Chapter 17
Body Weight Estimation through Bed Structural Vibrations

Yuyan Wu, Jiale Zhang, Moon Lee, Cherrelle Smith, Pei Zhang, and Hae Young Noh

Abstract Accurate body weight estimation is essential for patient care. Weight estimation is needed to inform medical treatments, such as medication dosages, nutrition needs, and the settings of mechanical ventilators. Current weight estimation methods involve using stand-on weight scales, in-bed pressure plates, or visual estimations, which require the patient to leave the bed, are often damage-prone, or are inaccurate. To overcome these challenges, we introduce a novel method for estimating human body weight through the structural vibrations of the bed board, i.e., the plate supporting the bed, excited by a speaker attached to the bed. Our method provides continuous body weight measurement in a non-intrusive way and does not require the patient to leave the bed while measuring the weight. This method is based on the intuition that the patient's weight affects the vibration response of the bed board under excitation. We first analytically formulate the inverse linear relationship between the body weight and the bed board's frequency response based on structural dynamics. Based on this, we extract the frequency spectrum of bed vibrations as a feature to develop a physic-informed machine learning model for body weight estimation. Our method is evaluated on a hospital bed with both stacked weights (simulating human body weight) and a human subject holding different weights of dumbbells. We achieved an average estimation error of 0.68 kg (0.93% error rate) for the human body weight estimation task in a hospital bed. This corresponds to a 36.8% error reduction compared to the baseline method without incorporating the inverse linear relationship.

Keywords Body weight · Structural vibrations · Humans · Hospitals · Body weight · Structure dynamics · Human health

Introduction

Estimating body weight is essential for developing treatment plans in clinical settings. It informs the calculation of medication dosages, the determination of nutritional needs, and the management of fluid levels [1–3]. Inaccurate estimation of body weight can result in overdosing or subtherapeutic dosing, leading to adverse drug reactions or inadequate treatment efficacy [4]. Moreover, it may prompt inappropriate nutritional interventions, potentially resulting in malnutrition and impeding recovery in patients, especially those who are critically ill or undergoing surgical procedures [5]. Additionally, errors in body weight measurement may lead to excessive or insufficient fluid administration, which can cause severe complications such as pulmonary edema, dehydration, and renal failure [3].

Current body weight measurement methods are not suitable for patients with limited mobility in hospital beds due to their critical illness. Limitations include high cost, intrusiveness, or the potential harm to bedridden patients. Standard weight scales, both digital and mechanical, provide straightforward and precise measurements for healthy individuals but are not accessible for patients unable to stand. Specialized devices, such as pressure mats, bed scales, and chair scales, offer alternatives that allow body weight measurement without requiring the patient to stand [6, 7]. However, these methods require the assistance of medical staff to position the patient on the pressure platform, which can pose a risk of injury to

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vulnerable individuals. Additionally, these devices are expensive, with pressure beds, for instance, costing approximately $3,000 [6, 8].

To overcome these limitations, we develop a novel method for estimating human body weight using speaker-induced bed vibrations. The main idea of this method is that when a person lies on a bed, their body weight affects the vibration response of the bed board. As a result, the vibration response patterns differ depending on the weight applied. By analyzing the vibration responses collected by vibration sensors attached to the bed board, we can estimate the body weight of the person lying on the bed. Compared to other body weight measurement methods, our method is non-intrusive and cost-effective, with minimal risk of interference to patients.

The main research challenge lies in the indirect and complex relationship between bed vibration response and the body weight applied to the bed board. Unlike weight scales and pressure sensors, which measure weight through the invariant relationship between the applied force and internal electronic elements, the relationship between the applied weight and bed vibration is indirect and complex. The main intuition of our method is that the vibration excited by the speakers travels through the bed board whose frequency response is affected by the body weight applied to it and then captured by the vibration sensor attached to the bed. This complex process is influenced by multiple variables, including the bed's material and structural properties, as well as the position of the body and the sensor, complicating the modeling and analysis.

To characterize this indirect and complex relationship, we model and formulate the effect of human body weight on the bed's vibration frequency response using both structural dynamics theories and empirical data. The formulation and analysis indicate an inverse linear relationship between body weight and frequency response, guiding the selection of features and the model for estimating human body weight. Based on this, we develop a physic-informed machine-learning model to realize human body weight estimation using speaker-induced bed vibrations.

