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Wearable Sensing of Cardiac Timing Intervals from Cardiogenic Limb Vibration Signals

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Abstract

In this paper we describe a new method to measure aortic valve opening (AVO) and closing (AVC) from cardiogenic limb vibrations (i.e., wearable ballistocardiogram [BCG] signals). AVO and AVC were detected for each heartbeat with accelerometers on the upper arm (A), wrist (W), and knee (K) of 22 subjects following isometric exercise. Exercise-induced changes were recorded with impedance cardiography. The method, Filter BCG, detects peaks in distal vibrations after filtering with individually-tuned bandpass filters. In agreement with recent studies, we did not find peaks at AVO and AVC in limb vibrations directly. Interestingly, distal vibrations filtered with FilterBCG yielded reliable peaks at AVO ($r^2 = 0.95$ A, 0.94 W, 0.77 K) and AVC ($r^2 = 0.92$ A, 0.89 W, 0.68 K). FilterBCG measures AVO and AVC accurately from arm, wrist, and knee vibrations, and it outperforms the standard R-J interval method.

Index Terms

BCG; ballistocardiography; SCG; seismocardiography; PTT; pulse transit time; PEP; pre-ejection period; PWV; pulse wave velocity

I. Introduction

Wearable sensing of cardiovascular health parameters – such as heartbeat timing intervals – can play an important role in the future of healthcare by potentially enabling proactive management of diseases at home. Each heartbeat is composed of two phases, systole (ejection) and diastole (filling), with each phase comprising two sub-phases delineated based on whether the volume of the ventricle is changing (due to emptying or filling) or remaining constant (due to contraction or relaxation of the heart muscle against closed input / output valves) [1]. Quantifying the relative timings of these phases and sub-phases can provide important information regarding the performance and mechanical health of the heart [2], [3]. In particular, the time intervals associated with the ejection phase of the heartbeat, i.e. systolic time intervals (STI), have been used to assess left ventricular function in healthy subjects and persons with cardiovascular diseases. Garrard, et al. demonstrated that there is a strong correlation between STIs and ejection fraction, a key marker of cardiovascular health used, for example, to diagnose and stratify heart failure patients [2]. Additionally, recent

work has shown that significant differences are found between compensated and decompensated heart failure patients in the response of STIs (specifically, pre-ejection period, PEP) to a six-minute walk test [4].

Wearable devices placed directly on the chest can be used to effectively extract STIs based on a combination of the electrocardiogram (ECG) and, typically, one of the following cardiomechanical measurement modalities: impedance cardiography (ICG) [5], [6], seismocardiography (SCG) [7], [8], or phonocardiography (PCG) [9], [10]. The fusion of the ECG and one of these signals then provides an estimate of the PEP – defined as the interval from the ECG Q-wave to the aortic valve opening (AVO) – and the left ventricular ejection time (LVET) – the interval from AVO to the aortic valve closing (AVC). A damaged or weakened left ventricle will typically have a longer PEP than a healthy counterpart. In particular, the ratio of PEP to LVET is an important indicator of *cardiac* health.

Measurement of these time intervals can also provide an indication of *vascular* health. Pulse transit time (PTT) is defined as the time it takes the pressure pulse to travel between two sites along the arterial tree [11], and is affected over the short-term by changes in blood pressure and over the longer-term by stiffening of the arteries. Specifically, a short PTT through the aorta – and thus a high aortic pulse wave velocity – indicates stiffening arteries and has been shown to be a cardiovascular risk factor on its own and, in some cases, better than all other traditional risk factors [12]. Ideally, measurement of PTT requires detection of both the AVO timing and the arrival of the pulse to a distal location (e.g., the femoral artery) [13].

In this paper we aim to investigate whether the cardiogenic mechanical vibrations of the limbs, measured at the upper arm, wrist, and knee, contain information related to the AVO and AVC events. While these limb vibrations have not been characterized extensively in the existing literature, we refer to them in this paper as wearable ballistocardiogram (BCG) signals because they represent the movements of the limbs in response to the central vibrations of the body associated with the heartbeat [14]–[16].

The majority of wearable devices available broadly to consumers are in form factors such that the hardware is worn on the limbs (e.g., wristwatch or armband) and thus these positions are of interest for determining the richness of cardio-mechanical information that can be obtained from them. In the case of wearable PTT measurement, such positions may be especially advantageous as both the proximal and distal timing events can be obtained from a single distal site on the body (i.e., the timing associated with the AVO [proximal event] and the timing associated with the distal pulse arrival to the wrist [distal event]).

