Ballistocardiography can Estimate Beat-to-Beat Heart Rate Accurately at Night in Patients after Vascular Intervention

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Christoph Hoog Antink, *Member, IEEE,* Yen Mai, Roosa Aalto, Christoph Brüser, Steffen Leonhardt, *Senior Member, IEEE,* Niku Oksala, and Antti Vehkaoja, *Member, IEEE,*

***Abstract*—While bed-integrated ballistocardiography (BCG) has potential clinical applications such as unobtrusive monitoring of patients staying in the general hospital ward, it has so far mainly gained interest in the wellness domain. In this work, the potential of BCG to monitor hospitalized patients after surgical intervention was assessed. Long-term BCG recordings (mean duration 17.7 h) of 14 patients were performed with an EMFit QS bed sensor. In addition, ten healthy subjects were recorded during sleep (mean duration 7.8 h). Using an iterative algorithm, beat-to-beat intervals (BBIs) and the ultra-short-term heart-rate-variability (HRV) parameters standard deviation of NN intervals (SDNN) and root mean square of successive differences (RMSSD) were estimated and compared to an ECG reference in terms of average estimation error and temporal coverage. While the absolute BBI estimation error was found to be higher when full-day patient data was used (16.5 ms), no significant difference between healthy subjects (12.7 ms) and patient nighttime data (11.0 ms) was observed. Nevertheless, temporal coverage of BBI estimation was significantly lower in patients (39.3 % overall, 51.7 % at night) compared to the healthy sleepers (73.2 %). This resulted in reduced HRV estimation coverage (9.7 % vs. 37.2 %) at comparable estimation error levels.**

***Index Terms*—Ballistocardiography, Beat-to-Beat Intervals, Heart Rate, Heart Rate Variability, Unobtrusive Sensing**

I. Introduction

NIGHT-time physiological monitoring with unobtrusive bed-integrated ballistocardiography (BCG) sensors has gained interest in the wellness domain as it enables easy-to-use approach for self-monitoring of sleep quality and quantity. So far, the use of BCG monitoring in clinical applications has been limited. A potential clinical application for this technology is unobtrusive monitoring of patients who are staying in beds in the general hospital ward.

Currently, monitoring of such patients is relatively sparse or unsystematic, and is mainly performed visually or with intermittent measurements. Continuous real-time monitoring of hospital patients would be beneficial for monitoring of recovery and early detection of the deterioration of a patient's condition e.g. due to postoperative complications. In addition, heart rate variability (HRV) is a potential, clinically underexploited measure of the state of the autonomic nervous system that could provide information on the recovery of a patient noninvasively. It has been shown in several studies that recovery of HRV parameters after surgery is altered in patients developing postoperative complications [1], [2], [3], [4].

Monitoring techniques based on cardiac-associated vibrations have been proven adequately accurate for heart rate (HR) and heart rate variability (HRV) measurements in healthy subjects with bed-integrated ballistocardiography (BCG) [5], [6], [7] as well as wearable seismocardiography (SCG) sensors [9]. Brüser et al. achieved 0.61 % relative error $\bar{E}_{\mathrm{rel}}$ with 85 % coverage in beat-to-beat interval (BBI) estimation with eight healthy subjects. Corresponding numbers in the study by Kortelainen et al. were 0.4 % and 88 % with six subjects. The same studies also included groups of patients suffering from insomnia or other sleep related disorders. In these groups, the performance of BCG monitoring was decreased to 1.8 % relative error and 80 % coverage with 28 insomniac subjects [6] and 1.61 % relative error and 69 % coverage with 25 subjects [5]. In addition to the scientific community, a few companies exist that provide ballistocardiography–based bed monitoring devices aimed either at the consumer marked (e.g. the "Beddit Sleep Monitor", Apple Inc., USA), at clinical applications (e.g. the "EarlySense" systems, EarlySense Ltd., Israel, [8]), or at both (e.g. the "EMFIT QS" product range, Emfit Ltd, Finland).

Wearable SCG is an alternative for bed-integrated BCG method. However, in high-risk cardiovascular patients, the technology has faced severe reduction in accuracy, as the signal induced by a heartbeat is often weaker and less consistent in shape. Kaisti et al. [10] reported over ten-fold increase in RMS error from 5.6 ms to 60.3 ms in study groups consisting of 29 healthy subjects and 12 coronary artery disease patients with a wearable SCG measurement method using a 6 degree of freedom motion measurement unit. The BBI signal coverage was 93.4 % and 92.6 % for the two groups, respectively. For a detailed review of other BCG and SCG applications as well as differences between the methods, we refer to [11].

The aforementioned studies have evaluated the accuracy of BCG and SCG based heart rate monitoring during sleep. For continuous monitoring of hospital patients, also the performance in day-time needs to be assessed, as the subject

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is awake and the data presumably contains more interfering components from movements. To the best of our knowledge, such studies have not been published to date. Further, as earlier stated, heart rate variability has been shown to correlate well with physiological status of the patient and even to predict upcoming postoperative complications [1], [2], [3], [4], thus the accuracy of HRV estimation is of interest for possible future clinical applications.

As BCG based measurement technique is extremely prone to movement artifacts, long segments of uncorrupted clean signal are unlikely, especially during daytime. Therefore the so called ultra-short HRV (< 5 min segments) is the approach of interest. Peccia et al. listed in their review 29 papers published since 2003 that utilize or assess the accuracy of ultra-short HRV analysis [12]. Segment lengths from 10 s upwards have been used in these studies.

In this work, we studied the accuracy of BBI and HRV estimation from BCG signals recorded with the commercially available Emfit QS monitoring system (Emfit Oy, Finland) in fourteen patients who underwent vascular intervention as well as ten healthy young adults. Typically, vascular patients have several comorbidities (such as diabetes, hypertension, dyslipidemia, coronary artery disease, cerebrovascular disease) and may have reduced cardiac function. For all patients, long-term recordings (mean 17.72 h, range 4.64 h to 22.96 h) including day- and nighttime were acquired. Healthy subjects were recorded for one night. For BBI estimation, the previously developed CLIE algorithm [5] was used and augmented with an iterative estimation approach [13].

