HB-Phone : a Bed-Mounted Geophone-Based Heartbeat Monitoring System

Abstract

Heartbeat monitoring during sleep has become critically important for many people. It is thus in a great demand to find a solution that is accurate and easy to retrofit existing beds. Much effort has been devoted to this problem, but very few proposed systems offer accuracy, low cost, and ease to retrofit at the same time. We take on this challenge by investigating whether the off-the-shelf analog geophone sensor, which is traditionally used to detect earthquakes, can be used to detect heartbeats when installed under a bed. The geophone has the nice property of being insensitive to lower-frequency movements, which lends itself to heartbeat monitoring as the heartbeat signal has harmonic frequencies that can be easily captured by the geophone. At the same time, lower-frequency movements such as respiration and body movements, can be naturally filtered out by the geophone.

By building a prototype and conducting detailed experiments, we demonstrate that the geophone sensor provides a compelling solution to long-term at-home heartbeat monitoring. We compare the average heartbeat rate estimated by our prototype and that reported by an ECG device, and find that the average error is around .879% over 382 data sets. We have also deployed the prototype in a subject's home for 10 nights, and find that our prototype can continuously and accurately monitor heartbeats. In addition, we find that the prototype can also be used to detect snoring and other body movements during sleep.

Categories and Subject Descriptors

[**Human-Centered Computing**]: Ubiquitous and mobile computing—*Ubiquitous and mobile computing systems and tools*; [**Computer Systems and Organization**]: Embedded and cyber-physical systems—*Sensors and actuators*

General Terms

Design, Human Factors, Measurement

SenSys'13, November 11–15, 2013, Rome, Italy.

Keywords

Heartbeat detection, Geophone, Sample Autocorrelation, Sleep monitoring

1 Introduction

When we consider people's well-being, it is natural to focus on a person's waking hours, when they are awake, active and engaged in their daily activities. However, a large fraction of a person's life is spent resting and sleeping. We generally consider times when we are not awake to be safe periods, free from danger and health risks. In actuality, this is not true: every year, roughly one in eight human deaths occur while people are sleeping. Many of these deaths are related to chronic health conditions, often unknown to the person, while many of the deaths result from acute causes, such as the over-consumption of alcohol. Often these health conditions, such as genetic heart disorders or over-dosing of prescription drugs, are represented by other phenomena, such as a person's heartbeat or breathing condition. While we are awake, we are naturally aware of these co-indicating phenomena and, for example, should a person suddenly feel their heart racing, they would quickly seek medical help. While we are asleep, however, it is much less-likely that we are aware of our general condition, much less the foresight to seek medical assistance before a medical calamity, such as death or slipping into unconsciousness. Consequently, it is immensely valuable to have the ability to monitor co-indicating phenomena, such as a person's heartbeats, while they sleep in order to support the analysis, in real-time, of a person's well-being and allow for pre-emptive actions to occur to prevent catastrophic health failure.

Due to the importance of heartbeat monitoring during sleep, many bed-mounted heartbeat sensing and monitoring systems have been proposed in the literature. However, few solutions managed to achieve ease to use, low cost, and high accuracy at the same time. Firstly, many systems, such as those proposed in [27, 21, 14], require custom-made sheets or mattresses. For example, an air cushion is required in [27, 14]; sensors need to be embedded in the mattress in [21]. Some systems require the user to place (film) sensors under a certain part of the sheet [26]. These requirements are rather inconvenient, which may greatly hinder the widespread adoption of the proposed systems. Secondly, many systems, such as those proposed in [16, 23], require special sensors that yield accurate heartbeat sensing, but can be quite costly. Thirdly, some systems are hard to install; for example, the system proposed in [28] needs to install a plywood board and an aluminum guide rail on the bed surface. Because of these limitations, even though a number of earlier studies have been conducted, at-home heartbeat monitoring during sleep still remains an unsolved problem.

In this study, we seek to fill this void and propose a system that is accurate, low cost, and easy to use, in which we deploy a commercial off-the-shelf analog geophone under the mattress to detect the user's heartbeats during sleep. Just like the geophone that can detect the sound in the earth, our system can detect the sound of heartbeats that are propagated through a mattress. Therefore, we refer to our system as heartbeat-phone, or *HB-Phone* in short. The geophone sensor has several advantages[1]. First, it is highly sensitive to movements. The geophone is often used to detect distant motions (such as earthquakes), and it can generate a significant response to minute movements such as heartbeats (after going through a normal mattress). Second, it is commercially available and rather affordable. Third, deploying the geophone-based system can be very easily done, without interfering with the bed. As a result, we believe that *HB-Phone* offers a very practical and convenient solution to at-home heartbeat monitoring during sleep, and in this study, we intend to provide details on how to set up the system and evaluate the results.

Using the geophone to detect heartbeats through a mattress, though a promising approach, poses serious challenges to the design of the system. The first challenge is that the geophone sensor is sensitive to any movements in the environment. During sleep, a person has many other movements such as body movements or snoring. At the same time, another person may be walking in the bedroom, or opening/closing the bedroom door. All of these movements will be picked up by the geophone that is installed under the bed mattress. Therefore, it is a daunting task to extract heartbeats from all of the noises, requiring very careful design of both hardware and software components. In hardware design, the tricky part is to control the amplification to ensure heartbeat responses are detectable and differentiable. In software design, the focus is on signal processing algorithms that can effectively filter out both noises caused by aperiodic movements (such as the user's body movements during sleep, or others' walking) and noises caused by other periodic behavior such as snoring.

The second challenge stems from the fact that the geophone is naturally a second-order high-pass filter, hence insensitive to low-frequency movements. Specifically, when a movement's frequency increases from 1Hz to 10Hz, the geophone's response may become 100 times stronger. Considering that the fundamental frequency range of the heartbeat signal falls between 0.45Hz and 3.33Hz (corresponding to a heartbeat rate range from 27 beats to 200 beats per minute), it is rather hard to detect the geophone response signal caused by heartbeats at their fundamental frequency. In this study, we address this challenge by considering harmonic frequencies of the heartbeat signal, i.e., integral multiples of its fundamental frequency. In particular, we find that the harmonics around 10Hz generate the strongest geophone responses – harmonic frequencies lower than 10Hz have much weaker responses while frequencies higher than 10Hz have much lower mechanical power. As a result, we focus on detecting geophone responses to the heartbeat signal's harmonic frequencies and extract heartbeat pulses accordingly.

To summarize, we have made the following contributions in this study:

1. We have developed an accurate, low-cost, and easy-to-use bed-mounted heartbeat monitoring system *HB-Phone*, which is centered around the commercial off-the-shelf analog geophone. The *HB-Phone* system consists of both hardware and software components. The hardware component includes a geophone, an amplifier and an A/D converter. The software component involves filtering, sample autocorrelation and its peak finding algorithm, and heartbeat extracting algorithm.
2. We have designed a voltage amplifier that can suitably amplify the heartbeat response – high enough so that heartbeat responses are detectable but low enough so that the responses to much larger body movements will not saturate the ADC and thus can be filtered.
3. We have designed a set of signal processing algorithms that can effectively filter noises, extract heartbeat pulses and calculate heartbeat intervals.
4. We have built a *HB-Phone* prototype and use it to instrument an experimental bed. We have used the experimental bed to collect 382 30-second heartbeat data from 16 subjects. We have compared the calculated heart rate with the results measured by an ECG, and found that the average error rate is .879%.
5. We have deployed the *HB-Phone* prototype in a house for 10 nights. We observe that 88% of the time, our prototype can correctly detect the heartbeats. We also find that *HB-Phone* can be used to detect snoring and other body movements.

