Heart Rate Variability During Deep Sleep Offers a Time-Efficient Alternative to Morning Supine Measurements – A Study in World Class Alpine Skiers

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Heart rate variability during deep sleep offers a time-efficient alternative to morning supine measurements – a study in world class alpine skiers.

Submission type: Original investigation

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Abstract

Background/Aim: There is increasing popularity for athletes to use heart rate variability (HRV) to tailor training. A time-efficient method is HRV assessment during deep sleep. The aim was to validate the selection of deep sleep segments identified by RR-intervals with simultaneous electroencephalography (EEG) recordings and to compare HRV parameters of these segments with those of standard morning supine measurements. Methods: In 11 world class alpine skiers, RR-intervals were monitored during ten nights and simultaneous EEGs were recorded in 2-4 nights. Deep sleep was determined from the HRV signal and verified by delta power from the EEG recordings. Four further segments were chosen for HRV determination, namely a 4-h segment from midnight to 4 am, and three 5 min segments: one just before awakening, one after awakening in supine position and one in standing after orthostatic challenge. Training load was recorded every day. Results: A total of 80 night and 68 morning measurements of 9 athletes were analyzed. Good correspondence between the phases selected by RR-intervals versus those selected by EEG was found. Concerning root-mean-squared-difference of successive RR-intervals (RMSSD), a marker for parasympathetic activity, the best relationship with the morning supine measurement was found in deep sleep. Conclusion: HRV is a simple tool for approximating deep sleep phases and HRV measurement during deep sleep could provide a time-efficient alternative to HRV in supine position.

Key words: Cardiac autonomic nervous system, Vagal-related HRV indices, Training, athletes, Sleep
Introduction

While high training loads are common amongst elite athletes, adequate recovery is needed in order to maximize training adaptations and to avoid overtraining. Heart rate variability (HRV) has become a widely used method to quantify cardiac autonomic activity (CANA). Effects of training on HRV in athletes have been assessed in several previous studies conducted in predominantly endurance athletes, while studies in strength/speed athletes are rare. Methodological differences including factors such as timing of the measurements or exercise modality have resulted in equivocal findings. Highly trained athletes show distinct HRV patterns that differ from moderately trained athletes with reduced markers of vagal activity in general and a reduction of vagal markers during deep sleep compared to wakefulness, which was absent in less trained athletes, implying that recommendations for elite athletes can only be based on studies with elite athletes. Morning supine HRV measurements are accepted as a valid monitoring tool of the athletes’ recovery state. However, compliance with regular measurements is poor. Consequently, there is a need for an easier method that allows measurement with minimal time requirement. HRV measurements during sleep would require no further time. HRV measurements during sleep have been assessed in several previous studies. While some studies have assessed HRV of a fixed time period in the night, such as from midnight to 4 am, some have pointed out that, contrary to other sleep stages, deep sleep provides an emotion free state with autonomic stability and regular breathing frequency, which provides ideal conditions for HRV assessment.

The aim of this study was to compare, in elite athletes, HRV measured in supine position after awakening to HRV measured during different segments of the night and in the morning after orthostatic challenge and to investigate the effects of training load on HRV measured in these different conditions. We further aimed to verify our method for selecting
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deep sleep phases based on HRV only, with simultaneous recording of brain delta wave activity measured in a home setting.

Methods

Subjects

Eleven male alpine skiers were recruited for this study (age: 25±9 years, BMI: 25.7±1.0 kg/m², VO₂max: 53.3±3.4 ml/kg/min). Athletes had a history of a cumulative 540 world-cup starts (ranging from 1-170 per athlete) resulting in a total of 22 World-cup podium positions. The study population included three participants of the Olympic games of whom two won gold medals. The study was approved by the local ethics committee. Written informed consent was provided by all athletes.