II. Algorithm

The original Continuous Local Interval Estimator approach used in this paper is described in detail in [5]. In addition, an outlier rejection method and an iterative estimation method as described [13] were later introduced. The algorithm estimates BBIs by assessing self-similarity of consecutive heartbeats using lag-adaptive versions of the short-term autocorrelation $S_{\mathrm{LASTA}}[i,\eta]$, the maximum amplitude pairs $S_{\mathrm{MAP}}[i,\eta]$ and the average magnitude difference function $S_{\mathrm{AMDF}}[i,\eta]$. The three functions return a probability that a candidate shift η of the signal corresponds to the actual BBI, $\eta_{\mathrm{opt},i}$ for each window i of the BCG-signal and fused using a Bayesian approach,

$$S_{\mathrm{f}}[i,\eta] = S_{\mathrm{LASTA}}[i,\eta] \cdot S_{\mathrm{MAP}}[i,\eta] \cdot S_{\mathrm{AMDF}}[i,\eta], \quad (1)$$

$$\eta_{\mathrm{opt},i} = \arg\max_{\eta} \left[S_{\mathrm{f}}[i,\eta] \right]. \quad (2)$$

As this algorithm makes no prior assumptions about BBIs it was proven to be capable of processing even severely arrhythmic data [14]. The threshold of self-similarity, q_{th} is the only tunable parameter: Only candidate intervals with $\left(S_{\mathrm{f}}[\eta_{\mathrm{opt},i}] / \sum_{\eta} S_{\mathrm{f}}[\eta] > q_{\mathrm{th}} \right)$ are accepted as valid intervals, forming a trade-off of accuracy and temporal coverage. In this full-day data of partially awake, non-healthy subjects, significant outliers were found and the algorithm was modified to increase robustness at the cost of generality. To remove outliers in the beat-to-beat interval estimates, a straightforward thresholding algorithm was applied: If beats exhibited a relative deviation from the median estimation bigger than Δ_{max}, the detected interval was considered an outlier and removed from the analysis.

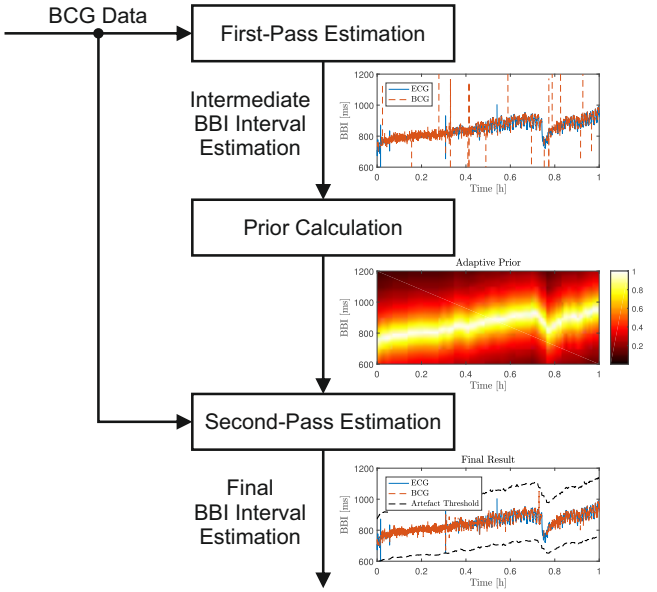


Fig. 1. Flowchart of the algorithm. In the first pass, the original CLIE algorithm is used for BBI estimation. Based on its results, an adaptive prior is calculated, which is used in the final step to calculate BBIs from the BCG signal.

In the first pass of the iterative algorithm [13], CLIE was used to estimated beat-to-beat intervals without prior assumption about the heart rate. Next, the detected intervals $\eta_{\mathrm{opt},i}$ were median filtered with a filter of width n_{median},

$$\hat{\eta}_{\mathrm{opt},i} = \mathrm{medianfilter}\left(\eta_{\mathrm{opt},i}, n_{\mathrm{median}}\right) \quad (3)$$

In the second pass, an adaptive prior was used in the interval estimation,

$$S_{\mathrm{prior}}[\eta, k, \hat{\eta}_{\mathrm{opt},i}] = \frac{1}{2k} e^{-\frac{|\eta - \hat{\eta}_{\mathrm{opt},i}|}{k}}, \quad (4)$$

$$S^{*}_{\mathrm{f}}[i,\eta,k,\hat{\eta}_{\mathrm{opt},i}] = S_{\mathrm{f}}[i,\eta] \cdot S_{\mathrm{prior}}[\eta,k,\hat{\eta}_{\mathrm{opt},i}]. \quad (5)$$

Based on previous observations [15], a Laplacian distribution with variable scale k was chosen. The process is visualized in Figure 1. Note that the threshold on self-similarity q_{th} is used in both the first- and the second-pass estimation, i.e. candidate intervals with $q < q_{\mathrm{th}}$ are removed. After the second pass, all remaining intervals exceeding their surrounding estimations by Δ_{max} (dotted line) are removed as well. In sum, four parameters can be set manually: The quality threshold q_{th}, the scale of the laplacian distribution k, the outlier threshold Δ_{max}, and the width of the filter to calculate the short-term median BBI, n_{median}. The sensitivity of the algorithm towards parameter variation is demonstrated in detail in [13]: q_{th} trades of accuracy and temporal coverage, see also [5]. Decreasing Δ_{max} decreases the amount of outliers, while at the same time decreases temporal coverage. On the other hand, choosing a smaller k increases coverage but leads to an increased error, in particular if the heart rate shows large variability. In this

study, the following set of parameters was used: $q_{\mathrm{th}} = 0.5$, $k = 0.18$, $\Delta_{\max} = 20\,\%$, and $n_{\mathrm{median}} = 51$.

Devices that have independent system clocks and are not synchronized can exhibit severe drifts in sampling rate [16], which we also observed in our recordings and which led to major deterioration in our previously published results [13]. This was less critical in the shorter measurements of healthy subjects. Here, an individual but constant multiplier of the sampling rate could be obtained for each recording that minimized the estimation error of the BBI intervals. In the longer recordings of the vascular patients, however, drift was found to be time-variant. Thus, an adaptive compensation algorithm was developed. In essence, the algorithm calculates a time-varying offset that minimized the median BBI estimation error in a moving window with the size of 1500 beats, which corresponds to approximately 25 minutes. The offset-vector was additionally median filtered with the same filter size to remove outliers.

III. Evaluation

The patient recordings were made in the vascular surgery ward of Tampere University Hospital. The subjects were monitored for up to 24 hours with an EMFit QS bed sensor. The bed sensor was placed between the hospital bed mattress and the bed frame. The sampling rate of the BCG signal obtained with the Emfit QS system was 100 Hz and the signal was bandlimited to 1-5 Hz. Reference ECG was recorded with a Faros 360 five-lead Holter monitor manufactured by Bittium Biosignals using 1 kHz sampling frequency. Ambu Blue sensor L-00-S electrodes were used in the recording. The average age of the subjects was 69.57 years. Two of the subjects were female. The subjects had undergone different vascular interventions such as aortic aneurysm endograting, carotid endarterectomy or femoropopliteal bypass surgery.