To evaluate our method, we conduct two types of experiments using a standard hospital bed: one with stacked steel weights to simulate human body weight and another with a person lying on the bed. The stacked steel weights experiment includes a broader range of weight options, allowing for more varied testing conditions. The human body weight experiment is conducted with a person holding dumbbells of varying weights. Our method achieves a mean absolute error of 0.119 kg (5.3% error rate) for the stacked weights estimation and 0.68 kg (0.93% error rate) for the human body weight estimation.

Our contributions are as follows:

- We develop the first human body weight estimation method based on speaker-induced bed vibrations, enabling a non-intrusive and cost-effective way of measuring body weight, with minimal risk of interference to in-bed patients.
- We model and formulate the effect of human body weight on the bed's frequency response using both structural dynamics theories and empirical data. Guided by this analysis, we develop a physics-informed machine-learning model for estimating human body weight.
- We evaluate our method on a hospital bed using two types of experiments: one with stacked steel weights to simulate human body weight, and another with human subjects. Both experiments yield promising results, showing significant improvements compared to baseline models.

In the remainder of this paper, we first review existing literature on body weight estimation methods and explore approaches that use structural vibrations to estimate loads. Subsequently, we detail the modeling and characterization of the relationship between body weight and bed vibrations. Following this, we present our body weight estimation method. Finally, we discuss the evaluation experiment and analyze the results of body weight estimation.

Related Works

Various methods are developed for measuring human body weight, including stand-on scales, manual observation, and pressure-based bed scales, each with advantages and limitations. The stand-on scale, a traditional and widely used method, utilizes mechanical or electronic components to provide precise weight measurements and additional body composition metrics such as body fat percentage and muscle mass. Despite its affordability and accuracy, this method requires standing, which is quite challenging or even impossible for in-bed patients or patients who may have physical limitations. In clinical environments, professionals often estimate body weight through visual assessment [9, 10]. While convenient, this technique is subjective and can vary significantly based on the observer's experience, often leading to inaccuracies exceeding 10 kg [11]. Pressure-based bed scales embedded in mattresses facilitate passive, continuous monitoring of body weight, offering a non-intrusive option for in-bed patients [12, 13]. However, this method requires medical staff to assist in positioning patients on the pressure bed, which may pose risks to vulnerable patients. In addition, this device can be costly priced at around $3,000 [8]. In this study, we develop a novel system that measures human body weight through speaker-induced bed vibrations. Our method is non-intrusive, cost-efficient (with each geophone costing around $65), with a minimal risk of interference to patients.

Structural vibrations are effective for estimating loads on structures and have been utilized for diverse applications including estimating vehicle weights on roads, detecting structural damage, and measuring animal weights [14–21]. In vehicle weigh-in-motion systems, vibrations induced by a vehicle as it traverses a sensor-equipped road segment are analyzed to determine the vehicle's weight [14–16]. The dynamic response of the pavement to the vehicle's load reflects the vehicle's weight, as different weights induce distinct dynamic interactions between the vehicle and the road surface, thereby generating unique vibration patterns. Structural damages, often simulated by adding weights to a structure, can also be detected through vibrations [17–19]. This is based on the similar impact of weight and damage on the structure's natural frequency, which can be captured through the structural vibrations. Additionally, recent studies have utilized structural vibrations to measure the weight of animals and other objects [20, 21]. These works support that vibrations contain rich information about weight, inspiring further investigation into using bed vibrations to estimate human body weight.

The Relationship between Body Weight and Bed Vibrations

To capture the indirect and complex relationship between human body weight and bed vibrations, we model and formulate the effect of the human body weight on the frequency response of the bed based on structural dynamics theories. The bed board is modeled as a rectangular thin plate with a thickness much smaller than its width and length and the human body is modeled as a static load on the plate (see Figure 1). In this model, we assume that the bed board satisfies the conditions of Kirchhoff–Love plate theory [22]. Both the excitation source and the sensor have areas small enough compared to the bed board to be modeled as points. The bed board is defined as a rectangular area with length a and width b (Without loss of generality, assume a is along the x-axis and b is along the y-axis.). The weight of the human body is simulated by a load m_0 at location (x_0, y_0), and the vibration sensor is positioned at (x, y). The excitation source stimulates the plate at the point (x_e, y_e) with the excitation time history function of $f_e(t)$. In addition, for the modeling simplicity, we assume that the bed has simply supported boundary conditions and static initial conditions, and the damping effect is negligible.