Study design/Measurement procedure

Measurements were performed during five consecutive nights in each of two different training phases. The first training phase consisted of strength and endurance training whereas the second training phase consisted mainly of alpine ski training with some additional strength and endurance training. All measurements were collected at an altitude of between 900 and 1800 m a.s.l. RR-intervals were recorded starting from lights off with a small electrocardiogram (eMotion, Mega Electronics Ltd, Kuopio, Finland) using two chest electrodes at a sampling frequency of 1000 Hz during the whole night. Before getting up, the athletes were instructed to perform an orthostatic challenge (OC) test. In a subsample of 2-4 nights in each athlete, a 1-channel electroencephalograph (EEG) was recorded at 256 Hz using a portable device (SOMNOwatch™, SOMNOmedics, Randersacker, Germany). Electrodes for the EEG-recording were placed on the surface of the scalp at the frontopolar position (Fp1 according to the international 10-20 system) and at the frontocentral position for the reference electrode (Fp1-Fz). During the nights with simultaneous EEG measurement,
actigraphy was recorded at a sampling frequency of 30 Hz with a sensor included in the SOMNOwatch™ device, which was worn on the chest. The device registers movements above 0.012 g in a bi-axial direction. Data was stored in 1 s epochs.

**Deep sleep selection**

By means of a custom built Matlab (2014a, The Mathworks, Natick, MA) procedure, Pearson correlation coefficients of consecutive RR-intervals (rRR) were calculated from 5-min windows moved in steps of 30 s over the whole night. Previous studies have shown specific HRV characteristics in deep sleep with stationary and uncorrelated consecutive RR-intervals. We have developed an algorithm to identify segments of deep sleep generally characterized by high delta wave activity, regular breathing and low HRV, similar to the algorithm used by Al Haddad. Deep sleep phases were defined when rRR was below 90% of mean rRR of the whole recording period during a minimum period of 10 min. Two 5-min segments were placed at the center of each of the two first identified deep sleep segments and used for HRV analysis (all nights had a minimum of two deep sleep segments). Segments were visually inspected for non-stationarities and manually shifted by a maximum of 1 min if necessary.

**EEG analysis**

Analysis was performed using the Matlab software (2014a, The Mathworks, Natick, MA). EEG data was band-pass filtered using a Butterworth filter with cut-off frequencies of 0.2 Hz and 35 Hz, respectively. Frequency analysis was performed in the two selected deep sleep segments using fast Fourier transformation. Spectra were calculated for consecutive 30-s intervals. Power in the delta frequency band was computed (DP, 1-4.5 Hz) and expressed as percent of the individual mean DP. DP was smoothed using a 121th-order median filter.
Verification of deep sleep with delta activity

In the nights with simultaneous EEG recording, delta power of the EEG in identified deep sleep phases (using HRV) was reported. Segments identified as deep sleep by HRV were classified as correct if corresponding delta power exceeded 200% of the mean of the corresponding night (Figure 1). Mean duration with movements during the total segment length was calculated.

4 hours segment

A 4 hours segment was selected from 12 a.m. to 4 a.m. regardless of the sleep stages participants were in.

Morning segment

A 5 min segment, in the last 30 min before awakening, with stationary HR, was visually selected and also chosen for analysis.

Supine position and orthostatic challenge test

The recordings were performed after awakening in the morning during 5 min in supine position and immediately after an orthostatic challenge during 5 min in standing position. A metronome was used to provide standardized breathing frequency of 0.25 Hz. 

HRV analysis

HRV analysis was performed using the Kubios software (V2.2, University of Eastern Finland, Finland). For all segments, following time and frequency domain parameter were calculated: Time-domain: Heart rate (HR [ms]), standard deviation of the RR intervals (SDNN [ms]), root-mean-squared-difference of successive RR-intervals (RMSSD [ms]); frequency-domain: low-frequency power (LF: 0.04 - 0.15 Hz [ms²]), high-frequency power (HF: 0.15 - 0.4 Hz [ms²]), total power (TP [ms²]) and the LF/HF ratio. For frequency analyses, RR trend components were removed using an advanced smoothness priors.
approach, with a smoothing parameter of $\lambda = 500$, which corresponds to a cut-off frequency of 0.035 Hz. The Welch’s periodogram method was used. All signals were corrected for ectopic beats with the automated correction filter from Kubios (artifact correction was set as low as possible to visually cut out all artifacts).

**Monitoring of training load**

Training load was quantified by multiplying rate of perceived exertion, measured using the modified Borg scale intensity score (scale from 1 to 10) by the duration of the training session. Daily training loads were calculated by summing session training loads of each day.

**Subjective rating of fatigue**

Subjective rating of fatigue was assessed every evening with the EBF–Sport questionnaire (German version of the RESTQ-Sport).

