Evolution of the Heart Rate Variability Complexity during Kangchenjunga Climbing

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Abstract

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 (ANS) regulation of the heart rate, allowing a noninvasive assessment of the ANS in extreme environments. The aim of this work was to assess the evolution of the HRV complexity during Kangchenjunga (8.586 m) climbing. Five spanish 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 1, Base Camp 2, Summit, Base Camp 3, and Kathmandu after expedition. At the submission time we had acces only to complete recordings from one climber. We assessed the complexity of HRV using sample entropy (SampEn) and normalized compression distance (NCD), which 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 stage. From the beginning and during acclimation dissimilarity (NCD) increased and then decreased once the climbers were acclimated. Dissimilarity jumped up in Base Camp stage and then decreased from that point until the end of the expedition. Both indices showed an initial change in the complexity until the Summit and from the Summit both showed a tendency to recover the complexity of the HRV. Results showed that NCD is able to measure the changes in complexity with a little more detail and smoother than SampEn.

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 [1]. Heart Rate Variability (HRV) is a 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 [2–4]. 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 [3, 5, 6]. 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 [1].

Acute hypoxia changes induce several autonomic adaptations, mainly in the respiratory and cardiovascular systems, sympathetic activation with heart rate and cardiac output increase [7, 8]. Previous studies have evaluated HRV in subjects exposed to acute hypobaric hypoxia in real settings. They reported a reduced HRV as measured by linear indices, consistent with an increased sympathetic tone and a decreased parasympathetic tone [7, 9–11].

The aim of this work is to assess the evolution of the HRV complexity during Kangchenjunga (8.586 m) climbing. Five climbers recorded their RR-interval time series every day during the expedition. We assessed the complexity of HRV using sample entropy (SampEn) and normalized compression distance (NCD). The first is a common information measure to assess irregularity [6], the later is a measure coming from Information Theory, which compares two arbitrary sequences and outputs the dissimilarity between them. NCD exploits linear and nonlinear relations in the data allowing the comparison of sequences of different sizes. In order to assess the change in complexity, we estimated the dissimilarity of every stage in the climb against the first stage.

The structure of the paper is as follows. First, HRV nonlinear indices are presented. Next, the data is described in

detail, and the results are presented. Finally, conclusions are summarized.

2. Methods

2.1. Normalized Compression Distance

NCD measures the similarity relations between sequences [12], being an universal similarity metric approximating the incomputable notion of Kolmogorov complexity [13]. The Kolmogorov complexity $K(x)$ (or algorithmic entropy) of a sequence x can be intuitively understood as the bitlength of the utmost compressed version of x. Likewise, the Kolmogorov complexity $K(x, y)$ of two sequences x and y is the length of the shortest program that calculates both the sequences and a description of the difference between them. And the conditional Kolmogorov complexity $K(x|y)$ of x relative to y is the length of the shortest program to calculate x if y is used as the input.

Furthermore, $K(x, y)$ can be used as a distance as $K(x, y) = K(y, x)$ holds up to an additive constant term (Eq. II.1, [12]), independent of x and y. The information about x contained in y is $I(y : x) = K(x) - K(y|x^*)$ (being x^* the compressed version of x) and it is symmetric.

Assuming finite order stationary Markov sources x and y, we define $x_{1:n}$ and $y_{1:n}$ as the temporally ordered sequences of the random variables $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$ emitted by x and y, respectively, at times $1, 2, \ldots, n$.

Consider the *entropy rate* $H_\mu(x)$ and the *joint entropy rate* $H_\mu(x, y)$ as [14]:

$$H_\mu(x) = \lim_{n\to\infty} \frac{1}{n} H(x_1, \ldots, x_n) \quad (1)$$

$$H_\mu(x, y) = \lim_{n\to\infty} \frac{1}{n} H\big((x_1, y_1), \ldots, (x_n, y_n)\big) \quad (2)$$

which calculate the average uncertainty about x and the pair (x, y), respectively.

