Monitoring the Relative Blood Pressure Using a Hydraulic Bed Sensor System

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***Abstract*—We propose a non-wearable hydraulic bed sensor system that is placed underneath the mattress to estimate the relative systolic blood pressure of a subject, which only differs from the actual blood pressure by a scaling and an offset factor. Two types of features are proposed to obtain the relative blood pressure, one based on the strength and the other on the morphology of the bed sensor BCG pulses. The relative blood pressure is related to the actual by a scale and an offset factor that can be obtained through calibration. The proposed system is able to extract the relative blood pressure more accurately with a less sophisticated sensor system compared to those from the literature. We tested the system using a dataset collected from 48 subjects right after active exercises. Comparison with the ground truth obtained from the blood pressure cuff validates the promising performance of the proposed system, where the mean correlation between the estimate and the ground truth is near 90% for the strength feature and 83% for the morphology feature.**

***Index Terms*—Ballistocardiogram, hydraulic bed sensor, long-term health monitoring, non-contact measurement, relative blood pressure.**

I. Introduction

In the United States, some of the most dangerous health concerns are related to cardiovascular diseases [1]. The blood pressure of an individual appears to be a reliable indicator of a health issue that could eventually lead to a cardiovascular related illness [2]. Monitoring the blood pressure can provide an early warning to prevent cardiovascular related problems whenever the blood pressure exceeds the normal range.

Estimating accurately the blood pressure, whether absolute or relative, is a challenging task. A number of previous studies [3]–[5] use several sensor modalities to obtain the bio-signals for blood pressure estimation. The sensor modalities used, broadly speaking, can be categorized as wearable and non-wearable. Techniques based on the electrocardiogram (ECG) and photoplethysmogram (PPG) [6]–[9] signals require wearable sensors. Another wearable technique is the oscillometric method [10]–[16]. There are a number of wearable devices on the market for blood pressure monitoring and cardiac health tracking as well, such as Finapres [17]. Non-wearable approaches include a weight scale sensor that explores the ballistocardiogram (BCG) [18] for blood pressure estimation. Wearable techniques can give better results than non-wearable. However, an individual may feel uncomfortable wearing the sensors all the time and may not be able to use them at all. Recharging for consistent use is also another consideration for wearable devices [19], [20]. The ability to completely monitor blood pressure changes in an unobtrusive manner can have huge benefits with enormous health care implications. Towards this goal, we propose the use of a low-cost non-invasive and non-wearable device, in particular, a hydraulic bed sensor [21], [22], for passive and unobtrusive relative blood pressure monitoring of an individual in an in-home environment.

The bed sensor system is placed under the mattress. This sensor system provides measurement that is the superposition of the ballistocardiogram (BCG) [23] and respiration signals. It is capable of capturing the BCG signal of an individual lying on the mattress. The signal obtained from the bed sensor contains information about the heartbeat, respiration and motion [22]. In this work, we explore the bed sensor BCG signal further and derive knowledge about the blood pressure of a subject. Although it does not provide the absolute blood pressure, our studies, as shown in this paper, show that we are able to obtain and track the relative blood pressure. The relative blood pressure differs from the actual by a scale factor and a constant offset only. The scale and offset parameters may be subject and sensor unit specific but can be obtained through calibration for generating an actual blood pressure from the relative. Also, tracking relative blood pressure with a bed sensor can be used to recognize changes in blood pressure over time. In our previous work, we have shown that recognizing changes in health parameters using in-home sensors is an effective approach for facilitating very early treatment for older adults, which results in better health outcomes [24], [25].

We propose two main features for systolic blood pressure monitoring. The first is based on the strength of the BCG pulses in the bed sensor signal. An increasing trend in pulse strength indicates the heart is exerting larger force and hence an increase blood pressure. The second is based on the shape of the BCG signal from cycle to cycle to indicate the variations of the blood pressure. Clinically, lowering systolic blood pressure is often the target of treatment [26], [27] and we focus on systolic blood pressure monitoring in this paper.

The paper is organized as follows. The related work is described in Section II. The overview of the hydraulic bed

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sensor system and the measurement settings are described in Section III. Section IV presents the features extracted from the BCG signal to estimate the relative blood pressure. Section V describes the datasets used for performance evaluation. Section VI presents the results, and we conclude the paper in Section VII.

II. Related Work

Over the past few years, more and more researchers are interested in exploiting the BCG for health care. Unlike the ECG which comes from the electrical signal, the BCG is produced from the mechanical behavior of the circulation system. When the blood flows through the body, it will generate a force that displaces the body as the center of mass changes. A well-known example of the BCG signal is the motion artifact in Magnetic Resonance Imaging (MRI) [28].

A. Traditional Methods

Two well-known traditional methods to measure the blood pressure are the arterial line blood pressure (ART) and blood pressure cuff. ART can provide the continuous blood pressure measurement, but it is only accessible in the hospital with well-trained staff. The blood pressure cuff is easy to use for daily life and is commercially available, but it cannot provide continuous blood pressure measurements.

B. PPG and Pulse Transit Time

In addition to the traditional methods, different approaches to estimate the blood pressure have been developed recently. One is the photoplethysmogram (PPG) that is capable of providing continuous blood pressure estimates [6]–[9] that are derived using the features extracted from the morphology of PPG. Yet another is the pulse transit time (PTT) [29]–[35]. It computes the time delay between the observations of ECG and PPG or two PPG devices from separate parts of the body to determine the relative blood pressure. The relative blood pressure from PTT can be mapped into the actual blood pressure when combined with other parameters.

C. Oscillometric Technique

The other well know method is based on oscillometric technique [10]–[16] that combines the observations from a blood pressure cuff and an oscilloscope to achieve better accuracy. This technique determines the blood pressure from the vibration signal indicated by an oscilloscope and uses a carefully designed threshold to obtain the systolic and the diastolic blood pressure. It gives good accuracy but is not able to provide continuous blood pressure measurements.

