Post-exercise heart rate variability in the acceleration photoplethysmogram

Mohamed Elgendi

Department of Computing Science, University of Alberta, Canada

E-mail: moe.elgendi@gmail.com

Abstract

There is a limited number of studies on heart rate variability (HRV) dynamics immediately after exercise. It is well-known that the electrocardiogram is a non-invasive method that can be used to measure heart rate variability (HRV) at rest and after exercise. Photoplethysmogram (PPG) signals also reflect the cardiac rhythm since the mechanical activity of the heart is coupled to its electrical activity. Photoplethysmography is a non-invasive, safe, and easy-to-use technique that has been developed for experimental use in vascular disease. In this study, HRV has been investigated over 27 healthy subjects measured at rest and after exercise using PPG signals. The use of the *aa* interval in APG signals showed very promising results in calculating the HRV statistical indices, SDNN and rMSSD. Moreover, the after exercise SDNN and rMSSD indices have shown negative correlation with age.

Keywords: heart rate variability, acceleration photoplethysmogram, heat stress signal analysis, PPG signals

1. Introduction

Heart rate variability (HRV) has been extensively studied in electrocardiogram signals. HRV has become the conventionally accepted term to describe variations of both instantaneous heart rate and RR intervals in electrocardiogram (ECG) signals. Therefore, 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.

HRV measures the heart rate variations around the mean heart rate (HR). HRV provides information about the sympathetic-parasympathetic autonomic stability and consequently about the risk of unpredicted cardiac death. The traditional method to detect heart beats is detecting R peaks in ECG signals; a very promising tool to derive useful information about the hemodynamics as well as autonomic nerve system is the photoplethysmogram (PPG) signals. Accurate detection of inter-beat intervals from fingertip PPG signals is considered difficult. Ventricular pressure and other parameters of cardiac output however 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 possible weaknesses of using the fingertip PPG signals in measuring HRV are mentioned by Bernston *et al.* [1]. Hence, they recommend the usage of RR intervals from ECG signals to determine inter-beat intervals. They do believe, however, that with a sophisticated peak detection algorithm the use of intra-arterial pressure pulses may be acceptable. According to them indirect measures, such as photoplethymographic signals need further validation.

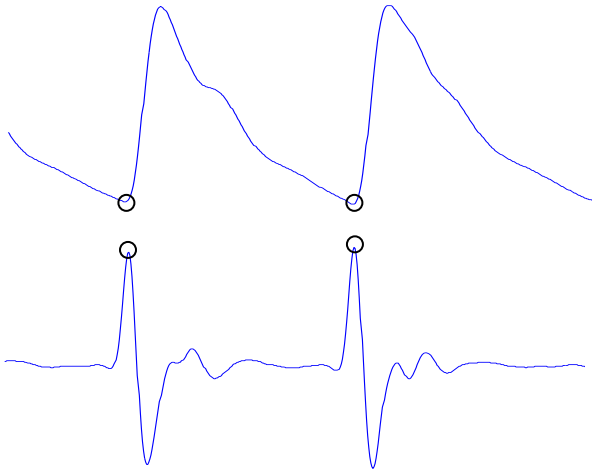


Figure 1 Two successive beats in (a) fingertip photoplethysmogram (PPG) signal (b) second derivative wave of photoplethysmogram (APG) signal.

Giardino *et al.*[2] 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 extra studies that include test–retest reliability evaluation of different data collection techniques.

These reasons may explain the lack in investigating the use of PPG signals instead of ECG signals to measure the heart rate (HR) and the heart rate variability (HRV).

The PPG contour itself can be used to detect the heart beat and consequently HRV can be measured [3], as shown in Figure 1 (a) the two circles represent two consecutive heart beats with the smallest positive values in the PPG signal. However, reliable detection of heart beats from the PPG contour is challenging due to PPG noise and its interference incorporated nature [4].