Then, let the *conditional entropy rate* $H_\mu(x|y)$ be

$$\begin{aligned} H_\mu(x|y) &= H_\mu(x, y) - H_\mu(y) \\ &= \lim_{n\to\infty} \frac{1}{n}\Big(H(x_{1:n}, y_{1:n}) - H(y_{1:n})\Big) \\ &= \lim_{n\to\infty} \frac{1}{n} H(x_{1:n}|y_{1:n}) \end{aligned} \quad (3)$$

which quantifies the average uncertainty about x while taking into account correlation between observations generated by x and given knowledge by observations generated by y.

As we previously saw, up to an additive constant we may approximate

$$E\left[K(x_{1:n})\right] \approx H(x_{1:n}) \quad (4)$$

So, using Eqs. (1) and (2), we may further approximate

$$E\left[K(x_{1:n})\right] = nH(x_{1:n}) \quad (5)$$

$$E\left[K(x_{1:n}, y_{1:n})\right] = nH(x_{1:n}, y_{1:n}) \quad (6)$$

From the previous measures of entropy rate and Kolmogorov complexity, a normalized distance metric has been proposed, the NID [12]:

$$\begin{aligned} \mathsf{NID}(\mathsf{x}, \mathsf{y}) &= \frac{K(x, y) - \min(K(x), K(y))}{\min(K(x), K(y))} \\ &= \frac{\max(H_\mu(x|y), H_\mu(y|x))}{\max(H_\mu(x), H_\mu(y))} \end{aligned} \quad (7)$$

NID has been used to measure dissimilarities between elements of the same family in various research fields, such as genome sequences (to establish relations between phyla), written language (to establish hierarchies of relations) and music (to establish relations between songs and genres).

As Kolmogorov complexity is non computable we use the Normalized Compression Distance (NCD) approximation for NID as follows: Given two signals $\mathbf{s_i}, \mathbf{s_j}$, the $\mathrm{NCD}(\mathbf{s_i}, \mathbf{s_j})$ is defined as

$$\mathrm{NCD}(\mathbf{s_i}, \mathbf{s_j}) = \frac{\mathbf{C}(\mathbf{s_i}, \mathbf{s_j}) - \min\{\mathbf{C}(\mathbf{s_i}), \mathbf{C}(\mathbf{s_j})\}}{\max\{\mathbf{C}(\mathbf{s_i}), \mathbf{C}(\mathbf{s_j})\}} \quad (8)$$

where $C(\cdot)$ is the compression length in bits given by the selected compressor C ($C(\mathbf{s_i})$ and $C(\mathbf{s_i}, \mathbf{s_j})$ are the number of bits needed to compress $\mathbf{s_i}$ and the concatenation of $\mathbf{s_i}$ and $\mathbf{s_j}$, respectively). This normalized measure has a simple interpretation, in the sense that the lower its value, the more similar the signals. In other words, they share more information and fewer bits are required to compress both signals together. The normalization term in the denominator of (8) enables the comparison among signals of different sizes.

In this work, NCD was computed using RR-interval time series and using *bzip2* as compressor. All the computations were performed under Python 3.

2.2. Sample Entropy

Entropy-based methods provide a quantification of the irregularity of a temporal series. Among them, SampEn [15] holds some properties which are appropriate for the study of physiological signals, namely it is robust to noise and outliers, and accordingly, it has been widely applied for characterizing the HRV signal. The SampEn, which is a modification of the Approximate Entropy [6], 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 [15].

