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Towards pulse rate parametrization during free-living activities using smart wristband

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Abstract

Objective: The growing interest to integrate consumer smart wristbands in eHealth applications spawns the need for novel approaches of data parametrization which account for the technology-specific constraints. The present study aims to investigate the feasibility of a consumer smart wristband to be used for computing pulse rate parameters during free-living activities. *Approach*: The feasibility of computing pulse rate variability (PRV) as well as pulse rate and physical activity-related parameters using the smart wristband was investigated, having an electrocardiogram as a reference. The parameters were studied on the pulse rate and step data from 54 participants, diagnosed with various cardiovascular diseases. The data were acquired during free-living activities with no user lifestyle intervention. *Main results*: The comparison results show that the smart wristband is well-suited for computing the mean interbeat interval and the standard deviation of the averaged interbeat intervals. However, it is less reliable when estimating frequency domain and nonlinear parameters. Heart recovery time, estimated by fitting an exponential model to the events, satisfying the conditions of the 3 min step test, showed satisfactory agreement (relative error $<$20%) with the reference ECG in one-third of all cases. On the other hand, the heart's adaptation to physical workload, expressed as the slope of the linear regression curve, was underestimated in most cases. *Significance*: The present study demonstrates that pulse rate parametrization using a consumer smart wristband is in principle feasible. The results show that the smart wristband is well suited for computing basic PRV parameters which have been reported to be associated with poorer health outcomes. In addition, the study introduces a methodology for the estimation of post-exercise heart recovery time and the heart's adaptation to physical workload during free-living activities.

1. Introduction

Advancements in smart wristband technology have led to compact and inexpensive consumer devices for unobtrusive acquisition of health-related information. Smart wristbands are most commonly used for self-monitoring, goal-setting, and performance feedback, thus usually only the parameters that cover the basic needs of health tracking, i.e. pulse rate, distance travelled, floors climbed and calories burned, are provided. However, there is a growing interest to take a further substantial step towards integration of such devices in eHealth applications (Steinhubl *et al* 2016). Unfortunately, the reliability and accuracy of consumer smart wristbands are often a concern due to undisclosed signal processing algorithms designed to deal with the noise-corrupted and lost data (Bai *et al* 2017). Therefore, novel approaches of data parametrization have to be established which account for the technology-specific constraints.

Most smart wristbands estimate pulse rate using a photoplethysmogram (PPG), assuming that a time interval between the adjacent pulse peaks corresponds to the time interval between heart contractions. Pulse rate does not always perfectly match the heart rate obtained from the electrocardiogram (ECG) due to various physiological factors, such as the presence of ectopic beats or bigeminy (Sološenko *et al* 2017). Nevertheless, it is widely considered as a satisfactory substitute of heart rate during rest and low physical activity in arrhythmia-free individuals (Jo *et al* 2016, Stahl *et al* 2016, Dooley *et al* 2017, Shcherbina *et al* 2017). There is an ongoing debate whether the well-established heart rate variability (HRV) parameters can be reliably estimated using PPG signals (Lu *et al* 2008, Choi and Shin 2017, Hejjel 2017). Numerous studies have shown a significant bond between the pulse rate variability (PRV) and HRV during rest (Hayano *et al* 2005, Gil *et al* 2010). However, a notable difference has been observed during moderate- and vigorous-intensity physical activity (McKinley *et al* 2003, Charlot *et al* 2009).

In addition to pulse rate, smart wristbands synchronously acquire physical activity, which is usually expressed as the number of steps per time interval (Strath *et al* 2013, Leininger *et al* 2016). Synergy of pulse rate and physical activity has been found to be useful for extracting additional information, such as sleep tracking and estimation of energy expenditure (Wallen *et al* 2016), however, it is still insufficiently exploited. In clinical practice, heart rate recovery after a standardized physical workload is a widely used parameter to assess the status of the heart, which has proven its value as a powerful predictor of mortality (Cole *et al* 1999, Jouven *et al* 2005). A similar approach has already been implemented by several smart wristband manufacturers, but is inconvenient due to the requirement of manual switching on the device into a recovery mode. Evaluation of heart rate recovery time in a daily-life scenario without disturbing the user is still a major challenge since physical workload is non-standardized. Accordingly, this study aims to provide insight on the feasibility of a consumer smart wristband to be used for pulse rate parametrization in free-living activities. Given that underestimation of pulse rate has been commonly reported (Wallen *et al* 2016, Bai *et al* 2017, Benedetto *et al* 2018), this study also evaluates the consumer smart wristband with respect to the established ECG-based method.

This paper is organized as follows. The smart wristband and collected dataset are described in section 2, followed by a description of pulse rate parameters under investigation in section 3. The results illustrating the performance of a smart wristband are presented in section 4. The paper finishes with a discussion and conclusions.

2. Devices and dataset

2.1. Study population

Fifty-four participants (28 women), 48.2 ± 13.2 years old, with a body mass index 27.2 ± 4.6 kg m^{-2} were enrolled in the study. Participants were diagnosed with various cardiovascular diseases, namely congestive heart failure, angina pectoris, myocardial ischemia, atrial fibrillation, hypertension, etc. No lifestyle intervention was introduced and participants were asked to maintain their usual physical activity regimens during 24 h of monitoring. Signed, written consent to participate in the study was obtained from all the participants, and the ethical principles of the Declaration of Helsinki were followed. Identifiable information was removed from the collected data to ensure participant anonymity.

2.2. Data acquisition and processing

Synchronously recorded pulse rate and step data were obtained using a Fitbit Charge 2 (Fitbit Inc., San Francisco, CA, USA) consumer smart wristband. The smart wristband provides minute-by-minute accumulated steps, as well as pulse rate at intervals of 5 s or longer, depending on data quality. Each pulse rate value, given in beats per minute, was converted to the corresponding interbeat interval, expressed in milliseconds. The smart wristband-derived parameters were investigated with respect to the ECG-derived parameters. The reference ECG signal was synchronously obtained using a Bittium Faros 180° (Bittium Corporation, Oulu, Finland) recorder at a sampling rate of 1000 Hz. Interbeat intervals were filtered using a 3-point median filter to remove sporadic ectopic beats (Petrėnas *et al* 2015).

