Robust Heartbeat Detection from In-Home Ballistocardiogram Signals of Older Adults Using a Bed Sensor

Katy Lydon, Bo Yu Su, Licet Rosales, Moein Enayati, K. C. Ho, Marilyn Rantz, and Marjorie Skubic

Abstract— **We propose a simple and robust method to detect heartbeats using the ballistocardiogram (BCG) signal that is produced by a hydraulic bed sensor placed under the mattress. The proposed method is found beneficial especially when the BCG signal does not display consistent J-peaks, which can often be the case for overnight, in-home monitoring, especially with frail seniors. Heartbeat detection is based on the short-time energy of the BCG signal. Compared with previous methods that rely on the J-peaks observed from the BCG amplitude, we are able to achieve considerable improvement even when significant distortions are present. Test results are included for different BCG waveform patterns from older adults.**

I. INTRODUCTION

In the United States, 37% of the population is affected by cardiovascular related diseases [1]. In order to avoid fatal consequences, in-home monitoring systems have been under development for the purpose of detecting early signs of cardiovascular abnormalities. Monitoring the pulse rate and other cardiac parameters during sleep can provide critical information about the health of a subject.

Our interest in health monitoring especially targets older adults with chronic health conditions, including cardiovascular diseases. We include cardiac and respiration monitoring in the home through the use of a bed sensor positioned under the mattress. Motion sensors and depth cameras also capture behavioral patterns, overall activity, and in-home gait patterns [2]-[4]. The system, with automated health change alerts, is currently installed in 75 senior apartments and runs continuously 24 hours a day as part of a longitudinal study.

Many challenges in longitudinal, in-home studies arise from the unstructured setting. Senior participants use different types of beds and pillows and sleep in varying body positions. Some are more restless than others; health conditions and medications can affect sleep patterns. Some participants sleep with their pets (cats and dogs). There is also limited ground truth. Thus, the setting is inherently noisy.

Other sensor systems have been proposed for pulse rate monitoring, including a video camera [5], ultrasonic device [6], mattress-based sensor [7], infrared diode [8], and pillow-based sensor [9]. Some are suitable for in-home sensing and some are not. However, in any case, robust methods are needed to address the noisy setting. Important cardiac parameters to track include heart rate, heart rate variability, and irregular heartbeats or arrhythmias. The detection of heartbeats in the BCG signal can aid in tracking these parameters noninvasively.

Wearable sensors are also emerging for tracking cardiac health. Although these can offer important alternatives for younger subjects, many older adults are unable to use and recharge wearable sensors consistently (e.g., those with cognitive problems) [10][11]. As a result, we have been exploring bed sensing.

In this paper, we use a hydraulic bed sensor for capturing Ballistocardiogram (BCG) [12] signals. It is composed of a water tube and a pressure sensor, and is placed under the mattress to maintain sleeping comfort. The data acquired from the sensor contain the BCG signal superimposed in the respiration signal. Compared with the previous method [13] that uses the same sensor, the proposed method of detecting heartbeats is simpler and more resilient to noise or distortions in the BCG signal.

This paper is organized as follows. The details of the hydraulic bed sensor and the measurement settings are described in Section II. In Section III, the heartbeat detection method based on energy is presented, and the algorithm is developed in Section IV. Section V describes the datasets used for performance evaluations. Results are given in Section VI. Finally, we conclude in Section VII.

II. THE HYDRAULIC BED SENSOR

The hydraulic bed sensor is composed of a transducer and a pressure sensor. The transducer is 6 cm wide and 50 cm long, and is filled with 0.4 liter of water. An integrated silicon pressure sensor is attached to one end of the transducer for measuring the vibrations of the discharged hose. In this study, four transducers are placed underneath the mattress as shown in Fig. 1 and the outputs are connected to the filtering circuit (Maxim MAX7401) that consists of an amplifier and a filter. The amplifier is the 741 op-amp and the filter is the 8th-order integrated Bessel filter. The four channel signal is sampled at 100 Hz and quantized to 12-bit precision using the analog to digital converter (ADC) (National Instrument NI6212).