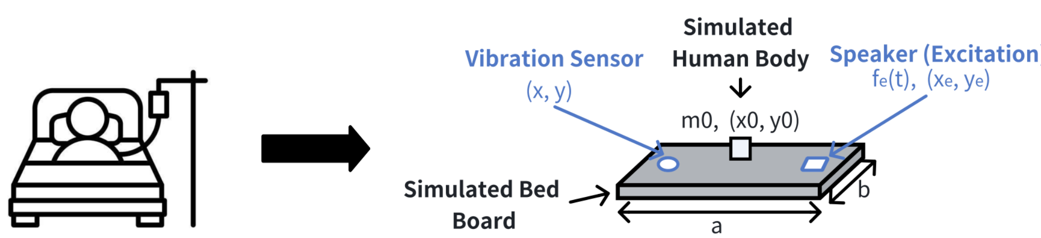

Fig. 1 Simplified Model Representing the Relationship Between Human Body Weight and Bed Vibrations.

We analytically formulate the relationship between the bed board's frequency response and the applied load (human body weight) using structural dynamics theories. The bed board's vibration can be written as Equation 1 [23]:

$$D\nabla^4 w(x,y,t) + \mu\frac{\partial^2 w(x,y,t)}{\partial t^2} = f_e(t)\delta(x-x_e)\delta(y-y_e) + \delta(x-x_0)\delta(y-y_0)(\frac{m_0}{S}g - \frac{m_0}{S}\frac{\partial^2 w(x,y,t)}{\partial t^2}). \quad (1)$$

In this equation, $w(x, y, t)$ denotes the vertical displacement of the bed board, representing its vibration at time t and location (x, y) (the location of the sensor). The parameters D, ρ, ν correspond to the bed board's flexural rigidity, mass per unit area, and Poisson's ratio, respectively. S denotes the contact area between the load and the bed board. We solve this equation using Galerkin's method [24, 25], which assumes $w(x,y,t) = \sum_{m=1}^{\infty}\sum_{n=1}^{\infty} q_{mn}(t)\phi_{mn}(x,y)$. With the simply-supported boundary condition and a static initial condition, the basis functions $\phi_{mn}(x, y)$ can be written as $\phi_{mn}(x,y) = sin\frac{m\pi x}{a}sin\frac{n\pi y}{b}$. The solution to Equation 1 is detailed in Equations 2, 3, and 4 as follows:

$$w(x,y,t) = \sum_{m=1}^{\infty}\sum_{n=1}^{\infty} sin\frac{m\pi x}{a}sin\frac{n\pi y}{b}q_{mn}(t), \quad (2)$$

where the $q_{mn}(t)$ satisfy:

$$\ddot{q}_{mn}(t) + \omega_{mn}^2 q_{mn}(t) = \frac{f_e(t)sin\frac{m\pi x_e}{a}sin\frac{n\pi y_e}{b}}{\frac{ab}{4}\mu + m_0 sin^2\frac{m\pi x_0}{a}sin^2\frac{n\pi y_0}{b}} \propto \frac{1}{1+\frac{4m_0}{\mu(ab)}sin^2\frac{m\pi x_0}{a}sin^2\frac{n\pi y_0}{b}} \sim \frac{1}{m_0}\ if\ m_0 >> \mu(ab), \quad (3)$$

where ω_{mn}^2 is defined in:

$$\omega_{mn}^2 = \frac{\frac{ab}{4}D[(\frac{m\pi}{a})^4 + (\frac{n\pi}{b})^4 + 2(\frac{m\pi}{a})^2(\frac{n\pi}{b})^2]}{\frac{ab}{4}\mu + m_0 sin^2\frac{m\pi x_0}{a} sin^2\frac{n\pi y_0}{b}}. \tag{4}$$

m and n denote the mode numbers of the vibration modes. The corresponding natural frequency for mode m, n is specified in Equation 4. As indicated in Equation 3, the amplitude of vibration for each mode is proportional to $\frac{1}{m_0}$ when $m_0 >> \mu(ab)$, where $\mu(ab)$ represents the weight of the bed board.

The analysis shows that the frequency spectrum of structural vibrations provides crucial information for estimating human body weight. Moreover, the frequency spectrum is inversely proportional to m_0 when the human body weight significantly exceeds the weight of the bed board. This observation suggests utilizing the frequency spectrum coefficients as features for weight estimation analysis, and $\frac{1}{m_0}$ as the target for linear estimation, which is subsequently converted back to estimate m_0.

