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Heartbeat Detection from a Hydraulic Bed Sensor Using a Clustering Approach

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Abstract—**Encouraged by previous performance of a hydraulic bed sensor, this work presents a new hydraulic transducer configuration which improves the system's ability to capture a heartbeat signal from four subjects with different body weight and height, gender, age and cardiac history. It also proposes a new approach for detecting the occurrence of heartbeats from ballistocardiogram (BCG) signals through the use of the k-means clustering algorithm, based on finding the location of the J-peaks. Preliminary testing showed that the new transducer arrangement was able to capture the occurrence of heartbeats for all the participants, and the clustering approach achieved correct heartbeat detection ranging from 98.6 to 100% for three of them. Some considerations are discussed regarding adjustments that can be done in order to increase the correct detection of heartbeats for the participant whose percentage of correct detection ranged from 71.0 to 92.5%.**

I. Introduction

Ballistocardiography (BCG) records the movements imparted to the body by the forces associated with contraction of the heart and acceleration and deceleration of blood as it is ejected and moved in the large vessels [1]. Recently, this old and noninvasive technique has gained renewed interest due to recent technological improvements; combined with advances in wireless and wired communications, it may serve as a strategy to provide the means for long-term monitoring.

Examples of BCG systems are bed-based systems such as a pneumatic-based system that measures heartbeat through a thin, air-sealed cushion placed under the bed mattress [2]; a system placed under the pillow composed of two incompressible vinyl tubes filled with water [3]; a pneumatic strip placed on top of the bed mattress, underneath the bed linens, that computes qualitative heartbeat (low, normal and high) [4]; a system consisting of four strain gauges, implemented by Bruse et al., which formed a full Wheatstone bridge glued to the center of the slat to measure its deformation in a slatted bed frame [5, 6]; and other sensing modalities such as charge-sensitive beds [7], piezoelectric films on chairs [8], and load cells [9].

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Since these novel approaches, all based on different devices and sensing modalities, generate non-standard BCGs, of particular interest are studies involving monitoring changes in the BCG over time [10]. For this purpose, the system described in [4] has been installed in the apartments of volunteer residents of TigerPlace, an active retirement community developed by Americare in affiliation with the MU Sinclair School of Nursing at the University of Missouri. As part of an integrated sensor network, it has already proven useful reporting qualitative changes on heart rate and respiration rate over time [11]. The need for quantitative measurements and additional information about the cardiovascular system motivated the development of a new transducer along with a new algorithm for detecting heartbeats and computing heart rate [12, 13]. This work presents a new transducer placement under the bed mattress and tests the system on subjects with different cardiac history, age, weight and height. It also shows preliminary results for detecting individual heartbeats using a clustering approach which addresses the potential variability across different subjects and mattress types.

II. Hydraulic Bed Sensor

A. Transducer construction

The overall procedure and materials for the transducer construction are the same as the working prototype described in [13]; however, the length and volume of water were modified to 22 in. and 14 oz. respectively. This new transducer and the placement experiments were introduced in order to improve the system's ability to capture heartbeat signals, since the transducer presented on [13] showed BCG segments where the heartbeat signals were not distinguishable for some participants of the study group [14]. One approach for solving this problem was to increase the sensitivity of the transducer by changing its length, volume of water, and position.

The series of experiments presented in [14] identified that the bed region where the transducer can effectively capture heartbeats is located between 7 in. and 24 in. (with respect to the headboard), which corresponds to the approximate position of the participant's upper torso. The new transducer length was modified to 22 in. and placed vertically under the mattress. The volume of water and placement were empirically chosen when tested on a diverse group of eight participants (ranging in age and body characteristics) [14]. The body characteristics considered were height and weight, under the assumption that the former will give an estimation of the transducer's length and the latter the approximate volume of water. The transducer's length was determined so that for all the participants it will be placed under the subject's upper torso. The volume of water to be filled into the transducer was estimated by considering the integrated pressure sensor features [15], verifying that the pressures transmitted from the weight of the body and mattress fall into its usable range and remain sensitive enough to detect the heartbeat signal.

B. Transducer Arrangement

The proposed bed sensor system uses four hydraulic transducers placed vertically under the mattress, covering the region located between 2 and 24 in. with respect to the headboard (Fig. 1).

