Biomed Tech 2006; 51:201–204 © 2006 by Walter de Gruyter • Berlin • New York. DOI 10.1515/BMT.2006.037

Changes in heart rate variability of athletes during a training camp

Mathias Baumert[1,4,5,*], Lars Brechtel[2], Juergen Lock[3] and Andreas Voss[4]

[1] Centre for Biomedical Engineering, The University of Adelaide, Adelaide, Australia
[2] Department of Sports Medicine, Humboldt University, Berlin, Germany
[3] SMS-Sports Medicine Service, Berlin, Germany
[4] Department of Medical Engineering, University of Applied Sciences Jena, Jena, Germany
[5] School of Electrical & Electronic Engineering, The University of Adelaide, Adelaide, Australia

Abstract

Heart rate variability (HRV) reflects regulatory processes of the cardiovascular system and reveals fractal characteristics. In this paper we investigated standard HRV parameters and scaling characteristics in ten athletes before, during, and after a 2-week training camp to assess the effects of short-term overtraining on cardiovascular control. High-resolution ECGs were recorded over 30 min under resting conditions 1 week before the training camp, after 1 week of training in the camp, and after 3–4 days of recovery. Standard HRV analysis was performed according to Task Force recommendations. Scaling characteristics were assessed, applying detrended fluctuation analysis (DFA). Standard HRV analysis showed significant changes in meanNN and rmssd during the training camp. DFA revealed three distinct regions of scale-invariance and significant alterations during the training camp. In conclusion, HRV might be used to monitor the training state in athletes.

Keywords: detrended fluctuation analysis; heart rate variability; overtraining.

Introduction

Physical training has been shown to influence autonomic cardiovascular control. Moderate endurance training increases parasympathetic activity and decreases sympathetic activity in the human heart at rest, which is considered a cardioprotective effect against lethal arrhythmias [6, 7]. In high-performance sports, overload training or overtraining is a widely used method to enhance the performance capacity. During such an overreaching training period, an imbalance between training/competition versus recovery is accepted, which is thought to negatively influence autonomic cardiovascular control [8]. A long-lasting overload could result in an (parasympathetic) overtraining syndrome. The term overtraining syndrome is defined as a condition of underperformance and fatigue, often associated with various and individual differing (vegetative) symptoms, muscle pain and fatigue while working at minimal work loads, as well as mental problems similar to endogenous depression [5].

In this study we investigated whether heart rate variability (HRV) analysis, in particular its scaling characteristics, is apt to detect changes in autonomic cardiovascular control due to an increased training load in the framework of a training camp. In addition, we determined whether HRV analysis could be used as a diagnostic tool to monitor overload training and to detect/prevent overtraining syndrome.

HRV shows fractal characteristics [11]. Analysis of these scale-invariant regions has become a popular tool and has been shown to be a useful diagnostic approach in patients with cardiac disease [9]. One widely applied approach to investigate scaling characteristics is detrended fluctuation analysis (DFA) [10]. Scale-invariance has commonly been observed over a wide range, with a characteristic break at scales around 16 heart beats. Consequently, two scaling exponents, termed α_1 and α_2, are computed in the ranges of 4–16 and 16–64 heart beats, respectively. Thus, two fixed *a priori* defined scaling ranges are commonly assessed in HRV analysis.

Subjects, materials and methods

Probands

Ten healthy experienced athletes (five males and five females from track and field or triathlon) participated in this study during a training camp. Anthropometric data and peak oxygen uptake are shown in Table 1. The results of the medical examination were negative. No athlete received drugs prior to the study. All subjects had fully recovered from the competition season. None of the participants showed any signs of overload or overtraining syndrome.

Test protocol

The training camp started after one day of travelling and acclimatisation and lasted for 13 days, with 1 day's rest after 6 days of training. The daily training program included a stepwise increasing cycling test and additional running of 40 min and cycling of 80 min. Additional step tests for performance diagnostics were carried out in an exercise laboratory using two calibrated ergometers 1 week before the training camp, after 1 week of training

*Corresponding author: Dr. Mathias Baumert, The University of Adelaide, School of Electrical and Electronic Engineering, Adelaide SA 5005, Australia
Phone: +61-8-83034115
Fax: +61-8-83034360
E-mail: mbaumert@eleceng.adelaide.edu.au

Table 1 Anthropometric data and peak oxygen uptake of the investigated athletes presented as median and interquartile range (IQR).

