Can heart rate variability (HRV) be determined using short-term photoplethysmograms?

Mohamed Elgendi[1], Ian Norton[2], Matt Brearley[2], Socrates Dokos[3], Derek Abbott[4], and Dale Schuurmans[1]

[1]Department of Computing Science, University of Alberta, Canada

[2]National Critical Care and Trauma Response Centre, Darwin, Australia

[3]Graduate School of Biomedical Engineering, UNSW, Australia

[4]School of Electrical and Electronic Engineering, University of Adelaide, Australia

April 13, 2016

Abstract

To date, there have been no studies that investigate the independent use of the photoplethysmogram (PPG) signal to determine heart rate variability (HRV). However, researchers have demonstrated that PPG signals offer an alternative way of measuring HRV when electrocardiogram (ECG) and PPG signals are collected simultaneously. Based on these findings, we take the use of PPGs to the next step and investigate a different approach to show the potential independent use of short 20-second PPG signals collected from healthy subjects after exercise in a hot environment to measure HRV. Our hypothesis is that if the PPG–HRV indices are negatively correlated with age, then short PPG signals are appropriate measurements for extracting HRV parameters. The PPGs of 27 healthy male volunteers at rest and after exercise were used to determine the HRV indices: standard deviation

of heartbeat interval (SDNN) and the root-mean square of the difference of successive heartbeats (RMSSD). The results indicate that the use of the *aa* interval, derived from the acceleration of PPG signals, is promising in determining the HRV statistical indices SDNN and RMSSD over 20-second PPG recordings. Moreover, the post-exercise SDNN index shows a negative correlation with age. There tends to be a decrease of the PPG–SDNN index with increasing age, whether at rest or after exercise. This new outcome validates the negative relationship between HRV in general with age, and consequently provides another evidence that short PPG signals have the potential to be used in heart rate analysis without the need to measure lengthy sequences of either ECG or PPG signals.

Pulse oximeter, exercise, affordable healthcare, photoplethysmography

1 Introduction

Heart rate variability (HRV) has been extensively studied in electrocardiogram (ECG) signals, having become the conventionally accepted metric to describe variations of both instantaneous heart rate (HR) and RR intervals. The metrics used in the literature to describe HRV include cycle length variability, heart period variability, RR variability, and RR interval tachogram.

The measurement of HRV captures HR variations of the mean HR and provides information on the sympathetic–parasympathetic autonomic stability and thus the risk of sudden cardiac death. For example, when subjects are continuously subjected to dry heat, the heat induces a stress response indicated by a significantly increased HR. This increase in HR appears to occur as a result of a significant reduction in parasympathetic control of the HR, indicated by reduced HRV [1].

The traditional method of identifying heartbeats in ECGs is by detect-

ing R peaks. In almost every study, comparisons are made between HRV calculated from ECG signals and those calculated from photoplethysmogram (PPG) signals. In these studies, the feasibility of using PPGs as an alternative simple, inexpensive, and convenient diagnostic tool was explored in parallel with the use of ECGs. The overall results showed that PPG is potentially an ideal stand-alone alternative but it has not been explored independently. These cautious evaluations may explain the lack of investigation into the use of PPG signals instead of ECGs to measure HR and HRV.

Interestingly, the accurate detection of inter-beat intervals from fingertip PPG signals is considered challenging [2, 3, 4]. The potential weaknesses in using fingertip PPG signals to measure HRV are raised by Bernston *et al.* [2], 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. The PPG contour itself can be used to detect the heartbeat, and thus HRV can be measured [5].

Giardino *et al.*[4] 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 [5], as shown in Figure 1 (a) where the two circles represent two consecutive heartbeats with the smallest positive amplitudes of the PPG

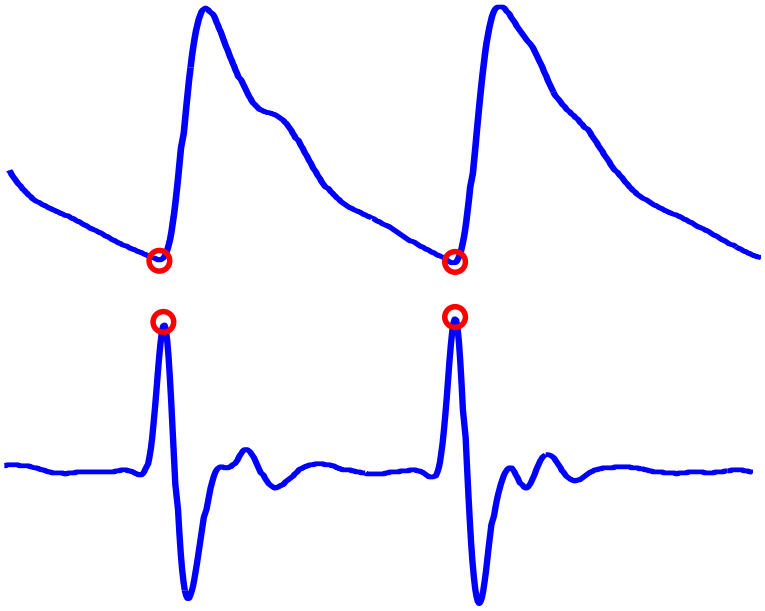

Figure 1: **Two successive beats in (a) fingertip photoplethysmogram (PPG) signal (b) second derivative wave of photoplethysmogram (APG) signal.**

signal. However, reliable detection of heartbeats from the PPG contour is challenging due to PPG noise and the nature of its associated interference with hemodynamic variables [6]. 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 signal, specifically the a wave, as shown in 2(b).