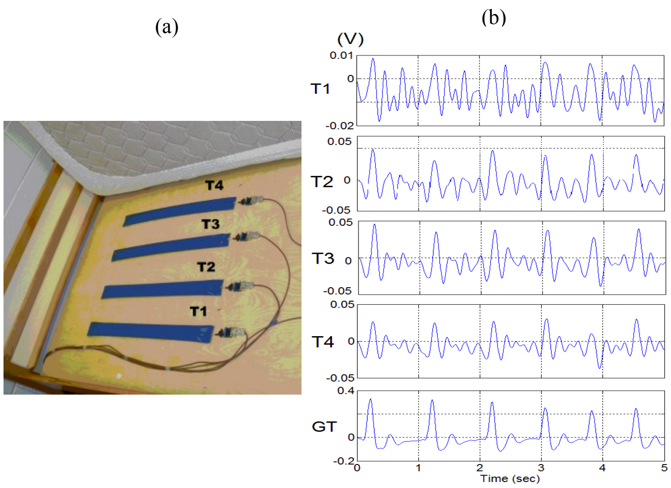

Fig. 1. Transducer arrangement and its BCG signals: (a) T1, T2, T3 and T4 are 22 in. long hydraulic transducers placed beneath the mattress at 2 in. with respect to the headboard of the twin size bed used for testing. (b) Five-second segments of the BCG signals corresponding to each transducer (from Subject 2) with ground truth (GT) from a finger sensor.

The new vertical transducer positioning was chosen since it effectively captured the heartbeat signal for the participants in [14], if placed between 2 in. and 24 in. and close to the subject's heart. This can be explained in part, since less of the transducer's area is being pressed on by other body parts, like shoulders and arms, allowing the transducer to capture only the chest movements. Additionally, the primary force being captured by the ballistocardiogram is the axial force (with respect to the body) of blood being ejected through the aorta [16]. Since monitoring during sleep is intended, three other transducers were added in order to cover the width of the twin-size bed used for testing. The distance between them was defined based on the neck-to-shoulder distance of the smallest participant, so two or more transducers would capture the heartbeat signals with the participant lying on the back, or at least one of the transducer if lying on the left or right side.

III. SYSTEM OVERVIEW

This section presents a block diagram (Fig. 2) of the new Hydraulic Bed Sensor (HBS) and describes the signal processing for detecting individual heartbeats.

BCG signals are recorded by four hydraulic transducers placed beneath the mattress (Fig. 1). Each transducer is connected to a pressure sensor; its corresponding heartbeat signal goes to the Analog-to-Digital converter (ADC) to get the subject's position, which is used to select the transducer signal to be processed for the heartbeat detection and the Amplifying/Filtering Card (AFC). Further filtering and amplification are performed by the AFC, details of the circuitry are presented in [13, 14]. The AFC output is digitized using an ADC connected to a PC for data storage with a sampling frequency of 100 Hz.

The transducer or transducers selected are the ones that exceed a voltage threshold, which is the voltage recorded when no one is lying on the bed. Every five seconds, the standard deviation of the transducer(s) signal is used as a threshold to evaluate the data (threshold = ±1*std). The segments labeled as valid are used in the heartbeat detection stage and are the ones that do not exceed the threshold specified.

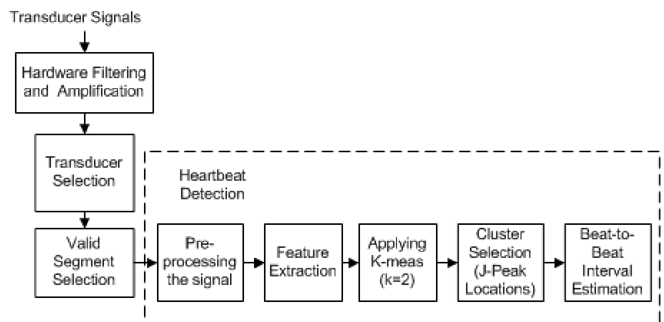

Fig. 2. Functional block diagram of the proposed system

IV. HEARTBEAT DETECTION

A. Pre-processing the HBS signal

The AFC output is bandpass filtered at 0.4-10 Hz to remove the low frequency respiratory components and filtered one more time using an 8-point average filter to smooth the signal before the feature extraction.