Sex	Women		Men	
	Median	IQR	Median	IQR
Age [years]	24.8	24.7–26.4	26.6	26.5–28.8
Body mass [kg]	54.8	50.4–61.8	72.0	69.0–86.8
Height [cm]	163	162–168	181	181–182
VO_2 peak [ml kg^{-1} min^{-1}]	51.1	48.9–52.2	65.9	61.4–74.6

and 3–4 days after the training period. The step test started at 50 W for females and 100 W for male athletes. The load was increased every 3 min by 50 W until subjective exhaustion. Objective criteria of exhaustion were taken from on-line monitoring of respiratory data (respiratory ratio >1.11 or levelling off of oxygen uptake). Running and cycling endurance exercise took place in the afternoon and was carried out individually or in small groups of individuals with nearly equal performance capacity. The training amount and intensity were above the normal activity level the athletes are adapted to. After returning home the athletes recovered for 3–4 days. In this period no or a maximum of 30 min of training of very low intensity was carried out.

Supine heart-rate recordings to assess autonomic control took place 1 week prior to training (M1), after 1 week of training (M2), and 3–4 days after the training period (M3).

The investigation conforms to the principles outlined in the Declaration of Helsinki. Written informed consent was obtained from all athletes.

Data recording and pre-processing

To assess HRV, high-resolution ECG (1600 Hz) was recorded over 30 min in a supine position under standardised resting conditions. Subsequently, time series of beat-to-beat intervals were extracted. Artefacts and ectopic beats were rejected and interpolated.

Standard HRV analysis

The following parameters were computed according to the HRV Task Force guidelines [12]:

- meanNN: mean of all normal beat-to-beat intervals in ms;
- sdNN: standard deviation of all normal beat-to-beat intervals in ms;
- rmssd: root-mean-square of all normal beat-to-beat differences in ms;
- HF: high-frequency power (0.15–0.4 Hz) in ms^2;
- LF: low-frequency power (0.04–0.15 Hz) in ms^2;
- VLF: very-low-frequency power (0.003–0.04 Hz) in ms^2; and
- LFn: LF power normalised to LF + HF power in normalised units.

Frequency domain analysis was performed on linear equidistantly interpolated time series with a resolution of 500 ms applying a Fast Fourier Transform and a Blackman-Harris window function.

Detrended fluctuation analysis

DFA has been developed to analyse long-range correlations (long-memory dependence) in non-stationary data for which conventional fluctuation analyses such as power spectra and Hurst analysis cannot be reliably used [11]. The method works as follows.

1. Compute the cumulative sum $c(k)=\sum_{i=1}^{k}[s(k)-\bar{s}]$ of the time series s, where $\bar{s}$ is the mean of s (using the concept of random walk analysis [2]).
2. Compute the local trend $c_n(k)$ within boxes of varying size n (least-squares fit).
3. Compute the root mean square of the detrended time series as a function of box size n as $F(n)=\sqrt{\frac{1}{N}\sum_{k=1}^{N}[c(k)-c_n(k)]^2}$, where N denotes the size of s.
4. Plot $\log_{10} F(n)$ against $\log_{10} n$.

If the data displays long-range dependence, then $F(n)\approx n^{\alpha}$, where α is the scaling exponent. For stationary data with scale-invariant temporal organisation, the Fourier power spectrum $S(f)$ is $S(f)\approx f^{-\beta}$, where the scaling exponent β is related to α by $\beta=2\alpha-1$. Values of $0<\alpha<0.5$ are associated with anti-correlation (i.e., large and small values of the time series are likely to alternate). For Gaussian white noise, $\alpha=0.5$. Values of $0.5<\alpha\leq 1$ indicate long-range power-law correlations (i.e., large values of the time series are likely to be followed by large values). Values $1<\alpha\leq 1.5$ represent stronger long-range correlations that are different from power-law correlations, where $\alpha=1.5$ for Brownian motion [11].

Statistics

To evaluate the HRV parameters calculated, non-parametric statistical tests were applied, including median and interquartile range and the Friedman test. Values of $p<0.05$ were considered to be statistically significant. Pearson's linear correlation coefficients were also computed between significantly different HRV parameters.

Results

Peak performance dropped slightly but significantly during the training camp [M1, 301 (219–350) W; M2, 279 (217–317) W] and returned to slightly above baseline levels after the recovery period [M3, 309 (234–338) W; $p<0.05$].

All computed HRV parameters are displayed in Table 2. Standard HRV analysis showed significant changes only for meanNN and rmssd. During the training camp,

Table 2 Heart rate variability before (M1), during (M2) and after the training camp (M3), presented as median and interquartile range (IQR).

