Heart rate variability in the acceleration photoplethysmogram at rest and after exercise—a preliminary study

Mohamed Elgendi[1,*], Socrates Dokos[2], Derek Abbott[3]

1 Department of Computing Science, University of Alberta, Edmonton, Alberta, Canada

2 Graduate School of Biomedical Engineering, University of New South Wales, Sydney, New South Wales, Australia

3 School of Electrical and Electronic Engineering, University of Adelaide, Adelaide, South Australia, Australia

∗ **E-mail: moe.elgendi@gmail.com**

Abstract

There are a limited number of studies on heart rate variability (HRV) dynamics immediately after exercise. The electrocardiogram (ECG) may be used to measure HRV, however acquiring ECG signals from subjects undergoing exercise is not convenient. Many researchers have demonstrated that photoplethysmogram (PPG) signals offer an alternative method to measure HRV when ECG and PPG signals are simultaneously collected. However, we investigate a different approach to potentially show that the PPG signals can measure HRV without collecting ECG signals. Moreover, we explore the extraction of the most suitable HRV-parameters from short PPG signal recordings. Our preliminary results now motivate further studies that cross check HRV parameters extracted from both ECG and PPG. In this study, PPG signals from an existing database were used to determine a range of HRV indices, including the standard deviation of heart beat interval (SDNN) and the root-mean square of the difference of successive heart beats (rMSSD). Results from this study indicate that the use of the a–a interval, derived from the acceleration of PPG signals, show very promising results in determining the HRV statistical indices SDNN and rMSSD over 20-second PPG recordings. Moreover, post-exercise SDNN and rMSSD indices show negative correlation with age.

Introduction

Heart rate variability (HRV) has been extensively studied in electrocardiogram (ECG) signals, having become the conventionally accepted term to describe variations of both instantaneous heart rate and RR intervals. A number of terms have been used in the literature to describe heart rate variability, for example cycle length variability, heart period variability, RR variability, and RR interval tachogram. The measurement of HRV captures heart rate variations around the mean heart rate (HR), and provides information on sympathetic-parasympathetic autonomic stability and consequently the risk of sudden cardiac death. The traditional method of identifying heartbeats in ECG is by detecting R peaks. Many researchers investigated the feasibility of using the photoplethysmogram (PPG) as an alternative simple, inexpensive, and convenient diagnostic tool. In almost every study, comparisons are made between HRV calculated from RR intervals and those calculated from PPG signals. However, accurate detection of inter-beat intervals from fingertip PPG signals is considered challenging [1–3]. This is because ventricular pressure and other parameters of the heart can influence the form and timing of the pulse waveform. In addition, peripheral effects such as changes in vascular tone, may also influence distal pulse peak detection. These potential weaknesses in using fingertip PPG signals in measuring HRV are raised by Bernston *et al.* [1], who recommend the use of RR intervals from ECG signals to determine inter-beat intervals. However, they note that with a sophisticated peak detection algorithm, the use of intra-arterial pressure pulses may be acceptable, but that indirect measures such as PPG signals need further validation. Moreover, Constant *et al.* [2] recommended the use of the ECG rather than the distal pulse wave signal for calculating HR.

Giardino *et al.* [3] demonstrated that under resting conditions the distal pulse pressure, as shown in Figure 1(a), is sufficient for determining the heart rate. However, they recommended additional studies including test-retest reliability evaluation of different data collection techniques. These cautious evaluations may explain the lack of investigation into the use of PPG signals instead of ECG to measure HR and HRV. The PPG contour itself can be used to detect the heart beat and consequently HRV can be measured [4], as shown in Figure 1 (a) where the two circles represent two consecutive heartbeats with the smallest positive amplitudes of the PPG signal. However, reliable detection of heartbeats from the PPG contour is challenging due to PPG noise and the nature of its incorporated interference with hemodynamic variables [5]. To overcome difficulties with PPG contour analysis, the second derivative of the photoplethysmogram waveform, also called the acceleration plethysmogram (APG), has been introduced, as shown in Figure 1 (b) where the two circles represent two consecutive heartbeats with the largest positive amplitudes of the APG signal. Because the peaks in the APG are more clearly defined than the peaks in the PPG contour, the heart rate can be more accurately detected using the APG.