A piezoelectric pulse sensor (ADInstruments MLT1010) is used to provide the ground truth to evaluate the performance of the proposed method. This sensor is attached to a finger; the ground truth signal is sampled synchronously with the hydraulic bed sensor.

Katy Lydon is with the Rock Bridge Senior High School (e-mail: 16kll01@gmail.com).

Bo Yu Su, Licet Rosales, Moein Enayati, K. C. Ho, and Marjorie Skubic are with the ECE Dept., University of Missouri (e-mail: bsdg6@mail.missouri.edu, lr5zf@mail.missouri.edu, mektb@mail.missouri.edu, HoD@missouri.edu, SkubicM@missouri.edu).

Marilyn Rantz is with the Sinclair School of Nursing, University of Missouri (e-mail: RantzM@missouri.edu).

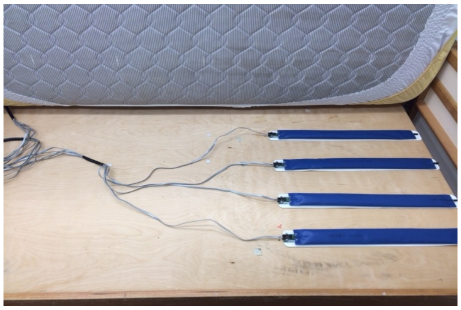

Fig. 1. Position of bed sensors.

III. METHODOLOGY

The data from a single transducer channel can be modeled as [14]

$$m(n) = r(n) + g(n) + \varepsilon(n) \tag{1}$$

where $r(n)$ is the respiration component and $g(n)$ represents the BCG signal. $\varepsilon(n)$ is the additive noise.

Due to the lower frequency of the respiration rate compared to the pulse rate, $r(n)$ can be removed easily by a high-pass filter. We use a band-pass filter instead for eliminating the high frequency noise as well. The filtered data is represented by

$$m'(n) = BPF(m(n)) = g(n) + \varepsilon'(n). \tag{2}$$

Typically the J-peaks appear in $g(n)$ with a periodic pattern at the pulse rate. Thus the heartbeat can be detected from $m'(n)$ by the J-peak locations. One strategy to detect the J-peaks in $m'(n)$ is to apply machine learning techniques [13][15], eg. feature extraction combined with clustering as in [13]. Quite often the captured BCG signal can be highly distorted by the position and body type of the subject, as well as the type of mattress, making the detection of J-peaks in $m'(n)$ difficult. To illustrate, Fig. 2(a) gives a segment of a typical output from one transducer, Fig. 2(b) shows the respiration component extracted from Fig. 2(a), and Fig. 2(c) depicts the band-pass filtered signal, yielding the BCG signal. When looking at $m'(n)$ at 2, 5, 13 seconds, the waveforms do not have consistent patterns that makes the machine learning method difficult to locate the J-peaks [13].

In this paper, we propose to use the short-time energy rather than the amplitude of $m'(n)$ to locate the peaks for heartbeat detection and pulse rate estimation. We use a sliding window of 0.3 second (30 samples) long to obtain the short-time energy. The window advances 0.01 second (1 sample) each time to produce a new energy value. We choose the window length to be 0.3 seconds due to the fact that the typical separation of two successive peaks in the observed BCG is about 0.2 second. The extra 0.1 second provides a margin to ensure multiple peaks can be observed within the window. The windowed data can be represented by the equation:

$$x_i(n) = w(n)m'(n+i) \tag{3}$$

where $x_i(n), i = 0, 1, ..., M-1$ denotes the windowed and segmented data, i is the segment number (frame index) and n is the sample number within a segment. N is the window size equal to 30 and $w(n)$ is the window function. We use a rectangular window in this study for simplicity.

The energy in segment i is obtained by:

$$\xi_i = \sum_{n=0}^{N-1} x_i(n)^2 . \tag{4}$$

We then locate the peaks from the result in (4) to detect heartbeats and to obtain a pulse rate estimate.