All of the above approaches and techniques are costly, not able to provide continuous measurements or require a wearable sensor. In our previous studies, the BCG signal obtained by a bed sensor can provide a reliable estimate of the heart rate and respiration rate [22], [36], [37]. We will further investigate the possibility of using the BCG signal from a hydraulic bed sensor system, which has the advantage of being contact-free, to monitor the blood pressure continuously. It is the objective of this paper to propose and analyze two features derived from the BCG signal observed by a low cost bed sensor system for relative systolic blood pressure monitoring.

III. System Description

The bed sensor system consists of four water tubes, placed in parallel under the mattress as shown in Fig. 1. A pressure sensor is attached at the end of each water tube to convert the hydraulic pressure to an electrical signal that represents the BCG. The signals from the four sensor channels are sampled synchronously at a rate of 100 samples/second. Further details about the hardware of the hydraulic bed sensor system are described in [21]. The data from one of the four channels are processed together for monitoring the relative blood pressure. There is a potential to process all four channels together to improve performance, which is a subject for future study.

The experimental system contains other sensors that serve to provide references for confirmation and validation. They include the 3-lead ECG sensor, finger pressure sensor and PPG sensor from ADInstruments [38]. The bed sensor data and those from the reference sensors are acquired synchronously using the data collection platform by PowerLab [38] from ADInstruments. In addition to the reference sensors, we also use the blood pressure cuff to obtain the ground truth (GT) of the blood pressure.

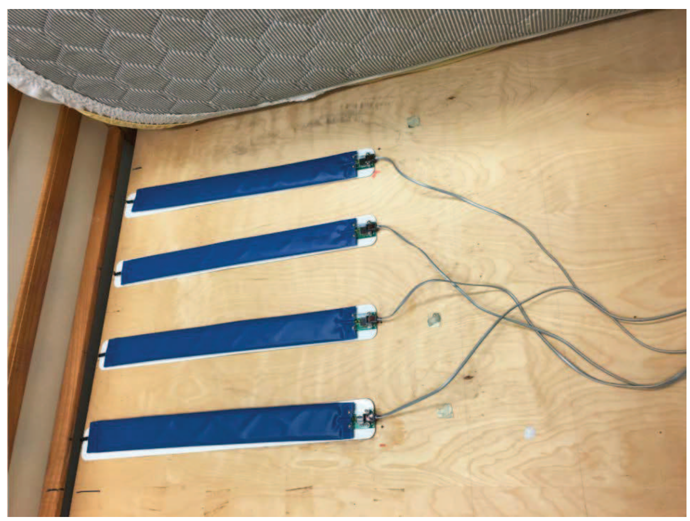

Fig. 1. The hydraulic bedsensor.

IV. Ballistocardiogram Features

The four-channel bed sensor is sensitive but has a low signal-to-noise ratio. Furthermore, various kinds of non-stationary interferences due to the motion of the subject in bed can be strong [21]. The crucial step is to extract reliable information (simply, called features) from the bed sensor data in order to be able to monitor the blood pressure.

Two main features are proposed and evaluated in this paper. The first is based on the strength and the other is based on the morphology of the bed sensor BCG pattern in each heartbeat cycle. In this preliminary investigation and for conceptual illustration, we process the data from one transducer only to obtain the features. The integration of the features from the four transducers to improve the robustness of obtaining the relative blood pressure is left for further study.

A. Ballistocardiogram Pulse Strength

The magnitude of the heartbeat signal captured by the hydraulic bed sensor is related to the stroke volume [39], which could provide some indications about the blood pressure. Fig. 2(a) shows an example of the bed sensor signal from a young healthy female captured by one of the transducers. The bed sensor data $X(n)$ can be modeled as [36], [37]

$$X(n) = r(n) + h(n) + \varepsilon(n) \tag{1}$$

where $r(n)$ is the respiration and $h(n)$ the heartbeat component and $\varepsilon(n)$ the additive noise. The respiration component is irrelevant to the relative blood pressure and is removed by a bandpass filter with a passband from 0.7 Hz to 10 Hz. The bandpass filtering is not expected to affect the heartbeat component since it lies within this frequency range. The filtered data is

$$X'(n) = h(n) + \varepsilon'(n)\,. \tag{2}$$

Fig. 2(b) shows the output after passing the signal in Fig. 2(a) through the bandpass filter.

We next form the short-term energy profile $E(n)$ by squaring the filtered data samples and applying an averaging filter with an impulse response equal to 1 for $n = 0, 1, \cdots, 29$. The span of the filter is 30 samples, corresponding to an averaging window of 0.3 seconds. In other words,

$$E(n) = \sum_{i=0}^{29} X'(n-i)^2\,. \tag{3}$$

The obtained energy profile is shown in Fig. 2(c). The feature for relative blood pressure is the local peak heights of the energy profile, and we shall call this local peak feature the Ballistocardiogram Pulse Strength (BPS). Fig. 2(d) shows the corresponding signal from a finger pressure sensor.

We shall provide an example to justify the use of BPS, the local peak heights of $E(n)$, as a feature for relative blood pressure. Fig. 3(a) is a segment of the bed sensor data obtained from a patient in the Cardiac Intensive Care Unit at University of Missouri hospital. Fig. 3(b) is the short-term energy profile with the local peak heights indicated by circles. The local peaks found from the energy profile are annotated in Fig. 3(a). The ECG signal and arterial line blood pressure (ART) are shown in Fig. 3(c). There is a premature atrial complex (PAC) at 5.9 seconds appearing in ECG and ART. Compared to the ECG and ART signals, the short-term energy $E(n)$ is able to indicate every heartbeat correctly, and its local peaks are proportional to the stroke volumes in each. Collecting the peak values over time can yield a non-invasive and non-wearable solution to monitor the blood pressure continuously.

