

Heart Rate Variability Analysis during Muscle Fatigue due to prolonged Isometric Contraction

Andrea Guidi, Alberto Greco*, Federica Felici, Andrea Leo, Emiliano Ricciardi, Matteo Bianchi, Antonio Bicchi, and Gaetano Valenza[‡], Enzo Pasquale Scilingo^{‡*}

Abstract—Fatigue can be defined as the muscular condition occurring before the inability to perform a task. It can be assessed through the evaluation of the median and mean frequency of the spectrum of the surface electromyography series. Previous studies investigated the relationship between heartbeat dynamics and muscular activity. However, exploitation of such cardiovascular measures to automatically identify muscle fatigue during fatiguing exercises is still missing. To this extent, HRV signals were gathered from 32 subjects during an isometric contraction task, and features defined in the time, frequency and nonlinear domains were investigated. We used surface electromyography to label the occurrence of muscle fatigue. Statistically significant differences were observed by comparing features related to fatigued subjects with the non-fatigued ones. Moreover, a pattern recognition system capable to achieve an average accuracy of 78.24% was implemented. These results confirmed the hypothesis that a relationship between heartbeat dynamics and muscle fatigue might exist.

I. INTRODUCTION

Fatigue is usually mechanically associated with the inability to further perform a task or sustain an effort, or to the inability to reach the same initial level of maximal voluntary contraction (MVC) force [1]. From an engineering point of view, the muscle fatigue process can be thought as the muscular condition occurring before the inability to perform a task [1]. Such a process can be fast or slow, but it leads to the “myoelectric manifestations of muscle fatigue” [1]. Fatigue can affect many potential sites in the neuromuscular system: the motor cortex, the excitatory drive, the control strategies of the spinal (upper) and the α (lower) motoneurons, the motoneuron conduction properties, the neuromuscular transmission, the sarcolemmal excitability and conduction properties, the excitation-contraction coupling, the metabolic energy supply, and the contraction mechanisms. According to the site, it is possible to define central fatigue or fatigue of the neuromuscular junction, or muscle fatigue [1]. All of them are directly or indirectly able to influence the electromyographic signal (EMG) in a very complex way. More specifically, a progressive slowing of

the EMG during isometric voluntary sustained contractions was observed [2]. Such a slowing has been easily described via the mean or median frequencies (*MNF* and *MDF*) of the power spectral density function, as suggested by [3]–[6]. For this reason, mean and median frequency are commonly considered as two meaningful frequency domain features for EMG analysis both in clinical and engineering applications. In fact, a decrease in these features is commonly used to detect fatigue in muscles using surface EMG (sEMG) signals [7].

The relation between muscular exercise and cardiovascular activity has been investigated in many previous studies. They reported an increasing heart rate (HR), and oxygen uptake [8]–[11], as well as changes in blood volume, due to a modification in left ventricular end-diastolic and end-systolic dimensions [10]. HR changes were also studied together with the EMG activity during fatiguing exercises [12], [13]. Specifically, similar rates of change in average HR and average EMG activity were reported. In addition, significant differences were observed in both EMG features, and HR in relation to different exercise durations.

Several studies have also observed significant changes in heart rate variability (HRV) spectra during aerobic exercise with different intensities or after fatiguing training sessions [14]–[16], whereas few studies have monitored heartbeat dynamics during a fatiguing task [17]–[19]. However, in all these studies, muscle fatigue was not assessed using objective measures such as those obtained by means of the EMG analysis. In addition, such parameters extracted from the analysis of the heartbeat dynamics were never used to perform an alternative automatic recognition of the muscle fatigue condition.

In sight of this, we performed an analysis of HRV series during a fatiguing exercise to evaluate differences between people with and without muscle fatigue. Moreover, the HRV features were used as input of a pattern recognition system in order to automatically detect the fatiguing condition. Such a condition was labeled by analyzing the sEMG signals during the muscular contraction.

II. MATERIALS AND METHOD

A. Experimental protocol

32 subjects (16 males and 16 females, 29.25 ± 3.38) were enrolled in this study. All the subjects were right-handers and did not have any physical disease at the muscular or bone system, as well as no past or current heart disease. The experimental protocol (Figure 1) consisted in three phases. In the first phase the evaluation of the maximum voluntary

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A.G., A.G., M.B., G.V., E.P.S. are with the department of Information Engineering and Research Center “E. Piaggio”, School of Engineering, University of Pisa, Via G. Caruso 16 - 56122, Pisa, Italy.

