

# Refinement and Evaluation of a Hydraulic Bed Sensor

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**Abstract**—Research indicates that long-term monitoring of vital signs and activity in elderly adults may provide opportunities for maintaining quality-of-life and extending independence into later years. Such a strategy requires development of a system to collect this data while imposing minimal intrusion into the lives of those being monitored. To further this goal, we have developed a hydraulic bed sensor to non-invasively monitor heartbeat and respiration during sleep. This paper describes the refinement of our developed prototype and signal processing methods, along with an evaluation of the robustness of our algorithms and results from testing. An evaluation of our sensor on a group of five diverse subjects (ranging in age from 24 to 67, two with cardiac history), in three different positions, demonstrates accuracy within 8 beats per minute up to 97.5% of the time.

## I. INTRODUCTION

Long-term monitoring of the elderly via discrete sensing technologies is emerging as a strategy for detecting early signs of illness and functional decline [1]. It is anticipated that such an approach may provide opportunities for appropriate interventions that will contribute to maintaining health, quality-of-life, and independence [2]. The motivation for this work is to support continuous, in-home monitoring of elderly residents via an integrated sensor network, capturing activity patterns and automatically recognizing changes in these patterns that may indicate a declining health condition. To this end, we have installed 38 sensor networks in the homes of elderly residents living in TigerPlace, an aging-in-place community located in Columbia, MO. We currently employ a bed sensor [3] within these networks, but desire an improved sensor that is better able to provide quantitative pulse and respiration rates during sleep.

In comparing sensor data changes to health changes, the bed sensor has proven to be a useful component of the sensor network. We have observed dramatic changes in bed sensor data over a very short time, as well as more gradual changes over 2-3 weeks, that correspond to impending changes in health condition, e.g., cardiac problems [1,4].

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Thus, our research has shown the importance of this type of continuous monitoring in the home environment.

Previously, we reported on the development of a hydraulic bed sensor capable of monitoring heartbeat and respiration during sleep [5]. This sensor is placed beneath a standard mattress, unnoticed by the subject, and detects subtle pressure differentials from which we can extract pulse and respiration. Our initial results indicated much promise, and we have since refined the hydraulic transducer and signal processing system (including hardware and software) to yield an improved system. We have tested the sensor on a wider range of subjects, and have demonstrated robustness of the signal processing algorithms using both real and synthesized signals. Efforts are underway to deploy this system as part of our existing sensor networks at TigerPlace, replacing the current transducer.

This paper details the improvements made since [5] and gives the results of our evaluation.

## II. METHODS

### A. Bed sensor hardware

The body of the transducer is constructed from commonly available materials acquired from a local hardware store. Three inch wide (7.6 cm) discharge hose is used to form a flat bladder of water for sensing physiological movement. This hose is sealed, bled of all air, and fitted at one end with an integrated silicon pressure sensor (Freescale MPX5010GP). The hardware of the prototype sensor and its position beneath the mattress is shown in Fig. 1. The overall mechanism and materials are substantially the same as our first working prototype, but we have made the following improvements:

1. PVC cement was used to seal one end completely, and the other end was sealed except for a short length (6 cm) of small (2.8 mm inside diameter) vinyl tubing providing a port for attaching the integrated pressure sensor.
2. The output signal of the integrated pressure sensor is carried over a one meter cable to the hardware filtering circuit.
3. Hardware filtering circuitry is implemented, comprised of an amplification and a filtering stage. We amplify the signal by a factor of 10 using a 741 op-amp, and then employ an 8th-order integrated Bessel filter (Maxim MAX7401) for anti-aliasing

and noise reduction, with a corner frequency of 38 Hz. We then sample the signal using a 12-bit ADC at a sampling rate of 100 Hz. Filtering in hardware eliminates the need to sample at a much higher frequency and then filter and downsample in software.

### B. Detecting heartbeats

The algorithm used to detect heartbeats from the signal generated by the hydraulic transducer may be summarized as follows:

1. Low-pass filter the sampled signal with a cutoff frequency of 10 Hz.
2. Find the windowed peak-to-peak deviation (WPPD), expressed by:

$$WPPD(t) = \underset{i=t}{\overset{t+winsize}{MAX}} [signal(i)] - \underset{i=t}{\overset{t+winsize}{MIN}} [signal(i)] \quad (1)$$

3. Low-pass filter the WPPD (appropriate cutoff frequencies are discussed in section IV).
4. Segment the signal into 15-second (non-overlapping) segments.
5. Validate each segment prior to processing, marking segments with too much noise, which correspond to restlessness in bed.
6. Determine heart rate within each segment by counting the peaks of the low-pass filtered WPPD within a segment and multiplying by 4 (consistent with clinical practice).

