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Non-contact home health monitoring based on low-cost high-performance accelerometers

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Abstract— **Many current home health monitoring systems are based on wearable sensors, which may compromise patient compliance and adherence due to the irritation or inconvenience of wearing, maintaining and charging such devices. In addition, most existing systems can only acquire limited relevant data and thus fall short of clinical value. In an effort to address these limitations, this paper reports the initial study of non-contact home health monitoring based on custom-designed low-cost ultrasensitive accelerometers. These sensors were developed based on a unique cascaded asymmetric-gapped cantilever structure and achieved a resolution orders of magnitude better than the ones used in smart phones and other wearable devices. Using these new sensors, we successfully demonstrated non-contact recording of ballistocardiogram (BCG), caused by the momentum of blood flow during cardiac cycle, mainly from beds, but also from the floor, chairs and sofas. Heart rate, respiration, and other physiological information can be extracted from the BCG data. We also demonstrated 3-dimensional (3-D) BCG measurement capability by mounting 3 sensors to the bed in orthogonal directions. 3D BCG not only offers richer vital signs potentially, but also enables identification of postures and thus more accurate tracking of BCG variation. This research may lead to a new home health monitoring system, which is not only unobtrusive, attendance-free, low-cost, but also offers rich physiological information.**

Keywords—home health monitoring; non-contact monitoring; Ballisocardiogram (BCG); accelerometer

I. INTRODUCTION

As our society ages, the number of patients with chronic cardiovascular diseases is growing, burdening the already over-stretched healthcare system. Home monitoring systems promise to improve the quality of life, provide early prognosis, reduce the chance of re-hospitalization, decrease mortality rate, and reduce the overall medical cost. Not surprisingly, this exciting field has attracted a lot of attention from both academia and commercial sector and many progresses have been achieved. However, up to now the potential of home health monitoring has not be fully realized. From hardware perspective, two major technical reasons for this exist. First, many home monitoring systems require attaching or wearing a device on the body. The advantage of wearable devices is their 24-hour continuous monitoring capability. Nevertheless, the patient compliance and adherence of wearable device is a concern due to the inconvenience, irritation, and the extra effort of wearing, maintaining and charging such devices. Actually, the poor patient adherence is already a big issue for disease management. For example, a study of 202 heart failure (HF) patients found out that only 14% of patients weighed themselves daily and only 34% taking all medications as prescribed [1]. Moreover, some wearable patches may cause skin irritation, redness or permanent damage with long–term use. Second, most existing home monitoring systems can only acquire limited vital sign information and thus fall short of clinical value. Heart rate monitors for example give some information on heart function but provide limited physiological insight for most patients with cardiovascular disease. The lack of usable data may also account for the ineffectiveness of home monitoring on HF found in a number of large scale randomized controlled trials [2, 3].

The ideal home monitoring systems should be unobtrusive, require minimum attendance, have little or no disruption to an individual's daily routine, affordable, and more importantly, be able to provide clinically important information. Toward this end, this paper reports a vibration-sensing based home monitoring system, which is not only unobtrusive, attendance-free, low-cost, but also offers a rich reservoir of physiological information.

It is well-known that the human body is a rich source of motions and vibrations, due to walking, running, posture change during sleep and other physical activities. That's the reason vibration/motion sensors have been integrated into smart wristbands or smart watches, e.g., Fitbit, Jawbone, Apple Watch, etc., for activity and sleep monitoring. Activity monitoring has also been demonstrated using accelerometers in smart phones. These devices use MEMS accelerometers, which typically have a noise floor in milli-gravity (mg)/√Hz or sub-

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mg/√Hz levels. For example, a typical MEMS accelerometer, VTI technologies CMA 3000-A01, has a resolution of 0.3 mg/√Hz [4] .

Our approach is based on the fact that physiological activities inside the human body are actually a constant source of vibration as well. For example, the blood circulation during every cardiovascular cycle (systolic and diastolic) generates a recoil vibration of the body, which can be captured and graphically represented as a ballistocardiogram (BCG) [5]. As explained later, BCG contains a rich reservoir of physiological information of cardiovascular and respiratory systems. By basic mechanical theory, this recoil vibration will propagate to objects, such as beds or chairs, where the subject is in contact. In principle, we can unobtrusively detect BCG by attaching accelerometers to beds or chairs. However, such BCG vibration is very weak and it is challenging to detect BCG from furniture using MEMS accelerometers. To measure BCG accurately and reliably, we developed a totally different category of accelerometers - those that can detect vibrations down to ~10s nano-gravity (ng)/√Hz level, 3-4 orders of magnitude better than typical MEMS ones used in smart phones and wristbands with noise floors in mg/√Hz or sub-mg/√Hz level. Achieving this would enable detection of very small BCG vibrations, and permit unobtrusive physiological activity monitoring.

