HRV4Training: Large-Scale Longitudinal Training Load Analysis in Unconstrained Free-Living Settings Using a Smartphone Application

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Abstract— **We describe an approach to support athletes at various fitness levels in their training load analysis using heart rate (HR) and heart rate variability (HRV). A smartphone-based application (HRV4Training) was developed that captures heart activity over one to five minutes using photoplethysmography (PPG) and derives HR and HRV features. HRV4Training integrated a guide for an early morning spot measurement protocol and a questionnaire to capture self-reported training activity. The smartphone application was made publicly available for interested users to quantify training effect. Here we analyze data acquired over a period of 3 weeks to 5 months, including 797 users, breaking down results by gender and age group. Our results suggest a strong relation between HR, HRV and self-reported training load independent of gender and age group. HRV changes due to training were larger than those of HR. We conclude that smartphone-based training monitoring is feasible and a can be used as a practical tool to support large populations outside controlled laboratory environments.**

I. INTRODUCTION AND RELATED WORK

Heart rate (HR) and heart rate variability (HRV) have long been used to monitor athletes fitness levels as well as recovery from previous workouts [1]. The rationale behind monitoring recovery using HR or HRV is that heavy training shifts the autonomic nervous system towards a sympathetic drive [2], which is reflected in higher HR and lower HRV within 24h to 48h after training. Monitoring recovery status by means of an HRV measurement is becoming more common among athletes as well as sport enthusiasts [3]. HRV features representative of parasympathetic activity and hence of recovery, which are typically reported in literature are the high frequency power and the square root of the mean squared difference between beat to beat intervals, or rMSSD [4]. Resting HR has been long used as a marker of fatigue, with an increase in HR typically being representative of a longer recovery time requirement [1]. Increases in HR have been linked to a shift towards the sympathetic drive of the autonomic nervous system, triggered by intense exercise [5]. However, HR changes after training are often in the order of a few beats and of limited practical applicability [3]. Other measures used as proxies to autonomic function include HRV features, showing stronger links with exercise intensity and recovery in recent studies [3], [2], [4].

Smartphone-based HR and HRV measurements have become popular during the last years [6], as smartphone-integrated sensors could be used, e.g. for photoplethysmography (PPG) [7]. Convenient PPG spot-measurement can be performed by monitoring blood flow using the phone's camera and flash light as light source [8], [9], [10]. The phone-based PPG approach has been validated and confirmed to provide reliable HRV estimates [8], [11].

HRV-based assessment of training load and recovery has been validated multiple times in clinical studies or on limited sample sizes of uniform samples of the population (e.g. a group of elite athletes [12], [13], a sport team, or college students [14]). Similarly, PPG-based tools aiming at replacing laboratory equipment were validated in laboratory conditions or on limited sample sizes.

However, single studies without longitudinal measurements (i.e. daily measurements taken for multiple weeks) cannot provide population-average quantifications of the training effect on HR, HRV. To date, no study considered the deployment of PPG-based HR and HRV monitoring to analyze training effect in unconstrained free-living conditions longitudinally and over a broad population.

We describe a PPG-based solution to acquire HRV data and relevant reference points (e.g. self-reported annotations on training days) using a mobile phone application and analyze data acquired from 797 users over a period of 5 months. The application was released on the Apple Store and could be downloaded by anyone with an iPhone, thus allowing us to investigate the relation between HR, HRV and training in unsupervised free-living settings. Additionally, we break down our results by gender and age groups, showing that PPG-based HR and HRV monitoring can be effectively used in free-living settings to monitor training load. In particular, we show $5.7 - 11.0\%$ differences in rMSSD and $1.0{-}1.9\%$ differences in HR between days following low and high training load, further validating the more discriminative power of HRV with respect to HR only.

II. DATA ACQUISITION AND DATA ANALYSIS

In this section we describe the following:

- *Signal processing*: signal processing techniques used to determine HRV features using a mobile phone.
- *Measurement protocol*: instructions provided to users of the application upon download, to ensure reliability of the measurements.
- *Features and annotations*: description of the parameters collected and used in this analysis.
- *Users*: description of anthropometric characteristics and other parameters of the users included in this analysis.
- *Data analysis*: analysis performed to determine the effectiveness of the proposed application in highlighting the relation between HR, HRV and training.