Pulse rate and step data of the entire 24 h monitoring period were used for computing the heart's adaptation to workload, as well as for finding physical activity events appropriate for estimation of post-exercise heart recovery time. However, to ensure that PRV is not influenced by physical activity, an hour immediately before awakening from sleep was used for parameter computation. The beginning and the end of sleep were determined based on the absence of physical activity. The onset of the night was set when the number of steps per hour decreased to less than 20. Similarly, the end of the night was set when the number of steps per hour exceeded 20. The participants were assumed to be sleeping during this time interval of inactivity.

3. Pulse rate parametrization

3.1. Pulse rate variability

Heart rate variability, derived from an ECG, has been investigated in numerous clinical studies and is considered as a biomarker of autonomic nervous control of the heart (ESC 1996, Thayer *et al* 2010). Since PRV is a phenomenon of pulsatile blood, it may differ from the HRV in several respects (Wong *et al* 2012). Consumer smart wristbands usually do not provide an instantaneous pulse rate for each contraction of the heart, but

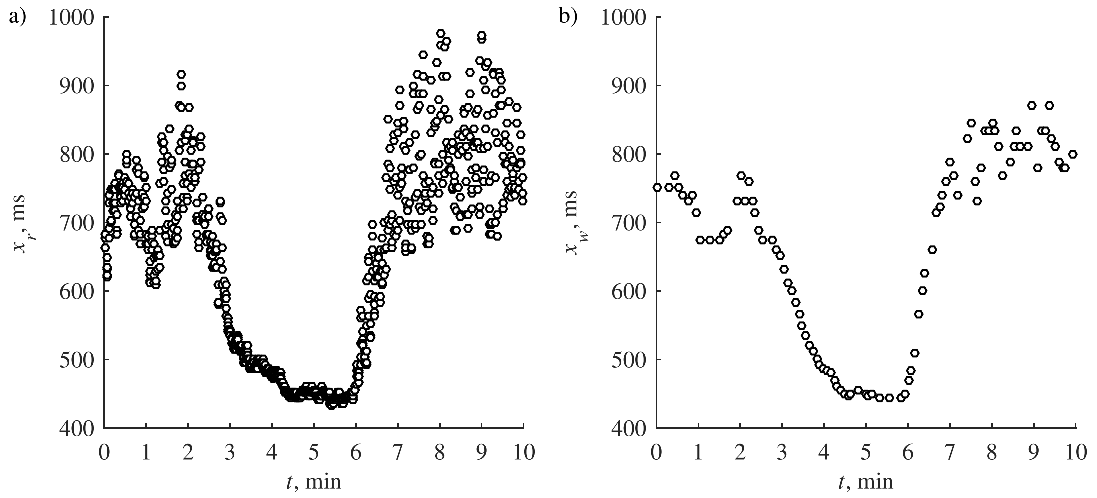

Figure 1. Synchronously recorded interbeat intervals using (a) the reference ECG and (b) the smart wristband during rest (first 2 min), exercise (from 2 to 6 min), and recovery (from 6 to 10 min). Note that the smart wristband is well-suited for tracking rhythm trend even during exercise; however, it is considerably less accurate in reproducing pulse rate variability.

rather averaged values over the time interval. Consequently, only a minority of HRV parameters, which are not restricted to the use of instantaneous pulse rate, are investigated.

The PRV parameters, inferred from HRV analysis, are classified into three major categories: time-domain, frequency-domain, and nonlinear (ESC 1996, Sassi *et al* 2015). The selected parameters are described in the subsections below.

3.1.1. Time domain

A visual comparison of the interbeat intervals, derived from the smart wristband and from the synchronously acquired reference ECG, denoted as x_r and x_w, respectively, shows that the smart wristband can accurately track the trend of the heart rate (figure 1). However, most of the information on rhythm variation is lost due to the in-built averaging and missed data. Based on these observations, only the mean and dispersion are considered as valid parameters for investigation.

The mean interbeat interval, $\bar{x}$, is given by

$$\bar{x} = \frac{1}{N}\sum_{n=1}^{N} x_n, \tag{1}$$

where x_n denotes the length of the nth interbeat interval (whose units are in milliseconds), and N is the total number of intervals over one hour of monitoring.

Given that the smart wristband is not able to detect every pulse reliably, and thus, provides pulse rate at irregular time intervals, appropriate data preprocessing is required to ensure reliable estimation of pulse rate dispersion. One possibility to mitigate this limitation is to compute the standard deviation of the averaged interbeat intervals (ESC 1996, Aronson *et al* 2004),

$$\sigma_a = \sqrt{\frac{1}{M-1}\sum_{m=1}^{M}(x_m - \bar{x}_m)^2}, \tag{2}$$

where x_m is the mth interbeat interval, averaged over the time window of duration T, $\bar{x}_m$ is the average of x_m in all windows, and M is the total number of windows over one hour of monitoring. Based on the recommendations of the standard of HRV measurements, T is set to 5 min (ESC 1996, Sassi *et al* 2015). Thanks to the pulse averaging, parameter σ_a minimizes the influence of missed data and abnormal rhythms, such as ectopic beats or bigeminy, and is less affected by the data processing errors.

3.1.2. Frequency domain

Frequency power distribution among different frequency ranges may vary depending on the changes in autonomic modulation of heart rate. Analysis of the power spectrum density (PSD) of smart wristband data revealed that only very-low-frequency components up to 0.04 Hz can be extracted, which mostly reflect circadian pulse oscillations (Fisher *et al* 2014). Figure 2 shows that all frequency components, especially those at higher frequencies (>0.02 Hz), are considerably more attenuated in the PSD of the smart wristband. Based on these

