MotionScale: A Body Motion Monitoring System Using Bed-Mounted Wireless Load Cells

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***Abstract*—In-bed motion detection is an important technique that can enable an array of applications, among which are sleep monitoring and abnormal movement detection. In this paper, we present a low-cost, low-overhead, and highly robust system for in-bed movement detection and classification that uses low-end load cells. By observing the forces sensed by the load cells, placed under each bed leg, we can detect many different types of movements, and further classify them as big or small depending on magnitude of the force changes on the load cells. We have designed three different features, which we refer to as Log-Peak, Energy-Peak, ZeroX-Valley, that can effectively extract body movement signals from load cell data that are collected through wireless links in an energy-efficient manner. After establishing the feature values, we employ a simple threshold-based algorithm to detect and classify movements. We have conducted thorough evaluation, that involves collecting data from 30 subjects who perform 27 pre-defined movements in an experiment. By comparing our detection and classification results against the ground truth captured by a video camera, we show the Log-Peak strategy can detect these 27 types of movements at an error rate of 6.3% while classifying them to big or small movements at an error rate of 4.2%.**

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

I. INTRODUCTION

The ability to accurately monitor a person's body movements during sleep can enable an array of applications, ranging from sleep monitoring to abnormal body movements detection, such as restless legs. A number of bed-mounted sensing systems have been proposed for this purpose, including pressure sensors [14], [18], temperature sensors [19], ultrasound sensors [30], load cell sensors [6] and custom-made sensors [9]. Among these sensors, load cells have been shown to provide a viable solution for several reasons. Firstly, load cells are very affordable and readily available. Secondly, deploying a load cell based system can be very conveniently done, without interfering with the bed or how it is currently used. Thirdly, load cells (when placed under the bed legs) can easily capture the changes in body weight distribution caused by movements, especially when the movements are rather noticeable. As a result, we believe that load cells could potentially offer a practical approach to on-bed body movement monitoring.

Even though earlier studies point out that low-end load cells can be integrated to beds to detect some large body movements, whether they are able to accurately detect both large and small movements at the same time still remain a question, especially due to their limited sensitivity. In this paper, we set out to fill this void by designing and developing an accurate and robust body movement monitoring system based upon low-cost load cells (around $.70 per unit). We refer to this system as *MotionScale* as it can "weigh" the motions on a bed.

With *MotionScale*, we can simultaneously detect both large and small movements and classify these movements. We address these challenges through the following techniques. As far as the hardware design is concerned, we have carefully designed the amplifier circuit so that the circuit can handle a wide range of movements – as large as the whole-body roll over while as small as hand movements. We have also made great effort to minimize the power consumption of the system by turning off the system when it is not needed, e.g., during the daytime. As far as the software design is concerned, we have adopted several signal processing algorithms that can efficiently extract body movement signals. Firstly, we have designed algorithms to deal with frequent packet losses due to wireless interference in the environment. Secondly, our detection and classification algorithms work across different body weights, adopting a uniform threshold value regardless of the user's body weight. Thirdly, we devise three types of features that leverage the redundancy between multiple load cells to infer different in-bed movements. Through these optimization techniques, our experimental results that involve 30 subjects show that we can detect 27 types of body movements with an error rate of 6.3%, and can classify these 27 types of movements into big and small movements with an error rate of 4.2%.

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

1) We have developed an accurate, robust, low-cost, and easy-to-use in-bed body movement monitoring system, which is centered around low-end load cell sensors. The system consists of both hardware and software components. Its hardware components include load cell sensors, an amplifier, a power control circuit, and a wireless communication unit (which consists of an A-to-D convertor); software components involve interpolation, normalization, filtration, feature extraction, and detection and classification.

2) We have built a prototype and used it to instrument an experimental bed. We have used the experimental bed to collect load cell signals from 30 subjects who make 27 different body movements during each experiment. We have compared the detected body movements against the ground truth observed captured by a video camera, and found that the average error rate is 6.3%.
3) We have also used the same data to classify these 27 body movements into big movements (those that involve the entire body) and small movements (those that only involve one part of the body). We compare the classification results against the ground truth observed by a video camera, and found that the average error rate is 4.2%.

The remainder of the paper is organized as follows. In Section II, we describe the hardware system design of *MotionScale*, and in Section IV, we describe *MotionScale*'s signal processing algorithms. We present our evaluation setup and experimental results in Section V. In Section VI, we summarize the existing bed-mounted body movement monitoring systems, and compare their pros and cons. Finally, we provide concluding remarks in Section VII.

II. Overview of *MotionScale*

A. System Overview

In-bed body motion detection can facilitate a variety of research in Human Computer Interactions (HCI), smart home, and healthcare, such as home environment control, sleep monitoring, etc. Our main goal is to detect in-bed body motions by utilizing low-cost, low-overhead sensing techniques. Toward this end, we devise a motion detection system based on low-cost load cell sensors. The system can be easily integrated to an existing bed by placing the load cell sensors under each bed leg. The basic idea is to observe the electrical resistance changes on each load cell to infer possible body motions on the bed. Intuitively, when a body motion occurs, the body weight distribution changes, causing each load cell's resistance to change accordingly. In this work, we also focus on utilizing the relative load cell resistance changes to discriminate two types of body movements: *Big Movements* and *Small Movements*. Big Movements usually happen when there is a motion in the body's torso, such as turning to the left or right, and Small Movements happen when just a small part of the body moves, such as re-positioning the arm or head. Since our system can accurately detect in-bed body motions using load cell sensors, we refer to it as *MotionScale*.