The remainder of the paper is organized as follows. In Section 2, we present the detailed system design of *HB-Phone*. We present our evaluation setup and experimental results in Section 3. In Section 4, we summarize the existing bed-mounted heartbeat monitoring systems, and compare their pros and cons. Finally, we provide the future direction and concluding remarks in Section 5.

2 *HB-Phone* System Design

In this section, we present the system design of *HB-Phone*, whose overview is shown in Figure 1. In *HB-Phone*, we place an analog geophone under the mattress to capture the movements in the environment, including the user's heartbeats. We first amplify the raw geophone response, and then convert it to digital signal. Next, we feed the signal to a series of signal processing functions, which will extract heartbeats and other relevant movements from the signal. The outcome from the *HB-Phone* system includes estimation of the average heartbeat rate, estimation of the instant heart-

[1] In this paper, we use the term geophone to refer to the analog geophone.

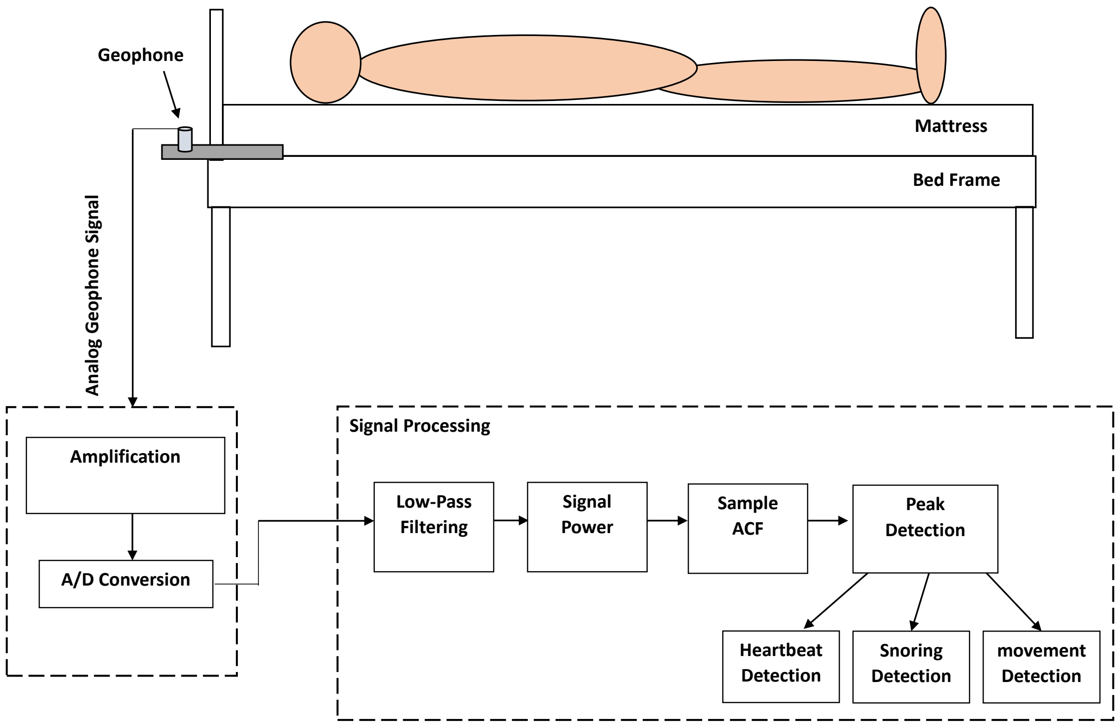


Figure 1: Overview of the *HB-Phone* system. In *HB-Phone*, we place an analog geophone under the mattress to capture the movements in the environment, including subtle movements such as the user's heartbeats. The raw geophone signal goes through amplification and A/D conversion to generate digital signal that is suitable for subsequent signal processing. A series of signal processing methods will then be applied to detect heartbeats from the signal.

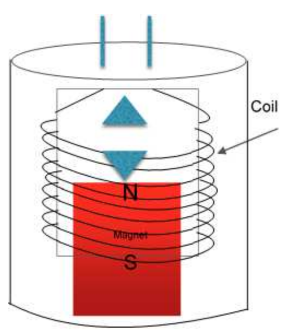


Figure 2: The geophone consists of a spring-mounted magnate that is moving within a wire coil to generate electrical signals, which can measure the movements in the environment.

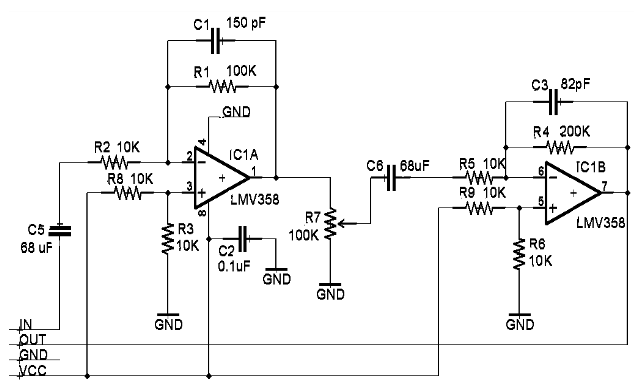


Figure 3: The AC amplifier circuit design

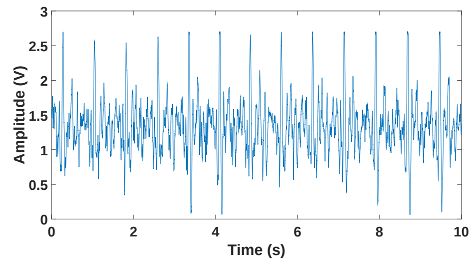
beat rate, detection of snoring during sleep, and detection of body movements during sleep, etc.

Below, we first discuss the hardware design of *HB-Phone*. Then we discuss the unique challenges caused by the geophone sensor. Finally, we discuss the signal processing methods we use to extract heartbeats from the geophone signal.

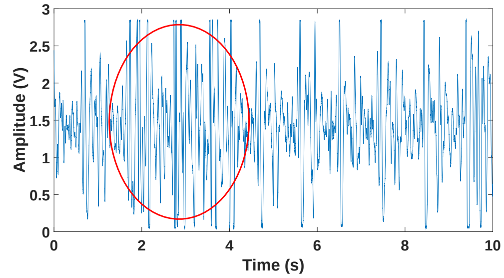
2.1 *HB-Phone* Hardware Design and Prototype

HB-Phone is centered around a geophone sensor. As shown in Figure 2, a geophone consists of a spring-mounted magnate that is moving within a wire coil to generate a voltage, which can thus measure the speed of a movement at

Figure 4: The picture of the experimental bed, where the geophone and the amplifier are glued to a wood board which is inserted between a memory foam mattress and the bed frame.