B. Extracting Features

The BCG signal captured by the system shows the occurrence of heartbeats for one or more transducers (Fig. 1); for convenience, we will assume that the beginning of an individual heartbeat is represented by the J-peak. Unlike the signal presented in [5, 6], our BCG signal does not exhibit a self-repeating pattern for the peaks that are around the J-peak, due to the presence of movement, respiration, or the system itself [17]. This approach will characterize only the J-peak and adjacent valley. Fig. 3 shows the three features extracted from the normalized BCGs.

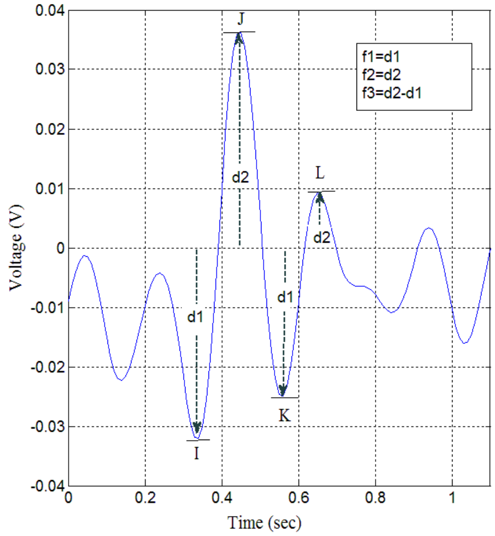

Fig. 3. Set of features: features extracted from the signal, f1: distance from 0 to depletion I, f2: distance from 0 to peak J, f3: summation of d1 and d2.

C. Heartbeat detection applying k-means clustering

Results from several tests have shown that the body characteristics, type of mattress and person's position with respect to the transducer will result in variations to the waveform and amplitude of the heartbeat signal. To address these variations, we investigated a clustering approach to identify the individual heartbeats. A machine learning approach using clustering techniques was presented in [5]. A modified version of the k-means algorithm was applied to a ballistocardiogram signal to extract the shapes of the repeating patterns. The signal captured by our system shows the occurrence of a heartbeat represented by the J-peak, but unlike the data presented in [5], it does not always exhibit a self-repeating pattern for the rest of the peaks.

Since the objective is to detect the occurrence of heartbeats, the k-means clustering algorithm was implemented with the number of clusters set to two, under the assumption that one of them will contain the J-peaks and the other will group the rest of the peaks. Then, the smallest cluster is assigned to the heartbeat class (HB) and the larger to the non-heartbeat class (NHB). Finally, the J-peak locations were compared to the ground truth (GT) signal extracted from a piezoresistive device worn on the subject's finger. K-means was chosen over other clustering techniques as a preliminary approach based on its simplicity and the data distribution observed for the study cases.

V. Experimental Methods

The new transducer arrangement was tested on a twin coil spring mattress with a thickness of 7 in.. Four participants, whose characteristics are described in Table I, were asked to lie down on the back for approximately 2 minutes for three consecutive times (total 6 min.). To provide ground truth, data were collected simultaneously from a pulse sensor connected to the subjects' finger. The BCG peaks were labeled manually as HB and NHB, based on the correlation between the J-peak and the pulse signal extracted from the GT signal.

Table I. Participants

Subject	Gender	Age	Weight (kg)	Height (cm)	Prior Cardiac History
1	male	31	79	187	No
2	female	32	54	163	Yes
3	Female	57	68	163	No
4	male	68	76	177	Yes

The set of features were extracted from the participants' signals as described in Fig. 3. The k-means algorithm was run with k=2. The performance criteria used in the evaluation was percentage of correct detection from the confusion matrix, where correct detection refers to the number of HB (J-peaks) and NHB (the rest of the BCG peaks) effectively grouped by the clustering approach when compared to the labeled peaks. Table II shows the number of instances, number of features computed, and number of NHB and HB for all the participants. Finally, the beat-to-beat intervals were estimated using the J-peak locations.