### C. Detecting respiration

Respiration is readily detected from the output of the hydraulic transducer via low-pass filtering. The respiratory component is of much lower frequency, has smoother transitions, and has greater amplitude than either the cardiac component or noise, so extraction of respiration is achieved via a low-pass filter. We utilize a low-pass filter with cutoff frequency of 1 Hz.

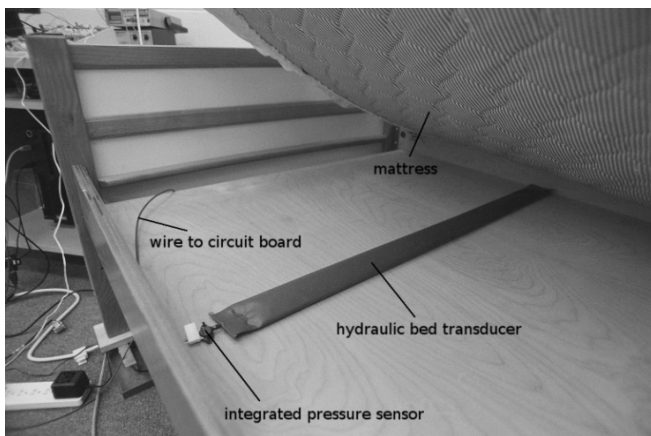


Fig. 1. Positioning of bed sensor for testing

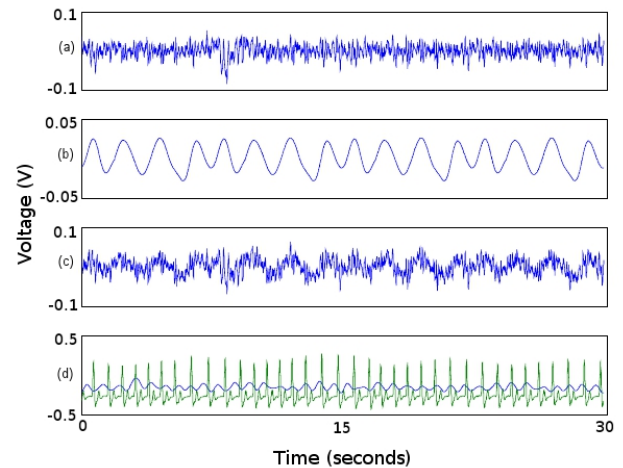


Fig. 2. Heartbeats detected from synthesized signal: (a) shows the cardiac component (extracted from real data), (b) shows the synthesized respiratory component (at 4 times the original captured frequency and  $\frac{1}{4}$  the amplitude), (c) is the resulting composite (our synthesized signal), (d) shows detection of heartbeats from our algorithm compared to the ground truth.

### D. Ground truth acquisition

Ground truth for validating the output of the hydraulic sensor is collected via a piezoelectric pulse sensor connected to the subject's finger (ADInstruments MLT1010) and a piezoelectric respiration band wrapped around the subject's torso (ADInstruments MLT1132). These signals are simultaneously acquired and sampled through the same ADC as the signal from the hydraulic sensor, using the same sampling rate and avoiding issues of synchronization between separate devices.

## III. EVALUATING THE ROBUSTNESS OF THE ALGORITHM

In order to evaluate the robustness of our algorithm, we generated synthetic signals, allowing explicit control of frequency and amplitude for both heartbeat and respiration. This approach was taken to provide a measure of confidence in our methods prior to embarking on a full study with human subjects. Additionally, we have an interest in distinguishing shallow breathing from low heart rate, and would like to demonstrate that our algorithm can handle such a scenario.

To generate synthetic signals, we acquired a real signal through our system, separated and extracted the cardiac and respiratory components of the original composite signal, and then manipulate the individual components in isolation before recombining into new composites. One of the questions we wish to address is whether our system is able to distinguish heartbeats in the presence of very high respiration rates; to address this, we change the rate and amplitude of the respiration component, recombine with the cardiac component, and then run our heartbeat detection algorithm.

