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

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***Abstract*—Heartbeat monitoring during sleep is critically important to ensuring the well-being of many people, ranging from patients to elderly. Technologies that support heartbeat monitoring should be unobtrusive, and thus solutions that are accurate and can be easily applied to existing beds is an important need that has been unfulfilled. We tackle the challenge of accurate, low-cost and easy to deploy heartbeat monitoring by investigating whether off-the-shelf analog geophone sensors can be used to detect heartbeats when installed under a bed. Geophones have the desirable property of being insensitive to lower-frequency movements, which lends itself to heartbeat monitoring as the heartbeat signal has harmonic frequencies that are easily captured by the geophone. At the same time, lower-frequency movements such as respiration, can be naturally filtered out by the geophone. With carefully-designed signal processing algorithms, we show it is possible to detect and extract heartbeats in the presence of environmental noise and other body movements a person may have during sleep.**

We have built a prototype sensor and conducted detailed experiments that involve 43 subjects (with IRB approval), which demonstrate that the geophone sensor is a compelling solution to long-term at-home heartbeat monitoring. We compared the average heartbeat rate estimated by our prototype and that reported by a pulse oximeter. The results revealed that the average error rate is around 1.30% over 500 data samples when the subjects were still on the bed, and 3.87% over 300 data samples when the subjects had different types of body movements while lying on the bed. We also deployed the prototype in the homes of 9 subjects for a total of 25 nights, and found that the average estimation error rate was 8.25% over more than 181 hours' data. Overall, the results shows that applying a low-pass filter with cutoff frequency range from 7Hz to 10Hz gives us a .

***Index Terms*—Heartbeat Sensor, Bed-Mounted Sensor, Sleep Monitoring, Signal Processing**

I. Introduction

When we consider a person's well-being, it is important to focus on the time when he/she is resting and sleeping. We spend a large fraction of our time in sleeping, and yet, reliable mechanisms that can monitor our sleep and heartbeats during sleep are still missing. In the last few years, we have seen an increasing number of wearable devices that can be used for this purpose, but they usually need to be bundled to other mobile devices and require frequent battery charging, which is rather cumbersome to many users, especially patients or elderly. As a result, we believe a better approach is to develop bed-mounted sensors that can monitor users in a completely unobtrusive manner. In this study, we aim to develop such sensors that are able to detect and monitor *heartbeats* during sleep. Detecting heartbeats and monitoring the heartbeat rate, is an important part of ensuring our well-being.

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 have managed simultaneously to achieve ease of use, low cost, high accuracy, and robustness. Firstly, many systems, such as those proposed in [30], [21], [14], require custom-made sheets or mattresses. For example, an air cushion is required in [30], [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 [29]. These requirements are rather cumbersome, which may greatly hinder the widespread adoption of the proposed systems, particularly amongst demographics that are adverse to noticeable changes in their routines. 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 [31] needs to install a plywood board and an aluminum guide rail on the bed surface. Because of these limitations, even though a number of systems have been proposed, at-home heartbeat monitoring during sleep still remains a problem for which there are no completely suitable solutions.

In this study, we seek to fill this void by proposing a system that is accurate, robust, low cost, and easy to use. Our solution involves the use of a commercial off-the-shelf analog geophone under the mattress to detect and monitor the user's heartbeats during sleep. Just like a geophone can detect pressure waves (i.e. "sounds") in the earth (e.g., [27], [24]), our system can detect the sounds of heartbeats that are propagated through a mattress. Therefore, we refer to our system as heartbeat-phone, or *HB-Phone* in short. Compared to other sensors, the geophone sensor has several advantages, which make it a suitable choice for heartbeat detection[1]. Firstly, it is highly sensitive to tiny motions – geophones are often used to detect distant motions (such as earthquakes), and can generate a noticeable response to minute movements such as heartbeats (after going through a normal mattress).

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

Secondly, it is commercially available and rather affordable. Thirdly, deploying a geophone-based system can be very conveniently done, without interfering with the bed or how it is used. As a result, we believe that *HB-Phone* offers a very practical solution to at-home heartbeat monitoring during sleep, and in this study, we show that such a solution is also accurate and robust against environmental noise or other body movements a person may have during sleep.

Extracting heartbeats from geophone signals, poses serious challenges to the underlying system design, which we have addressed in our study. The first challenge stems from the fact that the geophone is naturally a second-order high-pass filter, hence insensitive to low-frequency motions. 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 difficult to detect geophone responses 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, that are caused by a high-frequency component in a heartbeat.

The second challenge is that geophones are highly sensitive to noise in the environment. During sleep, a person may have various body movements including arm swings, leg kicks, or snoring [2]. 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 a geophone that is installed under the bed mattress. Therefore, it is a daunting task to extract heartbeats from all types of the noise, requiring very careful design of both hardware and software components to mitigate such harmful interference. In hardware design, the key is to control the amplification to ensure heartbeat responses are detectable and distinguishable from noise while maximizing the amplitude of noise that we can cope with. In software design, the key is to carefully devise signal processing algorithms that can effectively filter out both environmental noise and noise caused by a person's body movements while in sleep.

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

1) We have developed an accurate, robust, low-cost, and easy-to-use bed-mounted heartbeat monitoring system *HB-Phone*, which is centered around a commercial off-the-shelf analog geophone. The *HB-Phone* system consists of both hardware and software components. Its hardware components include a geophone, an amplifier and an A/D converter; software components involve filtering, sample auto-correlation calculation, peak finding, and heartbeat extraction. Though geophones were suggested for detecting the presence of heartbeats in [3], [25], to our knowledge, *this is the first geophone-based system that can accurately monitor the heartbeat rate in realistic settings.*
2) We have built a *HB-Phone* prototype and used it to instrument an experimental bed. We have used the experimental bed to collect 502 30-second geophone signals from 34 subjects while they lay still on the bed; 301 30-second geophone signals from these subjects when they had various types of gentle body movements while lying on the bed. We have compared the calculated heart rate with the results measured by a pulse oximeter, and found that the average error rate is 1.30% in the former case, and 3.87% in the latter case.
3) We have deployed the *HB-Phone* prototype in 9 homes for a total of 25 nights, along with a pulse oximeter and video camera. We observe that the average error rate is 8.25%, even though the subjects had various body movements and environmental noise during the experiments.

[2]Our system has an upper bound on the amplitude of the movements it can handle, which is dependent on the configuration of the hardware; in our prototype, we chose to use lower-end hardware components and can cope with body movements whose amplitude is 14 times of that of heartbeats.

