Evolution of the Heart Rate Variability Complexity during Kangchenjunga Climbing

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Abstract

Introduction. *At high altitude there is a reduced oxygen pressure in the atmosphere which results in physiological changes. Heart Rate Variability (HRV) is a technique to quantify the autonomic nervous system regulation of the heart rate, allowing a noninvasive assessment in extreme environments.*

Aim. *The aim of this work was to assess the evolution of the HRV complexity during Kangchenjunga (8.586 m) climbing.*

Data. *Three climbers recorded their RR-interval time series every day during the expedition. We divided the data in different stages: Spain Baseline, Kathmandu Baseline, Acclimation Trekking, Kathmandu After Acclimation, Base Camp, Camp 1, Camp 2, Summit, Camp 3, and Kathmandu after expedition.*

Methods. *We assessed the complexity of HRV using sample entropy (SampEn) and normalized compression distance (NCD), a measure coming from Information Theory, which compares two arbitrary sequences and outputs the dissimilarity between them. This measure exploits linear and nonlinear relations in the data and allows the comparison of sequences of different sizes. We estimated the dissimilarity of every stage in the climb against the first day using NCD.*

Results. *From the beginning and during acclimation dissimilarity (NCD) increased and then decreased once the climbers were acclimated. Dissimilarity jumped up in Base Camp stage. Then dissimilarity decreased from this point until the end of the expedition. SampEn showed an irregular behaviour without a clear pattern.*

Conclusion. *NCD provided a method to assess the dissimilarity of HRV between different stages in Kangchenjunga expedition climbing, and allowed to quantify the changes in HRV complexity.*

1. Introduction

A characteristic of physiologic systems is their deep complexity, arising from internal interactions and regulatory feedback loops which operate over a wide range of temporal and spatial scales [**?**]. Heart Rate Variability (HRV) is a relevant marker of the Autonomic Nervous System (ANS) control on the heart, and it has been proposed for risk stratification of lethal arrhythmias after acute myocardial infarction, as well as for prognosis of sudden cardiac death events [**?**, **?**]. A wide number of HRV indices have been proposed in the literature, many studies suggest that nonlinear methods are better suited to extract relevant information from HRV signal in terms of complexity. Nonlinear indices rely on the idea that fluctuations in the RR intervals may reveal characteristics from complex dynamic systems, and, under this assumption, healthy states will correspond to more complex patterns than pathological states [**?**, **?**, **?**]. Furthermore, many experts claim that no single index should be used to assess the complexity of physiologic systems, instead of that, a set of metrics is needed to measure different aspects of the complicated behavior of physiologic systems [**?**].

It has been shown that heart rate increases during dynamic exercise due to both a parasympathetic withdrawal and augmented sympathetic activity. The relative role of these two drives depends on the exercise intensity [**?**]. Parasympathetic activation is considered to be the main mechanism underlying the Heart Rate Recovery (HRR) after exercise. HRR immediately after high intensity exercise is used as a marker of physical condition, and also some studies have associated decreased HRR to cardiovascular risk increase [**?**]. In order to improve the understanding on the ANS changes in this context, HRV has been widely assessed by means of time domain and frequency domain indices, however nonlinear indices have recibed less attention.

In this work we propose to extend the knowledge of HRR after maximal exercise using a set of nonlinear in-

dices, which allow to measure different aspects of the underlying physiological mechanisms. The study focuses on HRV evolution before, during, and after an All Out Exercise Testing (AOET) in triathletes. Additionally, in order to quantify HRV Recovery (HRVR) after exercising, we propose a HRVR measure which can be used for any HRV index.

The structure of the paper is as follows. First, the database and the HRV nonlinear indices are presented, and the rationale for the study is highlighted. Next, the data analysis is described in detail, and the results are presented. Finally, conclusions are summarized.

2. Dataset

This study recruited eight Spanish male triathletes from Seville Metropolitan Area. For participating in this investigation, all subjects signed an informed written consent based on the Declaration of Helsinki. They also followed the recommendations for HRV data acquisition, by avoiding the use of stimulant substances the day of the trial, having the last meal at least two hours before performing the test, and not exercising the day before testing. Inclusion criteria were the following: (a) to be male and amateur triathlete; (b) not having any disease or medication that could affect the outcomes; (c) to train more than ten hours per week; and (d) to be competing actively in amateur circuits. All measurements of the study were made while subjects were sitting on a cycle ergometer.

The protocol included 5 minutes of HR recording in resting conditions, immediately before exercising, in order to provide the HRV basal data. Afterwards, subjects started an incremental exercise test which comprised 4 consecutive phases of 4 minutes. In the first three phases, subjects cycled at 50 rpm with 1, 2, and 3 Kp of load. The last part of the test was the so-called 'All Out', in which subjects cycled as fast as they could with 5 Kp of load during 4 minutes for achieving maximal exercise capacity. HR was recorded in the 'All Out' step. The exercise test was followed by 5 minutes of recovery, in which subjects remained seated on the cycle ergometer, but without cycling. HR was also recorded in the recovery stage.