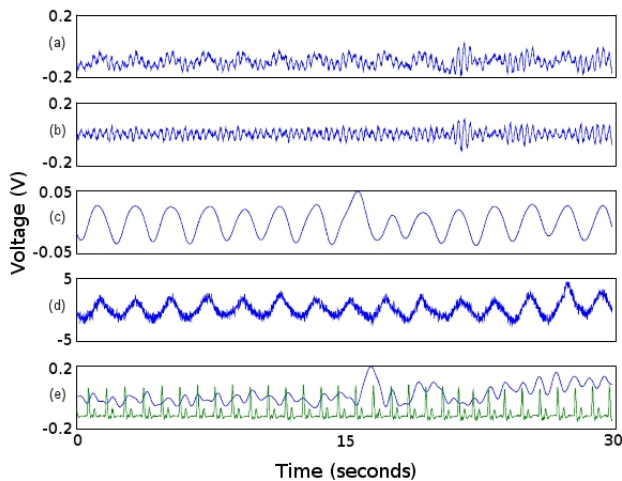


Fig. 3. Detecting heartbeats from real data. Here, the subject was asked to breathe at approximately 30 breaths per minute: (a) shows the collected signal, (b) shows the extracted cardiac component, (c) shows the extracted respiratory component, (d) shows the respiratory ground truth (from a piezoelectric respiratory belt), (e) demonstrates identification of heartbeats by the hydraulic sensor and algorithm compared to the ground truth. Note that the algorithm detects heartbeats directly from (a); (b) is only shown for reference and comparison to (a).

Manipulating amplitude of the respiratory component is achieved by simply scaling the sample values by a chosen constant. Frequency is controlled by choosing a segment of respiration, resampling at a higher or lower rate to yield the desired change, and repeating the resampled segment (choosing appropriate zero-crossing endpoints to avoid discontinuities). The respiratory component of the signal is of low enough frequency that such a resampling does not result in any corruption of the original signal, and provides a realistic model of breathing output at the target frequency.

We have synthesized signals with respiration rates that are 0.5, 1, 2, 4, and 8 times the frequency of the actual respiration signal captured. We have scaled the amplitude of the respiration by factors of 0.25, 0.5, 1, 2, and 4, and added every possible respiratory combination with an extracted cardiac component. In every case, we achieved 100% heartbeat detection (36 out of 36 over a 30 second segment). An example of the synthesized signal along with the detected heartbeats (superimposed over the ground truth) is shown in Fig. 2.

To confirm the validity of this approach to synthesizing a signal, we simulated similar conditions by having a subject breathe at a specified rate during data collection. The signals for a 30-second segment of this test are shown in Fig. 3.

We thus conclude that our algorithm for detecting heartbeats is relatively insensitive to changes in respiration, and there is very little chance of respiration being erroneously detected as low heart rate. Robustness of our heartbeat detection algorithm in the presence of varying respiration is expected due to the manner in which it

operates. Specifically, since the WPPD is effectively detecting a sudden increase (or impulse) of energy in the system within a small window, it should not be affected by respiration (because, even at 60 breaths per minute, respiration will not cause sudden impulses of energy since the lungs do not operate in a pulsatile fashion).

#### IV. EVALUATION TRIAL

After our preliminary testing of the system and evaluation of our algorithm [5], we conducted a small trial involving five subjects, utilizing our newly constructed transducer (see Table I for summary information).

This group, while small, was representative of a wide range of ages, gender, body types, and cardiac conditions. This is significant, given that our target eldercare population is of advanced age, often with diagnosed cardiac problems. Two of our subjects reported prior cardiac conditions; one had a previously repaired ventricular septal defect, and another had suffered a mild heart attack.

Subjects were asked to lie on the bed for periods of two minutes on the back, right side, back, left side, and back again (approximately 10 minutes in total). After collecting the data, we used our algorithm to detect heart rates. Preliminary examination of these data led us to modify two parameters of our algorithm: the size of the window,  $w_s$ , used for the WPPD, and the cutoff frequency,  $f$ , used for post-WPPD low-pass filtering. Choices of  $w_s$  included 150, 250, 400, and 600 ms; choices of  $f$  included 1, 1.5, and 2 Hz. Table II shows the results of our testing.

In reading Table II, the columns indicate different combinations of parameter values, and the three rows under each subject indicate the percentage of segments for which the detected heartbeats per 15-second segment were: zero or one beat away from the ground truth ( $< 2$ ), two beats away from the ground truth ( $= 2$ ), or three or more beats away from the ground truth ( $> 2$ ). We note that, due to possible drift of the detected heartbeats and windowing of the signal, plus or minus one heartbeat is within the expected margin, and plus or minus two heartbeats is actually the best we could guarantee with a perfectly reliable algorithm (one that never missed an actual heartbeat). Therefore, we emphasize that only the third row reported for each subject shows the representative error.