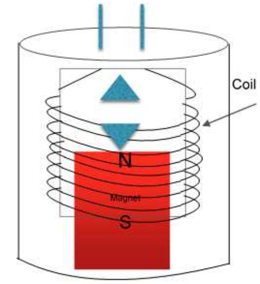


Fig. 2: The geophone consists of a spring-mounted magnet that is moving within a wire coil to generate electrical signals that measure movements in the environment.

The remainder of the paper is organized as follows. In Section II, we present the hardware system design of *HB-Phone*, and in Section III, we present the software design that we have built to support heartbeat monitoring. We present our evaluation setup and experimental results in Section IV. In Section V, we summarize the existing bed-mounted heartbeat monitoring systems, and compare their pros and cons. Finally, we provide concluding remarks in Section VI.

II. HB-Phone System Design

We show the overview of *HB-Phone* in Figure 1. In *HB-Phone*, we place an analog geophone under a mattress to capture movements in the environment, including the user's heartbeats. We first amplify the raw geophone response, and then convert it to a digital signal. Next, we feed the digital geophone signal to a series of signal processing functions, which 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 heartbeat rate, detection of snoring during sleep, and detection of body movements during sleep, etc.

In this section, we first present the hardware design of *HB-Phone*. Then we discuss the unique challenges we have faced in designing the *HB-Phone* system.

A. HB-Phone Hardware Design and Prototype

The *HB-Phone* system is centered around the use of a geophone sensor. As shown in Figure 2, a geophone consists

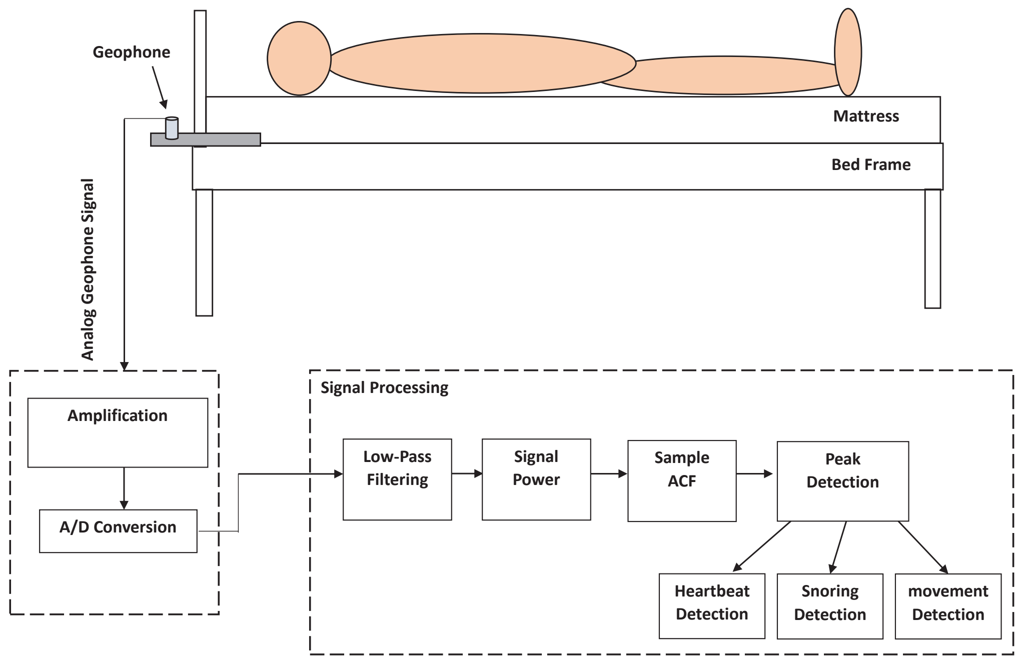


Fig. 1: Overview of the *HB-Phone* system. An analog geophone is placed under a mattress. The raw geophone signal goes through amplification and A/D conversion to generate a digital signal that is suitable for subsequent signal processing. A series of signal processing methods will then be applied to detect heartbeats in the signal.

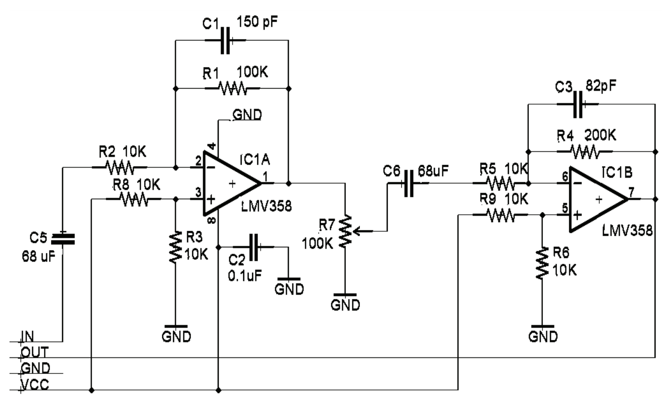


Fig. 3: The AC amplifier circuit design.

of a spring-mounted magnet that moves within a wire coil to generate a voltage, which can thus measure the speed of a movement at 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 movements with lower frequencies. 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 bandpass filter in the range from 0.25 to 10kHz, which is then fed to a TI LMV358 amplifier circuit [7]. We have carefully configured the amplifier circuit to ensure the *HB-Phone* is robust against other types of body movements during sleep (such as snoring, hand/arm swings, or leg kicks). For this purpose, we first need to make sure signals caused by such body movements stay within the range of the amplification circuit output after amplification, i.e., 0-3V in our case; once this range is reached, no information can be extracted from the resulting geophone signal. That is, if we desire to extract heartbeats in the presence of noise caused by body movements (whose amplitude is usually much larger than that of heartbeats), then the amplification should be kept sufficiently small to avoid the above-mentioned situation. On the other hand, we are limited by the ADC unit's resolution, especially that of a low-cost ADC unit: if the amplification is too small, then it is hard to correctly detect heartbeats due to a combination of low signal amplitude and low ADC resolution (i.e. quantization error becomes dominant). In this study, our objective is to maximize the amplitude of body movements that we can handle in the system while still being able to detect heartbeats. For this purpose, we configured the amplification circuit such that the heartbeat signal's amplitude falls within 0-200mV, which is a range determined by the resolution of our ADC. Given that the amplification circuit's output range is 0-3V, we leave 2.8V as the maximum amplitude for detectable body movements, which is roughly 14 times of the amplitude of a heartbeat motion.