In addition, reference sleep measurements from ten healthy subjects were recorded using the same sensor systems. The average recording duration was 7.77 h (range 3.88 h - 8.97 h). The average age of the subjects was 22.6 years and three of the subjects were male. A favorable statement was obtained for this study from the Regional Ethical Committee of Pirkanmaa Hospital District (R17027). The study was registered at ClinicalTrials.gov, identifier NCT03572751.

To evaluate the performance of the algorithm in terms of ultra-short-term HRV analysis, the two time-domain parameters standard deviation of NN intervals (SDNN) and root mean square of successive differences (RMSSD) were evaluated in overlapping 45-second windows. Here, a threshold on the coverage was set. Only if the window contained more than th_{cov} (for example 70 %) of beats, the window was used for analysis. Note that this coverage was calculated only based on the BCG signal itself without using the reference ECG.

IV. Results and Discussion

A. Adaptive Sample Drift Compensation

The effect of the adaptive sample drift compensation algorithm is showcased qualitatively for patient 8 in Fig. 2. If the nominal sampling rates of the devices are used, only the center of the measurement (middle column) is aligned properly as this minizes the difference between the two modalities. If an optimal constant multiplier is calculated, the beginning and the center of the measurement are aligned (first two columns). With adaptive drift compensation, all parts of the measurement are aligned. The gross average error over all patients and BBI estimates is 28.41 ms / 2.98 % if nominal sampling rate is assumed. If adaptive drift compensation is used, however, this error is reduced to 16.51 ms / 1.80 % (see also next section).

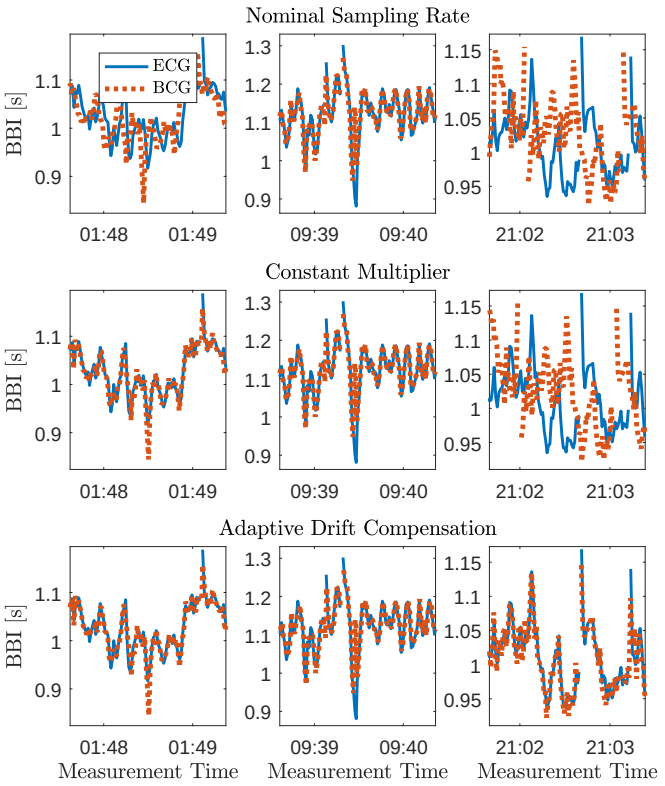


Fig. 2. Example of the operation of the developed drift compensation method. Top row: Only the center of the measurement (middle column) is aligned properly. Middle row: The beginning and the center of the measurement are aligned (first two columns). Bottom row: All parts of the measurement are aligned.

B. Beat-to-Beat Interval Estimation

Tables I and II show the results of BBI estimation for patients as well as healthy subjects. Several things can be observed. First, the average error is found to be slightly higher in the patient population compared to the healthy subjects (16.51 ms / 1.80 % and 12.67 ms / 1.22 %), while the coverage is lower (39.31 % and 73.24 % respectively). Moreover, the inter-subject variability is higher: While it ranges from 8.44 ms to 30.65 ms in terms of error and 60.44 % to 84.10 % in terms of coverage for the healthy subjects, it ranges from 11.13 ms to 37.60 ms and 7.52 % to 68.57 % in the patient data. One difference between the two sets of measurements is the different population of subjects. In addition, the measurements performed on the younger, healthy volunteers were overnight recordings, i.e. subjects can be assumed to be asleep and stationary most of the time. Thus, another analysis

TABLE I
DURATION, COVERAGE, MEAN ABSOLUTE ERROR $\bar{e}_{\mathrm{abs}}$ AND RELATIVE ERROR $\bar{e}_{\mathrm{rel}}$ OF BBI ESTIMATION FOR THE COMPLETE PATIENT DATA.

Patient ID	Duration [h]	Coverage [%]	$\bar{e}_{\mathrm{abs}}$ [ms]	$\bar{e}_{\mathrm{rel}}$ [%]
1	22.96	7.52	37.60	5.63
2	9.36	32.87	15.04	1.38
3	22.41	20.99	21.34	2.23
4	21.95	25.55	11.13	1.37
5	13.38	16.75	28.66	2.68
6	18.38	27.73	12.82	1.96
7	4.47	30.92	20.62	2.90
8	21.64	60.08	11.58	1.15
9	21.59	46.85	21.53	2.15
10	21.25	42.87	25.37	2.53
11	6.17	51.44	16.39	1.59
12	19.01	68.57	11.17	1.44
13	22.77	56.20	14.30	1.43
14	22.35	66.77	17.69	1.72
Mean	17.69	39.65	18.95	2.16
Gross Average		39.31	16.51	1.80

TABLE II
DURATION, COVERAGE, MEAN ABSOLUTE ERROR $\bar{e}_{\mathrm{abs}}$ AND RELATIVE ERROR $\bar{e}_{\mathrm{rel}}$ OF BBI ESTIMATION FOR HEALTHY SUBJECTS.

Healthy ID	Duration [h]	Coverage [%]	$\bar{e}_{\mathrm{abs}}$ [ms]	$\bar{e}_{\mathrm{rel}}$ [%]
1	8.99	82.33	8.77	0.89
2	7.69	63.27	12.73	1.30
3	8.97	78.39	18.29	1.93
4	8.04	60.44	11.60	1.07
5	3.88	84.10	8.44	0.80
6	7.54	79.18	9.57	0.82
7	8.09	81.10	11.64	1.26
8	7.85	61.19	30.65	2.17
9	8.05	77.43	9.91	0.99
10	8.49	66.74	10.76	1.19
Mean	7.76	73.42	13.23	1.24
Gross Average		73.24	12.67	1.22

TABLE III
DURATION, COVERAGE, MEAN ABSOLUTE ERROR $\bar{e}_{\mathrm{abs}}$ AND RELATIVE ERROR $\bar{e}_{\mathrm{rel}}$ OF BBI ESTIMATION FOR THE NIGHTTIME PATIENT DATA, I.E. ONLY DATA RECORDED BETWEEN 23:00 AND 07:00 IS CONSIDERED IN THE ANALYSIS.