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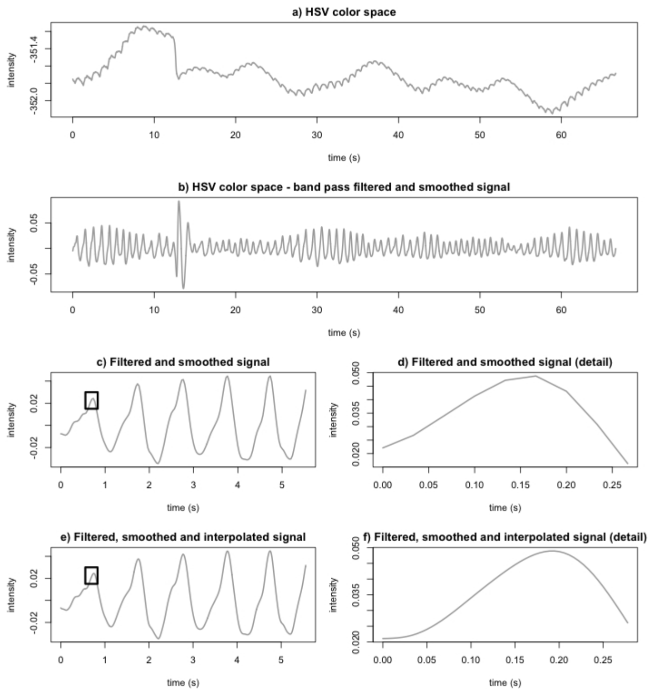

Fig. 1. Example of the data processing performed in the HRV4Training smartphone application. a) Recorded PPG signal intensity in HSV color space. b) Signal after band pass filtering between 0.1 and 10 Hz. c-d) Details of the filtered signal e-f) Signal after cubic spline interpolations and up-sampling to 180 Hz.

A. Signal Processing

PPG is an unobtrusive technique for detecting blood volume changes during a cardiac cycle. PPG is often measured using reflection by illuminating the skin using a LED (e.g. the phone's flash) and detecting the amount of light that is reflected by a photodetector or a camera located next to the light source. The resulting PPG signal is composed of a DC component, varying slowly depending on tissue properties and blood volume, and an AC component, i.e. the pulsatile component. After the systole, blood volume increases, reducing the received light intensity. On the contrary, during diastole blood volume decreases and hence light reflection increases [15].

Given the low frame rate of mobile phone cameras, different signal processing techniques need to be employed to derive HRV from the phone video stream [8]. First, we acquired a video stream at a frame rate of 30 Hz. Red, green and blue channels are averaged over the entire frame, before converting between the RGB and the HSV color space. Then, the intensity component of the HSV color space is filtered using a Butterworth band pass filter of order 4 and frequency pass band between 0.1 and 10 Hz, as shown in Fig. 1.a-b. The band pass filter is used to remove the DC component of the signal, as well as high frequency noise, while maintaining the AC component. Finally, cubic spline interpolation is used to up-sample the signal between 30 and 180 Hz (see Fig. 1.e-f). Up-sampling the data is a necessary requirement to have sufficient resolution for HRV features computation [16].

We implemented a peak detection algorithm to determine peak to peak intervals from up-sampled PPG data. Peak detection was based on a slope inversion algorithm. Finally, peak to peak intervals were corrected for artifacts by removing intervals differing more than 20% from the previous interval, similarly to clinical practice for ectopic beat and motion artifacts detection in electrocardiography (ECG) [17]. Peak to peak intervals were used to compute HRV features (rMSSD), similarly to RR intervals in ECG data.

B. Measurement Protocol

Users downloaded the HRV4Training application from the Apple Store and agreed to provide collected measurements and annotations for research purposes via a consent form embedded in the application. The application instructed users to perform the measurement right after waking up while still lying down, to limit the effect of other stressors. In addition, a breathing pattern was suggested to improve measurement consistency and reliability [18]. Instructions were provided to reproduce conditions similar to measurements at rest in laboratory settings, as shown in Fig. 2. Measurement duration was configurable between 1 and 5 minutes, since 1 minute measurements were previously validated and considered of sufficient duration for accurate HRV analysis of time domain features such as rMSSD, the feature used in this study [19].

C. Features and Annotations

HR was computed as the mean HR over the measurement window while as HRV feature we used rMSSD as it was shown to be a clear marker of parasympathetic activity and often used to determine physiological stress due to training load [12], [14], [4]. rMSSD was computed as the square root of the mean squared difference between PPG peak to peak intervals after artifact correction. Trainings were manually annotated inside the application using a short questionnaire that prompted the user right after the measurement. Training intensities were selected among four categories; rest, easy, average and intense. Fig. 2 shows screenshots of the application.