Figure 3 shows the resulting double-stage amplification 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 ADC output signal is thus ready for subsequent signal processing and heartbeat extraction. *In the rest of this paper, we use the term "geophone signal" to denote the signal after amplification and*

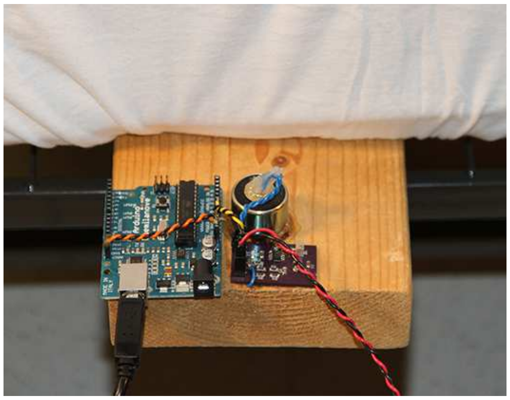


Fig. 4: The picture of our *HB-Phone* prototype, where the geophone and the amplifier are glued to a wooden board that is inserted between the memory foam mattress and bed frame.

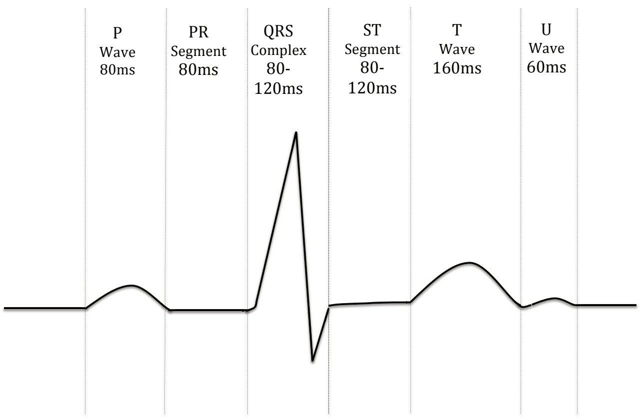


Fig. 5: In the ECG signal, each heartbeat pulse has a 0.1 second QRS peak [4], which is caused by the ejection of blood from the ventricle. This peak stores most of the energy during a heartbeat and causes strong harmonics.

ADC.

In Figure 4, we show the picture of our prototype *HB-Phone* system. We attached the geophone to a piece of wooden lumber 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.

B. Unique Challenges of the HB-Phone System

HB-Phone is intended to detect heartbeats that propagate through a mattress, which poses serious challenges to the underlying system design. Below we explain the two major challenges that we have faced in designing the system.

1) Insensitive to Heartbeats at the Fundamental Frequency: A geophone is essentially a second-order high-pass filter, which is sensitive to movements whose frequency is above a certain threshold, referred to as T_{freq}, while it is insensitive to movements with frequencies lower than the threshold.

This can be explained as follows. As Figure 6 shows, the geophone response increases quadratically with frequency when the frequency varies within the range of 1-10Hz for a given speed. 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 factor of 100 difference in the response between these frequencies. Hence, the geophone itself works as a high-pass filter, making it hard to detect responses to low-frequency movements. In the response curve shown in Figure 6, the value of T_{freq} is 10Hz.

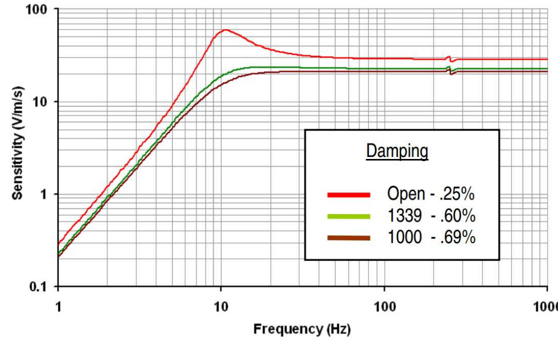


Fig. 6: The response curve from the data sheet of Geophone SM-24 [6] that we use in our prototype.

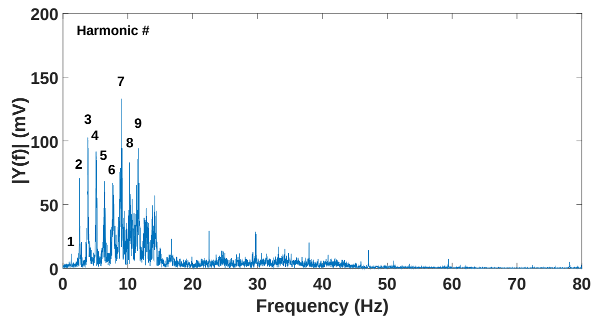
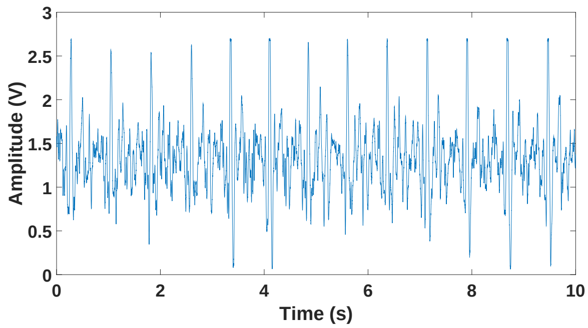


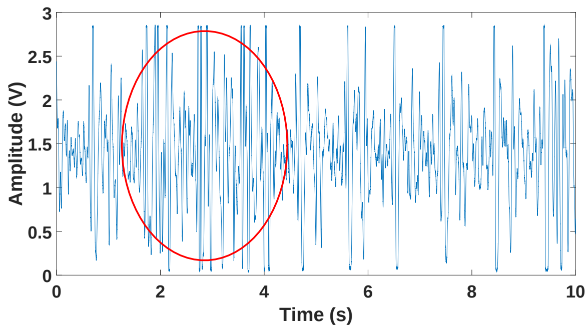
Fig. 7: FFT results of a 30-second geophone signal when a subject, with an average heartbeat rate of 76.86 bmp, lay still on the bed. In the figure, we mark the heartbeat signal's fundamental frequency (with the number 1) and a few harmonic signals (2 means the second harmonic frequency). In order to clearly show the harmonic frequencies in this result, we adjusted the amplification circuit such that the resulting heartbeat amplitude is close to 3V. In the rest of this paper, our amplifier circuit output for heartbeats is kept at 200mV.

Figure 5 illustrates an ECG heartbeat pulse, in which the QRS complex (caused by the ejection of blood from the ventricle) stores most of the heartbeat energy and has a frequency of 0.45 to 3.33Hz corresponding to the heartbeat rate of 27 bpm and 200 bpm. In general, we would directly detect vibrations caused by the QRS complex. However, considering the reduced response from the geophone in this frequency range and the noise from the environment, detecting heartbeat signals in this way would be infeasible. Instead, we would focus on the harmonics of the heartbeat signal as harmonics are at higher frequencies and have much stronger geophone responses.