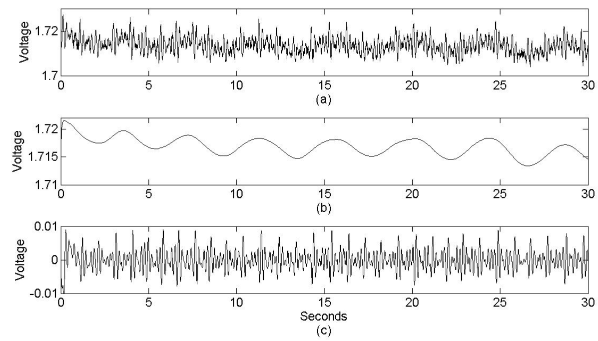

Fig. 2. Data from a young healthy female. (a) a channel of the bed sensor signal, (b) the respiration component, (c) the signal in (a) after band-pass filtering.

IV. ALGORITHM

Fig. 3 shows the processing block diagram. First, we apply a band-pass filter to remove the respiration component and high frequency noise. We separate the data into segments and compute the short-time energy individually for each of the four channels. Four heartbeat detections and pulse rate estimates are generated from the short-time energy profiles by locating the local peaks. Next, we select one of the four as the final estimate, based on the DC level. Outlier removal is then done by checking whether the estimate is too far away from the moving average pulse rate value. Outlier removal is also useful in many unpredictable situations such as the occurrence of body motion.

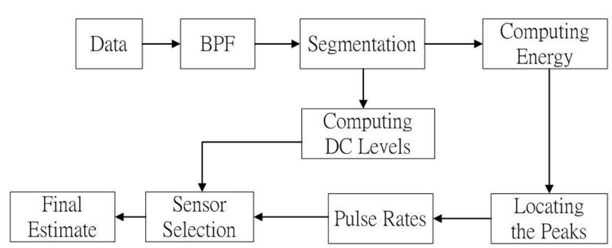

Fig. 3. The data processing blocks for heartbeat detection and pulse rate estimation.

A. Band-pass Filter

The bandpass filter is the Butterworth filter with an order equal to 6. The 3-dB cutoff frequencies are set to 0.7 Hz to 10 Hz. They are chosen based on the fact that a typical respiration rate is below 0.5 Hz and the frequency content of BCG is not higher than 10 Hz. Fig. 2(c) shows the result after band-pass filtering. When compared with Fig. 2(a) it is obvious that the heartbeat information appears on the time domain waveform.

B. Sequential Heartbeat Detection

Fig. 4(a) illustrates the short-time energy waveforms for the bandpass filter output given in Fig. 2(c). The red circles are the detection results of the local peaks. They coincide with the J-peaks in the bandpass filter signal which are illustrated in Fig. 4(b). We found that the algorithm works properly even when the BCG signal shows irregularity as around 2, 5 and 13 seconds as can be seen in Fig. 4(b). Fig. 4(c) shows the ground truth measurement using a finger sensor for reference purpose.

The beat-to-beat interval is the separation of two successive local peaks in the short-time energy profile. When the average pulse rate is of interest, we report the average of the beat-to-beat estimates over the latest 60 seconds, in every 15 second interval.

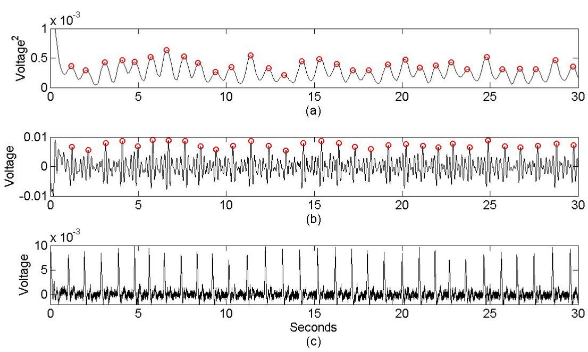

Fig. 4. Results of heartbeat detection (a) peak detection after smoothing the energy results, (b) locates the peaks in filtered data based on (a), (c) the ground truth signal from a finger sensor.