Table II. Instances and Features

	Number of Instances	Number of Features	Class Distribution	
			HB	**NHB**
Subject #1	3768	3	964	2804
Subject #2	2138	3	466	1672
Subject #3	3464	3	621	2843
Subject #4	1359	3	307	1052

VI. Experimental Results

A. System's ability to capture heartbeats

BCG signals captured by the hydraulic transducers show similarities in waveforms to the ballistocardiograms presented in [17, 18]. Visual inspection shows the presence of peak J and depletions I and K for all the recordings; however, peaks H, L and depletions G and M are not consistent for some segments of the BCG signals. Variation in waveforms can be explained by respiratory movements, involuntary movements and the system itself [17]. BCG signals for Subject 2 extracted from the four transducers are shown in Fig. 1(b), which illustrate the variation in waveforms due to the distance of the transducer with respect to the heart. BCG signals for Subjects 1 and 4 in Fig. 4 illustrate the variation in waveforms due to different heights and weights.

B. Heartbeat classification from clustering results

Table III presents the percentage of correct classification (CC[%]) of heartbeat and non-heartbeats, as well as the number of false positives and false negatives computed from the transducer(s) which showed the occurrence of a heartbeat signal (determined by visual inspection). T1 was not included since its BCG recordings did not show the occurrence of heartbeats. The BCG of Subject 1 was captured by three transducers, while for Subjects 2 and 4, only one transducer captured their heartbeats. This is in part

TABLE III. HEARTBEAT DETECTION CONFUSION MATRICES

		T2						T3						T4					
		B1		B2		B3		B1		B2		B3		B1		B2		B3	
		Predicted class																	
Subject	Actual class	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB
1	HB	120	0	120	0	81	1	120	0	119	0	81	1	120	0	120	0	79	2
	NHB	10	332	11	330	25	218	1	340	0	334	0	226	2	380	0	356	1	238
	CC[%]	97.8		97.6		92.0		99.8		100.0		99.7		99.6		100.0		99.1	
		HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB
2	HB							147	6	182	3	123	5						
	NHB							4	556	6	626	8	472						
	CC[%]							98.6		98.9		97.9							
		HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB
3	HB							110	0	110	0	90	0	110	0	111	0	88	2
	NHB							54	443	91	428	74	324	0	494	3	496	1	435
	CC[%]							91.0		85.5		84.8		100.0		99.5		99.4	
		HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB	HB	NHB
4	HB													51	57	85	24	64	26
	NHB													11	365	111	245	6	314
	CC[%]													86.0		71.0		92.2	

explained by the differences in body characteristics such as weight and can also be used for determining the position of the person on the bed.

Although percentages of correct classification for Subjects 1-3 were in the range of 97.9 to 100%, results for Subject 4 showed that some adjustment should be made. Fig. 4(c) shows a ten-second segment of the heartbeat detection for Subject 4, where the respiratory movement is still evident and artifacts due to other causes (such as involuntary movements) are also seen in the heartbeat signal.