We therefore sought to validate the usefulness of PPGs using an alternative method without the collection of ECGs based on the already established

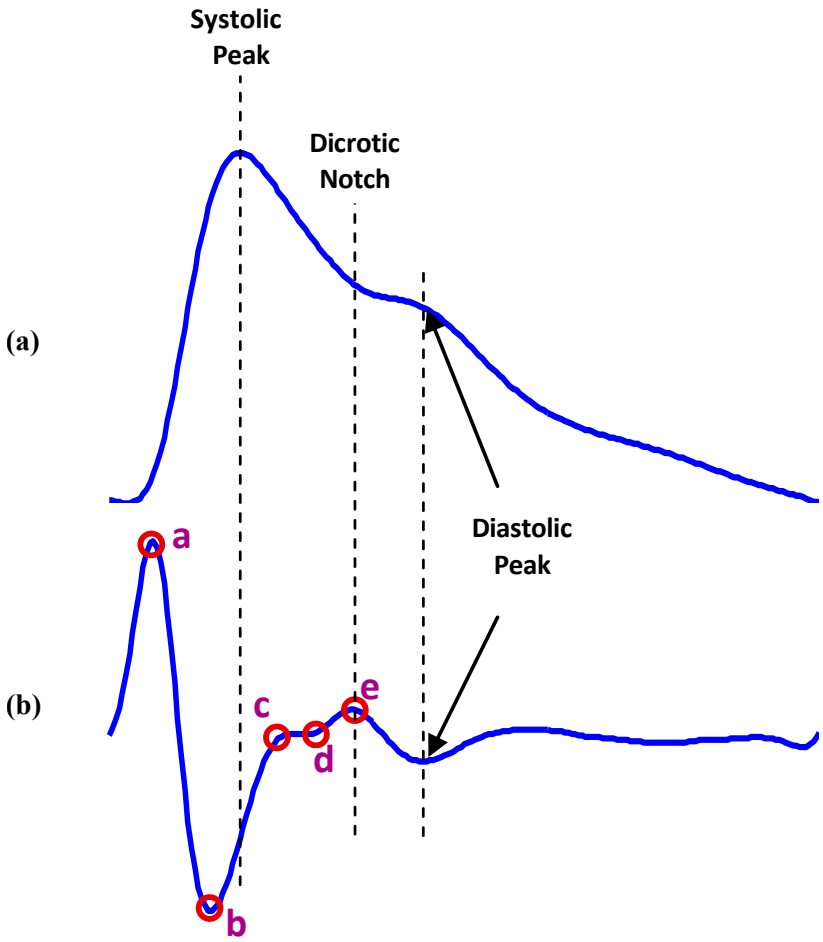

Figure 2: **Fingertip photoplethysmogram signal measurement [7].** (a) Fingertip photoplethysmogram. (b) Second derivative wave of photoplethysmogram. The photoplethysmogram waveform consists of one systolic wave and one diastolic wave, while the second derivative photoplethysmogram waveform consists of four systolic waves (a, b, c, and d waves) and one diastolic wave (e wave).

negative correlation between HRV and age [8]. We hypothesized that if the PPG–HRV indices calculated from short PPG signals are negatively correlated with age then a short PPG signal is an appropriate measurement for extracting HRV parameters. In this study, only the standard deviation of the heartbeat interval (SDNN) and the root-mean square of the difference of successive heartbeats (RMSSD) indices are investigated, as they are suitable

for short recordings based on the recommendation in [9]. Herein we investigate if the SDNN and RMSSD calculated from short PPG signals measured before and after exercise can potentially be correlated with age.

2 Materials and Methods

2.1 Ethics Statement

There is one annotated PPG database available at Charles Darwin University. The data were collected, in 2006, from participants during rest (before exercise) and after one hour of exercise (walking) on a treadmill in the climate control chamber at the Northern Territory Institute of Sport (Darwin, Australia). This protocol was repeated three times with PPG data collected during each rest period as shown in Figure 3.

