

## Predicting force loss during dynamic fatiguing exercises from non-linear mapping of features of the surface electromyogram

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### ABSTRACT

This study proposes a method for estimating force loss during fatiguing maximal isokinetic knee extension contractions using a set of features from surface EMG signals recorded from multiple locations over the quadriceps muscle. Nine healthy participants performed fatiguing tests which consisted of 50 and 75 isokinetic leg extensions at a speed of 30°/s and 80°/s in two experimental sessions on different days. The set of data recorded from one of the experimental sessions (at both velocities) was used to train a multi-layer perceptron neural network to associate force loss (direct measure of fatigue) to EMG features. The data from the other session (obtained from the tests at both velocities) were used for testing the neural network performance. The proposed method was compared with a previous approach for the assessment of fatigue (Mapping Index, MI) using a signal to noise metrics computed on the estimated trend of fatigue. The signal to noise ratio obtained with the proposed approach was greater ( $8.83 \pm 1.07$ ) than that obtained with the MI ( $5.67 \pm 1.17$ ) ( $P < 0.05$ ) when the subjects were analyzed individually and when the network was trained over the entire subject group (8.07 vs. 4.42). In conclusion, the proposed approach allows estimation of force loss during maximal dynamic knee extensions from surface EMG signals with greater accuracy than previous methods.

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### 1. Introduction

The fatigue-induced changes in neural drive to muscles and impaired contractility have been investigated during dynamic tasks by means of parameters extracted from the surface electromyogram (sEMG) (Komi and Tesch, 1979; Tesch et al., 1990; Gerdle et al., 2000; Bonato et al., 2001; Gonzalez-Izal et al., 2010). Amplitude and characteristic spectral frequencies of the sEMG signal have been often used to monitor the presence and progression of muscle fatigue. However, it has been difficult to relate consistent changes in EMG features with specific physiological adjustments.

During a sustained static contraction, the sEMG amplitude often increases (Lloyd, 1971; Maton, 1981; Moritani et al., 1982; Arendt-Nielsen and Mills, 1988) and mean power spectral frequency usually decreases (Viitasalo and Komi, 1977; Moritani et al., 1982; Naeije and Zorn, 1982; Arendt-Nielsen and Mills, 1988). These changes are consistent with the recruitment of additional motor units during the task (Moritani et al., 1982) and the decrease in the velocity of propagation of action potentials along the muscle fibers (Bigland-Ritchie et al., 1981), respectively. However, some

studies have also reported a decrease (Stephens and Taylor, 1972) or absence of change (Merton, 1954) in signal amplitude during fatiguing isometric contractions due to a complex combination of volume conductor effects and changes in the intracellular action potential shape. As suggested by Dimitrova and Dimitrov (2002), the amplitude of motor unit action potentials strongly depends on the position of the recording electrodes with respect to the active fibers and can change with fatigue in different ways depending on the electrode position. Action potential amplitude may decrease when recorded close to the active fibers, be unchanged at intermediate distances and increase when the electrodes are far from the active fibers, even though the amplitude of the intracellular action potential decreases. In addition, Arabadzhev et al. (2010) suggested, based on computer simulations, that one major factor accounting for increments in sEMG amplitude is lengthening of the intracellular action potential, which may influence the sEMG amplitude more so than changes in the number of active motor units or their discharge rates.

Despite a large amount of studies investigating myoelectric manifestations of fatigue in static conditions, most practical applications require the analysis of the sEMG during dynamic contractions. However, in dynamic tasks, the utility of surface EMG in the assessment of fatigue is limited due to several confounding factors (Farina, 2006). In these conditions, rapid changes in

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the number of active motor units, relative movement of the electrodes (De Luca, 1997), changes in fiber length (Inbar et al., 1987) and joint angle (Potvin, 1997) determine non-stationarities in the signal which are difficult to distinguish from the changes due to fatigue alone. Thus, in addition to the issues discussed above for isometric tasks, dynamic contractions present further complications in associating sEMG characteristics to the development of fatigue. Moreover, since the pattern of neural activation is likely to be different during dynamic and static contractions, extracting information from the EMG signal obtained during a static contraction to infer fatigue-elicited changes during dynamic contractions may be questionable (Cheng and Rice, 2005).

It is not surprising that changes in sEMG features during fatiguing dynamic contractions are less consistent compared with isometric tasks. The sEMG amplitude has been observed to increase during submaximal dynamic exercise (Petrofsky and Lind, 1978; Bouissou et al., 1989; Tesch et al., 1990; Arendt-Nielsen and Sinkjær, 1991) but usually it decreases during exercises at maximal force (Komi and Tesch, 1979). Some studies have reported a decrease in mean power spectral frequency during dynamic tasks (Horita and Ishiko, 1987; Bouissou et al., 1989; Tesch et al., 1990), whereas others have shown a different behavior (Arendt-Nielsen and Sinkjær, 1991; Ament et al., 1996). These results indicate that it is not possible to generate an analytical model which associates force loss to specific features of the sEMG (Vollestad, 1997). To circumvent these limitations, Maclsaac et al. (2006) proposed the use of a set of sEMG variables, that describe both amplitude and spectral characteristics of the signal. This set of variables was combined by an artificial neural network that was trained for the association between sEMG features and an index of fatigue. The rationale for this approach was that the neural network would determine the association between variables extracted from the sEMG, which are known to be influenced by fatigue, to the progression of fatigue. The neural network would determine this association by learning, contrary to an analytical approach that would be too complex. The index proposed by Maclsaac et al. (2006) showed superior performance in tracking fatigue than individual sEMG variables. However, one limitation of the index proposed by Maclsaac et al. (2006) is that it assumes a linear progression of fatigue over time whereas the decrease in maximal voluntary force (which is often assumed to be a direct measure of fatigue; Edwards, 1981; Vollestad and Sejersted, 1988) is rarely reported as linear during dynamic tasks, such as knee extension exercises (Komi and Tesch, 1979; Gerdle et al., 2000). Therefore, the Mapping Index proposed by Maclsaac et al. (2006) may not reflect a direct measure of fatigue during repetitive isokinetic knee extensions, such as force loss, but rather it maps sEMG features into an index that arbitrarily progresses linearly over time from one to zero.

