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Measuring vascular recovery rate after exercise

Halil Dijab ¹, Jordi Alastruey ¹  and Peter H. Charlton ^{1,*} 

¹ Department of Biomedical Engineering, School of Biomedical Engineering and Imaging Sciences, King's College London, King's Health Partners, St Thomas' Hospital, London, SE1 7EH, United Kingdom

* Correspondence: peter.charlton@kcl.ac.uk

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Abstract: The rate at which an individual recovers from exercise is known to be indicative of cardiovascular risk. It has been widely shown that the reduction in heart rate immediately after exercise is predictive of mortality. However, little research has been conducted into whether the time taken for the blood vessels to return to normal is also indicative of risk. In this study we present a novel approach to assess vascular recovery rate (VRR) using the photoplethysmogram (PPG) signal, which is monitored by smart wearables. The Vortal dataset (<http://peterhcharlton.github.io/RRest/>) was used for this study, containing PPG signals from 39 healthy subjects before (baseline) and after exercise. 31 VRR indices were extracted from the PPG pulse wave shape, as well as heart rate for comparison. The rate at which indices returned back to baseline after exercise was quantified, and the consistency of changes between subjects was assessed statistically. Many VRR indices exhibited changes after exercise which were consistent between subjects. Indices derived from the timings and second derivative of pulse waves were identified as candidates for future work. The rate at which the indices returned to baseline differed between indices and subjects, indicating that they may provide additional information beyond that of heart rate, and that they may be useful for stratifying subjects. This study demonstrated the feasibility of assessing vascular recovery rate after exercise from the PPG. Future studies should investigate whether VRR indices are associated with cardiovascular fitness, and the potential utility of incorporating the indices into wearable sensors.

Keywords: wearable sensors; arterial stiffness; photoplethysmogram; exercise; heart rate recovery

1. Introduction

The rate at which the body recovers from exercise is known to be indicative of cardiovascular risk. It has been widely shown that the rate at which the heart rate recovers immediately after exercise is predictive of cardiovascular events and all-cause mortality [1]. Indeed, heart rate recovery (the number of beats per minute by which the heart rate falls one minute after cessation of exercise) has recently been included in recommendations for cardiopulmonary exercise testing [2]. However, little research has been conducted into whether the time taken for the blood vessels to return to normal, termed the vascular recovery rate (VRR), is also indicative of risk. If the VRR could be easily measured using wearable sensors then it could be useful for assessing health and fitness.

Many smart watches and fitness bands measure the photoplethysmogram (PPG) signal [3]. The PPG is the amount of light either reflected from or transmitted through an illuminated tissue bed. Wrist-worn devices usually obtain the PPG signal by illuminating the skin at the wrist using a light-emitting diode, and measuring the amount of light reflected from the skin using a photodetector. The resulting PPG signal exhibits a pulse wave for each heart beat, as shown in Figure 1. The pulse waves are primarily caused by the expansion and relaxation of blood vessels due to the increase and

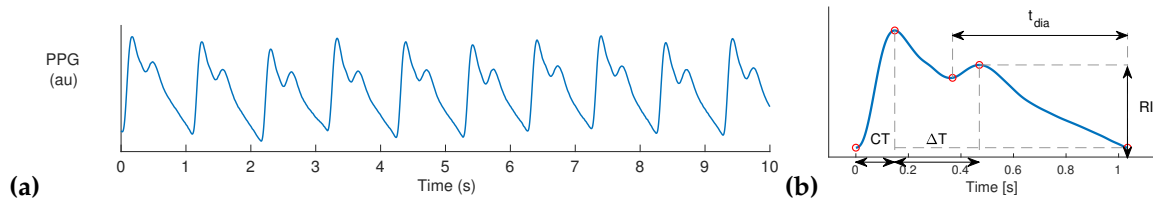


Figure 1. The photoplethysmogram (PPG) signal: (a) A 10-second recording, exhibiting a pulse wave for each heart beat - approximately one per second; (b) Extracting four exemplary vascular recovery rate (VRR) indices from a pulse wave (defined in Abbreviations section at end). au: arbitrary units

34 decrease in blood pressure with each heart beat. Consequently, pulse wave shape is influenced by both
 35 the ejection of blood from the heart and the mechanical properties of the blood vessels.