Figure 7 shows the FFT results of a 30-second geophone signal when a subject lay still on the prototype bed. On the figure, we mark a few harmonic frequencies of the heartbeat signal with their corresponding harmonic numbers; we use number 1 to mark the fundamental frequency. Clearly, the geophone's response to the fundamental frequency is very weak, and its response to the next few harmonics (within the frequency range of 2-13Hz) is much stronger. In this study, we then aim to detect heartbeats' harmonic signals at these



(a)



(b)

Fig. 8: (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.

frequencies.

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 noise caused by respiration. In our future work, we will study how we can detect respiration activities using the geophone.

2) Highly Sensitive to Noise Caused by Motion: The geophone is very sensitive to motions if their frequency is above the threshold T_{freq}, which is also the very reason why we choose this type of sensor in the first place. It responds to tiny motions or vibrations in the environment – when placed under a 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. Since many of these movements are more pronounced than heartbeats, detecting heartbeats in their presence is particularly challenging.

Here, we use an example to illustrate the impact of movements in the environment. Figure 8(a) shows a 10-second geophone 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 walk 1 meter from the bed (on a concrete floor). We show the resulting geophone response in Figure 8(b), and mark the affected area using the red circle. This example shows that the geophone is very sensitive to noise in the environment, making heartbeat detection a challenging task.

III. Extracting Heartbeats from Geophone Signals

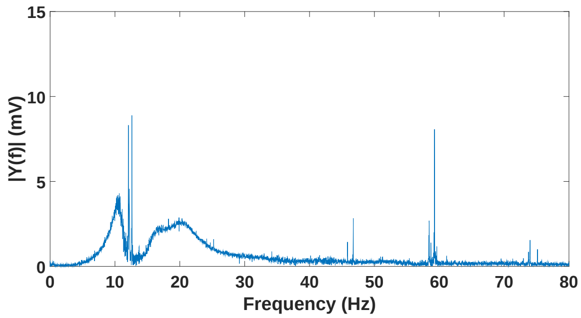
Next, we partition the geophone signal into equal-length windows (30 seconds in our case), and count how many heartbeats in each window. Our signal processing algorithm consists of the following steps: (1) applying a low-pass filter; (2) calculating sample auto-correlation function (ACF), (3) finding peaks in sample ACF data, and (4) detecting heartbeats. We choose this method because (i) we observe that it is possible to separate heartbeat signals from body movement signals by filtering, and (ii) heartbeats exhibit strong periodicity compared to most other body movements. Please note that geophone is very insensitive to respiration – another common periodic motion – due to its lower frequency.

A. FFT and Low-pass filtering

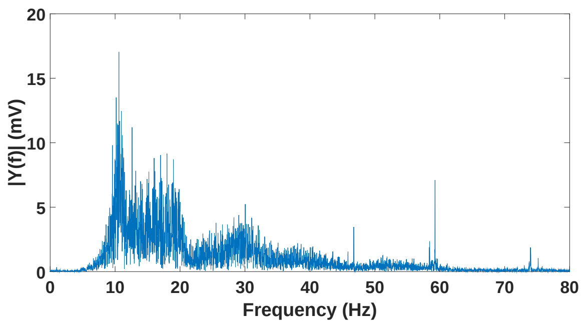
We first compute FFT on geophone signals from various body movement patterns (we only focus on body movements whose amplitude is at most 14 times of the heartbeat amplitude in this study as explained in Section II) to find out whether there is a clear separation between heartbeats and body movements in the frequency domain.

We collected geophone signals when a subject performed three different types of body movements while standing half a meter from the bed. In this way, we can separate the signals caused by heartbeats and those caused by body movements, and only focus on geophone responses to body movements. We show a few such FFT results in Figures 9(a)-(c). In these results, we shifted the signal mean to zero to remove the DC component. In Figure 9(a), we show the FFT results when a subject tapped the mattress a single time during a 30-second window, representing impulse or one-time body movements whose signal only shows a narrow peak in the time domain. In Figure 9(b), we show the FFT results when a subject tapped the mattress once a second for the entire 30-second window, representing long-term body motions that last for many seconds or even minutes, whose signal will show up in the entire signal window. In Figure 9(c), we show the FFT results when a subject scratched the bed sheet for a few seconds, representing body movements that last for a relatively short period whose signal covers a portion of the signal window.

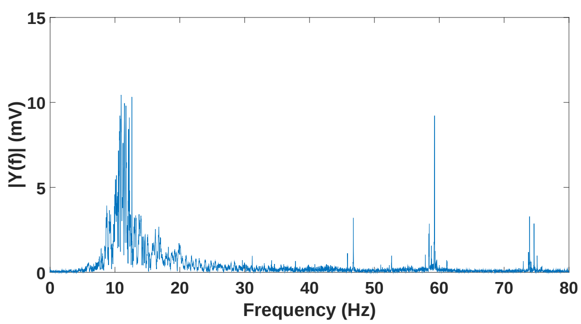
The FFT results suggest that most geophone signals caused by body movements have frequencies 6Hz and above, with a sudden rise after 8Hz. Considering this, as well as the heartbeat FFT results shown in Figure 7, we hypothesize that a low-pass filter with a cutoff frequency between 6 and 10Hz would be able to effectively separate heart beats and body movements.



(a) Subject tapped the mattress once during the 30-second experiment



(b) Subject tapped the mattress once a second for 30 seconds



(c) Subject rubbed bed sheet for a few seconds

Fig. 9: FFT results for geophone signals with different body movement patterns. According to the results, the majority of frequency components for different body movements are above 6Hz, and rise significantly after 8Hz.

B. Calculating Sample ACF

Sample ACF [9] is often used to extract periodicity from a time series. For this purpose, we need to shift the signal mean to zero and square the voltage signal to produce a power signal proportional to the instantaneous mechanical power in the system.

Next, we calculate the sample ACF of the geophone signal power. For a time series signal $x(t)$, we have the following normalized sample ACF:

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

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

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

with the sample mean

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

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. 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.

C. 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 peaks in the sample ACF results. Specifically, the algorithm detects the location and value of peaks using 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 noise, we smooth the signal using two passes of multi-point triangular smoothing with a proper window width.
3) We find peak maximums by checking whether the difference between the derivative of $\bar{f}'_{A\hat{C}F}(t)$ and $\bar{f}'_{A\hat{C}F}(t+1)$ exceeds the pre-determined threshold. If it does, then the peak lies in the vicinity of this location.
4) Since the smoothing step (step 2) could have distorted the original signal, we need to go back to the original signal and pick points that are near the peak location identified in step 3. Then we apply Least Square Curve-Fitting over these points to refine the peak location.