RR intervals were collected using a Firstbeat Bodyguard (Firstbeat Technologies Oy^{TM}, Jyväskylä, Finland) heart monitor, with sampling frequency of 1000 Hz. The recordings were preprocessed to exclude artifacts by eliminating RR intervals lower than 200 ms and greater than 2000 ms, as well as those which differed more than 20% from the previous and the subsequent RR intervals [**?**]. Removed RR intervals were replaced by conventional spline interpolation.

3. Methods

A set of HRV nonlinear indices were obtained, namely, Sample Entropy (SampEn), and $\alpha 1$ and $\alpha 2$ from the Detrended Fluctuation Analysis (DFA). These indices were obtained for 5 minutes during resting conditions before exercising (stage 1), for the last phase of the 'All Out' step (stage 2), for the first 2 minutes of the recovery step (stage 3), for the first 3 minutes of the recovery step (stage 4) and for the 5 minutes of the recovery step (stage 5). Furthermore, for the rest time, besides the cumulative measurements, the indices were obtained by using a sliding window of 3 minutes length with 1 minute overlapping, therefore obtaining two consecutive sets of indices (stage 4' and stage 5' respectively).

3.1. Normalized Compression Distance

here your code

3.2. Sample Entropy

Entropy-based methods provide a quantification of the irregularity of a temporal series. Among them, SampEn [**?**], which is a modification of the Approximate Entropy [**?**], holds some properties which are appropriate for the study of physiological signals. The SampEn is the negative natural logarithm of the conditional probability that two sequences which are similar for m points remain similar for $m + 1$ points. Thus, a lower value of SampEn indicates more self-similarity in the time series. SampEn is robust to noise and outliers, and accordingly, it has been widely applied for characterizing the HRV signal [**?**].

The DFA is a well-established method for assessing and quantifying fractal correlation properties in time series with non-stationarities [**?**]. This algorithm determines the scaling behavior of a time series based on the computation of a scaling exponent, α. HRV signals have been found to show, at least, bi-scaling (bi-fractal) behavior. Therefore, two scaling exponents are needed in order to characterize the fractal correlations properties of HRV signals, one for short-term (between 3 and 16 beats), denoted by $\alpha 1$, and the other for long-term (between 16 and 64 beats), denoted by $\alpha 2$. To obtain $\alpha 2$ we took into consideration that $N/4$, where N is the signal length, had to be greater than the highest scale, this is, 64 [**?**]. The shortest signal length considered was 2 minutes, given that the HR populational mean in that interval was 157 bpm, it yielded 314 beats in 2 minutes. Note that in these conditions, this requirement was tightly fulfilled for the shortest segments, and results for this index have to be examined with caution. We checked visually that the double slope and the disruption point were adequately quantified, and that low bias model in the linear regression adjustment was present.

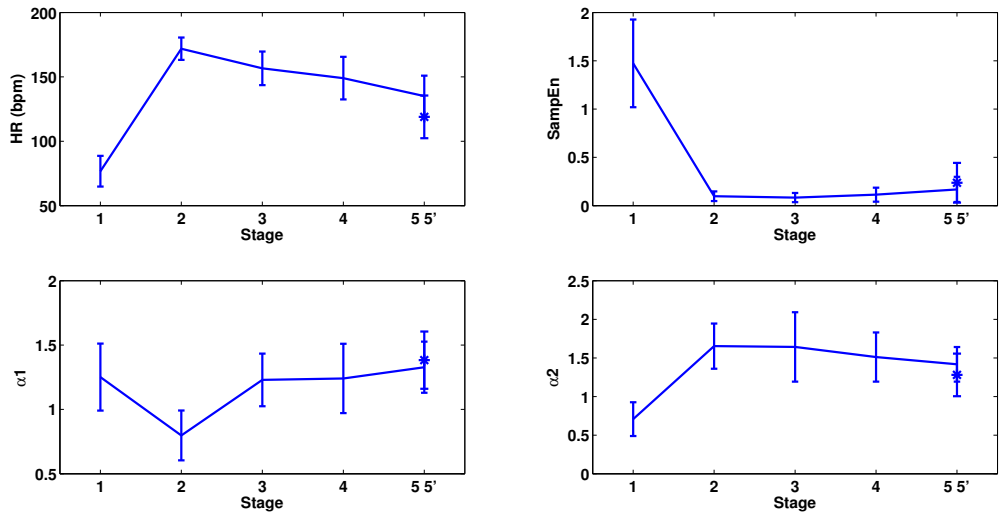

Figure 1. Mean HR (top left) and HRV indices: SampEn (top right), $\alpha 1$ (bottom left), $\alpha 2$ (bottom right), mean $\pm$ standard deviation, for each stage.