Patient ID	Duration [h]	Coverage [%]	$\bar{e}_{\mathrm{abs}}$ [ms]	$\bar{e}_{\mathrm{rel}}$ [%]
1	8.00	11.83	22.03	2.68
2	3.28	48.71	9.78	0.91
3	8.00	35.58	12.58	1.19
4	8.00	41.60	9.24	1.12
5	8.00	22.27	18.72	1.68
6	8.00	36.49	10.71	1.56
7	0.00	-	-	-
8	8.00	65.24	10.35	0.98
9	8.00	51.25	17.69	1.70
10	8.00	74.97	6.22	0.59
11	0.50	56.11	11.05	1.03
12	8.00	85.32	9.78	1.29
13	8.00	64.02	12.23	1.12
14	8.00	94.10	9.31	0.88
Mean	6.56	52.88	12.28	1.29
Gross Average		51.74	10.98	1.17

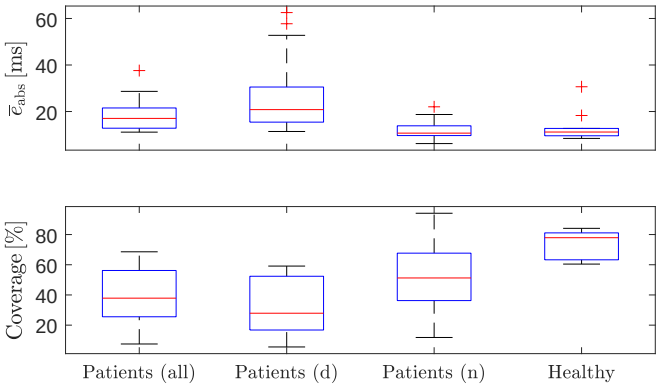
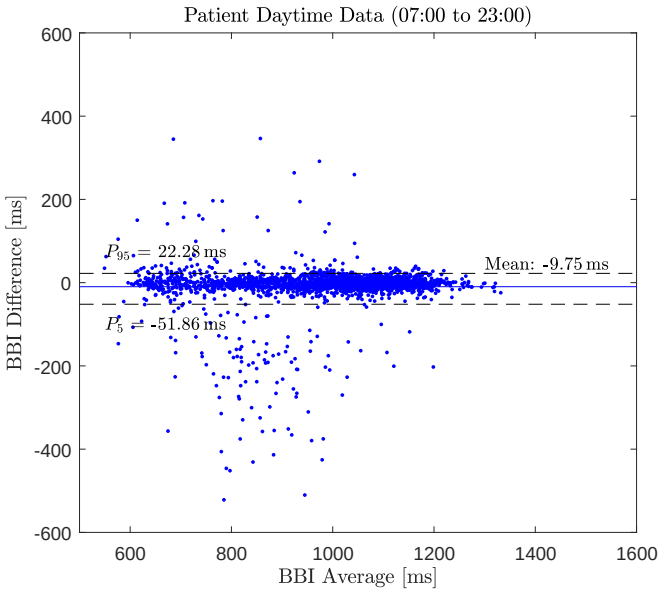


Fig. 3. Boxplot of the subject-wise absolute error (top row) and coverage (bottom row) for BBI estimation of the complete patient dataset (first column), patient daytime data (second column), patient nighttime data (third column), and healthy subjects (fourth column).

was performed separating the patient dataset into nighttime (23:00 to 7:00) and daytime data. Table III shows the results of the nighttime analysis. For patient 7, no nighttime data was available. On average, coverage was found to be higher (51.74 %) compared to the total recording (39.31 %), although still smaller compared to healthy sleepers (73.24 %). In terms of error, however, the results improved significantly, and the relative error of the patient nighttime analysis (1.17 %) even slightly outperforms those of the healthy subjects (1.22 %). These findings are summarized in the box-plot in Fig. 3. Using the Wilcoxon rank sum test no significant difference was found between the error of the healthy subjects and the nighttime patient data. Figures 4 and 5 show Bland-Altman plots comparing the three scenarios. Both healthy and patient nighttime data show very similar distribution and limits of agreement. During daytime, however, the spread is larger and more outliers are apparent. Moreover, a systematic bias (-9.75 ms) in beat-to-beat interval estimation can be observed during the daytime, which was smaller in both patients at night (-1.29 ms) and in the healthy sleepers (-2.80 ms). While the 5^{th} and 95^{th} percentile closely envelope most of the BBI differences, significant outliers in the range of more than 200 ms are obvious, in particular during daytime, indicating failure of the outlier rejection method.

Figure 6 shows an aggregated analysis of all patients over the time of day. For this, coverage and error were assessed in a 5-minute sliding window for all patients. Peaks in the error can be found at around 8:00 and 12:30, which correspond to breakfast and lunch time during which there are more move-



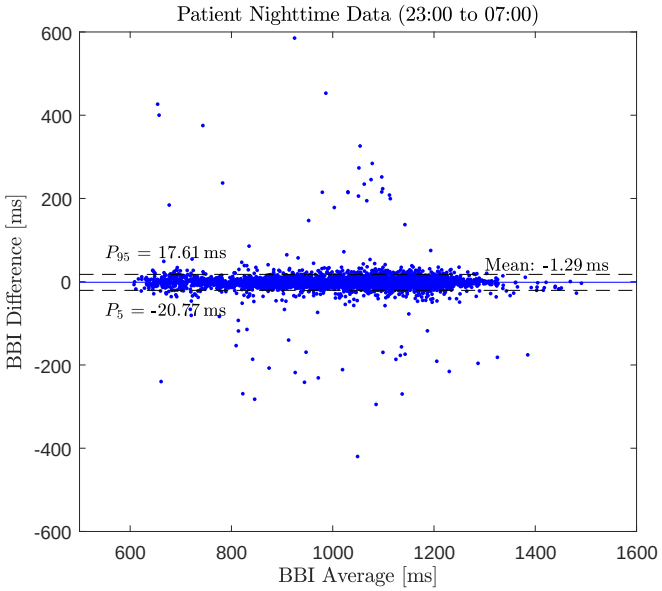


Fig. 4. Bland-Altmann-Plot of BBI estimation for the daytime section (top) and the nighttime section (bottom) of the patient data. To avoid clutter, 10,000 sample points were randomly selected for plotting.

ments and patients may be sitting on their beds. Note that the coverage is reduced in general during the day and in particular during the peaks in the error signal. The measurement were started on average at 19:18 (standard deviation 95 minutes). Given the average usable duration of 17 hours, 41 minutes, the set of peaks between 17:00 and 20:00 can probably be attributed to the interventions associated with attachment and detachment of the devices as well as dinner. Fig. 7 shows examples of raw signals for different subjects and different times of day. Mean BBI and SDNN are calculated on 20 consecutive beats for visualization purposes.