The rest of the paper is structured as follows: First, the clinical value of BCG for home health monitoring is discussed briefly. Next, the development of the new ultra-sensitive accelerometers, including a short review of existing BCG sensors and the operating principle, design and optimization of the cascaded asymmetric-gapped cantilever, is presented. Subsequently, the BCG measurement results recorded by newly developed accelerometers are presented and discussed. 3-D BCG and posture extraction are then discussed. The next section is a discussion of some practical issues of BCG based home health monitoring and future developments. Finally, a brief conclusion is presented.

II. Clinical value of BCG for home health monitoring

BCG is the body's reaction force to the ejection of blood during cardiac cycle and is affected by the hemodynamics of the cardiovascular system. The basic concept of BCG was first reported in 1877 by Gordon [6], and was extensively researched more than half century ago [7-14]. The amplitudes, time intervals and slopes of the BCG waveforms can be used to extract valuable clinical information, such as the left ventricle contraction force and the contractility [15]. However, BCG was not successfully adopted clinically as a diagnostic tool for a couple of reasons. First, the equipment for BCG measurement, typically a specially designed swing table, was bulky, heavy and expensive (e.g., $25000, 2008 dollars [16]). Second, there was significant variation from one subject to another, making the inter-subject comparison or interpretation difficult [16]. While such a concern is important, for home health monitoring, the ability to measure intra-individual variability in BCG signals with fidelity is of greater interest. Prior research demonstrated that a change in an individual's BCG over time provides clear prognostic information [9, 11, 14, 17]. For instance, by recoding BCG signals of 100 recovering myocardial infarction patients over 18 months or longer, Mandelbaum et al. concluded that the BCG was a valuable prognostic indicator of functional recovery of heart [17]. For 65 patients with improved BCG, 55 of them recovered well and returned to their normal duties. Of 35 patients whose BCG remained abnormal, 11 died and 19 were cardiac invalid. In another study, Starr et al. tracked BCG of 211 healthy subjects over 20 years and concluded that decreasing BCG amplitude (e.g., I to J amplitude in Fig. 4) is closely correlated to degrading cardiac health [18]. In these studies, it was found that the BCG can provide prognosis of heart disease years earlier than other clinical evidence. Recently, Etemadi et al. found that the root-mean-square (RMS) power of the BCG is a good reflection of clinical status of HF (85 patient days from 10 patients, $p<0.01$) [19]. Consequently, there has been renewed interest in BCG as a personal or home monitoring modality [5, 20, 21].

What makes BCG even more attractive is that respiration information such as rate and strength can be extracted. Therefore, we can unobtrusively detect abnormal respirations such as apnea, hypopnea, dyspnea, periodic breathing and Cheyne–Stokes respiration, which are common HF symptoms and of prognostic value [2, 22-25]. Based on a clinical study of 62 patients with chronic heart failure (CHF), the number of apneas and hypopneas per hour has been found to be a powerful independent predictor of poor prognosis [23].

III. Sensor development

Due to the potential of BCG in personal and home health monitoring, a variety of new BCG sensors have been developed, trying to overcome the cost and size limitations of the swing-table equipment. Commercially available weighing scales that have been modified to acquire BCG signals have been evaluated in several different studies [16, 26-30]. Electromechanical films (EMFi) sensors, which are based on permanently polarized polypropylene film, have also been developed and embedded in chairs or beds to detect BCG signals [31-33]. Additional attempts to incorporate BCG waveforms capture in everyday life include placement of piezoelectric film sensors under bed sheets [34, 35], fiber optic force sensors within chairs and beds [36-38], pneumatic pressure sensors in air mattresses and cushions [39-41], force sensors installed under the bed posts [42-44], and strain gauges mounted to the slats of a hospital bed frame [45].

Despite improvements, these new BCG devices still have a number of limitations. Some sensors, especially optical fiber force sensors, are expensive. Weighing scales are only used for intermittent BCG recording and are susceptible to motion artifacts. In addition, most existing sensors still cannot obtain high-quality BCG signals reliably. Some pneumatic sensors [39] and force sensors [43] are not optimal for capturing the details of BCG waveforms. Other sensors (such as EMFi, piezoelectric film and optical fiber sensors) are very sensitive to positions or postures. The signal can easily degrade or get lost when the subject moves away from the optimal contact location.

We developed ultra-sensitive accelerometers that effectively address limitations of current BCG sensors. The ultrahigh sensitivity of new sensors enables robust and accurate BCG acquisition from chairs, sofas, beds, and even directly from the floor. In addition, these sensors can be fabricated with a low cost, making them very affordable.

The ultra-sensitive accelerometer is based on an asymmetric-gapped cantilever structure, as schematically shown in Fig. 1 (a). The top beam formed by a piezoelectric sensing layer ($w_2 \times t_2 \times l$) is separated from the bottom mechanical beam ($w_1 \times t_1 \times l$) by a gap. It is worth noting that the strain experienced by the sensing layer is proportional to the distance between the sensing layer and the neutral plane. This distance for the asymmetric-gapped cantilever is $d_2 = y_2 - y_c$, whereas for the conventional cantilever shown in Fig.1 (b), it is typically only half of the cantilever thickness $h/2$. Because of the gap, d_2 is much larger than $h/2$. Therefore, if the spring constants of the two designs are equal, the sensitivity of the gapped design will be significantly higher than the conventional one.