Fingertip PPG, which mainly reflects pulsatile volume changes in the arterioles of the finger, has been recognized as a noninvasive method of measuring arterial pulse waves in relation to changes in wave amplitude [6]. However, the wave contour (cf. Figure 2 (a)) itself has not been analysed because of the difficulty in detecting minute changes in the phase of the inflections. Previous attempts at PPG analysis showed that such subtle changes in the waves were emphasized and easily quantified by quadratically differentiating the original PPG signal with respect to time [7]. Accordingly, the second derivative of the PPG (APG) was developed as a method allowing more accurate recognition of the inflection points and more convenient interpretation of the original plethysmogram wave. In this paper, the abbreviation PPG is used for photoplethysmogram and APG for the second derivative photoplethysmogram based on the recommendation in Ref. [8]. As shown in Figure 2 (b), the APG waveform consists of four systolic waves (a, b, c and d waves) and one diastolic wave (e wave) [9]. The height of each wave was measured from the baseline, with values above the baseline being positive and those under it negative. The first systolic wave, the a wave, is the most suitable wave for heart rate calculations because of its large amplitude and steepness. Taniguchi *et al.* [10] used the aa interval in the APG signals to determine HR instead of ECG when assessing the stress experienced by surgeons. In the present study, our goal is to explore an alternative methodology and investigate the feasibility of using PPG to analyse HRV without measuring ECG signals from heat-stressed subjects.

Materials and Methods

Ethics Statement

There is one annotated PPG database available at Charles Darwin University. The data were collected during rest (before exercise) and after one hour of exercise (walking) on a treadmill in the climate control chamber at Northern Territory Institution of Sport (Darwin, Australia). The speed of treadmill was set to 5 km/h with a one percent incline increment corresponding to the effort required to walk with 8 kg of webbing. The exercise was considered to be of moderate intensity, and the background of the entire project can be found in [11]. All subjects provided written informed consent before participation, which was approved by the Charles Darwin University Ethics Committee.

The PPGs of 27 healthy volunteers (males) with a mean $\pm$ SD age of 27 $\pm$ 6.9 were measured using a photoplethysmography device (Salus APG, Japan), with the sensor located at the cuticle of the second digit of the left hand, in which all subjects were included. Measurements were taken while the subject was at rest on a chair. The PPG data were collected at a sampling rate of 200 Hz and the duration of each recording was 20 seconds. The PPG recordings of 20 seconds are intentionally much shorter than is usual for ECG recordings to exclude motion artefacts and other noise [12]. This also serves as a preliminary test of feasibility, where the ease of shorter recording lengths is desirable in a clinical setting.

The annotations were carried out by only one PPG specialist, which is sufficient for this preliminary proof-of-concept study. The signals measured during rest (before exercise) contained a total of 584 heartbeats, whilst the PPG signals collected after one hour of exercise contained fast rhythm PPG signals, with a total of 885 heartbeats; the background of the entire project can be found in [11]. For signal conditioning and wave detection, MATLAB 2010b (The MathWorks, Inc., Natick, MA, USA) was used.

Methodology

The major reason for the interest in HRV stems from its ability to predict survival after a heart attack [13–15]. In ECG signal analysis, the interval between adjacent QRS complexes is termed as the normal to normal (NN) or RR interval. Here, HRV refers to the beat-to-beat alterations in the heart rate, portraying the physiological condition of the patient and is an important indicator of cardiac disease. Many studies have shown that reduced HRV predicts sudden death [16,17]. The low-cost and simplicity of APG signals can offer significant benefits to healthcare, for example in primary care, where non-invasive, accurate and simple-to-use diagnostic techniques are desirable. Further development of photoplethysmography may potentially lead to a new complementary tool in the management of vascular disease. The detection of the R peak of the ECG is the main step in measuring HRV. Precise RR interval calculations are necessary to accurately depict the physiological state. To date, over 20 different types of arithmetic manipulations of RR intervals have been described in the literature to represent HRV [18].

The Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [13] suggest a number of simple time domain measures to estimate HRV. Their discussion paper noted that HRV is calculated using the mean standard deviation of the length of the cardiac cycle. This can be determined using either the RR intervals of a short ECG segment or the *aa* intervals of the APG. Table 1 summarizes some simple time-domain HRV variables: MAX-MIN, SDNN, RMSSD, and SDSD, which can all be determined from APG signals.

Traditionally, HRV measures are based on cardiac inter-beat intervals using ECG. However, some practitioners have used distal measurements of the arterial pulse, such as the fingertip PPG, to measure heart rate. However, there are some potential obstacles to obtaining precise inter-beat intervals from arterial pressure pulses, especially when measured from a distal source such as fingertip PPG. The lack of sharp peaks in blood pressure pulses compared to R peaks in the ECG makes the accurate determination of heart rate challenging. In addition, the shape and timing of the pulse waveform may be influenced by ventricular pressure, flow rate, time period, or other cardiac hemodynamic parameters. Peripheral effects, such as changes in vascular tone, may also influence distal pulse peak detection. These disadvantages of the fingertip PPG have already been noted by Bernston *et al.* [1], who recommend the use of RR intervals from the ECG to determine interbeat intervals. However they note that with a sophisticated peak detection algorithm, the use of intra-arterial pressure pulses may still be acceptable. To this end, it has been demonstrated that under resting conditions, the distal pulse pressure is sufficient for determining heart rate [3]. Caution is required in the use of finger plethysmography in experimental studies, where manipulations might change the relationship between cardiac chronotropic control and distal blood pressure changes. Lu *et al.* [4] used the PPG contour itself without any derivatives as an alternative measurement for HRV. However, Taniguchi *et al.* [10] used the second derivative of PPG to determine heart rate when assessing the stress experienced by surgeons. In this study, our goal was to determine if variations in the APG signal can be used instead of the ECG for measuring HRV. In addition, the relationship between heart rate and HRV at rest and post-exercise was investigated. The annotated a waves are used to calculate the duration of each consecutive aa interval as follows