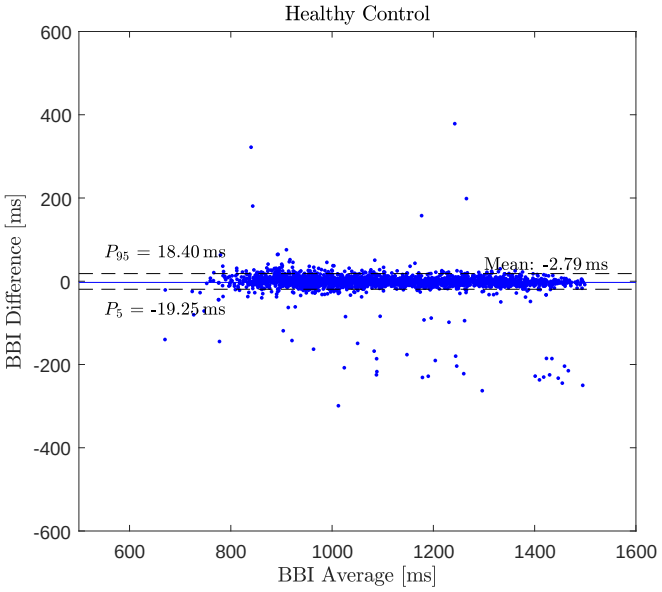


Fig. 5. Bland-Altmann-Plot of BBI estimation for the healthy subjects group. To avoid clutter, 10,000 sample points were randomly selected for plotting.

TABLE IV
RESULTS OF SDNN / RMSSD ESTIMATION FOR THE HEALTHY SUBJECTS. THE MEAN VALUE REPORTS THE GROUND-TRUTH MEAN VALUE OVER ALL SHORT-TERM WINDOWS DERIVED FROM THE REFERENCE DATA.

Healthy	SDNN [ms]		RMSSD [ms]		Coverage
ID	Mean	$\bar{e}_{\text{abs}}$	Mean	$\bar{e}_{\text{abs}}$	[%]
1	74.87	6.79	67.81	7.18	59.25
2	90.92	7.08	91.49	7.93	11.65
3	77.52	7.32	73.28	11.26	43.91
4	86.56	8.27	68.06	14.42	19.61
5	113.73	10.50	110.08	10.81	36.25
6	109.61	12.96	106.81	15.23	52.64
7	44.38	9.79	39.19	17.24	57.46
8	136.01	18.70	134.40	22.77	6.98
9	85.82	9.98	71.93	11.64	38.65
10	97.12	8.90	77.29	7.86	31.87
Mean	65.47	7.16	60.02	9.02	25.59
Gross Average	87.98	9.21	79.67	11.98	37.23

C. Heart Rate Variability Estimation

In Fig. 8, the effect of the coverage threshold th_{cov} for HRV analysis is demonstrated on the healthy subjects dataset. As expected, a decrease in t_{cov} leads to a higher coverage of HRV estimation while at the same time increasing error and vice versa. In the following analysis, a threshold of $t_{\text{cov}} = 0.7$ was arbitrarily chosen.

Tables IV and V show the results of the SDNN and RMSSD estimation for the healthy as well as the patient population. For the patient data, the complete recordings were used. Compared to BBI estimation, differences are more pronounced. While the average coverage is 37.23 % for the healthy subjects, it is only 9.65 % for the patient data. This can partly be explained by the fact that the included daytime data exhibits large portions where the coverage of BBI estimation is

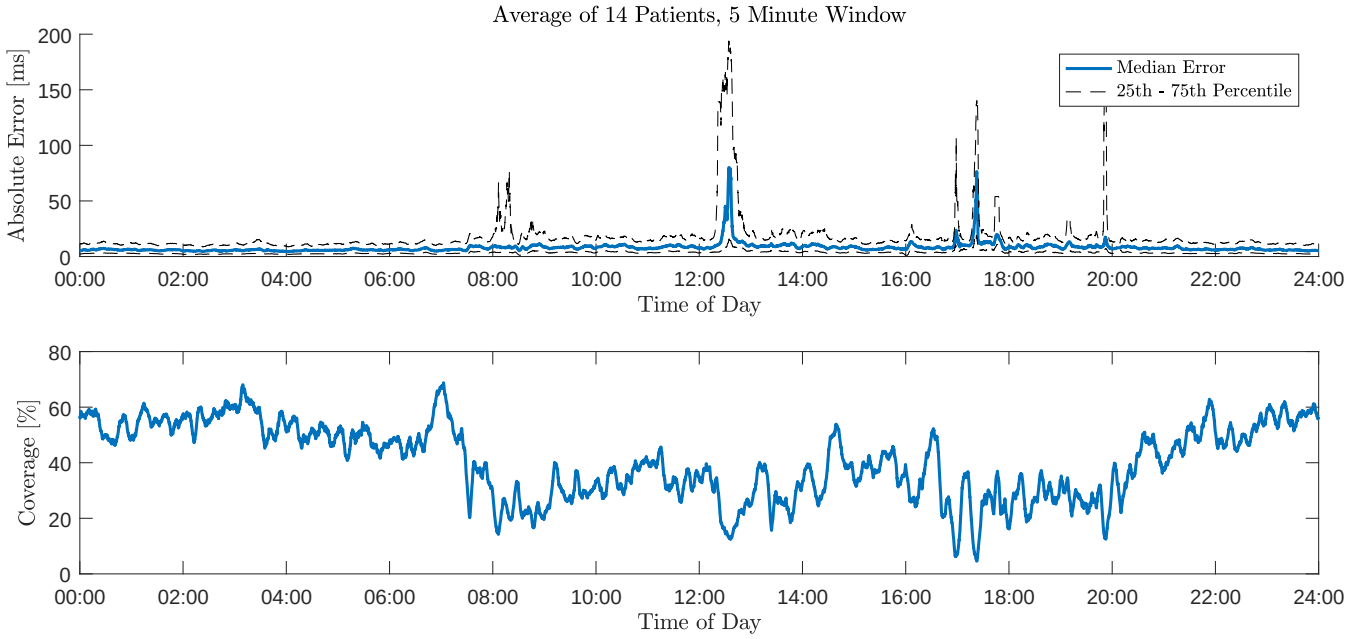


Fig. 6. Aggregated analysis over all patients and time of day. For calculation, a sliding analysis window of length 5 minutes was used.