As illustrated in Figure 1, in *MotionScale*, each load cell sends its data using a PIP-Tag (the wireless communication protocol described in Section III) with a sampling rate of 30 Hz. The base station, which is connected to the USB port of a laptop, conducts the following processing after receiving the data:

1) *Data Interpolation.* We first interpolate the data by applying the spline interpolation technique .
2) *Data Normalization.* We normalize the data by using subject's weight. Weight is also computed by our system. Because the system aims to detect motions, we just focus on the segment of data that contains large changes or oscillations. To achieve this, the system performs *Local Mean Removal* to remove the constant value in the load cell data by using a sliding window. we determine the segment of data only contains large changes and oscillations.

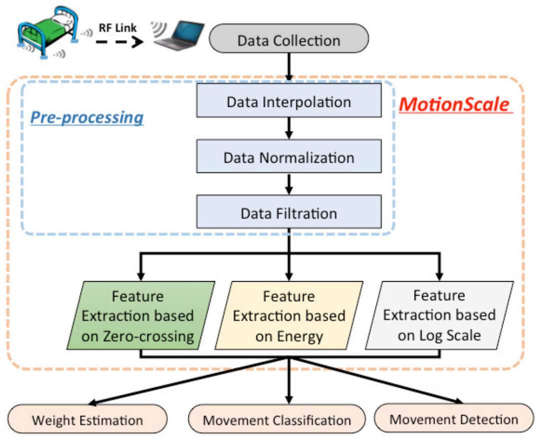


Fig. 1: Overview of system flow

3) *Data Filtration.* We filter the data by low pass filter with 10 Hz as a cutoff frequency. We remove the high frequency spikes or noise by this filtration.
4) *Feature Extraction.* We investigate three different features in this study, i.e., peaks in log-scaled sum of the square of the data (Log-Peak), peaks in the energy of the sum of the data (Energy-Peak), and valleys in zero crossing of the sum of the data (ZeroX-Valley).
5) *Motion Detection and Classification.* Using these features, we detect body movements and classify these movements as big or small movements using a simple thread-based scheme.

B. Design Challenges

Building *MotionScale* involves a number of challenges in design and implementation:

Load Cell Installation. Installing load cells under bed legs requires some careful consideration; direct installation may cause imbalance in pressure distribution on the surface. To address this challenge, we have designed a docking station for each load cell. This docking station consists of a washer that is placed under the load cell and a metal disk that is placed above with some pasting and cutting operations to get it fit.

Power Supplies. Each amplifier circuit need +3V, 0, and -3V. That could be something difficult because we use four load cells. We built 2 power sources with 3V and connect them together to provide all required voltages. We used these 2 power sources to feed all the four amplifier circuits. This could not be done easily on different places and different bed. probably need separate supplies for each circuit in a different environment.

Packet loss. Using wireless communication to transmit signal can lead to packet losses due to interference in the environment. For example, in our system, we observe an average packet loss rate of 10%. To address this challenge, we take into consideration the fact that we have multiple load cells in the system and there is sufficient redundancy in the data. Therefore, we use interpolation techniques to overcome the missing data problem, which will be explained in detail in Section IV. Moreover, we strive to minimize the packet losses through careful placement of the system, especially the base station.

III. MotionScale Hardware Design

Our *MotionScale* system consists of four major components: a load cell circuit, a differential amplifier circuit, a power switch circuit, and a wireless communication component. The load cell measures the voltage change due to motion. Because the raw voltage change values are usually very small, it is hard to accurately measure them directly. In order to capture such small changes in voltage, we design a differential amplifier circuit to amplify the raw voltage measurements for subsequent processing. In order to reduce its power consumption, our system exploits a power switch circuit that can switch the load cell and amplifier on or off, depending on a control signal from the communication component. In addition, we leverage a RF Transmitter (referred to as PIP-Tag, designed in our group [11]) that converts analog voltage signals to digital values, and send the digital values to the basestation Unit through low-energy wireless communications. The basestation is connected to a laptop through a USB port, from which we receive data for subsequent processing.

1) Load Cell Circuit: Our load cell circuit uses a half Wheatstone bridge, as shown in Figure 2 [1]. Specifically, it has two fixed-value resistors (the two resistors on the left-hand side of the bridge in the figure) and a three-wire load cell (shown on the right-hand side of the bridge in the figure). The voltage between the connection of two fixed resistors and the ground is a fixed value with/ without stress. The three-wire load cell is made of two single strain gauges in series. When the three-wire load cell is stressed, one of the strain gauges is compressed and results in a decreased resistance, and at the same time the other strain gauge is stretched and leads to an increased resistance. Thus, the voltage between the connection of these two strain gauges and the ground increases as a response to the introduction of the external weight.

The output of the load cell circuit is thus the voltage between these two connections, which is linear to the weight value

$$V_{in} = V_{in}^{+} - V_{in}^{-} = (\frac{R_3}{R_3 - R_4} - \frac{R_2}{R_1 - R_2}) * (V_{cc} - V_{ss}). \quad (1)$$

In our system, we use Generic YZC-161B load cells with a nominal load of 50 kg, as shown in Figure 3, which costs around $.70 and is generally used as a weighing scale.

2) Differential Amplifier Circuit: In general, the output of such a load cell is rather small – the maximum voltage change of the load cell is less than 6 mV under stress corresponding to the gravity of 50 kg object/subject (its capacity). This makes it difficult to get the accurate value from the A/D converter. Thus, we use a Differential Amplifier circuit to enhance the signal that we get from the strain gauge. The amplifier model that we use in our project is INA126 [2].

$$V_{out} = G * V_{in} = (5 + \frac{80k\Omega}{R_g}) \quad (2)$$

3) Power Switch Circuit: We also use a power switch circuit to turn on/off the power supply, which is a simple p-MOS FET and n-MOS FET circuit. The switch is controlled by the transmitter tag, which uses a pin to pull down to the ground to turn off the circuit or pull up to 3V to turn on the circuit. In this way, we can conserve a significant amount of energy when the measurement is not needed.

The whole circuit is shown in Figure 4.

