Short communication

Changes in power curve shapes as an indicator of fatigue during dynamic contractions

Fermin Mallor, Teresa Leon, Martin Gaston, Mikel Izquierdo

1. Introduction

Exercise-induced fatigue is defined as the reversible reduction in force- or power-generating capacity of the neuromuscular system (Fitts, 1994; Bigland-Ritchie et al., 1981). Assessment of exercise-induced leg fatigue is usually made before and immediately after isometric fatiguing exercise (Vollestad et al., 1988; Gandevia et al., 1995). In doing so, quantification of peripheral fatigue is based on comparison between pre- vs. post-exercise measures. Classically, these methods include either the assessment of effort-dependent contraction force (i.e., maximal voluntary isometric contraction force or isometric relaxation time) or effort-independent force generated by evoked muscle contractions (Aman and Calbet, 2008; Enoka and Duchateau, 2008).

Despite the fact that most muscles shorten during athletic and voluntary physical activities, many studies have frequently used isometric rather than dynamic fatiguing tasks to examine muscle fatigue (Izquierdo et al., 2006). During dynamic contractions, the impact of exercise-induced fatigue is classically assessed by measuring velocity and/or muscle power changes (i.e., peak or the mean velocity) over a set of repetitions at a given percentage of the maximal dynamic strength (1RM). Thus, it has been previously reported that, over a set of repetitions to failure muscle contraction, velocity slows naturally as fatigue increases (Izquierdo et al., 2006).

Although extracting discrete variables, such as peak, maximum or average values or time-integrated power/velocity values from data has remained the norm for biomechanical analysis (Ryan et al., 2006), this practice does not consider the unique waveform structure that may contain additional information about subtle changes in power/velocity vs. time relationships. Functional data analysis (FDA) is an extension of multivariate analyses that provides a way to analyze the dynamic nature of power curves (Ramsay and Silverman, 2005). The use of FDA in biomechanics has not yet been widely implemented but some recent examples are the study of patterns in sit-to-stand movement (Page et al., 2006; Epifanio et al., 2008), and the identification of the variation in kinematic and kinetic waveforms resulting from fatigue experienced over a 45-min lifting task (Godwin et al., 2009).

The purpose of the present study was to analyze exercise-induced leg fatigue during a dynamic fatiguing task by examining the shapes of power curves through the combined use of several
statistical methods: B-spline smoothing, functional principal components and (supervised and unsupervised) classification. Granulometric size distributions were also computed to allow for comparison of curves coming from different subjects.

2. Materials and methods

2.1. Subjects

Twelve physically active men (age, 34.55 ± 5.23 yr; height, 177.49 ± 5.78 cm; body mass, 73.65 ± 6.29 kg (mean ± SD)) volunteered to participate in the study. They had experience with recreational training. Subjects were informed about the experimental procedure and the purpose of the study and gave their written informed consent to participate. The experimental procedures were approved by the Institutional Review Committee of the Instituto Navarro del Deporte according to the Declaration of Helsinki. Before inclusion in the study, all subjects were medically screened and considered healthy by a physician.

![Fig. 1](image1.png)

Fig. 1. (a) Four power vs. time curves of different subjects, (b) Their granulometric size distributions. A gsd is a function of the structuring element size which plots the area under the opened curve versus the area of the original curve reflecting the shape-size of the original curve.

![Fig. 2](image2.png)

Fig. 2. Power vs. time curves corresponding to the first (a), second (b), and fifth (c) bout of a representative subject. A colour ramp from blue to red has been applied for a better visualization of the curves. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
2.2. Experimental design

The study comprised one acute heavy-resistance exercise protocol consisting of five sets of 10 repetition maximum bilateral leg press (10RM) with 120 s of rest between sets. One week before, the subjects participated in a control testing day where resistance–load verifications were made for one repetition maximum (1RM), muscle power and the maximum load of the experimental leg press for 10RM.

Each repetition was performed on a bilateral leg extension exercise machine press (Technogym, Gambettola, Italy). The sitting position was individually adjusted to minimize displacement between the lower back and the backrest during muscular force exertion. The repetition began with a knee angle of 90° and a hip angle of 45°, and ended when subjects extended their legs to achieve a knee angle of 180° and a hip angle of 90° (all the angles are included angles). Strong verbal encouragement was given to all the subjects to motivate them to perform each action as maximally and rapidly as possible. One attempt was made to determine the load at which the subject was just able to finish the required 10RM. If the subject did not accomplish 10RM in the first attempt, re-testing with the adjusted load was performed after 24 h rest. One to two subsequent attempts were made to determine the 10RM.

Muscle power output of the leg extensor muscles was measured during the concentric phase of leg press action. The exercise machine incorporates four force transducers on a foot platform located below the subject’s feet, which recorded the horizontal applied force to an accuracy of 1 N at a sampling rate of 1000 Hz. In addition, a rotational encoder (Computer Optical Products Inc., California, USA) was set to record the position and the displacement to an accuracy of 0.2 mm and time events to an accuracy of 1 ms (Izquierdo et al., 2009).