C. Sensor Selection

Whether we are interested in the beat-to-beat interval or average pulse rate, there will be four estimates, one from each transducer. The next step is to select the best estimate from the four. Based on the characteristics of the pressure sensor, a higher DC level in the measured transducer signal indicates that the transducer makes better contact with the body and hence produces a more reliable BCG signal for processing. Thus, we select the pulse rate estimate that comes from the transducer having the highest DC level as the final estimate.

Occasionally, body movement or other unknown conditions will generate unwanted distortion or noise in the data. Large movements are filtered out based on signal amplitude, which is significantly higher. Other artifacts are filtered by maintaining a moving pulse rate average and rejecting estimates if they deviate more than 15 beats per minute from the moving average.

TABLE I
DETAILS OF PARTICIPANTS.

Dataset	Subject	Gender	Age	Height (cm)	Weight (kg)	Cardiac history
D0	1	male	33	178	82	No
D0	2	female	16	173	63	No
D0	3	male	27	160	61	No
D1	1	male	91	170	81	No
D1	2	male	99	165	64	Yes
D1	3	male	86	188	99	Yes
D1	4	male	89	168	97	No

V. DATA DESCRIPTION

The performance of the proposed heartbeat detection method is evaluated using two datasets. The first dataset D0 contains three young, healthy subjects with different body types in a well-controlled environment. Subjects are asked to lie flat on their backs for 10 minutes while the data are being collected. The subject details are listed in Table I.

The second dataset, D1, consists of the measurements from four elderly people with an average age of 91, taken in their apartments at TigerPlace [16] on their own beds. Two of the subjects have had prior cardiac conditions. Based on the ages and heart conditions of the subjects, the acquired bed sensor data are expected to have inconsistent BCG signals with significant amounts of distortions. The details of the four subjects are listed in Table I. Subjects are asked to lie flat on their backs for 4 minutes during data collection. The data collection procedure was approved by the IRB.

VI. RESULTS

Two sets of results will be presented. One is for the beat-to-beat interval and the other for the average pulse rate estimate. In the former case, we compute the estimation error with respect to the finger sensor ground truth. Table II shows the average beat-to-beat error in seconds for dataset D0. When the signal contains a typical BCG pattern, we can obtain quite accurate detection results.

For the second case, we compute the error rate using

$$Error\ Rate = \frac{1}{M} \cdot \sum_{i=0}^{M-1} \frac{|GT(i) - Est(i)|}{GT(i)} \times 100\ \% \qquad (5)$$

where $GT(i)$ is the ground truth from the finger sensor, $Est(i)$ is the estimated pulse rate over a 60 seconds frame, M is the total number of frames, and i is the frame index. We ignore the frames that are recognized as invalid estimates when computing the error rate. In addition to the error rate, we also provide the detection rate. It is defined as the relative number of frames in which we are able to obtain average pulse rate estimates with sufficient confidence [13].

The results are shown in Tables III and IV. We also provide the results for the method from [13] for comparison, which uses the clustering approach (CA) to identify the J-peaks in the time-domain signal for pulse rate estimation.

For D0, we have clean BCG signals from the bed sensors due to the well-controlled environment and young and healthy subjects. The results in Table III illustrate that the proposed and CA methods both have 100% detection rates and low error rates, and their performances are very comparable in all three subjects. A Bland Altman plot of D0 compares the proposed method to ground truth, as shown in Fig. 5.

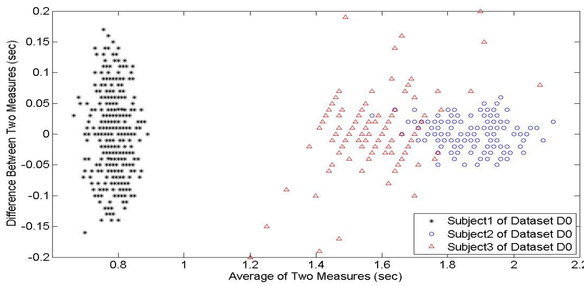

Fig. 5. The Bland Altman plot of D0 with proposed method compared to ground truth.