D. Extracting Heartbeats from Original Geophone Signals

Ideally, the number of peaks found from the sample ACF results is equal to the number of heartbeats within the time period. However, in practice, it is often the case that after the first few peaks, the remaining peaks found using the above algorithm may drift due to the quasi-periodic characteristic of the heartbeat signal, leading to incorrect peak numbers and locations. As an optimization technique, we only take the first 20% of the peaks from the sample ACF results to calculate average heartbeat interval. Suppose there are n peaks that belong to the first 20% of the established peaks. Further suppose the interval between the first peak and the n-th peak is T, then the average heartbeat interval I_{HB} is calculated as $\frac{T}{n-1}$. Based on the estimated I_{HB} value, we can go back to the original geophone signal and extract each individual heartbeat as follows:

1) We locate the geophone response to the first heartbeat[3] in the range of $[0, I_{HB}]$ by finding the maximum amplitude value. We use t_1 to denote its time.
2) Assuming that we have already detected h heartbeats, and that the h-th heartbeat occurs at t_h, then we intend to search for the $(h+1)$-th heartbeat within the time range of $[t_h + \frac{I_{HB}}{2}, t_h + \frac{3I_{HB}}{2})$. We locate the $(h+1)$-th heartbeat by finding the maximum amplitude value. in this range.
3) We repeat step 2 until we find all the heartbeats.

IV. Evaluation Results

In this section, we describe our evaluation effort and present detailed experimental results. In the first phase of evaluation, we focused on testing *HB-Phone*'s heartbeat rate estimation accuracy in a laboratory environment through controlled experiments, and considered noise caused by different body movements in the experiments. Our evaluation in this phase involved 34 subjects, and collected over 400 minutes of heartbeat signals. Then in the second phase, we investigated how *HB-Phone* performs in real-world settings through long-term field trials that involved 9 subjects for 25 nights. In total, we collected over 181 hours of data in the second phase[4].

In both phases, we obtained the ground-truth heartbeat rates, $\bar{H}$, by running a similar signal processing method (as described in Section III) on signals collected by a pulse oximeter. Assuming the estimated heartbeat rate in the *HB-Phone* system is H, then we report the estimation error rate as $|H - \bar{H}|/\bar{H}$.

A. Evaluation Phase I: Controlled Experiments

In the first phase of evaluation, we conducted a series of controlled experiments in a laboratory environment emulating a wide range of noise caused by human body movements that are possible during sleep, and report the average estimation accuracy of *HB-Phone* in these experiments.

Participants: We had a total of 34 healthy volunteer participants for this experiment, including a total of 26 males and 8 females. The mean age of the participants was 28.0 years with a standard deviation of 7.7 years. The youngest participant was 22 years old while the eldest was 65 years old.

Experiment Procedure: The controlled experiments in the first phase aimed to study the accuracy of *HB-Phone* by comparing the estimated heartbeat rate against the ground truth – the heartbeat rate measured by a pulse oximeter.

During the experiments, all participants were asked to lie on the prototype bed in our lab for the duration of a trial (30 seconds), during which we recorded the geophone signal and transported the data to a PC for subsequent signal processing. Meanwhile, we placed a pulse oximeter on the participant's index finger, whose data is transferred to a PC in real time for subsequent processing. We then obtained the number of heartbeats in both signals, and calculated the error rate for each trial. Each participant went through multiple trials, and we had more than 800 trials in total.

[3]Here, we do not distinguish a heartbeat and the geophone's response to this heartbeat.

[4]Our studies were approved by the Institutional Review Board (IRB) of our institution.

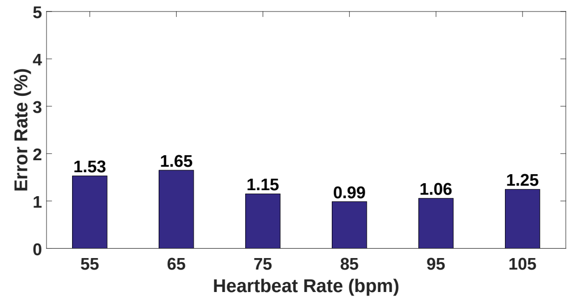


Fig. 10: Average error rates in the following heartbeat rate ranges: [50, 60), [60, 70), [70, 80), [80, 90), [90, 100), [100, 110]. The average error rate across all the ranges is 1.30%. The subjects were lying still on bed in these experiments.

Here, we emulated two groups of scenarios; in the first group, the subjects were asked to lie still on bed, and in the second group, the subjects were asked to perform body movements with varying durations while lying on bed. The participants were engaged in different activities before the trails. For example, some subjects just finished running before a trial; some subjects fell asleep during the trial (and sometimes these subjects just ran before the trial). Hence, subjects' heartbeat rates varied considerably across all trials.

In addition, we note that our prototype bed is located in a very noisy university lab. There are more than four hundred computers in the same room, which were on and off during our experiments. The bed is close to the entrance to the room, and often people were walking in/out of the lab during experiments. Our results show that the *HB-Phone* prototype is resistant against the noise.

When the Subject Has No Body Movements: In the first group of experiments, the subjects did not make any body movements during a trial. As a result, the geophone signal was dominated by geophone responses to heartbeats.

Despite the environmental noise, *HB-Phone* delivers very accurate results in this scenario. We report the average error rate of *HB-Phone* over 502 samples/trials in Figure 10. These data were collected over a period of 7 months, covering different environmental noise in the laboratory. Here, we group the samples into 6 groups, based upon the heartbeat rate reported by the pulse oximeter, 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 502 samples is 1.30%. In this scenario, the cutoff frequency value for the low pass filter does not have a noticeable impact on the average estimation accuracy; any value above 6Hz yields a comparable performance. These results demonstrate that geophones are able to detect heartbeats through a mattress.

When the Subject Has Body Movements: It becomes much more challenging to accurately extract heartbeats while the subject has body movements while lying on bed because their signals overlap with heartbeat signals in the frequency domain and their amplitude is usually much larger. In *HB-Phone*, we

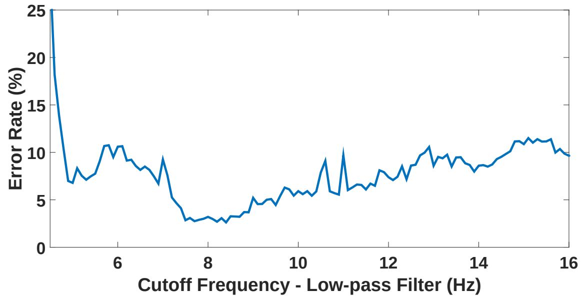


Fig. 11: The average estimation error rate with different cut off frequency values for the low-pass filter. Results show that a frequency value around 8Hz gives the best results, which also agrees with the observation in Figure 9.

