Muscle force estimation using a measure of muscle activation extracted from surface EMG

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Abstract: The aim of this paper is to introduce a new measure of muscle activation level that can be used for force prediction from surface EMG signals, or as an input into the biomechanical models as well. It is called activity index and its range is between 0 and 1, 0 meaning that no motor units are active in the observed muscle, while 1 stands for the maximal activity of all motor units in the muscle. The important property of activity index is that it increases and decreases in the same way as the force produced by the observed muscle does. It is a measure of global muscle activity and represents the summation of innervation pulse trains of all active motor units. Activity index is based on motor control information rather than EMG amplitude processing, which is the most common approach in muscle force estimation task nowadays. This estimator of the motor control information is obtained from multi-channel surface EMG signals. Our method was compared to the method known as MUAP rate, which estimates muscle force as the number of motor unit action potentials in a time epoch, so it uses the motor control information for the estimation purpose as well. Experimental data was obtained from biceps brachii muscle during elbow flexion task on 5 subjects using 2D matrix of surface electrodes (13 rows by 5 columns). Isometric constant force contractions at three different force levels were performed, i.e. at 5, 10 and 30 % of maximal voluntary contraction. Torque produced at the elbow joint was measured simultaneously with surface EMG. The performance of both methods was measured with root mean square error (RMSE) between real and estimated force. Average for all 3 contractions of 5 subjects (total 15 trials) produced the following results: activity index scored 13.46 % ± 6.26 % RMSE and MUAP rate scored 26.25 % ± 6.36 % RMSE. In all individual trials activity index was a better force estimator. This is due to the technique for extraction of motor control information out of surface EMG signals. However, the presented study is only preliminary and since the performance of the activity index can be enhanced in many ways, the activity index has vast potential to become the most commonly used muscle force estimation technique.

Key-Words: surface electromyography, muscle force estimation, EMG force relationship, MUAP rate, activity index

1 Introduction

Surface electromyography (sEMG) is an important tool in various research fields, including biomechanics and kinesiology, where it is used to understand how joints are loaded, passive tissues are stressed and muscles are activated under different working conditions [1]. Recently the use of sEMG is studied also in man-machine interaction for an intelligent machine control.

SEMG has been studied for over fifty years as a non-invasive measure of the muscle activity at voluntary contractions. It is a measure of the depolarization of muscle fibres, and when the sEMG signal is treated properly, it can be used as an indirect measure of muscle activity or force. Muscle force estimates can further be used in biomechanical models to estimate joint loads and kinematics [1]. However force estimation task is not so straightforward as it might seem. Forces or torques are usually measured externally about the joint, although they are in fact the resultant output of internal forces generated by muscles acting about the joints that they cross, as well as internal forces produced by stretching of ligaments and other passive tissues associated with the same joints. As a consequence the force of a single muscle is hardly measured and usually several muscles contribute to the detected forces. Moreover, when the electrical response of muscles is measured by sEMG, only part of the muscle and active motor units (MUs) can be detected, while measured force is actually produced by all MUs.

The paper is organized as follows. Section 2 contains a quick overview of the force estimation techniques. In the sequel, we reveal our new force estimation approach using activity index. The MUAP rate method is presented as well because it was chosen for comparison. Section 3 explains the experiments and shows experimental results, while the last section discusses the results and concludes the paper.

2 Force estimation techniques

Force production in a muscle is regulated by the central nervous system (CNS), which regulates two main mechanisms, i.e. the recruitment/derecruitment of MUs and the modulation of their discharge rates. The greater the number of MUs recruited and their discharge frequency, the greater force will be exerted by the muscle. The same two mechanisms determine also the electrical activity in a muscle. Thus, a direct relationship between the sEMG and exerted muscle force might be expected [2].

Methods based on the sEMG amplitude processing, such as average rectified value and root mean square, are commonly used for force estimation purpose. However, the sEMG amplitude is influenced not only by motor control aspects, but also by peripheral properties of the muscle, such as MU size, position (deep or superficial) and recording setup parameters (placement of the surface electrodes) [5]. Therefore the methods that are based on the motor control estimation were developed, such as MUAP rate and activity index, but it has to be considered that motor control information is also estimated from the sEMG signals, which means only a rough estimation of real motor control. Both methods are based on the motor control information, but they use totally different approach to extract this information from sEMG recordings.