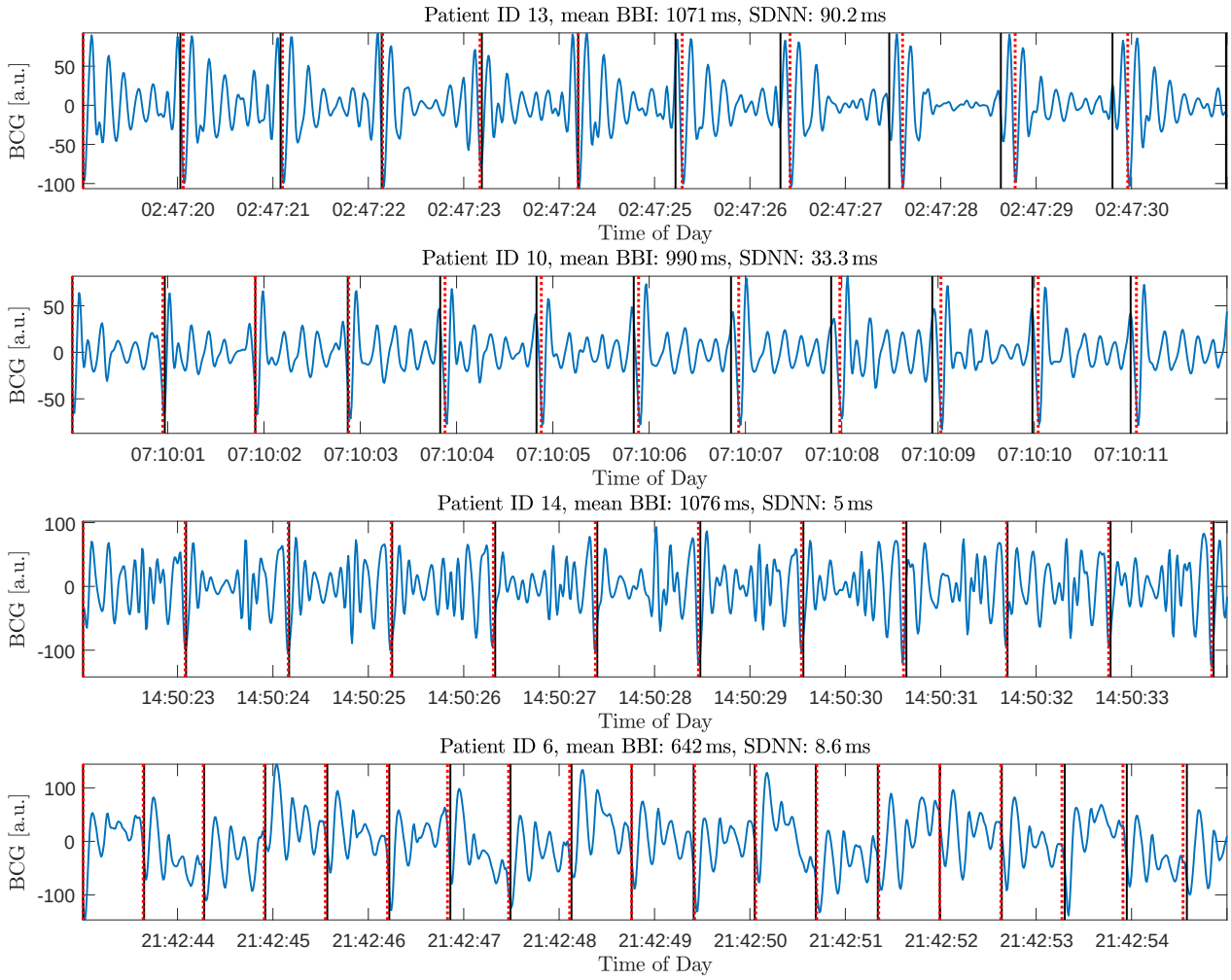


Fig. 7. Example snippets of 12 seconds of raw signal for different patients and different times of day. The solid black lines indicate the reference intervals derived from ECG, the dashed red lines the estimations from BCG. Both annotations were shifted to be aligned at the first beat.

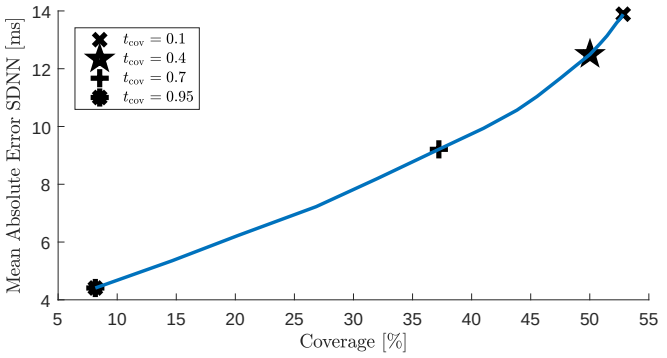


Fig. 8. Coverage and error of the SDNN estimation with different values of the threshold parameter t_{cov}.

TABLE V
RESULTS OF SDNN / RMSSD ESTIMATION FOR THE PATIENTS. THE MEAN VALUE REPORTS THE GROUND-TRUTH MEAN VALUE OVER ALL SHORT-TERM WINDOWS DERIVED FROM THE REFERENCE DATA.