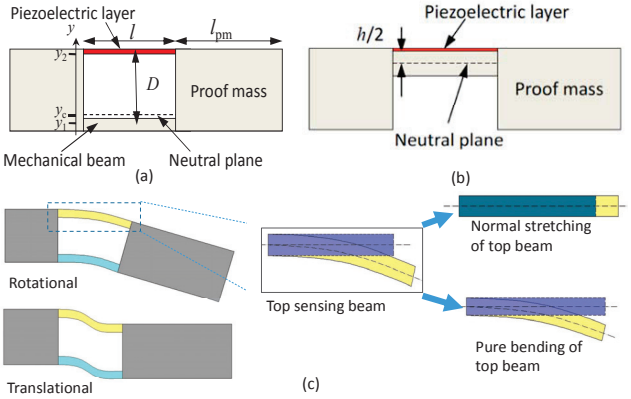


Fig. 1. (a) Cross sectional view of an accelerometer based on an asymmetric-gapped cantilever; y_1, y_2, are the positions of middle planes of bottom and top beams, respectively; y_c is the position of the effective neutral plane. (b) Cross sectional view of an accelerometer based on a conventional cantilever. (c) Energy distribution within the asymmetric gapped cantilever. What contributes to the output signal is the normal stretching of the top sensing beam.

This idea seems to be very straightforward. Nevertheless, the implementation of such an asymmetric gapped cantilever is actually very challenging. If not designed properly, the sensor's performance will be degraded instead of being improved. A comprehensive analytical model has been developed to fully understand and optimize the sensor design previously [46, 47].

It is worth noting that the deflection of the asymmetric-gapped cantilever under acceleration can be decomposed into rotational and translational/shear bending as shown in Fig. 1 (c). This is very different from the conventional Euler-Bernoulli beam theory where the shear bending is neglected. The vibration energy is distributed in different parts of the asymmetric-gapped cantilever with different forms as shown in Fig. 1 (c). What is effective in generating output voltage is only the energy stored in the top sensing layer in the form of normal strain. For instance, the shear bending leads to opposite stresses along the thickness direction of the piezoelectric layer, thus cancelling the voltage or charge generated. As explained in[46, 47], to maximize the energy in the top sensing in the form of normal strain, the following equation needs to be satisfied:

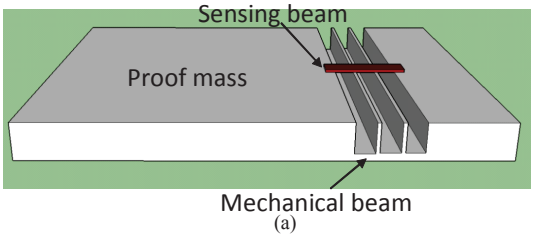
$$\frac{E_2 w_2 t_2}{E_1 w_1 t_1 + E_2 w_2 t_2} = \frac{1}{\sqrt{12}} \frac{t_1}{y_2 - y_1} \tag{1}$$

where E_1, w_1, t_1, y_1 and E_2, w_2, t_2, y_2 are the Young's moduli, width, thickness, and vertical position of the bottom and top beams, respectively.

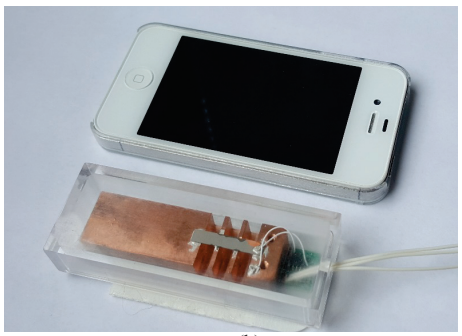
To sense low-frequency vibrations, such as BCG, it is necessary to reduce the spring constant to achieve an even higher sensitivity. For an optimized design, the effective spring constant k can be estimated by the following formula:

$$k \approx \frac{4 E_2 A_2 d_2^2}{l(l + l_{pm})^2} \tag{2}$$

Based on Eq. (2), the reduction of k in theory can be accomplished by reducing the cross sectional area of the sensing beam A_2. Practically, this will make the manufacturing or fabrication of the sensor challenging and pose reliability issues. Alternatively, we can increase the cantilever length l. However, this will make the shear deformation of the asymmetric-gapped cantilever dominant and reduce the energy efficiency. To address this issue, we invented a simple but effective cascaded asymmetric-gapped cantilever to lower the spring constant while maintaining the dominance of rotational bending. A design based on a three-stage cascaded gapped cantilever is schematically illustrated in Fig. 2 (a). The bottom mechanical beam has the same width as the proof mass, simplifying the machining process and thus reducing the cost. The sensor body was machined using cupper. The top sensing layer is lead zirconate titanate (PZT). The cross sections of the top and bottom beams are selected based on Eq. (1).



(a)



(b)

Fig. 2. (a) Schematic of the ultra-sensitive accelerometer based on a three-stage cascaded asymmetric-gapped cantilever structure. The red beam represents the piezoelectric sensing element (lead zirconate titanate, PZT). (b) Picture of an ultrasensitive accelerometer in comparison with an iPhone 4 smart phone.