Some possible wearable devices that could potentially measure PTT in a convenient form factor are illustrated in Figure 1 where the advantages and disadvantages of each approach are noted. Approaches to wearable cardiac parameter detection have proliferated in recent years [17] including sensing platforms for smartwatches [18]–[20] and smartphones [21]. Note that the knee based position offers an important advantage over the other two in that aortic PTT measures may be obtained. The reason for this relates to what the distal waveform measures. In the case of an armband or wrist based device, the distal waveform is

measured from small arteries branching off the brachial artery. Thus the PTT measured is from the aortic valve opening (detected from the BCG) to the distal pulse timing (when the arterial pulse arrives at the upper arm or wrist through the brachial). If, on the other hand, the sensor is positioned at the knee, the proximal timing is still the aortic valve opening (again, detected from the BCG) but the distal timing is from the small arteries branching off the femoral artery. Thus, the arterial pulse would travel through the aorta, along the femoral for a short segment, and then to the small arteries at the surface of the skin, and the PTT is aortic.

The goal of this work is to develop two new robust methods for measuring aortic valve timing from limb vibrations and to demonstrate the impact of sensor placement on measurement quality. We explain how to measure AVO and AVC – and thus LVET and PTT – in time series from an accelerometer worn on the upper arm, wrist, and knee. Note that while the need for initial training with both an ICG and BCG device may seem to be a major limitation, such a training opportunity would actually be quite standard in many situations where the device would ultimately be used. For example, consider the case of home monitoring of a patient with a cardiovascular disease; the patient would already be seen at the clinic or hospital upon the initial diagnosis, at which point the training of the device against ICG could be completed. Following the initial training, subsequent measurements at home would be conducted without the need for a simultaneously-obtained ICG.

II. Materials and Methods

This study was approved by the Institutional Review Board of Georgia Institute of Technology (Protocol H13512). Twenty-two healthy adults (8 females, 14 males), whose detailed demographics appear in Table 1, participated in this study. The age distribution of the participants was 23.9 ± 7.5 years, and the weight distribution was 70.4 ± 13.8 kg. For each subject, blood pressure was measured (BP786, Omron Corporation, Kyoto, Japan) and then the subject performed an isometric exercise (wall sit) for two minutes or until exhaustion, whichever occurred first. Each subject then stood vertically, motionless but relaxed, for a five-minute recovery period immediately after the exercise during which the time series were recorded. Five minutes was chosen as the recording length because it was observed that subjects nearly reached their resting PEP by that time. The purpose of the protocol was to perturb the system via the exercise intervention to acutely reduce PEP and LVET (due to increased sympathetic tone during exercise) compared to the resting values, and observe the return of both parameters back to resting values during recovery.

A. Equipment

A diagram of our recording setup appears in [22]. A commercial data acquisition system (MP150, BIOPAC Systems, Goleta, CA) was used to capture all physiologic signals with a standard PC. The physiologic instruments consisted of an ECG configured for a modified Lead II measurement (BN-EL50 wireless ECG, BIOPAC Systems), an 8-lead ICG providing a first derivative (dZ/dt) time series containing the AVO and AVC ground truth (NICO100C, BIOPAC Systems, Goleta, CA), and three triaxial accelerometers (3 x 356A32, PCB Piezotronics, Depew, NY) that were powered and amplified 100x with three Integrated

Electronic Piezoelectric (IEPE) signal conditioners (482C05, PCB Piezotronics, Depew, NY). ICG was chosen because it is easier to acquire than echocardiograms, which require a trained technician; ICG has been shown to measure AVO and AVC well in healthy subjects when compared to echocardiography [23]. All signals were sampled simultaneously at $f_s = 2$ kHz and saved for offline processing in MATLAB (MathWorks, Natick, MA). The accelerometers were chosen for their low noise properties as described in [14] and were attached laterally to the upper arm, wrist, and knee with kinesiology tape wrapped around each limb (Kinesio Tex, Kinesio, Albuquerque, NM).