Patient ID	SDNN [ms] Mean	SDNN [ms] $\bar{e}_{\mathrm{abs}}$	RMSSD [ms] Mean	RMSSD [ms] $\bar{e}_{\mathrm{abs}}$	Coverage [%]
1	50.17	-	46.10	-	0.00
2	20.34	3.05	13.93	3.88	1.33
3	53.66	1.77	39.95	2.86	0.26
4	20.44	4.10	18.73	10.36	1.12
5	74.99	5.90	63.52	11.89	0.02
6	23.02	1.87	15.90	5.45	1.28
7	15.52	7.94	13.35	14.02	1.81
8	72.26	8.34	36.08	4.65	9.36
9	43.58	4.25	36.81	6.66	10.67
10	40.20	2.87	34.52	5.81	20.79
11	39.39	5.80	21.15	7.74	15.02
12	24.39	8.08	18.03	9.95	23.57
13	54.42	7.26	36.57	7.30	10.18
14	14.74	5.91	13.65	7.99	37.34
Mean	39.08	5.16	29.16	7.58	9.48
Gross Average	39.35	5.84	29.42	7.47	9.65

low. In addition, even the analysis of the nighttime-only data showed a reduced BBI estimation coverage. If this reduced coverage stems from missing beats that are spread throughout the recording instead of being clustered at a singular locations, the coverage of HRV estimation is over proportionally reduced as it requires segments of valid data with high coverage. However, although the HRV coverage is relatively low it may still be enough to provide additional value for patient monitoring because HRV does not necessarily need to be assessed in a continuous manner. The inter-subject variability was also found to be more extreme, as coverage ranges from 0 to 37.34 % in the patients, while the range was 6.98 % to 59.25 % for the healthy sleepers. The mean absolute error for the patient data was 5.84 ms / 7.47 ms (SDNN / RMSSD), and 9.21 ms / 11.98 ms for the healthy subjects. Although this means that the error is smaller for patients in terms of absolute values, one can also see that the relative error is much higher: while the average ground truth values over all subjects

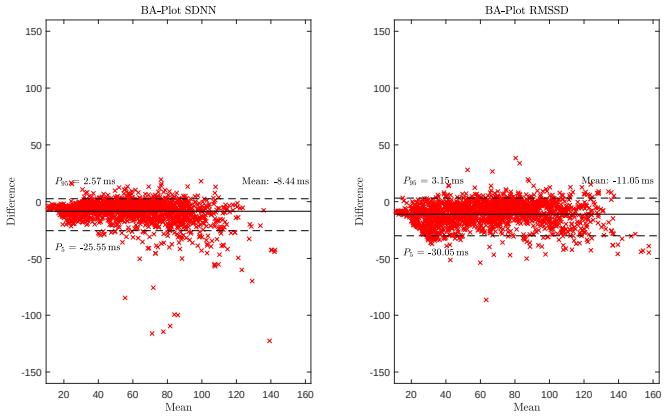


Fig. 9. Bland-Altmann-Plot of SDNN and RMSSD estimation for the healthy subjects group. To avoid clutter, 5,000 sample points were randomly selected for plotting.

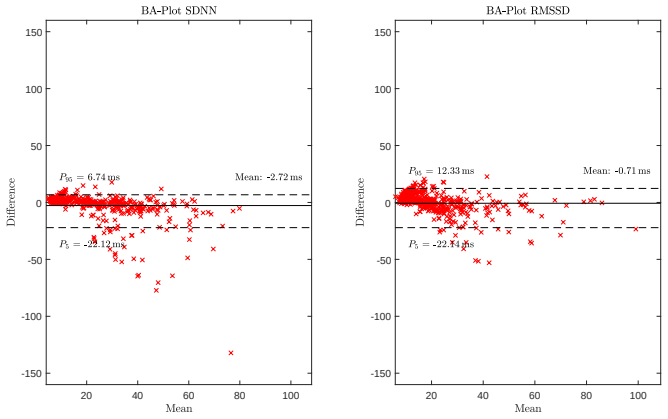


Fig. 10. Bland-Altmann-Plot of SDNN and RMSSD estimation for the patient group. To avoid clutter, 5,000 sample points were randomly selected for plotting.

and temporal windows is 87.98 ms / 79.67 ms for the healthy population, it is 39.35 ms / 29.42 ms in the patient dataset for SDNN and RMSSD respectively. This is visualized in the BA plots in Figures 9 and 10. In addition to the spread of the data, one can see that the proposed method underestimates SDNN / RMSSD, resulting in an offset of -2.72 ms / -0.71 ms for patients and -8.44 ms / -11.05 ms for healthy subjects. As HRV is higher in the healthy subjects, potential negative effects of the adaptive prior, such as systematic underestimation, become more severe.

V. CONCLUSION AND OUTLOOK

In general, our findings confirm that continuous monitoring of high-risk cardiovascular patients is possible with BCG. Our findings are consistent with previous findings presented by others [10] as well as our group [13] in that results are indeed inferior to those obtained from sleep laboratory studies [5], [17]. However, after careful compensation for time-varying sample drift and by analyzing nighttime data only, we were able to show that beat-to-beat interval estimation results are comparable between healthy subjects and our patient group in terms of average absolute estimation error. The coverage, on the other hand, was reduced notably. In combination with the

aforementioned findings in terms of a reduced signal quality we conclude that the CLIE algorithm performs very well in selecting only those parts of the signal that exhibit sufficient self-similarity for BBI estimation in sleeping subjects. Analyzing the daytime data as well, the results on the patient dataset are inferior. After aligning the data in terms of time of day, obvious peaks in the error corresponding to breakfast, lunch, and dinner become apparent. At the same time, the coverage also drops markedly. While this shows that the algorithm is capable of rejecting some portions of the signal associated with daytime motion artifacts, it fails to reject them completely. We assume that in particular rhythmic artifacts with relatively low amplitude, for example associated with talking or other voluntary movements, remain undetected and thus compromise results, in particular leading to systematic underestimation of BBIs. As a consequence, future work should focus on the undoubtedly difficult task of detecting these types of artifacts without decreasing estimator accuracy. In addition, the recording of sleep stages or at least a binary sleep / wake classification would allow further analysis of the exact origin of outliers in the data.

It is interesting to note that we did not observe a significant increase in error in the patient group as reported by others. While Kaisti et al. [10] found a ten-fold increase in RMSE in patients using a wearable seismocardiographic sensor, we could only find a significant reduction in coverage using the bed-integrated ballistocardiographic sensor and the proposed algorithm. However, Kaisti et al. did their analysis on short-term, controlled recordings of patients with coronary artery disease. Thus, future work is needed to show whether or not similar degradations are observed with ballistocardiography and the proposed algorithm when it is applied to coronary artery disease patients, whose cardiac function is likely to differ from the patients analyzed here.

When heart rate variability is to be estimated, the situation becomes even more challenging than BBI estimation alone. As consecutive segments of BBIs are necessary for HRV calculations, missing beats can have detrimental effects. Nevertheless, estimation of the time-domain HRV parameters SDNN and RMSSD was shown to be possible in principle. In terms of absolute values, the error was actually found to be smaller for the patient data. However, since both SDNN and RMSSD were significantly smaller in the patients, the resulting relative error was higher. Also, while the estimation of SDNN was more accurate in the ultra short window of 45 seconds, some authors suggest that shorter window sizes lead to different results compared to SDNN estimation in 5-minute windows, whereas RMSSD is largely unaffected, even if the window is reduced to only 30 seconds [18]. However, other authors have concluded that both RMSSD and SDNN can be calculated reliably from multiple windows of only 10 second [19]. In our study we found that both parameters were systematically under-estimated compared to the ECG reference with the same window size. One potential reason might lie in the developed iterative estimation approach itself: In contrast to the original CLIE algorithm [5], the estimation is augmented by an adaptive prior based on the median BBI interval. While this improved results in terms of BBI estimation accuracy and coverage in general, it might steer the estimation closer to the median, i.e. reduce variability. In the future, this should be analyzed in detail, preferably with synthetic data where HRV parameters can be controlled systematically [20]. In addition, we plan to investigate algorithms that allow estimation of surrogates that correlate well with established time- and frequency-domain HRV parameters but can be calculated from incomplete data and are more robust towards outliers.