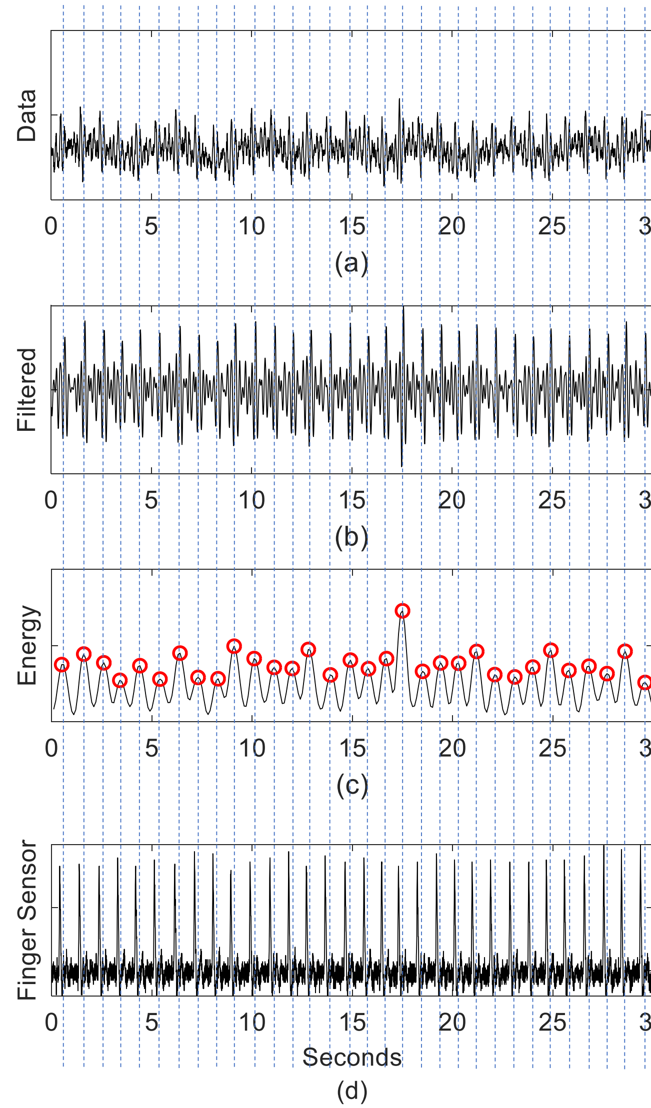

Fig. 2. (a) The 30 seconds signal obtained from hydraulic bed sensor, (b) filtered signal of (a), (c) the energy profile $E(n)$ where the BPS feature values are the values of the local peaks indicated by circles, (d) the corresponding signal from finger pressure sensor.

B. Ballistocardiogram Pulse Deviation

We believe that the shape of the BCG signal and the blood pressure are related. The shape of a BCG cycle is characterized by a number of peaks [23]. Fig. 4 shows a typical cycle obtained from the hydraulic bed sensor. Let the BCG value of the I extremum be A_I, and those for J and K extrema be A_J and A_K. We define

$$\begin{aligned} &IJ-amplitude = A_J - A_I,\\ &JK-amplitude = A_J - A_K,\\ &KL-amplitude = A_L - A_K. \end{aligned} \tag{4}$$

The first two are indicated by the red line and the blue line in Fig. 4.

Normally, the heart rate and respiration rate are closely related to the blood pressure. After an exercise session, the heart rate, respiration rate, and blood pressure will increase.

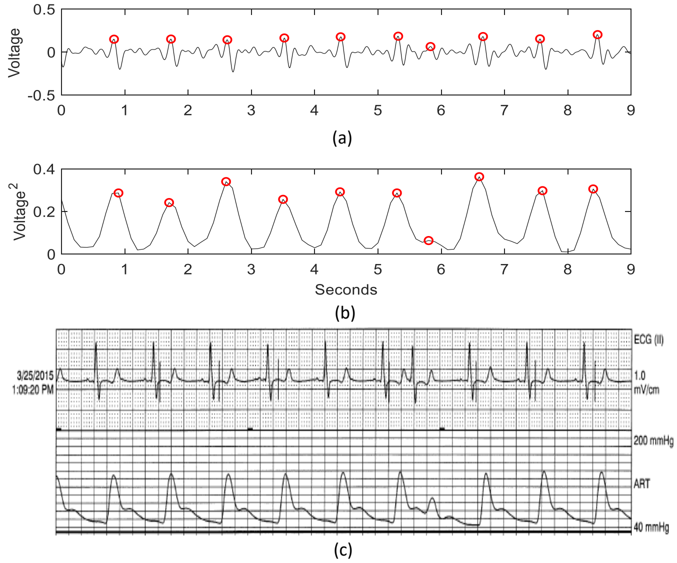

Fig. 3. (a) Pre-processed data from the hydraulic bed sensor, (b) Short-term energy profile of (a), (c) ECG and ART signals.

One can anticipate the heart rate and respiration rate can be used as features for obtaining the blood pressure. It should be noted, however, that the blood pressure is not always proportional to the heart rate and the respiration rate. An example is when someone suffering from hemorrhage is losing a large amount of blood, causing the heart rate and respiration rate to increase, but causing the blood pressure to decrease. In such a case, any feature related to the heart rate and respiration rate will not work properly. Consequently, features based on heart rate and respiration rate cannot be used reliably for blood pressure monitoring.

Fig. 5(a) shows the typical pattern of a BCG cycle of a subject immediately after exercise, and Fig. 5(b) is the pattern when the heart rate, respiratory rate, and blood pressure of the subject return to normal. We can observe that the BCG patterns are quite different in the two situations. Table I summarizes some differences in the two BCG patterns.

Table I provides some insight into possible features that might be used to measure relative blood pressure. Some of these candidate features, however, prove difficult to use in practice. The first possibility is the H peak value. Unfortunately, the H peak is not always clear enough which creates some uncertainty in its feature extraction. The IJK complex is the main part of the BCG signal. According to Fig. 5(a), we notice that the difference between the JK-amplitude and IJ-amplitude is large immediately after exercise, and there is almost no difference when the subject returns to rest. The difference between the JK-amplitude and IJ-amplitude can be a useful feature that relates to the blood pressure. In fact, we can use the IJ-amplitude or JK-amplitude directly as a feature to monitor the blood pressure. The L peak is like the H peak in that it is not always clear enough to be identified for feature extraction. The last three possible features are the time separations of HJ, IK, and JL. When the heart rate increases, the heart will pump faster and make the separations of HJ, IK, and JL decrease. As mentioned before, it is not reliable to use the feature related to the heart rate. Therefore, we do not use these three features to estimate the relative blood pressure.