This study proposes a new strategy based on the use of artificial neural networks to directly predict changes in force during isokinetic fatiguing exercise using a set of sEMG variables recorded from multiple locations of the quadriceps muscle. The variables chosen to characterize the sEMG are known to be influenced by fatigue. Therefore, it was hypothesized that there is a consistent association between sEMG variables and force loss which can be identified by a neural network. This new strategy was tested on a set of experimental signals and compared with the approach proposed by Maclsaac et al. (2006).

## 2. Material and methods

### 2.1. Subjects

Nine healthy men (age, mean  $\pm$  SD, 28.0  $\pm$  2.7 yr, body mass 74.1  $\pm$  13.5 kg, height 177.5  $\pm$  6.6 cm) participated in the study. The

study was conducted in accordance with the Declaration of Helsinki and approved by the Local Ethics Committee (N-20070019). Subjects provided informed written consent before participation in the study.

### 2.2. Experimental procedure

Fatiguing contractions of the right knee extensors were performed with a KinCom Isokinetic Dynamometer (Chattanooga, TN, USA). The subjects were seated on the KinCom's chair which was adjusted until the knee axis of rotation was aligned with the rotation axis of the KinCom's attachment arm. The subjects were fixed to the chair with straps across the chest and hips. The subject's right leg was also secured to the dynamometer attachment arm with a Velcro strap.

The subjects attended two sessions separated by 2 days. Within each session, the subjects performed 75 maximal concentric knee extension contractions at 80°/s and 50 maximal concentric knee extensions at 30°/s, both in the range 90–170° of knee extension. The exercises were performed in random order, with 40 min of rest in between. Verbal encouragement was provided to motivate the subjects to perform each leg extension at a maximal force.

### 2.3. Data acquisition

Force and sEMG of the quadriceps were concurrently measured during the isokinetic knee extension contractions. The peak force was calculated from the force signal during the extension exercise. The sEMG signals were recorded from nine locations over the right quadriceps using circular Ag-AgCl surface electrodes (Ambu Neuroline, Ambu A/S, Ballerup, Denmark; sensor area: 28 mm<sup>2</sup>, 2-cm interelectrode distance). The distance from the anterior superior iliac spine (ASIS) to the medial and lateral border of the patella was measured to mark the medial, middle, and lateral sides of the quadriceps, respectively (Zipp, 1982). The nine pairs of electrodes were placed longitudinally at a distance from the patella of 10%, 20% and 30% of the measured anatomical lengths. At each distance, three electrode pairs were placed longitudinally along the half circumference of the thigh, at distances of 20% (lateral), 50% (middle) and 80% (medial) from the midline of the thigh. The electrodes were positioned as described by Hedayatpour et al. (2008). The skin was shaved and lightly abraded prior to electrode placement. Electrode positions were marked on the skin during the first session, ensuring the same electrode positions in both sessions.

Surface EMG signals were amplified (EMG amplifier, EMG-USB, LISiN-OT Bioelettronica, Torino, Italy, bandwidth 10–500 Hz), sampled at 2048 Hz, and stored after 12-bit A/D conversion.

### 2.4. Signal analysis

Signal analysis was performed off-line using Matlab (The MathWorks Inc., Natick, MA, USA). The maximum force value during each knee extension contraction was calculated and normalized with respect to the value of the first contraction. Furthermore, the following sEMG variables were computed from each extension contraction.

- (1) Mean absolute value (MAV): the integrated EMG divided by the integration time. This parameter is influenced by the number of active motor units (Moritani et al., 1982), their discharge rates (Bigland-Ritchie et al., 1983), and by the shape and propagation velocity of the intracellular action potential (Dimitrova and Dimitrov, 2002).
- (2) Median frequency (F<sub>med</sub>) estimated from the power spectrum calculated using Fast Fourier Transform.

This parameter is related to changes in the duration of the motor unit action potential waveform and subsequent changes in muscle fiber conduction velocities (Bigland-Ritchie et al., 1981).

- (3) The spectral parameter proposed by Dimitrov et al. (2006) (Flnsm5):

$$\text{Flnsm5} = \frac{\int_{f_1}^{f_2} f^{-1} \cdot \text{PS}(f) \cdot df}{\int_{f_1}^{f_2} f^5 \cdot \text{PS}(f) \cdot df} \quad (1)$$

where  $\text{PS}(f)$  is the EMG power spectrum calculated using Fast Fourier Transform,  $f_1 = 10$  Hz and  $f_2 = 500$  Hz (determined from the bandwidth of the EMG amplifier).

