RR and QT Interval Variability as Biomarkers of Post-Exercise Recovery in Athletes

Matias Kanniainen, Johannes Mämmelä, Esa Räsänen

Tampere University, Tampere, Finland

Abstract

We investigated the behavior and variability of QT and RR intervals from 30-second ECG recordings to assess physiological recovery after different types of athletic training. We aimed to determine whether interval variability can serve as a marker of post-exercise autonomic recovery across exercise types. ECG data were analyzed from eight athletes (1 male, 7 females, age 18±2 years) from the Sport D.B. 2.0 database. Each athlete completed velocity, competition, and strength training sessions with ECGs recorded before, after warm-up, after training-specific exercises, and at 5, 10, and 15 minutes post-exercise. We assessed mean RRIs, QTIs, and Fridericia-corrected QTc. Variability was evaluated using RMSSD, SD1/SD2, DFA short-scale scaling exponent α_1 for RRIs, and SDQT for QTIs. RRIs and QTIs decreased during exercise and increased post-exercise across all sessions. Velocity training led to the largest reductions with incomplete recovery by 15 minutes, while RMSSD and SDQT remained suppressed and SD1/SD2 and α_1 rose above baseline. Competition training showed substantial reductions with recovery by 15 minutes, while strength training caused minor changes with rapid recovery. QTc remained stable across sessions. ECG-derived metrics may offer practical tools for monitoring autonomic recovery of athletes.

1. Introduction

Heart rate variability (HRV) metrics quantify the changes in the time intervals of consecutive RR intervals (RRI) of the electrocardiogram (ECG) [1]. HRV measurements are becoming increasingly more popular due to enhanced signal and algorithmic quality of consumer-grade wearable devices, such as smartwatches [2]. HRV measurements can be utilized to assess the nervous system controlling the heart, which often reflects the state of recovery of an athlete [3]. Therefore, competitive athletes tend to use HRV metrics to monitor their recovery from physical exercise to optimize training and performance.

Several HRV methods have been suggested, including time-domain, frequency-domain and non-linear metrics. Common time-domain metrics include root mean square of successive differences (RMSSD) and standard deviation of RRIs. Frequency-domain methods include low-frequency (LF) and high-frequency (HF) power, and their ratio (LF/HF), which can accurately reflect the activation of the autonomic nervous system. [1] Non-linear measures, on the other hand, quantify the correlations of RRIs. Commonly used methods are SD1/SD2 ratio of the Poincaré plot [4] and detrended fluctuation analysis (DFA) [5].

The QT interval (QTI) of the ECG represents the time of ventricular depolarization and repolarization. QTI is dependent on the heart rate (HR), and should therefore be adjusted to HR [6]. QTI typically shortens during exercise [7]. QTI variability (QTV) is often quantified by calculating the standard deviation of QT intervals (SDQT) during a measurement.

Here, we study whether the average behavior and variability of RR and QT intervals can serve as reliable markers of post-exercise autonomic recovery in different types of exercise in a group of athletes. Furthermore, we study the responses of the metrics and evaluate the training load in different types of exercise.

2. Data and Preprocessing

We analyzed ECG data from eight athletes (1 male, 7 females; age: 18 ± 2 years) from the Sport D.B. 2.0 database [8]. All subjects were healthy with no previous history of diseases and under no medication [9]. Originally, the dataset consists of 10 subjects, but due to poor data quality of subjects S2 and S7, they were excluded from the analysis. The open-source dataset [8] has an acceptance of the Ethics Committee of Università Politecnica Delle Marche, where the data was aquired, and it is in compliance with the ethical principles of the Helsinki Declaration.