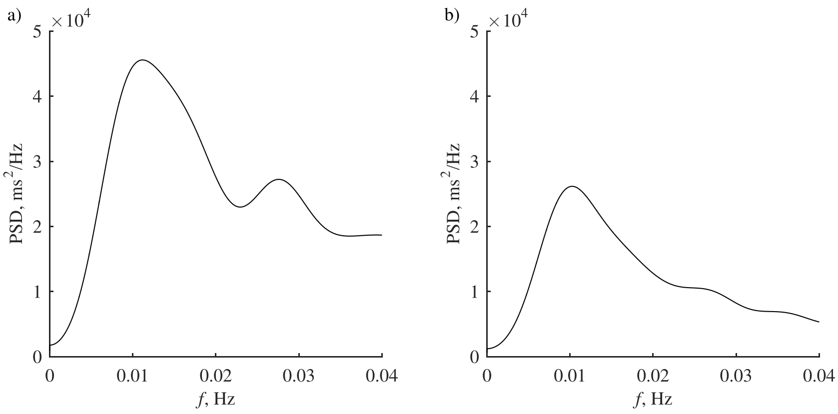

Figure 2. Power spectrum density (PSD) of synchronously recorded interbeat intervals using (a) the reference ECG and (b) the smart wristband.

restrictions, only spectral power in the very-low-frequency band, ranging from 0.0033 Hz to 0.04 Hz, is chosen for investigation. Since the methods for PSD estimation assume equidistant sampling, the interbeat intervals were linearly interpolated to a sampling rate of 4 Hz prior to spectrum estimation. Then, the interbeat intervals were detrended using a high-pass infinite impulse response (IIR) filter with a cut-off frequency of 0.0033 Hz. The PSD was obtained using Welch's method with a window of duration T and 50% overlap (Tarvainen *et al* 2014).

3.1.3. Nonlinear

Given the complex nature of heart rate control mechanisms, it is assumed that additional information on PRV can be extracted using nonlinear methods (Acharya *et al* 2006, Sassi *et al* 2015). Commonly, a two-dimensional scatter plot, also known as a Poincaré plot, is used to graphically represent the current versus preceding interbeat intervals.

The standard deviation of the points on the scatter plot perpendicular to the line-of-identity ($x_n = x_{n+1}$) represents short-term variability due to respiration activity and is given by

$$\sigma_1 = \sqrt{\frac{1}{2}\sigma_d^2}, \tag{3}$$

where σ_d is the standard deviation of the differences between the adjacent interbeat intervals Δx_n, defined by

$$\sigma_d = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(\Delta x_n - \overline{\Delta x})^2}, \tag{4}$$

where $\overline{\Delta x}$ is the mean value of all differences over one hour of monitoring.

The standard deviation along the line-of-identity represents long-term variability and is given by

$$\sigma_2 = \sqrt{2\sigma^2 - \frac{1}{2}\sigma_d^2}, \tag{5}$$

where σ is the standard deviation of the interbeat intervals defined by

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \overline{x})^2}. \tag{6}$$

Due to reduced variability, both σ_1 and σ_2 are lower when estimated using the smart wristband (see figure 3). Nevertheless, the ratio σ_2/σ_1 is retained since the shape of scattered points is affected proportionally in both directions by the reduced interbeat interval variability.

3.2. Post-exercise heart recovery time

Post-exercise heart recovery time is an essential parameter for assessing the reorganization of autonomic control of the heart (Cole *et al* 1999, Jouven *et al* 2005). Since smart wristbands provide synchronously recorded pulse and physical activity (e.g. steps or climbed floors), a combination of this information can be used for estimating heart recovery time. It has been shown earlier that heart recovery can be modelled by a first-order exponential model (Bartels-Ferreira *et al* 2015),

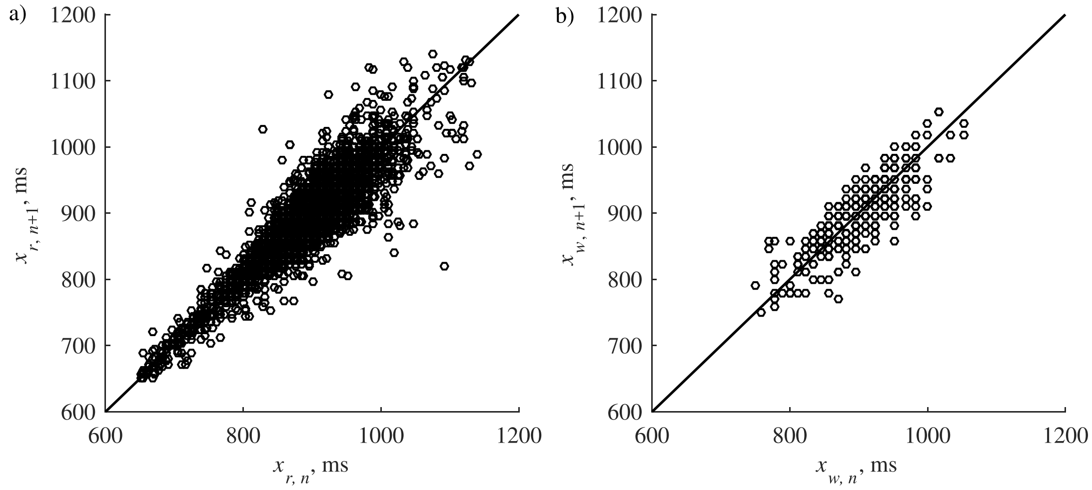

Figure 3. Scatter plots of synchronously recorded interbeat intervals using (a) the reference ECG and (b) the smart wristband. Scatter plot of x_w is proportionally narrower in both directions, causing the ratio σ_2/σ_1 to be similar to that of x_r.

$$x_e(t) = x_0 + x_{\Delta} e^{\frac{t}{\tau}}, \tag{7}$$

where x_0 is the interbeat interval immediately after the recovery period, x_{Δ} is the difference between the interbeat intervals at the end and at the beginning of the recovery period, and τ is the time-constant of exponential growth. The quality of exponential fitting is assessed via the coefficient of determination R^2. An acceptable fitting is considered when the R^2 value exceeds the fixed threshold δ, which is set to 0.75 based on the investigation results in Bartels-Ferreira *et al* (2015).