(a)



(b)

Figure 5: (a) A 10-second geophone response signal. In this experiment, the user was lying still on the experimental bed, without any movement in the environment. (b) A 10-second geophone response signal. In this experiment, the user was lying still on the experimental bed, while a second user was walking around 1 meter away from the bed.

different frequencies. The use of a powerful magnet and a differentially wound coil gives it low noise and high sensitivity at frequencies 7Hz and above, while being less sensitive to respiration and slower gross body movements. In our *HB-Phone* prototype, we use the SM-24 Geophone Element [2], whose natural frequency is at 10Hz.

The raw geophone signal is first filtered by a hardware band pass filter in the range from 0.25 to 10kHz. Next, we feed the filtered geophone signal to a TI LMV358 amplifier circuit [7], a widely used dual operational amplifier. We carefully configure the amplifier circuit to ensure the resulting voltage does not exceed the upper range of the A/D converter (3.3V in our prototype). Figure 3 shows the resulting double-stage amplifying circuit. Both the first-stage and second-stage amplifying circuit have a RC bandpass filter in the range from 0.25Hz to 10kHz. The gain of the first-stage amplifier is 10 so that we can reduce some noise from the circuit itself. The maximum gain of the second-stage amplifier circuit is 20 and the gain is adjustable by tuning the adjustable resistor R_7 shown in Figure 3. In total, the maximum gain of this circuit is 200. The amplified signal is based on 3.3V and quantized to 1024 levels (10 bits) using an Arduino Duemilanove A/D converter [1]. The output signal is then ready for subsequent signal processing and heartbeat extraction.

In Figure 4, we show the picture of our experimental bed that is instrumented with a prototype *HB-Phone* system. We attach the geophone to a piece of wood and insert the wood under a memory-foam mattress. Lying down on the bed, the user does not feel the geophone at all, and her sleep won't be interfered in any way.

2.2 Understanding Unique Challenges of the Geophone

Using the geophone to detect a heartbeat signal that propagates through a mattress poses serious challenges to the underlying system design. Below we discuss these challenges.

Noises Caused by Other Movements. The first challenge lies in the high sensitivity of the geophone sensor, which is also the very reason why we choose this sensor in the first place. The geophone responds to tiny motions or vibrations in the environment – when placed under the mattress, its response signal shows fluctuation when someone walks in the room or someone closes the door. Thus, we need to differentiate heartbeats from other movements from the same user, movements from other users, or movements/vibrations in the environment. Examples include the subject's body movements during sleep, snoring, other people walking around while the subject is in sleep, fans in the room, pets moving on the bed, etc. Some of these noises are aperiodic (such as body movements), while others are periodic like heartbeats, such as fans or snoring. Here, we note that respiration does not cause noises in geophone response, as we will explain below.

Here, we use two examples to show the impact of the movements in the environment. Figure 5(a) shows a 10-second geophone response signal when a user was lying still on our experimental bed. During the data collection period, we made sure that there was no other movements near the bed. Next, we introduced movements around the bed by having a second subject walks 1 meter from the bed (with a concrete floor). We show the geophone response in Figure 5(b), and mark the area that is affected by the movement using the red circle. These data show that the geophone is very sensitive to noises in the environment.

In order to address this challenge, we need to carefully

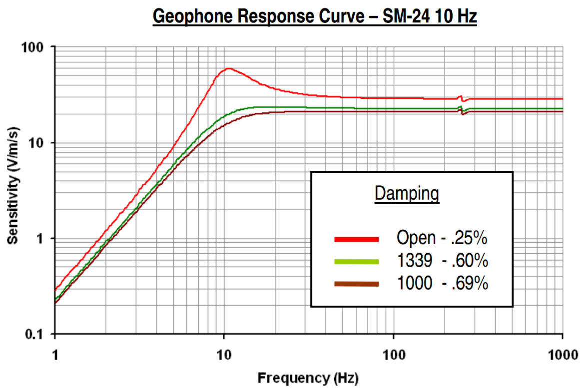


Figure 6: Geophone response curve from the data sheet of Geophone SM-24 [6].

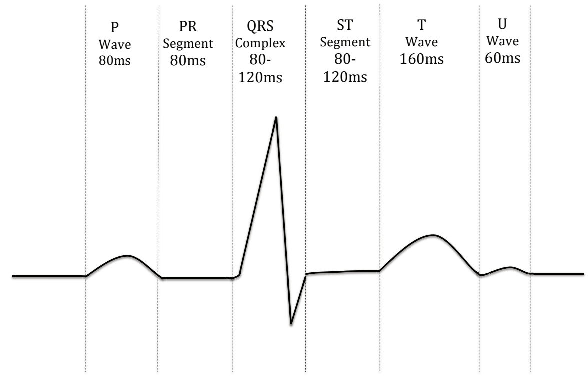


Figure 7: In the ECG signal, each heartbeat pulse has a 0.1 second QRS peak [4], which is caused by the ejection of blood from the ventricle. This peak causes the harmonic frequencies of the heartbeat to stop at 10π Hz.

design filters that can effectively filter out noises and extract heartbeats.

Insensitivity to Low Frequency Movements. Secondly, we note that the geophone sensor is only sensitive to signals that are higher than a certain frequency (7Hz in our case). This can be explained as follows. As Figure 6 shows, the geophone response increases quadratically with frequency when the frequency varies within the range from 1Hz to 12Hz if the movement speed is fixed. For example, let us consider a movement at 1m/s, the geophone generates a voltage about 20V when the frequency is at 10Hz, and a voltage of .2V when the frequency is 1Hz, resulting in a 100 times response increase. Hence, the geophone itself works as a second-order high-pass filter, which is hard to detect responses to low-frequency movements.

The fundamental frequency range of the heartbeat signal falls between 0.45Hz and 3.33Hz, corresponding to a heartbeat rate of 27 beats per minute (bpm) and 200bpm respectively. For example, for a heartbeat rate of 60bpm, the fundamental frequency of the heartbeat signal is at 1Hz. As explained above, the geophone response to movements at 10Hz would be 100 times as strong as the response to movements at 1Hz. As a result, it is hard to detect the geophone response to heartbeats at their fundamental frequency, especially in the presence of other noises.

After taking a closer look at the heartbeat signal and the corresponding geophone responses, we notice that each heartbeat pulse has a .1 second sharp peak caused by the ejection of blood from the ventricle, which corresponds to the QRS component shown in a ECG heartbeat pulse (Figure 7). This peak causes the harmonics of the heartbeat signal to stop at 10π Hz, a portion of which can be easily detected by the geophone.

Finally, we would like to point out that the geophone's response to respiration is much weaker than the response to heartbeats because respiration has even lower fundamental frequency. In this study, we focus on detecting heartbeats, and have not observed noises caused by respiration. In our future work, we will study how we can detect respiration activities using the geophone.

2.3 Extracting Heartbeats from the Geophone Signal

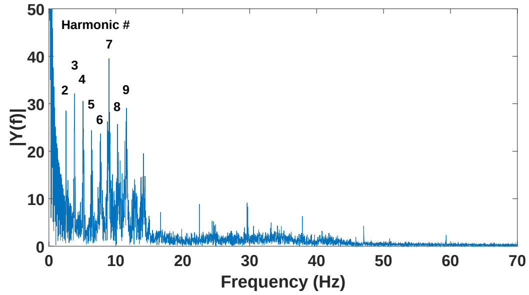
In this subsection, we discuss how we extract heartbeats from the signal after the ADC. Our signal processing consists of the following steps: (1) applying a low-pass filter; (2) computing signal power, (3) calculating sample autocorrelation (ACF), (4) finding peaks in sample ACF data, and (5) detecting heartbeats. Below, we discuss these steps one by one.