TABLE I  
DETAILS OF POPULATION FOR EVALUATION TRIAL

	Gender	Age	Weight (kg)	Height (cm)	Prior cardiac history
Subject #1	male	24	113	183	No
Subject #2	male	30	79	187	No
Subject #3	female	31	53	163	Yes
Subject #4	female	56	68	163	No
Subject #5	male	67	76	177	Yes

TABLE II  
RESULTS OF EVALUATION TRIAL, PROCESSING THE SIGNAL WITH VARYING ALGORITHM PARAMETERS

	A	B	C	D	E	F	G	H	I	J	K	L
	ws=150			ws=250			ws=400			ws=600		
	f=1 Hz	f=1.5 Hz	f=2 Hz	f=1 Hz	f=1.5 Hz	f=2 Hz	f=1 Hz	f=1.5 Hz	f=2 Hz	f=1 Hz	f=1.5 Hz	f=2 Hz
<b>Subject #1</b>												
<2	16.67	69.05	59.52	16.67	69.05	73.81	16.67	57.14	69.05	16.67	33.33	57.14
=2	0.00	11.90	23.81	0.00	11.90	19.05	0.00	14.29	23.81	0.00	14.29	21.43
>2	83.33	19.05	16.67	83.33	19.05	7.14	83.33	28.57	7.14	83.33	52.38	21.43
<b>Subject #2</b>												
<2	17.50	90.00	40.00	17.50	87.50	40.00	17.50	62.50	60.00	17.50	57.50	57.50
=2	5.00	2.50	15.00	5.00	2.50	17.50	2.50	27.50	17.50	2.50	12.50	15.00
>2	77.50	7.50	45.00	77.50	10.00	42.50	80.00	10.00	22.50	80.00	30.00	27.50
<b>Subject #3</b>												
<2	24.39	70.73	26.83	24.39	75.61	39.02	21.95	65.85	53.66	17.07	48.78	43.90
=2	9.76	21.95	12.20	4.88	7.32	9.76	2.44	21.95	14.63	2.44	21.95	29.27
>2	65.85	7.32	60.98	70.73	17.07	51.22	75.61	12.20	31.71	80.49	29.27	26.83
<b>Subject #4</b>												
<2	25.64	92.31	89.74	25.64	87.18	92.31	25.64	79.49	79.49	25.64	41.03	74.36
=2	0.00	2.56	5.13	0.00	5.13	2.56	0.00	12.82	15.38	0.00	25.64	15.38
>2	74.36	5.13	5.13	74.36	7.69	5.13	74.36	7.69	5.13	74.36	33.33	10.26
<b>Subject #5</b>												
<2	40.00	87.50	52.50	40.00	82.50	52.50	32.50	82.50	62.50	25.00	57.50	47.50
=2	15.00	10.00	7.50	10.00	17.50	15.00	12.50	10.00	10.00	5.00	15.00	17.50
>2	45.00	2.50	40.00	50.00	0.00	32.50	55.00	7.50	27.50	70.00	27.50	35.00

The table indicates, for each subject, and for each combination of algorithm parameters (ws is the WPPD window size, f is the post-WPPD filter cutoff frequency), the percentage of 15-second segments for which the hydraulic sensor reported heartbeat count:

- within one beat of ground truth (< 2)
- exactly two beats from ground truth (= 2), or
- three or more beats from ground truth (> 2).

Figs. 4-5 illustrate the processing behind the entries in Table II. Fig. 4 shows a particular 15-second segment (specifically, segment 39; ws=150 ms, f=1.5 Hz) of data from subject #5. The figure shows the detected heartbeats from the hydraulic sensor (the low-frequency signal), superimposed with the piezoelectric pulse sensor ground truth (with the characteristic heartbeat pattern). It is clear that the algorithm detects 15 heartbeats, which matches the ground truth exactly. We note that there is some “drift” between the detected heartbeats and the ground truth, but we find that this drift tends to average-out over time. Fig. 5 shows a comparison of the number of detected heartbeats versus ground truth for the entire 10+ minute period for subject #5 (ws=150 ms, f=1.5 Hz). It is from these data that Table II is generated, varying the algorithm parameters for each subject.

Examining Table II, we note that our original parameter values [5] in column F (ws=250 ms, f=2 Hz) work very well for subjects #1 and 4 (as do the parameters of Column I), but the results are much worse for subjects #2, 3, and 5. Column B demonstrates strong results for subjects #2-5, but is markedly worse for subject #1. We conclude, then, that we may choose some set of starting parameters, but the ideal values depend upon the particular subject.

Age did not appear to adversely affect the heartbeat discrimination ability of the hydraulic sensor. In fact, the

very best results were obtained from subject #5, who is closest in age to our target population (approximately 70-94 [1]). Additionally, he is the subject who reported a previous heart attack, providing further evidence that the hydraulic system will be suitable for our intended purpose.