To summarize, we only use the difference between JK-amplitude and IJ-amplitudes from the BCG pattern in each heartbeat cycle as a feature to monitor the relative blood pressure. We shall call this feature as Ballistocardiogram Pulse Deviation (BPD).

The two features BPS and BPD can be exploited in various ways. In this study, we shall focus mainly on their correlation with respect to the actual blood pressure. These two features will be interpreted as relative blood pressure. We shall compare them with the GT to validate the reliability of using the two features for the relative blood pressure.

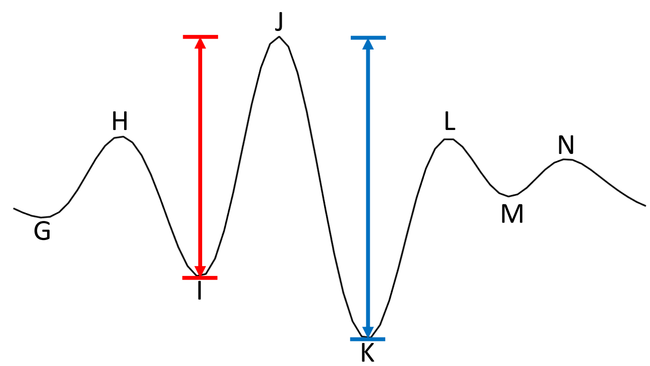

Fig. 4. The illustration of the features extracted from BCG signal to estimate the relative blood pressure.

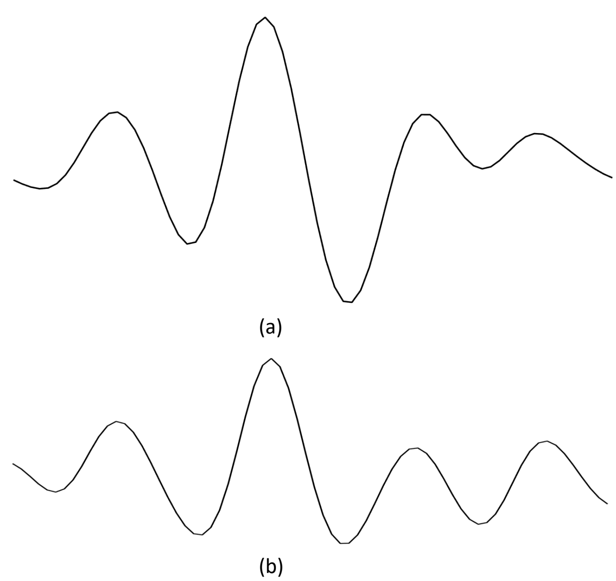

Fig. 5. The typical BCG signal comparison. (a) immediately after exercise, (b) settled-down.

V. DATA DESCRIPTION

The data collection from human subjects has been approved by the Institutional Review Board (IRB) at the University

TABLE I
DETAILS OF DIFFERENCE OF BCG BETWEEN CALM DOWN AND AFTER EXERCISE.

	Immediately after exercise	Settled-down
H peak	Strong	Weak
IJ-amplitude	Strong	Weak
JK-amplitude	Strong	Weak
KL-amplitude	Strong	Weak
HJ-distance	≈0.19 second	≈0.22 second
IK-distance	≈0.19 second	≈0.25 second
JL-distance	≈0.21 second	≈0.22 second

of Missouri. The performance of the proposed method for monitoring the blood pressure is evaluated using the dataset from 48 subjects. Before data collection begins, each subject was required to pedal a stationary upright bicycle for two minutes. Then, the subject was asked to lie flat on his back in a bed to limit the amount of nonstationary noise from motion. Data was collected over a duration of 6 to 10 minutes until the blood pressure did not change from one minute to the next. In addition, the blood pressure cuff was used to obtain the GT of the blood pressure every minute. The gender, age, weight and height of the subjects are listed in Table II. The subject pool consists of 37 males and 11 females. The age is from 18 to 49 with an average of 29. The weight varies from 48 to 120 (kg) with an average of 76.0 (kg). The height is between 156 and 190 (cm) with an average of 174.6 (cm).

Since we only asked the subjects to do exercise for 2 minutes, some of them who do exercises regularly will not show obvious blood pressure variation, which leads to a variance of the dataset that can further validate the robustness of the two features.

VI. EXPERIMENTAL RESULTS

We shall demonstrate the qualities of the proposed features through computing the correlation coefficient, which is invariant to scaling and offset, with the GT. Let us use the vector $\mathbf{x}$ to denote the collection of a feature over a certain time period and the vector $\mathbf{y}$ the collection of the GT values. The correlation coefficient is obtained by using

$$\rho(\mathbf{x},\mathbf{y}) = \frac{\mathrm{cov}(\mathbf{x},\mathbf{y})}{\sigma_{\mathbf{x}}\sigma_{\mathbf{y}}} \tag{5}$$

where $\mathrm{cov}(\mathbf{x},\mathbf{y})$ is the covariance between the elements of $\mathbf{x}$ and $\mathbf{y}$, and $\sigma_{\mathbf{x}}$ and $\sigma_{\mathbf{y}}$ are the standard deviations of $\mathbf{x}$ and $\mathbf{y}$. If $\mathbf{x}$ comes from a certain variable a and $\mathbf{y}$ from another variable b, we also use $\rho(\mathrm{a},\mathrm{b})$ to represent the cross-correlation.

A. Feature Performance

We shall use the well known relative blood pressure measurement method PTT [29]–[35] for comparison with our features. It is defined as the time difference between the QRS complex in ECG and the valley in PPG. Fig. 6 shows an example of PTT. The relative blood pressure is equal to $1/T$, where T is indicated in Fig. 6.