Fast Fourier Transformation (FFT) and Low-pass filter: We first compute FFT on the *HB-Phone* signal to identify a suitable cutoff frequency for our low-pass filter. The low-pass filter is critical to the performance of our system because the geophone is very sensitive to high-frequency noises.

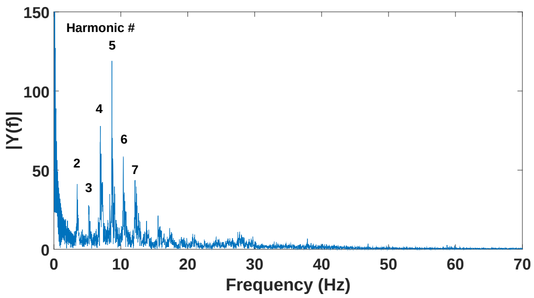
Figures 8(a) and (b) give two example FFT results, with an average heartbeat rate of 76bpm and 104bpm, respectively. In Figure 8(a), with a heartbeat rate of 76bpm, the fundamental frequency is 1.267Hz. By definition, the harmonics of this heartbeat signal would be 2.533Hz, 3.8Hz, 5.067Hz, 6.333Hz, 7.6Hz, 8.867Hz, etc. In Figure 8(a), we mark the first 9 harmonic frequencies. We have similar observations with Figure 8(b) (with the first 7 harmonic frequencies marked). In both examples, the *HB-Phone* signal is dominated by the first few harmonic frequencies of the heartbeat, especially around 10Hz. This is because the heartbeat signal itself decreases rapidly as the harmonic frequency increases, but at the same time the geophone response increases quadratically with the frequency. Both factors considered, the geophone response is dominated by the harmonic frequency around 10Hz.

After examining FFT plots for different average heartbeat rates, we find that the majority of the geophone responses below 18Hz. As a result, we decide to apply a high-order Butterworth Low-pass filter with a cutoff frequency of 20Hz.

Measuring mechanical power: In reality, the heartbeat signal is only quasi-periodic with jitter from pulse to pulse,



(a)



(b)

Figure 8: FFT results for the *HB-Phone* signal when the average heartbeat rate is (a) 76bpm and (b)104bpm. Both signals are dominated by the first few harmonic frequencies of the heartbeat, especially around 10Hz.

where jitters can be as large as 100 milliseconds. It is also often accompanied by a variety of non-pathological irregularities and even skipped beats. Thus, finding the average heartbeat rate with a standard autocorrelation filter on the voltage signal is difficult. Instead, we square the voltage signal from the ADC to produce a power signal proportional to the instantaneous mechanical power in the system and use autocorrelation to determine the average heartbeat rate.

Sample Autocorrelation: Next, we use Sample autocorrelation (ACF) [9] of the signal power to locate the harmonic frequencies. For a time series signal $x(t)$, we have the following normalized sample ACF function

$$\bar{f}_{A\hat{C}F}(h) = \frac{f_{A\hat{C}F}(h)}{f_{A\hat{C}F}(0)} \qquad 0 \le h < n, \tag{1}$$

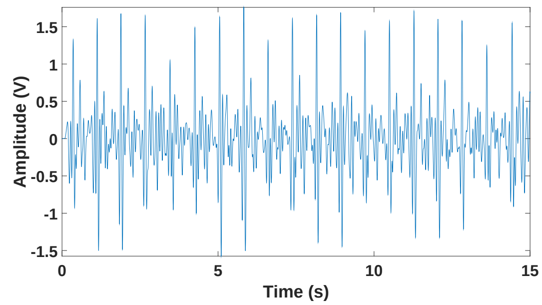
where n is the number of sampling points, h is the time lag. The Sample ACF function is defined as

$$f_{A\hat{C}F}(h) = \frac{1}{n}\sum_{t=1}^{n-h}(x_{t+h} - \bar{x})(x_t - \bar{x}) \qquad 0 \le h < n, \tag{2}$$

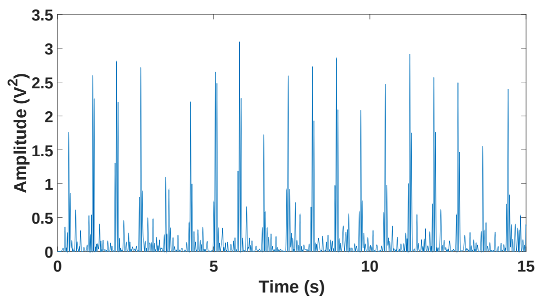
with the sample mean

$$\bar{x} = \frac{1}{n}\sum_{t=1}^{n} x_t. \tag{3}$$

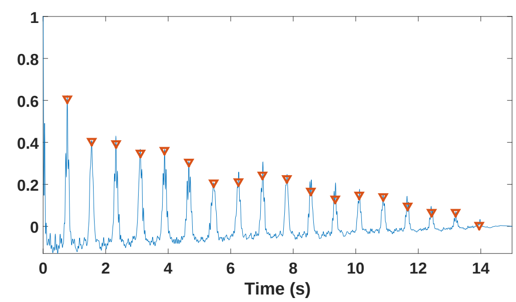
When the time lag is 0, the heartbeat power signal aligns perfectly with itself and the autocorrelation reaches the maximum value. When the time lag starts to increase, the first signal stays the same while the second signal shifts right.



(a)



(b)



(c)

Figure 9: Step-by-step results for a heartbeat signal with a heart rate of 76bpm: (a) the signal after low-pass filtering, (b) the signal power and (c) the sample ACF results with identified peaks.

The mismatch between two signals results in a decreased sample ACF value. However, when we have the time lag equal to a multiple of the heartbeat interval, heartbeat pulses in the first signal match nicely with pulses in the second signal, yielding a large sample ACF value. Thus, by detecting the peaks in the sample ACF results, we can infer the periodicity of heartbeats.

Sample ACF Peak Finding and Measurement: In this study, we adopt the peak finding and measure algorithm developed by Thomas C. O'Haver from University of Maryland [5] to locate the peaks in the sample ACF results. Specifically, the algorithm detects the location and value of peaks in the following steps:

1. We denote the first derivative of the sample ACF $\bar{f}_{A\hat{C}F}(t)$ as $\bar{f}'_{A\hat{C}F}(t)$. We have $\bar{f}'_{A\hat{C}F}(t_p) = 0$ at any peak maximum with time lag t_p and a downside going trend.

2. To prevent finding peaks caused by noises, the signal is smoothed by two passes of a multi-point triangular smoothing with a proper window width.

3. We find the peak maximums by checking whether the difference between $\bar{f}'_{\hat{ACF}}(t)$ and $\bar{f}'_{\hat{ACF}}(t+1)$ exceeds the pre-determined threshold.

4. Since the smoothing in step 2 would distort the original signal, we apply a Least Square Curve-fitting within a subgroup of points near the peak.