2.1 Activity index

Activity index is a measure of muscle activation level. It was first introduced in [4] as a first stage of the correlation-based sEMG decomposition algorithm, known as convolution kernel compensation. Its range is between 0 and 1, 0 being produced, when there are no MUs active in the observed muscle, and 1 stands for the maximum activity of all MUs. Compared to sEMG amplitude activity index is smoother, which certainly is a good basis for force estimation.

To understand the principle of activity index, the considered sEMG model is presented briefly. The most feasible model for multi-channel sEMG recordings is the discrete, shift-invariant MIMO modelling [4]. Each input in such MIMO system is considered a MU innervation pulse train triggering the muscle, while the system responses correspond to the MUAPs as captured by the pick-up electrodes. The individual sEMG measurements represent the model outputs.

Let N be the number of inputs (active MUs in our case) and M the number of measurements (number of recorded signals from pick-up electrodes over the muscle). Suppose the number of inputs N smaller than the number of measurements M, then a positive integer K can be found, so that satisfies $KM > N(L+K\text{-}1)$, where M is the number of measurements, N the number of inputs, L the length of MUAPs, and K an extension factor. The vector of measurements $\mathbf{y}(n)$ can be extended by K-1 delayed repetitions of each measurement. Correlation matrix of extended measurements $\overline{\mathbf{y}}(n)$ is then calculated as:

$$\mathbf{C} = \overline{\mathbf{y}}(n)\overline{\mathbf{y}}^T(n). \qquad (1)$$

Multiplying the extended measurements $\overline{\mathbf{y}}(n)$ by the Moore-Penrose pseudo-inverse of $\mathbf{C}$ (symbol #), we introduce the activity index:

$$I_A(n) = \overline{\mathbf{y}}(n)^T \mathbf{C}^{\#}\overline{\mathbf{y}}(n) \qquad (2)$$

A more detailed explanation on the activity index calculation can be found in [3] and [4]. Fig. 1 depicts an example of one sEMG channel along with its activity index.

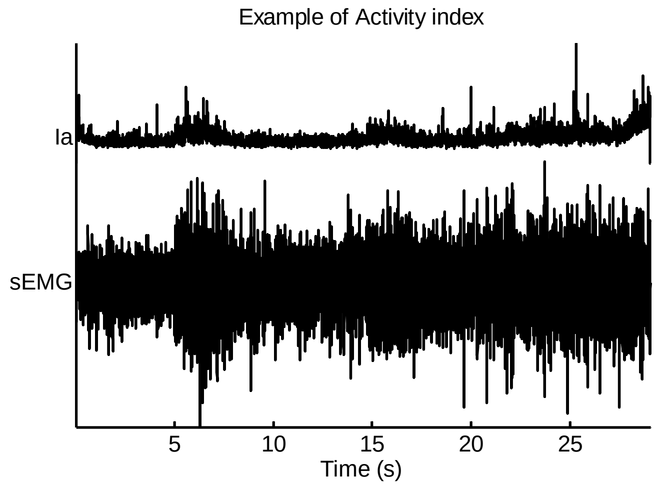

Fig. 1: Time plots of a single sEMG recording and its activity index (Ia) above show the activity index follows the changes in sEMG, but it is smoother.

2.2 MUAP rate

MUAP rate was introduced as a measure of the CNS input to the muscle [5]. It is obtained as the number of MUAPs per second, and equals the sum of firing rates of all active MUs. It reflects both parameters that CNS uses for motor control, the number of MUs and firing rate.

The first step extracts MUAPs from the sEMG. This task is performed by using continuous wavelet transform (CWT). Details of the approach can be found in [6]. Although this algorithm uses multi-channel information for MUAP extraction, only channels from the electrodes placed longitudinally to the muscle fibres are useful, because the propagation delay of MUAPs is searched between channels. Since our measurements were recorded using 2D arrays of electrodes, only the signals from the middle (3rd) electrode column were used.