In clinical practice, heart recovery time is usually estimated by applying a standardized physical workload. Given that most smart wristbands provide the number of steps per time interval, a step test can be regarded as the most appropriate way to estimate heart recovery time in free-living activities without any supervision. Out of several commonly used step tests, the YMCA 3 min Step Test requires minimal equipment and can be self-performed (Golding 2000). During the test, the participant has to perform the step test using a 30.5 cm-high bench for 3 min at a stepping rate of 96 steps per minute, resulting in 288 steps in total. After the exercise is finished, the participant has to sit down for at least 1 min, and then the heart rate is measured. A similar approach can be adopted to the data acquired during free-living activities, however a reasonable compromise has to be made since the exact conditions of the step test can never be satisfied. Accordingly, the events corresponding to the step test are identified using a sliding window of 7 min, of which the first 4 min must contain at least 288 steps, whereas the remaining 3 min must be nearly free of physical activity. Based on the step data analysis, $\leqslant$20 steps per minute is assumed to represent sedentary behaviour in this study. An example of the exponential fitting of synchronously acquired interbeat intervals during 'step test' in data, recorded during free-living activities, is shown in figure 4.

3.3. Heart's adaptation to workload

Interbeat interval duration is negatively correlated with physical activity intensity. Therefore, the ability of the heart to adapt to physical workload can potentially be assessed in terms of the relationship between the physical activity's intensity and the duration of the corresponding interbeat interval. This relationship is determined by applying a linear regression analysis, where the slope of the regression curve serves as a measure of the heart's adaptation to a different physical activity intensity. Given that most individuals tend to spend a large amount of time in sedentary behaviour, the periods of very low activity, defined as $\leqslant$20 steps per min, were excluded from the regression analysis. Figure 5 shows a linear regression fit together with the estimated slope coefficients for synchronously acquired x_r and x_w.

4. Results

Figure 6 shows Bland–Altman plots of interbeat intervals, derived from the reference ECG and smart wristband, for increasing intensity of physical activity. The smart wristband overestimates interbeat intervals for all physical activity intensity groups, with the largest positive bias of 16.6 ms (95% limits of agreement from −120.5 ms to 153.7 ms) during sedentary behaviour ($\leqslant$20 steps min^{-1}). Interestingly, positive bias is slightly reduced for higher intensity physical activity (>60 steps min^{-1}), which can probably be explained by the shorter interbeat intervals, resulting from increased physical workload. It should be noted that more than 87% of all interbeat intervals

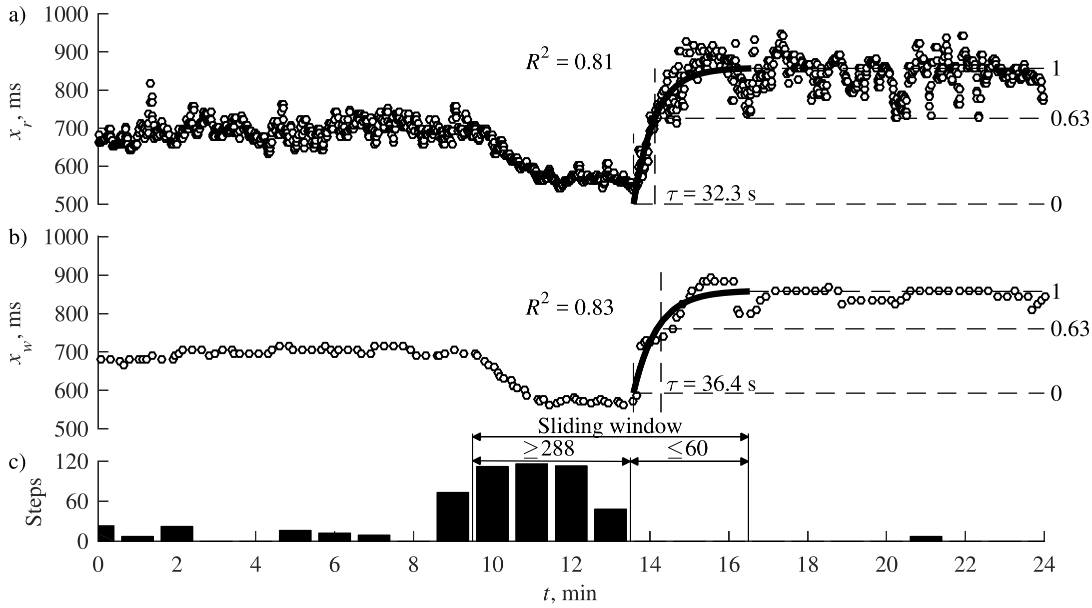

Figure 4. Exponential fitting of interbeat intervals, corresponding to the 'step test' in data recorded during free-living activities using (a) the reference ECG and (b) the smart wristband. (c) shows the minute-by-minute accumulated steps.

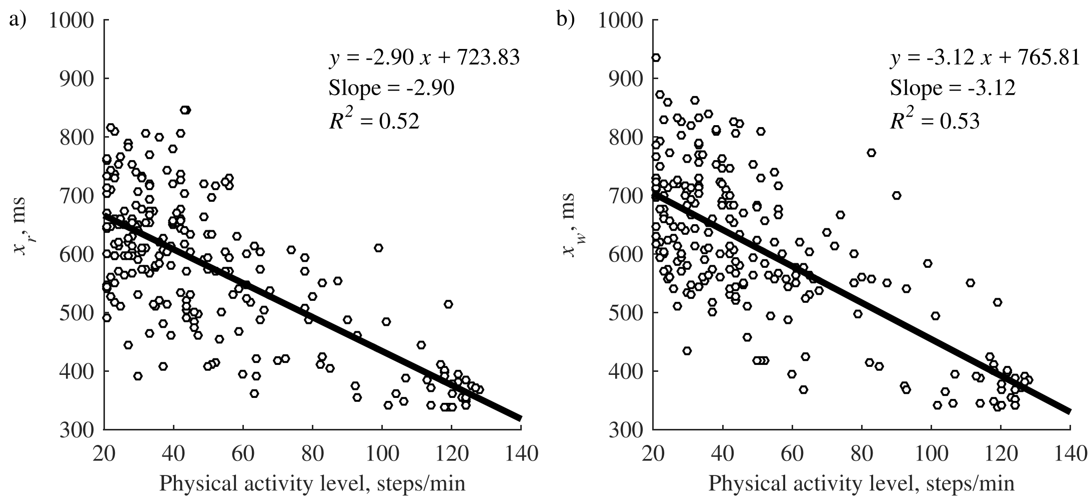

Figure 5. A linear regression analysis performed on synchronously recorded interbeat intervals using (a) the reference ECG and (b) the smart wristband. Interbeat intervals are averaged over 1 min windows.

of the entire database were obtained in sedentary behaviour, whereas only 1% during high intensity physical activity (>100 steps min^{-1}).