2.3. Analysis

All subsequent data manipulations were performed using R software (R Development Core Team, 2009) and fda (Ramsay et al., 2008) and cluster (Maechler et al., unpublished) packages (from http://cran.r-project.org).

The raw data comprised 600 power vs. time curves (corresponding to 50 repetitions per subject). B-spline smoothing provides an attractive way of smoothing noisy non-cyclical data values observed at distinct points on a finite interval. To obtain a smooth and accurate representation of the data, a basis of 180 B-splines was used (Ramsay and Silverman, 2005; Ramsay et al., 2009).

Functional principal components analysis (FPCA) is an adaptation of the classical multivariate procedure of principal component analysis to functional data. When the variability explained by the first components is close enough to 100%, then the PC scores constitute an accurate description of the curves and multivariate analyses can be performed (Ramsay and Silverman, 2005). The unsupervised classification technique partitioning around medoids (PAM) is suitable for problems in which the interest is in the characterization of the clusters by means of typical observations. The k-nearest neighbor (k-NN) method allows classifying new profiles to pre-defined groups (Ye, 2003).

Granulometries are size–shape distributions associated to the original functions defined to retain their shape characteristics; they are invariant to domain shifts (Fig. 1). Granulometries come from the mathematical morphology field (Serra, 1982; Soille, 2003). They have been widely used in image processing and are also useful for functional data (Ayala et al., 2008; Epifanio, 2008).

After smoothing the data, the FPCA of the power curves of a representative subject was performed and their unsupervised classification using the PAM method was obtained. The granulometries of the power curves of all the subjects were calculated and the k-NN method (taking as training set the scores of the granulometries of the representative subject) was used to classify them.

<table>
<thead>
<tr>
<th>Group</th>
<th>Set 1</th>
<th>Set 2</th>
<th>Set 3</th>
<th>Set 4</th>
<th>Set 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>1–7</td>
<td>11–15</td>
<td>21–23</td>
<td>31–36</td>
<td>41–44</td>
</tr>
<tr>
<td>G2</td>
<td>8, 9</td>
<td>16–19</td>
<td>24, 25</td>
<td>37</td>
<td>45, 46</td>
</tr>
<tr>
<td>G3</td>
<td>10</td>
<td>20</td>
<td>26–30</td>
<td>38–40</td>
<td>47–50</td>
</tr>
</tbody>
</table>

Table 1 Classification of the power vs. time curves of a representative subject in three clusters using the PAM method over the first five functional principal component scores.

Fig. 3. The curves in different clusters have been represented using different colours (black for G1, red for G2 and blue for G3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
3. Results

The first five PCs obtained from the FPCA of the curves of the representative subject accounted for 87% of the data variability (Fig. 2). The results of the PAM over the PC scores are shown in Table 1 and Fig. 3. The classification assigns the first repetitions of each bout to group G1, while last repetitions are included in group G3. The curves in between constitute G2.

Three PCs obtained from the FPCA of the granulometries accounted for 90% of the variation. The k-NN method with training set the scores of the granulometries of the curves in Table 1 provided a classification of all the curves in the three groups (Fig. 4).

4. Discussion and conclusions

The present study analyses exercise-induced leg fatigue during a dynamic fatiguing task by examining the shapes of power curves. FPCA found the dominant modes of variation in the curves. For a representative subject a multivariate cluster over the first five FPC scores led to three interpretable groups according to different levels of fatigue. These clusters provided the training set to perform a K-NN classification where the remaining individual repetitions were assigned to one of the clusters. All the procedures for classification of time-series face the problem of computing a similarity measure between them; some are based on Euclidean norms, piecewise linear approximations, global rescaling or dynamic time warping. Furthermore, they use a dimensionality reduction technique because indexing the original space directly is inefficient (Ramoni et al., 2002; Morchen and Ultsch, 2007; Zhong and Ghosh, 2003; Ye, 2003). The usefulness of our approach in a practical setting may be related with the fact that FPCA greatly reduces dimensionality and the use of granulometries allows for comparison of the curve shapes without distorting the time scale. In contrast to FDA, classical statistical approaches using summary parameters of time series

![Graphs](image)

**Fig. 4.** A sample of test curves classified by the K-NN method in three different groups.
may lead to limited information about the impact of dynamic fatiguing exercises on kinematic and kinetic time-course changes in curve shapes.

To the best of our knowledge this is the first study analyzing the changes in power curves in the context of muscular fatigue during a repetitive dynamic task. Fatigue-induced changes in the shapes of the power curves were evident, in which curves progressively flatten and develop a second power peak (Fig. 2). This may be explained by an increase of the concentric-phase duration and a variation in the acceleration–deceleration profile, induced by the fatigue, across a set of repetitions leading to failure (Izquierdo et al., 2006, 2009).

Conflict of interest

None of the authors have a conflict of interest.

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References