Detecting Heartbeats: Ideally, the number of peaks found in the step above is equal to the number of heartbeats within the corresponding time period. However, in practice, it is often the case that after the first so many peaks, the rest of the peaks that were found using the above algorithm may have increasing errors. As an optimization technique, we then take the first 20% of the peaks to calculate average heartbeat interval. Suppose there are n peaks that belong to the first 20% of the found peaks. Further suppose the interval between the first peak and the n-th peak is I, then the average heartbeat interval T is calculated as $\frac{I}{n-1}$. Based on the estimated average heartbeat interval, we can detect each individual heartbeat as follows:

1. We locate the first heartbeat in the range of [0, T] by finding the maximum value. We use t_1 to denote the time of the first heartbeat.

2. Assuming that we have detected h heartbeats, and that the h-th heartbeat occurs at t_h, then we intend to search for the $(h+1)$-th heart within the time range of $[t_h + \frac{T}{2}, t_h + \frac{3T}{2})$.

3. We would like to point out a caveat: very often, we find two strong peaks in a heartbeat pulse, and the second peak is often higher than the first one. If we always look for the maximum peak, we will likely identify the second one while the first one is the beginning of the pulse. To address this problem, after locating the maximum peak during an interval, we go backward and check whether there is another peak within a short range whose amplitude is close to that of the current peak.

4. We repeat the above steps until we find all the heartbeats.

Putting Things Together: Figure 1 shows all the hardware/software components that are included in the *HB-Phone* system. To summarize, the raw analog geophone response signal first goes through the amplification, then the A/D conversion, to convert the analog geophone signal to digital geophone signal. The signal then goes through a low-pass Butterworth filter, sample ACF calculation, peak finding, and heartbeat detection.

We next take an example signal (with the heartbeat rate of 76bpm), and show the signal after filtering, the signal power as well as the peaks found in the sample ACF data in Figure 9 (a-c).

Figure 10: The subject's heartbeats are monitored by both *HB-Phone* and an ECG device. The subject has to remain still on his back due to the constraints of the ECG.

3 Evaluation Results

In this section, we present the detailed experimental results. We first compare the average heartbeat rate estimated by the *HB-Phone* prototype with the result reported by an ECG device. Then we install the prototype in a home for 10 nights, and report the observations we have during the continuous monitoring.

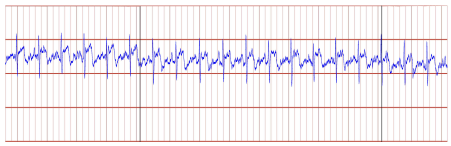
3.1 Comparing *HB-Phone* Estimation with ECG

In the first set of experiments, we intend to quantify the *HB-Phone* estimation accuracy by comparing the *HB-Phone* results with the results from an ECG device. In the experiments, we used a HeartCheck handheld ECG device [3]. In the comparison, we focus on the average heartbeat rate, measured by the number of heartbeats per minute. Specifically, suppose the estimated average heartbeat rate by our system is $BPM_{HB-Phone}$, and the heartbeat rate reported by the ECG is BPM_{ECG}. Then we calculate the error rate of *HB-Phone* as

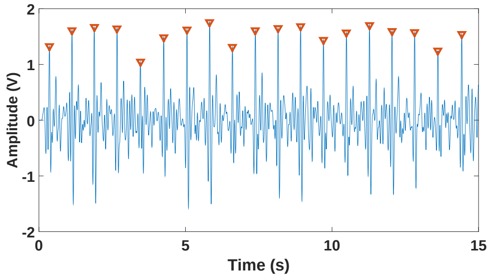
$$\frac{|BPM_{HB-Phone} - BPM_{ECG}|}{BPM_{ECG}}.$$

In addition to the average heartbeat rate, *HB-Phone* can also measure the instant heartbeat rate. In Section 2.3, we discuss how *HB-Phone* detects each individual heartbeat pulse. As a heartbeat pulse is detected, we can calculate the interval between this pulse and its previous one, t; then the instant heartbeat rate is calculated as $\frac{1}{t}$.

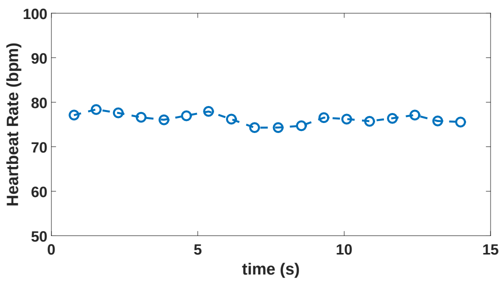
In this set of experiments, we collected 382 30-second data from 16 subjects, whose ages range from 23 to 34 years old. There are 14 male subjects and 2 female subjects. In each data collection period, we asked the subject to lie down on our experimental bed, and measured the subject's heartbeats using both *HB-Phone* and the ECG. Since the ECG device has a strict requirement that the subject should lie down without any movements to ensure the measurement accuracy, we could only ask the subject to lie down on their back, but not other lying positions. Figure 10 shows how the data is collected from each subject.



(a)



(b)



(c)

Figure 11: (a) a 15-second ECG heartbeat signal, (b) captured heartbeat pulses during the 15-second period, and (c) estimated instant heartbeats per minute during the 15-second period.

We collected data in the following four situations: (1) when the subject was awake and just finished running, (2) when the subject fell sleep after running, (3) when the subject was awake, without having any exercise on that day, and (4) when the subject fell asleep, without having any exercise on that day. By taking data from these four situations, we made sure that we evaluate the accuracy of *HB-Phone* under a wide range of real-life scenarios. We note that a person's heartbeat rate decreases from situations (1) through (4).

Finally, we note that our experimental bed is located in a very noisy university lab. There are more than four hundred machines in the same room, which were on and off during data collection sessions. Also, the bed is close to the entrance to the lab, and sometimes people were walking in/out of the lab during data collection sessions. Our results show that the *HB-Phone* prototype is resistant against these environmental noises.

First, in Figure 11, we use a specific example to visually show that our *HB-Phone* system can accurately extract heartbeat pulses from the geophone response. Figure 11(a) shows a 15-second heartbeat signal collected by the ECG. There are 19 heartbeat pulses during the 15 seconds. Figure 11(b) shows that *HB-Phone* captures 19 heartbeat pulses during these 15 seconds, which matches the ECG data and corresponds to a heartbeat rate of 76bpm. Finally, we show the calculated heartbeat rate in Figure 11(c). The example shows that our system yields accurate heartbeat rate estimation results.

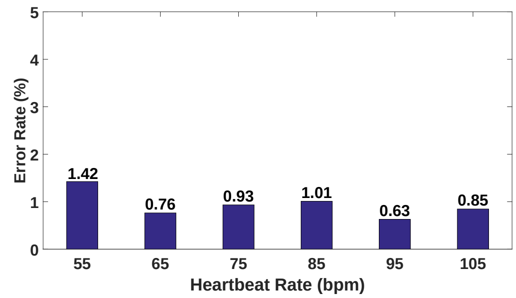


Figure 12: Average error rates in the following heartbeat rate ranges (according to the ECG data): [50, 60), [60, 70), [70, 80), [80, 90), [90, 100), [100, 110]. The average error rate across all the ranges is 0.8794%.