4) Wireless Communication Component: We use a wireless communication system developed in our group (details can be found in [12], [11]) to convert the analog signal to digital values and then transmit them through wireless links. The system consists a transmitter that we refer to as PIP-Tags which contains a 10-bit A/D converter with the range of 0 to 1.5V. It is low-cost, low-power, and easy to program. The PIP tag has its own processor and radio transceiver. The basestation has the same hardware as the PIP-Tags, with a tuned 900 MHz monopole antenna attached. The basestation is also equipped

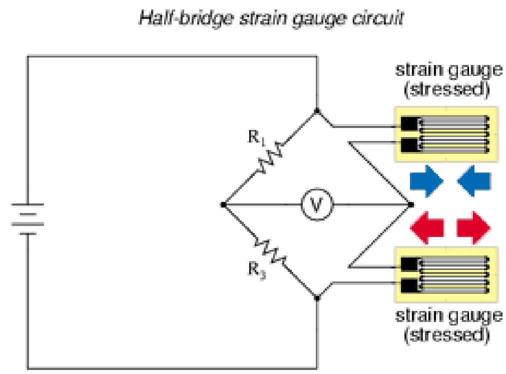


Fig. 2: Half bridge strain gauge circuit.

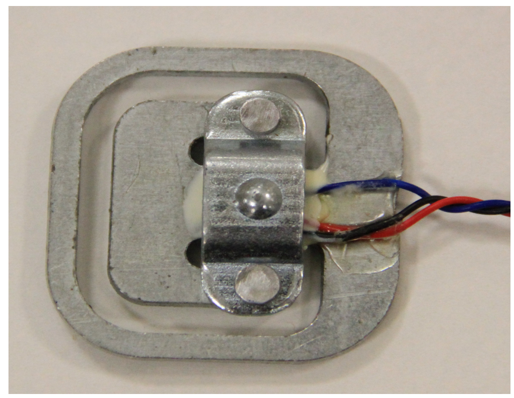


Fig. 3: The Load Cell.

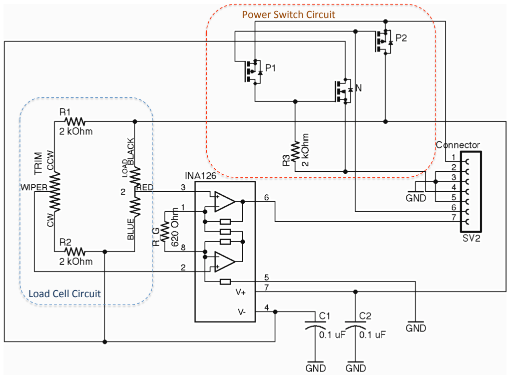


Fig. 4: The whole electrical circuit

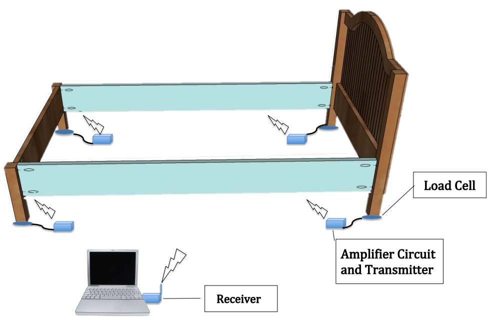


Fig. 5: The general overview of our system.

with a standard USB connection for data transfer to the laptop which runs the signal processing algorithms.

5) Assembling a *MotionScale* System: Our *MotionScale* system consists of four load cells, with each load cell placed under a leg of our experimental bed. We have 2 power supplies to provide the +3, 0, and -3V for all of the circuits. There is only one receiver that can be connected to any USB port in a laptop. This receiver collects all the data from the four load cells and transfer the data to a processing unit.

IV. MotionScale System Design

In this section, we explain how our system is designed to process the data from load cells to mitigate noise and further detect in-bed motions. The detection results can not only detect motions, distinguish big and small motions, but also can determine when the user lies on the bed, leaves the bed, and moves on the bed, which can facilitate a variety of applications in smart home and healthcare.

A. Data Pre-processing

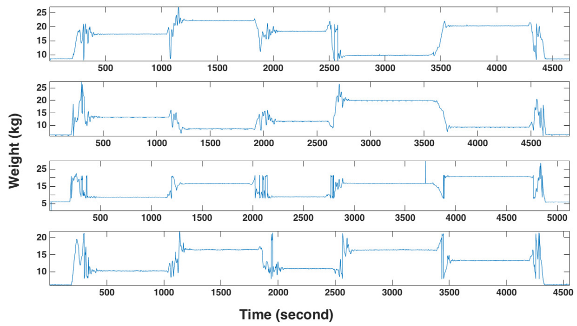
After raw data are collected from load cells, our system first performs a sequence of preprocessing steps to remove noise and determine the important segments that contain the data corresponding to motions on the bed. The Data Pre-processing is in three steps. First, the received data are interpolated to balance the samples that are unevenly distributed in time due to packet losses. Second, we normalize the data by estimating the body weight of the user and remove this constant bias from the data. Third, the system drops the local mean in the data and apply filtration with low pass filter to further remove the high-frequency noise.

Data Interpolation. In our work, multiple load cells use PIP-Tags to transmit the measured data in real time through wireless communications. Due to the high-noise nature of wireless communications, it is common to find that some data may be missing or have large errors when data packets from different load cells collide or corrupt with each other. To illustrate this, we conduct an experiment by collecting data from four load cells placed under the legs of a bed when a participant is asked to lie on the bed and perform some movements, such as turning left/right. Although the sampling rates are set to the same value on each of the load cells, the total number of data measurements received from four load cells are different. For example, when the sampling rate on load cells is set to 30 Hz, we find that about 10% of the total measurements from four load cells are missing in a time period of 3 minutes because of packet collisions. Such inconsistency in data from different load cells would severely impact the motion detection because the data cannot reflect the weight variation on different load cells during the same time period that has the same motion. In order to align the data from different load cells, we apply the spline interpolation technique to the data from different load cells to make sure the data from different load cells have the same length. From our experiments, we find that the frequency of most body movements is less than 2 Hz, and therefore, even after losing about 10% of the packets, we still have sufficient data samples for body movements according to the Nyquist Theorem [22]. Figure 6 presents the three-minute data measurements before and after the interpolation. In the original data, we can see that the data from the third row, for example, has about 5200 samples, which is more than others, and the variations caused by the user's movements are not properly aligned between different rows. After the interpolation, we have equal length and aligned activities in all rows.