To overcome the PPG contour analysis, the second derivative of photoplethysmogram, also called the acceleration plethysmogram (APG), has been introduced, as shown in Figure 1 (b); the two circles represent two consecutive heart beats with the largest positive values in the APG signal. Because the peaks in the APG signal are more clearly defined than the peaks in the PPG contour the heart rate can be more accurately detected using the APG.

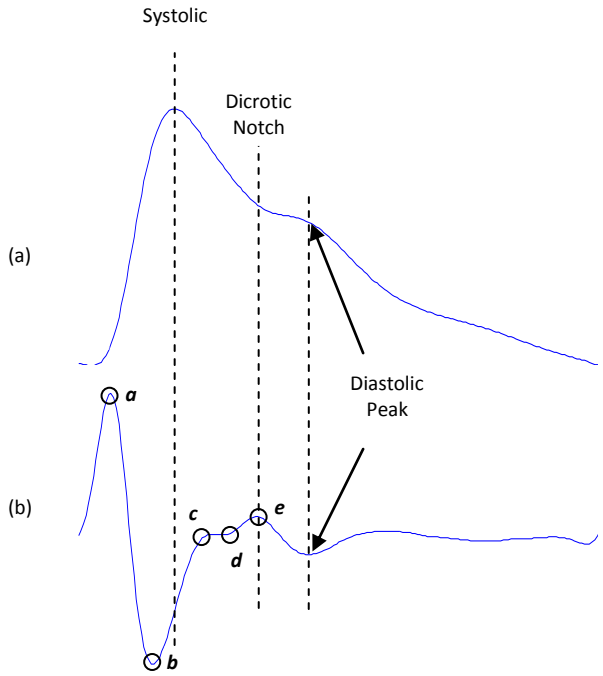


Figure 2 Signal Measurements [5] (a) fingertip photoplethysmogram (b) second derivative wave of photoplethysmogram. The photoplethysmogram waveform consists of one systolic wave and one diastolic wave while the second derivative photoplethysmogram waveform consists of four systolic waves (*a*, *b*, *c*, and *d* waves) and one diastolic wave (*e* wave).

Fingertip photoplethysmography mainly reflects the pulsatile volume changes in the finger arterioles, has been recognized as a noninvasive method of measuring arterial pulse waves in relation to changes in wave amplitude (Fichett [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 delicate changes in the waves were emphasized and easily quantified by quadratically differentiating the original PPG signal with respect to time (Seki [7]; Ozawa [8]). Accordingly, the second derivative of the PPG (APG) was developed as a method allowing more accurate recognition of the inflection points and easier interpretation of the original plethysmogram wave.

In this paper, the abbreviation PPG is going to be used for photoplethysmogram and APG for the second derivative photoplethysmogram based on Elgendi's recommendation [9].

As shown in Figure 2 (b), The waveform of the APG consists of four systolic waves (*a*, *b*, *c* and *d* waves) and one diastolic wave (*e* wave) Takazawa et al.[10]. The height of each wave was measured from the baseline, with the values above the baseline being positive and those under it negative. The first systolic wave, the *a*-wave seems the most suitable for heart rate calculations because of its amplitude and steepness.

Taniguchi *et al* [11] used the *aa* interval in the APG signals to determine HR instead of using the ECG when assessing the stress experienced by surgeons.

In the present study, our goal was to determine if variations in the APG signal can be used instead of the ECG for measuring the HRV. In addition, we investigate the relationship between HRV, HR and age at rest and after exercise.

2. Data

There are currently no standard PPG databases available to evaluate the developed algorithms. However, Charles Darwin University has PPG dataset measured at rest and after exercise, as shown in Figure 3. Two independent annotators annotated *a* and *b* waves in APG signal.