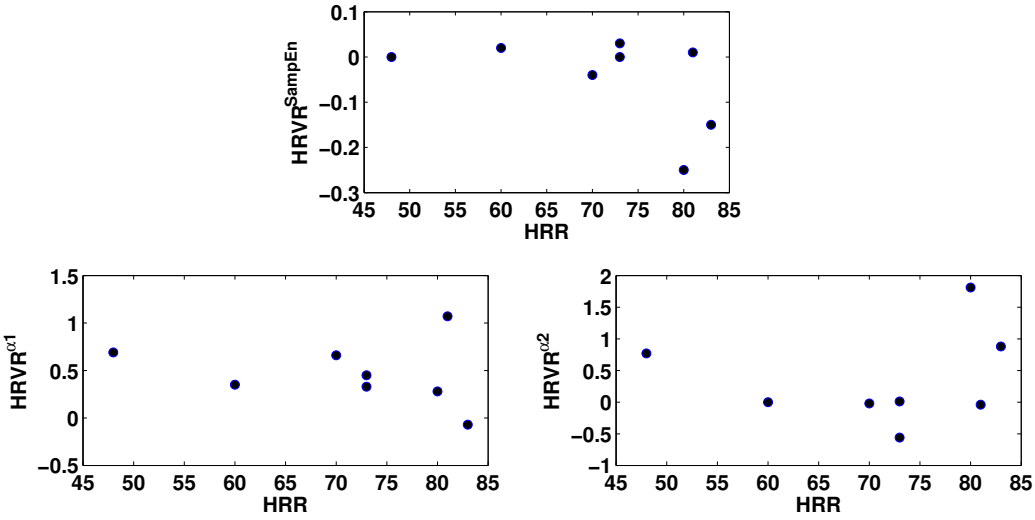

Figure 2. HRR vs HRVR for stage 5: SampEn (top), $\alpha 1$ (bottom left), $\alpha 2$ (bottom right).

Mean HR of each stage was obtained for comparison. We also obtained the HRR, which is commonly used as a marker of physical condition and even of cardiovascular risk. HRR was defined as

$$HRR = HR_{max} - HR_{min}$$

where HR_{max} stands for the HR average from the last 5 seconds from the 'All Out' stage, and HR_{min} stands for the HR average from the last 5 seconds of the recovery time.

Furthermore, in order to quantify HRVR and to compare it with HRR, we calculated a new HRVR measurement, which can be obtained for any HRV index I, and can be defined as

$$HRVR^I = \begin{cases} HRV^I_{EN} - HRV^I_{RN} & \text{if } HRV^I_{EN} \leq 1 \\ HRV^I_{RN} - HRV^I_{EN} & \text{if } HRV^I_{EN} > 1 \end{cases}$$

where

$$HRV^I_{EN} = \frac{HRV^I_E}{HRV^I_B}; HRV^I_{RN} = \frac{HRV^I_R}{HRV^I_B}$$

and where HRV^I_B stands for the basal value of the HRV index I; HRV^I_E stands for the HRV index value of the 'All

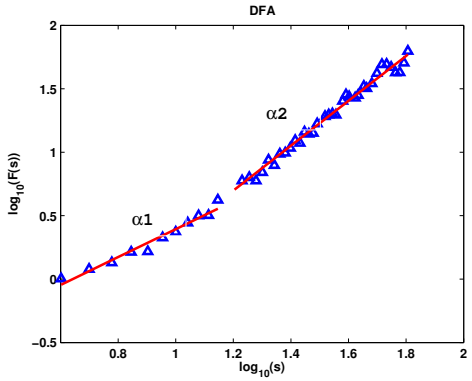

Figure 3. Example of $\alpha 1$ and $\alpha 2$ computation for one of the 2 minutes segment.

Out' stage; and HRV_R^I stands for the HRV index value of the recovery time. A particular HRV index I may increase or may decrease with exercising, depending on what it measures, therefore, the taxonomy into two cases according to HRV_{EN}^I value is made in order to achieve always a measurement indicating increasing HRV recovery when its value increases. This makes comparison and benchmarking straightforward.

4. Results

Fig. 1 shows mean HR and HRV indices (mean $\pm$ standard deviation) for each stage. Mean HR strongly increased during exercise (from 77 bpm mean basal value to 172 bpm) and moderately decreased (until 135 bpm) in the rest time. SampEn decreased dramatically during the exercise, it did not recover at all in stage 3, and it increased slightly within the 5 minutes of rest (stage 5), which means that the irregularity the HRV signal lost during high intensity exercise, was not recovered at all immediately after the exercise, and it was slightly recovered in the rest period.