B. Statistical Methods

Standard methods from BCG and ICG literature were applied. The locations of the ECG R-waves were determined with a peak detector and used to segment each BCG and ICG recording into individual beats. Peaks were identified as locations satisfying (1) where sign and diff are the MATLAB sign and difference functions and $\times$ is the input discrete-time series. Then, every nine beats ($N = 9$) in each time series were averaged sample-by-sample to generate ensemble averages, and the B-wave (AVO) in each dZ/dt beat was determined [6]. The dZ/dt X-wave (AVC) was determined as the lowest trough from 150–330 ms after the B-wave. This range corresponds approximately to the expected range of LVET for healthy subjects, and it covered this dataset. Each detected B-and X-wave (AVO and AVC) was then inspected manually beat-by-beat to ensure that the ground-truth was accurate.

$$\text{diff}(\text{sign}(\text{diff}(x))) < 0 \quad (1)$$

First, a modified version of the standard method to obtain AVO from R-J intervals via regression that we first used in a recent pilot study [22] was applied to the BCG. The difference between the R-J interval method and that of this work is that individual regressions were found from the R-J intervals of each subject to ground-truth PEP after bandpass filtering. In contrast, the standard R-J interval method in the literature typically assumes that intra-subject variation is small and fits one linear trendline to results from a sample of individuals. (For a more detailed explanation of the standard R-J interval method, we refer the reader to [24].) Each beat was filtered with a 6th-order Butterworth infinite impulse response (IIR) filter in the forward and reverse direction to achieve zero phase delay. Then, the filter cutoff frequencies, axes (x, y, z), and polarities (non-inverted or inverted) of the sensors that resulted in the lowest root mean square error (RMSE) after linear regression with ground-truth PEP were chosen for each subject and location (upper arm, wrist, and knee). The result was a single-axis filtered BCG for each location that contained the best possible J-wave measurement.

After determining R-J intervals, a new method called FilterBCG was applied to determine AVO and AVC using a peak-detection approach. First, subject-specific IIR bandpass filters (6th-order Butterworth IIR, forward and backward) were trained to produce peaks between 1–150 ms and 200–475 ms after the ECG R-wave that resulted in the lowest RMSE after regression with ground-truth AVO and AVC, respectively. In other words, for each wearable location (upper arm, wrist, knee) and event (AVO or AVC) of each subject, the bandpass

cutoff frequencies, feature type (peak, trough), and accelerometer axis (x, y, z) that produced the lowest RMSE after regression were selected.

Figure 2 shows an example of the filtered R-J interval and FilterBCG methods applied to vibrations of the wrist for one heartbeat aligned with several other time series. Trained IIR bandpass filters result in J-waves, AVO peaks, and AVC peaks that are more distinct than those appearing in the raw BCG waveform. These peaks are then regressed linearly to ground-truth AVO (or PEP), AVO, and AVC, respectively. Pseudocode for FilterBCG is shown in Figure 3 where the inputs are the result from this optimization step.

III. Results and Discussion

The correlations between BCG- and ICG-derived AVO and AVC for all subjects and methods are shown in Figure 4 and Figure 5. Additionally, Figure 6 quantifies the effect of ensemble averaging on the FilterBCG correlations. The latter plot can be used to pick a suitable ensemble average length in future work. A total of 9648 heart beats from 22 subjects were processed, which resulted in 1072 beats after nine-beat ensemble averaging. For AVO and AVC from every location except the knee, FilterBCG resulted in better correlations than R-J intervals or filtered R-J intervals. Filtered R-J intervals was the best method at the knee. This could be due to more attenuation of higher frequencies used in FilterBCG, since the R-J interval relies on lower frequencies to determine PEP.

Overall, the knee was worse than the upper arm and the wrist. As shown in Table 2, the within-subject RMSE differences of the wrist and upper arm AVO and AVC were not statistically significant in paired t-tests, but the wrist and knee were significantly different ($p < 0.05$). We believe that the knee was inferior to the wrist and upper arm due to higher attenuation of cardiogenic vibrations. Since the feet are grounded to a solid surface while standing, attenuation should increase and the BCG signal-to-noise ratio (SNR) should decrease as the sensor is worn lower on the body; this could be a question for further study.

Table 2 also shows that the difference between FilterBCG and filtered R-J intervals was not statistically significant. However, the trained bandpass filter significantly reduced the RMSE of each subject in both the FilterBCG and filtered R-J interval methods. The trained bandpass filter introduced in this paper is therefore a significant improvement over the unfiltered R-J intervals method, which is the current standard.