Each athlete completed three exercise sessions: velocity training, strength training and competition. For velocity and strength training, 30-second ECGs were recorded (i) before, and (ii) after warm-up, (iii-iv) after training-specific exercises, and at (v) 5, (vi) 10, and (vii) 15 minutes

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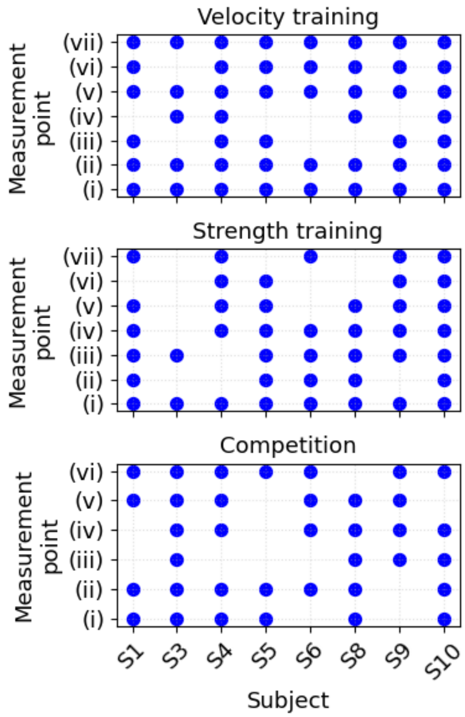

Figure 1. Analyzed measurement points of each subject (S1 etc.) after the preprocessing in each exercise mode.

post-exercise. For velocity training, the recording (iii) is measured after two 120m sprint runs and (iv) is measured after a 150m sprint run. For strength training, the recording (iii) is measured after six series of mid squat jumps and (iv) is measured after six series of step jumps. For competition, 30-second ECGs were recorded (i) before, and (ii) after the warm-up, (iii) after competition, and at (iv) 5, (v) 10, and (vi) 15 minutes post-competition. The competition was a sprint race of 200 m. [9]

ECGs were measured with a sampling rate of 300 Hz and the QTIs and RRIs were extracted with an in-house algorithm [10]. To ensure sufficient data quality, we resorted to the following preprocessing procedure: (i) the local median μ from each 30-second recording was calculated, and the values outside of the range 0.75μ - 1.50μ were excluded, (ii) the interval pairs for which the RR (QT) intervals deviated more than 500 ms (300 ms) from the preceding intervals were discarded, and (iii) the recordings from which 20% or more interval pairs were filtered were discarded from the analysis. The remaining preprocessed measurement points for each subject in each exercise mode are shown in Fig. 1.

3. Methods

To quantify the time-dependent variability of RRIs, we utilize RMSSD, which quantifies the variance in the subsequent beats in the time series. This common HRV measure is in use in several wearable devices to assess recovery. To analyze the non-linear properties of the RRIs, we utilize the SD1/SD2 ratio [4], and DFA short-scale scaling exponent α_1 [5]. The SD1/SD2 ratio quantifies the correlation between successive RRIs, and its increase is often associated with sympathetic activation. DFA short-scale scaling exponent α_1, on the other hand, describes the correlations over scales of 4–16 RRIs [11]. Decrease of DFA α_1 is a well-known effect during physical exertion [12]. In all calculations, we use second-order polynomial fitting in the calculations of detrended variances of DFA. In this study, frequency-domain measures are excluded because of the limited length of the ECG recordings [1].

For QTV, we utilize SDQT. We also considered Fridericia-corrected QTc, defined as $\mathrm{QTc} = \mathrm{QT}/\sqrt[3]{\mathrm{RR}}$ [13]. Along with the variability measures, we calculate the mean values of RRIs, QTIs and QTc:s.

4. Results

The results of velocity training are shown in Fig. 2. After baseline, mean RR (baseline at 755 ms), mean QT (413 ms), RMSSD (140 ms) and SDQT (76 ms) decrease during the exercise, and do not reach their initial level during the recovery up to 15 minutes. Mean RR, mean QT, RMSSD and SDQT reach values of 430 ms, 361 ms, 65 ms, and 51 ms after 15 minutes of recovery, respectively. This indicates incomplete recovery relative to the baseline. QTc remains relatively stable across the measurement points (baseline at 455 ms), reaching its lowest value of 371 ms at (iv) after two 150 m sprint runs. SD1/SD2 (baseline at 0.69) increases directly after exercise to 0.82 indicating a rise in sympathetic activity, but decreases during the recovery (0.56-0.76) suggesting autonomic balance restoration. DFA α_1 shows normal baseline values (0.99) and decreases to its minimum following exercise (0.80). During recovery, DFA α_1 rises again, surpassing baseline after 10 and 15 minutes (1.21 and 1.38, respectively), reflecting autonomic nervous system recovery.