A sensor prototype packaged with an acrylic case is shown in Fig. 2(b), in comparison with an iPhone 4 smart phone. The PZT layer is 0.5 mm thick and 2.7 mm wide. A charge amplifier is also integrated inside the case. For this sensor, more than 80 % of the energy is concentrated on the PZT in the form of normal stress. The resulting voltage sensitivity is 12.9 V/g (before charge amplifier), and resonant frequency is 230 Hz. As explained in [48], this accelerometer can reach ~10s ng/√Hz level, much better than typical MEMS ones used in smart phones. More detailed discussion, analysis and characterization of accelerometers based on cascaded asymmetric-gapped cantilever can be found in [48]. It is worth noting that this type of accelerometers can be readily mass-produced with a low cost, a highly desirable feature for the home health monitoring application.

IV. BCG RECORDING

The newly developed ultra-sensitive accelerometer has been demonstrated for detecting BCG on beds. The sensor was conveniently attached to the front frame of a bed using 3M damage free strips as shown in Fig. 3 (a). This sensor measures BCG in *x* direction, i.e., the head-to-toe direction. It is worth noting that the sensor can also be mounted in the inner surface of the frame or other locations. The output of the sensor (amplified by a charge amplifier) is recorded by a 16-bit data acquisition board (National Instrument, USB 6210) with a sampling rate of 120 Hz. Overnight sleep data have been successfully acquired from healthy volunteers. Figure 3 (b) plots a 2-hour period of representative sleep data. The large spikes are caused by body movements such as rolling. The detail of the BCG signal is revealed in Fig.3 (c). Figure 3 (d) shows the enlarged view of the signal caused by the body movement, together with the BCG pulses. During this 2-hour period, there were approximately 20 large-spike scenarios, most likely caused by body motions. In the remaining 98% or 99% of the period, BCG can be reliably recorded. All presented data are bandpass filtered from 0.2 Hz to 20 Hz. Note that both BCG signals and body movements are useful information in evaluating the sleep quality.

The basic information that can be easily extracted from BCG is the heart rate. Compared with other methods, such as photoplethysmography (PPG) and electrocardiography (ECG), the most significant advantage of BCG approach is that the heart rate is measured in a non-contact way. Namely, no devices or sensors need to be attached to the human body. Therefore, it is hassle free and will not cause any irritation.

It can also be observed from Fig. 3 (c) and (d) that the amplitude of BCG pulses is not constant. This is mainly because of the modulation of respiration. A more obvious result is presented in Fig. 4. The heart rate is 60 beats/min and the respiration rate is 7 breaths/min. The respiration information such as rate and magnitude can be derived from the envelope of BCG waveforms. Obviously, a promising application will be sleep quality monitoring. The cardiovascular and respiratory information extracted from BCG signals, and body movements are useful information in evaluating the sleep quality. This is also very beneficial for HF monitoring since dyspnea/apnea is an important symptom related to HF. It is worth noting that in Fig. 3 (d) there appears to be a short period of apnea (manifested by the constant amplitude of BCG) right before and after the posture change.

We have tested our sensors on 5 different beds and 5 healthy subjects. In all these cases, BCG signals have been successfully recorded. Generally, the BCG strengths are different among the subjects and different beds may modulate BCG differently. This will pose challenges on algorithms development.