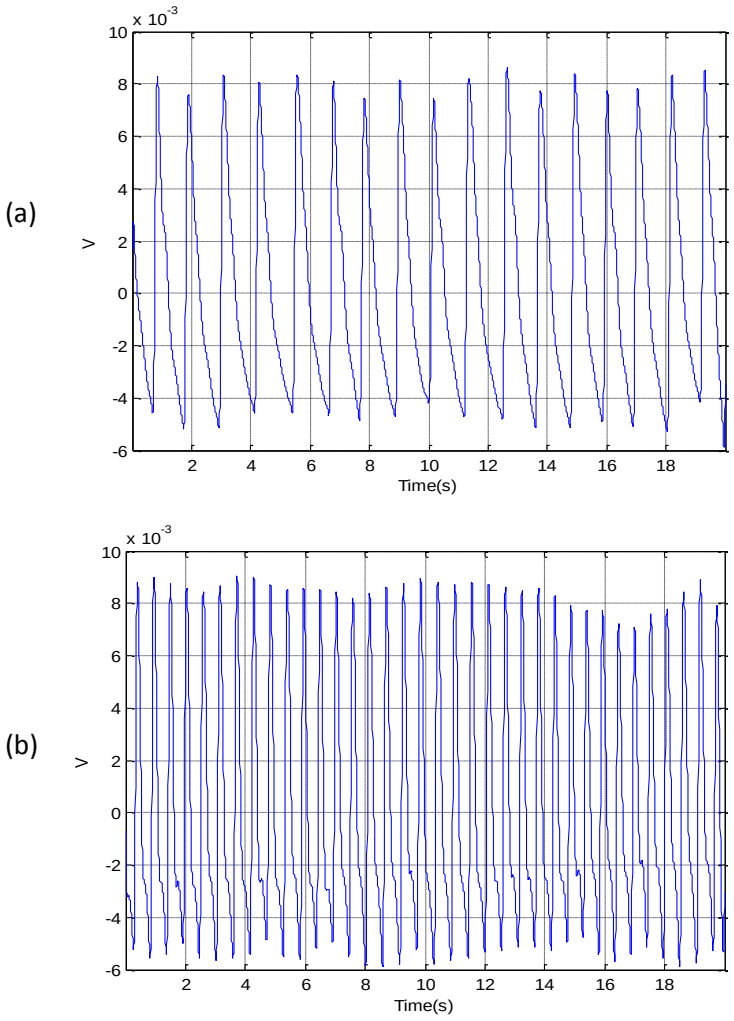


Figure 3 PPG signals: 20-seconds recording for the same volunteer, measured (a) at rest and (b) after exercise. It is clear that the heart rate after exercise is higher than at rest. This issue makes it challenging to detect heartbeats from APG signals.

The PPG data were collected as a minor part of a joint project between Charles Darwin University, the Defence Science and Technology Organisation (DSTO) and the Department of Defence. The background of the entire project can be found in [12].

PPGs of 27 healthy volunteers (males) with a mean±SD age of 27±6.9 were measured using a photoplethysmography device (Salus PPG), with the sensor located at the cuticle of the second digit of the left hand. Measurements were taken while the subject was at rest on a chair. PPG data were collected at a sampling rate of 200 Hz. The duration of each data segment is 20 seconds.

Annotations is a difficult task due to inter-annotator discrepancy, as the two annotators will never agree completely on what and how to annotate the *a* wave. Despite the annotation process being significantly time-consuming, discrepancies can be found in many records. Three cases will be discussed below to show how the discrepancies were adjudicated:

- Case 1:
  Annotator 1 agrees with Annotator 2 on all of the *a* wave positions within an APG record. When both annotators have no discrepancies, it is an optimal situation.
- Case 2:
  Both annotators agree on most of the *a* wave positions except the first a wave at far left and the last *a* wave at the far right.
- Case 3:
  Annotator 2 considered these two waves *a* waves while Annotator 1 did not.

One annotation file has been saved to present the two annotated *a* waves by considering the *a* waves that have been missed by one of the annotators, or perhaps isolating *a* wave that is not consistent with the beat rhythm within the APG recording.

3. Methodology

The major reason for the interest in measuring HRV stems from its ability to predict survival after a heart attack. In ECG signals analysis, the interval between adjacent QRS complexes is termed as the normal to normal (NN) or RR interval. HRV refers to the beat-to-beat alterations in the heart rate. The results of a HRV analysis portray the physiological condition of the patient and are important indicator of cardiac disease. Many studies have shown that reduced HRV predicts sudden death in patients.