$$aa[i] = A[i+1] - A[i], \tag{1}$$

where A contains the annotated a waves in each APG signal, and aa contains the a–a intervals. Note, as the main interest is to analyze the aa duration rather than the amplitude, no pre-processing is needed. It is known that HRV decreases with normal aging from the analysis of R peaks in ECG signals [19–21].

Therefore, based on using a waves in APG signals, if the correlation between HRV and age is decreasing, APG signals can potentially measure HRV. To find the correlation between age and HRV, two time-domain HRV parameters are calculated and compared. These parameters are often used with ECG signals. The first parameter, SDNN, is the standard deviation of heartbeat duration; here, the RR interval is replaced by aa intervals. The SDNN is calculated as follows:

$$\mathrm{SDNN} = (1/N)\sum_{i=1}^{N}(aa[i])^2 - \{(1/N)\sum_{i=1}^{N}(aa[i])\}^2. \tag{2}$$

The second parameter, rMSSD, is the root-mean square of the difference of successive heartbeats, or RR intervals in ECG signals. Here, the RR interval is replaced by aa intervals, and rMSSD is calculated using:

$$\mathrm{rMSSD} = \sqrt{(1/N)\sum_{i=1}^{N}(aa[i])^2}. \tag{3}$$

Results and Discussion

Here, SDNN and rMSSD indices are calculated for 27 subjects using PPG recordings of 20 seconds in duration during rest and after exercise. To evaluate the HRV indices, two parameters are used: the steepness of the relationships (slope) and the correlation coefficient (r). Calculating r is carried out as follows:

$$r = \frac{\mathrm{Cov}(u, v)}{\sigma_u \sigma_v}, \tag{4}$$

where $\mathrm{Cov}(u, v)$ is the covariance between data u and data v, σ_u is the standard deviation of data u and σ_u is the standard deviation of data v.

As shown in Figures 4 (a) and 4 (b), there is a negative correlation between heart rate and the HRV indices. The rMSSD index is more negatively correlated with the HR ($r = -0.565$) with more negative slope (-0.022) than the SDNN index ($r = -0.39$ and slope $= -0.011$). Figure 5 illustrates the correlation between the two HRV indices (rMSSD and SDNN), showing a strong positive correlation ($r = 0.894$). Figures 6 (a) and 6 (b) reveal the relationship between age and the SDNN index at rest and after exercise respectively. The SDNN index at rest is more negative correlated with age ($r = -0.271$) and has a steeper negative slope (-0.004) than after exercise ($r = -0.12$ and slope $= -0.001$). Figures 7 (a) and 7 (b) show the relationship between the age and the rMSSD index at rest and after exercise respectively. The rMSSD index at rest is more negatively correlated with age ($r = -0.217$) and has a more negative slope (0.004) than the rMSSD index after exercise ($r = -0.091$ and slope $= -0.001$).

It is clear that the correlation between SDNN and rMSSD has a strong correlation, although that is to be expected given the respective definitions, both of which use the same $aa[i]$ term. However, the remainder of the correlations are not as strong, specifically with the correlation between SDNN or rMSSD and age. Nevertheless, the slope demonstrates significance between HRV indices measured at rest and after exercise. The combination of the correlation coefficient and the slope provides more precise evaluation. It is also worth noting that PPGs measured at rest have a greater negative slope compared to measurements after exercise .

Results from various cross-sectional studies have shown a linear decrease in HR during exercise with increasing age. Interestingly, our results confirm the inverse linear relationship between HRV measures (SDNN and rMSSD) and age. This new outcome shows that HRV can potentially be measured using PPG signals without using ECG signals. This now motivates a larger study that directly validates HRV obtained from PPG with that of ECG.