36 Previous research indicates that the stiffness of arteries changes during exercise, and these changes
 37 persist for several minutes afterwards [4]. The changes may be beneficial to health and fitness as they
 38 reduce the work required for the heart to pump blood around the body [5]. The effects of these changes
 39 on pulse wave shape have been investigated in [5,6]. However, to our knowledge no tool has been
 40 developed for analysing PPG pulse waves to derive a measure of the VRR.

41 The aim of this study was to investigate the feasibility of measuring VRR indices from the PPG.
 42 Several measurements of pulse wave shape were extracted from a dataset of PPG signals acquired
 43 before and after exercise. The inter-subject consistency of changes in VRR indices during recovery from
 44 exercise, and the rate at which indices returned to baseline values, were assessed. If this approach is
 45 found to provide useful indicators of cardiovascular health then it could be incorporated into wearable
 46 sensors for use in both everyday and clinical settings.

47 2. Methods

48 2.1. Dataset of Photoplethysmogram (PPG) Signals Acquired Before and After Exercise

49 The VORTAL dataset contains PPG signals acquired in a controlled laboratory setting. Signals
 50 were acquired from 39 young, healthy subjects whilst lying down for approximately 10 minutes both
 51 before and after exercise, as described in [7]. The PPG signals were measured using an MLT1020FC
 52 finger clip infrared reflection plethysmograph and digitised at 500 Hz. The exercise consisted of
 53 running on a treadmill until 30 s after the heart rate (HR) reached 85% of the age-predicted maximum.

54 2.2. Extracting Vascular Recovery Rate (VRR) Indices from the PPG

55 VRR indices were extracted from the PPG as follows. PPG signals were band-pass filtered to
 56 eliminate very low and very high frequency content, using -3 dB cut-offs of 0.07 and 16.75 Hz. Signal
 57 quality was assessed for consecutive 10 s signal segments using the approach in [8]. Low quality
 58 segments were excluded from the analysis. Pulse waves were identified using the algorithm described
 59 in [9]. Pulse wave analysis techniques were used to extract 31 vascular stiffness indices (termed VRR
 60 indices) and HR from each PPG pulse wave, as described in [10]. These time series were median
 61 filtered to attenuate high frequency variations (using a filter of order 15 beats).

62 2.3. Identifying Significant Changes in VRR Indices

63 The Wilcoxon Rank Sum test was used to identify any statistically significant changes in VRR
 64 indices during recovery from exercise (at the 5 % significance level). This was performed by comparing
 65 the initial and final 5 % of beats in the recovery recording. Two tests were performed for each VRR:
 66 one to identify a positive change, and one to identify a negative change.