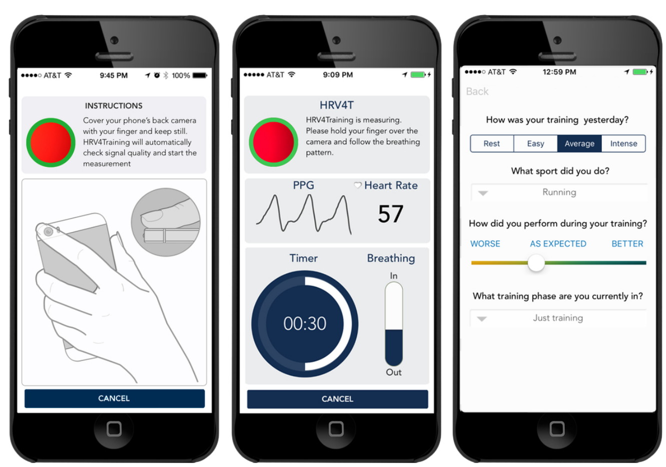

Fig. 2. Screenshots of the HRV4Training application used to acquire HR, HRV, and training data by participants on their own.

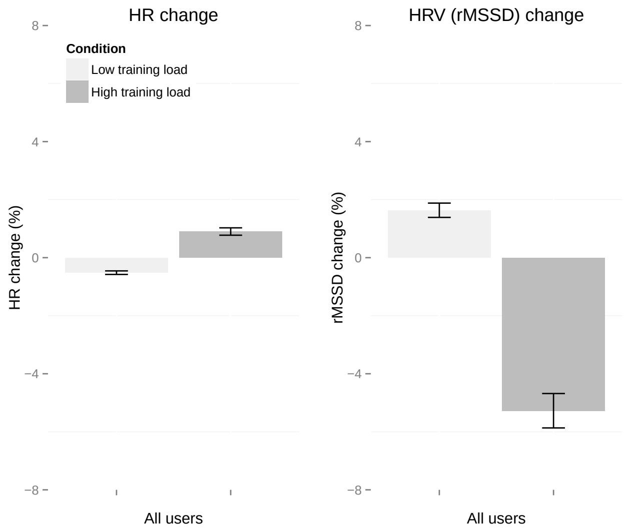

Fig. 3. Relation between HR, HRV and training on the entire dataset. HR is consistently increased on days following higher training load, while rMSSD is consistently decreased. Relative changes in rMSSD are bigger, highlighting how HRV can be more discriminative of training load. Error bars indicate the standard error.

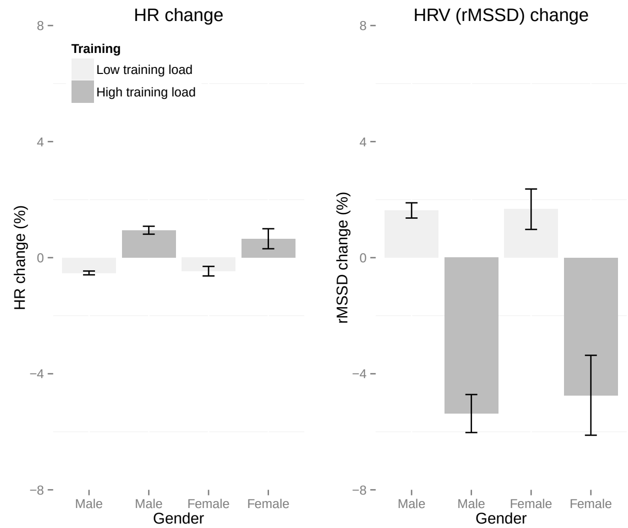

Fig. 4. Relation between HR, HRV and training for male and female users. In both conditions HR is consistently increased on days following higher training load, while rMSSD is consistently decreased.

D. Users and Measurements

We included in this analysis all users that recorded at least 20 HRV measurements and 7 annotated trainings since we considered 3 weeks and one training every 3 days the minimum amount of data necessary to investigate the relation between HRV and training longitudinally in each individual. Additionally, we excluded all measurements which resulted in more than 10% RR intervals to be discarded after applying the artifact correction method described in Sec. II-A. After applying our inclusion criteria we were left with 797 users (674 male, 123 female) and 55426 measurements, i.e 70 measurements per user on average. Mean age was 39.8 ± 10.6 years, mean weight was 76.9 ± 12.3 kg, mean height was 177.9 ± 7.9 cm and mean BMI was 24.2 ± 3.1 kg/m^2. Most users reported training 3 or more times per week (N=711). Users were also grouped by age in order to analyze the relation between physiological data and training across age groups. Age groups were 20 to 30 years old (N=132), 30 to 40 years old (N=280), 40 to 50 years old (N=243) and 50 to 60 years old (N=95). Mean rMSSD over the entire dataset was 77.9 ± 45.3 ms while mean HR was 58.8 ± 9.4 bpm.

E. Data Analysis

The relation between physiological data and training was analyzed by first computing day to day differences in HR, HRV for each user. Subsequently, we analyzed the change in HR and HRV on days following trainings of different intensities for each user. We clustered training intensities in two groups; *low training load* comprising rest days and training days annotated as easy, and *high training load* comprising training days annotated as average or intense by users. We additionally analyzed the relation between HR, HRV and training by age group and gender.