This parameter relates the spectral moment of order  $(-1)$  and the spectral moment of order 5. The spectral moment of order  $(-1)$  is influenced by the increase in the power at low frequencies of the EMG, related to increased negative afterpotentials during fatigue. The spectral moment of order 5 is influenced by the decrease in the power at high frequencies, related to increments in the duration of the intracellular action potentials and decrements of the action potential propagation velocity (Dimitrov et al., 2006).

The following parameters, defined by Hudgins et al. (1993), are associated to the EMG spectral content, and consequently can be influenced by the same physiological changes as the median frequency.

- (4) Zero-crossing (ZC) rate:

$$\text{ZC} = \frac{N_{\text{zc}}}{K} \quad (2)$$

where  $K$  is the number of samples,  $N_{\text{zc}}$  is incremented if  $\{x_k > 0 \text{ and } x_{k+1} < 0\}$  or  $\{x_k < 0 \text{ and } x_{k+1} > 0\}$  while  $|x_k - x_{k+1}| \geq \varepsilon$ , where  $\varepsilon$  is the noise threshold and  $x_k$  represents the  $k$ th sample of the contraction.

This parameter is a simple measure of the main frequency of the signal, as the number of times that the waveform crosses zero.

- (5) Rate of slope sign changes (SSC):

$$\text{SSC} = \frac{N_{\text{ssc}}}{K} \quad (3)$$

Where  $K$  is the number of samples,  $N_{\text{ssc}}$  is incremented if  $\{x_k > x_{k-1} \text{ and } x_k < x_{k+1}\}$  or  $\{x_k < x_{k-1} \text{ and } x_k > x_{k+1}\}$  while  $|x_k - x_{k+1}| \geq \varepsilon$ , where  $\varepsilon$  is the noise threshold and  $x_k$  represents the  $k$ th sample of the contraction.

This feature provides another measure of frequency content, as the number of times that the slope of the waveform changes sign.

- (6) Wavelength (WL):

$$\text{WL} = \frac{1}{K} \sum_{k=1}^K |x_k - x_{k-1}| \quad (4)$$

where  $K$  is the number of samples and  $x_k$  represents the  $k$ th sample of the contraction.

This parameter provides information on the waveform complexity in each segment.

Each EMG variable was normalized with respect to corresponding values of the first contraction.

These EMG variables were chosen because they provide information on both the total power and the distribution of power across frequency bands of the sEMG signal. In addition, Flnsm5 was chosen since it has been shown to provide accurate estimation of muscle power changes during several concentric knee extensions in a previous study (Gonzalez-Izal et al., 2010). As indicated above, each variable is influenced by multiple physiological changes that may

occur with fatigue. Moreover, some changes may influence several of the sEMG features chosen for this study. Since there are no forward models that accurately associate these sEMG variables to force loss, it is not possible to analytically derive an inverse model and thus determine directly this association. Moreover, it is likely that the inverse model is non-linear. Therefore, the association between force loss and sEMG features should be identified with a learning procedure and a system that allows for the identification of non-linear relations, such as a neural network.

## 2.5. Multi-layer perceptron neural network

An artificial neural network consists of an interconnected group of artificial neurons and changes its structure depending on the information received during the learning phase. Due to the complex relations between sEMG variables and force, these techniques seem to be appropriate to develop a method to map changes in force using changes in sEMG variables.

The artificial neural network chosen to relate changes in sEMG variables and force in the present study was the multi-layer perceptron (MLP). The MLP is based on the combination of layers (one or more hidden) of perceptrons. Each perceptron combines its inputs after weighting them with an appropriate weight. The sum of the weighted inputs and the bias forms the input of a threshold function.

The learning or training phase of the MLP consists of changing the weights of all the artificial neurons in such a way that the errors between the desired outputs and the corresponding outputs of the neural network are minimized. The training and testing of the MLP were performed using Matlab Neural Network Toolbox (The MathWorks Inc., Natick, MA, USA).

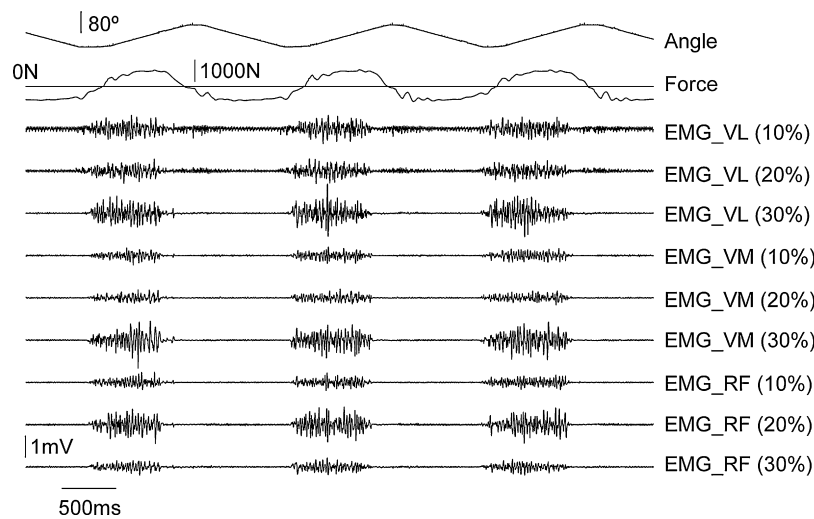
## 2.6. Force loss prediction

A MLP neural network was used to map the EMG variables into the exerted force and, for comparison, into the Mapping Index (MI) proposed by MacIsaac et al. (2006). The input parameters to obtain the Mapping Index were MAV, ZC, SSC and WL, as previously proposed (MacIsaac et al., 2006). The Mapping Index is built by assuming that its value at the beginning of the test is equal to 1 (non-fatigued state); the index decreases linearly during the contraction and reaches its minimum value equal to 0. Although the MI was previously assumed to be equal to 0 at the time of task failure (MacIsaac et al., 2006), it is also possible to map it over a shorter time interval since its trend is linear. In the present study the MI was mapped to 1 at the beginning of the contraction and to 0 at the end of the contraction even if task failure was not reached.