This theoretical relationship is further validated through laboratory experiments on a hospital bed. In the experiment, various weights are placed on the hospital bed, and the bed's structural vibration signals, excited by the speakers, are captured by vibration sensors which are attached to the bed board. First, it is observed that vibration patterns are distinguishable with varying loads as shown in Figure 2 (a) (each line representing one of the repeated experiments). Second, increasing the load by increments of 0.5 kg results in progressively smaller variations in the FFT frequency spectrum as the load increases. This trend is attributed to the frequency spectrum magnitude changing inversely with the mass, as detailed in Equation 3. In Figure 2 (b), the 260 Hz frequency component is used to demonstrate how the changes in the FFT component decrease with increasing weight, following the $\frac{1}{m_0}$ relationship. To show the linearity of this relationship, we plot the reciprocal of the weight against the FFT component and fit a linear curve. The resulting correlation coefficient value of 0.9915 indicates an inverse linear relationship between the weight applied to the bed and the frequency component of the bed vibrations.

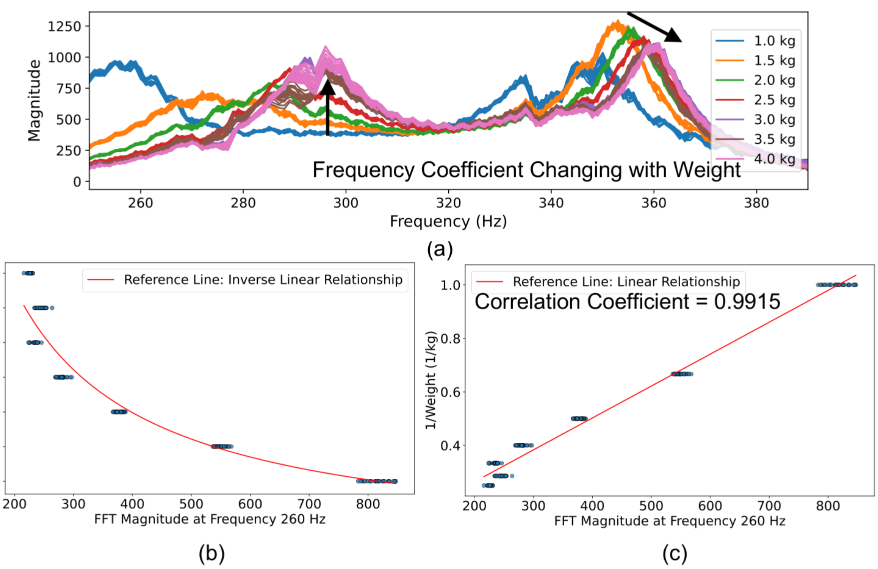

Fig. 2 Characterization of Bed Vibration Frequency Response with Varying Weights on Hospital Bed. (a) FFT spectrum with various weights placed on the bed, indicating various vibration patterns; (b) Scatter plot depicting the relationship between the FFT magnitude at 260 Hz and the corresponding weights; (c) Regression analysis showing the relationship between the FFT magnitude at 260 Hz and the reciprocal of the weight, fitted with a linear model (correlation coefficient: 0.9915)

Body Weight Estimation Using Bed Structural Vibrations

Our method consists of three main steps: bed vibration excitation and sensing, physics-informed bed vibration processing, and body weight estimation modeling (see Figure 3). The main insight of our method is that the bed's structural vibration response varies with different body weights applied on the bed board. By analyzing these vibration responses, captured by sensors attached to the bed board, we can estimate the body weight on the bed structure.

