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Determining cardiac vagal threshold from short term heart rate complexity

DOI 10.1515/cdbme-2016-0036

Abstract: Evaluating individual aerobic exercise capacity is fundamental in sports and exercise medicine but associated with organizational and instrumental effort. Here, we extract an index related to common performance markers, the aerobic and anaerobic thresholds enabling the estimation of exercise capacity from a conventional sports watch supporting beatwise heart rate tracking. Therefore, cardiac vagal threshold (CVT) was determined in 19 male subjects performing an incremental maximum exercise test. CVT varied around the anaerobic threshold AnT with mean deviation of 7.9 ± 17.7 W. A high correspondence of the two thresholds was indicated by Bland-Altman plots with limits of agreement −27.5 W and 43.4 W. Additionally, CVT was strongly correlated AnT ($r_p = 0.86$, $p < 0.001$) and reproduced this marker well ($r_c = 0.81$). We conclude, that cardiac vagal threshold derived from compression entropy time course can be useful to assess physical fitness in an uncomplicated way.

Keywords: aerobic threshold; anaerobic threshold; exercise; HRV.

1 Introduction

The assessment of aerobic exercise capacity is an essential part for the determination of physical fitness, evaluation of training effects as well as for exercise prescription and risk stratification. Most approaches of adequate performance diagnostics require sophisticated organizational and instrumental effort. Recently, attempts have been made to reproduce common performance markers by analyzing temporal change of heart rate variability during exercise [1, 2]. Investigating the decline of vagal mediated heart rate variability indices were shown to be a promising approach. At rest, compression entropy H_c has become an established information-theoretic method to assess complexity at small time scales [3–5]. We determined the minimum in H_c time course and compared this characteristic point to aerobic threshold (AeT) and anaerobic threshold (AnT).

Maximal parameters like maximal oxygen uptake and maximal power output attained during exercise testing are the most frequently applied indicators of aerobic endurance capacity and physical fitness. The determination of these maximal performance parameters requires an adequate motivation and maximal effort of participants. Therefore, the AeT and the AnT were often used to determine aerobic fitness. Both thresholds are common in clinical exercise testing and are known to be reproducible submaximal indicators of endurance and physical fitness. In contrast to peak parameters, the determination of these thresholds offers the great advantage that maximal effort and motivation in subjects are not mandatory. AeT demarcates the upper limit of a range of exercise intensities (moderate exercise domain) that can be accomplished almost entirely aerobically. AnT indicates the transition between heavy and very heavy exercise domains.

In this study we extract cardiac vagal threshold from compression entropy time course and relate this index to the individual aerobic and anaerobic threshold, for estimation of exercise capacity from a wearable heart rate monitor on beat-to-beat basis.

2 Methods

2.1 Incremental maximum exercise test IMET

Spiroergometries of 19 male students were conducted in a climate-controlled room at 22°C. Participants had no

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present or past history of any clinically significant disorders. Informed written consent was obtained in accordance with the protocols approved by the ethics committee of Jena University Hospital in accordance with the ethical guidelines of the Helsinki Declaration. A bicycle ergometer (SRM System, Schoberer Radmesstechnik, Jülich, Germany) was used to perform the IMET. The incremental bicycle protocol started after a resting period of 5 min at 50 W and increased by 50 W every 3 min until volitional exhaustion.

2.2 Data recordings

Breath-by-breath gas exchange measurements were carried out during the test (Ganshorn, Medizin Electronic GmbH, Niederlauer, Germany). VO_2 data were time-averaged using 10 s intervals to assess maximum VO_2. Power output was linearly interpolated throughout the stages to monotonically increasing load. P_{max} was defined as the maximal achieved power output.

Capillary blood samples for lactate measurements (Enzymatic-Amperometric Measuring System, Eppendorf, Hamburg, Germany) were taken at the end of each stage. AeTs and AnTs were determined using the lactate-power output plot. Special software (ERGONIZER, Freiburg, Germany) was used for the calculation of AeTs, which represents the first increase in blood lactate concentrations above resting state values during incremental exercise. The AnT describes the maximal lactate steady state and refers to the exercise intensity above which a continuous increase in blood lactate is unavoidable. AeT and AnT were determined according to the method described by Dickhuth et al. [6].