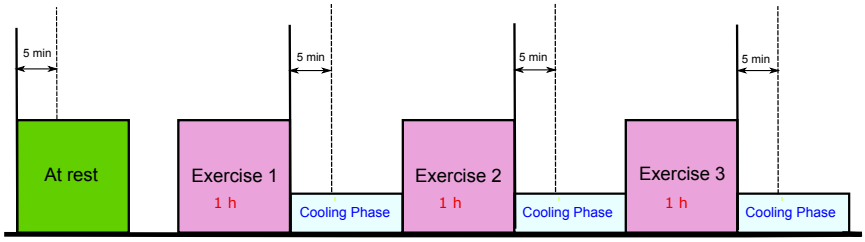

Figure 3: **Measurement Protocol.** The duration of the whole experiment was approximately 4 hours, each exercise consumed approximately 1 hr while the PPG signals collected during the 5 minutes break of each exercise at a sampling rate of 200 Hz. The length of each PPG recording is 20 seconds.

The treadmill speed was set to 5 km/h with a 1% incline increment corresponding to the effort required to walk on 8 kg of webbing. The exercise was considered to be of moderate intensity. Background information about the entire project can be found in [10]. All subjects provided written informed consent before participation, and the Ethics Committee of Charles Darwin University approved the study. The study was performed in accordance with

relevant guidelines and regulations. The database is available upon request at Charles Darwin University (`http://www.cdu.edu.au/ehse`).

2.2 Database Used

The PPGs of 27 healthy male volunteers with a mean ± SD age of 27 ± 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. The measurements were taken while each 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.

We used one PPG oximeter to collect the data from all subjects measured after each exercise. It was not plausible to collect data for a longer period of time as we needed to measure other subjects waiting in line. The longer the waiting time, the more the heat stress impact due to cooling of the body is lost. Therefore, it was convenient to collect data for a consistent recording length of 20 seconds. This also serves as a preliminary test of feasibility, where the ease of shorter recording lengths is desirable in a clinical setting.

The beat annotations were carried out by a cardiologist, and each beat was labeled as an a wave after processing the PPG signals with a second-order bandpass Butterworth filter from 0.5–8 Hz of the unfiltered PPG signal, based on the recommendation in [11]. 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. MATLAB 2012a (The MathWorks, Inc., Natick, MA, USA) was used for PPG signal analysis.

2.3 Methodology

Detection of a wave

In this study, the a wave detection algorithm published in [12] in will be used. The algorithm is adapted from the framework proposed by Elgendi for detecting systolic waves in PPG signals [11], for detecting QRS complexes in ECG signals [13, 14], and for detecting c, d, and e waves in APG signals [15]. The same approach will be used here to detect the a waves. The algorithm consists of four stages: bandpass filtering, squaring, generating potential blocks, and thresholding and uses five parameters F_1, F_2, MA_{peak}, MA_{beat}, and β. Each stage is explained in more detail as follows.

- *Bandpass Filter:* A zero-phase second-order Butterworth filter, with bandpass 0.5–15 Hz, was implemented to remove the baseline wander and high frequencies that do not contribute to the a wave. The output of the zero-phase Butterworth filter applied to the PPG signal—at rest and after exercise—produced a filtered signal $S[n]$. Therefore, $F_1 = 0.5$ Hz and $F_2 = 15$ Hz based on a brute force search that is discussed in the parameter optimization section in [12].

- *Second Derivative:* To obtain the APG signals, the second derivative was applied to the filtered PPG in order to analyze the APG signals. Equations 1 and 2 represent a non-causal filter; the three-point centre derivative was created with a delay of only two samples.

$$S'[n] = \frac{dS}{dt}|_{t=nT} = \frac{1}{2T}(S[n+1] - S[n-1]), \tag{1}$$

$$Z[n] = \frac{dS'}{dt}|_{t=nT} = \frac{1}{2T}(S'[n+1] - S'[n-1]), \tag{2}$$

where T is the sampling interval and equals the reciprocal of the sampling frequency and n is the number of data points.

- *Cancellation of b wave:* At this stage, the a wave of the APG needs to be emphasized to distinguish it clearly for detection. This can be done by clipping the negative parts of the APG signal ($Z[n] = 0$, if $Z[n] < 0$).

- *Squaring:* Squaring emphasizes the large differences resulting from the a wave, which suppress the small differences arising from the diastolic wave and noise. This step results in the output

$$y[n] = Z[n]^2, \tag{3}$$

which is important for improving the accuracy in distinguishing the a wave segment in APG signals.

- *Generating Blocks of Interest:* Blocks of interest are generated using two event-related moving averages that demarcate the a wave and heartbeat areas.

In this procedure, the first moving average ($\mathrm{MA}_{\mathrm{peak}}$) is used to emphasize the a wave area, and is given by

$$\begin{aligned} \mathrm{MA}_{\mathrm{peak}}[n] = \frac{1}{W_1}(y[n-(W_1-1)/2] + \ldots \\ +y[n] + \cdots + y[n+(W_1-1)/2]), \end{aligned} \tag{4}$$

where W_1 represents the window size of the systolic-peak duration. The resulting value is rounded to the nearest odd integer. The exact

value for W_1 of 175 ms is determined based on a brute force search that is discussed in the parameter optimization section in [12].