**Statistical Analysis**

Statistical analysis was performed using the software R (R Core Team, 2015). Normality of the data was visually assessed using QQ-plots. Comparisons of the non-normally distributed HRV parameters between segments were done by Friedman testing based on median values of the nights in each athlete. Between segment differences were assessed by post-hoc comparisons using Wilcoxon rank testing with significance levels for $p$-values set at 0.005 to adjust for multiple comparison ($\alpha = \frac{0.05}{n(n-1)/2}$, $n =$ number of segments). The hierarchical data structure (several nights per athlete) required the use of linear mixed-effects models (LMEM). Non-normally distributed data were log transformed. The large influence of HR on HRV parameters required the inclusion of HR as a covariate. LMEMs using the software package *nlme* were performed to assess the effects of training load on HRV parameters and to compare HRV parameters from the morning awake segment.
with HRV parameters analyzed in the other segments. For the effect of training load on HRV parameters, training load and HR were entered as fixed effects. In order to adjust for inter-individual differences, intercept and slope of the effect of training load were included as random effects. For the comparison of HRV parameters between the phases, LMEMs were performed for the dependent variables HR, SDNN, RMSSD, HF, LF, TP and LF/HF of the morning supine segment. The corresponding HRV variable and HR of a given segment were entered as fixed effects and separate models were applied for each segment. Random intercepts for each athlete were included in the respective models. A p-value of less than 0.05 was considered statistically significant.

Results

Subjects

Data of two athletes had to be excluded due to the absence of a permanent sinus rhythm leading to less than 90% valid data. Thus, 9 athletes were analyzed in a total of 80 nights and 68 morning measurements, ranging from 5 to 10 nights and morning measurements per athlete.

Identification of deep sleep phases

In the 80 included nights, a mean of 5.3 ± 1.8 deep sleep phases per night were detected (range 2 to 8 phases per night), with a mean duration of 17 ± 5 min per deep sleep phase.

Eighteen EEG measurements were performed of which 16 recordings were of sufficient quality to be used in the analysis. Because this analysis was of descriptive nature, all nights were included into a pooled data set (all valid nights of all athletes). Median delta power of deep sleep phases was 279% of mean power of the respective night (IQR 163% - 345%) and 75% of the detected phases were correctly identified. An example of a typical
night’s EEG is shown in Fig. 1. In 89% of the available deep sleep segments, there was complete absence of movement. In the remaining 11% there were minimal movements lasting less than 10 s during each segment.

**HRV parameters**

Time domain parameters and parameters from the frequency analyses show high correspondence. Correlations between SDNN and total power as well as between RMSSD and HF power were >0.9 and showed the same patterns over the different segments. Thus, in order to avoid redundancy, we chose to focus on time domain parameters only. Median values of HR, RMSSD and SDNN in the different segments are depicted in Figure 2.

**HRV in supine position awake with HRV analyzed in the other segments**

For RMSSD and HF (both markers of vagal activity) high associations (all standardized β > 0.68) between the morning segment measured in supine position and the two deep sleep segments were found. Only small to moderate associations were observed between HRV parameters of the supine wake segment and those of segments regardless of sleep stages during sleep (4 hours and morning supine segments) as well as of the standing segment after an orthostatic challenge. Outcomes from the LMEMs are reported in Table 1. Visual inspection of residual plots did not reveal deviations from homoscedasticity or normality. Relationship between RMSSD/RR in supine position and during deep sleep as well as RMSSD/RR values for two athletes over all analyzed segments are illustrated in Figure 3.

**Training**

No difference was found in training load between the two training phases (p≥0.4). Median daily training duration was 232 min (IQR 180-240) and median daily training load was 1380 AU (arbitrary units) (IQR 905-1470).
Effect of training load on HRV

Training load showed no effect on any HRV parameters analyzed in any of the measured phases (all p > 0.1). Visual inspection of residuals plots did not reveal deviations from homoscedasticity or normality.

Subjective rating of fatigue

None of the athletes showed any signs of overtraining during the duration of the study.

Discussion

This is the first study to compare HRV values measured during sleep with those measured in the following morning in a homogenous group of world class athletes. Close correspondence was found between HRV parameters measured during deep sleep and HRV parameters measured in supine position after awakening. Only low to moderate associations were found between morning supine HRV measurements and HRV of night segments chosen irrespective of sleep phases or after awakening in standing position. Training load of the previous day showed no acute effect on HRV parameters of any of the analyzed segments, possibly due to a relatively homogeneous training load.

