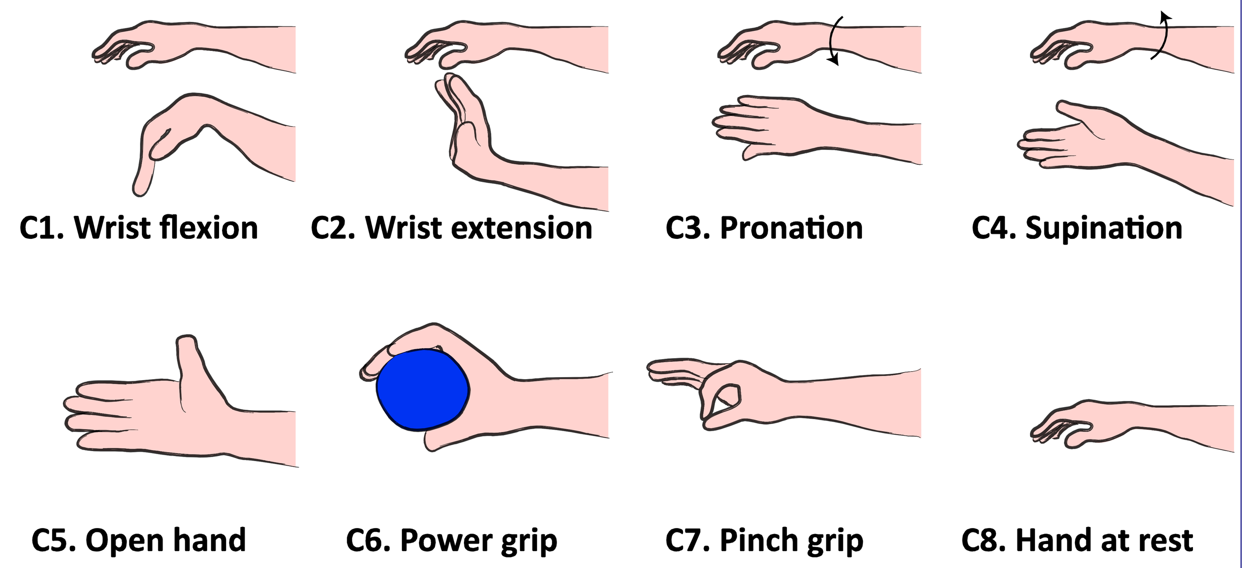
2 accelerometers (3-axis):

1) Forearm
2) Biceps brachii

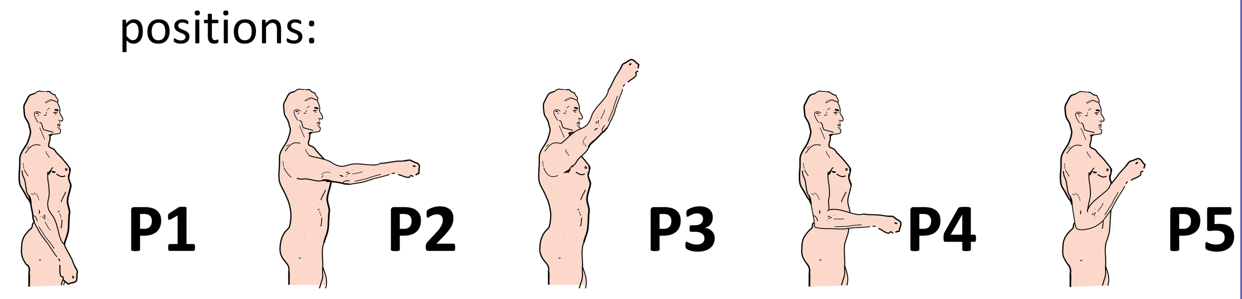
Experimental setup:



8 motion classes were used:



10 trials were recorded in each of these 5 limb positions:



EMG data were low pass filtered at 500Hz and notch filtered at 60Hz.

EMG time-domain (TD) features (mean absolute value, zero-crossings, slope sign changes and wavelength) were calculated using 250ms windows with 50ms overlap.

Average values of the accelerometer data were calculated over the same time windows.

Linear discriminant analysis (LDA) was used for classification.

Results

Inter-position classification

Five different position-specific classifiers were trained, each using EMG data from one position only. Fig 1 shows the results when training in one position and testing in each other position (averaged over all classes and subjects).