In the correlation summary in Figure 5, the best axis was used. In 41 out of 66 (62%) of the sensors in the study for 22 subjects and three wearable locations on the body, the best axis was the head-to-foot axis. To better understand the impact of the physical orientation of the sensor, FilterBCG was applied to each of the other two axes as well. In this case, the correlations were lower but still strong (AVO: $r^2 = 0.82$ A, 0.74 W, 0.49 K; AVC: $r^2 = 0.68$ A, 0.58 W, 0.45 K). The difference between the best axis and the other axes was statistically significant in all cases, and the p-values are shown in Table 2. However, the results were still acceptable from the suboptimal axes, especially for AVO from the upper arm ($r^2 = 0.82$). This suggests that it may be possible to obtain acceptable results even when the accelerometer is placed haphazardly on the body. This is important because single-axis

accelerometers can be lower in cost and power consumption than multi-axis variants, and the ability to place a BCG device on the body without great care also simplifies the technique for the end-user.

Nevertheless, the optimal axis seems to vary from subject to subject. We hypothesize that differences in the optimal axes *between subjects* for sensors mounted at the same site on the body depends primarily on *local* mechanical effects relating to A) the precise orientation of the sensor on the body, B) the individuals' body composition at the mounting site, and C) other higher-order effects of the sensor-body mechanical system. On the other hand, we suspect that the differences in the optimal axis between sensor locations *on the same individual* arise from more general mechanical differences between locations on the body. For example, in comparison to a sensor mounted proximally on the sternum or chest area, we would expect a sensor on the upper arm or wrist to register vibrations more strongly in the head-to-foot direction than other axes because the arm is free to move laterally (side-to-side) but not vertically due to the shoulder's ball-and-socket joint.

Although the vibrations are typically strongest in one of the axes, we observe that measurable cardiogenic vibrations are usually still present in all accelerometer axes. Therefore, better results can generally be obtained with a multi-axis accelerometer. Developing better methods to combine several BCG axes could be a topic of future study. Also, increasing the total number of axes beyond three – for example, with a gyroscope to measure angular motion – or even analyzing the limb vibrations based on non-contact measurements [25], [26] could also be a topic for future study.

It should also be noted that the fact that wearable BCG signals from distal locations on the body can facilitate extraction of AVC is not obvious, and warrants discussion. We know from studying the waveforms of the BCG that the BCG contains primarily low-frequency components (< 01 Hz.) These low-frequency components reflect the mass of blood pumped out of the heart into the aorta during myocardial contraction, and the movement of the blood through the vascular tree, as described in a recent paper elucidating the mechanism of the BCG signal [27].

However, what may have been overlooked until now is that higher-frequency components are still present in the wearable BCG. When the BCG is appropriately filtered, as we do with FilterBCG, very faint vibrations overlapping the lower frequencies – possibly emitted from the heart valves – can be extracted just above the frequency range containing the loud vibrations from blood movement. Thus, both the opening of the aortic valve (associated with blood movement) and the closure of the valve (associated with the aortic valve closure sound) can be extracted from the wearable BCG.

Table III shows group statistics for the FilterBCG method (with 9-beat ensemble averaging) and its cutoff frequencies. While filtering improved AVO results significantly over R-J intervals, for example, the filter cutoff frequencies varied greatly subject-to-subject. Each individual's particular body structure appears to have a large effect on the signal's characteristics, and it is therefore important to tune the method on each subject.

Effects of body-mass-index (BMI) are also shown in Table III. Interestingly, we found that there were negative correlations between BMI and signal quality as quantified by R^2 between the measurements from FilterBCG and ICG. The correlation was negative for both AVO and AVC and all locations, and this effect was most evident at the wrist as shown in Figure 7; however, in general the BMI effect was quite weak ($|r| < 0.30$). A more in-depth study of this effect could be a topic for future work.

The principal limitations of FilterBCG include subject-specific training and requiring the subject to reduce body movements during measurements. Subject-specific training on time series during which AVO and AVC are changing may be inconvenient for some users. Future work should focus on reducing or eliminating the training step. That said, it is important to note that this paper provides important information regarding which locations on the body may ultimately be feasible in terms of providing high quality measurements of proximal timings.