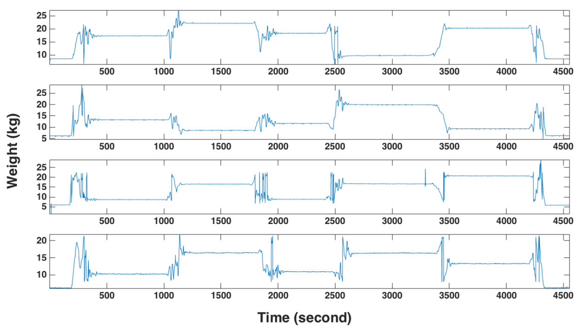
Calibration and Weight Estimation. Each load cell circuit and amplifier circuit has a voltage regulator to adjust the amplified voltage. However, that regulator is not exactly the same to all circuits. We propose to use calibration equations to determine the relationship between voltage values and corresponding weight values. Calibration was done separately to each load cell. We applied some known weight to each load cell and observe the corresponding output voltage, from which we derive the weight calculation parameters for each load cells. This step is a one-time effort, and the derived parameter values can be applied to all subsequent experiments.

In the experiment, we first collect weight measurements from the empty bed for 10 seconds, and then ask the participants to get in the bed and record the weight measurements. Intuitively, to determine the weight of a participant on the bed, we first need to remove the weight of the bed and and find the mean of the raw weight data.

Mean Removal and Filtration. We find that when in-bed movements happen, the weight measurements from load cells have oscillations. However, the oscillations are not obvious in the raw data. After we remove the local mean from the raw data, the oscillation associated with every movement

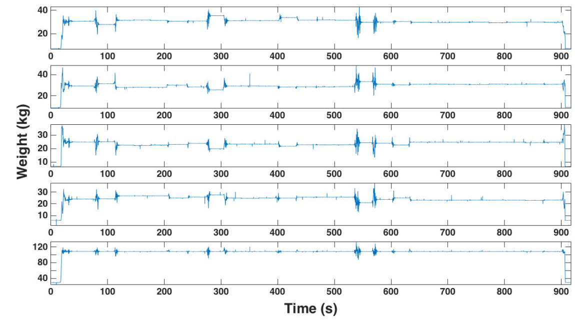


(a) The data before Interpolation

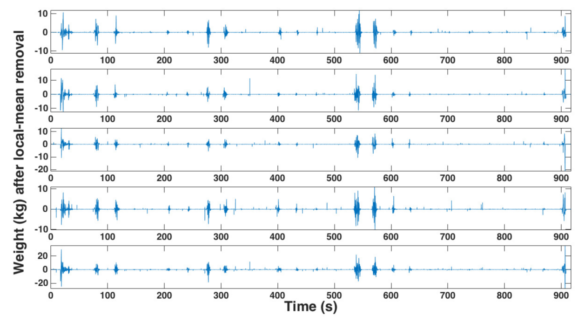


(b) The data after Interpolation

Fig. 6: The four raws of data before and after doing the interpolation on the data of 3 minutes experiment with some movements of a subject on the bed.



(a) The data before removing the local mean



(b) The data after removing the local mean

Fig. 7: The raws of data with their summation before and after removing the local mean. Local means 50 samples.

become more noticeable. In particular, we calculate the mean values in a moving time window of 50 samples. Figure 7 shows the weight measurements before and after removing the local means, where the data is collected from one of our participants with 27 in-bed movements. We can see that local mean removal can amplify the oscillation to improve the movement detection.

After that, the data is filtered using a low pass filter of a 10 Hz of cutoff frequency.

B. Feature Extraction

Next, we extract features from the preprocessed data and adopt a simple threshold-based detection/classification strategy. Below, we describe the three features we have explored and the corresponding detection schemes one by one.

Log-Peak Feature Extraction: Log-Peak uses the logarithm of a physical quantity instead of the quantity itself, which has the potential to have a good view to show both small values and large ones. Moreover, we find a way to merge the four signals into one and supply it to the log scaling to simplify the further processing. Specifically, we first square every raw data signal collected from each load cell sensor and sum them up to create a new merged signal, which is the summation of their squares. To make the system applicable for all people or subjects, we normalize the merged signal by dividing by the subject's weight. Log (i.e., natural log where log to the base e) is applied to the merged signal. The output of log scaling is very messy and doesn't reflect any good information, therefore we apply a low pass filter with a cutoff frequency

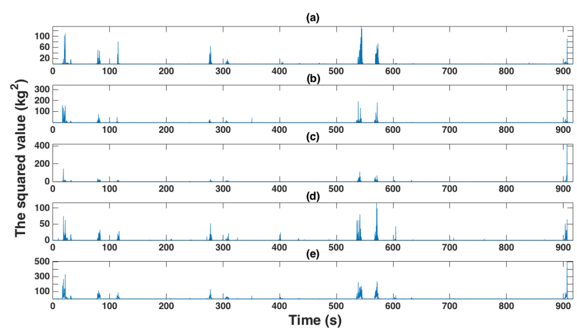


Fig. 8: (a) Square of the data from load cell 1. (b) Square of the data form load cell 2. (c) Square of the data form load cell 3. (d) Square of the data form load cell 4. (e) The summation of all squares.

