Using the Lag of Autocorrelation Function in Order to Identify the Anaerobic Threshold During Dynamic Physical Exercise

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Abstract

The Anaerobic Threshold (AT) is one of the best parameter to quantify aerobic capacity at sub-maximal dynamic physical exercise power levels. By the other side, there is a function in nonlinear dynamics called Aurocorrelation Function (ACF). We measure the AT, in this work, in a non-invasive way, using the ACF. The results exhibited a perfect correlation with previous works that used the same set of data, but the method now proposed is faster and easier to apply, producing an almost instantaneous visual outcome.

1. Introduction

The Anaerobic Threshold (AT) is a changing point in the physiological state that can be identified during dynamic physical exercise [1]. It can be measured directly, with invasive procedures but we have been looking for a non-invasive way of doing the task. A first trial was made using an Auto Regressive Integrated Moving Average Model (ARIMA) [2-4], followed by a second trial that used the Kolmogorov-Sinai entropy (K-S) [5, 10]. Both methods were based on the findings that changes in cardio respiratory variables, including heart rate variability (HRV), occur at this point [11].

The Autocorrelation Function (ACF) is a mathematical tool used in dynamic to study the stationarity of time series and to produce the time lag used in the reconstruction of a chaotic attractor, if one is present.

Let us suppose a time series $x_1, \dots, x_N$. We then define the Autocovariance coefficient at lag k, c_k, as:

$$c_k = \frac{1}{N-k} \sum_{t=1}^{N-k} (x_t - \bar{x})(x_{t+k} - \bar{x}) \tag{1}$$

where $\bar{x}$ is the overall mean, defined as:

$$\bar{x} = \frac{1}{N} \sum_{t=1}^{N} x_t \tag{2}$$

We then define the Autocorrelation Function, ACF(k) as:

$$ACF(k) = \frac{c_k}{c_0} \tag{3}$$

The ACF is a useful statistical tool that measures if earlier values in the series have some relation to later values. As many statistical measures were built for independent data, it is important to know if they are really independent. A diagram called "correlogram" where we can see these effects can be built. The correlogram is a plot of the ACF(k) versus k, the time lag.

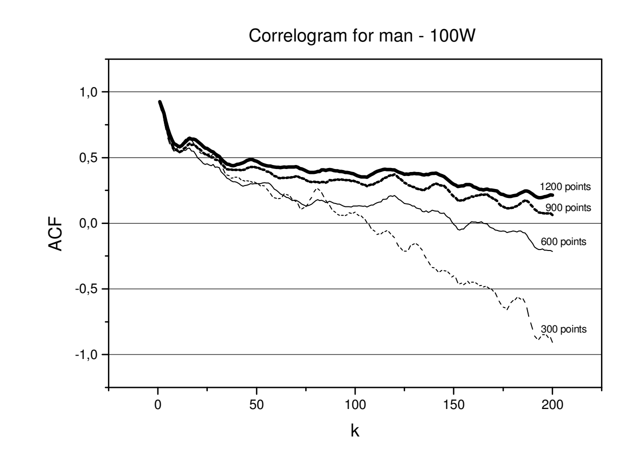


Fig 1: Correlogram for one of the individuals studied, showing the dependence on the number of points considered on the computations.

We define the decorrelation time lag as the smallest value of k that makes ACF(k) < K, where K is usually taken as 0.5 or 1/e, e = 2.71828… [12, 13]. In this work, we find the best value for K to be 0.55. But the correlogram depends on the number of points (n), as can be seen from the fig (1) above, where one of the series studied in the present work is showed. As a consequence, the decorrelation time lag also depends on n.

The main goal of the present work is to evaluate the tool: the decorrelation time lag when applied to HRV time series in different random powers levels of dynamic exercise, in order to quantify the AT in healthy individuals. The results were compared to the AT values obtained using ARIMA model.

