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Analysis of muscle coupling during isokinetic endurance contractions by means of nonlinear prediction*

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Abstract—**Isokinetic exercises have been extensively used in order to analyze muscle imbalances and changes associated with fatigue. It is known that such changes are difficult to assess from EMG signals during dynamic contractions, especially, using linear signal processing tools. The aim of this work was to use nonlinear prediction in order to analyze muscle couplings and interactions in this context and to assess the load-sharing of different muscles during fatigue. Results show promising for detecting interaction strategies between muscles and even for the interaction between muscles and the output torque during endurance tests.**

I. Introduction

Low-effort repetitive contractions have been associated to upper limb disorders such as lateral epicondylitis in different studies in the literature [1, 2]. Isokinetic exercise has been extensively used in order to analyze muscle imbalances and changes associated with muscle fatigue [1, 2], specifically, by studying the exerted torque and its agonist-antagonist ratio. However, changes at neuromuscular level can be better described by the analysis of electromyographic signals (EMG) which reflect the one-to-one relationship between the activation of motor units and the neural code being transferred from the motor cortex to the muscles.

When referring to fatigue assessment in isometric-contractions, there is a large amount of evidence of changes in features extracted from EMG (e.g. mean frequency of the power spectrum, signal amplitude, etc) using linear processing techniques. Additionally, there is evidence of time-variations in the co –activation pattern (load-sharing) of synergistic muscles during both, isometric and dynamic fatiguing contractions [3, 4].

However, the EMG signal cannot be considered as wide sense stationary when involving joint movement or changes in the length of the muscle fibers [3] and therefore results obtained by linear methods in dynamic contractions are not consistent [5]. In this condition, the nature of the signal is influenced by various confounding factors, affecting the estimation of EMG features [5]. On the other hand, recent studies support the use of nonlinear techniques for detecting changes in surface EMG (sEMG) during fatigue [6]. Particularly, our group has successfully applied nonlinear prediction based on locally-linear models to study muscle couplings and interactions between respiratory muscles [5]. Assuming that EMG data are associated with an underlying nonlinear dynamical system, it is possible to evaluate correlations between muscles using a simple nonlinear prediction algorithm as described in [7].

The purpose of this study was to evaluate the information that can be extracted from nonlinear prediction and associate it with muscle coupling (load- sharing) during fatiguing dynamic contractions of the wrist.

sEMG signals recorded in isokinetic condition from four muscles were studied: Extensor Carpi Radialis (ECR), Extensor Carpi Ulnaris (ECU), Extensor Digitorum Communis (EDC) and Flexor Carpi Radialis (FCR). Different preliminary analyses were performed in order to characterize their coordination and also the coupling between muscles and output torque. Although results showed different interaction strategies for different subjects, it was possible to observe fatigue-related changes in such interactions. Future work will comprise the application of the technique in the assessment of lateral epicondylitis.

II. Methodology

A. Experimental recording

The experimental protocol was approved by the Local Ethics Committee and participants gave their written informed consent.

Four healthy male subjects (age, mean ± standard deviation: 30.8 ± 4.35 years; height: 181.3 ± 3.4cm; weight: 79.3±12 kg) with no history of musculoskeletal and/or neuromuscular disorders of the upper extremity participated in the experiment.

Single differential sEMG signals were recorded in four muscles: ECR, ECU, EDC and FCR by means of linear arrays of 8 electrodes (Ag-AgCl, IED 0.5 cm, LISiN-SpesMedica) connected to two sEMG amplifiers with synchronized sampling (LISIN/OT Bioelettronica 16 channels, sampling frequency= 2048 Hz). Electrode arrays were used in order to decide the best location for the recording of the signals, that is, away from innervation zones and tendons. For the rest of the analysis, one single-differential channel was chosen on the basis of high cross-correlation coefficient with neighboring channels (>0.7) and where it was possible to observe propagation of motor unit action potentials with conduction velocity ranging in the expected physiological values as described in [8].