Regarding DFA, α_1 decreased during exercise and then it showed a reestablishment of its values immediately after exercise in stage 3. Moreover, in stage 5, mean α_1 value was higher than mean α_1 basal value (1.25 and 1.32 respectively). Oppositely, α_2 increased during exercise, and then it just showed a slight reestablishment of its values in the rest time. Fig. 3 shows an example of the computation of α_1 and α_2 for one of the 2 minutes segment displaying a correct fitting of the regression lines.

Fig. 1 also shows, with a thicker line, the results for stage 5', since results for stage 4' are the same as for stage 4. With this approach, by using a sliding window of 3 minutes with 1 minute overlapping, we have consecutive information about the indices in the recovery time rather than cumulative information. As expected, in the last 3 minutes of rest time (stage 5'), mean HR decreased and SampEn increased, however this increment was still weak. Regarding α_1 , its mean value remained increasing (1.38) above the basal value, while α_2 decreased moderately.

Fig. 2 shows scatter plots of HRR vs HRVR for stage 5 and for each nonlinear index. This representation evidences that no correlation was found in this study between HRR and HRVR.

5. Conclusions

The performance of nonlinear HRV indices during and after high intensity exercise suggests that they could be assessing relevant information about underlying physiological recovery. In this context, information provided by HRR may not be enough to evaluate the complex mechanisms behind these physiological changes. Therefore, HRV nonlinear indices should be also taken into account to assess physical condition or cardiovascular risk. In this study, HRVR did not correlate with HRR for any of the selected nonlinear indices, which reinforces the idea of these indices providing complementary information to HRR.

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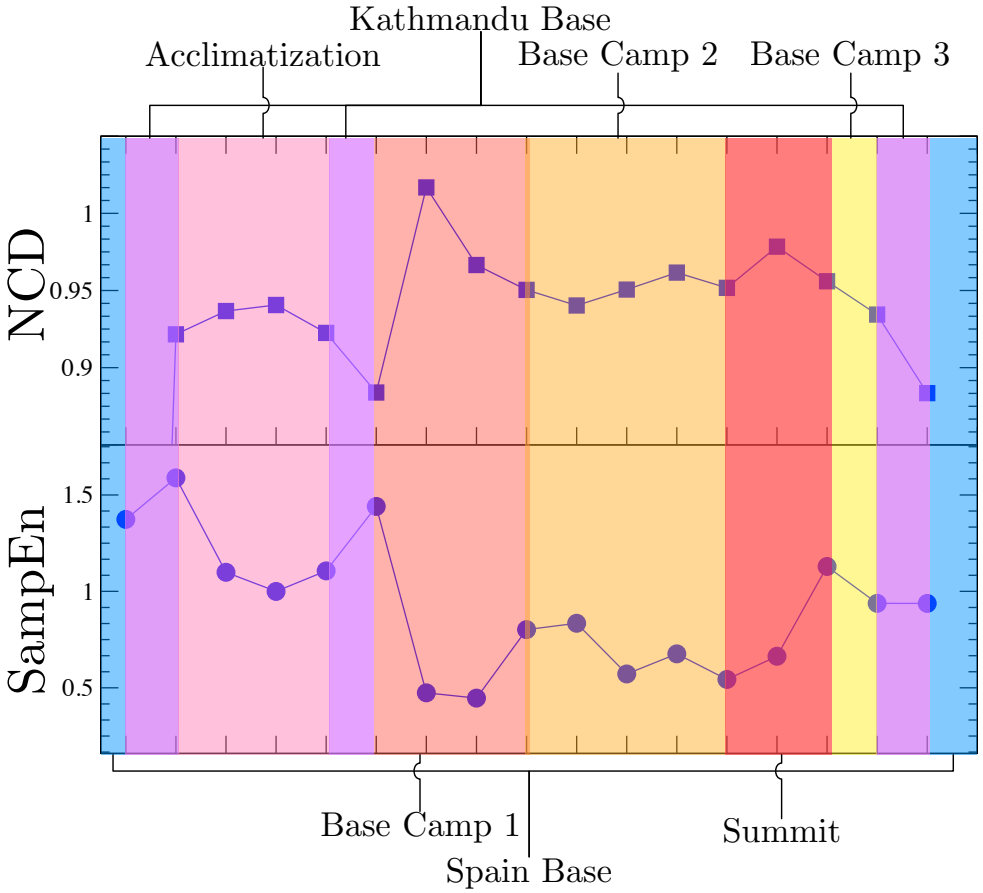

Figure 4. NCD and SampEn evolution during the expedition for one climber.