- Average Intra-position error: 3.8%
- Average Inter-position error: 21.1%
- Average overall error: 17.6%

Training position \ Test position	P1	P2	P3	P4	P5
P1	2.8%	13.8%	22.8%	23.4%	34.2%
P2	7.2%	3.4%	12.6%	16.3%	27.3%
P3	14.2%	7.7%	5.8%	21.2%	29.2%
P4	18.3%	23.1%	34.6%	3.6%	9.6%
P5	27.4%	31.5%	40.8%	6.3%	3.4%

Fig. 1: Interposition classification error matrix.

Training in multiple limb positions

In order to investigate the generalizability of the training set as a function of the number of training positions in the set, the following procedure was employed:

For each test position, all possible subsets of the remaining positions were applied as a training set. The result is presented in Fig. 2.

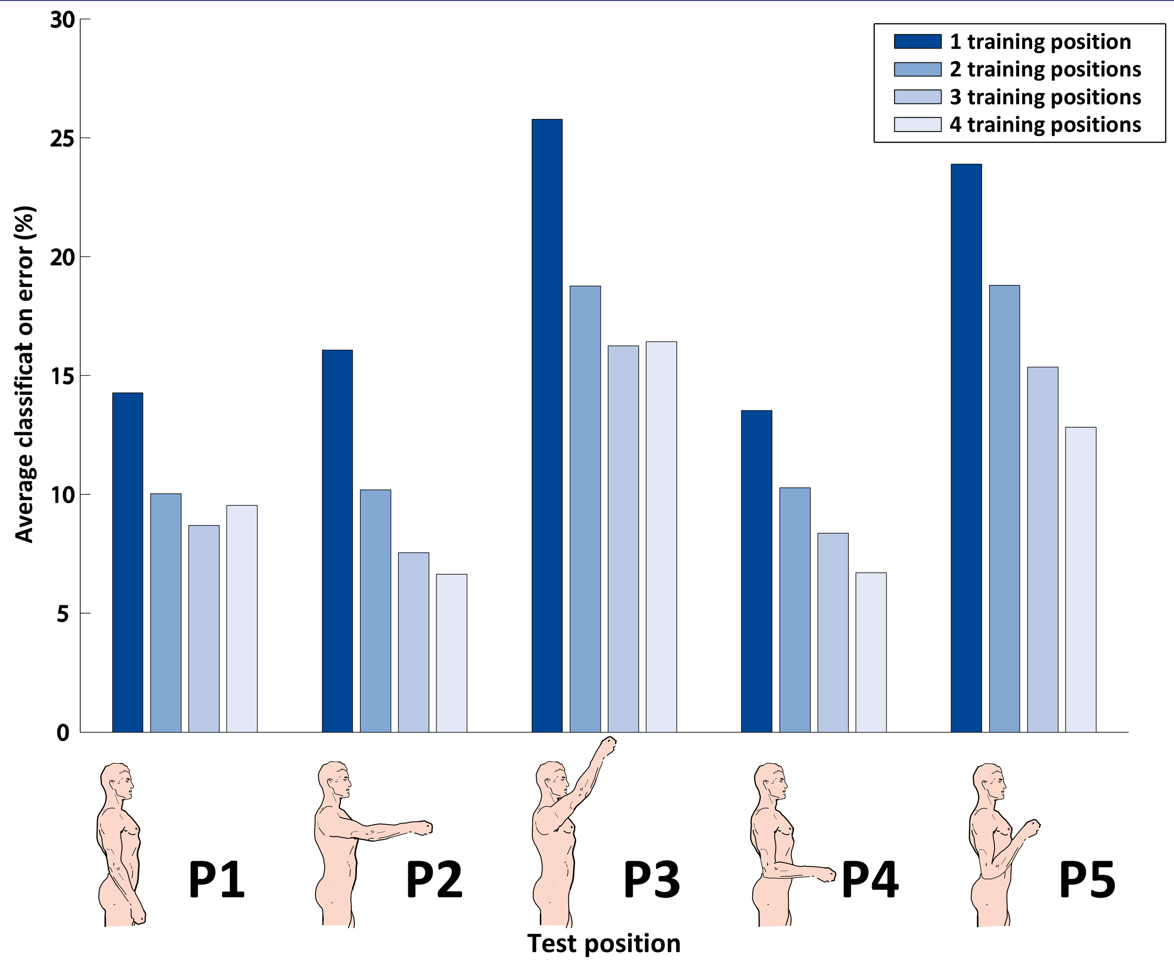


Fig. 2: Classification error as a function of training positions ("Leave-one-out Strategy").

Add accelerometers or more EMG sensors?

Sensors were added to the system one by one by always choosing the combination so far with the best result. This method was used on systems with 5 and 8 motion classes. Results are shown in Fig. 3.