Figure 7 shows Bland–Altman plots of the PRV parameters computed for interbeat intervals synchronously acquired from 51 participants using the reference ECG and smart wristband. The pulse rate data of three participants were excluded from the PRV study due to unexpected participant activity during the night. The results demonstrate that the smart wristband is well-suited for computing basic PRV parameters, i.e. $\bar{x}$ and σ_a, however overestimates the mean interbeat interval by 8 ms on average, with the discrepancy between methods being larger for lower interbeat interval values. Study findings indicate that the smart wristband is less suitable for computing frequency domain parameters, since the spectral power in a low-frequency band is estimated with an insufficient accuracy in nearly half of all cases. The difference increases proportionally for higher spectral power due to an inability of the smart wristband to reproduce pulse rate variability. Similarly, the errors in estimating nonlinear ratio σ_2/σ_1 are unacceptably large.

Analysis of the entire dataset collected during free-living activities resulted in 32 events in total which satisfied the conditions of the 'step test' (figure 8). Thirty-two recordings were free of events attributed to the 'step test', whereas one participant had four such events. Due to decreased pulse variability, all R^2 values exceeded the threshold for fitting an exponential model to x_w intervals. However, the relative error between the time-constants,

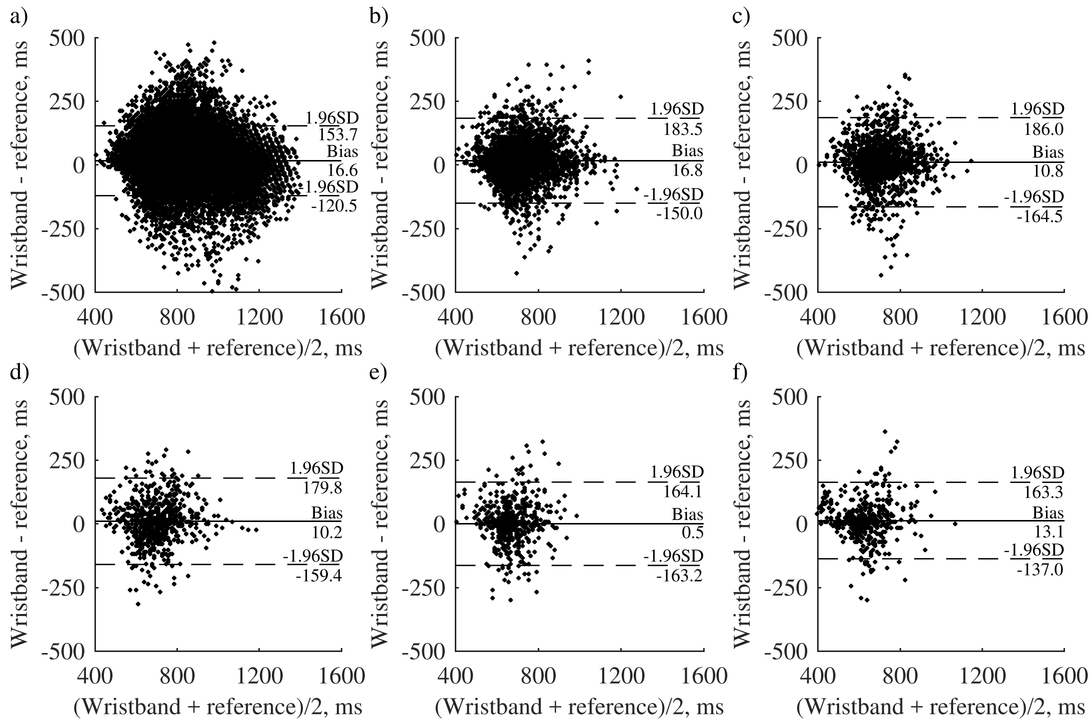

Figure 6. Bland–Altman plots of interbeat intervals synchronously acquired using the reference ECG and smart wristband for increasing intensity of physical activity: (a) ⩽20 steps min^{-1}, (b) 21–40 steps min^{-1}, (c) 41–60 steps min^{-1}, (d) 61–80 steps min^{-1}, (e) 81–100 steps min^{-1}, (f) ⩾100 steps min^{-1}. Data were synchronized by averaging interbeat intervals from the reference ECG over pulse update intervals of the smart wristband.