The Borg 6-to-20 scale was used to assess the degree of subjective effort perceived by the participants. Maximal blood lactate concentration ≥8 mmol/l and Borg rating of perceived exertion ≥18 were applied to guarantee an accurate assessment of fitness and training indices during IMET.

2.3 Cardiac vagal threshold

During IMET heart rate was recorded by telemetric HR monitor (RS800CX, Polar Electro, Kempele, Finland). Time series exported from the device were post-processed by adaptive filtering [7]. To analyze temporal evolution of parasympathetic cardiac activity, compression entropy H_c was calculated in sliding windows of 512 BBI with 480 BBI overlap. In each window temporal change of heart beat intervals was transferred to symbols. An adaptive approach based on statistical properties of the BBI segment was used, in contrast to the conventional method [3, 4]. Thresholds l_i of i-th window were defined as multiple of standard deviation sd ($l^i = 0.2sd_i$; $0.4sd_i$; $0.6sd_i$; … $2sd_i$) leading to an alphabet of 19 possible symbols.

$$s_i = \begin{cases} 1; & |x_n - x_{n-1}| \leq 0.2sd_i \\ 2; & x_n - x_{n-1} > 0.2sd_i, x_n - x_{n-1} < 0.4sd_i \\ 3; & x_n - x_{n-1} < 0.2sd_i, x_n - x_{n-1} > 0.4sd_i \\ \ldots & \\ 18; & x_n - x_{n-1} > 1.8sd_i, x_n - x_{n-1} < 2sd_i \\ 19; & x_n - x_{n-1} < 1.8sd_i, x_n - x_{n-1} > 2sd_i \end{cases} \tag{1}$$

In short, compression entropy estimates to which extend a symbol series can be reproduced by its own past, i.e. when patterns of the signal recur at frequent intervals. Information is compressed by encoding symbols in the look-ahead buffer regarding redundant symbol series that have already been encoded. Identical substrings can be passed and the number of iterations needed to encode the signal can be reduced without losing information. Standard sizes for analysis windows of memory window $w = 7$ BBI and buffer $b = 3$ BBI were used [4, 5].

To characterize parasympathetic withdrawal, cardiac vagal threshold CVT was extracted by separating initial decline of H_c from subsequent saturation phase. Therefore, a polynomial of third order was fitted to the time course minimizing the squared error. The minimum of the fit was defined as vagal threshold. An example is illustrated in Figure 1.

2.4 Statistical analysis

We assessed linear dependence of vagal cardiac threshold VCT and anaerobic threshold AnT by Pearson correlation coefficient r_p, i.e. the quotient of covariance of X and Y (S_{XY}) and the standard deviations of X and Y (S_X, S_Y), with X = VCT, Y = AnT.

$$r_p = \frac{S_{XY}}{S_X S_Y} \tag{2}$$

In Lin et al. concordance coefficient r_c (eq. 4) was used to assess degree of reproducibility, that is not sufficiently covered by Pearson correlation coefficient [8].

$$r_c = \frac{2S_{XY}}{S_X^2 + S_Y^2 + (\bar{y} + \bar{x})^2} \tag{3}$$

Bland-Altman plots were generated by plotting differences of CVT and AnT against mean value of them.