0.2 Hz to the log's output. We get an observable pattern with a clear peak whenever there is an in-bed body movement. Figure 8 shows the squares of the four raw signals and their summation in the bottom line. Figure 9 shows the log output of the normalized summation result before and after filtration. Threshold is applied to find peaks, which also means to find movements. Also, another threshold is applied to classify these movements as big and small. More details about thresholds and movements classification will be discussed in V.

Energy-Peak Feature Extraction: We observe that there exists stronger oscillation with high amplitude in the collected load cell readings if an in-bed movement is performed. It means that signal has more energy in that portion of oscillation. Similar with log-peak feature extraction, we first sum

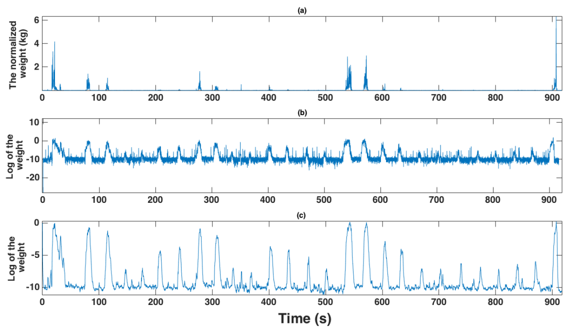


Fig. 9: (a) The Normalized summation of the squares. (b) The log result of the normalized summation before filtration. (c) The log result of the normalized summation after filtration (using 0.2 Hz low pass filter).

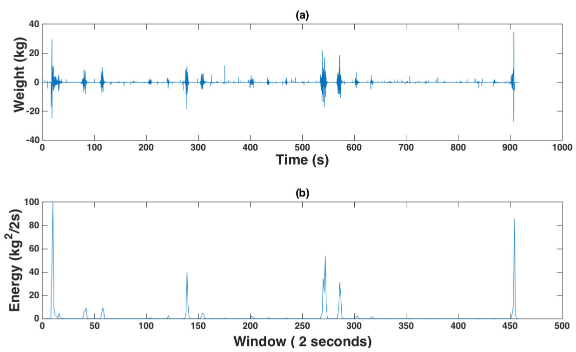


Fig. 10: (a) The summation of load cells data after dropping the local mean and filtered with 10 Hz low pass filter. (b) The Energy for signal (a) computed for 2 seconds window.

the four collected load cell signals up to create a new merged signal, and use a low pass filter to remove the un-relative high frequency components. Then we extract the energy in every 2 seconds window. That window size came form the fact that body's motion cannot be more than 2-3 Hz. So we just pick a size that can cover all possible movements. Extracted energy features will give a peak whenever there is a movement. The height of the peak depends on the strength of movement. The stronger movement results in higher energy peak. All energy widows are normalized with highest value window. Peak detection is applied with some threshold values to find all movements in the data. Also, another threshold is used to classify movements as big or small. Figure 10 shows the filtered summation signal and its energy graph for 2 seconds window. We can see the peaks whenever we have movements.

Zero-Crossing (ZeroX-Valley) Feature Extraction: We use the same input signal used in the Energy-Peak feature extraction, which is the filtered summation of load cells' readings with local mean removal. There is stronger oscillation in the signal with high amplitude if any in-bed movement is performed. This portion will cross the zero axis less than than the surrounding low amplitude parts of signal. So, we use the same size of 2 seconds window used before, and compute the ZX rate in each one. As a result, we see that low value ZX rate window is always connected to the part where we

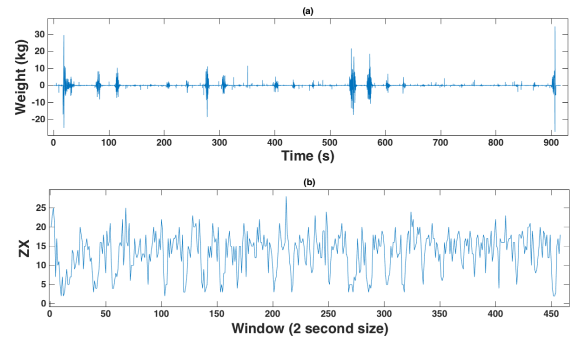


Fig. 11: (a) The summation of load cells data after dropping the local mean and filtration with 10 Hz low pass filter. (b) The ZX rate computed for 2 seconds window.

have motion. We used that to get a graph for ZX and try to find valleys. Thresholds also applied here to find these valleys, which also means find movements. Another threshold is applied to distinguish between movements, big or small. As previous, more about choosing these threshold and movement classification will be explained in V. Figure 11 shows the input filtered summation signal(after removing the local mean) with its ZX rate graph per 2 seconds window. We have Valley with every movement.

V. Performance Evaluation

In this section, we first describe the experimental methodology, and then present the evaluation results. In this study, we have carefully evaluated *MotionScale* for its performance in body motion detection and classification.

A. Experimental Methodology

The experiments are conducted on a twin size bed in a university laboratory with 30 healthy subjects (22 males and 8 females, age ranging from 22 to 42 years old) over a three-month time period [1]. A common innerspring mattress with dimension of 90cm (width)$\times$185cm (length)$\times$20cm (height) is on the bed, and the *MotionScale* prototype is mounted under the four legs. During the experiments, we ask each subject to perform 27 pre-defined in-bed movements with 20 seconds quiet period after each movement. Among all 27 pre-defined movements, there are 8 large movements involving the entire body (e.g., getting in/off bed, turning left, turning right or rolling over), and 19 small movements that only involve parts of the body (e.g., head, arms and legs). More specifically, 6 of the 19 small movements are leg movements, and the rest are arm and head movements.

We record all the data using the same prototype and laptop to avoid any possible bias in readings. A camera is mounted on a tripod 1.5 meter away from the bed to record videos for the ground truth recording. In order to select a suitable threshold for motion detection and classification, as we discussed in Section IV, we randomly choose 10 subjects' data-sets for the training purpose. Additionally, we repeat this process 100 times to find the most suitable threshold.