Over the 6 to 10 minutes after active exercise, the blood pressure of a subject would decrease gradually. To reduce the random variations, the BPS feature values are averaged over

TABLE II
DETAILS OF PARTICIPANTS IN BLOOD PRESSURE CHANGE ESTIMATION.

ID	Gender	Age	Weight(kg)	Height(cm)
1	male	39	74.0	172.0
2	male	27	86.0	177.8
3	male	29	79.0	183.0
4	male	23	68.0	172.0
5	female	28	48.0	162.0
6	male	27	70.0	170.0
7	male	49	83.0	190.0
8	male	28	73.0	185.4
9	male	26	86.0	178.0
10	male	21	75.0	184.0
11	male	25	60.0	172.0
12	female	24	62.0	165.0
13	male	33	78.0	181.0
14	male	26	83.0	187.0
15	male	26	65.0	175.0
16	male	32	82.0	165.0
17	male	27	70.0	177.8
18	male	25	86.0	178.0
19	male	27	77.0	180.0
20	male	28	60.0	163.0
21	male	38	120.0	180.3
22	male	36	107.0	183.0
23	female	37	70.0	170.0
24	male	34	64.0	162.0
25	male	34	84.0	181.0
26	female	32	77.0	165.1
27	male	32	92.0	180.0
28	male	33	75.0	166.0
29	male	31	68.0	174.0
30	female	22	51.0	156.0
31	male	31	100.0	186.0
32	male	28	100.0	184.0
33	female	34	64.0	167.6
34	female	21	57.0	171.0
35	male	18	83.0	180.0
36	male	29	79.0	175.0
37	male	33	82.0	167.6
38	male	23	73.0	172.0
39	female	28	73.0	168.0
40	female	22	48.0	163.0
41	male	35	80.0	173.0
42	male	22	90.0	183.0
43	male	27	86.0	184.0
44	male	43	74.8	179.0
45	female	24	60.0	170.0
46	male	32	99.0	179.0
47	female	30	57.0	170.0
48	male	24	70.0	172.0

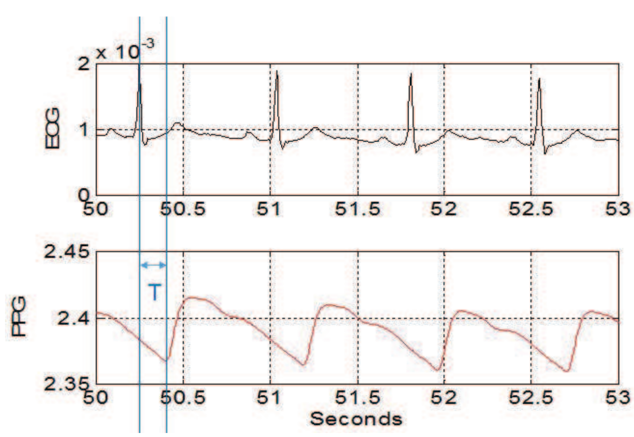

Fig. 6. An example of Pulse Transit Time PTT.

TABLE III
THE AVERAGE CORRELATION COEFFICIENTS OF PTT, BPS AND BPD WITH GT.

Feature correlated with GT	Average correlation coefficient
PTT	0.5500 (0.8022 if subject with negative correlation ignored)
BPS	0.9070
BPD	0.8368

5 seconds and BPD over 10 seconds. The averaging duration for the latter is longer since it has higher random variations. In acquiring the GT, the blood pressure cuff took about one minute to give a reading. When computing the correlation coefficients between a proposed feature and the GT, only the feature value at the beginning of 5 (for BPS) and 10 (for BPD) seconds of each one minute in collecting the GT is used. Since we take the data right after the subject finished exercise, the blood pressure will decrease continuously. The beginning of 5 and 10 seconds in each one minute can better correspond with the blood pressure cuff reading. Thus the length of the two vectors in computing the correlation coefficient ranges from six to ten.

An ideal BCG pulse cycle always has the JK amplitude larger than the IJ amplitude [40]. Noise and interference appear in the BCG signal from the bed sensor system. When extracting the BPD feature, the feature value from a cycle is discarded if it is negative. In the dataset used, about 27% of the cycles have negative BPD values. In contrast, no feature values for BPS were removed.

Fig. 7 and Fig. 8 present the correlation coefficients between GT and the two proposed features among the 48 subjects. The figures are sorted based on the BPS feature correlation result in decreasing order and the entries in Table II is also arranged in such an order.

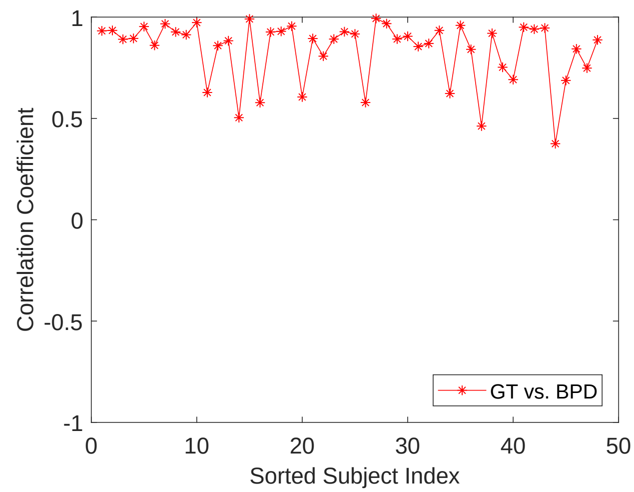

Fig. 8. The correlation coefficient between GT and BPD, $\rho(\mathrm{GT},\mathrm{BPD})$.