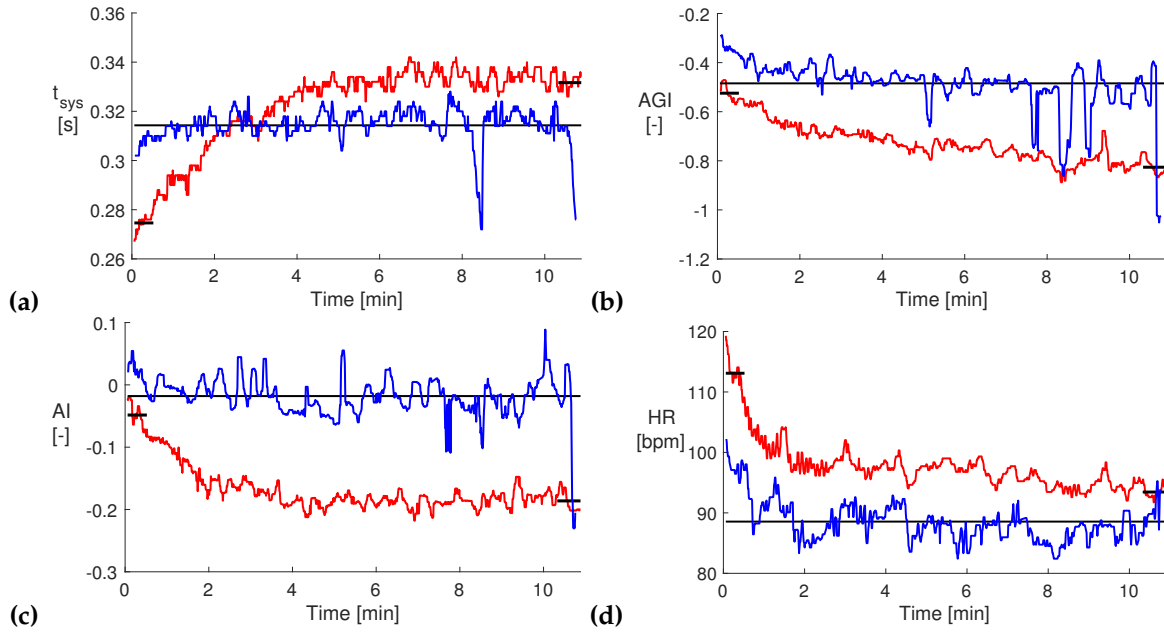


Figure 2. Exemplary Changes in VRR Indices After Exercise: (a) duration of systole (t_{sys}); (b) ageing index (AGI); (c) augmentation index (AI); (d) heart rate (HR). Red lines indicate the recovery recording, blue lines the rest recording prior to exercise, and black lines show the mean VRR values during the initial and final parts of the recovery recording and the baseline mean during the rest recording. bpm: beats per minute; au: arbitrary units

67 2.4. Quantifying Changes in VRR Indices After Exercise

Changes in VRR indices immediately after exercise were assessed as follows. The mean values of each VRR index during the initial and final 5 % of beats in the recovery recording were calculated ($\overline{VRR}_{i,init}$ and $\overline{VRR}_{i,final}$). The baseline value of each VRR index was calculated as its mean value during the recording at rest prior to exercise ($\overline{VRR}_{i,base}$). The percentage change in each VRR index (VRR_i) per minute was calculated using (where T is the duration of the recovery recording in minutes):

$$\text{Percentage change in } VRR_i \text{ [\% min}^{-1}\text{]} = 100 \times \frac{\overline{VRR}_{i,final} - \overline{VRR}_{i,init}}{|\overline{VRR}_{i,init} - \overline{VRR}_{i,base}|} \times \frac{1}{T} . \quad (1)$$

68 3. Results and Discussion

69 3.1. Exemplary Changes in VRR Indices After Exercise

70 Figure 2 shows exemplary changes in selected VRR indices after exercise for one subject. In
 71 this example the duration of systole (t_{sys} , shown in (a)) increased over the first five minutes of the
 72 post-exercise recording, and plateaued at a slightly higher value than the baseline value. In contrast,
 73 the ageing index (AGI) and augmentation index (AI) in Figure 2 (b) and (c) decreased after exercise,
 74 moving further from their baseline values. Previous studies have also found that AI remains below its
 75 baseline value for 10s to hours of minutes after exercise. Finally, the HR (shown in (d)), almost returned
 76 to its baseline value during the 10 minutes after exercise. Most of the change in HR occurred within the
 77 first two minutes, as opposed to the five minutes for t_{sys} . This indicates that even though both these
 78 indices are based on timings of the pulse wave, the mechanisms responsible for their changes may
 79 differ. Some high frequency variation in indices was still present, despite the use of median filtering,
 80 indicating that in the future it may be useful to adopt stricter signal quality criteria when selecting
 81 which pulse waves to include in the analysis. The VRR indices had not returned to baseline values