Parameter	M1		M2		M3		p
	Median	IQR	Median	IQR	Median	IQR	
meanNN	1042	937–1194	933	832–1103	1055	947–1183	0.008
sdNN	91	64–96	74	60–95	83	64–99	ns
rmssd	68	52–95	52	38–71	61	48–78	0.046
LF	226	80–632	211	85–443	139	60–226	ns
HF	201	42–351	108	46–292	79	53–260	ns
LFn	0.53	0.46–0.71	0.70	0.44–0.73	0.50	0.40–0.67	ns
VLF	261	133–397	223	130–260	386	290–524	ns
α_{HF}	1.15	0.96–1.22	1.14	0.94–1.19	0.89	0.79–1.04	ns
α_{LF}	0.68	0.57–0.84	0.91	0.76–0.95	0.74	0.64–0.89	0.008
α_{VLF}	0.83	0.82–0.99	1.03	0.94–1.17	1.02	0.90–1.14	ns

ns, not significant, i.e., $p > 0.05$.

both parameters were lower and largely returned to normal values after the recovery period.

DFA revealed three distinct regions of scale-invariance for most athletes. Figure 1 shows an example. Investigating the location of the break points, we found a direct relationship to the well-known VLF, LF and HF bands of HRV. Consequently, three separate scaling exponents were computed and termed α_{HF}, α_{LF}, and α_{VLF}, respectively. The two break points marking the three regions of scale-invariance correspond to the border frequencies of power spectrum analysis, i.e., 0.04 and 0.15 Hz. Since the beat-to-beat interval values are not taken at regular intervals (the intervals vary with the heart period), they cannot be assigned to a frequency scale in Hz. To overcome this problem, we used the individual mean heart rate to estimate the 'sampling' interval between consecutive values. Lower and upper boundaries for DFA were $n = 4$ and $n = 64$, respectively, as proposed in the original work by Peng et al. [11].

All three scaling exponents were significantly different from each other ($p < 10^{-5}$) and indicate the presence of correlations. Comparison of the HRV scaling exponents

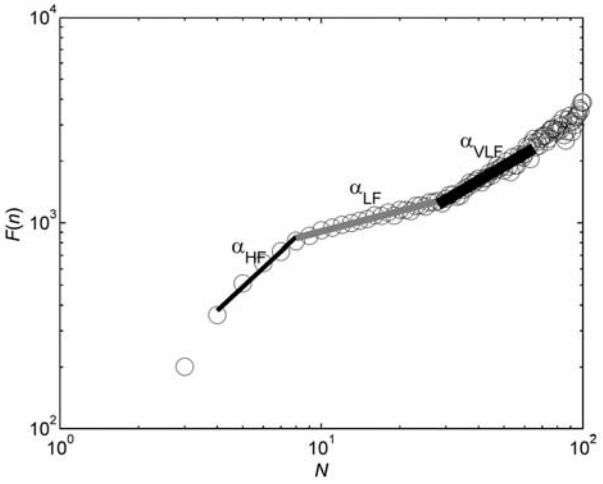

Figure 1 Detrended fluctuation analysis of heart rate time series in athletes.
F(*n*), root-mean-square of the detrended time series: *N*, segment size for linear trend elimination. Black thin line, scaling range equivalent to the HF band, starting with $n = 4$. Grey line, scaling range equivalent to the LF band. Bold black line, scaling range equivalent to the VLF band, truncated at $n = 64$.

before, during, and after the training camp showed that the medium scaling range (α_{LF}) revealed significantly increased correlation during the training camp, which largely returned to baseline after the recovery period.

Correlation analysis between the significantly altered parameters showed no correlation between meanNN and α_{LF} ($r = -0.05$), but a slight correlation between rmssd and α_{LF} ($r = -0.44$), and between rmssd and meanNN ($r = 0.48$).

Discussion

In this study we investigated the effects of an increased training load on autonomic cardiovascular control in athletes. By monitoring HRV under resting conditions, we aimed to identify markers that can assess training effects at the level of sympatho-vagal activity.

Decreased peak performance is a typical initial finding after an increase in training load. The elevated heart rate during the training camp, recovering after 3–4 days of rest, clearly indicates increased sympathetic activation due to increased training. The decrease in beat-to-beat fluctuations (rmssd), which are predominantly accomplished by vagal efferents [12], indicate a shift of the sympatho-vagal balance towards sympathetic activity due to the increased training load. This is in agreement with other studies [13]. A previous study revealed less complex heart-rate modulation during a training camp [1].