The latter limitation of reducing body movement applies to any method relying on small body vibrations, including all techniques in the BCG literature to date. Even standard electrophysiology recordings such as ECG and ICG exhibit motion artifacts. The method in this paper is no different; FilterBCG cannot be used while the subject is moving, for example, during exercise. However, measurements can still be made during a rest period in the middle of an exercise, and small vibrations, such as from heavy breathing or fatigued muscles, are largely eliminated by the ensemble averaging.

Finally, future work will focus on the miniaturization of the sensing hardware and integration of the electronics. For the sensing, commercially available microelectromechanical systems (MEMS) based accelerometers can be used with noise floor only slightly higher than the larger piezoelectric accelerometer used in this work (e.g., the ADXL354, Analog Devices, Norwood, MA, with a noise floor of $20 \mu\text{g} / \text{Hz}$). This accelerometer can be paired with the same embedded systems based hardware design implemented in Etemadi, et al. [28] to facilitate wearable, low-power BCG measurement.

IV. Conclusion

In this paper two new methods to measure AVO and AVC from distal body vibrations were demonstrated. Both methods exceeded the standard method of R-J intervals in the existing literature that uses unfiltered BCG waveforms. This confirms our previous findings that R-J intervals do not correlate well to ground-truth PEP (AVO) in wearable BCG signals. In general, we recommend FilterBCG over other methods because its AVO and AVC measurements correlated the best to an ICG ground truth in all but one case which was not statistically significant. We also believe that this is the first work to demonstrate AVC measurement from distal vibrations thus enabling measurements of LVET from distal vibrations for the first time. Future work will focus on reducing or eliminating the training step, which we believe is the main limitation of the methods we present in this paper. In particular, the training step requires an ECG and ICG, two signals that a low-cost consumer device typically would not have.

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Biographies

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Omer T. Inan (S'06, M'09, SM'15) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Stanford University, Stanford, CA, in 2004, 2005, and 2009, respectively.

He joined ALZA Corporation (A Johnson and Johnson Company) in 2006, where he designed micropower circuits for iontophoretic drug delivery. In 2007, he joined Countryman Associates, Inc., Menlo Park, CA where he was Chief Engineer, involved in designing and developing high-end professional audio circuits and systems. From 2009–2013, he was also a Visiting Scholar in the Department of Electrical Engineering, Stanford University. Since 2013, Dr. Inan is an Assistant Professor of Electrical and Computer Engineering at the Georgia Institute of Technology. He is also an Adjunct Assistant Professor in the Wallace H. Coulter Department of Biomedical Engineering. His research focuses on non-invasive physiologic monitoring for human health and performance.

Dr. Inan is an Associate Editor of the IEEE Journal of Biomedical and Health Informatics, Associate Editor for the IEEE Engineering in Medicine and Biology and IEEE Biomedical and Health Informatics conferences, Invited Member of the IEEE Technical Committee on Translational Engineering for Healthcare Innovation, and Technical Program Committee Member or Track Chair for several other major international biomedical engineering conferences. He has published more than 90 technical articles in peer-reviewed international journals and conferences, and has five issued and five pending patents. Dr. Inan received the Gerald J. Lieberman Fellowship (Stanford University) in 2008–'09 for outstanding scholarship, and the Lockheed Dean's Excellence in Teaching Award (Georgia Tech) in 2016. He was a National Collegiate Athletic Association (NCAA) All-American in the discus throw for three consecutive years (2001–2003).

Wearable Pulse Transit Time Modalities Potentially Enabled by Distal Aortic Valve Opening Detection

Modality	Advantages	Disadvantages
<p>Wrist Watch</p>	<ul style="list-style-type: none"> ➤ Convenient ➤ Ubiquitous ➤ Perfusion ↑ for reflective PPG 	<ul style="list-style-type: none"> ➤ Not aortic PTT ➤ Motion noise ↑ ➤ Strap tightness changes signal
<p>Armband</p>	<ul style="list-style-type: none"> ➤ Convenient ➤ Motion noise ↓ 	<ul style="list-style-type: none"> ➤ Not aortic PTT ➤ PTT ↓ relative to the wrist
<p>Knee Brace/Wrap</p>	<ul style="list-style-type: none"> ➤ Aortic PTT ➤ PTT ↑ relative to the wrist 	<ul style="list-style-type: none"> ➤ Less convenient ➤ Motion noise ↑

Fig. 1.

Comparison of wearable pulse transit time (PTT) measurement modalities that can potentially be enabled by the technologies described in this paper. Distal aortic valve opening detection using ballistocardiogram (BCG) signals can even allow, for the first time, the measurement of *aortic* PTT in a knee brace form factor.