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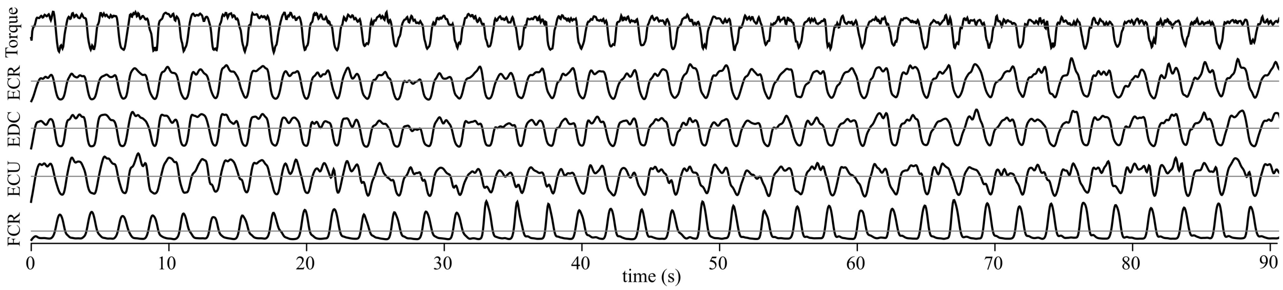

Figure 1. Example of demodulated and normalized EMG signals and torque obtained from subject 3.

Subjects performed a series of isokinetic contractions at the wrist up to exhaustion in order to assess muscular fatigue. An isokinetic dynamometer in concentric mode was used for this purpose (Biodex System III; Biodex Medical Systems, Shirley, NY). Subjects were seated with the back straight, the forearm supported and in full pronation and the elbow flexed at 60º. The joint axis of the wrist was aligned with the rotational axis of the dynamometer. The velocity of the device was set to 60º/s in wrist extension and 180º/s in wrist flexion in order to emphasize the role of the wrist extensor muscles which are commonly associated with upper limb disorders such as lateral epicondylitis [9]. The range of motion was 70º (30º in dorsal flexion and 40º in palmar flexion measured from the neutral position of the wrist).

The exerted torque was measured over the entire range of motion and its output signal was simultaneously sampled at 100 Hz and digitalized for offline analysis.

B. Data preprocessing

The EMG signals were pre-filtered between 20 and 350 Hz with a 4th order Butterworth filter for reducing motion artifacts and to remove the baseline. Then, the signals were demodulated, that is, full-wave rectified and filtered by means of a 400 ms moving average window [7, 10]. This demodulation integrated the contributions of all motor units, obtaining a signal related to the whole muscle action [11]. The resulting demodulated EMG signals and the torque signal were resampled to obtain a final sampling frequency of 20 Hz [7]. Signals were also normalized by subtracting the mean and then dividing over their standard deviation to have zero mean and unit variance, so that subsequent analysis of their dynamics was independent from their amplitudes (see Fig. 1). The normalization avoided the effect of the relative electrode- muscle distance on amplitude of the signal.

The zero-crossings of the torque signal were used to calculate the duration of the duty cycle, given that some variation in the velocity of the exercise can be expected.

C. Nonlinear prediction

Nonlinear prediction was carried out by means of locally linear models, which in turn were based on the reconstruction of the "state of the system" obtained by lag embedding [12]. The Taken's theorem was applied to the demodulated EMG and torque signals, with the embedding dimension (*ED*) set to 4 and the delay time between samples (*DT*) set to ¼ of the total duration of 1 duty cycle (~ 2 s). Hence, the embedding process of a single signal results in an *ED*-dimensional time series that follows the equation:

$$\mathbf{z}_t = (x_t, x_{t-DT}, \dots, x_{t-(\mathrm{ED}-1)\mathrm{DT}})\big|_{t=1,..,M} \tag{1}$$

where x_t represents a sample at time t and M $\mathbf{z_t}$ points in the *ED*-dimensional space were obtained, depending on the total duration of the signal (M is limited to $M=N-DT*(ED-1)$).

Thus, the 4-dimensional series of a signal was used to model its dynamics, and its model was in turn employed to predict other epochs of the same signal (auto-prediction) or of a different signal (cross-prediction), taking into account a range of prediction horizons (*PH*) up to 10 s.

In theory, it should be possible to predict the future value of a point in the embedded space just by looking at the future value of its closest neighbor, but in practice some more points have to be considered. In this work $3 \cdot ED = 12$ nearest neighbors were used to obtain sensible prediction values. Solving the linear system that maps some neighbors to their future counterparts a nonlinear regression model, which can be understood as the linearization of a global nonlinear dynamics at the considered points in the embedded space, could be implemented.

Nonlinear prediction was assessed in the following cases:

- EMG auto-prediction for the four selected muscles (ECR, EDC, ECU and FCR).
- EMG-EMG cross-prediction. In this case, the demodulated EMG signal from the ECR was used to predict the signals of the other muscles, because it has been associated with forearm disorders [1, 2]
- EMG-Torque cross-prediction. The demodulated signal of each muscle was used to predict the output torque.