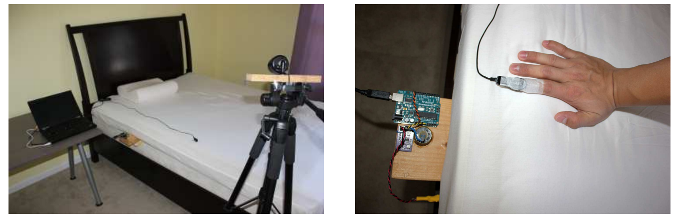
carefully design the low-pass filter to minimize the impact of body movements on the geophone signal, as discussed in Section III-A. Our results show that while challenging, *HB-Phone* is able to detect heartbeats with an average error rate around 3.87%.

In order to separate geophone responses caused by heartbeats and those caused by body movements, our signal processing method takes the following two measures: (1) applying a low pass filter to filter out frequency components above a certain threshold (since we observe that there are several heartbeat harmonic frequencies that are lower than body movement signals), and (2) finding the periodicity within the signal (since heartbeats have stronger periodicity than other movements). As a result, the cutoff frequency's value is the key to *HB-Phone*'s estimation accuracy. We varied the cutoff frequency from 4.5 to 16Hz and reported the resulting average estimation error rate in Figure 11. We find that when the cutoff frequency is around 8.4Hz, *HB-Phone*has the best estimation accuracy, with an average estimation error rate of 3.87%. This also agrees with our observation in Section III-A from the FFT results shown in Figure 9 – the majority of body movements' frequency components have a sudden rise around 8Hz.

As in Section III-A, we categorize usual body movements into the following three groups: (i) impulse movements that include one-time movements; (ii) movements that last for seconds or even minutes, thus longer than an experiment window (30 seconds); and (iii) movements that last for a few seconds, thus occupying a portion of an experiment window. Fixing the cutoff frequency at 8.4Hz, we show the detailed estimation error rate for the three types of body movement patterns in Table I. We find that the average error rate is the highest for long-duration movements, and the lowest for impulse motions.

	Impulse Motion	Long Motion	Short Motion	Overall
Error Rate (%)	3.34	4.07	3.89	3.87

TABLE I: The average error rate for three types of body movement patterns. The error rate is the highest for long periods of movements and lowest for impulse motions.



(a) (b)

Fig. 12: Our deployment setting. (a) The *HB-Phone* prototype was easily installed on the bed. A video camera was used to collect ground-truth data for the subjects' movements. (b) A pulse oximeter was used to collect ground-truth data for the subjects' heartbeat rate.

B. Evaluation Phase II: Long-Term At-Home Deployment for Heartbeat Monitoring During Sleep

In the second phase of evaluation, we deployed the *HB-Phone* system in 9 subject's homes for a total of 25 nights. We also deployed a pulse oximeter and a video camera to obtain ground truth for heartbeat rates and body movements[5]. In total, we collected 181.1 hours' data. Our results show that *HB-Phone* is easy to use and robust against many different types of events that occurred during sleep.

Participants: We had a total of 9 volunteer participants for these experiments, including a total of 8 males and 1 female. The mean age of the participants was 26.3 years with a standard deviation of 3.9 years. The youngest participant was 22 years old while the eldest was 34 years old.

Experiment Procedure: Table II summarizes the 9 subjects' house, floor, and bed information, among whom 7 subjects had experiments for multiple nights, and 2 subjects had experiments for a single night each. In total, we conducted experiments for 25 nights.

For each experiment, we arrived at the subjects' home 30-60 minutes before their bed time and it took about 20 minutes to install a *HB-Phone* prototype, a pulse oximeter, and a video camera. Among these three devices, the latter two usually took more time to install – we had to make sure the pulse oximeter was secured on the subject's index finger, and the video camera could capture the view of an entire bed. The actual installation of the *HB-Phone* hardware was very straightforward; we just inserted the wood board (to which the geophone and amplifier are attached) between the bed frame and the mattress.

Right before the subject turned off lights, we turned on the system and started with a simple synchronization process: the subject uses the hand that has the pulse oximeter on to tap the mattress 20 times. We could capture this motion from all three devices, thus synchronizing their data. During our experiments, all participants slept through the night until the next morning. Upon waking up, they turned off all three devices. All the data collected were transferred to a PC for offline processing.

The average system "on" time per night was 7.2 hours. When processing the data, we removed the first few minutes data as well as the last few minutes data.

[5]We obtained the consent from all the participants before deployment.

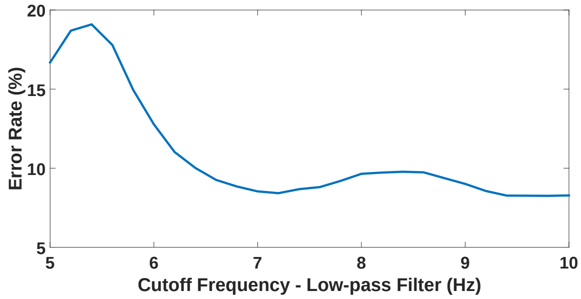


Fig. 13: The average estimation error rate with different cut off frequency values for the low-pass filter for the 25 nights' deployment data. The error rate drops significantly when the cutoff frequency is above 6Hz. In this study, we choose the cutoff frequency of 9.8Hz which gives us an error rate of 8.25%.

Cutoff Frequency for the Low-Pass Filter: In real-world deployment, the cutoff frequency value plays a very important role in determining the overall performance of *HB-Phone*. We first report the average estimation error rate with different cutoff frequency values in Figure 13. The results show that when the cutoff frequency is above 6Hz, the average error rate decreases significantly, which agrees with the observation presented in Figure 9. In the rest of this study, we choose the cutoff frequency value of 9.8Hz, which leads to an average error rate of 8.25%.