For the strength training, the results are shown in Fig. 3. Following baseline measurements, all HRV and ECG parameters demonstrate a notable decrease during the exercise phases. Specifically, mean RR intervals drop significantly from baseline (762 ms) to exercise (around 520 ms), reflecting increased heart rate during strength activity. Similarly, RMSSD and SD1/SD2 decrease during exercise, indicating reduced parasympathetic activity and a shift toward sympathetic dominance. However, after 5-10 minutes of recovery, mean RR, mean QT, RMSSD, and SDQT reach their baseline level indicating complete recovery. Again, mean QTc yields relatively stable values across the measurement (413 - 475ms), implying a successful HR-independence. DFA α_1 (1.25 at rest) shows a slight decline during exercise (0.97). SD1/SD2 (0.55) in-

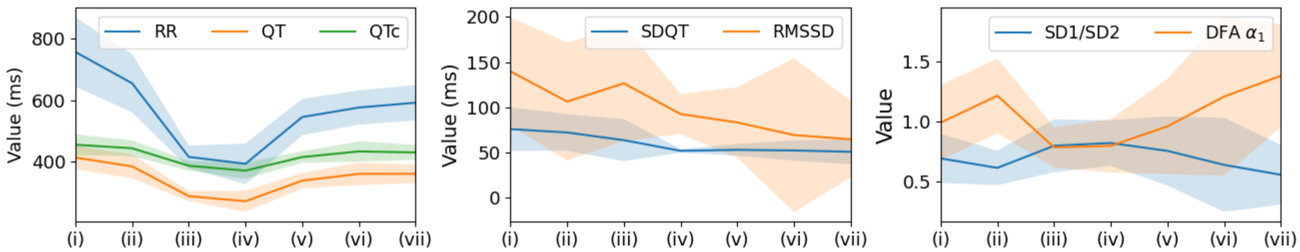

Figure 2. Mean (solid line) and standard deviation (shaded areas) of velocity training. (i) before, and (ii) after warm-up; after (iii) two 120 m, (iv) two 150 m sprint runs; recovery after (v) 5, (vi) 10, and (vii) 15 minutes.

creases slightly after warm-up to 0.75, but decreases during the exercise phase (0.62, 0.60 after mid squat and step jumps, respectively). Notably, DFA α_1 rises above baseline levels reaching a value up to 1.46, after 10 minutes of recovery. This behavior implies a post-exercise parasympathetic rebound and enhanced autonomic regulation, reflecting good recovery capacity and autonomic adaptability following strength training.

Finally, the results of competition are shown in Fig. 4. Mean RR (684 ms), QT (400 ms), RMSSD (187 ms) and SDQT (83 ms) decrease rapidly after warm-up period to 587 ms, 356 ms, 90 ms, and 50 ms, respectively. After the competition, there is further decrease in mean RR (436 ms) and QT (289 ms) but RMSSD and SDQT increase slightly to 109 ms and 54 ms, respectively. After the competition, the values increase steadily during the recovery, reaching the maximum values at measurement point (vi) (15 minutes post-competition) (RR: 606 ms; QT: 397 ms; RMSSD 143 ms; SDQT: 69 ms). There is a notable decrease from QTc baseline (454 ms) to after the competition (380 ms). This implies that QTc is not adjusted to the HR globally over the measurements. From the non-linear measures SD1/SD2 decreases rapidly from 0.75 post-warm-up to 0.5 implying psychological stress before the competition, but it reaches the maximum value of 1.00 directly after the competition. From there, SD1/SD2 decreases steadily to the baseline value of 0.75 during recovery. From all three exercise modes, DFA α_1 has the lowest value of 0.85 at the baseline, which may imply psychological stress before the competition. It reaches its maximum value of 1.13 after the warm-up, from where it decreases below baseline to 0.73 after the competition. During recovery, DFA α_1 increases steadily above the baseline to 1.00 indicating physical recovery after the competition.

All three different exercise types cause significant reduction in mean RR and QT intervals, i.e., increase in HR. In velocity training and competition, the drop is more significant compared to the strength training, indicating greater cardiac stress. Strength training shows the fastest and most complete recovery based on RMSSD, SDQT, SD1/SD2 and DFA α_1, whereas velocity training exhibits the slowest and least complete recovery based on the HRV values compared to their respective baseline values before the excercise. Even though the mean RR and QT values recover close to the baseline values in competition, RMSSD and SDQT remain low after recovery, indicating sustained sympathetic domincance. Small baseline value of DFA α_1 in competition may suggest psychological stress before the competition, and the values approach normal behavior ($\alpha_1 = 1.0$) by the end of the recovery [11].