The MUAP extraction approach needs some specific parameters to be set. We used the same values as those reported in [5]. The algorithm started with calculating the CWT for the first channel. When the scalogram reached a maximum that was higher than a user predefined threshold (set to 0.1), a candidate MUAP was indicated. The algorithm then searched for candidate MUAPs located in the surrounding channels within a time delay corresponding to conduction velocities between 2 and 8 m/s. When the same shape was found in a minimum number of channels (set to 3), the candidate was considered a MUAP. Then, the CWT was calculated for the next channel. The algorithm cycled through all the channels in this way. Outputs of the algorithm were the firing moments of all detected MUAPs (see Fig. 2). Then the number of detected firing moments in the epoch of 1 second was calculated and this is the MUAP rate estimation.

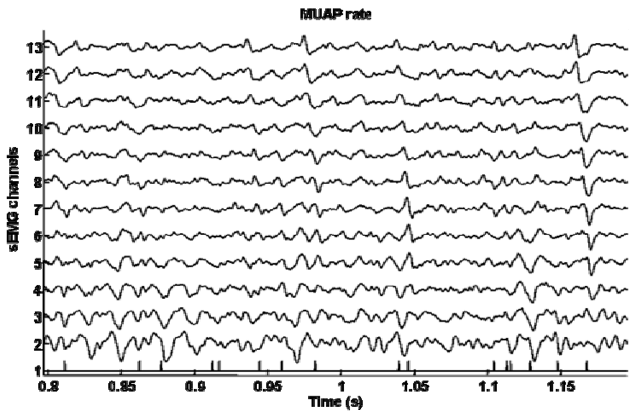

Fig. 2: Rows from 2-13 depict sEMG channels (inputed into the algorithm), while row 1 below shows the firing moments of detected MUAPs.

3 Experimental Results

5 young healthy male subjects participated in the experiment. SEMG signals were recorded with a matrix of 61 electrodes arranged in 5 columns and 13 rows (Fig. 3). Inter-electrode distance was set to 5 mm. Recordings were performed in single differential configuration during isometric, constant-force contractions of the dominant biceps brachii muscle. The matrix was connected to four 16-channel EMG amplifiers (LISiN; Prima Biomedical & Sport, Treviso, Italy). The EMG signals were amplified, band-pass filtered (3 dB bandwidth, 10-500 Hz), sampled at 2500 Hz, and converted to digital form by a 12-bit A/D converter.

The dominant arm of the subject was placed into the isometric brace at 120°. Three five-second contractions at maximum voluntary contraction (MVC) force were performed separated by 2 minutes. Using the torque sensors, the maximum contraction force was measured and averaged over all three measurements.

Fig. 3: 2D matrix (13 rows and 5 columns) of surface electrodes used for sEMG acquisition.

The sEMG signals were recorded during 30 seconds long contractions at 3 different constant force levels, i.e. 5, 10, and 30 % MVC. The noise and the movement artefacts were visually controlled and reduced by applying water to the skin surface. The contraction force was measured by the torque sensor and displayed on the oscilloscope to provide the visual feedback to the subjects.

The performance of the methods was obtained by calculating the root mean square error (RMSE) between the recorded and the estimated force in percents:

$$RMSE(\%) = \frac{RMS\left[F_{real} - F_{est}\right]}{RMS\left[F_{real}\right]} \cdot 100 \qquad (3)$$

Prior to calculation of RMSE, both the estimated and real force were smoothed by 1st order Butterworth low-pass filter with cut-off frequency 10 Hz. Smoothed signals were normalized with respect to the maximum value.