Limitations of the Study and Future Work

The HRV indices are usually calculated over a period of 5 minutes from the ECG signals; however, the PPG recordings in this study were very short (20 seconds). Studies that evaluate the extracted HRV indices as a function PPG duration record, are suggested as an item for future work. It is important to note that the number of PPG records (total of 27) used is modest: a larger sample size and a more diverse data set are needed in order to generalize the findings of this study. The collection of ECG signals as a reference for the PPG is an optimal setting for the experiment; however, it is difficult to obtain these signals from subjects in heat-stress conditions. Also, the automatic detection of a waves may be of interest for investigating systolic peak detection. However, as mentioned in the introduction, there has been an attempt by Matsuyma [11] who demonstrated that applying a simple threshold is not sufficient. We also recommend that future larger studies are carried out with multiple annotators to evaluate inter-observer variability.

Conclusion

The findings of this preliminary study indicate that heart rate can be calculated using APG. The length of the *aa* interval can be accurately determined if the *a* peaks are detected correctly. As discussed above, HRV indices can be calculated using the APG, with values similar to those obtained using ECG signals. The SDNN and rMSSD indices are suitable for short-duration signals and can be applied to 20 second APG recordings. Both indices show a negative correlation with heart rate, especially the rMSSD index. There is a strong positive correlation between the two HRV indices, indicating that the 20-second APG recordings are sufficient to reliably measure the HRV. As expected, there is a negative correlation between age and the two HRV indices. Results of this study indicate that APG can be a potential modality for heart-rate-variability analysis and identification of individuals at risk. The possibility of replacing ECG-based HRV is motivated by the desire for simpler high-throughput measurements in a clinical setting. Our preliminary study demonstrate indicative results, and now motivates the need for a larger study that validates HRV measures from PPG against those obtained from ECG.

Acknowledgments

Mohamed Elgendi would like to gratefully acknowledge the Australian government and Charles Darwin University, as their generous scholarships facilitated this research. He appreciates the support of Prof. Friso De Boer, who provided access to the PPG database and valuable comments.

References

1. Berntson G, Bigger J, Eckberg D, Grossman P, Kaufmann P, et al. (1997) Heart rate variability: origins, methods, and interpretive caveats. Psychophysiology 34: 623–48.

2. Constant I, Laude D, Murat I, Elghozi JL (1999) Pulse rate variability is not a surrogate for heart rate variability. Clinical Science 97: 391–397.

3. Giardino ND, Lehrer PM, Edelberg R (2002) Comparison of finger plethysmograph to ECG in the measurement of heart rate variability. Psychophysiology 39: 246–253.

4. Lu S, Zaho H, Ju K, Shin K, Lee M, et al. (2008) Can photoplethysmography variability serve as an alternative approach to obtain heart rate variability information? Journal Clinical Monitoring and Computing 22: 23–9.

5. Jianfeng W, Zhiqian Y, Jianling W (2005) An improved pre-processing approach for photoplethysmographic signal. In: Proc. 27th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. pp. 41–44.

6. Fitchett D (1984) Forearm arterial compliance: a new measure of arterial compliance? Cardiovascular Research 18: 651–656.

7. Seki H (1977) Classification of wave contour by first and second derivative of plethysmogram (in Japanese). Pulse Wave 7: 42–50.

8. Elgendi M (2012) Standard terminologies for photoplethysmogram signals. Current Cardiology Reviews 8: 215–219.

9. Takazawa K, Fujita M, Kiyoshi Y, Sakai T, Kobayashi T, et al. (1993) Clinical usefulness of the second derivative of a plethysmogram (acceleration plethysmogram). Cardiology 23: 207–217.

10. Taniguchi K, Nishikawa A, Nakagoe H, Sugino T, Sekimoto M, et al. (2007) Evaluating the surgeon's stress when using surgical assistant robots. In: Proc. 16th IEEE International Symposium on Robot and Human Interactive Communication, August 26–29, 2007, Jeju, South Korea, pp. 888–893.

11. Matsuyama A (2009) ECG and APG Signal Analysis during Exercise in a Hot Environment. PhD Thesis, Charles Darwin University, Darwin, Australia.

12. Maniwa Y, Amata M, Uchida I, Ohta S, Nunokawa T (2003) The chaos and complex system in medicine. Nihon Chinou Joho Fuzzy Journal 15: 635–642.

13. Task Force of the European Society of Cardiology the North American Society of Pacing and Electrophysiology (1996) Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. Circulation 93: 1043–1065.

14. Buchman T, Stein P, Goldstein B (2002) Heart rate variability in critical illness and critical care. Curr Opin Crit Care 8: 311–315.

15. Kleiger RE, Stein PK, Bigger JT (2005) Heart rate variability: Measurement and clinical utility. Annals of Noninvasive Electrocardiology 10: 88–101.

16. Tsuji H, Larson MG, Venditti FJ, Manders ES, Evans JC, et al. (1996) Impact of reduced heart rate variability on risk for cardiac events: The framingham heart study. Circulation 94: 2850–2855.