The force loss during the task was estimated using MAV, Fmed, and Flnsm5, as input parameters to the MLP.

For both approaches, the variables extracted from the sEMG signals recorded from all electrode locations were used as an input to the neural network, providing more complete information of the changes in the sEMG signals observed in the quadriceps muscle. In addition, the data from the first experimental session (obtained from the two tests at  $30^\circ/\text{s}$  and  $80^\circ/\text{s}$ ) were used to train the MLP whereas the data from the second session (from the tests at both velocities), performed on a different days, were used for testing. In doing so, a more general approach was developed which is valid for mapping force using sEMG variables recorded from leg extensions at different velocities (high and low speed contractions). The performance of the two estimators was quantified by the signal to noise ratio (SNR) for the outputs:

$$\text{SNR} = \frac{R}{\sqrt{1/N \sum_{n=1}^N (I_n - \hat{I}_n)^2}} \quad (5)$$



**Fig. 1.** Angle, force and raw surface EMG signals recorded from the nine locations of the quadriceps during a 80°/s test for Subject 2. The recording positions of each surface EMG signal are indicated as the relative distance (in percentage) from the patella (10%, 20%, 30%). The horizontal line in the force trace represents the baseline force (ON).

where  $R$  represents the range of the desired outputs (calculated as the maximum minus the minimum of the percentage change in force or MI) and the denominator represents the root mean square error between the estimated ( $\hat{I}_n$ ) and desired outputs ( $I_n$ ), across  $N$  contractions.

The MLP was trained and tested on each subject separately as well as on the features extracted from all subjects.

## 2.7. Statistical analysis

Unpaired Student's  $t$ -tests were used to detect significant differences in the SNR associated to the two estimators (MI and force estimates). A two-way ANOVA was applied to establish significant changes in force over time. Individual sEMG variables were tested for dependency on time and electrode location with a two-way

**Table 1**  
Percent change (% mean  $\pm$  SD) in force and sEMG parameters averaged across 80°/s tests for each subject and for the group of subjects. The mean average voltage (MAV) and median frequency (Fmed) are presented as an average of the values recorded from the three locations over the vastus lateralis (VL), vastus medialis (VM), and rectus femoris (RF).

Subject	Force (%) (mean $\pm$ SD)	VL MAV (%) (mean $\pm$ SD)	VM MAV (%) (mean $\pm$ SD)	RF MAV (%) (mean $\pm$ SD)	VL Fmed (%) (mean $\pm$ SD)	VM Fmed (%) (mean $\pm$ SD)	RF Fmed (%) (mean $\pm$ SD)
1	-52.3 $\pm$ 6.6	-6.9 $\pm$ 15.6	-1.7 $\pm$ 0.1	25.9 $\pm$ 9.8	0.0 $\pm$ 4.6	-15.3 $\pm$ 4.3	-24.7 $\pm$ 11.2
2	-72.2 $\pm$ 7.0	-27.2 $\pm$ 39.2	-19.4 $\pm$ 52.6	-35.7 $\pm$ 50.2	-2.7 $\pm$ 35.6	-15.9 $\pm$ 0.9	-21.8 $\pm$ 1.4
3	-38.8 $\pm$ 9.1	-15.4 $\pm$ 25.2	-15.9 $\pm$ 27.9	-15.6 $\pm$ 27.1	-3.4 $\pm$ 5.9	-3.0 $\pm$ 1.3	-6.2 $\pm$ 5.0
4	-43.2 $\pm$ 13.2	-3.7 $\pm$ 17.1	8.6 $\pm$ 21.6	-23.4 $\pm$ 0.8	-1.4 $\pm$ 3.1	-8.1 $\pm$ 4.5	-11.3 $\pm$ 2.3
5	-48.2 $\pm$ 17.1	-38.9 $\pm$ 7.5	-36.6 $\pm$ 13.8	-42.0 $\pm$ 9.6	-1.8 $\pm$ 0.6	4.1 $\pm$ 10.2	-4.3 $\pm$ 4.6
6	-32.5 $\pm$ 25.5	5.4 $\pm$ 32.5	25.8 $\pm$ 7.4	25.3 $\pm$ 27.1	-11.5 $\pm$ 17.8	-24.7 $\pm$ 12.4	-26.5 $\pm$ 2.7
7	-49.5 $\pm$ 10.0	40.6 $\pm$ 23.0	63.0 $\pm$ 40.2	64.2 $\pm$ 33.0	-28.8 $\pm$ 6.1	-24.5 $\pm$ 8.7	-26.2 $\pm$ 7.9
8	-64.7 $\pm$ 9.4	0.4 $\pm$ 12.8	19.1 $\pm$ 0.7	-6.7 $\pm$ 5.7	-19.2 $\pm$ 6.3	-17.9 $\pm$ 7.8	-18.7 $\pm$ 7.9
9	-47.2 $\pm$ 4.3	-32.6 $\pm$ 21.3	-27.4 $\pm$ 11.9	-13.9 $\pm$ 0.9	-5.6 $\pm$ 13.6	-7.8 $\pm$ 1.5	-17.0 $\pm$ 5.5
Mean $\pm$ SD	-49.9 $\pm$ 6.5 <sup>▲</sup>	-8.7 $\pm$ 24.0	1.7 $\pm$ 31.2	-2.4 $\pm$ 34.4 <sup>*</sup>	-7.7 $\pm$ 10.4 <sup>▲</sup>	-12.6 $\pm$ 9.7 <sup>▲</sup>	-17.4 $\pm$ 8.4 <sup>*,†,▲</sup>

<sup>\*</sup> Significant differences between rectus femoris and vastus medialis ( $P < 0.05$ ).