Next, we look at the average error rate of *HB-Phone* over 382 samples, and report the results in Figure 12. Here, we group the samples into 6 groups, based upon the heartbeat rate reported by the ECG, namely, [50, 60), [60, 70), [70, 80), [80, 90), [90, 100), [100, 110]. Then we report the average error rate of each group. The total average rate across all 392 samples is .879%. These results confirm that the *HB-Phone* system can extract heartbeat pulses accurately when the user lies down on our experimental bed.

3.2 Long Term Heartbeat Monitoring During Sleep

In the second set of experiments, we deployed our *HB-Phone* prototype in a subject's home for 10 nights. The installation process was very simple; we just inserted the wood board (to which the geophone and amplifier are attached) under the bed frame (we didn't place it under the mattress because the mattress on the bed was too thin). As a result, the raw geophone signal in the subject's home is weaker than the signal from our experimental bed. In each of the 10 nights, the subject turned on the system before he turned off the light and went to sleep, and turned off the system after he woke up. The average system "on" time each night was about 7 hours. For each night, we removed the first 10 minutes' data because the subject was not in sleep and there were a large number of body movements during that time. Similarly, the last 10 minute's data were also removed.

Heartbeat Rate Monitoring: We have processed the *HB-Phone* output data for all 10 nights. In this paper, in the interest of space, we take one night's data (on March 30, 2015, with a duration of 7 hours), and report the calculated bpm for every 30-second window in Figure 13. Our reporting duration of 7 hours consists of 840 30-second windows. Here, for each 30-second window, we take the *HB-Phone* signal during that window, and perform filtering, sample ACF calculation, peak finding, and heartbeat pulse extraction one by one. Then we count the number of heartbeat pulses during the 30-second window, and then double the number and use

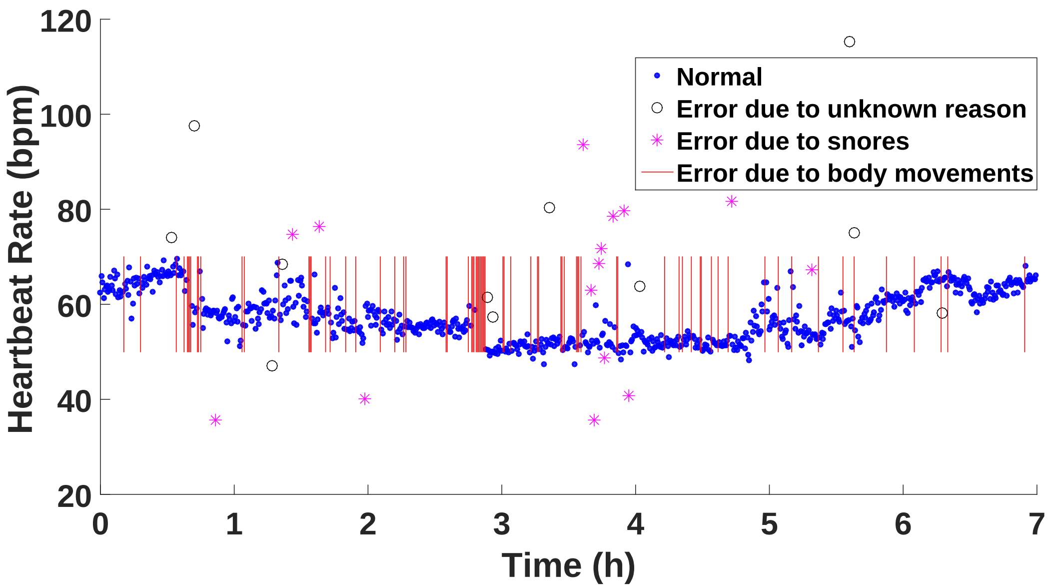


Figure 13: We deployed *HB-Phone* in a subject's home for 10 nights. In this figure, we calculate the subject's bpm every 30 seconds for 7 hours on the night of March 30, 2015. Here, each blue dot represents the calculated bpm within the corresponding 30-second window. *HB-Phone* can effectively filter out many noises (e.g., body movements, snoring), but it yields errors or invalid estimations from time to time. We mark the time windows that yield erroneous or invalid bpm estimations on the figure as well. Specifically, a red bar means that the body movement during those 30 seconds generated responses that are too strong to extract any heartbeats during that period. A magenta asterisk marks the period within which the subject had a few snores (e.g., two second of snoring out of the total 30 seconds) which we failed to filter out. A black circle marks those windows during which we had unknown noises. Among 840 30-second windows, we have 730 normal windows (88%), 79 invalid windows caused by body movements (8.9%), 15 erroneous windows caused by snoring (1.8%), and 11 erroneous windows caused by unknown reasons (1.3%).

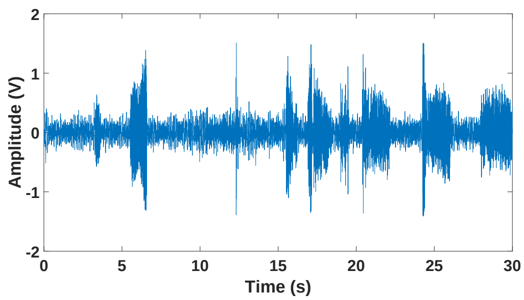


Figure 14: This signal gave erroneous bpm estimation due to the sporadic snoring.

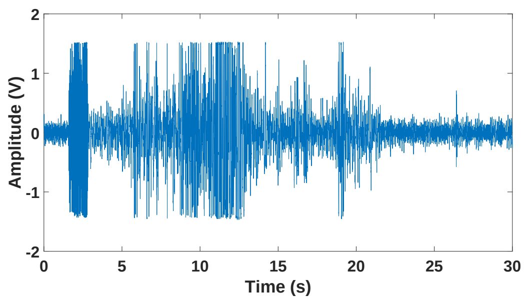


Figure 15: This signal gave invalid bpm estimation due to body movements.

it as the bpm during that window. In processing the data, we find that one of the following situations may occur during a 30-second window:

- *Normal.* In this case, we can obtain a correct bpm estimation from our system. We use a blue dot to mark that window in Figure 13. Among 840 time windows, 739 fall into this category, counting a 88% of success rate.
- *No heartbeat detection due to strong body movements.* In this case, the peak finding algorithm failed to find enough number of peaks in the sample ACF plot. Figure 15 shows a typical signal in such a window where the heartbeat signal is overwhelmed by another much stronger signal. We suspect that the much stronger signal is the geophone's response to body movements. Since these body movements have very similar frequencies as heartbeats, it is hard to filter them out. Since we can't calculate the bpm for these windows, we use a red bar to mark the window in Figure 13.

  Among 840 time windows, 79 fall into this category, counting 8.9% of the total windows. In our follow-up work, we will focus on differentiating heartbeats and body movements when they share the same frequencies.
- *Wrong bpm estimation due to snoring.* In this type of windows, we usually observe periodic noises that are stronger than heartbeat signal and whose peaks are 3-4 seconds apart, as shown in Figure 14. We then recorded the subject's snoring audio and found that his snoring period is around 3-4 seconds. In fact, the subject snored during a large portion of the night. By carefully examining the signal in each time window, we found continuous snoring in the following time periods: minutes 48-62minutes 154-169, minutes 177-180, minutes 182-206, and minutes 211-240. *HB-Phone* successfully dealt with most of the snoring windows by the filter. However, in the erroneous time windows, the subject only snored a few times instead of continuously, which is harder to filter out and leads to errors in bpm estimation. In Figure 13, we mark these erroneous windows using magenta asterisk, whose bpm values are significantly different from that of their neighbors.