For each *PH*, the prediction model was estimated M times following a leaving-one-out approach and the goodness of the prediction was evaluated by the R^2 coefficient. For details on the actual prediction algorithm, please refer to [7]. The values used for the parameters of the models and in the pre-processing of the signals were also chosen according to [7].

From the trends of R^2 as function of *PH*, three variables were obtained: 1.The slope of the linear regression of R^2, and its regression coefficient r, 2. The value of R^2 at the minimum *PH* (R_o), and 3. The value of R^2 at the maximum *PH* (R_f).

III. RESULTS

A. Auto-prediction

The auto-prediction model using the whole signal (corresponding to the entire duration of the endurance test) revealed an important decrease of R^2 with increasing *PH*. An example of the obtained results for one subject can be observed in Fig. 2 (left). The decrease of the R^2 coefficient was lower for ECU when compared with the other muscles,

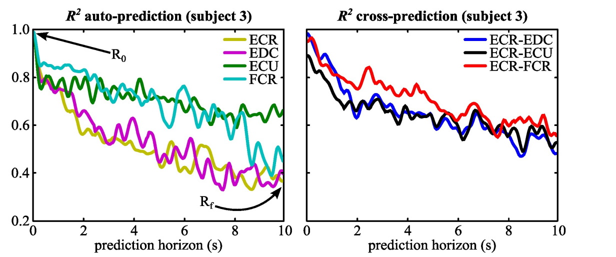

Figure 2. R^2 coefficient as function of the prediction horizon for EMG auto-prediction (left) and EMG-EMG cross-prediction (right) in subject 3

as can be inferred from the slope of the linear regression of R^2 and from the R_f value at a PH = 10 s (see Table I).

B. Cross-prediction

R^2 also showed a sensitive decrease with increasing PH for the ECR EMG pairs using the entire duration of the test (see Fig.2 right as an example). In general, similar couplings between ECR and the rest of the muscles were observed from the slope and the initial (R_o) and final (R_f) values of R^2 in Table II. Note that the ECR-ECU presented the lower initial values R_o when compared to the rest and this result was consistent for all of the subjects (see Table II).

Additionally, decreasing R^2 values with increasing prediction horizon were obtained for the prediction of the developed torque from each muscle. The variables extracted from R^2 as function of PH and for the four subjects are presented in Table III. Note that the steepest decrease was obtained for the FCR in three of the four subjects.

In order to obtain information about possible changes in the performance during the endurance test, the prediction was calculated by using a 15 cycles-epoch at the beginning, the middle and the end of the exercise. This analysis revealed that the prediction deteriorate (lower R^2 values) at the middle and final stages of the exercise. This behavior was globally consistent for the three pairs of muscles and similar for the four subjects. An example is given in Fig. 3, where it is possible to observe a very good prediction during the first 15 cycles even for PH = 10 s, (R^2>0.9, Fig. 3, top left), followed by a slow decay in the middle of the test (Fig. 3, center left) and a dramatic decay at the end, reaching R2 values close to 0.5 for PH = 10s for all pairs of muscles (Fig. 3, bottom left). Similar results were obtained for the cross-prediction between EMG and isokinetic torque. An example for the same subject is presented in the right column of Fig. 3.

Based on these findings, a more detailed analysis was carried out with the purpose of evaluating the instant where

TABLE I. VARIABLES OBTAINED FROM R^2 AS FUNCTION OF THE PREDICTION HORIZON (PH) FOR THE AUTO-PREDICTION. THE SLOPE, THE COEFFICIENT OF THE LINEAR REGRESSION (r) AND THE VALUES AT MINIMUM (R_O) AND MAXIMUM (R_f) PH ARE PRESENTED

Slope, r [R_o, R_f]	***S1***	***S2***	***S3***	***S4***
ECR	**-0.026**, *0.86* [0.99, 0.54]	**-0.074**, *0.97* [0.99, 0.33]	**-0.041**, *0.89* [0.99, 0.37]	**-0.04**, *0.97* [0.99, 0.58]
EDC	**-0.044**, *0.93* [0.99, 0.26]	**-0.033**, *0.91* [0.99, 0.57]	**-0.046**, *0.93* [0.99, 0.4]	**-0.055**, *0.96* [0.99, 0.44]
ECU	**-0.014**, *0.7* [0.99, 0.67]	**-0.021**, 0.9 [0.98, 0.66]	**-0.019**, *0.86* [0.99, 0.66]	**-0.035**, 0.94 [0.98, 0.53]
FCR	**-0.077**, *0.86* [0.98, 0]	**-0.081**, *0.92* [0.98, 0]	**-0.041**, *0.93* [0.99, 0.45]	**-0.095**, *0.99* [0.99, 0]