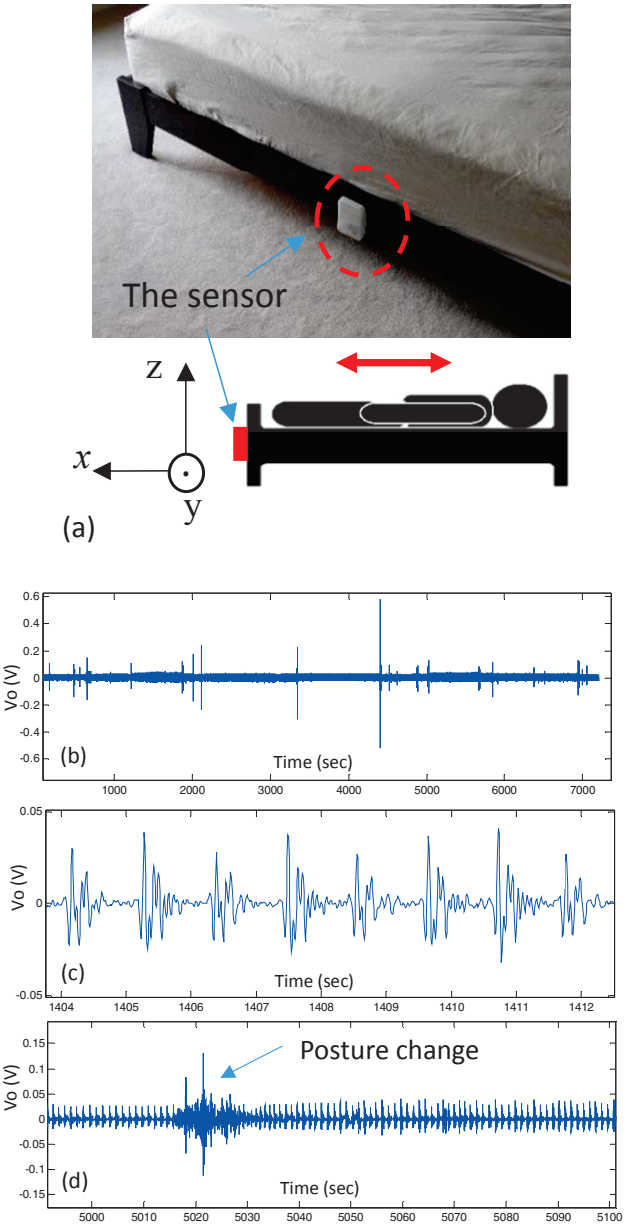


Fig. 3. (a) An ultra-sensitive accelerometer mounted on the front frame of a king-size bed; (b) representative sleep data (2 hours); (c) enlarged view illustrating the detail of BCG pulses; (d) enlarged view illustrating large spikes caused by body movement.

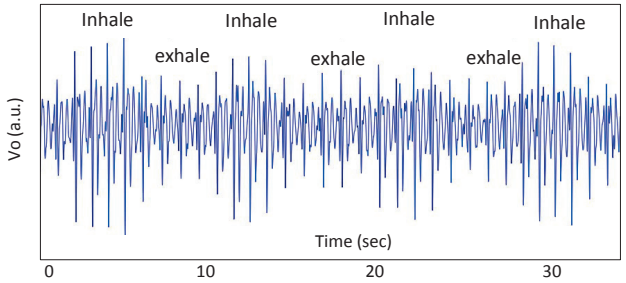


Fig. 4. Modulation of BCG signal by respiration.

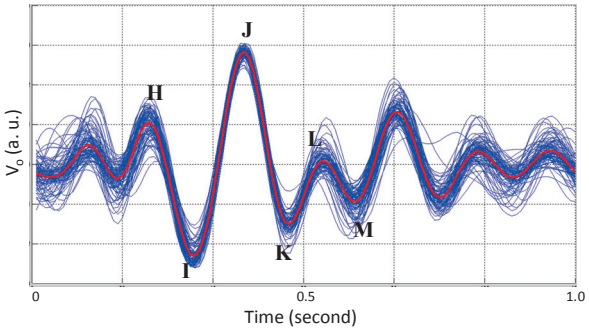


Fig. 5. Ensemble overlay (blue) and averaging (red) of 100 heart beats.

To extract the heart rate, we divided BCG signal into patches based on the heart beat cycle. Heart beat cycle segmentation in BCG is a challenging task because of motion artifacts or BCG fluctuations. We employed a novel BCG signal segmentation method using autocorrelation - the correlation of a signal with itself for finding repeated patterns in the signal. The period of a heart beat can be systematically determined by the autocorrelation function of a noise attenuated signal. Specifically, we first locate the S1 (systole) and S2 (diastole) components of heart beat that have higher energy in a heartbeat cycle and then find their period through autocorrelation. There will be several peaks in autocorrelation result, corresponding to the fundamental frequency of a signal as well as harmonic frequencies. Since the locations of peaks can be mapped to the period of a beat cycle as well as its multiples, the distance between two peaks can be recognized as the period of a heat beat cycle. Similarly, the respiration cycle can be segmented, and the respiration rate can be determined from BCG.

The ensemble average BCG waveform (t=100 beats, red curve in the figure) is computed as shown in Fig. 5 and will be used for feature extraction. Specific extrema in the cardiac cycle are denoted by the letters H, I, J, K, L, and M [49]. BCG waveforms are associated with different cardiovascular events[15]. For instance, the foot-ward I wave is caused by the rapid ejection of blood in the ascending aorta and pulmonary arteries, whereas the deceleration of blood in the ascending aorta and the descending blood in the abdominal aorta lead to J wave [50]. Decreasing BCG amplitude over time has been found to be closely correlated to degrading cardiac health [18]. In many cases, the BCG prognosis preceded other clinical evidence of heart disease by years. Therefore, in addition to sleep tracking of healthy subjects, the sensors developed can be used for long-term and home monitoring of patients with heart diseases.

The bed is an excellent platform for BCG monitoring at home, ensuring daily monitoring with minimum effort/attendance from the patient. Simultaneously, BCG can also be recorded from other furniture using our sensor. We have demonstrated the recording of BCG from a chair and a sofa by mounting the sensor underneath. Figure 6 plots recorded BCG signals from a 3-person sofa when a subject sit in the center and side sequentially. It is worth noting that the head-to-toe BCG force deflects the sofa in vertical direction like a bridge. As expected, the amplitude of the signal is larger when the subject sits in the center. Similar to bed BCG, the amplitude is also modulated by respiration.