The second moving average ($\mathrm{MA}_{\mathrm{beat}}$) is used to emphasize the beat area to be used as a threshold for the first moving average, and is given by

$$\mathrm{MA}_{\mathrm{beat}}[n] = \frac{1}{W_2}(y[n-(W_2-1)/2] + \cdots + y[n] + \ldots + y[n+(W_2-1)/2]), \tag{5}$$

where W_2 represents a window size of approximately one beat duration. Its value is rounded to the nearest odd integer. The exact value for W_2 of 1000 ms is determined based on a brute force search that is discussed in the parameter optimization section in [12].

- *Thresholding:* The equation that determines the offset level (α) is $\beta\bar{z}$, where $\beta = 0$ based on a brute force search that is discussed in the parameter optimization section in [12], while $\bar{z}$ is the statistical mean of the squared filtered PPG signal. The first dynamic threshold value was calculated by shifting the $\mathrm{MA}_{\mathrm{beat}}$ signal with an offset level α, as follows:

$$\mathrm{THR}_1 = \mathrm{MA}_{\mathrm{beat}}[n] + \alpha. \tag{6}$$

In this stage, the blocks of interest were generated by comparing the $\mathrm{MA}_{\mathrm{peak}}$ signal with THR_1. Many blocks of interest will be generated, some of which will contain the APG feature (a wave), while others will primarily contain noise. Therefore, the next step is to reject blocks

that result from noise. Rejection is based on the anticipated systolic-peak width. In this paper, the undesired blocks are rejected using a threshold called THR_2, which rejects the blocks that contain diastolic wave and noise. By applying the THR_2 threshold, the accepted blocks will contain a waves only,

$$\mathrm{THR}_2 = W_1. \tag{7}$$

As discussed, the threshold THR_2 corresponds to the anticipated a wave duration. If a block is wider than or equal to THR_2, it is classified as an a wave. If not, it will be classified as noise. The last stage is to find the maximum absolute value within each block to detect the a wave. Not all the blocks contain potential a waves; some blocks are caused by noise and need to be eliminated. Blocks that are smaller than the expected width for the a wave duration are rejected. The rejected blocks are considered to be noisy blocks and the accepted blocks are considered to contain an a wave. The detected a waves are compared to the annotated a waves to determine whether they were detected correctly.

Performance of the a wave detector

We used two statistical measures to evaluate the a wave detection performance: sensitivity (SE) and positive predictivity (+P); whereas $\mathrm{SE} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN})$ and $+\mathrm{P} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FP})$. Here, TP is the number of true positives (a wave detected as an a wave), FN is the number of false negatives (a wave has not been detected), and FP is the number of false positives (non-a wave detected as an a wave). The SE reported the percentage of true a waves that were

correctly detected by the algorithm. The +P reports the percentage of the detected a waves that were true a waves.

Calculation of HRV indices

The detected a waves (heartbeats) are used to calculate the duration of each consecutive aa interval, as follows: $aa[i] = A[i+1] - A[i]$, where A represents the annotated a waves in each PPG signal, and aa represents the aa intervals. Note that 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 based on the analysis of R peaks in ECG signals [16, 17, 18]. Therefore, based on using a waves in PPG signals, if the correlation between HRV and age is decreasing, PPG 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 SD of heartbeat duration; here, the RR interval is replaced by aa intervals. The SDNN is calculated, as follows:

$$\text{SDNN} = (1/N)\sum_{i=1}^{N}(aa[i])^2 - \{(1/N)\sum_{i=1}^{N}(aa[i])\}^2. \tag{8}$$

The second parameter is RMSSD, which is calculated as follows:

$$\text{RMSSD} = \sqrt{(1/N)\sum_{i=1}^{N}(aa[i])^2}. \tag{9}$$

Analysis of trend

As we have a small sample size, there is a need to examine both the correlation coefficient (r) and the slope. Note that it is common to obtain a

small correlation with a small sample size, and therefore the slope can be used as an alternative to determine the relationship. Here, r is calculated as follows: $r = \frac{\mathrm{Cov}(u,v)}{\sigma_u \sigma_v}$, where $\mathrm{Cov}(u, v)$ is the covariance between data u and data v, σ_u is the SD of data u and σ_v is the SD of data v. Here, u and v refer to the HRV indices.

Significance of trend

To test the significance of the slope, we performed a multilinear regression of the responses in y on the predictors in x for all lines in Figures 4 and 5. The null hypothesis states that the slope is equal to zero, and the alternative hypothesis states that the slope is not equal to zero.