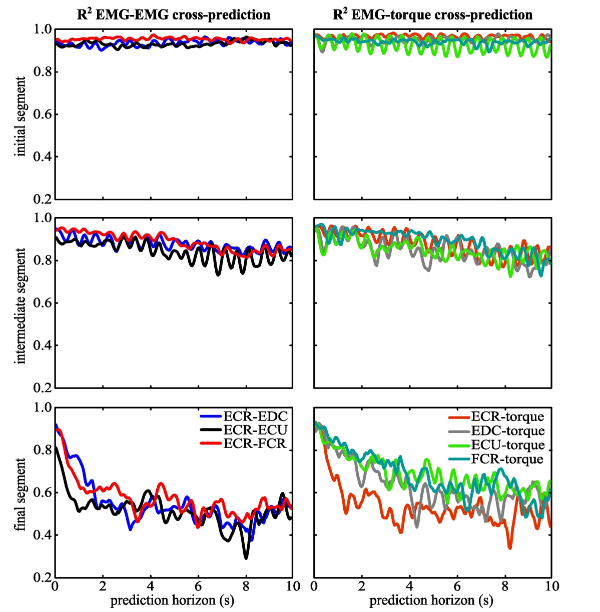

Figure 3. R^2 (PH) for the EMG-EMG *(left)* and EMG-Torque *(rigth)* cross-prediction in subject 3. The R^2 was obtained from the first 15 cycles *(top)*, the 15 intermediate cycles *(middle)* and the final 15 cycles *(bottom)* of the test. Different pairs of signals are indicated by different colors.

the forecasting gets worse during the test. R^2 at PH = 4 s (~ 2 cycles) was calculated using a 15-cycles sliding window. Since each subject performed a different number of cycles and given that R_o can be different for different muscles, R^2 was normalized with respect to R_o and the traces were analyzed as function of the relative total duration time (TDT, 0 to 100% of the number of cycles). Coupling patterns between ECR and the other muscles for the four subjects are shown in Fig. 4. Although each subject presented different strategies for the activation of these muscles, it was possible to observe steep decreases in R^2 beyond 60% of the total number of cycles in more or less extent depending on the subject. Such changes were also observed from the cross-prediction EMG-torque models (Fig 4. bottom) though not as clear as in the case of EMG-EMG pairs.

Therefore worsening in the prediction could be partially attributed to changes in the coupling between ECR and the rest of the muscles. Finally, it was possible to notice that the R^2 coefficient for the pair FCR-torque was not as good as that obtained for the extensor muscles, but this could be related to the high velocity of the wrist flexion that caused a lower activation of the flexor muscles with respect to the extensors.

IV. Discussion and Conclusions

Nonlinear prediction models were successfully applied to the analysis of coupling between muscles and between muscles and output torque. The R^2 coefficient was very high (R^2 > 0.8 in most of the cases) for short prediction horizons when analyzing the entire duration of the exercise.

When the interactions at different stages of the test were considered (Fig. 3), the prediction of the models degraded at the final stage of the exercise when the effects of the myoelectric fatigue were more evident. This finding was consistent for the four subjects in the study and suggests a high coordination of muscles in early stages of the test that

TABLE II. VARIABLES OBTAINED FROM R^2 AS FUNCTION OF THE PREDICTION HORIZON (*PH*) FOR THE EMG-EMG CROSS-PREDICTION. THE SLOPE, THE COEFFICIENT OF THE LINEAR REGRESSION (*r*) AND THE VALUES AT MINIMUM (R_O) AND MAXIMUM (R_f) PH ARE PRESENTED.

Slope, *r* [R_o, R_f]	***S1***	***S2***	***S3***	***S4***
ECR-EDC	**-0.022**, *0.91* [0.89, 0.56]	**-0.052**, *0.96* [0.9, 0.44]	**-0.034**, *0.89* [0.89, 0.4]	**-0.033**, *0.98* [0.94, 0.66]
ECR-ECU	**-0.009**, *0.51* [0.73, 0.55]	**-0.043**, *0.97* [0.84, 0.42]	**-0.024**, *0.88* [0.8, 0.45]	**-0.029**, *0.97* [0.9, 0.64]
ECR-FCR	**-0.025**, *0.88* [0.81, 0.55]	**-0.061**, *0.95* [0.96, 0.39]	**-0.031**, *0.93* [0.86, 0.47]	**-0.032**, *0.96* [0.95, 0.66]

TABLE III. VARIABLES OBTAINED FROM R^2 AS FUNCTION OF THE PREDICTION HORIZON (*PH*) FOR THE EMG-TORQUE CROSS-PREDICTION. THE SLOPE, THE COEFFICIENT OF THE LINEAR REGRESSION (*r*) AND THE VALUES AT MINIMUM (R_o) AND MAXIMUM (R_f) PH ARE PRESENTED.