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 could place this methodology among other tools used in the management of vascular disease.

The detection of R peak is the main step in measuring HRV. Precise R-R interval calculations are necessary to accurately depict the physiological state. To date, over 26 different types of arithmetic manipulations of R-R intervals have been described in the literature to represent HRV [13].

Table 1 HRV Statistical Variables

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

The Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [14] suggest a number of simple time domain measures to estimate HRV. Their paper discussed that HRV is calculated using the mean standard deviation of the

length of the cardiac cycle. This can be determined using either the R-R intervals of a short ECG segment or the *a-a* intervals. Table 1 shows some simple time–domain HRV variables: MAX-MIN, SDNN, RMSSD, and SDSD, which can be calculated based on APG signals.

Can HRV be Measured by APG?

Traditionally, HRV measures are based on cardiac inter-beat intervals using the ECG. However, some practitioners have used a distal measurement of the arterial pulse, such as the fingertip PPG, to measure the 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 the fingertip PPG. The lack of sharp peaks in blood pressure pulses compared to the 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 parameters of cardiac output. Peripheral effects, such as changes in vascular tone, may also influence distal pulse peak detection. These possible weaknesses of the fingertip PPG were observed by Bernston et al. [15]. Hence, they recommend the use of R-R intervals from ECG signals to determine interbeat intervals. They believe that, with a sophisticated peak detection algorithm the use of intra-arterial pressure pulses may be acceptable. According to them indirect measures, such as photoplethymographic signals need further validation.

It has been demonstrated that under resting conditions the distal pulse pressure is sufficient for determining the heart rate [2]. 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. Giardino et al. [2] recommended extra studies that include test–retest reliability evaluations of different data-collection techniques.

These reasons may explain the lack of investigating the use of PPG signals instead of ECG signals to measure the HRV.

Lu et al. (2008) used the PPG contour itself without any derivatives as an alternative measurement for HRV [16]. However, Taniguchi et al. (2007) [16] used the second derivative of PPG to determine the heart rate instead of using the ECG when assessing the stress experienced by surgeons. As shown in Figures 1 the two circles of R peaks in the ECG signal can be replaced by *a* waves in the second-derivative PPG signal.

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 is investigated.

To detect the heart rate using the APG, precise detection of individual *a* waves is critical. The *a* wave detection algorithm used here was described in Section 8.1. The detected *a* waves will be saved in the array *A*. The duration of each consecutive *a-a* interval is calculated as

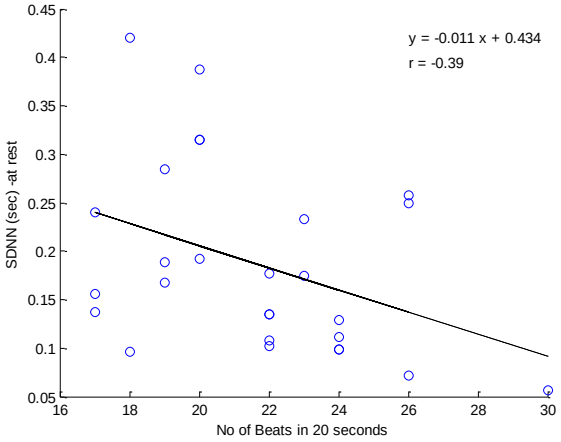
$$x[i] = A[i+1] - A[i] \qquad \text{Eq. 1}$$

where $x[i]$ will contain the *aa* intervals.

It is known that HRV decreases with normal aging using R peaks in ECG signals [17-19]. Therefore, if the same correlation between HRV using *a* waves in APG signals and age is decreasing, APG signals can measure HRV accurately.