F.F. and A.B. are with the Advanced Robotics Department, Istituto Italiano di Tecnologia (IIT), Genova, Italy

A.L. and E.R. are with the IMT School for Advanced Studies Lucca, Piazza San Ponziano, 6, I-55100 Lucca, Italy

[‡] Senior Authors

* Corresponding author.

e-mail: alberto.greco@centropiaggio.unipi.it

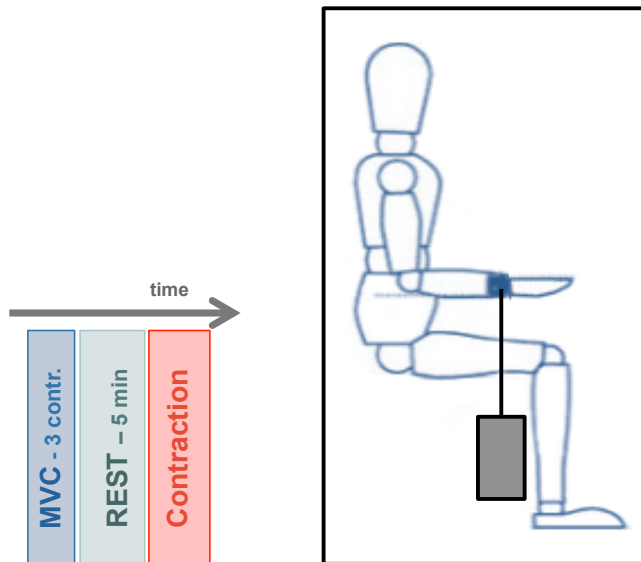


Fig. 1. Timeline of the experimental protocol (left) and position of the subject during contraction (right).

contraction (MVC) was performed by using a dynamometer and asking the subject to maximally contract the biceps three times for three seconds. MVC was determined as the mean of the three maximum forces. In the second phase, a 5 minute-long resting state was recorded. After that, in the third phase, a static contraction of the biceps brachii long head (Figure 1) was required to the subjects. A load equal to the 40% of the previously estimated MVC was used in this task [20], and the position was maintained till fatigue. The fatigue was detected when the subject was no longer able to maintain the position of the limb. During the whole experimental protocol, subjects were comfortably sat on a chair, straightening their back. A Biopac MP35 was used to acquire ECG signals, while a Bagnoli Desktop EMG Delsys was used to record sEMG signals related to the biceps brachii long head muscle. A sampling frequency equal to 2000 Hz was used to record both signals.

B. Algorithm

1) *sEMG processing*: Firstly, sEMG signals were filtered with a Infinite Impulse Response (IIR) comb notch filter (50 Hz). Then a zero-phase Butterworth IIR band-pass filter was used to retain frequencies between 30 and 500 Hz. At the end, Fourier approach was used to estimate the spectrum and thus mean (MNF) and median (MDF) frequencies within non-overlapping epochs. The Hamming window was used. Moreover, in this study, epochs lasting 1 second were chosen to estimate MNF and MDF. In fact, it was proven that in case of isometric, constant force, fatiguing contractions, the signal might be considered stationary for epoch durations of the order of about 1 – 2 seconds [1]. In addition, no overlap was performed between consecutive epochs. Such a choice was suggested by Farina et al. [21] which states that overlaps do not provide significant benefits.

2) *ECG processing*: ECG signals were digitally filtered via a zero-phase Butterworth IIR band-pass filter (1 - 40 Hz)

and an IIR comb notch filter (50 Hz). Then, the well known Pan-Tompkins method [22] was used to detect R-peaks. At the end, a regularly sampled HRV series was obtained via a spline interpolation, fixing the sampling frequency equal to 4 Hz. A set of features in the time and frequency domain was estimated from every HRV series. Specifically, they were: mean RR (meanRR), standard deviation of RR (stdRR), the square root of the mean squared differences of successive NN intervals (RMSSD), the number of interval differences of successive NN intervals greater than 50 ms (NN50), the proportion derived by dividing NN50 by the total number of NN intervals (pNN50), the HRV triangular index (HRVtri), and the triangular interpolation of NN interval histogram (TINN), the power spectrum estimated at low frequency (LF), at high frequency (HF), their ratio (LF/HF), and finally the standard deviations (SD1 and SD2) estimated along the two axes of the ellipse in the Poincare plot [23]. Frequency features were estimated via the autoregressive model (AR).