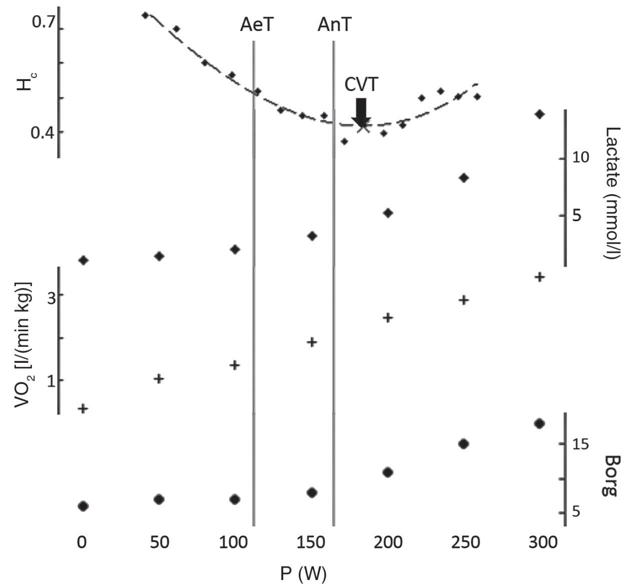

Figure 1: Example of CVT (black arrow) estimated on compression entropy time course (asterisks). AeT and AnT derived from lactate levels are indicated by vertical gray lines. Dashed line: polynomial of third order fitted to data points. crosses: Lactate concentration. diamonds: VO_2. circles: Borg ratings, load of P = 0W equals baseline.

Limits of agreement were calculated by mean ± twice the standard deviation [9].

3 Results

In Figure 1 the determination of vagal and aerobic threshold is illustrated for one example recording. Compression entropy (asterisks) initially declines in a linear fashion and levels out around the AnT, which was determined from the lactate time course (crosses). The third order polynomial (dashed line) fits H_c anchor points quite well. For comparison the change of Borg scale (diamonds) and VO_2 (circles) was plotted below.

Our study population was quite young (24.2 years) and normal weighted (BMI = 23.7, body fat = 15%, fat free mass FFM = 64.6%). Mean heart rate and global variability were 62.2/min and 82.7 ms. Short term vagal fluctuations estimated by RMSSD and H_c were 44.5 ms and 0.75 at rest. On average participants achieved maximum load of 300 W. Baseline lactate concentration and Borg rating increased from 0.8 mmol/l and 6.2 to 11.8 mmol/l and 19.4. Maximum heart was 190/min and oxygen uptake VO_{2max} reached 45.2 l/min·kg. Mean aerobic and anaerobic thresholds achieved were AeT = 123 W and AnT = 184W. Cardiac vagal threshold derived from H_c time course was 192 W. Mean deviation of CVT from AeT was 69.0 ± 19.1 W and 7.9 ± 17.7 W from AnT. T-Test confirmed that the deviation from AeT was systematic (divergence high significantly greater zero). Whereas, the difference to AnT varies around zero ($p < 0.05$). In Figure 2 CVT was plotted against AnT. A linear correlation ($r_p = 0.86$, $p < 0.001$) was apparent. Concordance coefficient of both thresholds was $r_c = 0.81$. On the right side of Figure 2 the difference of AnT and CVT (ΔT) was drawn dependent on the mean of both (AnT-CVT)/2. Limits of agreement were −27.5 W and 43.4 W with one outlier under the lower limit. CVT was correlated to AeT (r = 0.85**), maximum load (r = 0.49*) and maximum lactate concentration (r = −0.48*). ΔT was not correlated to thresholds AeT (r = 0.17) and AnT (r = 0.11), P_{max} (r = −0.18), HR_{max} (r = 0.27), HR_{rest} (r = 0.04) and Hc_{rest} (r = 0.27).

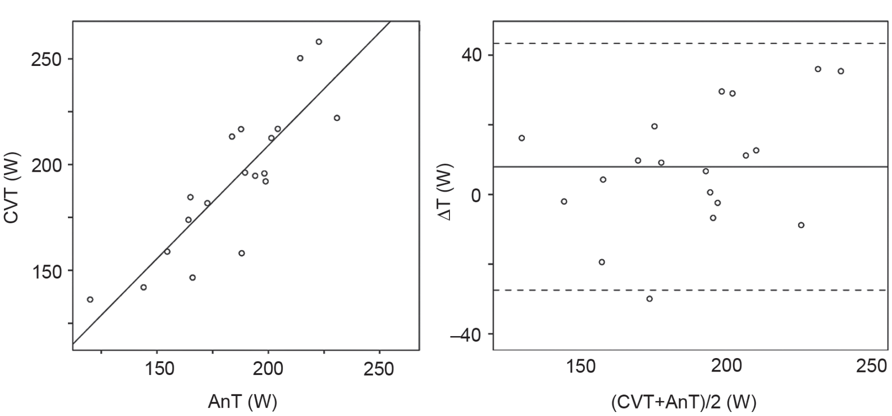

Figure 2: Left: cardiac vagal threshold (CVT) plottet against anaerobic threshold (AnT) with linear regression line. Right: Bland-Altman plot of deviation CVT-AnT dependent on their mean (AnT + CVT)/2.