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

B. Performance of Motion Detection

Comparison of Three Features: We first compare the performance of the three features extracted from the collected load cell data, i.e., Log Peak, Energy Peak, and Zero-X Valley. In order to conduct a fair comparison, we report each feature's performance using the best threshold value for that feature. From our experiments, we observe that each feature presents an obvious peak or valley whenever there is a motion. These peaks/valleys are very different in amplitudes and widths (even for the same movement) among the three features, which suggests that we need to find a general threshold (i.e., height of peak) to detect the 27 performed in-bed movements[2] [3]. In order to find the best threshold value for each feature, we apply different threshold values on data collected from 10 randomly selected subjects for a total of 100 times and choose the one that gives the best performance. Specifically, we identify a range of values for each feature's threshold – the peak value threshold for Log-Peak is varied from -12 to 0 in 30 steps, the peak value threshold in Energy-Peak is varied from 0.01 to 0.31 in 30 steps, and the valley value threshold for ZeroX-Valley is varied from 3 to 18 in 30 steps.

We have a total of 30 subjects, and for each of the 100 tests, we randomly choose 10 subjects as training subjects and use the remaining 20 subjects as test subjects. For each test subject, our detection algorithm detects n movements, and the detection error rate is thus calculated as $\left|\frac{27-n}{27}\right|$ where 27 is the number of known movements in each experiment. Figure 12 reports the detection error rate distribution of the 100 experiments for each feature. It is very clear that Log-Peak is the best among the three features, delivering a detection error rate of 6%. We therefore believe that *MotionScale* is a viable movement detection system during sleep.

Study of the Impact of Parameters: We next study the impact of threshold values on the performance of different detection strategies, and report the results in Figures 13(a)-(c) respectively. All three curves exhibit a "U" shape, meaning that there is an optimal value for each threshold. When the threshold is properly chosen (around the optimal value), the corresponding strategy only detects the peaks/valleys caused by valid body motions and ignores the peaks/valleys caused by noise. In this way, we achieve the lowest error rate. When the threshold is too small (starting from the left hand to the bottom area of the U shape), the corresponding strategy detects noise in the environment as body motions, leading to a higher error rate. When the threshold is too large, the corresponding strategy misses legitimate body motions by treating them as noise, resulting in a higher error rate as well. This suggests that by having a suitable training dataset, we are able to learn the optimal threshold values that can minimize the detection error rate for *MotionScale*.

[2]To prevent the inference from other noise, we apply a threshold to the minimum distance between two neighboring peaks based on the time interval between each two consecutive movements. Specifically, since there is a 20 second quiet period between two consecutive movements in our experiments, we set the threshold of the minimum distance between two neighboring peaks as 20 seconds as well.

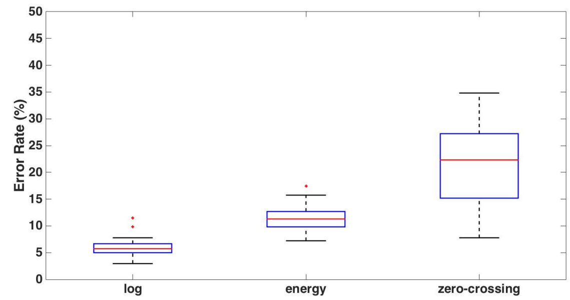
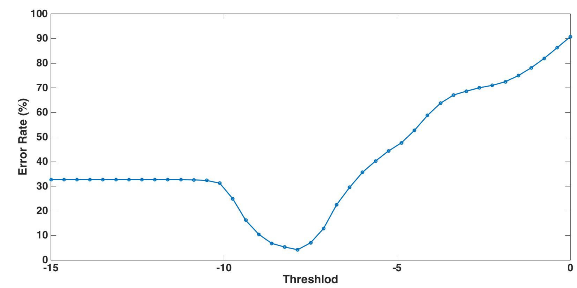
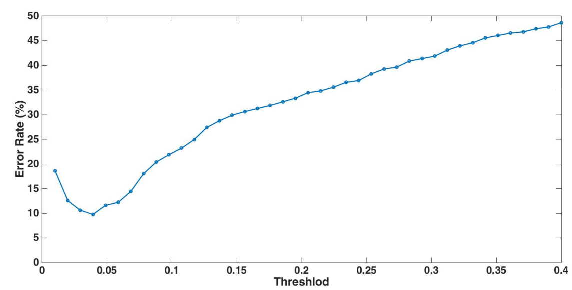


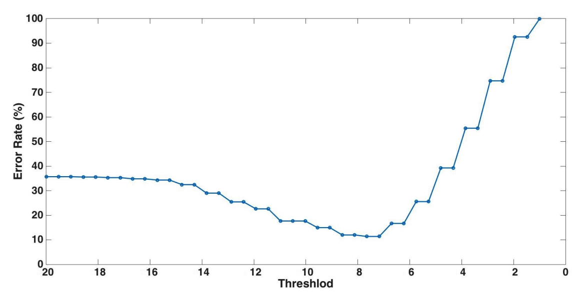
Fig. 12: The error rate for testing phase.



(a) The error rate of variation the threshold in Log Peak strategy



(b) The error rate of variation the threshold in Energy Peak strategy

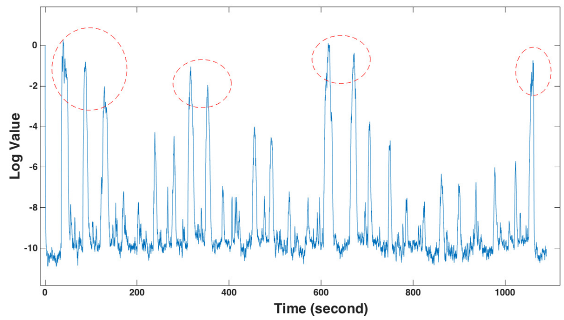


(c) The error rate of variation the threshold in ZX strategy

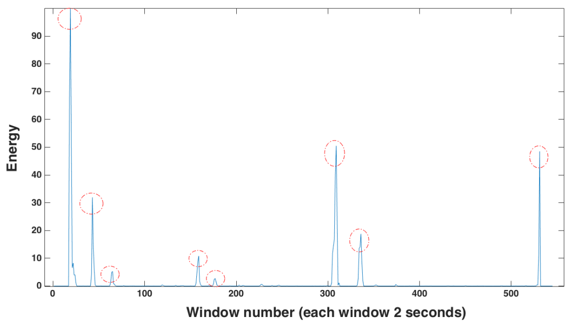
Fig. 13: The error rate of the three strategies when we varied the threshold. All the 30 subjects are tested here.