C. Statistical analysis

Statistical analysis was performed to investigate potential statistically significant differences in HRV-features related to muscle fatigue. To this aim, subjects were divided in two groups according to their MNF and MDF trends during the task. In fact, subjects showing decreasing trends were grouped and considered as fatigued (F). On the contrary, the remaining subjects, showing non-decreasing trends, were grouped and considered as non-fatigued ($N-F$). In this frame, a Mann-Whitney U-test was used to compare the features belonging to the two different groups. Of note, the corresponding resting phase value was subtracted from every feature ($Feat = Feat_{Task} - Feat_{Rest}$).

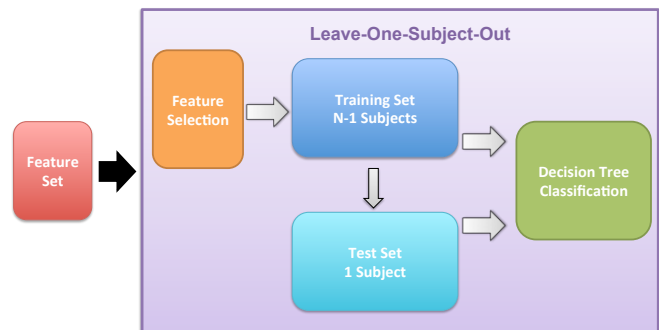


Fig. 2. Scheme of the proposed Leave-One-Subject-Out architecture (LOSO) architecture.

D. Pattern recognition

A Leave-One-Subject-Out architecture (LOSO) was applied to recognize subjects belonging to the two different groups, i.e. fatigued and non-fatigued, using a Decision Tree (DT) classifier and a nested feature selection. Only the features showing a statistical significant difference between the two groups were used. The DT classifier was iteratively trained on $N-1$ subjects, and then tested on the remaining 1 subject. The algorithm of feature selection consisted in selecting only the features showing, during the training test,

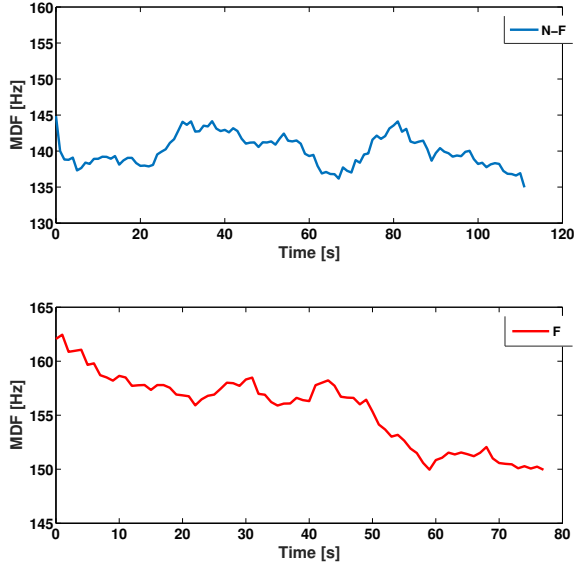


Fig. 3. Example of MDF trends. In red it is reported a decreasing MDF trend related to a subject belonging to the F group. Differently, in blue it is reported an example of a subject who did not experience the fatigue condition.

a correlation ratio higher than a threshold. Such a threshold was set as the median value of the correlation ratios estimated in that specific iteration. A confusion matrix was returned by the proposed algorithm as a result.

III. RESULTS

According to the MNF and MDF trends, 17 subjects (9 females and 8 males) experienced muscle fatigue (F-group), while the remaining 15 subjects (7 females and 8 males) did not. Figure 3 shows two MDF curves over time relative to a fatigued subject (upper) compared to non-fatigued subject (lower) A decreasing MDF trend, indicating fatigue condition, is reported in red, while in blue it is shown a MDF trend related to a subject who did not experience the fatigue condition.

The results concerning the statistical analysis between the features estimated from the subjects belonging to the fatigued and non-fatigued groups are reported in Table I. Significant results (p -value < 0.05) are highlighted in bold, while an arrow indicates the lower (\downarrow) or higher (\uparrow) feature value in the fatigue (F) state. More specifically, a significant lower feature value was observed in F-group by analyzing RMSSD, NN50, HF and SD1. Differently, a higher LF value was observed in F-group.