Obtaining heartbeat detections and pulse rate estimates for the dataset D1 is more challenging. Fig. 6 shows a typical portion of the bed sensor data from subject 3 as an example. T1 to T4 denote the signals from the four transducers. The BCG signals show the data highly distorted. Table IV gives the numerical results. Subject 1 has a high pulse rate. Subject 2 has a low pulse rate with high variations. Subject 4 has two dogs that slept with him. The CA method has a low detection rate for subjects 1, 3 and 4 while the proposed method maintains 100% detection rate for all 4 subjects. The proposed method appears to have a much lower error rate than CA for this dataset. The proposed method has the highest error rate of 4.86% for subject 2, possibly caused by a high pulse rate variation.

As a further test, in-home, overnight bed sensor signals were selected from three TigerPlace residents; Table V shows details of these residents, which we will call dataset D2. Bed sensor signals were sampled from longitudinal data and processed using the proposed energy algorithm. During these overnight periods, we do not expect the subjects to always lie on their backs. Fig. 7-9 show the heartbeat detection for these segments, even with different BCG waveform patterns. Finally, we tested BCG signals from a patient in the cardiac intensive care unit (ICU) who was recovering from an aortic valve replacement and a bypass graft (age 57). Fig. 10 shows the heartbeat detection in the case of arrhythmia, with the corresponding ECG and arterial pressure signals. IRB-approved procedures were followed for data collections.

VII. CONCLUSIONS

In this paper, we propose a simple and yet effective algorithm to obtain the heartbeat detection and pulse rate of a subject using a hydraulic bed sensor. The sensor data

TABLE II

BEAT-TO-BEAT DETECTION RESULTS OF DATASET D0.

Subject	Average beat-to-beat error (seconds)
1	0.058 seconds
2	0.037 seconds
3	0.063 seconds

TABLE III

PULSE RATE DETECTION AND ESTIMATION RESULTS OF DATASET D0.

Subject	Error Rate		Detection Rate	
	Proposed Method	CA	Proposed Method	CA
1	0.90 %	3.09 %	100 %	100 %
2	0.67 %	1.56 %	100 %	100 %
3	1.85 %	2.52 %	100 %	100 %

TABLE IV

PULSE RATE DETECTION AND ESTIMATION RESULTS OF DATASET D1.

Subject	Error Rate		Detection Rate	
	Proposed Method	CA	Proposed Method	CA
1	3.14 %	18.49 %	100 %	15.39 %
2	4.86 %	7.77 %	100 %	88.89 %
3	4.06 %	17.86 %	100 %	21.43 %
4	2.74 %	18.00 %	100 %	31.25 %

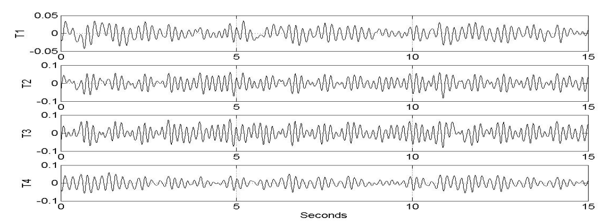

Fig. 6. Example data segment from subject 3 for the four transducers, T1-T4.

TABLE V

DETAILS OF IN-HOME, OVERNIGHT PARTICIPANTS (D2).