17. La Rovere MT, Pinna GD, Maestri R, Mortara A, Capomolla S, et al. (2003) Short-term heart rate variability strongly predicts sudden cardiac death in chronic heart failure patients. Circulation 107: 565–570.

18. MacArthur Research Network on SES & Health (2008) Heart Rate Variability. University of California San Francisco, http://www.macses.ucsf.edu/research/allostatic/.

19. Umetani K, Singer DH, McCraty R, Atkinson M (1998) Twenty-four hour time domain heart rate variability and heart rate: Relations to age and gender over nine decades. Journal of the American College of Cardiology 31: 593–601.

20. Bansal D, Khan M, Salhan AK (2009) A review of measurement and analysis of heart rate variability. In: Proc. International Conference on Computer and Automation Engineering, March 8–10, 2009, Bangkok, Thailand, pp. 243–246.

21. Laguna P, Caminal P, Jane R, Rix H (1990) Evaluation of HRV by PP and RR interval analysis using a new time delay estimate. In: Proc. IEEE Computers in Cardiology, Sep 23-26, 1990, Chicago, USA, pp. 63–66.

22. Elgendi M (2012) On the analysis of fingertip photoplethysmogram signals. Current Cardiology Reviews 8: 14–25.

Tables

Table 1. HRV Statistical Variables.

Variable	**Statistical measurement**
MAX-MIN	Difference between shortest and longest aa interval
SDNN	Standard deviation of all aa intervals
RMSSD	Root mean square of the difference of successive aa intervals
SDSD	Standard deviation of differences between adjacent aa intervals

Figures

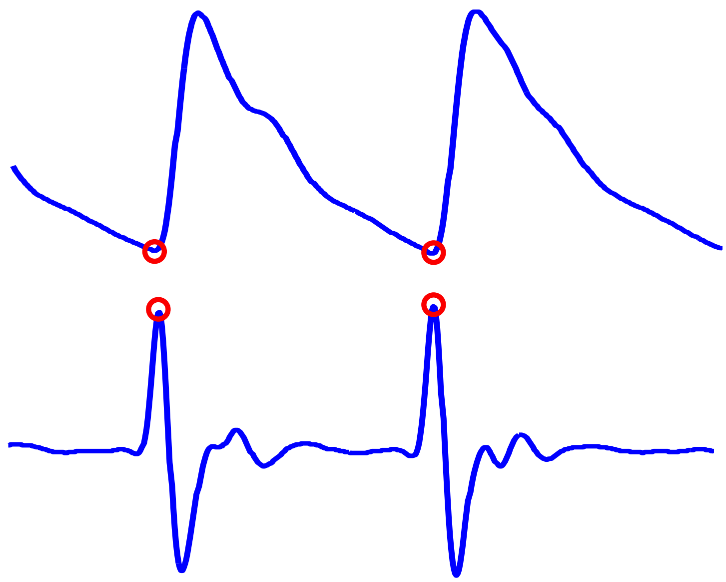

Figure 1. Two successive beats in (a) fingertip photoplethysmogram (PPG) signal (b) second derivative wave of photoplethysmogram (APG) signal.