Heartbeat Rate Estimation Accuracy: Next we discuss the details involved in processing the long-term deployment data. We have collected data for a total of 25 nights. For each night, we partition the data sets into 30-second windows, and apply our signal processing algorithm to each window to count the number of heartbeats contained in that window. We compare this number against the number calculated from the pulse oximeter data, and compute the error rate in each window. The detailed results are summarized in Table III. We note that there are windows during which we were unable to detect heartbeats, and thus we categorize each window into one of the following four groups:

- *Ground Truth Missing.* On average, for 13.83% of the total number of windows, the pulse oximeter data was missing. We checked the video data during these windows and found out that the missing ground truth happened when the finger that had the pulse oximeter on moved. For these windows, we did not attempt to extract heartbeats from the geophone signal.
- *Amplifier Range Exceeded.* On average, for 5.22% of the total number of windows, the geophone signal amplitude reached the amplifier range (3.0V in our case) and no useful information could be extracted from these signals. We checked the video data and found out that during these windows, the subject had large body movements; for example, we observed turning, and leg/arm twitches. For these windows, we did not attempt to extract heartbeats from the geophone signal.
- *Heartbeats Undetectable.* On average, for 2.87% of the total number of windows, our signal processing algorithm failed to detect heartbeats – the number of detected heartbeats was either too small or too large to be reasonable. We checked the video data and found that there were usually moderate movements during these windows, such as rubbing the face, changing the lying position, moving the arm position, etc.
  To identify those windows that fall into this group, we searched all the ground truth results, and found the minimum heartbeat rate value (r_{min} = 41.6bmp) and maximum heartbeat rate value (r_{max} = 91.4bmp). Then assuming a 20% estimation error rate, we set the normal heartbeat rate range as $[.8\times r_{min}, 1.2\times r_{max}] = [33, 109]$. If the calculated heartbeat rate from our signal processing algorithm is outside of this range, we declare heartbeats are undetected during this window.
- *Heartbeats Detected.* On average, for 78.08% of the windows, we were able to detect heartbeats and compare the results from *HB-Phone* against the ground truth. The overall estimation error rate is 8.25%.
  We further broke down these windows into the following two groups: (1) windows without motions, and (2) windows with motions. Specifically, we look at the geophone signal during each window; if the difference between the maximum and minimum voltages in a window is less than 200mV, then we categorize this window as without motions (it could still contain minor motions such as finger movements). By looking at the data collected in 25 nights with an average error rate of 8.25%, we find that 45.70% of the windows are no-motion windows, which have an average error rate of 5.23% , while 54.30% of the windows have motions and their average error rate is 10.28%.

Subject	House Type	Floor Type	Bed Size	Bed Frame /Box	Mattress
S_1	Condo mini	Thick carpet over wood	Queen	Hardwood box	Thin sheet
S_2	Condo mini	Thick carpet over wood	Queen	Hardwood box	Thin sheet
S_3	Single family	Thin carpet over wood	Queen	Hardwood box	Spring mattress
S_4	Apt	Thin carpet over concrete	Queen	Hardwood box	Spring mattress
S_5	Single family	Thin carpet over wood	Queen	Steel platform	Spring mattress
S_6	Single family	Thin carpet over concrete	Queen	Box spring	Memory foam
S_7	Condo mini	Thick carpet over wood	Queen	Hardwood box	Thin sheet
S_8	Dorm	Wood	Twin	Hardwood frame	Futon
S_9	Apt	Thin carpet over concrete	Full	Steel platform	Memory foam

TABLE II: We have deployed *HB-Phone* in 9 subject's homes. This table summarizes the house type and bed information of these deployments.

Motions During Sleep: Finally, we take the geophone signal collected in the night of Sep. 30, 2015 (which has the lowest average error rate, 3.05%), and plot the error rate in every 30-second window in Figure 14. In the figure, we mark the 9 windows whose error rates are above 15%, and figure out the movements in these windows by looking at the video data.

In the first marked window, the subject stretched his leg and then scratched the face with his right hand. In the

Subject	% of windows ground truth missing	% of windows amplifier range exceeded	% of windows heartbeats undetectable	% of windows heartbeats detected	Average error rate (%)
S_1	5.87	6.73	2.58	84.82	14.08
S_2	9.86	3.14	1.94	85.06	6.64
S_3	28.16	6.22	3.62	62.00	13.53
S_4	19.34	6.97	3.48	70.21	8.43
S_5	10.18	0.60	1.20	88.02	3.05
S_6	12.93	0.49	2.20	84.38	5.31
S_7	10.18	4.38	2.19	83.25	5.41
S_8	23.66	1.10	4.88	70.36	7.22
S_9	8.69	0.36	0.84	90.11	4.45
Overall (25 nights)	13.83	5.22	2.87	78.08	8.25

TABLE III: We deployed the *HB-Phone* prototype in 9 subjects' homes. For each subject's data, we report the percentage of windows (30 seconds) during which the ground truth data was missing (P_m), the percentage of windows during which the amplification maximum range was reached (P_r), and the percentage of windows during which our signal processing algorithm failed to detect heartbeats (P_f). Then the percentage of windows during which we detected heartbeats is calculated as $1-(P_m+P_r+P_f)$. For these windows, we report the average estimation error rate. On average, we could detect heartbeats for 78.08% of the windows, with an average error rate of 8.25%. The results strongly suggest that *HB-Phone* provides a compelling solution for heartbeat monitoring during sleep.

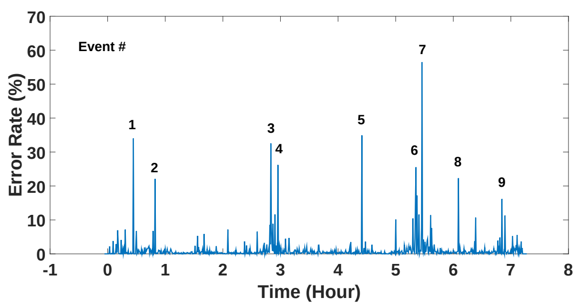


Fig. 14: In this figure, we calculate the error rate every 30 seconds for 7.3 hours on the night of Sep. 30, 2015 from 11:57 PM to 7:16 AM. Here, we mark 9 events on the figure whose error rate is above 15%.

second marked window, the subject's chest twitched. In the third marked window, the subject scratched his chest. In the fourth marked window, the subject scratched his face and then placed the hand back to the chest. In the fifth marked window, the subject scratched his face and then changed his facing direction. In the sixth and seventh marked windows, the subject scratched his nose. In the eighth window, the subject had an twitch in his left arm and then moved his left hand. In the ninth marked window, the subject scratched his face and placed the hand back to the chest. Then, he stretched his leg.

We note that these windows had high error rates mainly because the subject had a combination of multiple body movements – each single movement alone usually could be effectively filtered out by *HB-Phone* as observed in other windows. In our ongoing research, we will continue to improve the effectiveness of *HB-Phone* and lower the overall error rates.