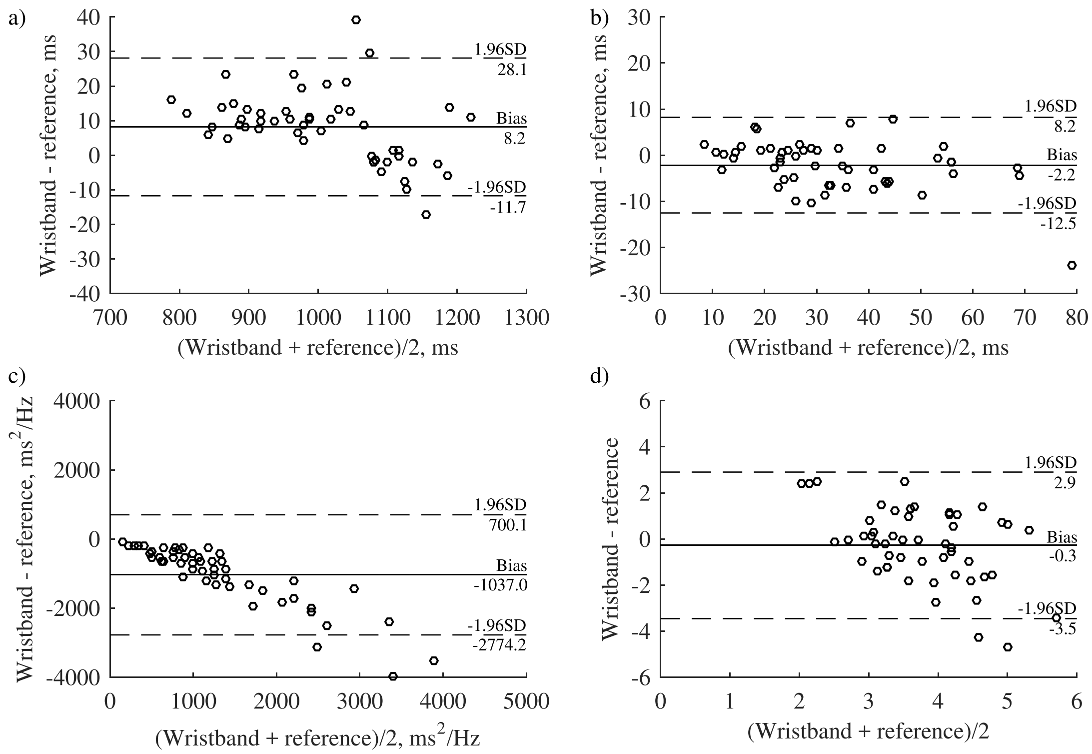

Figure 7. Comparison of PRV parameters computed from x_r and x_w intervals: (a) mean interbeat interval $\bar{x}$, (b) standard deviation of the average interbeat intervals σ_a, (c) spectral power in a very-low-frequency band, and (d) ratio σ_2/σ_1. The solid line stands for the mean difference, whereas the dashed lines show ±2 standard deviation limits of the differences between the methods.

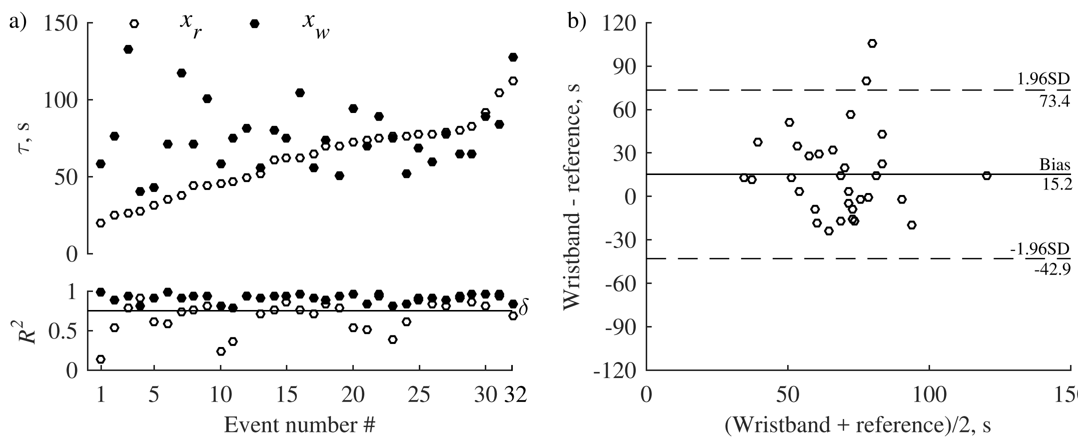

Figure 8. (a) Time-constants of the exponential fitting to the interbeat intervals corresponding to the 'step test' in data recorded during free-living activities, and (b) the corresponding Bland–Altman plot.

estimated using the reference ECG and smart wristband, was lower than 20% in only one-third of all cases. The agreement improves with an increasing τ value, which can be explained by a more accurate fitting to interbeat intervals of low variability during prolonged recovery periods.

Figure 9 shows the results of the linear regression slope estimation for a sub-dataset of 44 participants. After comparing interbeat intervals to the reference ECG, 10 participants were excluded due to the occurrence of various rhythm disturbances which may influence a linear regression analysis. Study findings demonstrate that the quantitative relationship between the physical activity intensity and interbeat interval duration is highly individual, resulting in slope values ranging from -2.8 to -0.2. It is difficult to speculate what physiological factors contributed most to the substantial difference in the estimates of the linear regression slope. However, the slope parameter has potential to be useful for discriminating among those with different heart responses to physical activity. It should be noted that the slope is underestimated in most cases using the interbeat intervals of the smart wristband.

5. Discussion

A major breakthrough in smart wristband technology can be attributed to the capability to acquire pulse rate via photoplethysmography. In such a way, this opens an opportunity to provide more comprehensive information about health status (Rawassizadeh *et al* 2015). Unfortunately, contemporary technology for PPG signal acquisition is sensitive to various extrinsic factors, which decrease PPG signal quality and may lead to incorrect pulse detection. The most important are ambient light, temperature, sweat, anatomical placement, skin contact force, and motion artefacts (Allen 2007, Lu *et al* 2009, Schöfer and Vagedes 2013, Zhang 2015). To deal with the noise-corrupted data, consumer smart wristbands use undisclosed algorithms of which moving average, the repetition of the last reliable pulse value, and omitting of unreliable values are the most commonly encountered (see figure 10). Corrupted and temporarily lost data are the main reasons causing an inaccurate estimation of frequency domain and nonlinear PRV parameters. Therefore, investigation of the reliability and accuracy of a smart wristband, as well as identification of the particular device-related constraints, are crucial before computing any parameters.

A low PPG sampling rate, e.g. 25 Hz in the case of the Fitbit Charge 2, is usually preferred to prolong the battery life of a consumer smart wristband. Reduced sampling rate decreases the accuracy of fiducial point detection, nevertheless recent studies have considered even such low frequencies as sufficient for computing some PRV parameters (Polimeni *et al* 2014, Choi and Shin 2017, Hejjel 2017). It is obvious that re-computation of interbeat intervals from the pulse rate, given at irregular time intervals by a smart wristband, leads to further reduced accuracy. Therefore, to ensure better data quality, and thus a more reliable parameter estimation, a sleep period with supposedly no physical activity was selected for computation of PRV parameters. However, even the sleep period was contaminated with intermittent bursts of physical activity for the majority of participants. Therefore, only the last hour before waking up was used for analysis.