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 the duration of heart beats; here, the R-R interval is replaced by *a-a* intervals. The SDNN will be calculated as follows:

(a)



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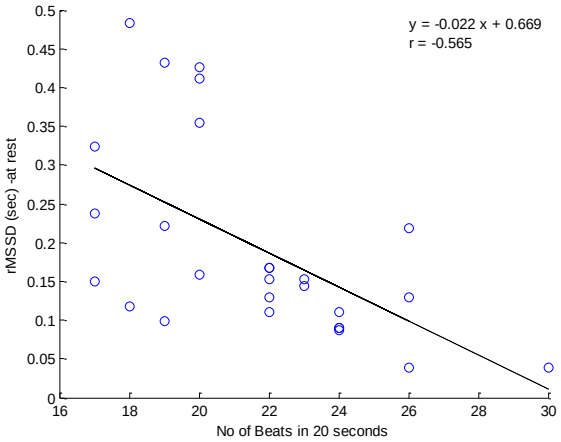

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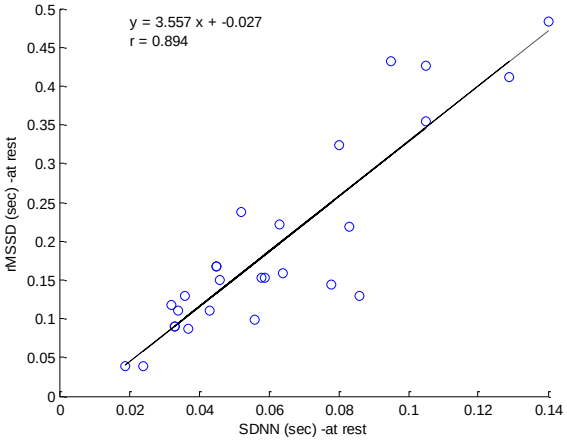


Figure 4 Demonstrating the correlation between heart rate and heart rate variability indices. (a) HR and SDNN, (b) HR and rMSSD, (c) SDNN and rMSSD calculated from APG signals for all subjects measured at rest. It is clear that the rMSSD index is more negatively correlated with HR for APG signals measured at rest than the SDNN index.

Table 2 HRV indices calculated using the APG

Record	No of beats	SDNN (sec)	rMSSD (sec)
A1	26	0.024	0.013
A2	24	0.033	0.030
B1	17	0.080	0.108
B2	26	0.086	0.043
C2	20	0.105	0.118
C3	20	0.105	0.142
D2	22	0.059	0.051
D3	19	0.063	0.074
E1	22	0.045	0.056
E2	22	0.045	0.056
E3	19	0.095	0.144
G2	30	0.019	0.013
G3	19	0.056	0.033
H3	23	0.058	0.051
I1	22	0.034	0.037
I2	17	0.052	0.079
J2	23	0.0778	0.048
L2	24	0.033	0.030
L3	24	0.037	0.029
N2	18	0.032	0.039
N3	20	0.064	0.053
O1	24	0.043	0.037
O2	17	0.0459	0.050
P1	26	0.083	0.073
P2	20	0.129	0.137
Q1	22	0.036	0.043
Q2	18	0.140	0.161

$$\mathrm{Var}(x) = \frac{1}{N}\sum_i (x[i])^2 - \left(\frac{1}{N}\sum_i x[i]\right)^2 \quad \text{Eq. 2}$$

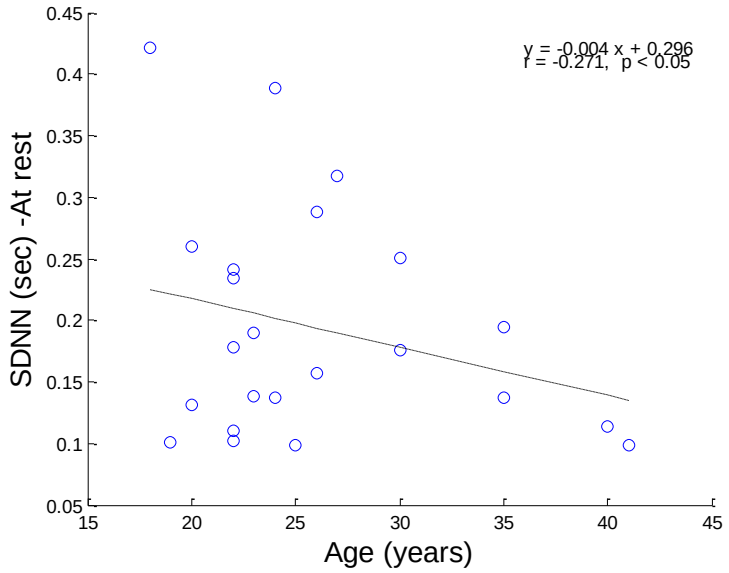
$$\mathrm{SDNN} = \sqrt{\mathrm{Var(x)}} \quad \text{Eq. 3}$$