C. Performance of Movement Classification

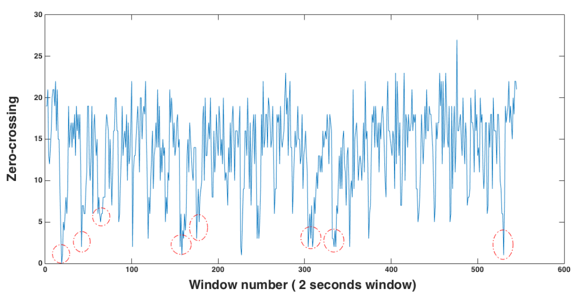
In the second part of the evaluation, we attempt to classify each detected movement as either a big movement or a small movement. In the experiments, we ask the subjects to perform both big and small movements: in a big movement the subject moves her entire body from one position to another, or moves the most part of the body; while in a small movement the



(a) The Log scale of the data with big movements on red circles



(b) The Energy of the data with big movements on red circles



(c) The Zero-Crossing of the data with big movements on red circles

Fig. 14: Data with big movements.

subject moves only one part of her body, such as arms, legs, or head. The rationale behind discriminating these two types of movements is that big movements normally possess higher energy and longer duration than small ones. We thus expect higher peaks (or lower valleys) for these motions in our peak detection system. Figure 14 shows all the movements that are detected for a subject using the three strategies. In the figure, we label all the big movements using red dashed circles.

Figure 15 shows the classification error rate distribution over 100 experiments, and in each experiment we randomly choose 10 subjects's data as training data and use the remaining as test data. Here, we vary the threshold value for Log-Peak threshold from -5 to -1, the threshold for Energy-Peak from 0.1 to 10, the threshold is from -10 to -5, each in 80 steps. It is obvious from Figure 15 that Log-Peak is the best strategy to distinguish between small and big movements, with a mean classification error rate of 4.27%. Across all the data, we find that Log-Peak exhibits the largest gap between small and big movements.

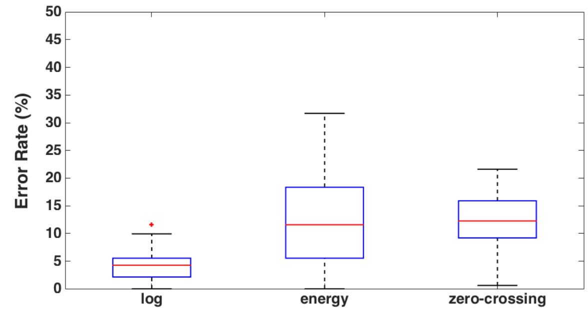


Fig. 15: The Cross Validation error rates for the three strategies: Log, Energy, and ZX.

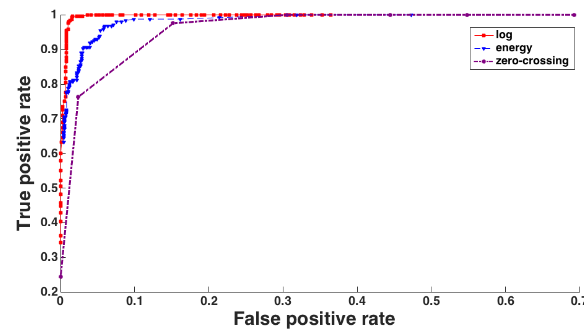


Fig. 16: The The ROC curve for the three strategies applied on 30 subjects.

Figure 16 shows the ROC curves of the three strategies in classifying big and small movements. We obtain the ROC curves with the threshold value that gives the same false positive rate and false negative rate. These results also indicate that Log-Peak has the best classification performance.

Figure 17 shows how Log-Peak's classification algorithm fares with varying threshold values. The results show that Log-Peak reaches the minimum classification error of 5% when the threshold is -2.9. Finally, Table I summarizes the results with best threshold values and error rates.

VI. Related Work

In the past years, many bed motion sensing systems have been developed. Most of these systems used high-cost sensors, complicated signal processing techniques, and wired communication. Also, many of them are only focused on the movements detection without movements discrimination. Moreover, some of these systems require special mattress which may reduce their wide use. In this section, we describe some of the existing in-bed motion detection systems.

Strategy	Movement Detection		Movement Classification	
	Best Threshold	Error rate	Best Threshold	Error Rate
Log	-7.6	6.3%	-3.16	4.2%
Energy	0.0445	12.4%	2.2	11.5%
ZX	11	18.1%	2.99	12.2%

TABLE I: Best Thresholds and their associated error rate to detect all movements and the big and small movements.

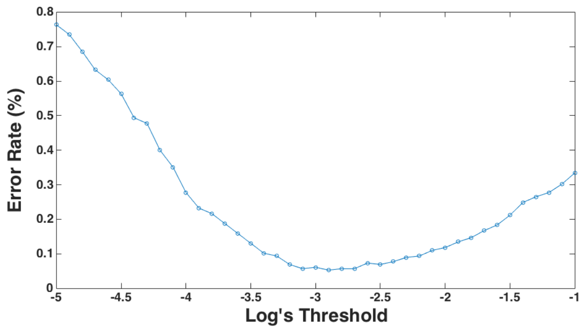


Fig. 17: The error rate of Log Peak applied on 30 subjects.