Under favourable conditions with no motion and good contact of the PPG sensor, the Fitbit Charge 2 smart wristband may provide pulse rate at intervals as short as 5 s. However, our findings show that even during sleep the pulse rate is given at unequal time intervals, with the average pulse rate update interval ranging from 6.4 s to 10.1 s for different participants. Despite considerable difference in pulse rate update interval, we could not identify a relationship between the update interval and the absolute error of the PRV parameters, computed

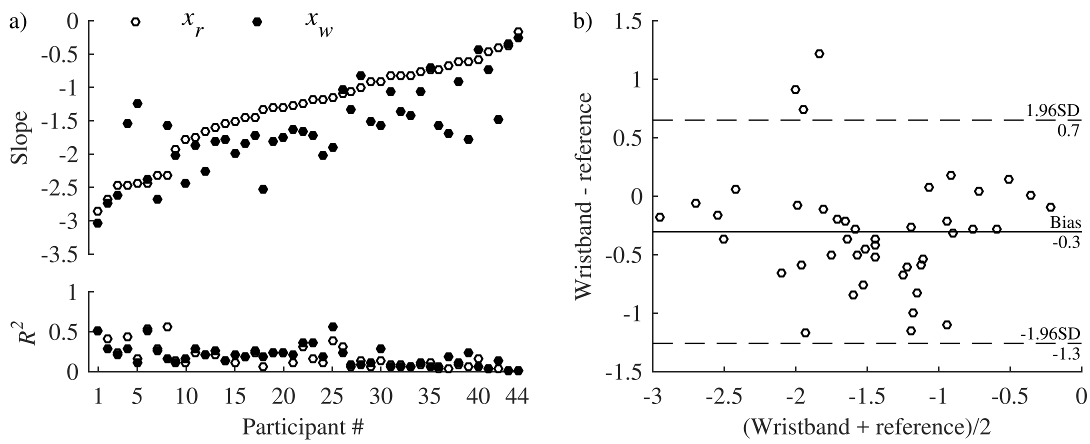

Figure 9. (a) Slope coefficients estimated from x_r and x_w intervals, and (b) the corresponding Bland–Altman plot.

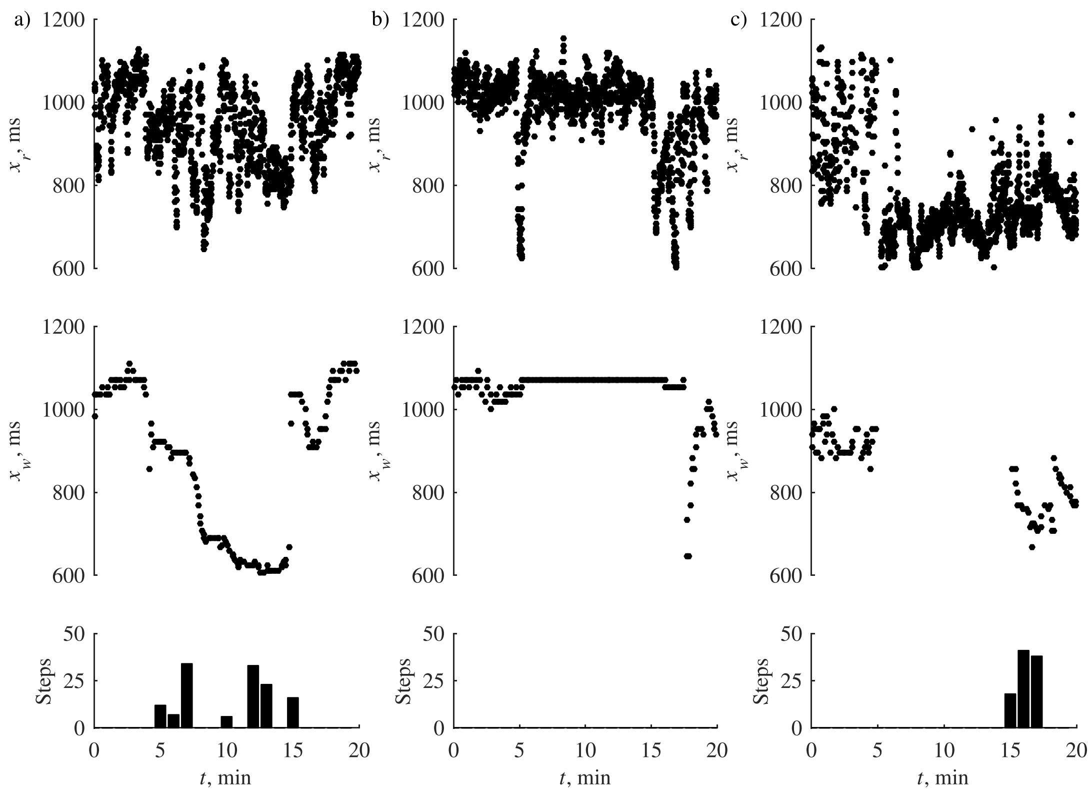

Figure 10. The most commonly observed errors in interbeat intervals using smart wristband (middle row): (a) incorrect pulse estimation due to moving averaging during motion, (b) repetition of the same pulse value due to lost contact, (c) missing data during the period in which the device is taken off. The top row shows the reference interbeat intervals, whereas the bottom row shows physical activity expressed as the number of steps.

using the reference ECG and smart wristband. Nevertheless, other smart wristband manufacturers prefer even longer pulse rate update intervals, which may have a substantial detrimental effect on the estimation of frequency domain and nonlinear PRV parameters.

Ectopic beats may have an adverse influence on PRV parameters, therefore such beats have to be removed from the interbeat intervals prior to analysis. Due to restrictions of the smart wristband, only low-frequency variations are reflected in the interbeat intervals, thus a simple 3-point median filter is appropriate for suppressing such beats. However, more sophisticated approaches to ectopic beat filtering, e.g. those proposed proposed in Mateo and Laguna (2003), may be considered instead if higher-frequency variations are of interest for investigation. On the contrary, irregular heart rhythms, such as ectopic beats and atrial fibrillation, are hardly identifiable in the interbeat intervals from the smart wristband (see figure 11) therefore no ectopic beat filtering is needed.