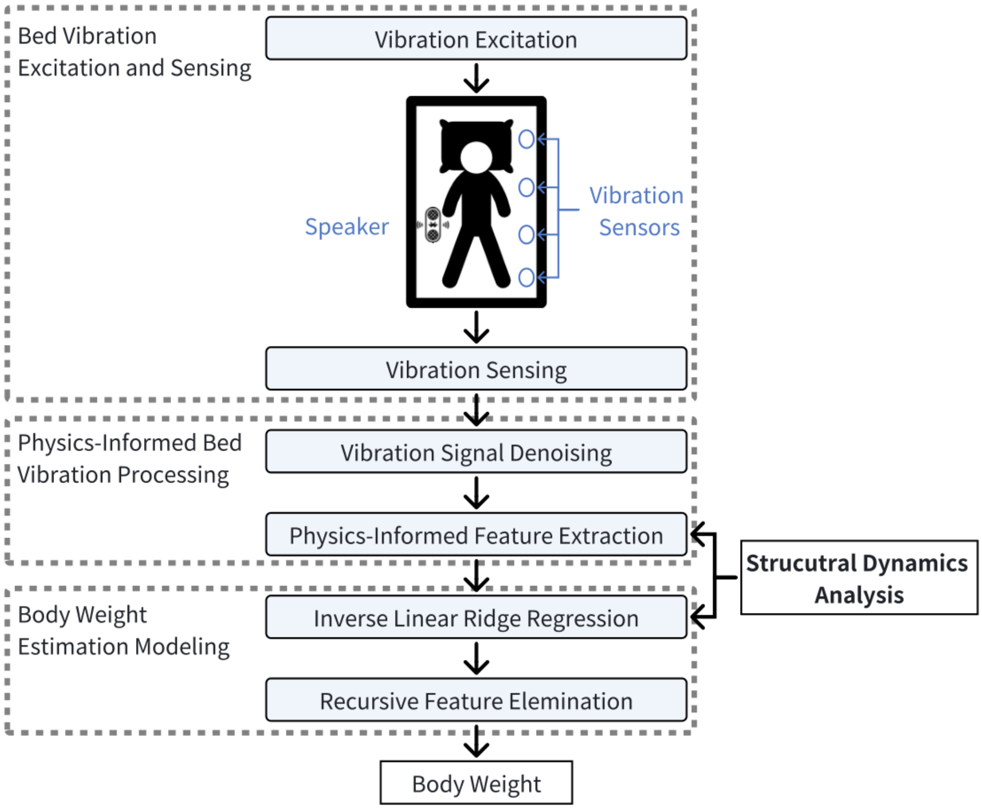

Fig. 3 Bed Vibration-based Body Weight Estimation Method Overview

Bed vibration excitation and sensing

We attach the speaker and vibration sensors to the bed board to excite and collect the bed structural vibrations. The bed vibrations are induced by speakers emitting chirp signals, which traverse the bed board and are then captured by the vibration sensors on the other side of the bed. The vibration response of the bed board is influenced by the human body weight as discussed in the previous section. Thus the signals received by the vibration sensors contain the information of the human body weight applied to the bed structure. The chirp signal is chosen for excitation as it includes a broad frequency range and thus can excite diverse vibration modes. The excitation source and sensors are positioned on opposite sides of the bed to capture structural vibrations to estimate human body weight. A vertical vibration sensor is used because the vertical axis predominantly characterizes bed vibrations, which are significantly greater than those in the horizontal direction [26]. In addition, we avoid the placement of the sensor on the bed board's supporting points to ensure effective measurement of the vibrations [27].

Physics-informed bed vibration processing

The physics-informed bed vibration processing mainly includes two steps: first, we mitigate the impact of noise on the vibration signal through denoising; second, we extract features from the vibration signals, guided by the formulation results derived from structural dynamics theories (as discussed in the previous section).

To reduce noise in vibration signals, we first record vibrations without excitation to establish an environmental noise profile. A threshold in the frequency spectrum is set based on this noise profile, and a gate is employed to attenuate frequencies predominantly associated with noise. For each timeframe of the captured vibrations in the later experiments (the vibrations excited by the speaker), the algorithm masks frequencies below this threshold [28, 29]. This helps in retaining frequencies for the actual vibration signals while reducing those that are likely to be noise.

Guided by the formulation results based on structural dynamics theories, the absolute values of Fourier transform coefficients are extracted as features for inferring human body weight. As discussed in the previous section, these coefficients reflect the load (body weight) applied to the bed structure. A frequency band covering the chirp signal's frequency range is selected, with an expanded scope to cover additional vibrations resulting from the non-ideal performance of the speaker.

The frequency coefficients from all sensors are concatenated as features for body weight estimation modeling to incorporate the weight information from all four plates that comprise the bed board.