Morning wake supine HRV measurements are recommended by the ESC Task Force and are frequently used in athletes. In a previous study at our center performed in elite cross-country skiers, HRV measurements were performed in the morning in supine and standing position on a weekly basis over the course of one year, we found that compliance was poor due to the time requirement of the measurements. This stands in contrast to the necessity to conduct measurements on a regular basis, and makes alternative HRV measurements with a lesser time requirement attractive. Thus, sleep is a promising time
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efficient alternative to measurements in supine position after awakening, especially with the emerging possibilities of measuring RR-intervals using wearable technologies.

The method used in the present study to select a segment for HRV analysis during deep sleep by relying merely on the HRV signal itself is based on findings from studies that have used polysomnography with simultaneous HRV recordings. They reported a good correspondence between cortical activity typical of deep sleep and HRV parameters such as rRR, LF/HF, or HF in normalized units (which is identical to LF/HF). Our study verifies and supports the idea of identifying deep sleep selection by HRV only.

In previous studies assessing HRV during sleep, a 4-hour segment (often from midnight to 4 am) irrespective of sleep stages has frequently been used. In our study, there was a moderate association between HRV parameters analyzed during this 4-hour segment with HRV measured in the awakened supine state. This suggests that a predefined segment may not be optimal for performing HRV analyses, because HRV varies greatly between different sleep stages, with sleep stages other than deep sleep being characterized amongst others by body movements and irregular breathing, making the interpretation of HRV parameters more difficult. Likewise, HRV values of a manually chosen stationary segment just before awakening showed a weaker correspondence to the supine segment after awakening than HRV values from the deep sleep segment, probably because of sympathetic activation in the morning before waking. Our data supports the notion that nocturnal HRV should be determined for individual sleep stages rather than averaged over a fixed time window in order to reduce the variance and satisfy the requirement for signal stationarity.

Our study further confirms that deep sleep phases for HRV determination can be reliably determined from the RR-interval signal itself.

Recent studies in athletes have suggested a benefit of assessing HRV during an orthostatic test additional to the supine measurement to identify athletes at risk of
overtraining. Furthermore, effects of exercise may be visible for a longer time period in standing compared to supine measurements. Within athletes, values of HRV parameters after the orthostatic challenge only correlated weakly with those of supine position in wake state, indicating that the activation of the sympathetic nervous system by the orthostatic challenge is likely to provide additional information. For example, vasomotor mediated oscillations at 0.1Hz could be quantified by frequency analysis. An example of different reactions of two athletes to an orthostatic challenge is shown in Fig. 3 (right panel).

No effect of training load was found on any HRV parameter in any of the analyzed segments. This is in agreement with findings from a recent study where no association between daily fluctuating training load and HRV parameters, measured during the recovery period immediately after submaximal exercise, were found in elite soccer player. In our study, the range of measured training loads was rather small, which probably provided insufficient heterogeneity. There was no indication for overtraining for any athlete according to the recovery-stress questionnaires. Further, training load from strength/speed training is more difficult to quantify than training load from endurance training and therefore effects on HRV parameters may be more difficult to identify. This is in contrast to studies with endurance athletes where endurance training load was found to have an effect on HRV. However, the mechanisms behind the effect of endurance training on HRV are still poorly understood. Whether HRV during deep sleep reflects recovery status and can predict overtraining needs to be investigated further in studies in athletes with highly heterogeneous training loads. Moreover, quantifying training load from duration and intensity as used in our study has some limitations. Training modality varied greatly in our athletes, with skiing training on the slopes, strength training or endurance training, hence making it difficult to compare training loads from different activities.
We found reduced SDNN (only in the second deep sleep segment) in deep sleep compared to supine wake measurements, while RMSSD was comparable between the two segments. This finding may be specific to elite athletes and cannot be generalized to less trained athletes, as has been shown by a previous study comparing highly trained athletes with moderately trained athletes and sedentary people. Their results indicate both reduced LF and HF power during deep sleep compared to supine wake morning measurements in all three groups.

A major strength of our study was the inclusion of a homogenous group of world-class athletes. Further, HRV data variance could be reduced by our longitudinal study design, and the use of linear mixed models allowed us to analyze the data at both, a group and on the individual athlete’s level.