The second parameter—*rMSSD*—is the root-mean square of the difference of successive heart beats, or RR intervals in ECG signals. Here, the R-R interval is replaced by *a-a* intervals. *rMSSD* will be calculated as follows:

$$\bar{x} = \frac{1}{N}\sum_i (x[i])^2 \quad \text{Eq. 4}$$

$$\mathrm{rMSSD} = \sqrt{\bar{x}} \quad \text{Eq. 5}$$

(a)



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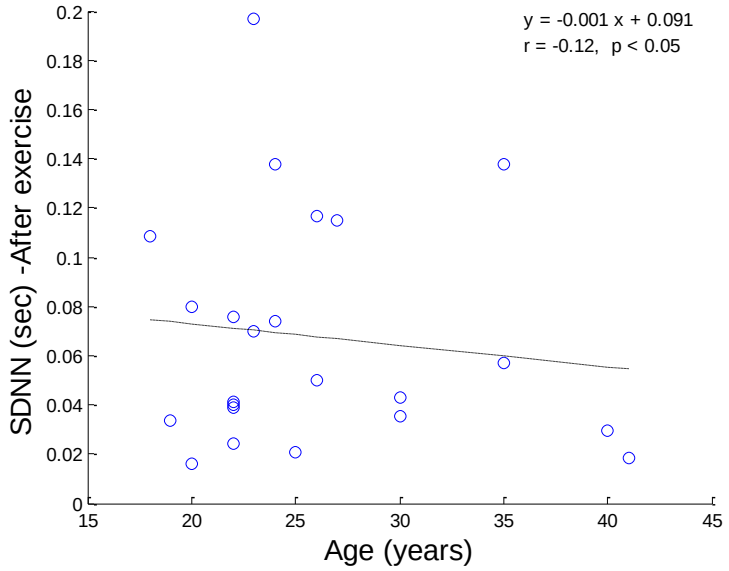

Figure 5 Demonstrating the correlation between Age and heart rate variability indices (a) Age and SDNN calculated from APG signals for all subjects measured at rest, (b) age and SDNN calculated from APG signals for all subjects measured after exercise. It is clear that the SDNN index is more negatively correlated with age for APG signals measured at rest compared to after-exercise measurements.