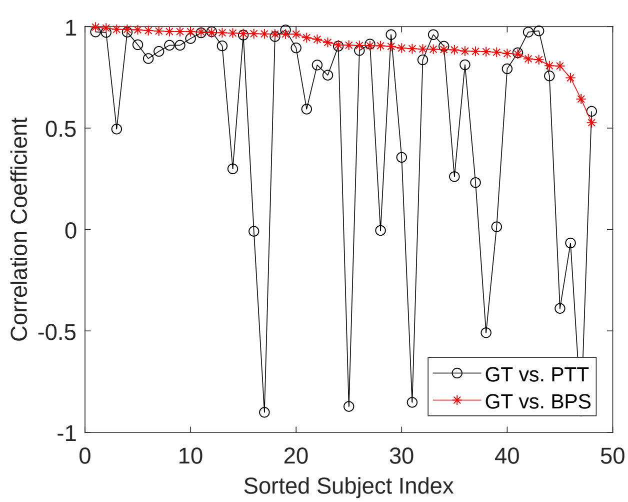

Fig. 7. The correlation coefficient between GT and BPS, $\rho(\mathrm{GT},\mathrm{BPS})$.

Table III tabulates the average of the correlation coefficients over the 48 subjects and the features. For PTT, 8 subjects have negative correlation coefficients, causing low average correlation value. If we exclude these 8 subjects, the average correlation coefficient for PTT becomes 0.8022. The proposed two features do not have this problem and they show better match with the GT and provide better results than PTT. Most of the subjects had 75% or better correlation with the proposed features, particularly for BPS. Unlike PTT, the proposed two features do not have negative correlation for any of the subjects.

In addition to the correlation plots in Figs. 7-8, we also generated the scatter plots between the GT and the bed sensor blood pressure estimate to gain additional understanding. The bed sensor feature, either BPS or BPD, differs from the absolute blood pressure by a scale and an offset factor, that is

$$ActualBloodPressure \approx scale \times Feature + offset. \quad (6)$$

These two parameters are expected to be subject dependent and sensor unit specific. We obtain them separately for each subject by applying a least-squares fit of the bed sensor feature value to the GT blood pressure to generate the blood pressure estimate. Fig. 9 depicts the scatter plot for the blood pressure estimate derived from the BPS feature. It clearly shows the results fit well to the 45-degree line, confirming high correlation between the ground truth and the BPS feature. For reference purposes the blood pressure estimate deduced from PTT using the same least-squares fitting process is shown in Fig. 10. The subjects having negative PTT and GT correlation as indicated in Fig. 7 are excluded in Fig. 10 since the scale factor will be negative which is invalid. The superiority of BPS over PTT is obvious. The results for the BPD feature are illustrated in Fig. 11 and the observations are consistent with Fig. 8. From Figs. 9-11, the mean absolute error between GT and the blood pressure estimate is 1.8081 (mmHg) for BPS and 2.3350 (mmHg) for BPD, while that of PTT is 2.4221 (mmHg).

We would like to determine whether the feature performance is related to gender. Table IV gives the averages of the correlation coefficients separately for male and female subject. It seems both features have higher correlations with the GT for

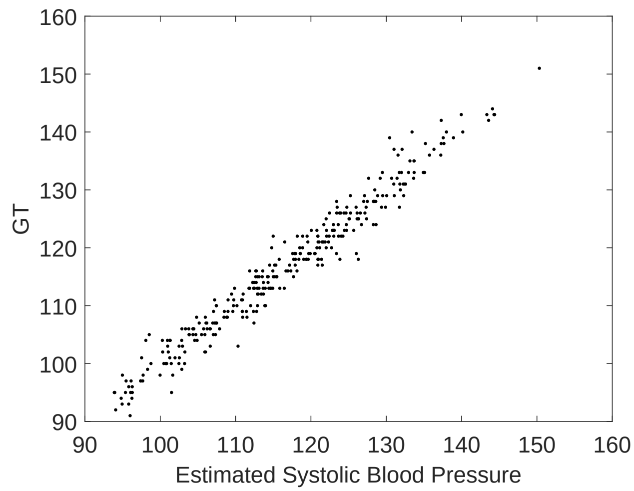

Fig. 9. Scatter plot for the blood pressure estimate derived from the BPS feature vs GT.

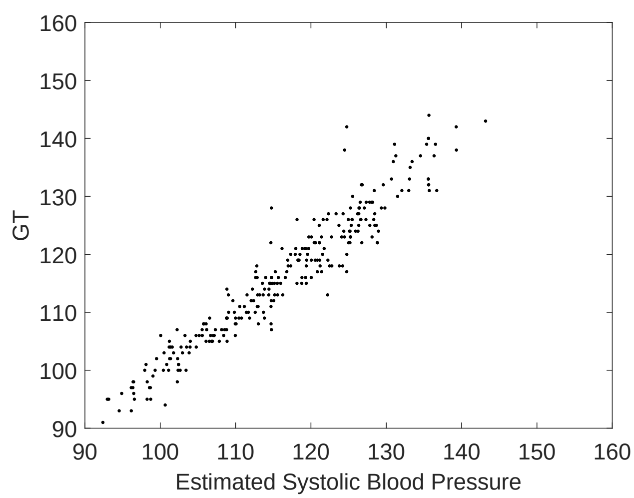

Fig. 10. Scatter plot for the blood pressure estimate derived from the PTT feature vs GT.

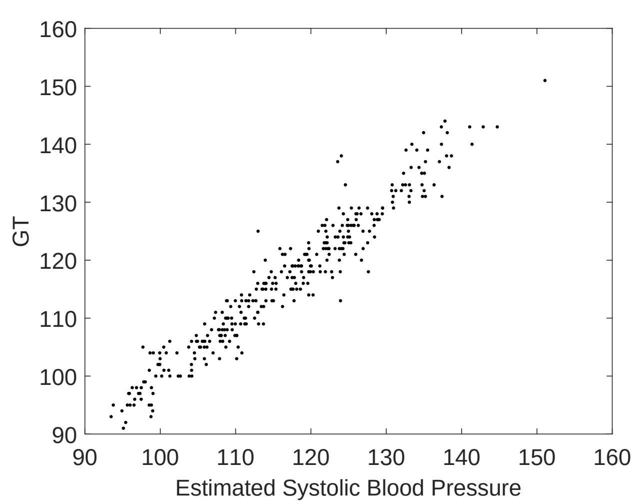

Fig. 11. Scatter plot for the blood pressure estimate derived from the BPD feature vs GT.