V. Related Work

A. Overview of Existing Bed-Mounted Heartbeat Sensors

Quite a few bed-mounted heartbeat sensing systems have been developed. We can broadly categorize existing bed-mounted heartbeat monitoring sensors into the following categories (based upon the sensor modality): air/water pressure sensors, e.g., those in [30], [14], [28], [26], [19], [18], [17], or piezoelectric sensor [13], [29], [23]; force sensors, e.g., those in [16], [12], [10]; optical sensor, e.g., those in [11]; radar sensor, i.e., those in [15]; ultrasound sensors, e.g., those in [31], and foil pressure sensor, e.g., those in [21], [8].

We note that, among these systems, few satisfies the following requirements – i.e., accuracy, low cost and ease to use – at the same time.

Sensors that Require Special Mattress/Cushion: Some systems require specialized mattresses to monitor heartbeats, which is cumbersome and may curb their wide adoption. For example, Watanabe et al. [30] proposed 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 a user's heartbeats. In [28], Tanaka et al. proposed 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] proposed 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] proposed to build a mattress embedded with a sensitive motion detector. The sensor has two sheets of different dielectric constants which generate an electric charge while rubbing against each other, where the charge is picked up by a capacitor-like antenna. Heartbeats are thus detected by observing the charge variation.

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] proposed to use a piezoelectric film sensor under one's back, near the heart. The sensor measures pressure fluctuation due to heartbeats. Wang et al. [29] proposed to use a polyvinylidene fluoride piezopolymer film sensor in the thorax area under the sheet. The sensor picks up pressure fluctuation on the bed caused by the heartbeats. In [8], a foil pressure sensor is placed in the thorax region under a thin mattress. Then a specially designed mattress is placed on top of the existing mattress and bed frame. Similarly, Zhu et al. [32] proposed to place two pressure sensors under a pillow, assuming that the user will always use the pillow during sleep.

Some systems assume users always sleep on the same spot. Mack et al. [22] proposed to place two pressure pads on the bed surface assuming the user always sleeps in the same location. Bruser et al. [11] proposed 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] proposed to place a slat of four strain gauges under the thorax area in the bed slatted frame. Rosales et al. [26] proposed to use four water transducers that are placed vertically between mattress and bed frame, close to the subject's back area.

Custom-Built Sensors: Some systems require custom-built sensors. Heise et al. [18] proposed to use a hydraulic bed sensor that consists of a self-built hydraulic transducer and an integrated pressure sensor. Choi and Kim [15] proposed 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. Heartbeats and respiration are captured by detecting the phase shift between the original signal and the reflected signal.

Costly Commercially Off-the-Shelf (COTS) Sensors: Some systems use expensive COTS sensors. For example, sensitive load-cell sensors placed underneath bed legs can measure the vibration of heartbeats as discussed in [16]. Nukaya et al. [23] proposed to use a piezoceramic system to detect heartbeats. The sensor is bonded to the stainless steel plate sandwiched between floor and bed legs.

Sensors That are Hard to Install: Some systems require a considerable amount of manual installation effort. For example, Yamana et al. [31] proposed 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.

B. Overview of Signal Processing for Heartbeat Detection

One of the main challenges faced by many heartbeat sensors is to differentiate heartbeats from respiration. Most of studies address this challenge through the fact that these two activities have very different frequencies. Below we summarize popular signal processing methods for heartbeat detection:

- *Filtering*. In [28], bandpass filters are applied to differentiate these two. In [18], a low pass filter and windowed peak-to-peak deviation is computed for heartbeat detection. In [11], highpass and lowpass filters are applied and continuous local interval estimation algorithm is used to extract the beat-to-beat intervals. In [31], envelope detector and bandpass filter are applied for different detection purposes.
- *Decomposition*. In [13], Empirical Mode Decomposition (EMD) is applied to the signal, and respiration and heartbeat waves are reconstructed by summing up waves from EMD at different frequency ranges. In [29], wavelet multi-resolution decomposition analysis is used for the detection of respiration and heartbeats.
- *Peak Finding Algorithm*. In [15], the peak finding with power spectral density is utilized to extract heartbeats. 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.
- *Machine Learning*. In [12], an 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 [26], a k-means clustering method is used to extract heartbeats from the input signal.
- *Discrete Fourier Transform Analysis*. In [21], sliding Discrete Fourier Transform is applied on heartbeat signal and principal component analysis on respiration signal.

The problem we face in this study is more challenging than merely differentiating heartbeats and respiration. Firstly, geophone is insensitive to low-frequency movements such as respiration. Secondly, in this study, we seek to extract heartbeats in the presence of other types of body movements, which are often within the same frequency range as heartbeats. Finally, in addition to controlled experiments within the laboratory environment, we also installed our system in 9 subjects' homes and measured their heartbeats for 25 nights.

VI. Concluding Remarks and Future Direction

In this paper, we have developed *HB-Phone*, a bed-mounted heartbeat monitoring system that uses a geophone sensor to capture and extract heartbeats during sleep. The geophone is highly sensitive to movements whose frequency is above a certain threshold, while insensitive to lower-frequency motions such as respiration. This characteristic lends itself to heartbeat detection since each heartbeat pulse contains a high-frequency component that can generate harmonic frequencies that geophones can easily detect. Compared to other existing solutions, *HB-Phone* uses affordable off-the-shelf hardware, making it is very easy to deploy with an individual's existing bed, while also providing accurate and robust heartbeat detection.

We have built a *HB-Phone* prototype and conducted extensive experiments that involved 43 subjects. We compared the heartbeat rate estimated by our prototype with that reported by a pulse oximeter. From a sample of 34 subjects, we collected 502 30-second heartbeat data during a time when the subject was lying still, and found that the average estimation error rate was 1.30%. We also collected 301 30-second heartbeat data from a time when the subject was lying on bed and making a variety of different movements. During this scenario, we found that the average estimation error rate was 3.87%. We have also installed our prototype in the homes of 9 different subjects for a period of 25 nights, and found that *HB-Phone* can detect heartbeats with an average error rate of 8.25%. These results demonstrate that *HB-Phone* provides a viable solution to at-home heartbeat monitoring during sleep. In particular, this study provides the first, strong evidence that geophones can be used as a low-cost solution for at-home sleep monitoring. Looking forward, there are several challenges that remain before such a technology can be deployed as a long-running solution to sleep monitoring. Notably, our future work will focus on developing detailed signal processing algorithms that focus on detecting and classifying the heartbeat shape and other detailed information about heartbeats.

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