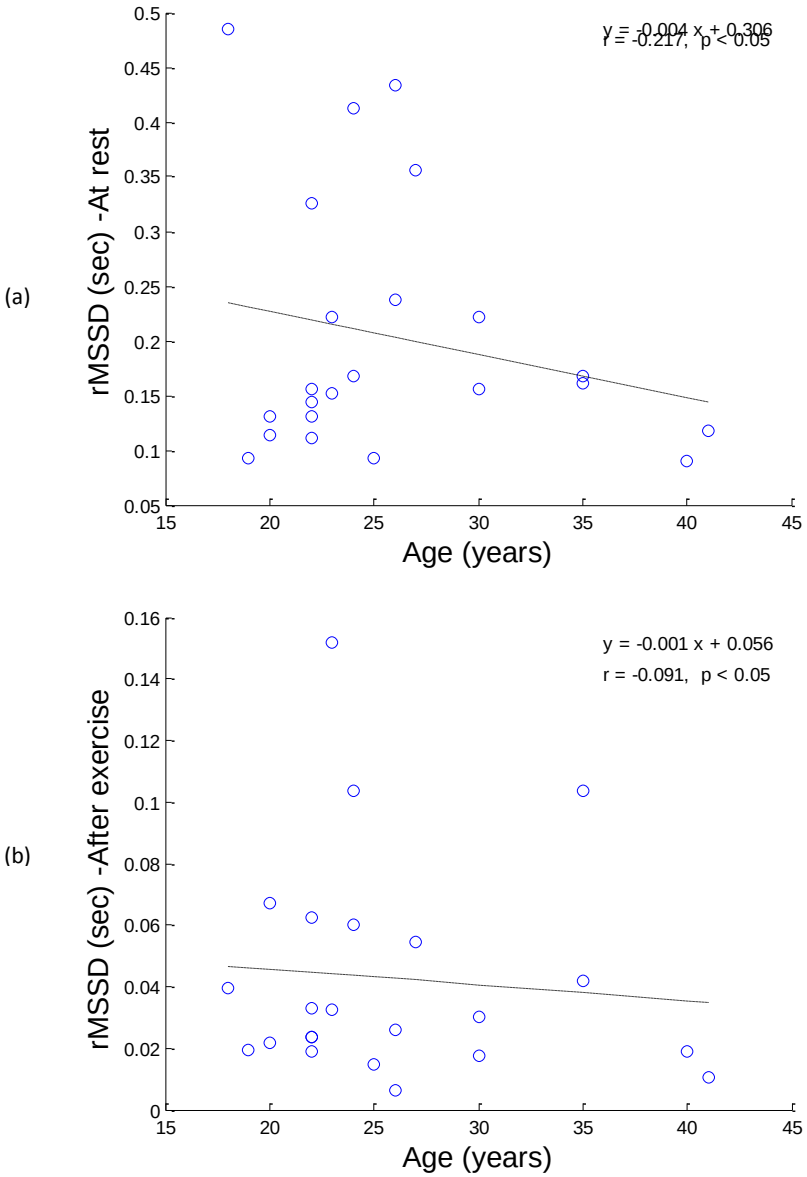

Figure 6 Demonstrating the correlation between age and rMSSD (a) Age and rMSSD calculated from APG signals for all subjects measured at rest, (b) age and rMSSD calculated from APG signals for all subjects measured after exercise. It is clear that the rMSSD index is more negatively correlated with age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

Results

The SDNN and rMSSD indices were calculated for 26 subjects at rest, using recordings of the PPG of 20 seconds. The results are shown in Table 2.

To calculate the correlation between the heart rate and the HRV indices, the following correlation coefficient is used:

$$r = \frac{Cov(u,v)}{\sigma_u \sigma_v} \qquad \text{Eq. 6}$$

Where r is the correlation coefficient, $Cov(u,v)$ is the covariance between data u and data v, σ_u is the standard deviation of data x and σ_v is the standard deviation of data v.

As shown in Figures 4 (a) and 4 (b) there is a negative correlation between the heart rate and the HRV indices. The rMSSD index is more negatively correlated with the HR (r = - 0.565) than the SDNN index (r = - 0.39).

Figure 4 (c) shows the correlation between the two HRV indices. As expected, there is a strong positive correlation (r = 0.894).

Figures 5 (a) and 5 (b) show 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) than the SDNN index after exercise (r = - 0.12).

Figures 6 (a) and 6 (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 the age (r = - 0.217) than the rMSSD index after exercise (r = - 0.091).

Conclusion

The heart rate can be calculated using the APG. The length of the *a-a* interval can be accurately determined if the *a* peaks are detected correctly.

As discussed above, HRV indices can be calculated using APG similar to ECG signals. The SDNN and rMSSD indices are suitable for short-duration signals and can be applied to 20 second APG recordings. Both indices showed 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.

The usage of APG can be useful for heart-rate-variability analysis and identification of individuals at risk and may replace the traditional ECG diagnostic system.

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