Subject	Gender	Age	Height (cm)	Weight (kg)	Cardiac history
1	male	91	170	79	No
2	female	92	171	100	Yes
3	male	86	188	98	Yes

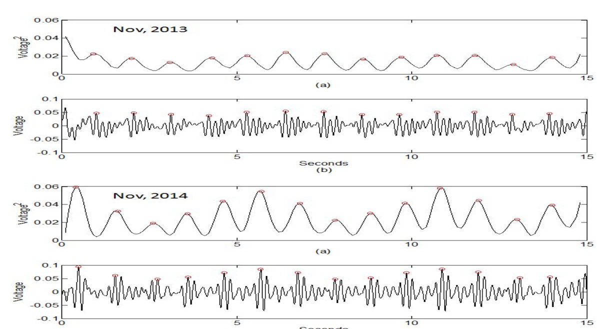

Fig. 7. Overnight, in-home BCG segments from subject ♯1 (a) energy-based heartbeat detection, (b) detected peaks in the BCG.

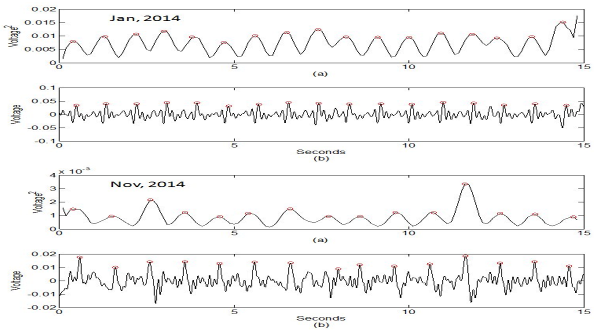

Fig. 8. Overnight, in-home BCG segments from subject ♯2 (a) energy-based heartbeat detection, (b) detected peaks in the BCG.

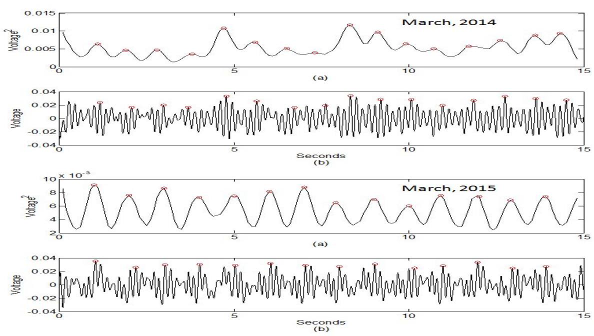

Fig. 9. Overnight, in-home BCG segments from subject ♯3 (a) energy-based heartbeat detection, (b) detected peaks in the BCG.

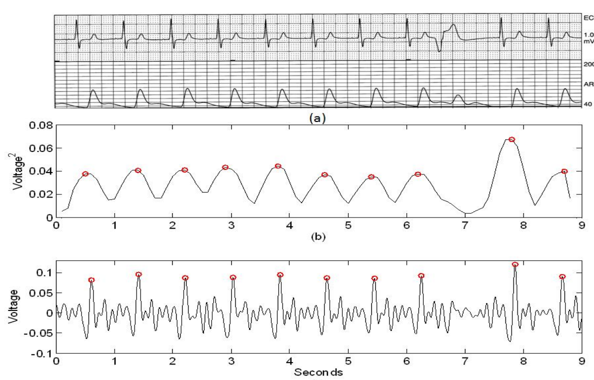

Fig. 10. Cardiac ICU patient after surgery. (a) ECG and Arterial pressure, (b) energy-based heartbeat detection, (c) detected peaks in BCG.

contains the respiration and BCG signals. A band-pass filter is used to remove the respiration component and noise. A short-time energy profile is generated whose local peaks are used to detect heartbeats and estimate pulse rate. We maintain a moving average of the pulse rate estimates to remove the estimation outliers caused by significant distortions in the BCG signal resulted from body movements. Compared to the previously developed clustering based method CA, the proposed method has a higher detection rate and a lower error rate even when the bed sensor data have noisy BCG signals, often found in overnight, in-home data, especially from frail older adults. We plan to conduct a more detailed study on how the subject's posture and body movement affect the measurement signal quality, consistency and the performance of the proposed method, using the Electrocardiogram and other cardiac signals for reference.

REFERENCES

[1] P. A. Heidenreich *et al.*, "Forecasting the future of cardiovascular diease in the United States: a policy statement from American Heart Association," *Circ.*, vol. 123, pp. 933-944, Jan. 2011.

