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Prediction of Intermuscular Co-Contraction Based on the sEMG of Only one Muscle With the Same Biomechanical Direction of Action

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Abstract

Research aims to enhance physical abilities using exoskeletons and limb movement prediction. SEMG signals are used for intuitive control, but their measurement is limited to shallowly under-the-skin muscles, making deep muscle signals less frequently used. Here we extended a previously proposed method to train a virtual sensor for the difficult to access muscles (deep muscles e.g. *brachialis*). The method is extended from signals from the same muscle to intermuscular signals and the results confirm simple biomechanical assumptions. The trained virtual sensors are ready for further investigations by being used in a biomechanical model.

Keywords: Electromyography, virtual sensor, regression

1. Introduction

For an intuitive control of exoskeletal devices an intuitive and non-delayed control scheme is an important part of success. Electromyographic (EMG) signals are often used to enable such control. This study uses the flexor muscles of the elbowjoint as the object of investigation. The flexion of the joint is possible by three flexors. The flexors are the *biceps brachii* (shallow, often used in this application) *brachialis* (deep, below the *biceps brachii*) and the *brachioradialis* (shallow, located on the forearm). Even though the three flexors share elbow flexion as their main task, they have different attachment points and therefore different lever arm courses across the elbow angle. As the biceps and *brachialis* are located close to each other, sEMG signals are prone for picking up signal components from the other muscle. This phenomenon is called crosstalk.

As shown in previous work, the movement of the elbow can be predicted by the sEMG signals of the two *biceps brachii* heads and the two shallow *triceps brachii* heads [1]. Previous work has also shown that a virtual sensor that predicts the activation for one *biceps brachii* head can be trained from the other head with a shallow feedforward neural network (ffn) [2]. This can be used as a replacement for a sEMG channel or for the evaluation of the sEMG.

Therefore, this is further used to guide the training for a virtual *brachialis* sensor by domain knowledge. This can lead to more explainable behaviour of the trained virtual sensors. The previously proposed method allows for a robust training process with a domain based foundation which is used in this work to interpret the results (e.g. co-activation and crosstalk).

2. Methods

2.1. Experiment and Used Dataset

The underlying experiment with which the data was recorded is based on [3]. In addition, two sEMG sensors were added to the setup to measure the signals

of the *brachialis*. This deep muscle was measured by one sensor each on the medial (ME) and lateral (LA) side of the distal *biceps brachii* tendon.
The preparation and attachment of the sensors were also described in detail in [3]. After these steps, the verification of the correct placement of the two sensors for the *brachialis* and two sensors for the *biceps brachii* was done by isolating the muscles and compare the resulting sEMG amplitudes visually. The movement is performed at two speeds [0.5 Hz and 1 Hz] and with two different weights [2 kg and 4 kg]. The sequence of the four combinations is randomly selected in advance for each subject. The age of the 13 subjects was 24.7 ± 2.6 years.

2.2. Biomechanics of *Brachialis* and *Biceps Brachii*

The muscle origins and insertions have different distances to the centre of rotation. This results in different lever-arm courses over the elbow angle. Furthermore, the possible force development of a skeletal muscle depends on its length [4].Due to these properties, the *brachialis* and *biceps brachii* have different possible force generation via the elbow angle [5].
The force vector generated by the muscle can point more or less in the direction of a possible joint rotation or in the direction of the joint, depending on the position of the muscle in relation to the bone and the joint.Both of these properties can lead to different activation of muscles although their biomechanical direction of action is in principle the same [6].

2.3. Training Pipeline and Strategies

The data was preprocessed in a the same way as in [2]. The training strategies are also unchanged and a detailed description can be found in the previous paper. The first strategy for training is training at the level of the individual experiment variations. The performance of the virtual sensors is measured using the mean absolute error (MAE) between predicted and measured activation.
Contrary to the previous work, the regression from the activation of the *brachialis* to the activation of the *biceps brachii* is now learned. The second training strategy is to exclude a subject from training and use its data for the test.The baseline for both training strategies is setting the output of the virtual sensor to the input.

3. Results

The first training strategy results in no performance increase compared to the baseline. The baseline of the lateral *brachialis* (BRA) regressed from the *bicpes brachii* (BIC) long head (LH) is lower than the other three regression configurations.

The results for the second training strategy are shown in Table 1. The regression with only one input dimension performs similarly to the first training strategie. If the input dimension is expanded, the error decreases slightly. When introducing a nonlinearity through the activation function rectified linear unit, the error decreases further. The virtual sensor for the lateral *brachialis* shows lower errors than that for the medial *brachalis* sensor.

Table 1: The MAE (lower = better performance) of the virtual sensor for the leave one out strategy. For the two muscles [*bicpes brachii* (BIC), *brachialis* (BRA)] with the respective muscle heads [long head (LH), short head (SH)] and sensor position [lateral (LA), medial (ME)]

input: output:	BIC SH BRA ME	BIC SH BRA LA	BIC LH BRA ME	BIC LH BRA LA
baseline	0.461	0.467	0.472	0.393
Train lin. 1d	0.436	0.453	0.426	0.374
Test lin. 1d	0.439	0.453	0.426	0.376
Train lin. 5d	0.412	0.413	0.409	0.354
Test lin. 5d	0.418	0.421	0.415	0.366
Train nlin. 5d	0.379	0.281	0.377	0.228
Test nlin. 5d	0.404	0.314	0.391	0.257

4. Discussion

The lower baseline for the virtual sensor of the *brachialis* lateral with the *biceps brachii* long head as input compared to the other three baselines could be cases by the short distance on the arm. Therefore, this could indicate a pickup of a *biceps brachii* long head sEMG from the *brachialis* lateral sensor (crosstalk).
The better performance by adding the nonlinearity fit the biomechanical structure described in Section 2.2 These two hypotheses could potentially be verified by using the virtual sensors as an input for a biomechanical model as in [2] also suggested.

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