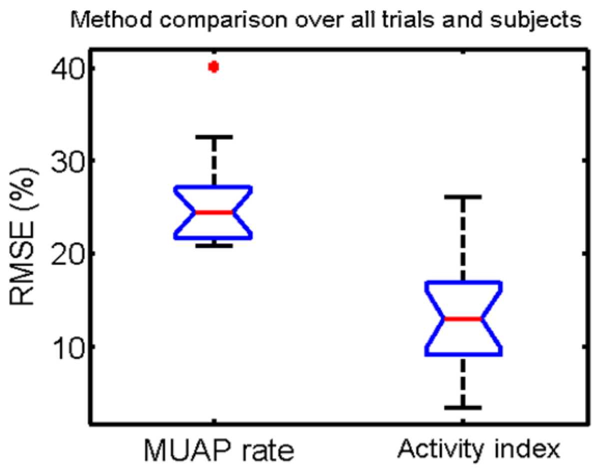

Fig. 4: Comparison of the estimation error for both methods on all trials from all subjects. The plot depicts median (middle line), upper and lower quartiles, whereas whiskers represent outliers.

The results of the method comparison are presented in Fig. 4 and Table 1. Activity index proved to be better estimator of muscle force, producing lower estimation errors than MUAP rate in all trials.

Table 1: Comparison of the estimation error.

	RMSE (%)	
Method	mean	std
MUAP rate	26.25	6.36
Activity index	13.46	6.26

Fig. 5 and Fig. 6 show estimation errors for each individual trial for all subjects.

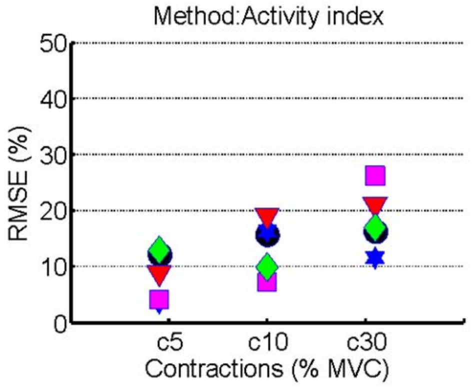

Fig. 5: The figure shows RMSE versus contraction levels for each individual trial of each subject obtained by the activity index method: the different shapes stand for different subjects.

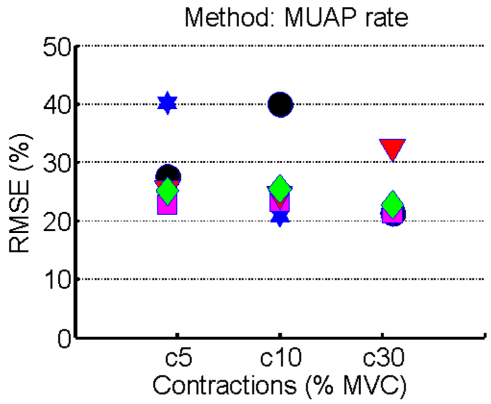

Fig. 6: The same plot as Fig. 5, except it shows the results of the MUAP rate method.

4 Discussion and conclusion

Both methods compared in this study are based on the principle of motor control, i.e. the number of active MUs and their firing rates, but the way the motor control information is extracted from sEMG differs for the two methods. The MUAP rate extracts the number of MUAPs directly from sEMG measurements applying the CWT, while the activity index uses correlation-based approach instead. However, both estimates represent the global muscle activity (activity of all detected MUs). When additional MUs are activated, the global activity increases, because the firing moments of these MUs contribute to the global activity. The same happens if firing rate of already active MUs increases. The global activity decreases when MUs are derecruited or their firing rates decrease.

The MUAP extraction method has some drawbacks in comparison to the activity index, i.e. it operates only on linear array of electrodes that must be placed longitudinally to the muscle fibres. On the contrary, activity index can be calculated using the electrode arrays and, thus, considers more spatial information, which improves the activity estimation.

A drawback of both methods is that only the global muscle activity is observed, so the important information about which firing belongs to which MU is missing. From the point of presented methods, a new MU activated or the firing rate of an already active MU increased causes the same effect. But most widely accepted force models suppose each individual MU has a different force contribution [7]. From this aspect the global muscle activity itself is not enough to complete the force estimation. Ideally, an indicator would be needed to recover individual MUs and their strength at the same time.

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