  Among 840 time windows, 15 fall into this category, counting 1.8% of the total windows.
- *Unknown Errors.* There are also a few windows that have erroneous BPM estimations, but we cannot find out the source of the noises in these windows. In Figure 13, we mark these windows using black circles. Among 840 time windows, 11 fall into this category, counting 1.3% of the total windows.

4 Related Work

4.1 Background on Bed-Mounted Heartbeat Sensors

Quite a few bed-mounted heartbeat sensing systems have been developed, but very few are accurate, low cost and easy to use at the same time. In order to maximize their benefit, such a system should take little effort to retrofit the existing beds. Below we discuss in detail how the existing systems work and why they fall short of this requirement.

Sensors that Require Special Mattress/Cushion: Some systems require specialized mattresses to monitor heartbeats, which may curb their wide adoption. For example, Watanabe et al. [27] proposes to use a pneumatic system that consists of an air cushion, a pressure sensor, and electric filters for heartbeat monitoring. The air cushion is placed under the mattress, and the sensor detects the change of pressure due to human vital functions. Similarly, the air mattress sensor system proposed in [14] requires an air-cell mattress. By measuring the air pressure difference between two air cells during heartbeats, the system can monitor the user's heartbeats. In [25], Tanaka et al. proposes to place a phonocardiographic sensor on the edge of a water-mat. The sensor detects the acceleration of vibration caused by heartbeats. Kortelainen et al. [21] proposes to measure heartbeat intervals using a foil pressure sensor (piezoelectric or ferroelectric) with electronic casing boxes placed inside of the mattress. Hansen et al. [20] proposes to build a mattress embedded with a sensitive movement detector. The sensor has two sheets of different dielectric constants which generate an electric charge while rubbing against each other. The charge is picked up by a capacitor-like antenna.

Sensors that Require Special Handling of Bedding: Some systems need to place sensors (usually film sensors) in specific locations (usually near the heart) under the sheet, which entails a great deal of manual overhead as it requires adjustment every time when the user changes sleeping position/pose, or changes the sheet. For example, Bu et al. [13] proposes to use a piezoelectric film sensor under ones back, near the heart. The sensor measures the pressure fluctuation due to heartbeats. Wang et al. [26] proposes to use a polyvinylidene fluoride piezopolymer film sensor in the thorax area under the sheet. The sensor picks up the fluctuation of the pressure on the bed caused by the heartbeats. In [8], a foil pressure sensor is placed in the thorax region under a thin mattress. Then the specially designed mattress is placed on top of the existing mattress and bed frame. Similarly, Zhu et al. [29] proposes to place two pressure sensors under the pillow, which assumes that the user will always use the pillow during sleep. Some systems assume that the user always sleeps in the same position on the bed. Mack et al. [22] proposes to place two pressure pads on the surface of the bed assuming the user always sleeps in the same location. Bruser et al. [11] proposes to monitor heartbeats by placing four optical ballistocardiography (BCG) sensors in a diamond configuration in the thorax area underneath a regular bed mattress. The sensor generates light and measures the intensity of light which is reflected or scattered back from the mattress. Bruser et al. [12] proposes to place a slat of four strain gauges under the thorax area in the bed slatted frame. Rosales et al. [24] proposes to use four water transducers that are placed vertically between the mattress and the bed frame, close to the subject's back area.

Custom-Built Sensors: Some systems require custom-built sensors. Heise et al. [18] proposes to use a hydraulic bed sensor that consists of a self-built hydraulic transducer and an integrated pressure sensor. Choi and Kim [15] propose to build RF circuits to capture human heartbeats. The transmitter continuously emits a sinusoidal signal and the receiver captures the signal reflected from human body. The heartbeat and respiration are captured by detecting the phase shift between the original signal and the reflected signal.

Costly Off-the-Shelf Sensors: Some systems use sensors that are commercially available, but costly. For example, sensitive load-cell sensors placed underneath the legs of the bed can measure the vibration of heartbeats as shown in [16]. Nukaya et al. [23] proposes to use a piezoceramic system to detect heartbeats. The sensor is bonded to the stainless steel plate sandwiched between the floor and each leg of the bed.

Sensors That are Hard to Install: Some systems require a considerable amount of manual installation effort. For example, Yamana et al. [28] proposes a system that has a 40-kHz ultrasound transmitter and receiver pair, a plywood board, aluminum support under the board, and aluminum guide rail on the bed surface. The wood board and aluminum guide rail are used to hold transmitter and receiver in place while the aluminum support is used to prevent the board from bending. The ultrasound signal is transmitted toward the head side, and the receiver obtains the ultrasound reflected at the below-surface of the mattress.

4.2 Bed-Mounted Heartbeat Sensor Categorization and Their Signal Processing Algorithms

Broadly speaking, we can categorize the existing bed-mounted heartbeat monitoring sensors into the following categories:

- Air/Water pressure sensors, i.e., those in [27, 14, 25, 24, 19, 18, 17], or piezoelectric sensor [13, 26, 23]. The main challenge in these systems is to different heartbeat signal from respiration signal. Most of studies address this challenge taking advantage of the fact that these two activities have very different frequencies. In [25], bandpass filters are applied to the signal to differentiate these two. In [13], Empirical Mode Decomposition(EMD) is applied to the signal. Respiration and heartbeat waves are reconstructed by summing up waves from EMD at different frequency ranges. In [26], wavelet multi-resolution decomposition analysis is used for the detection of respiration and heartbeat from the sensor output. In [18], low pass filter and windowed peak-to-peak deviation is computed for heartbeat detection. In [24], a k-means clustering method is used to extract heartbeats from the input system.
- Force sensors, i.e., those in [16, 12, 10]. Here, the main challenge in these systems is also to different heartbeat signal from respiration signal. In [12], unsupervised learning technique with three indicators (cross correlation, euclidean distance, HV signal) is used to extract the shape of a single heart beat from the recorded signal. In [10], the signal is first low-pass filtered, and then heartbeats and respiration are detected by a peak finding algorithm within a moving window. The size of the window is decided by the sampling frequency and the frequency of the desired signal.
- Optical sensor, i.e., those in [11]. In [11], highpass and lowpass filters are applied and continuous local interval estimation algorithm is used to extract the beat-to-beat intervals.
- Radar sensor, i.e., those in [15]. In [15], the peak finding with power spectral density is utilized to extract heartbeats.
- Ultrasound sensor, i.e., those in [28]. In [28], envelope detector and bandpass filter are applied for different detection purposes. Here, the authors report a detection accuracy of 84.2%.
- Foil pressure sensor, i.e., those in [21, 8]. In [21], sliding Discrete Fourier Transform is applied on heartbeat signal and principal component analysis on respiration signal.

5 Future Direction and Concluding Remarks

In this study, we develop *HB-Phone*, a bed-mounted heartbeat monitoring system that uses the geophone sensor to capture and detect heartbeats. The geophone is highly sensitive to movements whose frequency is above a certain level (10Hz in our prototype), while insensitive to lower-frequency respiration and other motions, lending itself to heartbeat detection as each heartbeat pulse contains a high-frequency component that can generate harmonic frequencies that can be easily detected by the geophone. Compared to other existing solutions, *HB-Phone* uses affordable off-the-shelf hardware, is very easy to retrofit the exiting bed, and provides accurate heartbeat detection.