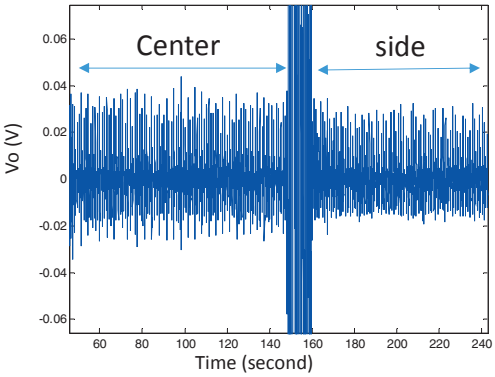


Fig. 6. The recorded BCG signal when the subject sit in the center and side of the sofa sequentially.

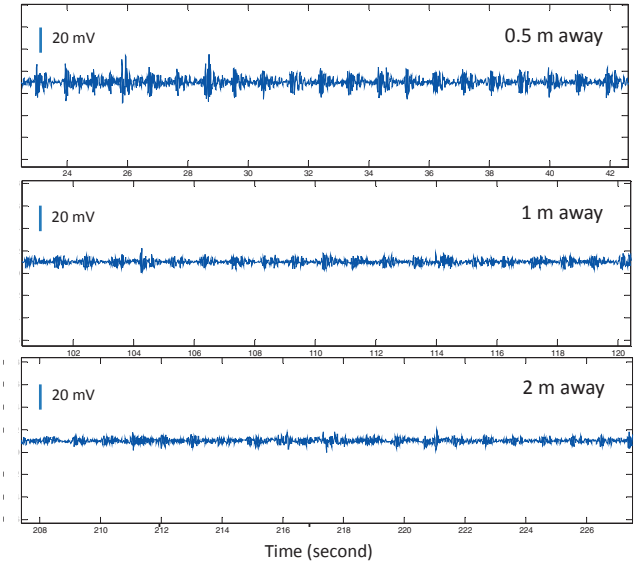


Fig. 7. BCG detection on the floor of a residential house.

Due to its ultra-high sensitivity, it is possible to detect BCG signals directly on the floor where the subject stands or sits on, as shown in Fig. 7. Therefore, it is possible to monitor BCG by simply attaching our sensors to the floors of the home. Nevertheless, it is worth noting that when the distance between the subject and sensor increases, the signal quality deteriorates.

The data in Fig. 7 were recorded on a carpet-covered plywood floor supported by 4 cm thick, 23 cm wide lumbers (with a pitch of 40 cm) in a residential house. It is more challenging to achieve BCG recoding directly from a floor of a commercial building, which not only is more rigid, but also experiences more environment vibrations.

V. 3-D BCG

As indicated previously, BCG is a 3-D vector; however, due to the limit of existing instruments, only 1-D BCG is measured for most studies. By attaching 3 sensors to the bed in orthogonal directions, 3-D BCG capability can be realized, as shown in Fig. 8. This 3-D capability is not possible with other sensors based on pneumatic pressure or contact forces. Note that signal amplitudes recorded by sensors do not represent the real amplitudes of the 3 BCG components of the subject, because the bed has different spring constants in 3 directions. It can also be observed that all the three components are modulated by respiration. However the strength of the modulation could be different on the three BCG components. For example, in Fig. 8, the *z* component is not modulated as much as the *x* component.

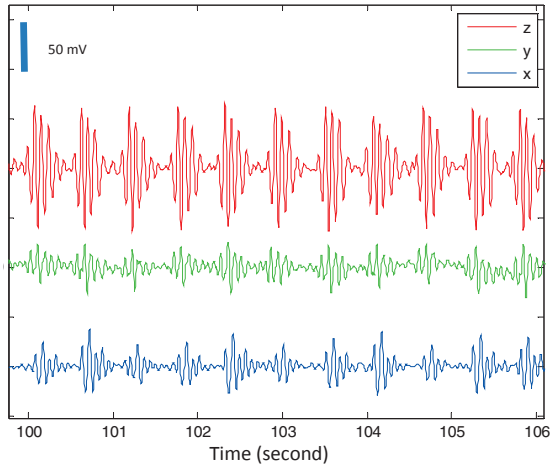


Fig. 8. 3-D BCG signal acquired from a regular bed (supine position, bandpass filtered from 0.2 Hz to 20 Hz). *x, y,* and *z* directions are illustrated in Fig. 1 (a).

Compared with other BCG sensors based on contact forces, an advantage of our sensor is that the signal can always be robustly acquired. As shown in Fig. 9, for all the three positions (left, center, and right of a king-size bed), 3-D BCGs were successfully recorded. Moreover, it can be observed that there are no significant changes of the amplitudes of *x* and *y* components when the subject moved from left to right. This is because under the BCG force, the bed moves in *x* and *y* directions similar to a rigid body. One the hand, in vertical direction, the bed deflects as an edge-fixed diaphragm. Therefore, *z* component is a function of position. As can be observed, the *z* component decreases as the subject moves from left to right, since the *z* direction sensor is placed on the left side of the bed.