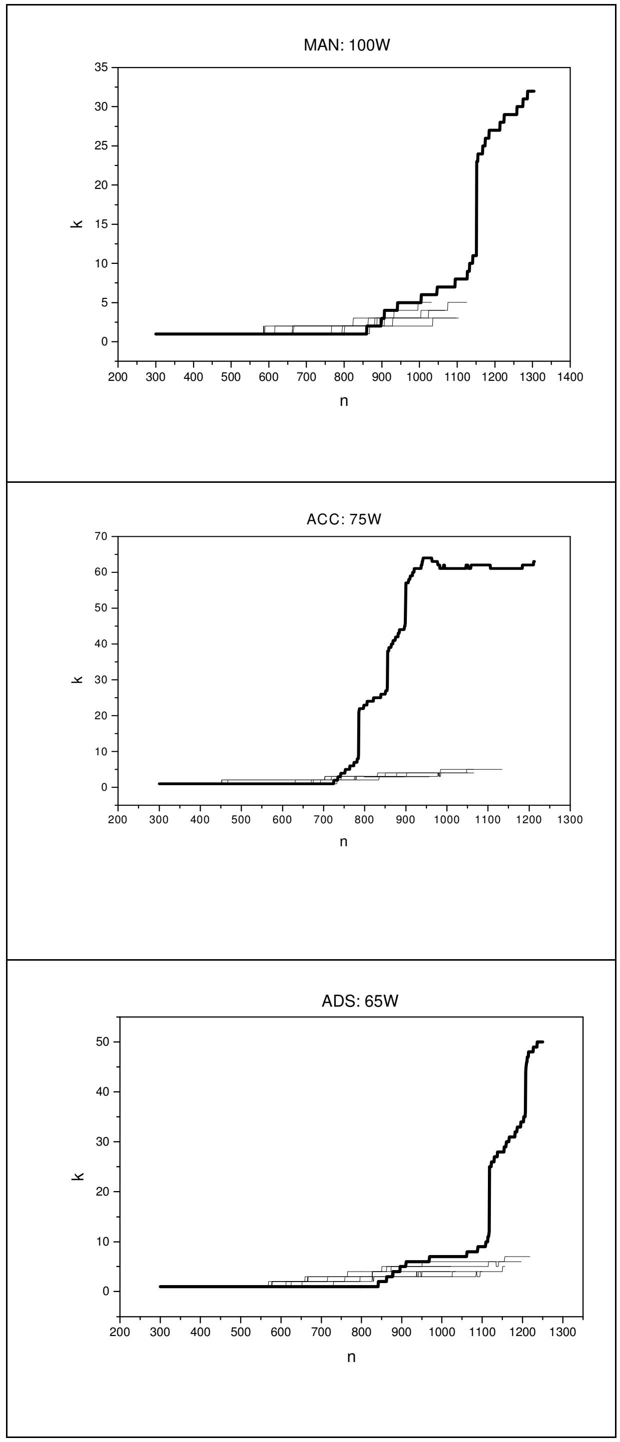
2. Methods

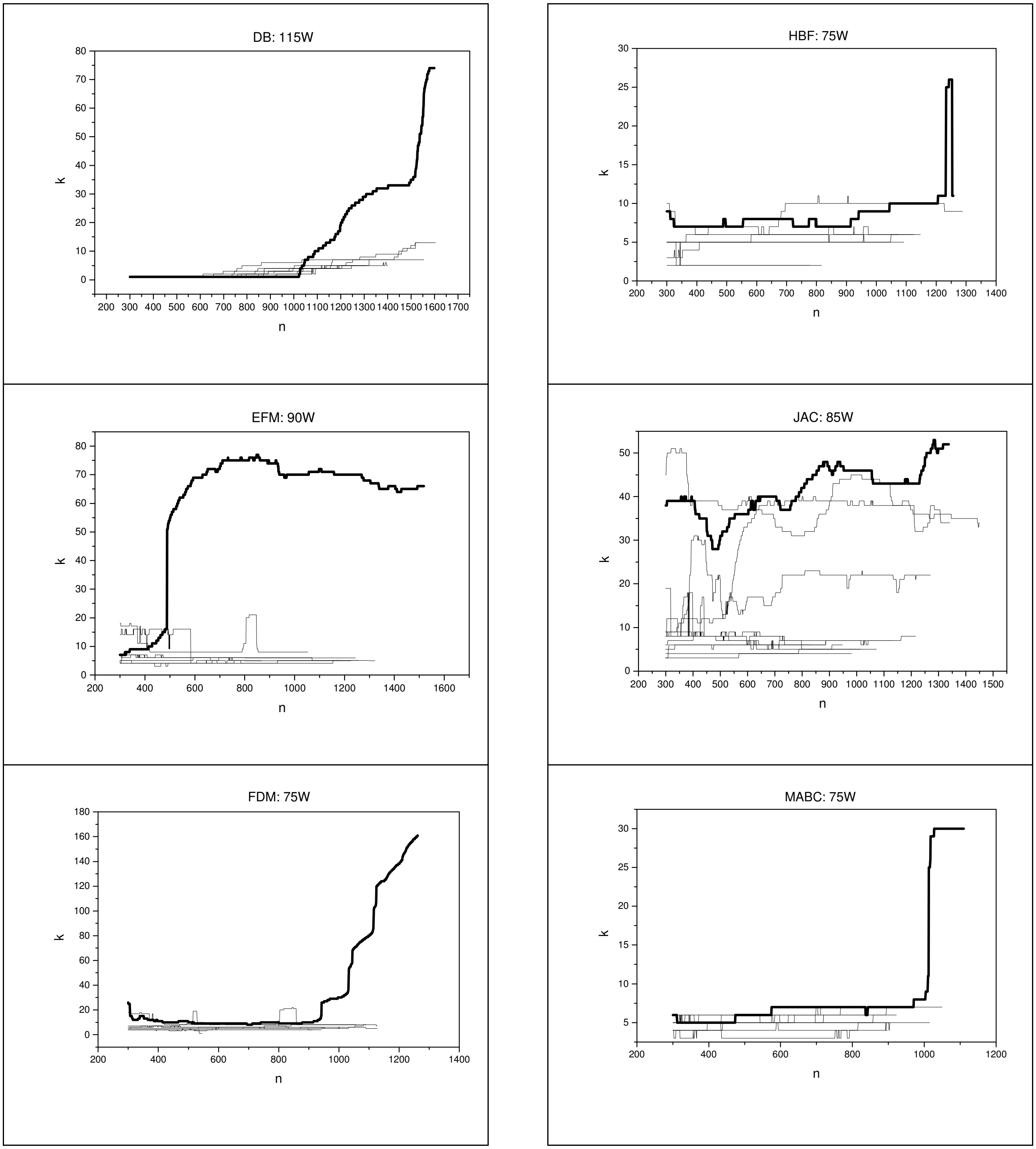
We used the same time series in all works [2-6]. They were obtained from ten healthy male volunteers (23 ± 2.0 years), who exhibited a sedentary life style. Dynamic exercise tests (discontinuous steps) included two experimental protocols (undertaken two days apart), that is, progressive (EPI) and random (EPII) power levels, lasting fifteen minutes, with a rest period among them.