Fig. 2.

Bandpass filtering enhances peaks in a distal vibration heartbeat from the wrist. Time series of a phonocardiogram (PCG), electrocardiogram (ECG), and impedance cardiogram 1st derivative (ICG dZ/dt) are shown as temporal references to the wrist ballistocardiogram (BCG). Three bandpass filters are trained on each BCG sensor: one for filtered R-J interval detection and two for AVO and AVC detection with FilterBCG. In this example, an 8–30 Hz passband produced the best R-J intervals, and 18–30 Hz provided the best AVO and AVC

peaks for FilterBCG. When applied to a distal BCG recording, FilterBCG results in a BCG signal resembling an SCG that has two peaks coinciding with AVO and AVC.

Algorithm FilterBCG

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1: procedure GETVALVEEVENTS( $fLow$ ,  $fHigh$ ,  $N$ ,  $type$ )
2:    $bcg \leftarrow \text{Filter}(\text{vibrations}, \text{Bandpass}(fLow, fHigh))$ 
3:    $bcgBeats \leftarrow \text{EnsembleAverage}(bcg, rPeaks, N)$ 
4:    $icgBeats \leftarrow \text{EnsembleAverage}(icg, rPeaks, N)$ 
5:   if  $type$  is AVO:
6:      $groundTruth \leftarrow \text{DetectPeaks}(icgBeats, 1-150 \text{ ms})$ 
7:      $avoPeaks \leftarrow \text{DetectPeaks}(bcgBeats, 1-150 \text{ ms})$ 
8:   if  $type$  is AVC:
9:      $groundTruth \leftarrow \text{DetectPeaks}(icgBeats, 200-475 \text{ ms})$ 
10:     $avcPeaks \leftarrow \text{DetectPeaks}(bcgBeats, 200-475 \text{ ms})$ 

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Fig. 3.

Pseudocode of FilterBCG. Definitions: $vibrations$:= vibration discrete-time series; icg := the impedance time-derivative (dZ/dt) discretetime series; $fLow$:= 3-dB lower cutoff frequency; $fHigh$:= upper cutoff frequency; $type$:= the heart valve event to measure (AVO for aortic valve opening or AVC for closing); N := number of heartbeats in the ensemble average; $rPeaks$:= location of each R-peak in the ECG.

Fig. 4.

Scatterplots of FilterBCG measurements versus an ICG ground-truth for the three accelerometers worn on the body after training. The ICG and vibration time series were nine-beat ensemble averaged, and each subject's ICG measurements were centered about zero before FilterBCG to remove differences between the subjects' AVO and AVC baselines. When intra-subject means are not subtracted, the resulting correlations tend to be optimistic because most of the variance is represented by inter-subject spread rather than the method of measurement. AVO measurements via Filtered R-J intervals were very similar to FilterBCG, and unfiltered R-J intervals exhibited almost no linear trend due to the presence of very high numbers of outliers due to peak detection in a noisy signal.

Fig. 5.

Correlations of BCG to ICG for all methods after nine-beat ensemble averaging. R-J intervals do not measure AVC and thus do not appear on the right. A key contribution of this paper is the finding that wearable ballistocardiogram signals from the limbs can measure AVC after bandpass filtering. In the case of the wrist and upper arm, such measurements are quite accurate. FilterBCG exceeded other methods in this study. Although filtered R-J intervals did have a higher correlation than FilterBCG at the knee, the differences between FilterBCG and filtered R-J intervals were not statistically significant as shown in Table 2.

Fig. 6.

Correlations of FilterBCG to ICG for several ensemble average lengths where a length of one is equivalent to no ensemble averaging. Cross validation was not used here. This plot can be used to determine a suitable ensemble average length for a given application. Measurements from the knee deteriorate more rapidly than the other locations for shorter ensemble averages.

Fig. 7.

The quality of the wearable BCG signal had a weak negative correlation with body mass index. Body-mass-index of each subject is plotted against the R^2 correlations between the wrist FilterBCG AVC measurement and ICG baseline. This effect was strongest at the wrist as shown in Table III.