If the ideal parameter values are known, using 15-second segments, we are able to report heart rates within 8 beats per minute (bpm) of ground truth from 92.7 to 97.5% of the time. While this is not perfect, it is certainly enough to detect long-term trends in data, which is our target application. Additionally, we have found that the percentage of beats detected over the entire data run for each subject indicates success rates of 95.6 to 99.8%, using the best values for ws and f identified for each subject from Table II.

The data demonstrates that the captured signal can vary from person to person, and may therefore require optimized parameters for each individual; this is consistent with the observations of Starr [6]. By showing that we can achieve acceptable results by variation of only two parameters, we open the possibility of developing a method of automatically tuning the parameters based upon some initial estimate. Keeping in mind our goal of long-term monitoring, this approach is entirely possible, potentially including some manual input based upon prior knowledge of the subject's medical history.

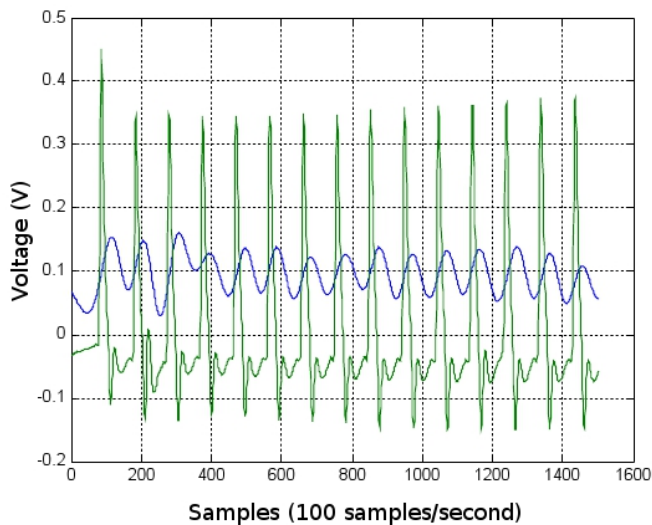


Fig. 4. 15-second segment of data from subject #5. This figure shows that detected heartbeats (the low-frequency signal) correspond well with the ground truth (the pulsed signal).

## V. CONCLUSION

The hydraulic bed sensor described here demonstrates great potential for use in long-term monitoring of heartbeat and respiration. To date, we have focused our efforts on reliable detection of heartbeats; respiration and bed restlessness are also readily detected, but algorithms need to be implemented to automate the reporting of this information. Current results indicate that accurate reporting of heart rate depends on appropriate choices of parameter values for our heartbeat detection algorithm, and it may be possible to further improve accuracy and robustness by incorporating adaptive features. In the future, we will pursue more rigorous evaluation through development of metrics that go beyond comparisons of heart rate, evaluating the confidence of each detected heartbeat and reporting on a beat-by-beat basis the number of true positives (correctly detected heartbeats) versus false positives (no corresponding heartbeat in ground truth) and false negatives (missed heartbeats). Our research group is moving forward to integrate the device into our sensor networks at TigerPlace, which will facilitate further evaluation of the device and refinement of its algorithms.

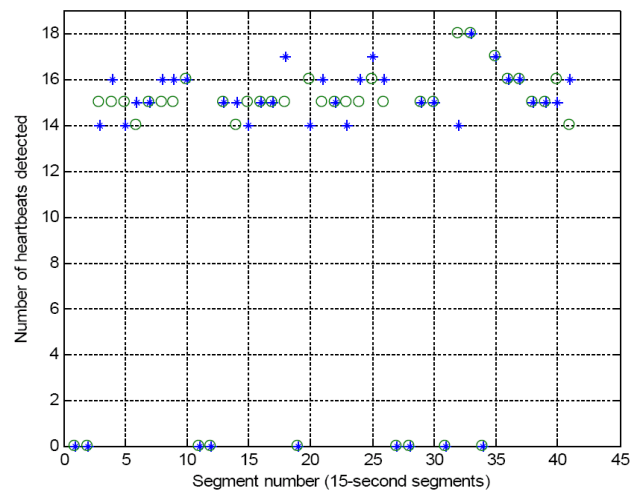


Fig. 5. Correspondence of the number of heartbeats detected via the hydraulic sensor (asterisks) and ground truth (circles). These data are for subject #5, using a WPPD window size of 150 ms and post-WPPD filter cutoff frequency of 1.5 Hz. Segments showing zero heartbeats were periods of noise due to movement.

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