TABLE IV
EFFECT OF GENDER ON THE PERFORMANCE OF BPS AND BPD.

Gender (GD)	Count	avg. of $\rho(BPS,GT)$	avg of $\rho(BPD,GT)$
Male	37	0.92	0.85
Female	11	0.88	0.78

TABLE V
EFFECT OF AGE, WEIGHT, HEIGHT, AND BMI ON THE PERFORMANCE OF BPS AND BPD.

Subject characteristics (SC)	$\rho(\mathrm{SC},\rho(GT,BPS))$	$\rho(\mathrm{SC},\rho(GT,BPD))$
Age	0.0660	-0.0773
Weight	0.0550	0.1428
Height	0.1046	0.2278
BMI	0.0174	0.0380

male than for female subjects. The difference is larger for the BPS feature. Based on [41], men and women have different cardiovascular systems. We believe the BCG signal from men and women will be different. The higher number of male than female subjects in the data set may also contribute to the variation. We plan to collect more data for further investigation in the future.

B. Feature Performance and the Subject Characteristics

To examine if the performance is affected by the age, weight, height and body mass index (BMI) of a subject, we evaluate the dependency of the results in Fig. 7 and Fig. 8 with these subject characteristics in Table V. Based on the results, we believe that there is not much dependency of the performance of the two proposed features BPS and BPD with the age, weight, height and BMI of a subject.

C. Performance Comparison Between BPS and BPD

The BPD feature performs better than BPS in 15 subjects among 48. We examine further in Fig. 12 the relative performance of BPD and BPS with respect to age, weight, height and BMI characteristics of the subjects. The black bar represents the count that BPD has higher correlation coefficient with the GT than BPS, and the green bar denotes those that BPS has higher. The results do not indicate that BPD has a better performance for any special group of population distribution.

D. Other Possible Features

Table I implies that the IJ-amplitude and the JK-amplitude can also be possible features to estimate the relative blood pressure. These two features can be highly correlated with BPS. For completeness, we also examine the performance of these two features in Fig. 13 and Fig. 14 by showing their correlation coefficients with the GT. The IJ-amplitude feature gives an average correlation coefficient of 0.87 and the JK-amplitude feature 0.88. They have similar performance with BPS but with larger variations. The larger variations may be due to the fact that these two features come from BCG morphology and have more noise compare to BPS where it can smooth out some noise effect from the averaging filter. Fig. 15 shows the performance comparison for all four features. BPS has best performance on average. Combining the features may be able to produce a better blood pressure estimate; this is a subject for future study.

We then examined the possibility of using the valleys in the short-term energy profile $E(n)$ to obtain the relative diastolic blood pressure. The correlation coefficients with the GT are shown in Fig. 16 and the average correlation value is 0.67. It is not advisable to use the valleys in estimating the diastolic blood pressure.

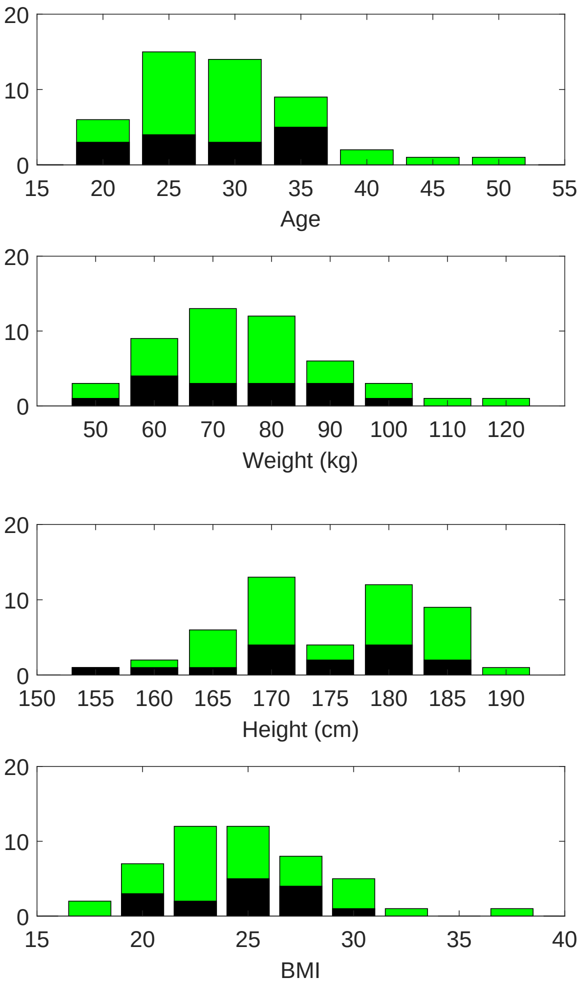

Fig. 12. The histogram of the performance comparison in age, weight, height and BMI between the two features.

Finally, we tested the use of the difference between peak and valley in each cycle of the short-term energy profile to deduce the relative pulse pressure (the difference between systolic blood pressure and diastolic blood pressure), and the result is shown in Fig. 17. The average correlation coefficient over the 48 subjects is 0.78.