TABLE I

Subject Demographics

#	Sex	Age	Weight	Height	Systolic BP *	Diastolic BP *
0	F	19 yrs	59 kg	165 cm	97 mmHg	75 mmHg
1	F	19	68	170	93	59
2	M	20	57	170	100	64
3	F	18	66	175	100	67
4	M	33	79	185	144	97
5	F	23	52	160	96	68
6	M	25	102	183	146	89
7	M	33	78	180	122	70
8	F	19	59	173	103	60
9	M	24	68	178	121	69
10	M	23	88	191	126	76
11	M	20	61	180	117	66
12	M	31	86	175	131	75
13	F	49	70	163	118	74
14	F	16	53	170	120	76
15	M	31	83	178	100	65
16	F	23	61	165	104	70
17	M	19	57	165	93	64
18	M	19	57	175	113	82
19	M	22	76	173	104	65
20	M	20	88	188	114	63
21	M	20	82	193	113	71

* BP, blood pressure.

TABLE II

Summary of Statistical Significance

<i>t</i> -Test*	p-values	
	AVO	AVC
FilterBCG vs. Filtered R-J Interval [†]		
Wrist	0.16	N/A
Knee	0.06	N/A
Upper Arm	0.53	N/A
Location (FilterBCG)		
Wrist vs. Upper Arm	0.62	0.56
Wrist vs. Knee	++	++
Best Axis vs. Other Axes (FilterBCG)		
Wrist	++	++
Knee	++	++
Upper Arm	++	++
With vs. Without Filter (Upper Arm)		
FilterBCG	++	++
Filtered R-J Interval [†]	++	N/A

* Paired *t*-tests of the root mean square error of each subject.

[†] R-J interval does not measure AVC.

++Indicates $p < 0.01$.

TABLE III

Group Statistics[†]

Statistic	AVO				AVC			
	Wrist	Knee	Upper Arm	Wrist	Knee	Upper Arm	Wrist	Upper Arm
R ² (FilterBCG to ICG)								
Mean	0.91 [*]	0.78	0.92[*]	0.84 [*]	0.67	0.87[*]		
Standard deviation	0.13	0.16	0.10	0.20	0.21	0.16		
Max	0.99	0.99	0.99	1.00	0.96	1.00		
Min	0.56	0.44	0.60	0.26	0.31	0.40		
r (correlation) with BMI	-0.50	-0.25	-0.25	-0.79	-0.29	-0.52		
R ²	0.25	0.06	0.06	0.62	0.08	0.27		
Intercept (R ² -value)	1.36	1.08	1.11	2.01	1.10	1.48		
Slope	-0.020	-0.013	-0.008	-0.051	-0.019	-0.027		
RMSE (FilterBCG to ICG)								
Mean (ms)	2.35	4.50	2.27	4.16	7.74	3.91		
Standard deviation (ms)	1.00	2.38	0.88	2.47	2.39	1.78		
Max (ms)	4.76	11.04	4.12	9.46	12.40	7.63		
Min (ms)	1.25	1.66	1.35	1.44	3.71	1.35		
r (correlation) with BMI	0.18	-0.01	-0.33	0.55	-0.03	0.14		
R ²	0.03	0.00	0.11	0.30	0.00	0.02		
Intercept (RMSE-value, ms)	1.02	4.73	4.35	-5.74	8.22	2.06		
Slope	0.058	-0.010	-0.091	0.434	-0.021	0.081		
FilterBCG Tuned Lower 3-dB Cutoffs								
Mean (Hz)	10.21	8.76	10.72	12.17	7.61	10.47		
Standard deviation (Hz)	3.27	4.35	4.54	4.40	5.05	3.91		
Max (Hz)	16.11	16.11	27.02	23.75	18.34	18.34		
Min (Hz)	5.03	3.00	4.42	3.89	3.00	3.41		

Statistic	AVO				AVC			
	Wrist	Knee	Upper Arm		Wrist	Knee	Upper Arm	
FilterBCG Tuned Upper 3-dB Cutoffs								
Mean (Hz)	23.62	17.88	22.56		24.9	15.05	23.79	
Standard deviation (Hz)	8.15	8.05	7.24		8.30	9.75	7.91	
Max (Hz)	35.00	30.75	35.00		35.00	35.00	35.00	
Min (Hz)	9.61	5.73	9.61		5.03	3.89	6.52	

* Note that the mean R^2 values here are lower than in Figure 5 because the Correlation Summary represents R^2 of correlation of *all* subjects, i.e. on one graph, while the values in this table are averages of the correlations for each individual subject.

[†] With 9-beat ensemble averaging.