Body weight estimation modeling

We develop a physics-informed machine learning model for body weight estimation guided by the analytical formulation results based on structural dynamics theories. Inspired by the inverse linear relationship between frequency components and the body weight formulated in Equation 3, the label for learning is selected as the reciprocal of body weight ($\frac{1}{m_0}$) during training. In addition, we employ a linear regression model to learn the relationship between the reciprocal of body weight and the frequency components features extracted. The linear regression model is selected because it effectively captures this linear relationship by fitting a linear line between the observed frequency components and corresponding weights [30]. Due to the limited data available, we utilize linear regression with ridge regularization to penetrate large coefficients in the model, thereby reducing overfitting [31].

To enhance model performance and efficiency with limited data, we employ Recursive Feature Elimination (RFE) to reduce the feature dimensions [32]. Initially, we train a model using all available features and rank them by importance. The least significant feature is removed, and the model is retrained with the remaining features. This iterative process continues until optimal performance is achieved. RFE is effective in identifying the most important features for body weight estimation. Additionally, it helps mitigate overfitting and reduces data requirements due to the decreased number of features.

Evaluation with Laboratory Bed Experiment

We evaluate our method in a laboratory setting by conducting two types of experiments on a standard steel hospital bed: 1) experiment with stacked steel weight to simulate human body weight; and 2) experiment with a human subject. The first one includes a broader range of weights while the second one is closer to the real clinical settings. This section first outlines the experiment setups, followed by a discussion of the results obtained.

Laboratory experiment setup

The experiments are conducted on a standard hospital bed with a bed board consisting of four plates (see Figure 4). The dimensions of the bed are 2.31 m × 0.91 m, and the widths of the individual plates are 87 cm, 36 cm, 32 cm, and 33 cm. SM-24 geophone sensors (vertical vibration sensors) are attached to the side of the plate to capture bed vibrations. The signals from the geophones are amplified by the hardware module to enhance the signal-to-noise ratio. Vibrations are excited using a one-second chirp signal emitted from a speaker, with a frequency range from 10 Hz to 1000 Hz to cover the bed's primary natural frequencies. In experiments with stacked steel weights, the sensor and the speaker are located on the same plate, with the speaker positioned at the center of the plate (See Figure 4 (a) (b)). The cylindrical steel weights (steel weights placed in a plastic cylindrical container) weigh 0.5 kg each. They are vertically stacked for varying weight requirements, and placed between the sensor and the speaker. In the experiment, the load varied from 1 kg to 4 kg in 0.5 kg increments. For each weight situation, the chirp signal is repeated 30 times.

To approximate real-world clinical scenarios, we conduct experiments with a student volunteer weighing 71.4 kg, with additional variable weights provided by dumbbells. Due to the larger size of the human body, using a single plate is impractical. Therefore, one sensor is placed on each of the four plates (four sensors in total), and the speaker is attached to one of the plates to induce bed vibrations. Features extracted from the vibrations of the four sensors are concatenated to estimate the human body weight. The following five experimental conditions are included: a human lying on the bed; a human lying on the bed while holding one 3-pound dumbbell; a human lying on the bed while holding two 3-pound dumbbells; a human lying on the bed while holding a 5-kilogram dumbbell; and a human lying on the bed while holding a 7.5-kilogram dumbbell. Each condition is tested with five trials, during which the participant lies supine on the bed. After one experiment round, he stood up and then lay down again for another trial. Each trial included 30 chirp signal excitations (750 samples in total). This experiment was conducted in accordance with the approved IRB protocol (No.: IRB-76030).

Evaluation results

Our method achieves a mean absolute error of (5.3% error rate) when estimating the weight of stacked steel and 0.68 kg (0.93% error rate) when estimating human body weight (see Figure 5). During the training of the linear ridge regression model, we utilize the vibration data from the maximum and minimum weight from the data collected as the training set,