We have built a *HB-Phone* prototype and conducted extensive experiments to compare its performance with an ECG device. We have collected 382 30-second heartbeat data from 16 subjects from both *HB-Phone* and the ECG, and found that the average estimation error rate is as low as .879%. We have also installed our prototype to a subject's home for 10 nights, and found that *HB-Phone* can not only detect heartbeats, but it can also be used to detect snoring and other body movements. Our results show that during the 7-hour sleep interval, 88% of the time we could correctly estimate the average heartbeat rate in a 30-second window. 8.9% of the time, our algorithm resulted in invalid heartbeat rate estimation due to body movements. 1.8% of the time, our algorithm results in erroneous heartbeat rate calculation due to snoring. These results demonstrate that *HB-Phone* provides a viable solution to at-home heartbeat monitoring during sleep.

In this study, we have taken the first step towards using the geophone for at-home sleep monitoring. There are many challenges to address towards this goal. In our follow-up work, we will investigate how we can use the geophone to accurately detect respiration, snoring, and other body movements during sleep. We will also investigate whether it is possible to monitor more than one person on the bed using multiple geophones.

6 References

[1] Arduino duemilanove. `http://arduino.cc/en/Main/arduinoBoardDuemilanove`.

[2] Geophone sm-24. `https://www.sparkfun.com/products/11744`.

[3] Heartcheck ecg. `http://www.theheartcheck.com/products/ekg_device.html`.

[4] Medical decoded. `http://lessons4medicos.blogspot.com/2008/06/basic-ecg-waveform-ecg-vitals.html`.

[5] Peak finding and measurement. `http://terpconnect.umd.edu/~toh/spectrum/PeakFindingandMeasurement.htm`.

[6] Sparkfun. `https://www.sparkfun.com/datasheets/BreakoutBoards/OpAmp_Breakout-v16.pdf`.

[7] Ti lmv358. `http://www.ti.com/product/lmv358`.

[8] X. L. Aubert and A. Brauers. Estimation of vital signs in bed from a single unobtrusive mechanical sensor: Algorithms and real-life evaluation. In *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, pages 4744–4747. IEEE, 2008.

[9] J. Box and G. M. Jenkins. *Reinsel. Time Series Analysis, Forecasting and Control*. Prentice Hall, Englewood Cliffs, NJ, USA, 3rd edition edition, 1994.

[10] M. Brink, C. H. Müller, and C. Schierz. Contact-free measurement of heart rate, respiration rate, and body movements during sleep. *Behavior research methods*, 38(3):511–521, 2006.

[11] C. Bruser, A. Kerekes, S. Winter, and S. Leonhardt. Multi-channel optical sensor-array for measuring ballistocardiograms and respiratory activity in bed. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pages 5042–5045. IEEE, 2012.

[12] C. Bruser, K. Stadlthanner, S. de Waele, and S. Leonhardt. Adaptive beat-to-beat heart rate estimation in ballistocardiograms. *Information Technology in Biomedicine, IEEE Transactions on*, 15(5):778–786, 2011.

[13] N. Bu, N. Ueno, and O. Fukuda. Monitoring of respiration and heartbeat during sleep using a flexible piezoelectric film sensor and empirical mode decomposition. In *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, pages 1362–1366. IEEE, 2007.

[14] Y. Chee, J. Han, J. Youn, and K. Park. Air mattress sensor system with balancing tube for unconstrained measurement of respiration and heart beat movements. *Physiological measurement*, 26(4):413, 2005.

[15] J. H. Choi and D. K. Kim. A remote compact sensor for the real-time monitoring of human heartbeat and respiration rate. *Biomedical Circuits and Systems, IEEE Transactions on*, 3(3):181–188, 2009.

[16] G. S. Chung, B. H. Choi, D.-U. Jeong, and K. S. Park. Noninvasive heart rate variability analysis using loadcell-installed bed during sleep. In *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, pages 2357–2360. IEEE, 2007.

[17] Y. Hata, Y. Kamozaki, T. Sawayama, K. Taniguchi, and H. Nakajima. A heart pulse monitoring system by air pressure and ultrasonic sensor systems. In *System of Systems Engineering, 2007. SoSE'07. IEEE International Conference on*, pages 1–5. IEEE, 2007.

[18] D. Heise, L. Rosales, M. Skubic, and M. J. Devaney. Refinement and evaluation of a hydraulic bed sensor. In *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 4356–4360. IEEE, 2011.

[19] D. Heise and M. Skubic. Monitoring pulse and respiration with a non-invasive hydraulic bed sensor. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, pages 2119–2123. IEEE, 2010.

[20] B. H. Jansen, B. H. Larson, and K. Shankar. Monitoring of the ballistocardiogram with the static charge sensitive bed. *Biomedical Engineering, IEEE Transactions on*, 38(8):748–751, 1991.

[21] J. M. Kortelainen, M. van Gils, and J. Parkka. Multichannel bed pressure sensor for sleep monitoring. *Computing in Cardiology*, 39:313–316, 2012.

[22] D. C. Mack, J. T. Patrie, P. M. Suratt, R. A. Felder, and M. Alwan. Development and preliminary validation of heart rate and breathing rate detection using a passive, ballistocardiography-based sleep monitoring system. *Information Technology in Biomedicine, IEEE Transactions on*, 13(1):111–120, 2009.

[23] S. Nukaya, T. Shino, Y. Kurihara, K. Watanabe, and H. Tanaka. Noninvasive bed sensing of human biosignals via piezoceramic devices sandwiched between the floor and bed. *Sensors Journal, IEEE*, 12(3):431–438, 2012.

[24] L. Rosales, M. Skubic, D. Heise, M. J. Devaney, and M. Schaumburg. Heartbeat detection from a hydraulic bed sensor using a clustering approach. In *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, pages 2383–2387. IEEE, 2012.

[25] S. Tanaka, Y. Matsumoto, and K. Wakimoto. Unconstrained and non-invasive measurement of heart-beat and respiration periods using a phonocardiographic sensor. *Medical and Biological Engineering and Computing*, 40(2):246–252, 2002.

[26] F. Wang, M. Tanaka, and S. Chonan. Development of a pvdf piezopolymer sensor for unconstrained in-sleep cardiorespiratory monitoring. *Journal of intelligent material systems and structures*, 14(3):185–190, 2003.

[27] K. Watanabe, T. Watanabe, H. Watanabe, H. Ando, T. Ishikawa, and K. Kobayashi. Noninvasive measurement of heartbeat, respiration, snoring and body movements of a subject in bed via a pneumatic method. *Biomedical Engineering, IEEE Transactions on*, 52(12):2100–2107, 2005.

[28] 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 *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pages 5323–5326. IEEE, 2011.

[29] X. Zhu, W. Chen, T. Nemoto, Y. Kanemitsu, K. Kitamura, K.-i. Yamakoshi, and D. Wei. Real-time monitoring of respiration rhythm and pulse rate during sleep. *Biomedical Engineering, IEEE Transactions on*, 53(12):2553–2563, 2006.