3 Results and Discussion

To date, several studies have evaluated the agreement between HRV calculated from PPG and ECG signals; however, some results remain controversial [19, 20]. This disagreement is due to applying inappropriate methodologies or inefficient experimental settings. Recent study by Chen *et al.* [21] showed that the accuracy of HRV obtained from PPG is mostly incommensurable across 26 unhealthy subjects. However, HRV calculated from PPG signal has been proved to be sufficiently accurate only for healthy (and mostly younger) subjects at rest [22]. Therefore, in our study, fit and healthy subjects were only considered. Because of this selection, it is expected that there will be *no* apparent differences between subjects. Moreover, we can focus on the age impact—without any dependencies such as arrhythmia, transvenous cardiac pacing, and heart transplant—as an indirect assessment for the usefulness of HRV calculated from PPG signals.

It is worth noting that the heat stress PPG data were collected for this

study as a part of the project funded by the Australian Department of Defence. As mentioned in the Database Used subsection, there was no exercise test with the same subjects in a cooler (or normal) environment included in the main project protocol. Therefore, we are unable comment, compare or discuss the HRV calculation in two different conditions, hot and cool environments.

The designed exercise length for the heat stress test was four hours; however, only 16 out of 27 subjects completed the full duration. All subjects were able to complete the first 1-hr exercise, and therefore we analyzed all PPG signals collected only after 1-hr exercise.

After collecting the PPG signals, perhaps the question was how can we calculate the HRV from these PPG signals more accurately. In the literature, we found that the second derivative of the PPG signal enhances its frequencies and improve waveform characteristics especially in heat stressed PPG signals [23]. Moreover, we found that detection of a waves in APG signals slightly increases the accuracy of detecting heart beats compared to systolic peaks in PPG signals. For example, the overall a wave detection rate was 99.9% [12], while the overall systolic wave detection rate was 99.8% [11]. Therefore, we applied the second derivative to the PPG signal to obtain APG signals and then applied the a wave detection algorithm described in the Methodology section.

The a wave detection algorithm was evaluated using 27 records, containing 1,540 heartbeats (584 heartbeats measured at rest and 956 heartbeats measured after 1-hr exercise), with an overall SE of 99.8%, and the overall +P of 100%. The overall accuracy was sufficient enough to calculate the HRV indices automatically.

After the automatic detection of a waves, SDNN and RMSSD indices are

calculated for 27 healthy subjects using PPG recordings each of 20 seconds duration during rest and after exercise. Figures 4 (a) and 4 (b) show the relationship between age and the SDNN index at rest and after exercise, respectively. The SDNN index at rest is more negatively correlated with age ($r = -0.271$) and has a steeper negative slope (-0.004) than after exercise ($r = -0.12$ and slope $= -0.001$). The slope significance for SDNN before exercise was with $p = 0.001$, and the slope significance for SDNN after exercise was $p = 0.04$.

Figure 5 (a) shows the relationship between the age and the RMSSD index at rest and Figure 5 (b) shows the relationship between the age and the RMSSD index after exercise. 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 $= -0.001$). The slope significance was achieved by RMSSD before exercise with $p = 0.04$, while it failed for RMSSD after exercise as $p = 0.18$.

It is worth mentioning that the remainder of the correlations is not as strong, specifically the correlation between SDNN and age and that between 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 a more precise evaluation for the trend analysis. Note that PPGs measured at rest have a greater negative slope compared to those measured after exercise. Although it was known that long-term exercise exerts significant effects on the HRV [24], it has not been investigated over short PPG signals. This study is important because it reports the effect of exercise on HRVs calculated from short PPG signals and compared their results in subject measured at rest and after exercise.

The results of various cross-sectional studies have shown a linear decrease

in HRV during exercise with increasing age using only ECG signals [25, 26, 16]. Interestingly, our results confirm the inverse linear relationship between HRV measure (SDNN and RMSSD) and age. Moreover, SDNN is statistically significant with age for PPG measured before and after exercise. This new outcome shows that HRV can potentially be measured using short PPG signals.

The proposed method was only tested on healthy subjects. The physiology of the subject significantly changes according to the health status, which can be reflected in the PPG signal. Therefore, the robustness of the proposed method needs to be verified by a study with unhealthy subjects. One of the next steps regarding the results of this study is to examine the HRV indices calculated from PPG signals in the diagnosis and monitoring of abnormalities, such as arrhythmia, hypertension, diabetes, and hyperlipidemia. The HRV indices are usually calculated over a period of five minutes from the ECG signals; however, the PPG recordings in this study were very short (20 seconds). Additional studies to demonstrate the 20-second recordings are equivalent in terms of usefulness to the standard length of time (5 minutes) are needed to further validate our findings. Studies that evaluate the extracted HRV indices as a function of PPG duration are recommended. The PPG database contains signals collected from subjects of approximately the same age (about 22 years old), which creates imbalance in the age distribution. Therefore, a larger and more diverse sample size with a balanced age distribution is needed to generalize the findings of this study.