VII. Conclusion

In this study, we propose two features from the bed sensor data to estimate the relative systolic blood pressure. The first feature, BPS, is derived from the strength of the BCG cycle in each heartbeat, and the second feature, BPD, uses the difference between the IJ-amplitude and JK-amplitude of the

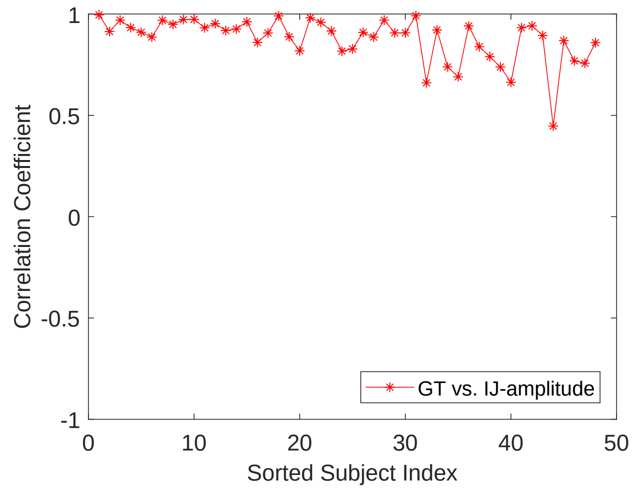

Fig. 13. The correlation coefficient between the GT and feature from the IJ-amplitude.

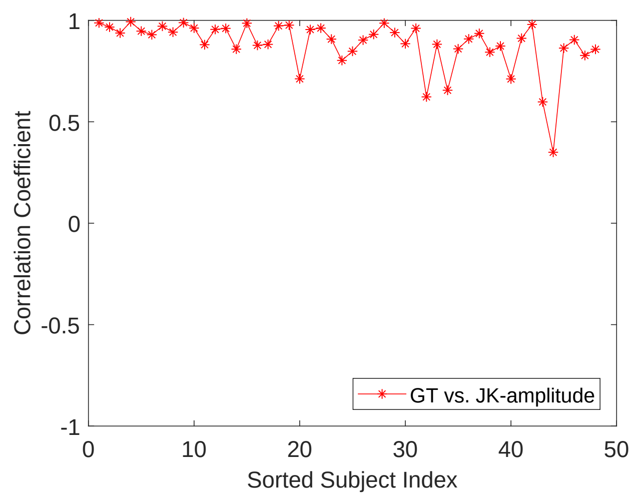

Fig. 14. The correlation coefficient between the GT and feature from the JK-amplitude.

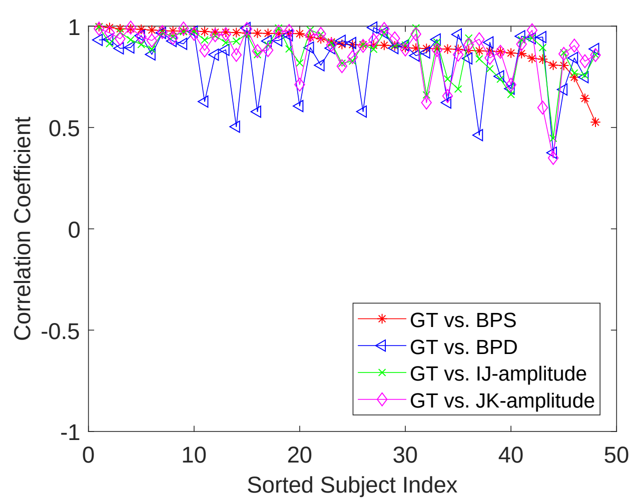

Fig. 15. Performance comparison of four features for relative systolic blood pressure estimation.

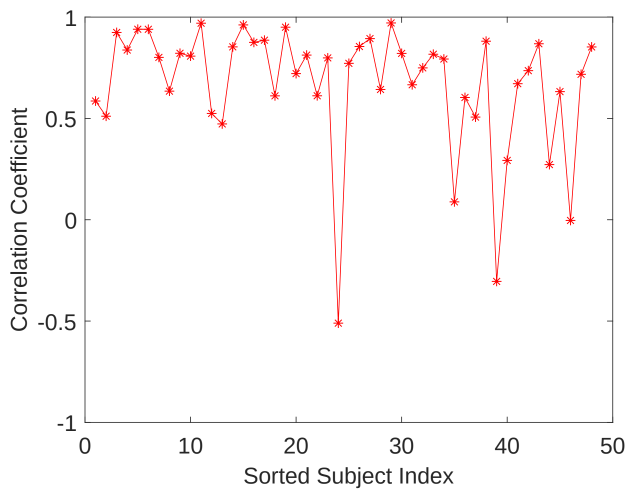

Fig. 16. The diastolic blood pressure correlation coefficient between the GT and feature from energy.

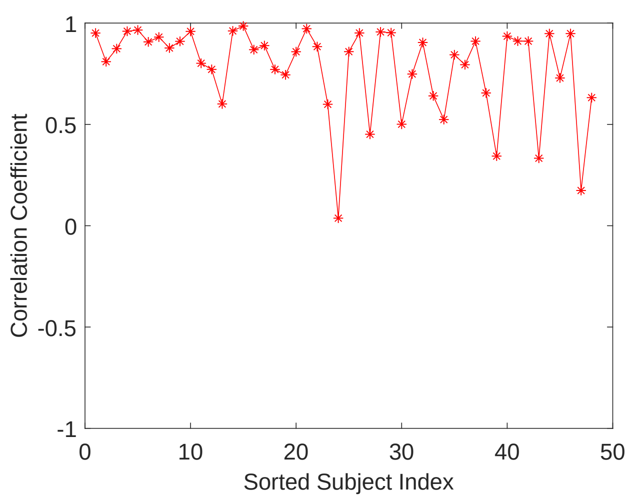

Fig. 17. The pulse pressure correlation coefficient between the GT and the $E(n)$ peak-to-valley feature.

BCG pattern. We then demonstrate the qualities of the features using the data collected from 48 subjects of different gender, age, weight, height and BMI. Compared to the pulse transit time method, the proposed features have higher correlations with the ground truth. They open the possibility of monitoring the relative systolic blood pressure continuously using a non-wearable hydraulic bed sensor system. Future work includes the performance study with sufficient number of female subjects and with overnight data collection from high systolic blood pressure patients. Fusion of the features for better performance of relative systolic blood pressure estimation will be investigated. Features for the diastolic blood pressure and pulse pressure monitoring will be developed as well. We also plan to combine the blood pressure monitoring results with our previous studies in which health changes are tracked using non-obtrusive in-home sensors [24], [25].

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