REFERENCES

[1] P. Scheffler, S. Muccio, G. Egiziano, R. J. Doonan, A. Yu, F. Carli, and S. S. Daskalopoulou, "Heart rate variability exhibits complication-dependent changes postsurgery," *Angiology*, vol. 64, no. 8, pp. 597–603, 2013.

[2] T. Ushiyama, K. Mizushige, H. Wakabayashi, T. Nakatsu, K. Ishimura, Y. Tsuboi, H. Maeta, and Y. Suzuki, "Analysis of heart rate variability as an index of noncardiac surgical stress," *Heart and Vessels*, vol. 23, no. 1, pp. 53–59, 2008.

[3] P. K. Stein, R. E. Schmieg, A. El-Fouly, P. P. Domitrovich, and T. G. Buchman, "Association between heart rate variability recorded on postoperative day 1 and length of stay in abdominal aortic surgery patients," *Critical Care Medicine*, vol. 29, no. 9, pp. 1738–1743, 2001.

[4] G. Ernst, L. O. Watne, F. Frihagen, T. B. Wyller, A. Dominik, and M. Rostrup, "Decreases in heart rate variability are associated with postoperative complications in hip fracture patients," *PLOS ONE*, vol. 12, no. 7, p. e0180423, jul 2017.

[5] C. Brüser, S. Winter, and S. Leonhardt, "Robust inter-beat interval estimation in cardiac vibration signals," *Physiological Measurement*, vol. 34, no. 2, pp. 123–138, 2013.

[6] J. Kortelainen, M. V. Gils, and J. Pärkkä, "Multichannel Bed Pressure Sensor for Sleep Monitoring," in *Computing in Cardiology*, vol. 39, 2012, pp. 313–316.

[7] A. Vehkaoja, S. Rajala, P. Kumpulainen, and J. Lekkala, "Correlation approach for the detection of the heartbeat intervals using force sensors placed under the bed posts," *Journal of Medical Engineering and Technology*, vol. 37, no. 5, pp. 327–333, 2013.

[8] Y. Katz, R. Karasik, and Z. Shinar, "Contact:Free Piezo:Electric Sensor Used for Real:Time Analysis of Inter Beat Interval Series," in *Computing in Cardiology*, vol. 43. CCAL, sep 2016, pp. 769–772.

[9] M. Di Rienzo, E. Vaini, and P. Lombardi, "An algorithm for the beat-to-beat assessment of cardiac mechanics during sleep on Earth and in microgravity from the seismocardiogram," *Scientific Reports*, vol. 7, no. 1, pp. 1–12, 2017.

[10] M. Kaisti, M. J. Tadi, O. Lahdenoja, T. Hurnanen, A. Saraste, M. Pankaala, and T. Koivisto, "Stand-Alone Heartbeat Detection in Multidimensional Mechanocardiograms," *IEEE Sensors Journal*, vol. 19, no. 1, pp. 234–242, 2019.

[11] O. T. Inan, P. F. Migeotte, K. S. Park, M. Etemadi, K. Tavakolian, R. Casanella, J. Zanetti, J. Tank, I. Funtova, G. K. Prisk, and M. Di Rienzo, "Ballistocardiography and Seismocardiography: A Review of Recent Advances," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 4, pp. 1414–1427, 2015.

[12] L. Pecchia, R. Castaldo, L. Montesinos, and P. Melillo, "Are ultra-short heart rate variability features good surrogates of short-term ones? State-of-the-art review and recommendations," *Healthcare Technology Letters*, vol. 5, no. 3, pp. 94–100, 2018.

[13] C. Hoog Antink, Y. Mai, J. Ranta, A. Tarniceriu, C. Brüser, S. Leonhardt, N. Oksala, and A. Vehkaoja, "On the Performance of Bed-Integrated Ballistocardiography in Long-Term Heart Rate Monitoring of Vascular Patients," in *Computing in Cardiology*, vol. 46, 2019, p. in print.

[14] C. Hoog Antink, S. Leonhardt, and M. Walter, "Reducing false alarms in the ICU by quantifying self-similarity of multimodal biosignals," *Physiological Measurement*, vol. 37, no. 8, pp. 1233–1252, 2016.

[15] ——, "Local Interval Estimation Improves Accuracy and Robustness of Heart Rate Variability Derivation from Photoplethysmography," in *41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2018, pp. 3558–3561.

[16] M. Vollmer, D. Bläsing, and L. Kaderali, "Alignment of Multi-Sensored Data: Adjustment of Sampling Frequencies and Time Shifts," *Computing in Cardiology*, vol. 46, 2019.

[17] M. D. Zink, C. Brüser, B. O. Stüben, A. Napp, R. Stöhr, S. Leonhardt, N. Marx, K. Mischke, J. B. Schulz, and J. Schiefer, "Unobtrusive Nocturnal Heartbeat Monitoring by a Ballistocardiographic Sensor in Patients with Sleep Disordered Breathing," *Scientific Reports*, vol. 7, no. 1, pp. 1–13, 2017.
[18] H. J. Baek, C. H. Cho, J. Cho, and J. M. Woo, "Reliability of ultra-short-term analysis as a surrogate of standard 5-min analysis of heart rate variability," *Telemedicine and e-Health*, vol. 21, no. 5, pp. 404–414, 2015.
[19] M. L. Munoz, A. Van Roon, H. Riese, C. Thio, E. Oostenbroek, I. Westrik, E. J. De Geus, R. Gansevoort, J. Lefrandt, I. M. Nolte, and H. Snieder, "Validity of (Ultra-)Short recordings for heart rate variability measurements," *PLoS ONE*, vol. 10, no. 9, pp. 1–15, 2015.
[20] C. Hoog Antink, S. Leonhardt, and M. Walter, "A synthesizer framework for multimodal cardiorespiratory signals," *Biomedical Physics & Engineering Express*, vol. 3, no. 3, p. 035028, jun 2017.

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