<sup>▲</sup> Significant differences between the first and the last contraction ( $P < 0.05$ ).

**Table 2**  
Percent change (% mean  $\pm$  SD) in force and sEMG parameters averaged across 30°/s tests for each subject and for the group of subjects. The mean average voltage (MAV) and median frequency (Fmed) are presented as an average of the values recorded from the three locations over the vastus lateralis (VL), vastus medialis (VM), and rectus femoris (RF).

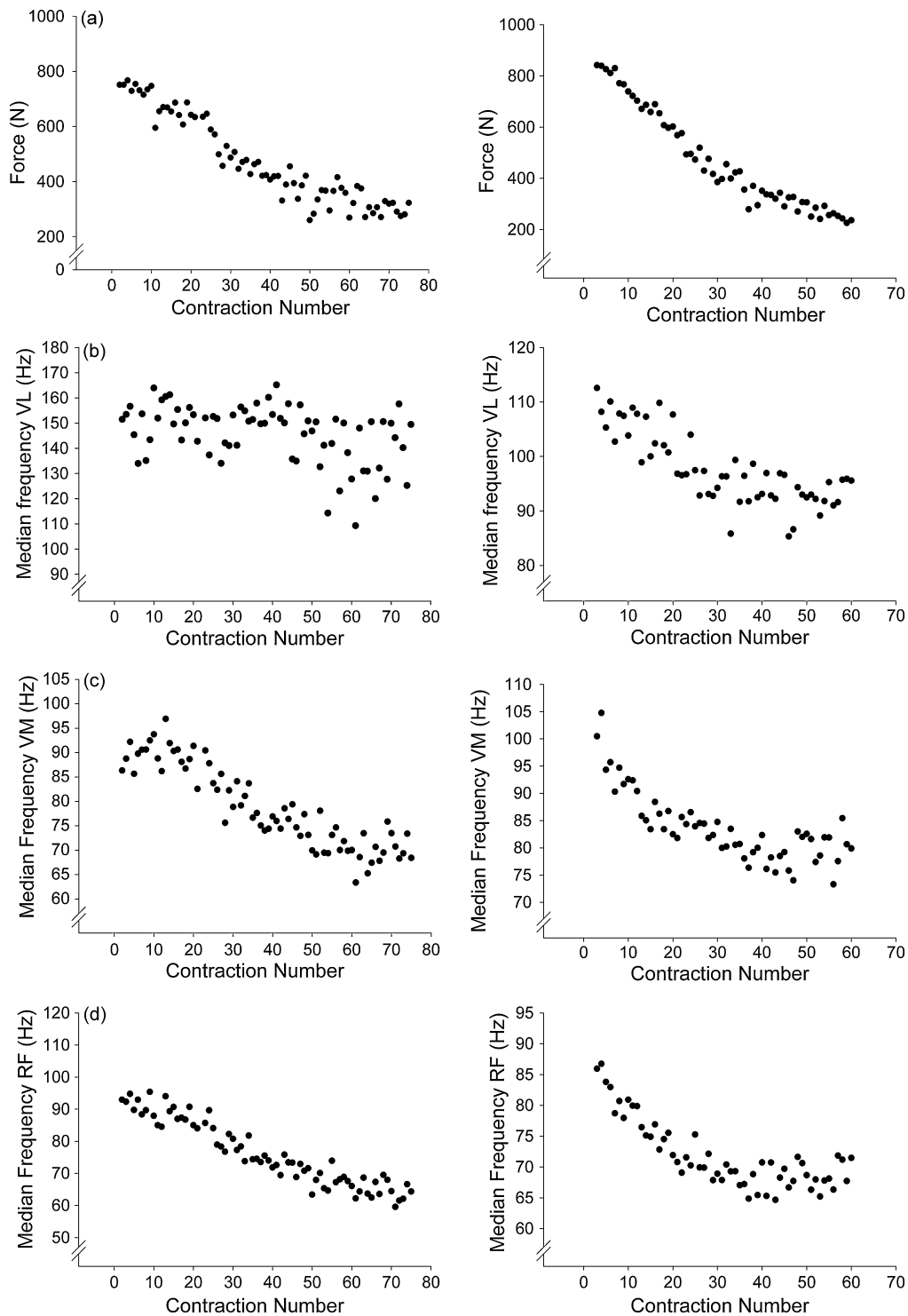
Subject	Force (%) (mean $\pm$ SD)	VL MAV (%) (mean $\pm$ SD)	VM MAV (%) (mean $\pm$ SD)	RF MAV (%) (mean $\pm$ SD)	VL Fmed (%) (mean $\pm$ SD)	VM Fmed (%) (mean $\pm$ SD)	RF Fmed (%) (mean $\pm$ SD)
1	-43.4 $\pm$ 7.2	24.7 $\pm$ 35.3	-2.5 $\pm$ 0.4	-19.9 $\pm$ 9.1	5.7 $\pm$ 29.9	-13.3 $\pm$ 5.5	-24.7 $\pm$ 0.0
2	-25.1 $\pm$ 9.8	14.9 $\pm$ 0.4	15.1 $\pm$ 12.8	1.4 $\pm$ 11.1	-5.4 $\pm$ 0.7	-11.4 $\pm$ 7.6	-13.9 $\pm$ 10.4
3	-29.6 $\pm$ 3.9	-4.9 $\pm$ 1.0	-13.1 $\pm$ 12.4	-10.3 $\pm$ 4.3	6.4 $\pm$ 3.1	-2.5 $\pm$ 1.7	-2.7 $\pm$ 9.6
4	-23.6 $\pm$ 18.2	-6.3 $\pm$ 25.1	-13.3 $\pm$ 21.1	-2.2 $\pm$ 19.7	5.3 $\pm$ 7.8	-1.7 $\pm$ 1.0	-12.2 $\pm$ 4.4
5	-45.9 $\pm$ 2.9	-33.7 $\pm$ 9.3	-36.5 $\pm$ 5.5	-33.4 $\pm$ 15.3	1.7 $\pm$ 9.6	-0.5 $\pm$ 8.1	-2.8 $\pm$ 8.3
6	-29.5 $\pm$ 3.6	8.3 $\pm$ 6.2	-1.3 $\pm$ 0.2	-1.1 $\pm$ 0.5	-4.5 $\pm$ 0.9	-11.6 $\pm$ 11.6	-12.6 $\pm$ 20.6
7	-29.0 $\pm$ 11.2	-1.8 $\pm$ 2.5	1.5 $\pm$ 3.6	-4.3 $\pm$ 4.4	-4.2 $\pm$ 9.9	-8.2 $\pm$ 0.2	-11.5 $\pm$ 6.8
8	-67.8 $\pm$ 9.4	-33.0 $\pm$ 19.6	-38.9 $\pm$ 17.5	-47.2 $\pm$ 14.0	11.4 $\pm$ 9.0	-5.0 $\pm$ 9.9	-7.9 $\pm$ 2.7
9	-18.0 $\pm$ 0.6	9.8 $\pm$ 6.6	3.9 $\pm$ 7.9	7.9 $\pm$ 5.1	8.1 $\pm$ 5.3	6.0 $\pm$ 0.3	-8.7 $\pm$ 8.7
Mean $\pm$ SD	-34.7 $\pm$ 15.3 <sup>▲</sup>	-2.4 $\pm$ 20.1 <sup>†</sup>	-9.5 $\pm$ 18.2	-12.1 $\pm$ 18.1	2.7 $\pm$ 6.1 <sup>‡</sup>	-5.4 $\pm$ 6.3 <sup>▲</sup>	-10.8 $\pm$ 6.6 <sup>*,†,▲</sup>