III. RESULTS AND DISCUSSION

Data from 797 users was analyzed as described in Sec. II-E. Fig. 3 shows day to day changes in HR and HRV across all users. HR decreased by 0.3 bpm (0.5%) on average after rest days or easy trainings (case *low training load*), while rMSSD increased by 1.3 ms (1.6%). On the contrary, HR increased by 0.5 bpm (0.9%) on average after average or intense trainings (case *high training load*), while rMSSD decreased by 3.5 ms (5.3%). Differences in HR and rMSSD on days following low and high training loads were both significant (p-value=6.408^{-14} for HR, p-value=1.997^{-14} for rMSSD). These results are consistent with previous small-scale studies showing reduced parasympathetic activity after trainings of higher intensity [3], [2], [4]. HR changes between training conditions were on average rather small (between 1.0% and 1.9% across the groups analyzed) while changes in rMSSD were between 5.7 and 11.0%, highlighting the higher discriminative power of HRV features in the context of monitoring training load.

We analyzed the relation between training load and physiological data separately in male and female users as well as in different age groups. Results reported in Fig. 4 and Fig. 5 show consistent findings, with HR and rMSSD being respectively increased and decreased on days following higher training load. In particular, in male users the relative difference between low and high training load was 7.0% for rMSSD and 1.5% for HR. In female users percentage differences were 6.4% for rMSSD and 1.1% for HR (see Fig. 4). rMSSD percentage differences across age groups and training conditions were 6.8% for the $20-30$ years old group, 6.8% for the $30-40$ years old group, 5.7% for the $40-50$ years old group and 11.0% for the $50-60$ years old group. HR percentage differences across age groups and training conditions were 1.9% for the $20{-}30$ years old group,

1.9% for the $30-40$ years old group, 1.0% for the $40-50$ years old group and 1.2% for the $50-60$ years old group (see Fig. 5). Finally, we built two linear models where HR and rMSSD were the dependent variables, and the independent variables were age group and gender. All coefficients for the independent variables of the HR prediction linear model were close to zero (-0.28 to 0.02) and were not significant ($p > 0.07$). Similarly, all coefficients for the independent variables of the rMSSD prediction linear model were close to zero (-0.44 to 0.34) and were not significant ($p > 0.31$). Thus, the relation between HR, rMSSD and training load was independent of gender and age group.

IV. CONCLUSIONS

In this paper we investigated the relation between HR, HRV and training data as acquired in unsupervised free-living settings. We first introduced the signal processing techniques developed to acquire HR and HRV data using only a mobile phone. Using the developed application we were able to acquire longitudinal data comprising measurements from 797 users that monitored their HR and HRV for a period of 3 weeks to 5 months. Given the greater sample size compared to typical studies we could provide confirmative insights on the feasibility and efficacy of such monitoring in users of different gender and age groups. Our analysis showed small but consistent increases in HR as well as reductions in rMSSD following trainings of higher intensity, regardless of gender and age group. Hence, HR and HRV-based training guidance might be effective on a broad set of individuals. As we grow our dataset and we collect more data and additional self-reported annotations (e.g. sleep quality, traveling, perceived physical condition, etc.) we will be extending our analysis to better understand complex relations between physiological, behavioral and lifestyle factors, in uncontrolled free-living settings.

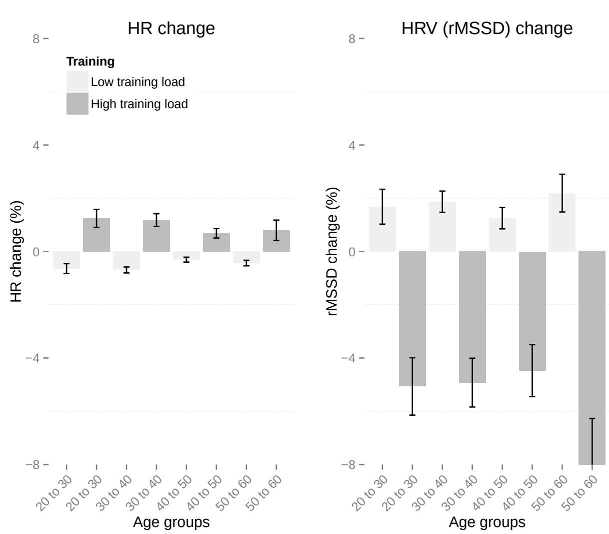

Fig. 5. Relation between HR, HRV and training for different age groups. In all conditions HR is consistently increased on days following higher training load, while rMSSD is consistently decreased.

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