Despite the aforementioned constraints, our findings show that basic PRV parameters $\bar{x}$ and σ_a, which are least sensitive to the inaccuracy of interbeat interval estimation, can still be computed. Meta-analysis of prospective

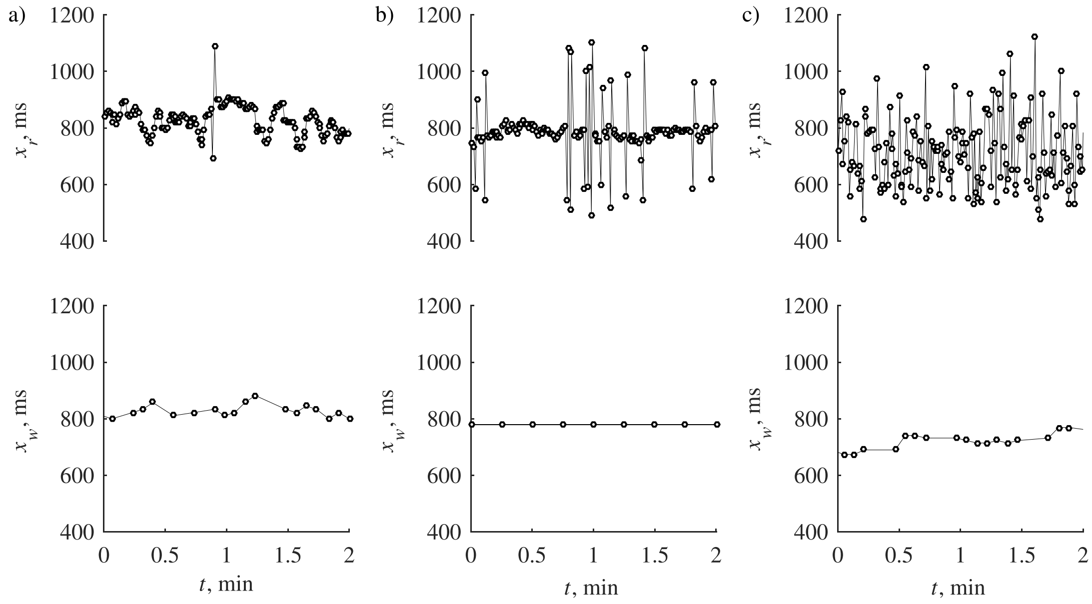

Figure 11. Examples of interbeat intervals with various abnormal heart rhythms: (a) a single ectopic beat, (b) multiple ectopic beats, (c) atrial fibrillation.

studies demonstrated that an increase in resting heart rate is linearly associated with the incidence of hypertension and heart failure (Shi *et al* 2018). Meanwhile, the reduction in σ_a is usually associated with poorer health outcomes, including increased risk of cardiovascular events and higher mortality rates in patients with heart failure (Aronson *et al* 2004, Landolina *et al* 2008). In connection with these findings, even monitoring of basic PRV parameters may provide additional information about health status.

Slower post-exercise heart recovery is associated with aging, decreased physical fitness and cardiovascular diseases, and is an independent predictor of an increased risk of death (Cole *et al* 1999, Jouven *et al* 2005, Peçanha *et al* 2014). The present study is among the first which investigates the feasibility of a consumer smart wristband to be used for estimation of heart recovery time in an unobtrusive way without user intervention. This is in contrast to the several consumer smart wristbands on the market which estimate heart recovery time by asking the user to follow specific recommendations, such as a certain amount of workload followed by a rest period.

Post-exercise heart recovery can be divided into fast and slow recovery phases (Coote 2010). The fast recovery phase of a rapid decrease of heart rate takes the first minute and is related to vagal reactivation. Meanwhile, the slow phase begins at the end of the fast phase and is continuous until the heart rate reaches its resting value. The slow phase has been associated with interconnected vagal reactivation and sympathetic withdrawal (Buchheit *et al* 2007). Since estimation of the fast phase requires a precise detection of the end of the exercise, this is difficult to accomplish using smart wristband data recorded during free-living activities. Therefore, exponential fitting to both phases was decided as a more reliable way to estimate heart recovery time.

In this study, we propose a parameter which relates physical activity intensity and pulse rate. Assuming that the slope of the regression curve largely depends on the heart's ability to adapt to physical workload (Tao *et al* 2015), such a parameter can be useful for evaluating and monitoring the level of physical fitness. Usually, most daily pulse rate values are recorded during rest and low physical activity, thus the slope highly depends on the resting pulse rate, which is also influenced by other factors such as mental stress (Krantz *et al* 1999). Therefore, sedentary-behaviour-related pulse rate has to be removed before applying a linear regression analysis. We define sedentary behaviour as a physical activity of $\leqslant$20 steps per minute, which is motivated by the observation that such activity is common among those working at an office or spending most of the time at home.

5.1. Limitations and future directions

Study findings show that consumer smart wristband technology still needs improvement to ensure reliable estimation of more sophisticated parameters. Only a small fraction of manufacturers provide access to their data, therefore the smart wristband of only one manufacturer has been investigated, thereby limiting the generalizability of the results. Since manufacturers do not provide raw data and use their own undisclosed algorithms, it is desirable to investigate other commercial devices relying on the proposed methodology. Prohibited access to the data significantly limits the development of signal processing algorithms which account for the technology-specific constraints. Therefore, the manufacturers could contribute to the acceleration of smart wristband research by ensuring easier access to the unprocessed data.

Only participants diagnosed with cardiovascular diseases were enrolled in the study. Therefore, healthy individuals of different age and gender as well as well-defined groups of patients with cardiovascular conditions should preferably be included to draw more general conclusions. Since post-exercise heart recovery time and the heart's adaptation to workload are not expected to change significantly over a short time span, parameter reproducibility could be investigated by involving participants in prolonged monitoring, i.e. over weeks or months.

6. Conclusions

This study demonstrates that pulse rate parametrization using a consumer smart wristband is in principle feasible. The results show that the smart wristband is well-suited for computing the mean interbeat interval and the standard deviation of the averaged interbeat intervals, which have been reported to be associated with poorer health outcomes. However, the technology still requires improvement to ensure reliable estimation of frequency domain and nonlinear parameters. In addition, the study introduces a methodology for the estimation of post-exercise heart recovery time and the heart's adaptation to physical workload, which are expected to have clinical relevance when assessing the status of the heart in free-living activities, e.g. during home-based cardiac rehabilitation.

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