We measured the RR intervals, in seconds, from each one of the following situations: at rest, in supine and seated positions; in the last position during exercise, using an electromagnetic braked cycle-ergometer at several power levels (W). A specific software was used to detect R waves of ECG signals and the respective periods [14]; the RR interval were then obtained. For each one of the studied powers, the n-time lag was computed, using computational programs written and compiled for the present work. All the series were displayed in a graphic, allowing a visual outcome. Such computational programs were fed by the original RR intervals time series, dropping out the first and the final 1.5 minutes in order to assure a stability period for the studied signal.

3. Results

RR interval time series (N=191) obtained from the ten men with both protocols, EPI and EPII, were analyzed in order to estimate the decorrelation time lag for each set of data. We have plotted the values of the decorrelation time lag against the number of points for each series of data. The results were not encouraging for the progressive protocol but were excellent for the random powers level protocol. The fig (2) bellow shows the outcomes for the later protocol:

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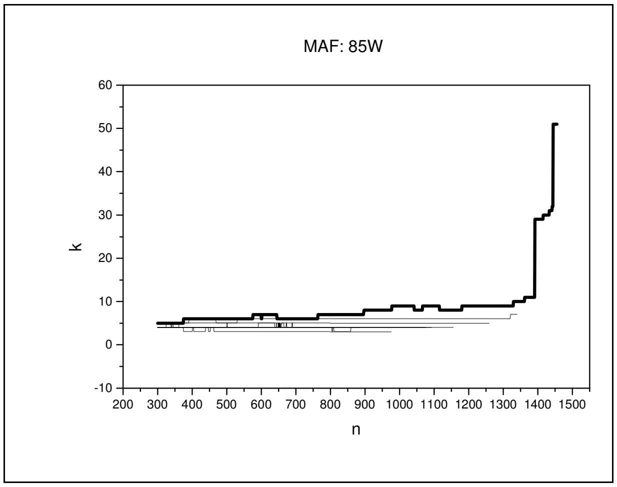

Figure 2**:** Diagrams of the time lag as function of n for all the ten individuals. The thickest line corresponds to the AT predicted by ARIMA.

The decorrelation time lag showed, in a phenomenological way, a very distinct change in the system response patterns at a specific power. The line grows up, above the others, for all indivuduals. This occurred in a power value, which corresponds to the AT.

The results obtained from this method and ARIMA method are perfectly correlated: they match for all the individuals.

4. Discussion and conclusions

As in our previous work, we have described an alternative non-invasive way to obtain the Anaerobic Threshold. Our conclusions can be summarized as follows: the decorrelation time lag exhibited, in a phenomenological way, a different pattern, showing a graphic line completely different from the others at power values that agreed with the AT obtained from the ARIMA model. This difference can not be explained just by the larger number of points in the series corresponding to the AT, as, for some cases, series with more points than that indicated by ARIMA do no exhibited the same behavior. Also, the "growing up" behavior shows itself for values of n smaller than the maximum value, at points where many others series still have data. We reached the conclusion that this method can be used to obtain the AT. The advantages of the decorrelation time lag are:

- It involves a fast computational procedure.
- It does not require elaborate statistical analysis. This means that it does not need a statistician to assist the work.
- It is easier to apply than the K-S method.

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