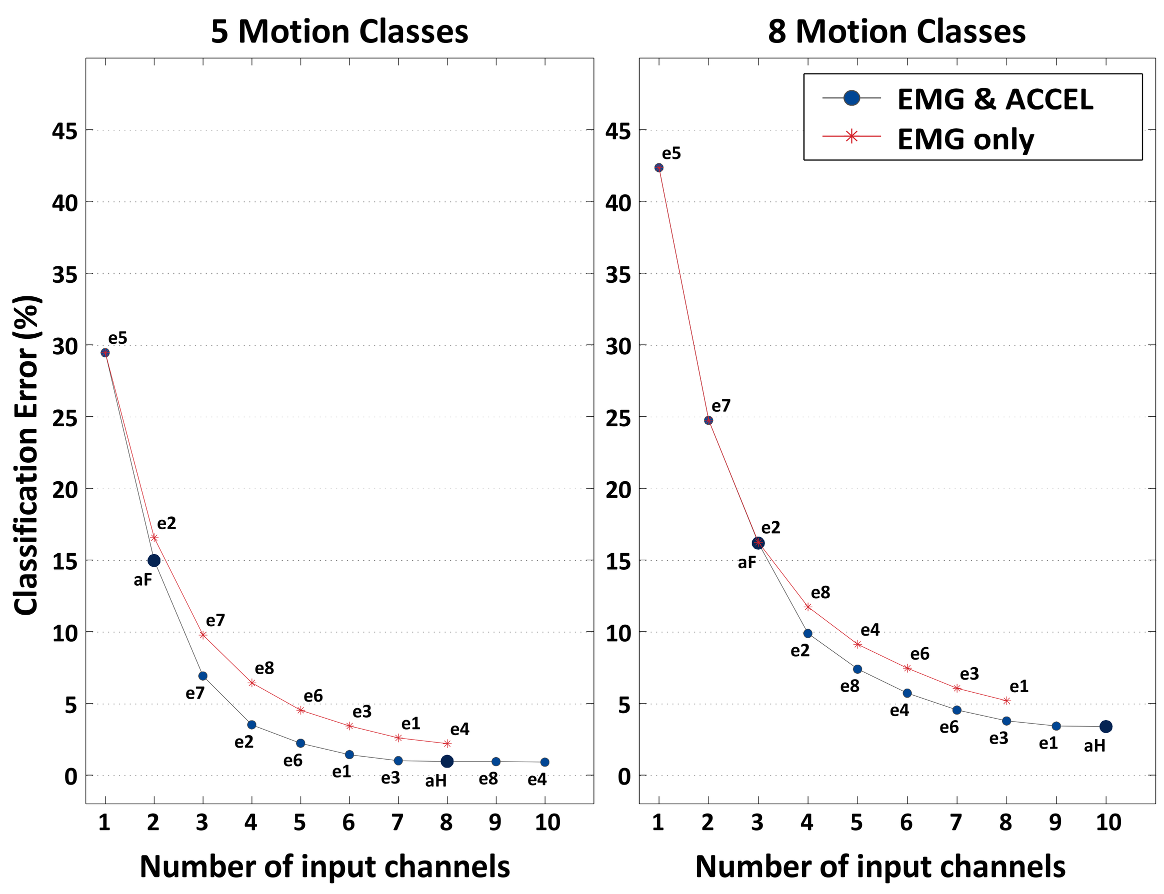


Fig. 3: Classification error as a function of selected input channels.

Discussion

These results indicate that EMG classification error is strongly dependent on limb position.

We have shown that the limb position effect can be partially solved by training the classifier in multiple positions. Most of the improvement is achieved already when increasing from one to two training positions.

Previously we have also shown [1] that that it is important to have a training set containing a variation of elbow angle.

The accelerometer does not provide an estimate of muscle force, but it provides useful information that can supplement EMG. If one wants to improve a system originally having two EMG electrodes, a multi-modal approach can be taken.

The results demonstrate that it is more advantageous to add an accelerometer affixed to the forearm rather than increase the number of EMG channels.

References

[1] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and Ø. Stavdahl, "Resolving the Limb Position Effect in Myoelectric Pattern Recognition", to be published in *IEEE Trans. Neural Syst. Rehabil. Eng*.

[2] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and Ø. Stavdahl, "A Multi-Modal Approach for Hand Motion Classification Using Surface EMG and Accelerometers", to be published at *Conf. Proc. IEEE Eng. Med. Biol. Soc., 2011*.

[3] A. Fougner, E. Scheme, A. D. C. Chan, K. Englehart, and Ø. Stavdahl, "Resolving the Limb Position Effect", to be published at *Proc. of MEC Symposium, 2011*.