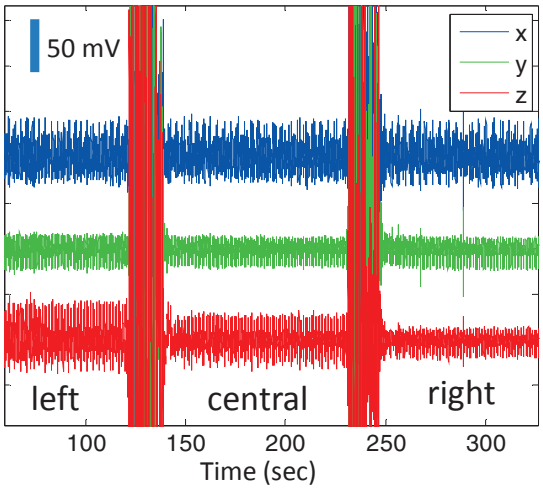


Fig. 9. Recorded 3-D BCG signals when the subject lay in the left, center and right (supine posture) of the bed sequentially.

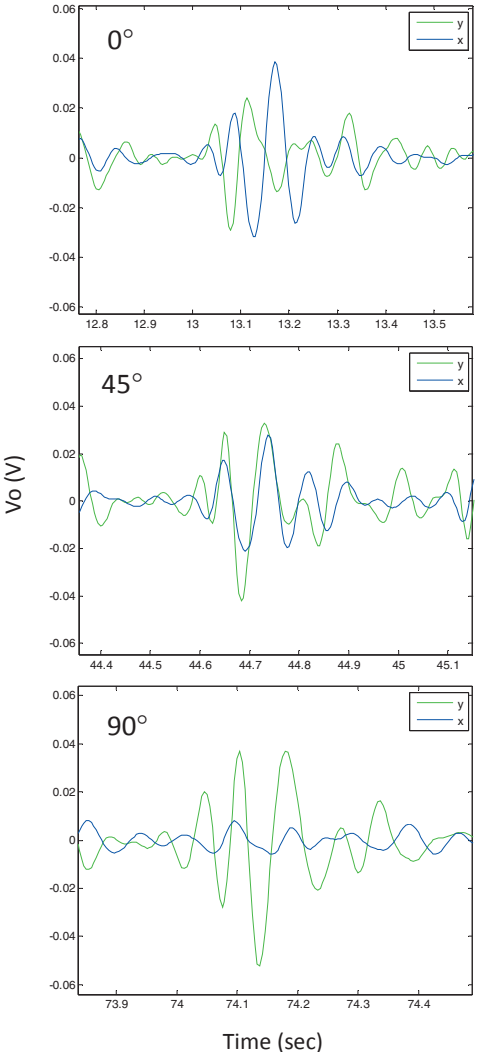


Fig. 10. The impact of the subject-bed angle on *x* and *y* components.

Figure 10 plots recorded BCG components in *x* and *y* directions as functions of the angle between the subject and the bed. As expected, as the angle increases, the *x* components decrease whereas *y* component increases. However, if the subject moves in a parallel way (i.e., the angle remains constant), then *x* and *y* components are insensitive to this position change.

It is worth noting that the posture could have significant impact on the recorded BCG signals. As shown in Fig. 11, the BCG components obtained from a healthy volunteer exhibit amplitude, morphology, and phase differences in three common sleeping postures. These results show that it is feasible to extract posture signatures from two main groups of 3-D BCG parameters: (1) the morphology, amplitude change of individual components; (2) phase and amplitude ratio among 3 BCG components.

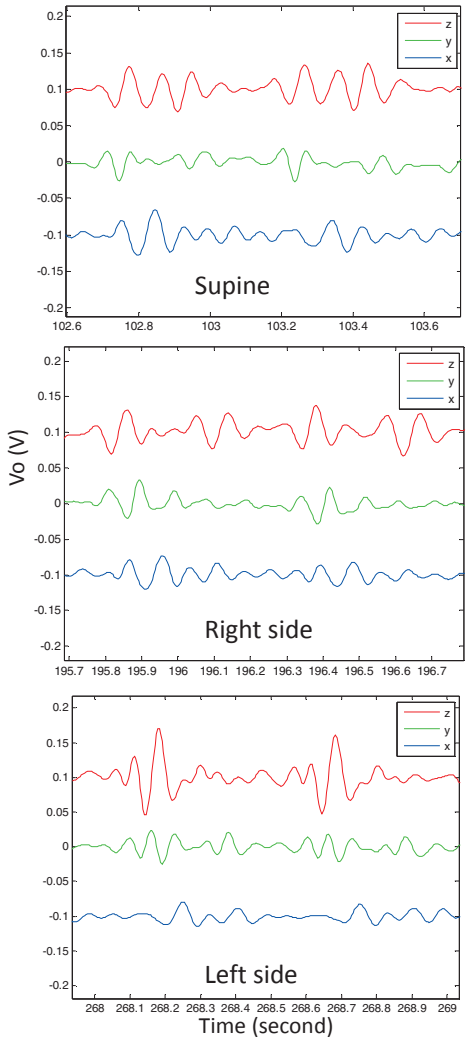


Fig. 11. 3-D BCG of a healthy volunteer in three different sleeping postures. *x* and *z* components are shifted vertically for clarity.