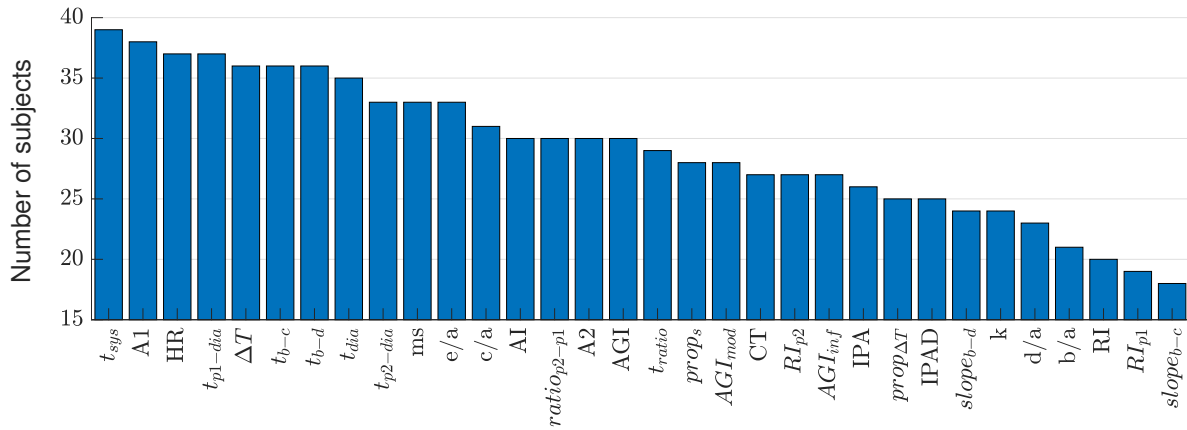


Figure 3. The number of subjects (out of 39) who exhibited a significant change in each VRR index in a particular direction after exercise. Indices are defined in the Abbreviations section (see end).

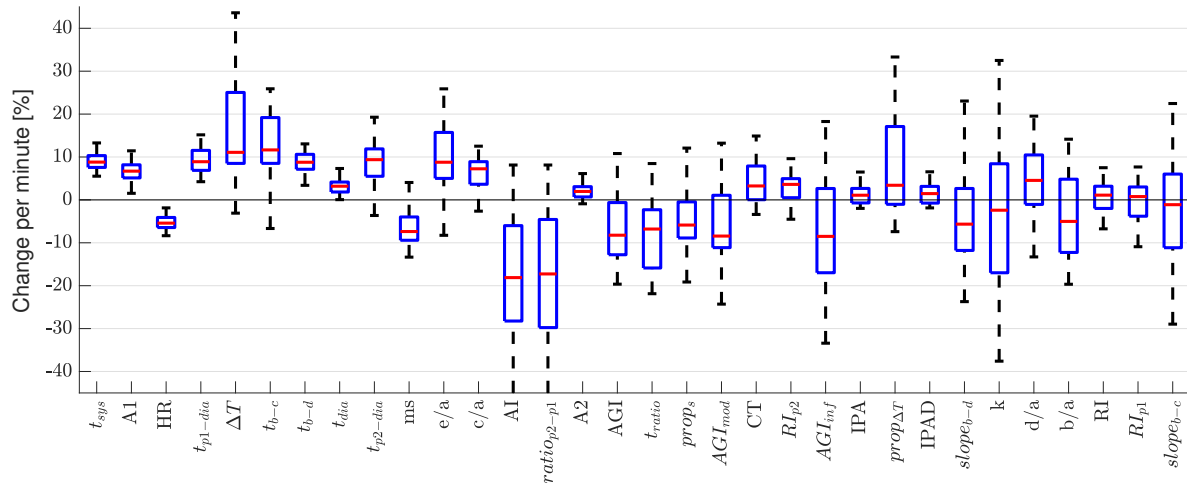


Figure 4. The distributions of the percentage change in each VRR index per minute during recovery from exercise. Boxplots show the median, lower and upper quartiles.

82 by the end of the recording, indicating that future studies should record signals for longer than 10
 83 minutes post-exercise (which is supported by [4]).

84 3.2. The Consistency of Changes in VRR Indices Between Subjects

85 Figure 3 shows the number of subjects who exhibited a significant change in each VRR index in a
 86 particular direction after exercise. Several indices changed in a consistent direction for most subjects.
 87 These included indices calculated from the timings (indicated by t) and second derivative of the pulse
 88 wave (e.g. e/a , c/a and AGI). For instance, the duration of systole (t_{sys}) increased during recovery
 89 for all 39 subjects. Similarly, the systolic pulse wave area (A1) and several timing measurements all
 90 increased in most subjects, and the HR decreased as observed previously [4].