4 Conclusion

The findings of this preliminary study build on previous studies that discussed the potential use of only PPG to measure HRV (i.e., without col-

lecting ECG data). The SDNN and RMSSD indices are suitable for short duration signals and can be applied to 20-second PPG recordings. Both indices show a negative correlation with age at rest. Interestingly, only SDNN shows significance for after exercise measurements. Since long signal measurement can be challenging due to pesrpiration, calculating SDNN using short PPG measurements from subjects after exercise in hot and humid weather is an appealing approach that needs to be explored on a larger scale. The overall result of this study indicates that short PPG signals can be a potential modality for HRV analysis and the identification of individuals at risk.

.

References

[1] S. S. Bruce-Low, D. Cotterrell, and G. E. Jones, "Heart rate variability during high ambient heat exposure," *Aviation, space, and environmental medicine*, vol. 77, no. 9, pp. 915–920, 2006.

[2] G. Berntson, J. Bigger, D. Eckberg, P. Grossman, P. Kaufmann, M. Malik, H. Nagaraja, S. Porges, J. Saul, P. Stone, and M. van der Molen, "Heart rate variability: origins, methods, and interpretive caveats," *Psychophysiology*, vol. 34, no. 6, pp. 623–648, 1997.

[3] I. Constant, D. Laude, I. Murat, and J.-L. Elghozi, "Pulse rate variability is not a surrogate for heart rate variability," *Clinical Science*, vol. 97, pp. 391–397, 1999.

[4] N. D. Giardino, P. M. Lehrer, and R. Edelberg, "Comparison of finger plethysmograph to ECG in the measurement of heart rate variability," *Psychophysiology*, vol. 39, no. 2, pp. 246–253, 2002.

[5] S. Lu, H. Zaho, K. Ju, K. Shin, M. Lee, K. Shelly, and K. Chon, "Can photoplethysmography variability serve as an alternative approach to obtain heart rate variability information?" *Journal Clinical Monitoring and Computing*, vol. 22, no. 1, pp. 23–9, 2008.

[6] W. Jianfeng, Y. Zhiqian, and W. Jianling, "An improved pre-processing approach for photoplethysmographic signal," in *Proc. 27th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2005, pp. 41–44.

[7] M. Elgendi, "On the analysis of fingertip photoplethysmogram signals," *Current Cardiology Reviews*, vol. 8, no. 1, pp. 14–25, 2012.

[8] I. O'Brien, P. O'Hare, and R. Corrall, "Heart rate variability in healthy subjects: effect of age and the derivation of normal ranges for tests of autonomic function." *British Heart Journal*, vol. 55, no. 4, pp. 348–354, 1986.

[9] H.-M. Wang and S.-C. Huang, "SDNN/RMSSD as a surrogate for LF/HF: a revised investigation," *Modelling and Simulation in Engineering*, vol. 2012, p. 16, 2012.

[10] A. Matsuyama, "ECG and APG Signal Analysis during Exercise in a Hot Environment," PhD Thesis, Charles Darwin University, Darwin, Australia, 2009.

[11] M. Elgendi, I. Norton, M. Brearley, D. Abbott, and D. Schuurmans, "Systolic peak detection in acceleration photoplethysmograms measured from emergency responders in tropical conditions," *PLOSONE*, vol. 8, no. 10, art. no. e76585, 10 2013.

[12] M. Elgendi, I. Norton, M. Brearley, D. Abbott, and D. Schuurmans, "Detection of *a* and *b* waves in the acceleration photoplethysmogram," *Biomedical Engineering Online*, vol. 13, no. 1, p. 139, 2014.

[13] M. Elgendi, "Fast QRS detection with an optimized knowledge-based method: Evaluation on 11 standard ECG databases," *PLoS ONE*, vol. 8, no. 9, p. e73557, 09 2013. [Online]. Available: http://dx.doi.org/10.1371%2Fjournal.pone.0073557

[14] M. Elgendi, M. Jonkman, and F. De Boer, "Frequency bands effects on QRS detection," in *the 3rd International Conference on Bio-inspired Systems and Signal Processing (BIOSIGNALS2010)*, 2010, pp. 428–431.

[15] M. Elgendi, "Detection of c, d, and e waves in the acceleration photoplethysmogram," *Computer Methods and Programs in Biomedicine*, vol. 117, no. 2, pp. 125–136, 2014.

[16] K. Umetani, D. H. Singer, R. McCraty, and M. Atkinson, "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*, vol. 31, no. 3, pp. 593–601, 1998.

[17] D. Bansal, M. Khan, and A. K. Salhan, "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, 2009.

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

[19] E. Gil, M. Orini, R. Bailón, J. Vergara, L. Mainardi, and P. Laguna, "Photoplethysmography pulse rate variability as a surrogate measurement of heart rate variability during non-stationary conditions," *Physiological Measurement*, vol. 31, no. 9, pp. 1271–1290, 2010.

[20] J.-S. Wong, W.-A. Lu, K.-T. Wu, M. Liu, G.-Y. Chen, and C.-D. Kuo, "A comparative study of pulse rate variability and heart rate variability in healthy subjects," *Journal of clinical monitoring and computing*, vol. 26, no. 2, pp. 107–114, 2012.