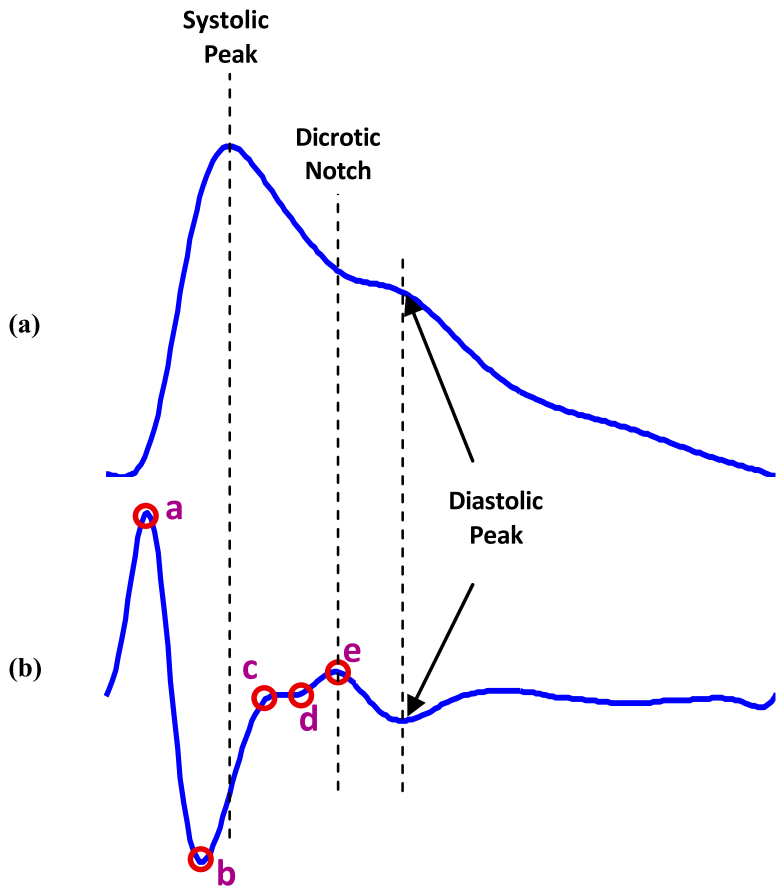

Figure 2. Fingertip photoplethysmogram signal measurement [22]. (a) Fingertip photoplethysmogram. (b) Second derivative wave of photoplethysmogram. The photoplethysmogram waveform consists of one systolic wave and one diastolic wave, while the second derivative photoplethysmogram waveform consists of four systolic waves (a, b, c, and d waves) and one diastolic wave (e wave).

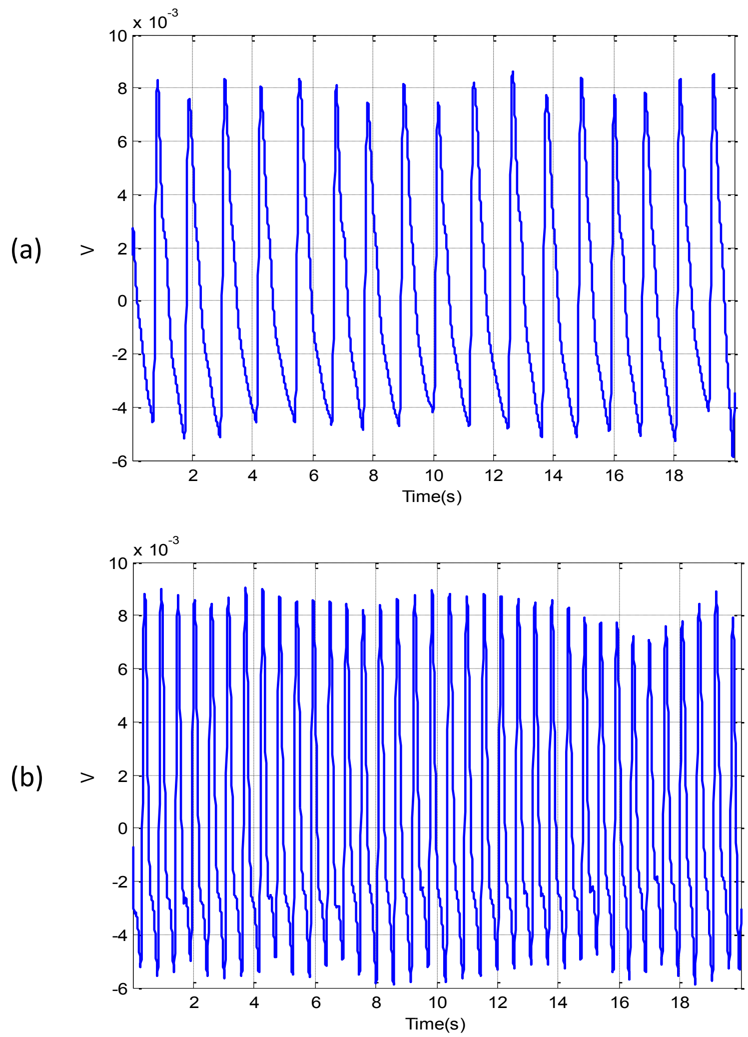

Figure 3. An example of PPG recordings for the same volunteer measured (a) during rest and (b) after exercise. It is clear that the heart rate after exercise was higher than during rest.

(a)

(b)