Table 1: Characterization of the data set. Results at rest and during exercise (maximum) are given in mean ± standard deviation.

Parameter	Mean ± Standard deviation
Age (years)	24.22 ± 1.06
Height (cm)	179 ± 4
Weight (kg)	76.2 ± 7.7
BMI	23.7 ± 2.4
Body fat (%)	15 ± 3
FFM (%)	65 ± 5
$Lactate_{rest}$ (mmol/l)	0.8 ± 0.2
$Borg_{rest}$	6.2 ± 0.4
HR_{rest} (1/min)	62.2 ± 7.5
$sdNN_{rest}$ (ms)	82.7 ± 23.5
$RMSSD_{rest}$ (ms)	44.5 ± 18.6
H_{crest} (ms)	0.75 ± 0.04
VO_{2max} (l/min·kg)	45.2 ± 4.6
$Lactate_{max}$ (mmol/l)	11.8 ± 2.1
$Borg_{max}$	19.4 ± 0.6
P_{max} (W)	300.0 ± 29.4
HR_{max} (1/min)	190.2 ± 6.4
AeT (W)	123 ± 21
AnT (W)	184 ± 28
CVT (W)	192 ± 34

BMI, body mass index; FFM, fat free mass; HR, heart rate; sdNN, standard deviation of BBI; RMSSD, root mean square of successive BBI; H_c, compression entropy; P_{max}, maximum load; VO_2, oxygen uptake; AeT, aerobic threshold; AnT, anaerobic threshold; CVT, cardiac vagal threshold.

4 Discussion

In this study we applied a new approach of deriving cardiac vagal threshold from temporal evolution of short-term complexity of heart rate assessed by compression entropy. In 19 young male participants we found a high correlation and concordance to the AnT. Accurate reproduction of this established marker of physical fitness (with 8 W mean deviation) indicates that cardiac vagal threshold is capable of revealing exercise performance.

In Figure 1 time course of compression entropy H_c, lactate levels, oxygen uptake (VO_2) and Borg ratings. CVT was estimated at load 9.1 W after AnT was reached. An abrupt increase of lactate concentration and Borg rating is obvious at AnT. That indicates the importance of this characteristic time point.

Our group of male participants is young and sporty, with low BMI, body fat and resting heart rate. This sample is obviously not representative for normal population but probably quite adequate to represent active male people interested in sports. Maximum parameters indicate that subjects were relatively well-trained and performed the exercise test until individual limit of tolerance. CVT was close to the AnT with a mean error of about 8 W. Pearson correlation coefficient of $r = 0.86$ ($p < 0.001$) demonstrated a strong linear relationship. Reproducibility of AnT by CVT with $r_c = 0.81$ seems high compared to the examples given in Lin et al. [8]. There was no systematic error evoked by resting heart rate and its compression entropy or maximum parameters of physical effort. Neither a dependency on the aerobic and anaerobic thresholds was found.

In comparison to other approaches using compression entropy to evaluate vagal short-term modulation of heart rate has some advantages. The symbolization procedure is robust against outliers, makes BBI efficient to store and is not dependent on highly precise r-wave detection allowing lower ECG sample rates. Compression algorithm can easily be implemented in analysis software as data compression based on string matching has become a common tool e.g. for producing zip-archives [4, 10]. We conclude, that CVT extracted from short term heart rate complexity is useful for evaluating aerobic exercise capacity. The presented strategy is simple and inexpensive and the findings of the present study offer an advance in the determination of the AnT, which is amongst other things important for developing health promotion exercise programs.

Author's Statement

Research funding: The author state no funding involved. Conflict of interest: Authors state no conflict of interest. Ethical approval: The research has been complied with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the ethics committee of Jena University.

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