<sup>\*</sup> Significant differences between rectus femoris and vastus medialis ( $P < 0.05$ ).

<sup>†</sup> Significant differences between rectus femoris and vastus lateralis ( $P < 0.05$ ).

<sup>‡</sup> Significant differences between vastus lateralis and medialis ( $P < 0.05$ ).

<sup>▲</sup> Significant differences between the first and the last contraction ( $P < 0.05$ ).



**Fig. 2.** Representative data showing the progression of force and median frequency over time for each muscle during a test at  $80^\circ/s$  in two subjects (left column: Subject 1, right: Subject 2). Data represent force (a), and median frequency averaged for the three locations of the vastus lateralis (VL) (b), vastus medialis (VM) (c) and rectus femoris (RF) (d).

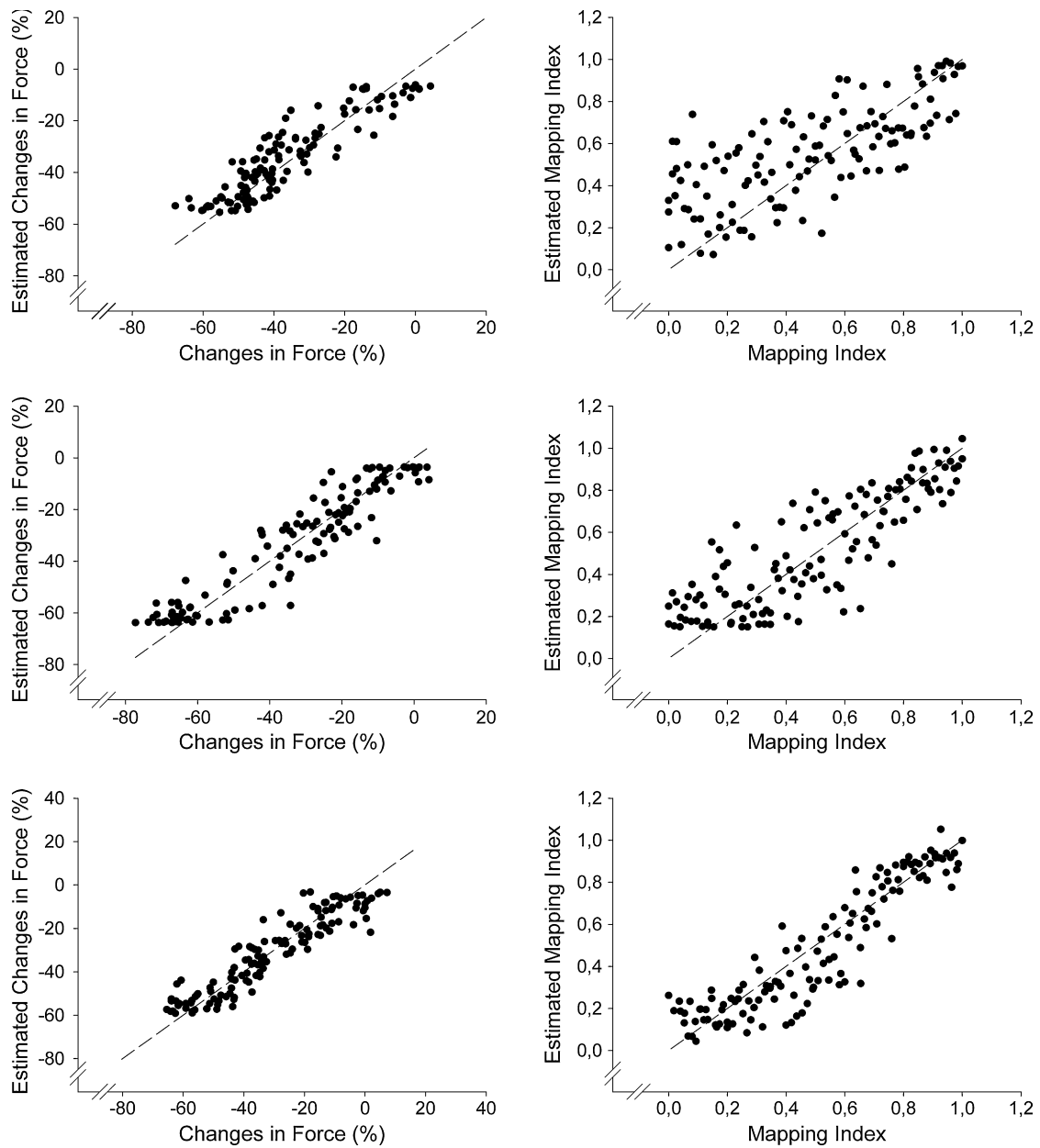
ANOVA. When ANOVA was significant, the Sheffé post hoc test was used for pair-wise comparisons. Statistical significance was set at  $P < 0.05$ . Results are presented as mean and SD.

### 3. Results

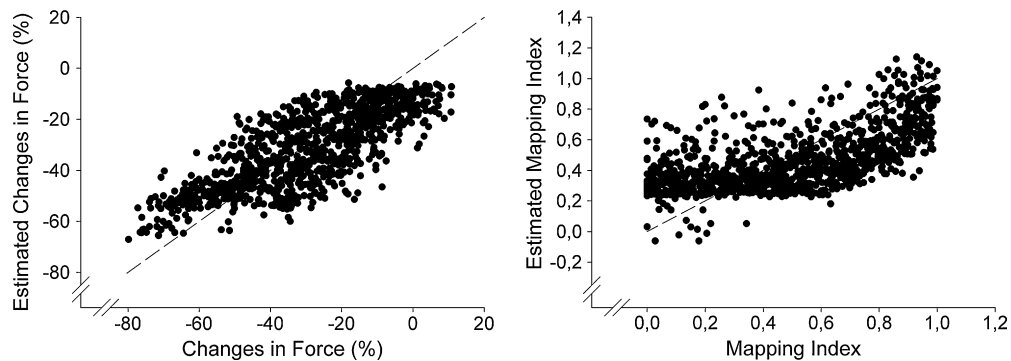
No significant differences were found for the various variables collected at the start of the session for the 2 days. Fig. 1 shows an

example of angle, force and raw surface EMG signals from multiple locations of the quadriceps muscle during consecutive leg extensions and flexions of one subject.

Tables 1 and 2 show the percent change in force, MAV and Fmed for each subject and for the entire group of subjects during both tasks at  $80^\circ/s$  and  $30^\circ/s$ . The exercise-induced decrease in force followed a non-linear trend over time for all subjects (Fig. 2).



**Fig. 3.** Output of the neural network vs. the desired output for three representative subjects. The graphs in the left column illustrate the performance of the neural network trained to map force loss for each subject, while the graphs on the right illustrate the performance when the network was trained to estimate the Mapping Index. Each point represents the corresponding value of each knee extension. The dashed line in each figure illustrates the desired output.



**Fig. 4.** Group data for the output of the neural network using force (left) and the MI (right) (i.e., outputs of a neural network using the data from all the subjects). Each point represents the corresponding value of each knee extension. The dashed line illustrates the desired output.

Subjects showed a variety of behaviors for sEMG variables. As an example, Fig. 2 presents the data from Subjects 1 and 2. In Subject 1, Fmed of the vastus lateralis decreased substantially less than in vastus medialis and rectus femoris whereas the trends in Fmed were similar for the three muscles in Subject 2.

Despite the variability among subjects, the median frequency of the vastus medialis and rectus femoris significantly ( $P < 0.05$ ) decreased during both protocols. Moreover, the greatest decrease in Fmed (average across all subjects) was observed for the rectus femoris muscle ( $P < 0.05$ ). However, no significant changes were found for the amplitude variables across the fatiguing contraction.