A limitation of our study is the assessment of training load. Training loads are difficult to quantify in alpine skiers because their training consists of various elements that cannot be easily compared. All trainings were performed in a real life setting and changing their training schedule would not have been feasible in these elite athletes. This, unfortunately, led to a rather small range of training loads in our data. Further, the self-reported subjective nature of the training load measure is only an estimation of training induced stress, however, the method used in this study has been shown to be an effective way for quantifying training load. Our sample size was limited by the small number of top athletes in this discipline in Switzerland. We did not include a time delay between cardiac autonomic nervous system activity and cortical activity, as suggested in a previous study, because we did not determine individual delays. Determination and inclusion of individual time delays would have probably improved the correspondence between rRR and delta power found in this study, however this was not the primary focus of this study.
The present study provides evidence that HRV measurements during the night can be used for daily monitoring of HRV and may replace morning supine measurements, in particular when HRV is assessed during deep sleep phases identified by reduced rRR (corresponding to reduced total power or SDNN). The ease of time-efficient nocturnal measurements may result in higher compliance of the athletes.

Acknowledgements

DH, MT, DS, PA, DE, PE and MW designed the study. M.T was involved in data acquisition. D.H, M.T, D.S, DE and PE were involved in data analysis. DH, MT and PE composed the manuscript. All authors reviewed and approved the manuscript. Dr. Olstad currently works as researcher at Polar Electro Oy, Finland. Prof. Wilhelm reports a grant from the Swiss Society of Sports Medicine, during the conduct of the study. The other authors declare no competing interests. We would like to thank all athletes who participated in the study. This study was funded by a scientific prize of the Swiss Society of Sports Medicine, who had no influence on any part of the study. The results of the current study do not constitute endorsement of the product by the authors or the journal.
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Figure 1: Example of a typical night recording. Time course over one night of rRR (blue) and DF (green) are illustrated in the upper panel. The blue dashed line represents the cut-off (90% of mean rRR) used for detecting deep sleep using the rRR signal. Detected deep sleep phases are shown in light grey and the chosen segments for later HRV analysis are highlighted in red. RR intervals in the segments later used for HRV analysis are shown in the lower panels.

DF, delta power (1-4.5 Hz; normalized to mean delta power of the recording); rRR, Pearson correlation coefficients between two successive heart beats.
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**Figure 2**: Box plots showing group medians and quartiles of HRV parameters for the five different segments using each athlete’s median of all nights. The selected HRV parameters are heart rate (HR, left panel), root-mean-squared difference of successive RR-intervals (RMSSD, middle panel) and standard deviation of the RR-intervals (SDNN, right panel). Box plots show median values (solid line), IQR (box outline), spread of data points without outliers (whiskers) and outliers identified as 1.5 * IQR (open circles).

DP, Deep sleep segment; M-Sleep, Morning sleep segment; Sup, Morning awake supine segment; Stand; Morning awake standing segment.

** Significantly different from all other segments

* Significant difference between the two segments
Figure 3: Relationship between RMSSD normalized for RR interval measured during the first deep sleep segment and the supine segment in the morning (left panel). Regression lines are shown for individual athletes. RMSSD/RR values over the 5 analyzed segments for two athletes are shown in the right panel. Two different reactions to an orthostatic challenge are displayed.

DP, Deep sleep segment; M-Sleep, Morning sleep segment; Sup, Morning awake supine segment; Stand; Morning awake standing segment; RMSSD, root-mean squared successive differences; RR, time interval between two heart beats; ln, natural logarithm
Table 1: Mixed linear models for HRV parameters of individual segments with those of the morning supine segment. The interpretation of the table is similar to a correlation matrix. However, the use of mixed models allows accounting for different slopes and intercepts of individual athletes.

<table>
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<th>Deep Sleep 1</th>
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<th>Morning Sleep</th>
<th>Morning Awake Standing</th>
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<td>0.26</td>
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</tr>
</tbody>
</table>

Beta, standardized beta-coefficients; HRV, heart rate variability; HR, heart rate; SDNN, standard deviation of the RR intervals; RMSSD, root mean square of successive differences; HF, high frequency power; LF, low frequency power; TP, total power; Mixed linear models were performed for the dependent variables HR, SDNN, RMSSD, HF, LF and TP of the morning supine segment. The corresponding HRV variable and HR for a given segment were included as fixed effects and intercepts for each athlete were included as random effects for the respective models.