Slope, *r* [R_o, R_f]	***S1***	***S2***	***S3***	***S4***
ECR-TOR	**-0.026**, *0.9* [0.83, 0.62]	**-0.058**, *0.95* [0.93, 0.43]	**-0.031**, *0.92* [0.89, 0.49]	**-0.027**, *0.97* [0.94, 0.71]
EDC-TOR	**-0.031**, *0.93* [0.91, 0.57]	**-0.02**, *0.95* [0.95, 0.71]	**-0.036**, *0.94* [0.89, 0.6]	**-0.033**, *0.93* [0.94, 0.66]
ECU-TOR	**0.003**, *0.36* [0.72, 0.72]	**-0.021**, *0.91* [0.88, 0.63]	**-0.021**, *0.9* [0.93, 0.66]	**-0.03**, *0.97* [0.88, 0.62]
FCR-TOR	**-0.078**, *0.95* [0.92, 0.13]	**-0.062**, *0.95* [0.89, 0.24]	**-0.035**, *0.96* [0.94, 0.61]	**-0.067**, *0.99* [0.88, 0.23]

degrades as the exercise progresses in time as consequence of myoelectric fatigue.

Furthermore, the analysis with a sliding window of 15 cycles (Fig. 4) allowed an evaluation with better temporal resolution, showing that the prediction worsened after 60% of the total duration of the test (for both the EMG-EMG and EMG-torque cross-prediction models), and in some cases with dramatic changes in the prediction, even when the exercise was performed at the target velocity and no visual changes could be observed in the signals (see Fig. 1). This effect could be related to changes in the load sharing of the muscles during myoelectric fatigue and shows that there is no unique strategy of muscular coordination for all subjects, but each strategy can be detected by means of nonlinear prediction. With this respect, Roy et al. in [4] suggested possible variations in the load sharing of the muscles based on changes on the instantaneous median frequency within the overall duration of a cyclical lifting exercise. Such variations were hypothesized to correspond to a strategy of the neuromuscular system to avoid fatigue in a single muscle. In contrast, results presented in this study allowed exploring the interaction between muscles from the amplitude of the sEMG signals itself, which is directly related to the modulation of the active motor units [13]. The presented results showed that nonlinear prediction is a promising technique for the assessment of myoelectric fatigue during dynamic contractions. Future research will comprise the use of a bigger database and the inclusion of patients with lateral epicondylitis in order to obtain a better insight in the reasons of changes in the prediction performance and to analyze its eventual application in clinical settings.

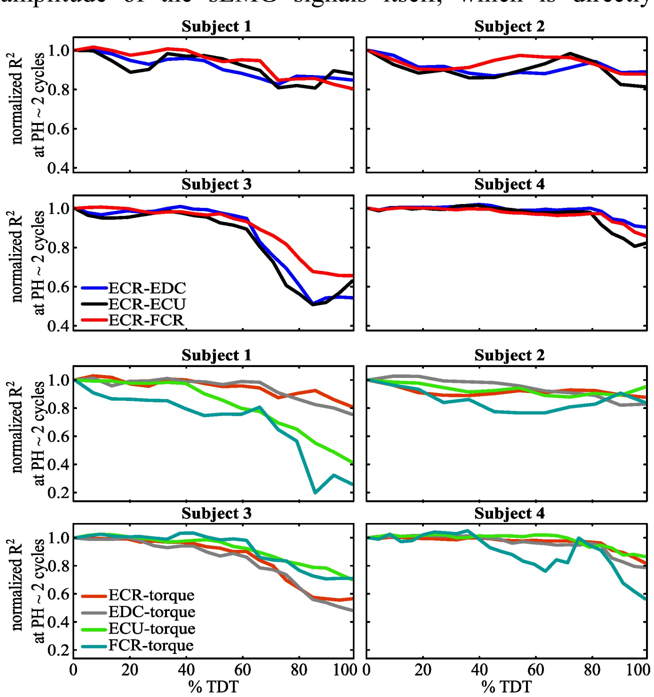

Figure 4. Normalized R^2 at PH = 4 s (~2 cycles) as function of the starting point of a moving window of 15 cycles. The horizontal axis was normalized with respect to the total duration (TDT) time of the test.

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