In our preliminary studies, we divided the collected data into one-second segment with 50% overlapping and then extracted the following time domain features from each segment: short-time amplitude, short-time energy, short-time zero-crossing-rate (ZCR), and the statistical features for these absolute attributes, such as the mean, maximum, minimum, one-order and two-order change rate and variance of short-time amplitudes, short-time energy and short-time ZCR, root mean square (RMS) energy. The time-domain signal is then converted into frequency domain using Fast Fourier transform. From Fourier power spectrum, we extracted frequency energy dynamic coefficient and frequency cepstral coefficients on 12 frequency band. We fused the time and frequency domain features of the corresponding segments into one feature vector, i.e., the signature, and use it to identify different postures using Support Vector Machines (SVM). SVM is a non-probabilistic classifier, which maximizes the margin (space) between the two closest samples in different classes using hinge-loss function. SVM has been shown to be highly effective for classification tasks, including automatic sound analysis. Our preliminary results show that SVM can successfully detect the postures with an accuracy higher than 95%. The identification of postures will help us to monitoring the BCG amplitude change more accurately.

DISCUSSION

Our ultimate goal is to investigate if the BCG signals recorded by the ultra-sensitive accelerometers can offer any clinical values for the management of some chronic diseases such as HF. For instance, we will verify if the change of BCG of the same subject over time is a good indicator of cardiovascular health. Nevertheless, to extract any clinically valuable information from longitudinal change of BCG, we have to eliminate other non-physiological factors that contribute to the variation of recorded BCG signals, for instance, sleeping posture. To obtain meaningful result, we must compare BCG under the same posture. 3-D BCG makes it feasible to develop algorithms that recognize bed postures.

Since our accelerometers are not directly attached to the human body, it is important to note that what they record are the mechanically modulated BCG signals. The mechanical properties of beds, chairs, sofas or buildings could vary significantly and there is a high likelihood of inter-subject differences in BCG signals. Therefore, it is a concern whether the algorithms developed for specific beds and limited amount of subjects can be applied to different beds and different subjects. It is expected that the heart rate and respiration detection will be robust. However, it is challenging to identify specific postures for different subjects on different beds. Fortunately, to extract longitudinal BCG variation caused by clinical factors, it is only necessary to group BCG sessions under the same posture, without knowing what specific posture it is. Because beds typically have anisotropic mechanical properties, i.e., different rigidity in *x, y, z* directions, we will avoid using features that are specific to a certain bed or subject, such as the absolute amplitude and only normalized features will be used for posture recognition. Alternatively, a training

session can be included in the beginning, to facilitate more accurate posture identification.

Another critical issue is that the resonant frequency of the furniture to which the sensor is attached could fall well within the bandwidth of the BCG signal. For example, some beds are very flexible vertically and thus have a low resonant frequency in *z* direction. This could impede the proper acquisition of BCG.

The environmental background noise is also a concern. For most residential homes or apartments, these background vibrations are intermittent and will not be catastrophic, especially during night. For example, when the air conditioning unit is on, the noise floor is only slightly higher. We can also use reference sensors to cancel these common mode noises if necessary. On the other hand, in some commercial buildings, such as hospitals, the environment vibration could overwhelm the BCG signal.

Another problem commonly encountered in real world is the multi-occupancy issue. Namely, two or more subjects can be present simultaneously. Accelerometers will record BCG signals from both or all occupants. Separation of individual BCGs is a classic but challenging signal processing problem [51]. Using 3-D BCGs or mounting multiple sensors in *z* direction will make the separation of BCGs from two or more subjects easier and more reliable.

While the bed-based system can continuously monitor BCG and respiration during sleep, we want patients to be monitored in daytime as well. This will be achieved through a future goal of developing smart homes by embedding multiple accelerometers in various locations. Other sensors such as humidity and temperature sensors, can also contribute to the intelligence of smart homes.

CONCLUSION

Low-cost ultra-sensitive accelerometers based on a novel cascaded asymmetric-gapped cantilever structure have been developed. These new sensors have been successfully demonstrated for non-contact BCG monitoring, especially from beds. Both cardiovascular and respiration information can be extracted from BCG signals. The unobtrusive nature of this new method causes minimum disruption to an individual's daily routine. Furthermore, with minimum required attendance of the patient, the bed-based BCG system guarantees daily monitoring, effectively addressing the patient adherence issue. Moreover, these new sensors can readily convert a regular bed to a 3-D BCG measurement instrument, potentially providing more complete information of the cardiovascular system, and also enabling the identification of sleep postures. Importantly, our novel sensor has low cost, minimizing the financial burden on patients and medical systems. This paper mainly reports the development of the ultra-sensitive accelerometer and sensor's capability of recording BCG signals in a non-contact way. In the future study, we plan to deploy our sensors to monitor real patients, investigate the feature extraction from the recorded BCG data, and explore how this information can benefit home health monitoring, such as sleep monitoring and the management of heart failure patients.

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