DFA revealed interesting characteristics. Despite a single characteristic break point at 16 heart beats, as has commonly been described [9, 11], we found two break points that correspond to the well-studied VLF, LF, and HF oscillations of HRV. Our analysis shows that DFA scale-invariance of HRV is directly linked to these well-known physiological phenomena. Although the relationship between DFA and power spectra has previously been shown mathematically [14], we were able to show this relationship directly in the scaling graphs of experimental data [3]. Obviously, the relatively low mean heart rate in athletes reveals the separate VLF, LF and HF scaling regions, while those might remain masked in untrained probands. Furthermore, a change in cardiac activity mediated by sympathetic and vagal efferents, as observed in athletes, might play a role [8]. Interestingly, such three-region scaling behaviour has also been found

in beat-to-beat blood pressure time series in healthy probands and in patients with dilated cardiomyopathy [2].

The HF short-term correlations were not significantly altered during the training camp and might be caused by the strict time regime for respiration. The LF scaling exponent, usually associated with sympathetic and vagal cardiac and vascular control, reveals weak correlation. During the training camp, the correlation was significantly increased and might reflect sympathetic activation. The VLF exponent shows more pronounced correlations than the LF exponent, but no significant changes during the training camp. Although a physiological explanation of VLF oscillations is still under debate, links have been found with the renin-angiotensin system, for example [4].

Conclusion

HRV analysis might be useful for monitoring changes in the autonomic cardiovascular control of athletes. DFA scaling exponents of HRV should be computed adaptively, based on the mean heart rate and VLF, LF, and HF ranges. In particular, the LF scaling exponent may represent a useful measure for overtraining diagnostics.

Acknowledgements

This study was partly supported by grants from the Australian Research Council (DP0663345), the German Federal Ministry of Economics and Labour (BMWA – PRO INNO, KF 0317302KLF3), Stiftung Warentest Berlin, and the Sports Medicine Service (SMS), Berlin, Germany.

References

[1] Baumert M, Baier V, Brechtel L, Haueisen J, Voss A. Estimating the complexity of heart rate fluctuations – an approach based on compression entropy. Fluct Noise Lett 2005; 5: L557–L563.

[2] Baumert M, Baier V, Voss A. Long-term correlations and fractal dimension of beat-to-beat blood pressure dynamics. Fluct Noise Lett 2005; 5: L197.

[3] Baumert M, Brechtel LM, Lock J, Voss A, Abbott D. Scaling graphs of heart rate time series in athletes demonstrate the VLF, LF and HF regions. Physiol Meas 2006; 27: N35–N39.

[4] Bonaduce D, Marciano F, Petretta M, et al. Effects of converting enzyme inhibition on heart period variability in patients with acute myocardial infarction. Circulation 1994; 90: 108–113.

[5] Brechtel LM, Braumann KM, Wolff R. Time course of symptoms during the development of a parasympathetic overtraining syndrome. Med Sci Sports Exerc 1999; 31: 176.

[6] Buchheit M, Simon C, Piquard F, Ehrhart J, Brandenberger G. Effects of increased training load on vagal-related indexes of heart rate variability: a novel sleep approach. Am J Physiol Heart Circ Physiol 2004; 287: H2813–2818.

[7] Carter JB, Banister EW, Blaber AP. Effect of endurance exercise on autonomic control of heart rate. Sports Med 2003; 33: 33–46.

[8] Hedelin R, Wiklund U, Bjerle P, Henriksson-Larsen K. Cardiac autonomic imbalance in an overtrained athlete. Med Sci Sports Exerc 2000; 32: 1531–1533.

[9] Ho KK, Moody GB, Peng CK, et al. Predicting survival in heart failure case and control subjects by useful automated methods. Circulation 1997; 96: 842–848.

[10] Peng CK, Buldyrev SV, Goldberger AL, et al. Long-range correlations in nucleotide sequences. Nature 1992; 356: 168–170.

[11] Peng CK, Havlin S, Stanley HE, Goldberger AL. Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. Chaos 1995; 5: 82–87.

[12] Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. Heart rate variability. Standards of measurement, physiological interpretation, and clinical use. Eur Heart J 1996; 17: 354–381.

[13] Uusitalo AL, Uusitalo AJ, Rusko HK. Heart rate and blood pressure variability during heavy training and overtraining in the female athlete. Int J Sports Med 2000; 21: 45–53.

[14] Willson K, Francis DF, Wensel R, Coats AJS, Parker KH. Relationship between detrended fluctuation analysis and spectral analysis of heart-rate variability. Physiol Meas 2002; 23: 385–401.