In Table II the confusion matrix concerning the proposed LOSO algorithm is reported. The elements on the main diagonal report the percentage of correct recognition, while the other elements report the percentage of incorrect detection. An overall accuracy equal to 78.24% was achieved.

IV. DISCUSSION AND CONCLUSION

In this study HRV-features were analyzed in relation to muscle fatigue. In the literature, muscular activity has

TABLE I

IN TABLE THE P-VALUES CORRESPONDING TO THE MANN-WHITNEY U-TEST ARE REPORTED. THE SIGNIFICANT RESULTS (p -VALUE < 0.05) ARE HIGHLIGHTED IN BOLD. AN ARROW INDICATES A DECREASE (\downarrow) OR INCREASE (\uparrow) OF THE MEDIAN VALUE IN THE FATIGUED (F) STATE AS COMPARED TO THE NON-FATIGUED STATE.

N-F vs F		
Features	p-value	Trend
meanRR	6.47E-02	
stdRR	1.16E-01	
RMSSD	1.27E-02	\downarrow
NN50	4.44E-02	\downarrow
pNN50	7.31E-02	
HRVtri	9.81E-02	
TINN	1.69E-01	
LF	4.44E-02	\uparrow
HF	4.44E-02	\downarrow
LF/HF	9.89E-01	
SD1	1.27E-02	\downarrow
SD2	1.27E-02	

TABLE II

CONFUSION MATRIX RELATED TO THE PROPOSED LOSO ALGORITHM (AVERAGE ACCURACY EQUAL TO 78.23%).

		Predicted	
		N-F	F
Actual	N-F	80.00%	20.00%
	F	23.53%	76.47%

been usually investigated by studying post-fatigue or over-training states caused by exercises at increasing intensities or aerobic exercises. In this study, 32 healthy subjects were enrolled to evaluate HRV-features during fatiguing exercises, i.e. a prolonged isometric contraction of the biceps brachii long head muscle. Subjects performed an isometric exercise lifting a load equal to 40% of their MVC to a horizontal position and maintaining it until it became impossible to keep the horizontal position. Median and mean frequency was estimated from the spectrum of the sEMG signals and were used as reference parameters to detect fatigued subjects.

HRV features were extracted in the time, frequency and nonlinear domains. A statistical analysis and a pattern recognition was applied on HRV feature-set to characterize and distinguish fatigued subjects from the non-fatigued ones. Results of the statistical analysis showed relevant HRV-features, in all domains, able to significantly characterize subjects according to their actual muscular conditions. More specifically, time-domain features showed significant reduced RMSSD and NN50 values in the fatigued group. This might indicate an increasing heart rate in presence of fatigue. Moreover, frequency-domain features showed an increased LF, and a reduced HF in fatigued subjects. Such a condition is usually detected in stressed people [24]. Furthermore, a study of HRV non-linear features revealed that a lower SD1 value can be detected in subjects experiencing muscle fatigue.

The significant features were also used as input of a pattern recognition system. Classification results revealed that the proposed algorithm was able to correctly recognize muscular conditions by means of HRV-features with an

overall accuracy of 78.24%.

In conclusion, these results confirm that perceived exertion might not be related to the actual muscle-fatigue-state of the subjects. Indeed, nearly half of the subjects interrupted the exercise before the arise of the real state of muscle fatigue. Our preliminary results suggest that real-time monitoring of HRV during exercises might provide an important help in detecting actual muscle states. In addition, according to the study of Mehta and Agnew [25], mental workload adversely affects physical capacity. Since HRV is commonly used to investigate emotional and psychological states (e.g., [26]–[29] and references therein), as well as stress conditions (e.g., [30] and references therein), its study might provide a description of both phenomena, i.e. muscle fatigue and mental state.

A possible future application might be related to the development of novel prosthesis. In fact, criteria based on these phenomena might help researcher in evaluating both stress and fatigue in residual muscles during the testing phases [31] in a non-invasive way.

Future works will be focused on the study of the temporal evolution of HRV-related features during fatiguing exercise. Gender differences will be also investigated to better clarify the gender effect on the relationship between HRV and sEMG.

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