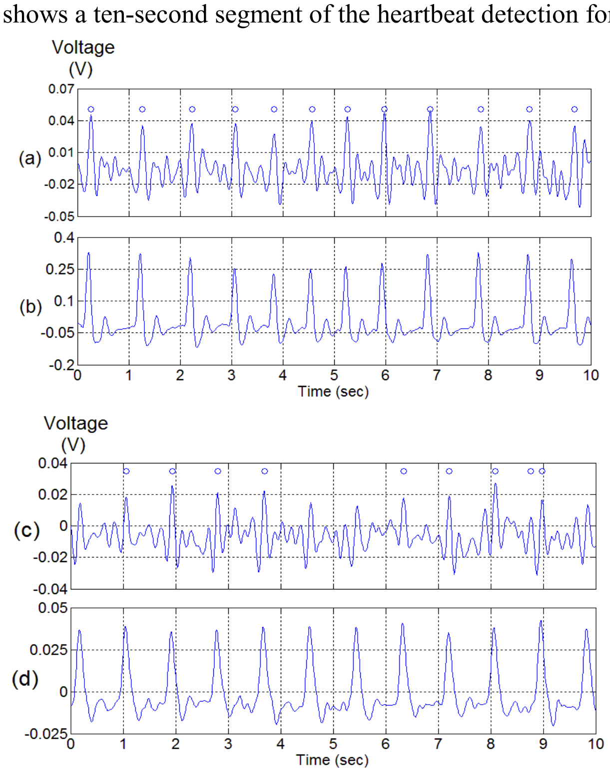

Fig. 4. Heartbeat detection using k-means algorithm: The J-peak is marked by a circle "o". (a) Ten-second segment of the BCG's recordings for Subject 1. (c) Ten-second segment of the BCG's recordings for Subject 4. (b) and (d) show the GT signal extracted from a piezoresistive transducer worn on the subject's finger.

The number of false positives and false negatives reflects this observation. It is clear from Fig. 4(d) that the heartbeat detection algorithm does not cluster the heartbeats that are at the beginning and the end of the inhalation and exhalation, due to differences in amplitude of the J-peak. Starr [18] suggests this is because the maximal cardiac force varies from beat-to-beat as the respiratory cycle alters the filling of the heart, decreasing the amplitude of the J-peak and I-depletion.

This problem can be addressed by testing new features and clustering algorithms. Also, the transducer length and volume of water can be modified to suit very tall/short and heavy/light individuals. Since the system is designed for sleep monitoring, we anticipate better performance when detecting the occurrence of heartbeats on sleeping segments, when the subject is still.

C. Beat-to-Beat interval

Additional information can be extracted from the J-peak locations such as beat-to-beat intervals, which open the possibility of the heart rate variability (HRV) studies. Fig. 5 shows beat-to-beat intervals for the best and worst cases of the study. Correlation between the beat-to-beat intervals extracted from the GT signal and the HBS signal can easily be observed from (a) and (b), whereas (c) and (d) shows the discrepancy. A different clustering approach, additional features, along with an efficient selection of useful segments could improve these results.

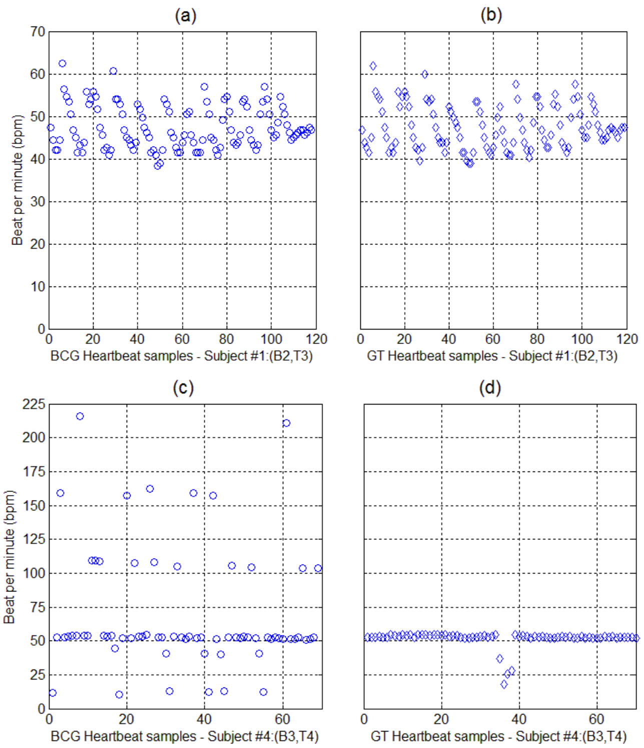

Fig. 5. Beat-to-Beat interval: (a) Subject 1: Segment B2 captured by T4. (b) Subject 1 GT. (c) Subject 4: Segment B3 captured by T4. (d) Subject 4 GT.

VII. Conclusion

Results indicate that the clustering technique applied to the BCG signals captured by the new HBS arrangement is effective at detecting the occurrence of heartbeats. Its simplicity and relative accuracy appear to be suited for routine use in heart rate estimation and HRV studies.

Keeping in mind our goal of long-term monitoring, future work has to be done to automatically assess the signal-to-noise ratio for different body characteristics, sleeping postures, bed mattresses, and body movements. More testing is envisioned for a new set of features and clustering techniques in order to characterize all the components of an individual heartbeat.

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