91 3.3. The Rate of Changes in VRR Indices

92 Figure 4 shows the percentage change in VRR indices per minute during recovery from exercise.
 93 There was a wide variety in the rate at which different indices changed after exercise. This indicates
 94 that different indices may be influenced by different cardiovascular properties, and may therefore
 95 contain complementary information on the state of the vasculature. In addition, the rate of change of
 96 some indices differed substantially between different subjects (e.g. ΔT), whereas others showed similar
 97 rates of change between subjects (e.g. t_{sys}). This indicates that the changes in indices may be indicative
 98 of subject-specific recovery from exercise, and may therefore be useful for stratifying subjects.

99 3.4. Limitations and Future Work

100 Firstly, the dataset used in this study was acquired from a relatively homogeneous group of healthy
101 subjects. In the future it would be helpful to investigate whether VRR indices change differently after
102 exercise in different groups of subjects (for instance with different levels of health or fitness). This
103 would allow one to assess the potential utility of VRR indices for clinical decision support. Secondly,
104 the post-exercise recordings were acquired shortly after exercise ceased (after time for subjects to move
105 from the treadmill to the bed), and for approximately 10 minutes. In the future it would be helpful to
106 study recordings from immediately after exercise, and for a longer time period to capture more of the
107 recovery. Thirdly, future work should investigate the mechanisms underlying changes in VRR indices
108 to determine which indices would be most suitable for assessing cardiovascular health.

109 3.5. Applications

110 We envisage two settings in which VRR could potentially be used: in daily life, and in exercise
111 tests. If the approach was implemented in smart wearables (*e.g.* fitness bands), then individuals could
112 measure their VRR in routine activities, such as stair climbing, walking, and running. The challenges
113 for this application are that: (i) the activities would not be standardised, so further work would be
114 required to contextualise the VRR according to the level of activity; and (ii) subjects may still be moving
115 after the end of the activity, impairing PPG signal quality. The Parkrun initiative provides a convenient,
116 relatively standardised, weekly exercise regime [11] which could allow self-assessment of VRR. If
117 VRR is found to give clinically useful information then it may be useful to measure it in exercise tests,
118 potentially providing additional insight into the body's ability to recovery from exercise.

119 4. Conclusions

120 This study demonstrated the feasibility of extracting VRR indices from the PPG signal, which is
121 routinely acquired by smart wearables. VRR indices which exhibited consistent inter-subject changes
122 after exercise were identified as candidates for future research (namely those extracted from pulse wave
123 timings and from its second derivative). We observed that the rates of changes in VRR indices differed
124 between indices, and between subjects. This indicates that different indices may be influenced by
125 different physiological mechanisms, and that the recovery may be subject-specific. Therefore, further
126 work should investigate the physiological origins of changes in VRR indices, and determine whether
127 they could be used to usefully assess cardiovascular health in both clinical settings and everyday life.

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134 study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to
135 publish the results.

136 **Data Access Statement:** The data used in this research are available subject to the terms of access, as described
137 at <http://peterhcharlton.github.io/RRest> . Further information about the data and conditions of access can be
138 found by emailing research.data@kcl.ac.uk .

139 Abbreviations

140 The following abbreviations are used to denote the VRR indices. Further explanation is provided in [10, Table 3].

141

t_{sys}	duration of systole	t_{ratio}	time of s divided by time of time of dic
$A1, A2$	systolic, diastolic area	$prop_s$	time of s divided by pulse wave duration
HR	heart rate	RI_{p1}	reflection index calculated using $p1$
t_{p1-dia}	time between $p1$ and dia	CT	time of s
ΔT	time between s and dia	RI_{p2}	reflection index calculated using $p2$
t_{b-c}	time between b and c	AGI_{inf}	informal ageing index
t_{b-d}	time between b and d	IPA	$A2/A1$
142 t_{dia}	duration of diastole	$prop_{\Delta T}$	ΔT divided by duration of pulse wave
t_{p2-dia}	time between $p2$ and dia	$IPAD$	$IPA = d/a$
ms	maximum slope	$slope_{b-d}, slope_{b-c}$	slope from b to d , or c
e/a	amplitude of e divided by that of a	k	spring constant
c/a	amplitude of c divided by that of a	d/a	amplitude of d divided by that of a
AI	augmentation index	b/a	amplitude of b divided by that of a
$ratio_{p2-p1}$	amplitude of $p2$ divided by $p1$	RI	reflection index calculated using s
AGI, AGI_{mod}	(modified) ageing index		

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