[21] X. Chen, Y.-Y. Huang, F. Yun, T.-J. Chen, and J. Li, "Effect of changes in sympathovagal balance on the accuracy of heart rate variability

obtained from photoplethysmography," *Experimental and therapeutic medicine*, vol. 10, no. 6, pp. 2311–2318, 2015.

[22] A. Schäfer and J. Vagedes, "How accurate is pulse rate variability as an estimate of heart rate variability?: A review on studies comparing photoplethysmographic technology with an electrocardiogram," *International journal of cardiology*, vol. 166, no. 1, pp. 15–29, 2013.

[23] M. Elgendi, R. R. Fletcher, I. Norton, M. Brearley, D. Abbott, N. H. Lovell, and D. Schuurmans, "Frequency analysis of photoplethysmogram and its derivatives," *Computer Methods and Programs in Biomedicine*, vol. 122, no. 3, pp. 503–512, 2015.

[24] J. Zhang, "Effect of age and sex on heart rate variability in healthy subjects," *Journal of manipulative and physiological therapeutics*, vol. 30, no. 5, pp. 374–379, 2007.

[25] I. A. O'Brien, P. O'Hare, and R. J. Corrall, "Heart rate variability in healthy subjects: effect of age and the derivation of normal ranges for tests of autonomic function." *British Heart Journal*, vol. 55, no. 4, pp. 348–354, 1986.

[26] V. K. Yeragani, E. Sobolewski, J. Kay, V. Jampala, and G. Igel, "Effect of age on long-term heart rate variability," *Cardiovascular Research*, vol. 35, no. 1, pp. 35–42, 1997.