[2] M. Skubic, R. D. Guevara, and M. Rantz, "Automated health alerts using in-home sensor data for embedded health assessment," *IEEE J. Transl. Eng. Health Med.*, to be published.

[3] M. Rantz *et al.*, "Evaluation of health alerts from an early illness warning system in independent living," *CIN*, vol. 31, no. 6, pp. 274-280, Jun. 2013.

[4] E. E. Stone and M. Skubic, "Unobtrusive, continuous, in-home gait measurement using the Microsoft kinect," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 10, pp. 2925-2932, Oct. 2013.

[5] T. Kitajima, S. Choi, and E. A. Y. Murakami, "Heart rate estimation based on camera image," in *Proc. 14th Int. ISDA Conf.*, Okinawa, Japan, Nov. 2014, pp. 50-55.

[6] Y. Yamana, S. Tsukamoto, K. Mukai, H. Maki, H. Ogawa, and Y. Yonezawa, "A sensor for monitoring pulse rate, respiration rhythm, and body movement in bed," in *Proc. 33th Annu Int. IEEE Eng. Med. Biol. Soc. Conf.*, Boston, Massachusetts, Aug. 2011, pp. 5323-5326.

[7] J. H. Shin, Y. J. Chee, D. U. Jeong, and K. S. Park, "Nonconstraint sleep monitoring system and algorithms using air-mattress with balancing tube method," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 1, pp. 147-156, Jan. 2010.

[8] H. Maki, H. Ogawa, S. Tsukamoto, Y. Yonezawa, and W. M. Caldwell, "A system for monitoring cardiac vibration, respiration, and body movement in bed using an infrared," in *Proc. 32th Annu Int. IEEE Eng. Med. Biol. Soc. Conf.*, Buenos Aires, Argentina, Sept. 2010, pp. 5197-5200.

[9] X. Zhu, W. Chen, T. Nemoto, Y. Kanemitsu, K. Kitamura, K. Yamakoshi, and D. Wei, "Real-time monitoring of respiration rhythm and pulse rate during sleep," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 12, pp. 2553-2563, Dec. 2006.

[10] G. Demiris *et al.*, "Older adults attitudes towards and perceptions of "smart home" technologies: a pilot study," in *MED INFORM INTERNET*, vol. 29, no. 2, pp. 87-94, Jun. 2004.

[11] G. Demiris *et al.*, "Smart home sensors for aging in place: older adults' attitudes and willingness to adopt," in *The Gerontologist*, vol. 46, Special Issue 1, pp. 430, 2006.

[12] I. Starr, A. J. Rawson, H. A. Schroeder, and N. R. Joseph, "Studies on the estimation of cardiac output in man, and of abnormalities in cardiac function, from the heart's recoil and the blood's impact; the ballistocardiogram," *OAm. J. Physiol.*, vol. 127, pp. 1-28, Aug. 1939.

[13] L. Rosales, M. Skubic, D. Heise, M. J. Devaney, and M. Schaumburg, "Heartbeat detection from a hydraulic bed sensor using a clustering approach," in *Proc. 34th Annu Int. IEEE Eng. Med. Biol. Soc. Conf.*, San Diego, California, Aug. 2012, pp. 2383-2387.

[14] B. Y. Su, K. C. Ho, M. Skubic, and L. Rosales, "Pulse rate estimation using hydraulic bed sensor," in *Proc. 34th Annu Int. IEEE Eng. Med. Biol. Soc. Conf.*, San Diego, California, Aug. 2012, pp. 2587-2590.

[15] C. Bruser, K. Stadlthanner, S. de Waele, and S. Leonhardt, "Adaptive beat-to-beat heart rate estimation in Ballistocardiograms," *IEEE Trans. Inf. Technol. Biomed.*, vol. 15, no. 5, pp. 778-786, Sep. 2011.

[16] TigerPlace is an assisted living facility in Columbia, Missouri, USA. Available at : http://eldertech.missouri.edu/