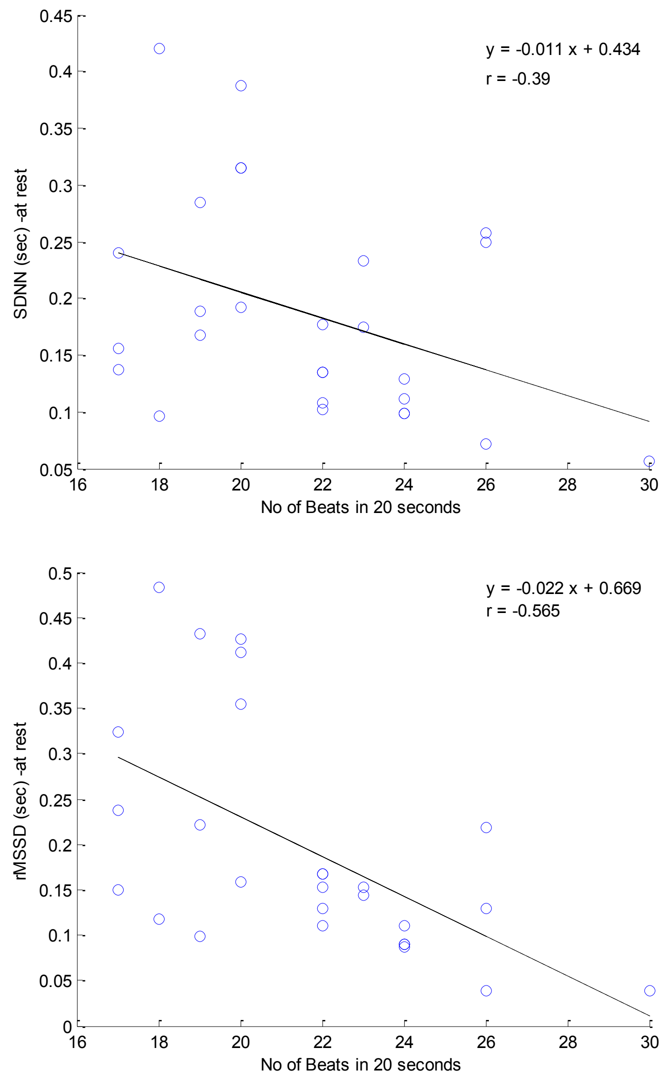

Figure 4. Correlation between heart rate and HRV indices. (a) HR and SDNN, (b) HR and rMSSD. It is clear that the rMSSD index is more negatively correlated with HR for APG signals measured at rest than the SDNN index

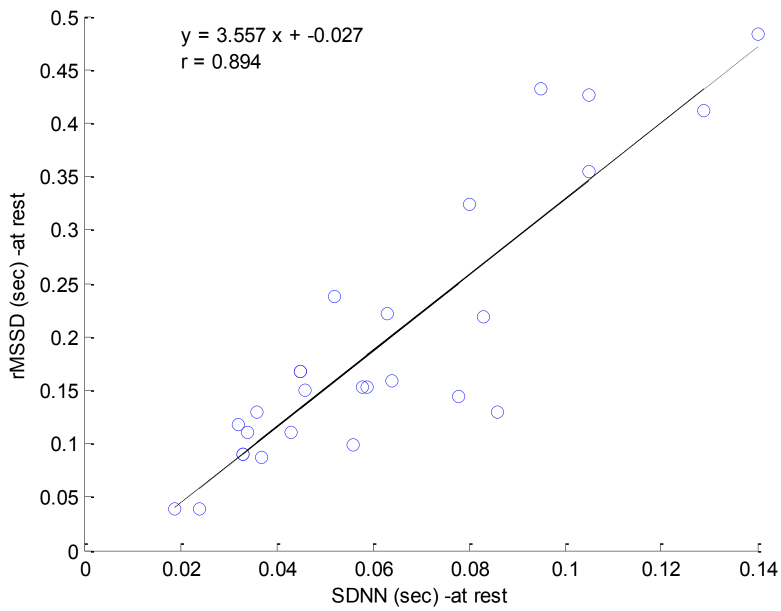

Figure 5. Correlation between SDNN and rMSSD calculated from APG signals for all subjects measured at rest. It is clear that the SDNN index is highly correlated with rMSSD index.

(a)

(b)