5. Conclusions

HRV metrics and QT variability provide promising biomarkers for the evaluating of recovery after exercise. The same eight athletes completed three different exercise sessions (velocity and strength training, competition), and in each exercise session the mean RR and QT inter-

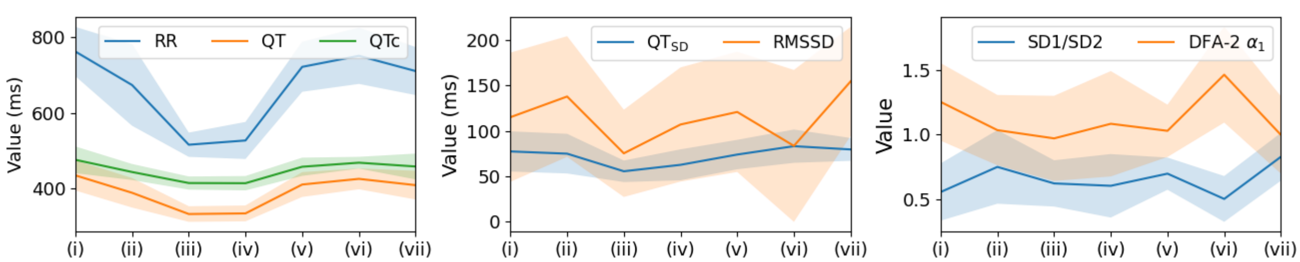

Figure 3. Mean (solid line) and standard deviation (shaded areas) of strength training. (i) before, and (ii) after warm-up; after six series of (iii) mid squat jumps, (iv) step jumps; recovery after (v) 5, (vi) 10, and (vii) 15 minutes.

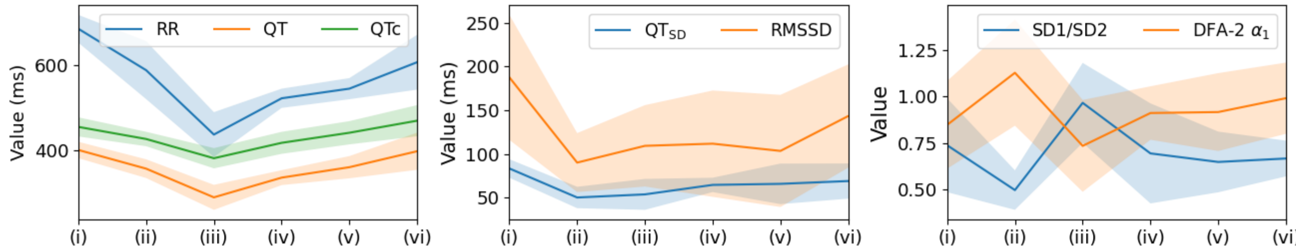

Figure 4. Mean (solid line) and standard deviation (shaded areas) of competition. (i) before, and (ii) after warm-up; (iii) after 200 m sprint race; recovery after (iv) 5, (v) 10, and (vi) 15 minutes.

vals were reduced during physiological exertion. The decrease of several HRV metrics, e.g., RMSSD, SD1/SD2, SDQT and DFA α_1 provided insight about the recovery and the respective differences between different exercise modes. Velocity training exhibited the least complete and the strength training exhibited the most complete recovery from the baseline within 15 minutes of the end of the exercise session. In competition, especially the low baseline value of DFA α_1 implied psychological stress before the exercise, while RMSSD and SDQT indicated moderate recovery and incomplete parasympathetic activation after the exercise session. While HRV is already widely used in consumer-grade wearables, it could be leveraged more comprehensively to assess recovery. In addition, QTI variability – though more challenging to capture reliably in wearables – may offer complementary insights into short-term recovery following exercise alongside existing recovery metrics.

Acknowledgments

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Address for correspondence:

Matias Kanniainen

Computational Physics Laboratory, Tampere University, P.O. Box 692, FI-33014 Tampere, Finland

matias.kanniainen@tuni.fi