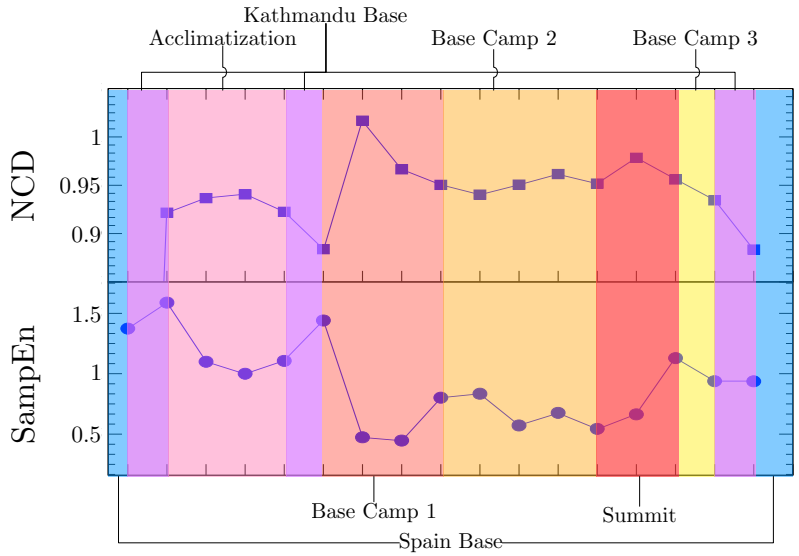

Figure 1. NCD and SampEn evolution during the expedition for one climber. Each point in the figure corresponds a single recording (RR-interval time series), and each colored area corresponds to a single stage.

Given N data points $B_i^m(r)$ is defined as $(N-m-1)^{-1}$ times the number of template vectors $\mathbf{x}_m(j)$ similar to $\mathbf{x}_m(i)$ (within *r*) where $j = 1...N-m$ with $j \neq i$. Then the average of $B_i^m(r)$ for all i is calculated as

$$B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r) \tag{9}$$

Similarly $A_i^m(r)$ is defined as $(N-m-1)^{-1}$ times the number of template vectors $\mathbf{x}_{m+1}(j)$ similar to $\mathbf{x}_{m+1}(i)$ (within *r*) where $j = 1...N-m$ with $j \neq i$. The average of $A_i^m(r)$ for all i is calculated as

$$A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r) \tag{10}$$

Finally, *SampEn(m,r)* and its statistic *SampEn(m,r,N)* are defined as

$$SampEn(m,r) = \lim_{N\to\infty} \{-\ln [A^m(r)/B^m(r)]\} \tag{11}$$

$$SampEn(m,r,N) = -\ln [A^m(r)/B^m(r)] \tag{12}$$

In order to compute SampEn, the embedded dimension m, i.e., the length of the vectors to be compared, and the noise filter threshold r need to be specified. In this study the values for these parameters are set to $m = 2$ and $r = 0.2$. the standard deviation of the signal, since they are common values used in the literature [6].

3. Dataset

In this work we gathered RR-interval time series from 5 spanish members on an expedition to climb the Kangchenjunga, which is the third highest mountain in the world (8.586 m) located in eastern Nepal. The climbing was conducted between April and May 2014. The 5 climbers recorded 30 min of RR-interval time series every day and, whenever possible, at the same time of the day (usually between 12:00 and 14:00). The cardiac signals were recorded using FirstBeat Bodyguard 2. The electrodes were attached by a member of the expedition who is a doctor.

The data was divided in different stages:

1. Spain Baseline
2. Kathmandu Baseline
3. Acclimation Trekking
4. Kathmandu After Acclimation
5. Base Camp 1
6. Base Camp 2
7. Summit
8. Base Camp 3
9. Kathmandu After Expedition
10. Spain Baseline

Since some stages lasted more than one day, they contained more than one recording.

Due to the extreme conditions some of the signals are very noisy and we had to proceed a visual inspection to remove unusable segments. At the time of the submission of this work we had available recordings for every stage only for one of the climbers. Therefore, our results are preliminary.

4. Results

Figure 2.1 shows NCD and SampEn values for the climber with all the recordings available. Each point in

the figure corresponds a single recording, and each colored area corresponds to a single stage. To compute NCD the first stage (Spain Base) was used as reference, so that any other NCD value was obtained by comparision with this reference. Therefore, the NCD computed by self-comparison should be small (zero ideally) and it was not shown in the figure, for the sake of detail. In the first two stages (Kathmandu Base and Acclimatization) the NCD first increased and then decreased. From this point, the NCD jumped up to the highest value in the second recording in Base Camp 1, meaning that this point was the most different comparing to the reference. Then, from this point (Base Camp 2, Summit and Base Camp 3), the NCD remained almost stable and higher than initial stages (Acclimatization and Kathmandu Base). Finally, NCD started a descending trend from Base Camp 3, Acclimatization and, again, Spain Base, meaning a recovery of the HRV.