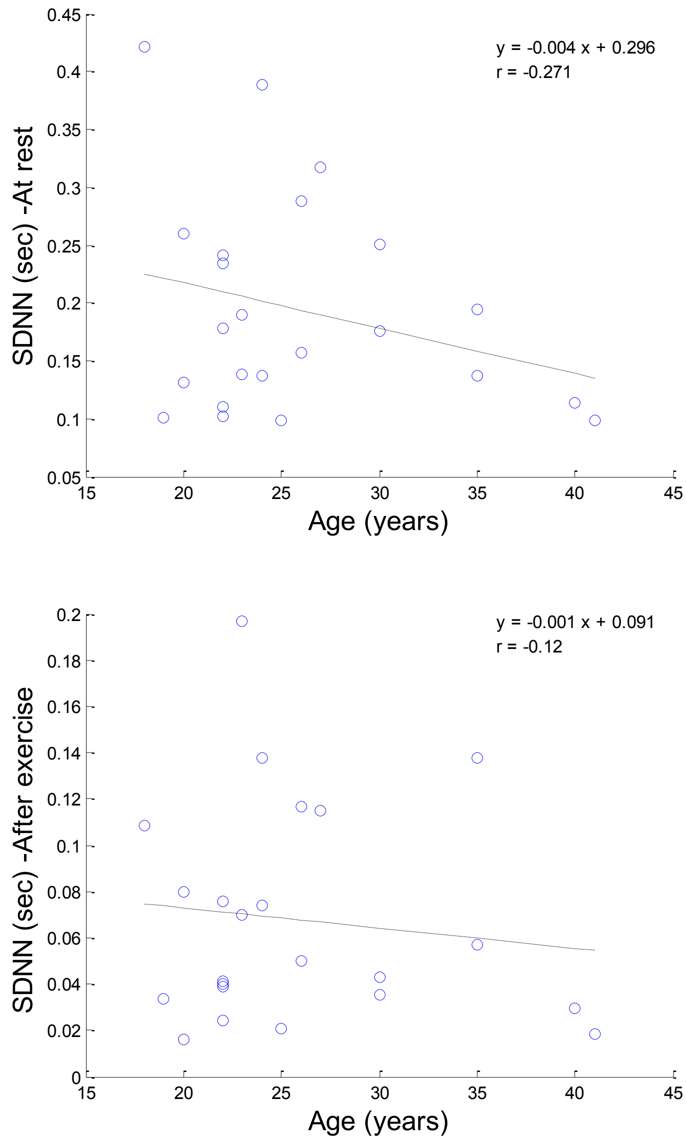

Figure 6. Correlation between age and SDNN index. (a) Age and SDNN calculated from APG signals for all subjects measured at rest, (b) age and SDNN calculated from APG signals for all subjects measured after exercise. It is clear that the SDNN index is more negatively correlated with age for APG signals measured at rest compared to after-exercise measurements.

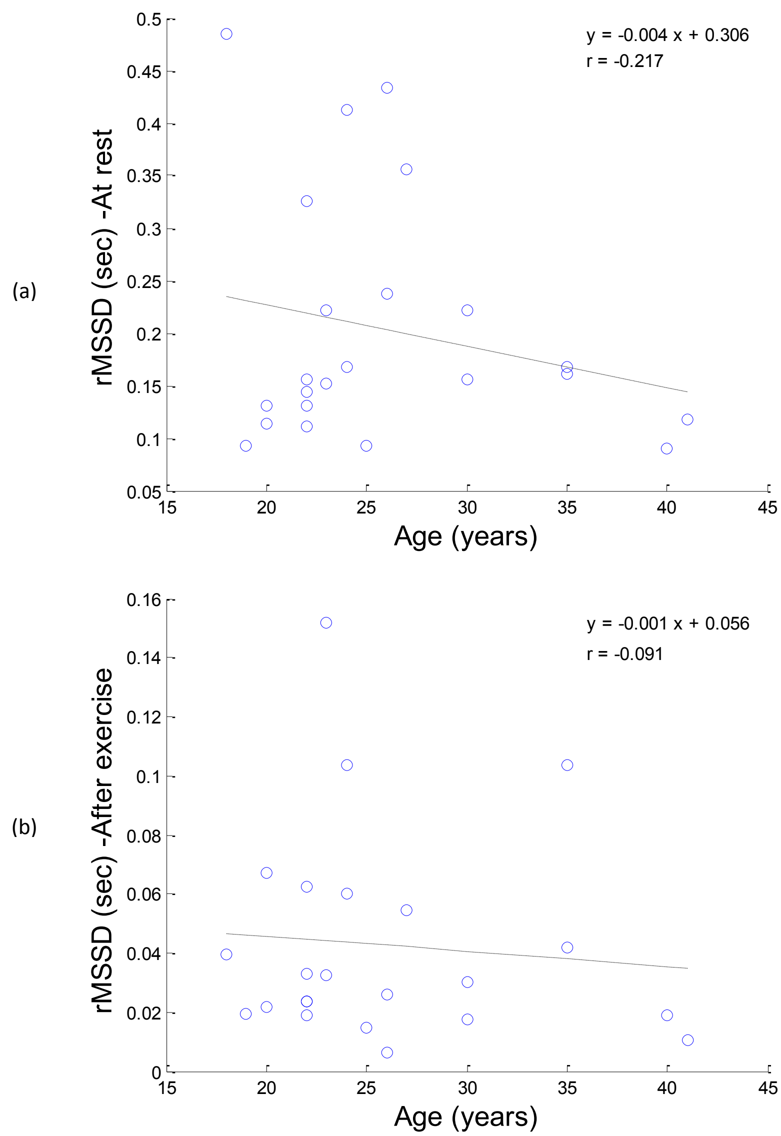

Figure 7. Correlation between age and rMSSD. (a) Age and rMSSD calculated from APG signals for all subjects measured at rest, (b) age and rMSSD calculated from APG signals for all subjects measured after exercise. It is clear that the rMSSD index is more negatively correlated with age for APG signals measured at rest compared to after-exercise measurements.