Kortelainen et al. [18] proposed a movement detection system, including heartbeat and respiration, using a foil pressure sensor placed inside the mattress. It requires special mattress with wired communication and it does not classify the type of movements. Watanabe et al. [29] developed a noninvasive pneumatics-based system that uses an air cushion and a pressure sensor. The air cushion is placed under the mattress while the pressure sensor detects the change of the pressure due to body movements, respiration, and heartbeat. This system needs special cushion with wired communication. Aubert et al. [8] proposed to use an electric foil pressure sensor to detect three vital signs during sleep, namely, heartbeat, respiration, and activity index related to body movements. This sensor needs specific technical installation to be placed in the thorax region under a thin mattress. Nukaya et al. [21] proposed a bed sensing system by using piezoceramic bonded to stainless steel plate sandwiched between the floor and bed legs. This system can sense many human biosignal, including body movements. It needs high-cost sensor and it does not classify the type of movements. Yamana et al. [30] developed a non-constraint cardiac vibration, respiration, and body movement monitoring system. It has a 40-kHz ultrasound transmitter and receiver pair. The transmitted signal is reflected on the mattress' undersurface, and the received signal is processed to know the information about human vital signs, including body movements. Special, hard, installation is required for this system. Brink et al. [9] proposed a non-contact sensing system of in-bed heartbeat, respiration, and body movement. This system uses four sensors, one in each corner of the bed. Each sensor is composed of two aluminum plates and reflex light barrier in between. The reflex light barrier senses the distance between the plates . This distance changes with the amount of applied force. There is no movement classification in this study and it uses wired communication. Harada et al. [14] proposed a human's body in-bed movement sensing system. It can detect human's existence, posture, articular movement, and respiration. This system uses a special, high-cost, sheet with 210 pressure sensors. Joned et al. [16] proposed a movement Identification system using pressor sensor array. This system needs special handling of bedding and it cannot classify the type of movements. In [27] and [19] temperature sensors, thermistors, systems are proposed for in-bed movement detection. These systems detect torso and legs movements by using two arrays of 16 thermistors placed under the waist and under the legs. The proposed systems cannot detect head or hand movements. Also, they cannot classify the type of movements. Tamura et al. [25], and [26] proposed systems to detect body movements during sleep by tempreature monitoring. The proposed systems sonsist of 16 temaperature sensors. Each system requires special installation for these sensores in the mattress. Hoque et al. [15] propose a Wireless Identification and Sensing Platform system (WISPs) for monitoring body position and movement during sleep. The WISP tags are attached to the bed mattress to collect accelerometer data from them. Movement and body position can be detected. This system does not give any information about movements type. Walsh et al. [28] proposed a system composed of a grid of 24 fiber optic based pressure sensors integrated into a foam mat. The proposed system can detect movements without classification. Adami et al. [6] proposed a system to detect and classify in-bed movements. It uses load cell sensors, one under each of the bed's legs. This system is very close to our system but it uses wired communication with complex signal processing techniques. In [7], [5], and [10], load cell sensor is used to detect movements. All these systems don't give any movement classifications and use wired communication. In [4], load cell also used but for detecting periodic leg movements only. Spillman et al. [24] proposed a fiber optic system for monitoring patient respiration, heart rate, and movements without classification. Nishyama et al [20] developed a system to monitor respiration and body motions. Pressure sensors based on hetro-core fiber optics are used in this proposed system. This is high-cost system and requires special installation. Hao et al. [13] proposed a system for sleep quality monitoring. This system uses a smart phone with an app called iSleep and the phone should be placed somewhere close to the bed. The built in microphone in the smartphone is used to detect the required activities such as body movement, couch, and snore. The proposed system does not classify the type of movements. Rofouei et al. [23] proposed non-invasive, wearable neck-cuff system capable of real-time monitoring and visualization of physiological signals. This system is used for sleep quality purposes. It has many sensors housed in a soft neck-worn collar and the data send by Bluetooth to a cell phone which stores the data. It uses accelerometer sensor for body movement detection. This system cannot classify movements and requires some intrusive system to attached to human body. Kaartinen et al. [17] proposed a system for long-term monitoring of movements in bed using static charge sensitive bed (SCSB) sensors. This system can detect body movements, respiratory movements and heartbeat. It does not classify movements and uses wired communication.

We developed a system that can detect and classify in-bed body's movements. It can sense all motion form all body's parts. It uses low-cost load cells under the bed. It does not need any change in the mattress and can be done at home and hospital with no subject's complain requirements.

VII. Concluding Remarks and Future Direction

In this paper, we propose a low-cost, low-overhead, and highly robust system for in-bed movement detection and classification, the MotionScale, which can facilitate many smart home and healthcare applications. The system utilizes four low-end load cell sensors installed under the legs of a bed to capture the weight distribution on the bed and further accurately determine the movements on the bed. Compared to existing solutions, the MotionScale can use more low-cost hardware to achieve comparable results, and it's very easy to apply in our lives unobtrusively. By utilizing the load cell based system, MotionScale can detect different types of in-bed body movements with different scales, ranging from parts of body (e.g., arm, head) movements to whole body movements (e.g., turn over, get off bed). To evaluate our system, we build a prototype with off-the-shelf low-cost load cells and PIP-tags and extensively experiment the prototype with 30 participants over three-month time period. The results show that by utilizing our three main strategies, Log-Peak, Energy-Peak, and ZeroX-Valley, the MotionScale can effectively extract body movement signals from load cell data and detect in-bed movements with a low error rate of 6.3%, and classify them to big or small movements with an error rate of 4.2%.

Looking forward, there are many challenges need to be solved for wider deployment to MotionScale system in many applications, like sleep monitoring. Classification of lying position, and knowing which part of the body moves are the main ideas for our future work.

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