The estimation of force and MI is shown for three representative subjects in Fig. 3 (i.e., force and MI estimations using different neural networks, each of them trained and tested with the data from each subject). The outputs of the MLP are represented as a function of the desired output (i.e., the force value of that contraction or the corresponding value of the MI). The output of the MLP was more accurate when the network was trained to map force (left column in Fig. 3) than the MI. Accordingly, over all subjects, the SNR (defined in Eq. (5)) was greater when using force ( $8.83 \pm 1.07$ ) as an output compared to the Mapping Index ( $5.67 \pm 1.17$ ) ( $P < 0.05$ ).

Fig. 4 illustrates the performance of the neural network when it was trained and tested with the data from all subjects for both indices (i.e., force and MI estimations using one neural network trained and tested with the data from all the subjects). The SNR obtained using force as the output of the MLP (8.07) was greater than that observed when using the MI (4.42).

#### 4. Discussion

The main results of the present study show that the loss in maximal force generation capacity of the quadriceps muscles during repetitive isokinetic knee extensions was predicted from a set of sEMG variables with greater accuracy than previously proposed indexes of muscle fatigue. These results suggest that this strategy could be a useful tool to map changes in force during isokinetic contractions.

The behavior of sEMG variables over time during the dynamic tasks varied greatly among subjects. However, some common behavior was identified. The median frequency of the EMG decreased more for the rectus femoris than for other muscles. These results are consistent with previous results from fatiguing dynamic knee extension protocols (Karlsson et al., 2003; Pincivero et al., 2006) and sustained isometric knee extension contractions (Mannion and Dolan, 1996; Bilodeau et al., 2003). However, other authors (Tesch et al., 1990) observed no differences in the mean power frequency between the rectus femoris and vastus lateralis.

The measure of force (and force loss) is a challenging technical task during free daily movements (e.g., walking or cycling). On the contrary, with current technology, sEMG can be measured in almost all these types of movements. The main issue when using sEMG variables to quantify fatigue is their poor association with the direct measure of fatigue, i.e. the maximal force generation capacity of a muscle or muscle group. After decades of research in finding the physiological determinants of various sEMG variables, it is now evident that intra-individual factors, such as muscle anatomy, affect the estimate and hinder the association between myoelectric and mechanical variables (Farina et al., 2004). Thus, a more suitable approach is to identify the association between sEMG characteristics and force generation capacity with a learning algorithm. The method proposed in this study follows this approach and is a modification of the original technique proposed by MacIsaac et al. (2006). The main difference between the two methods is the objective function that the MLP maps. In the current study this function is the

mechanical output whereas MacIsaac et al. (2006) used an index of fatigue which was considered a-priori as changing linearly over time. Moreover, we proposed a new set of sEMG features as input to the MLP.

The new approach developed in this study, tracked the loss of force using myoelectric variables with higher values of SNR compared to the MI approach proposed by MacIsaac et al. (2006) during repetitive isokinetic knee extensions. One of the reasons for this difference is that the changes in force generation capacity and, thus, the fatigue development over time are non-linear over time. This non-linear trend of maximal force was observed for all subjects and is consistent with previous results in dynamic fatiguing protocols (Komi and Tesch, 1979; Gerdle et al., 2000). Because of the non-linear decay of force over time, an index that changes linearly over time does not represent the force loss. Moreover, our results showed that the non-linear decay of force can be tracked better than a linear trend when the mapping was tested on different days. Thus, the association between change in force and sEMG variables is stronger than that between an index linearly decaying over time and sEMG.

The proposed fatigue assessment strategy is a promising method to track changes in muscle force (direct estimator of muscle fatigue) using myoelectric signal features during repetitive isokinetic knee extensions. However, the method requires that the neural network is trained using myoelectric variables (which reflect muscle fatigue) for each participant. Although this is a drawback for practical applications, this result was expected because of the large variability in sEMG features across subjects. However, when training the network using the data from all subjects, the method proposed was still able to track changes in force (Fig. 4). As expected, the predictive capacity was poorer than using different networks for each individual subject. In this case, larger variations were found in both analyses (force and MI), as revealed by lower SNR values. Moreover, in the MI approach a larger deviation from the identity line (that corresponds to the real value equal to the estimated output) was found. Although a lower accuracy was observed, training the network with data from all subjects was a more powerful approach as it provides a more general technique to track changes in force loss for different subjects using just the one neural network. In addition, since the neural network was trained and tested using data collected on different days, the effects of repositioning electrodes are taken into account. Therefore, the proposed approach may be useful to track force loss during repetitive isokinetic knee extensions performed on different days, using a neural network previously trained, after repositioning the electrodes in the same recording sites according to standards for electrode location. Nevertheless, it is unknown whether the neural network can track muscle fatigue during a dynamic exercise for which it has not been trained. It is also unknown whether the neural network is capable of tracking muscle fatigue for a subject not used for training of the network or whether it is able to track changes in force during submaximal contractions after being trained with data from maximal efforts. Additionally, in this study, the neural network was trained and tested using myoelectric variables for each subject recorded from the same recording sites. It is not known whether the network could be trained and tested using myoelectric variables recorded from different recording sites as these aspects were not investigated in the current study. However, the training and test were performed in different sessions over separate days, therefore the performance accounts for the repositioning of electrodes from session to session, and thus reflect the practical condition.

In conclusion, this study showed good accuracy of an artificial neural network to estimate muscle force losses using a set of sEMG variables as inputs during an isokinetic knee extension exercise. In addition, a single neural network trained on a group of subjects could also track the force loss with good accuracy.

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