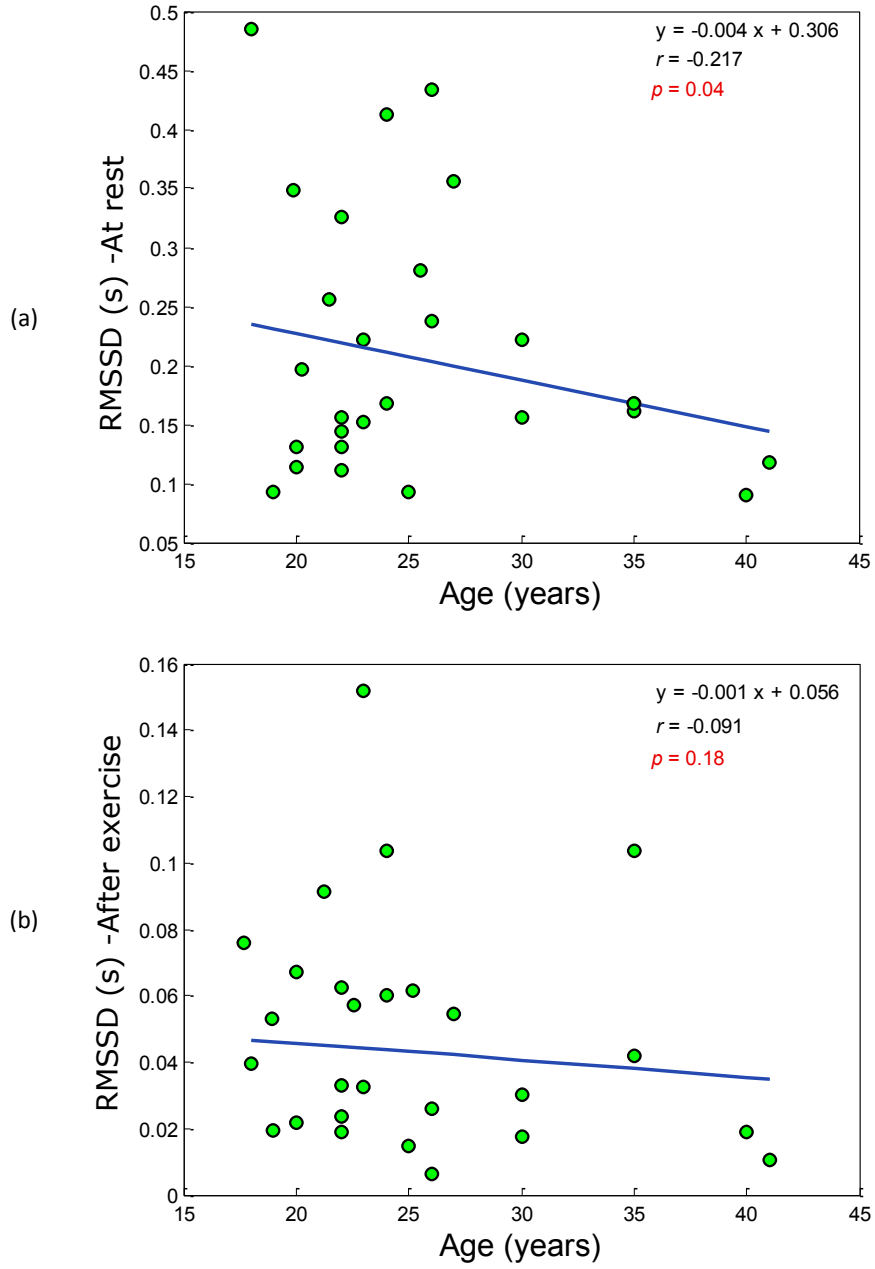

Figure 4: **Correlation between age and SDNN index.** (a) Age and SDNN calculated from PPG signals for all subjects measured at rest, (b) age and SDNN calculated from PPG signals for all subjects measured after exercise. It is clear that the SDNN index is more negatively correlated with age for 20-second PPG signals measured at rest compared to after-exercise measurements. Here, the p-value shows the significance for testing the slope of the linear regression.

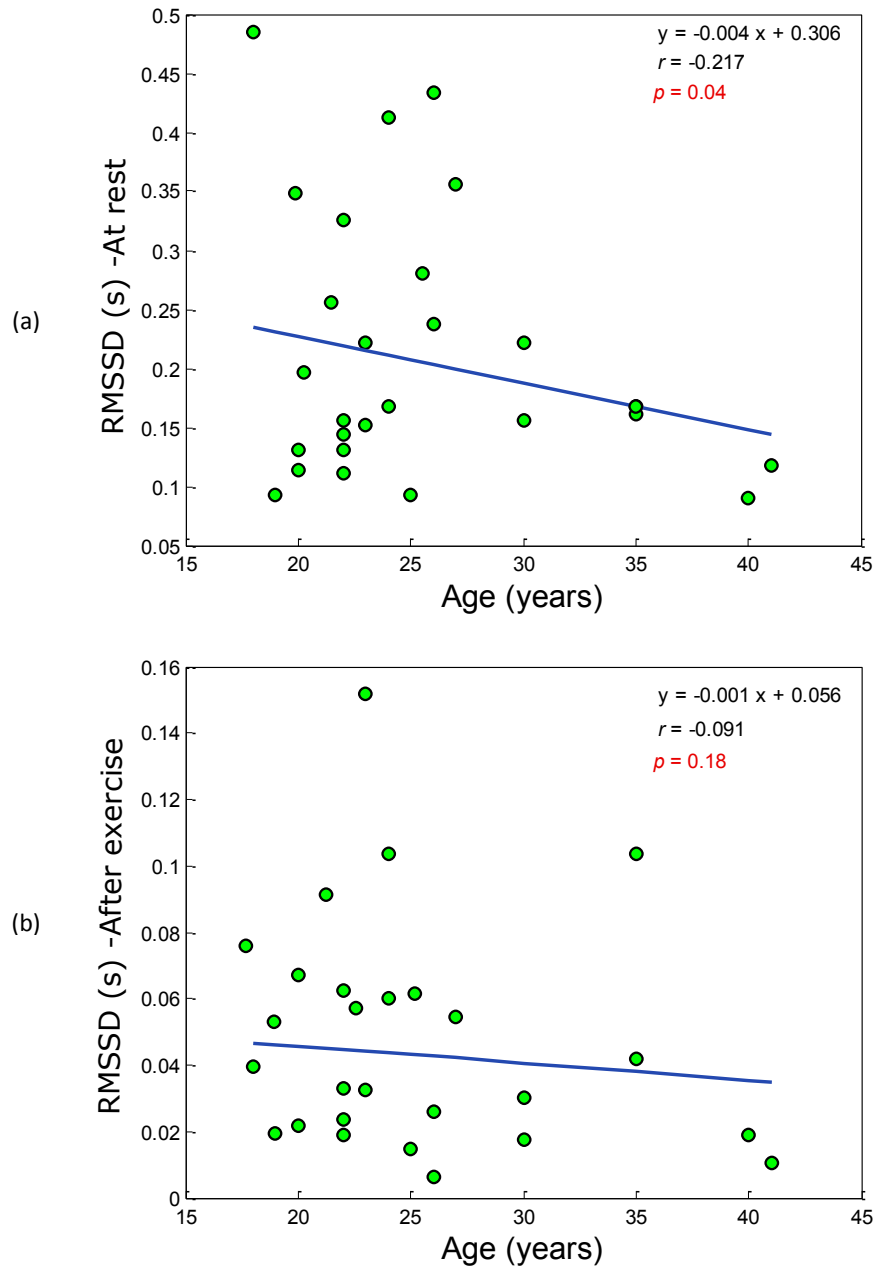

Figure 5: **Correlation between age and RMSSD index.** (a) Age and RMSSD calculated from PPG signals for all subjects measured at rest, (b) age and RMSSD calculated from PPG signals for all subjects measured after exercise. It is clear that the RMSSD index is more negatively correlated with age for 20-second PPG signals measured at rest compared to after-exercise measurements. Here, the p-value shows the significance for testing the slope of the linear regression.