SampEn series showed a more noisy behaviour. It is possible to distinguish three different parts. First, from Spain Base to Base Camp 1, SampEn showed values ranging from 1 to 1.5. Then a second part, from Base Camp1 to the Summit, SampEn was low compared with the previous part, with values below 1 and around 0.5. Finally, after the Summit, the SampEn recovered a little bit and showed values around 1.

5. Conclusions

In this work we studied the complexity of HRV in climbers during the expedition to the Kangchenjuna (8.586 m). We used two different indices to assess the complexity, namely, SampEn that is a well known, and commonly used in the literature, indices to assess irregularity in cardiac signals. We also proposed to use NCD, a dissimilarity measure from information theory, that tries to estimate the Kolmogorov complexity.

At the time to summit this work we only had access to the complete recordings from one of the 5 climbers, so our findings are preliminary. Results showed that NCD is able to measure the changes in complexity with a little more detail and smoother than SampEn. Both indices showed an initial change in the complexity until the Summit and from the Summit both showed a tendency to recover the complexity of the HRV.

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References

[1] Goldberger AL, Peng CK, Lipsitz LA. What is physiologic complexity and how does it change with aging and disease? Neurobiology of aging 2002;23:23–26.

[2] Malik M, Cripps T, Farrell T, Camm A. Prognostic value of heart rate variability after myocardial infarction. A comparison of different data-processing methods. MBEC 1989; 27(6):603–11.

[3] Huikuri HV, Makikallio T, Peng C, Goldberger AL, Hintze U, Moller M. Fractal correlation properties of RR interval dynamics and mortality in patients with depressed left ventricular function after an acute myocardial infarction. Circulation 2000;101:47–53.

[4] Karinen HM, Uusitalo A, Vähä-Ypyä H, Kähönen M, Peltonen JE, Stein PK, Viik J, Tikkanen HO. Heart rate variability changes at 2400 m altitude predicts acute mountain sickness on further ascent at 3000–4300 m altitudes. Frontiers in physiology 2012;3:1–7.

[5] Goldberger AL. Is the normal heartbeat chaotic or homeostatic? News Physiol Sci 1991;6:87–91.

[6] Pincus SM. Approximate entropy as a measure of system complexity. Proc Natl Acad Sci 1991;88:2297–301.

[7] Vigo DE, Pérez Lloret S, Videla AJ, Pérez Chada D, Hünicken HM, Mercuri J, Romero R, Nicola Siri LC, Cardinali DP. Heart Rate Nonlinear Dynamics During Sudden Hypoxia at 8230 m Simulated Altitude. Wilderness Environmental Medicine January 2010;21(1):4–10.

[8] Hackett PH, Roach RC. High-altitude illness. New England Journal of Medicine 2001;.

[9] Kanai M, Nishihara F, Shiga T, Shimada H, Saito S. Alterations in autonomic nervous control of heart rate among tourists at 2700 and 3700 m above sea level. Wilderness Environ Med 2001;12(1):8–12.

[10] Bhaumik G, Dass D, Bhattacharyya D, Sharma YK, Singh SB. Heart rate variability changes during first week of acclimatization to 3500 m altitude in indian military personnel. Indian Journal of Physiology and Pharmacology 2013; 57(1):16–22.

[11] Di Rienzo M, Castiglioni P, Rizzo F, Faini A. Linear and Fractal Heart Rate Dynamics during Sleep at High Altitude. Methods Inf 2010;.

[12] Li M, Chen X, Li X, Ma B, Vitanyi P. The Similarity Metric. IEEE Trans Inf Theory December 2004;50(12):3250–3264.

[13] Kolmogorov AN. Three approaches to the definition of information. Probl Peredachi Informatsii 1965;1(1):3–11.

[14] Cover TM, Thomas JA. Elements of information theory. John Wiley & Sons, 2012.

[15] Richman J, Moorman J. Physiological time-series analysis using approximate entropy and sample entropy. Am J Physiol Heart Cir Physiol 2000;278(6):2039–49.

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