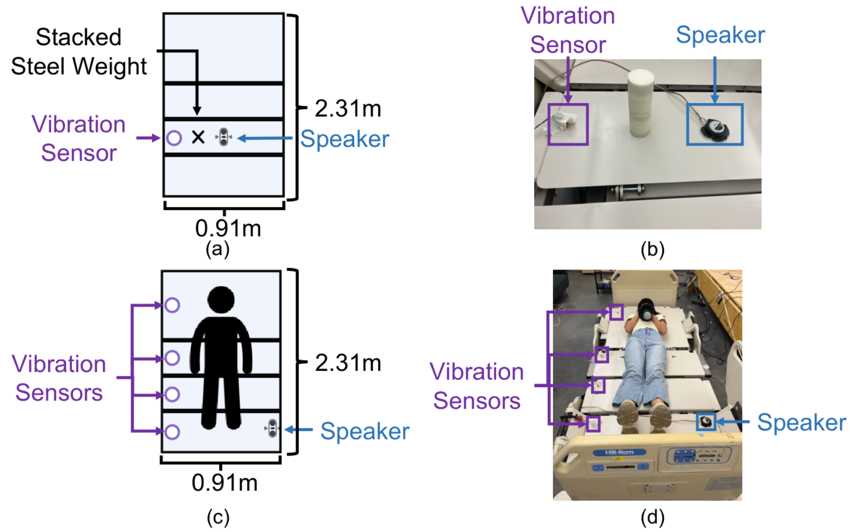

Fig. 4 Laboratory Setup for Estimating Weight through Bed Structural Vibrations: (a) Schematic representation of the experiment setup with stacked steel weights. (b) Laboratory experiment setup with a hospital bed loaded with stacked steel weights (0.5 kg each) placed in a cylindrical container. (c) Schematic representation of the experiment setup for human body weight estimation. (d) Laboratory experiment setup demonstrating the experiment with a human subject on the bed to estimate body weight via bed structural vibrations.

while the weights in between are used as the test set for evaluation. For estimating stacked steel weight, the model is trained using the vibration data corresponding to 1 kg and 4 kg, with the remaining weights forming the test set. In the estimation of human body weight, data for individuals weighing 71.2 kg (without carrying any additional load) and 78.7 kg are used for training, while the other data are used as the basis for testing. The comparison between the estimated and actual weights is shown in Figure 5. Overall, the estimated weights are generally close to the 1:1 line representing the ideal situation of weight estimation. The estimation of human body weight generally exhibits greater errors compared to the estimation of stacked steel weights. This is likely due to the larger contact area of the human body on the bed, which may not be uniformly distributed. The larger contact area may cause deviation from the point load assumption used in structural dynamics theory, potentially causing greater inaccuracies in linear ridge regression methods. Although the estimation of human body weight shows larger errors and greater variation, it remains acceptable for clinical settings.

To prove the effectiveness of regularization and the utilization of the inverse strategy, we compare the weight estimation errors against several common regression models and conduct ablation tests. As illustrated in Figure 6, our method

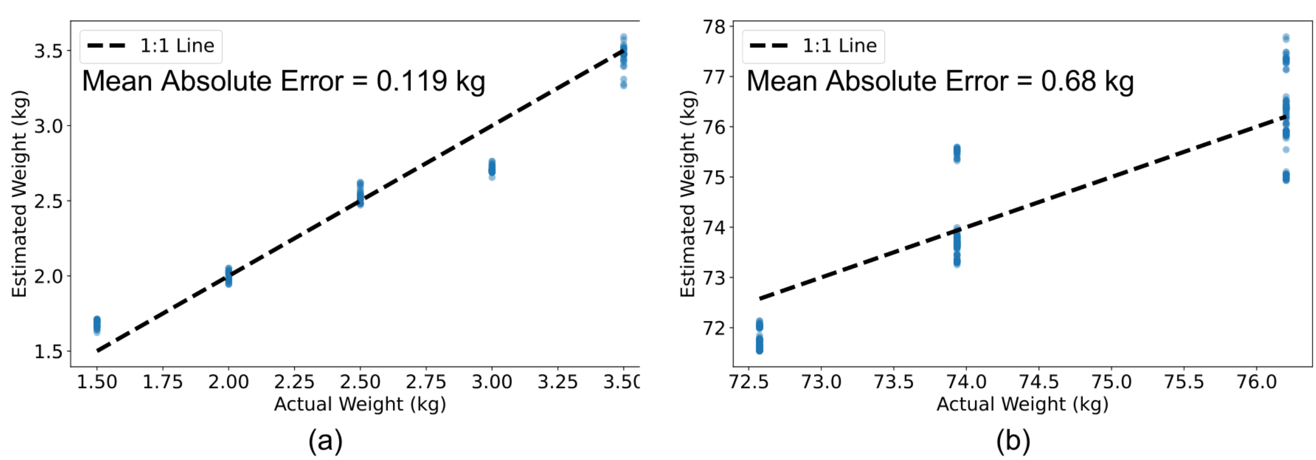

Fig. 5 Evaluation of Weight Estimation Models: (a) Scatter plot comparing the estimated and actual weights of stacked steel weights. (b) Scatter plot comparing the estimated and actual human body weights

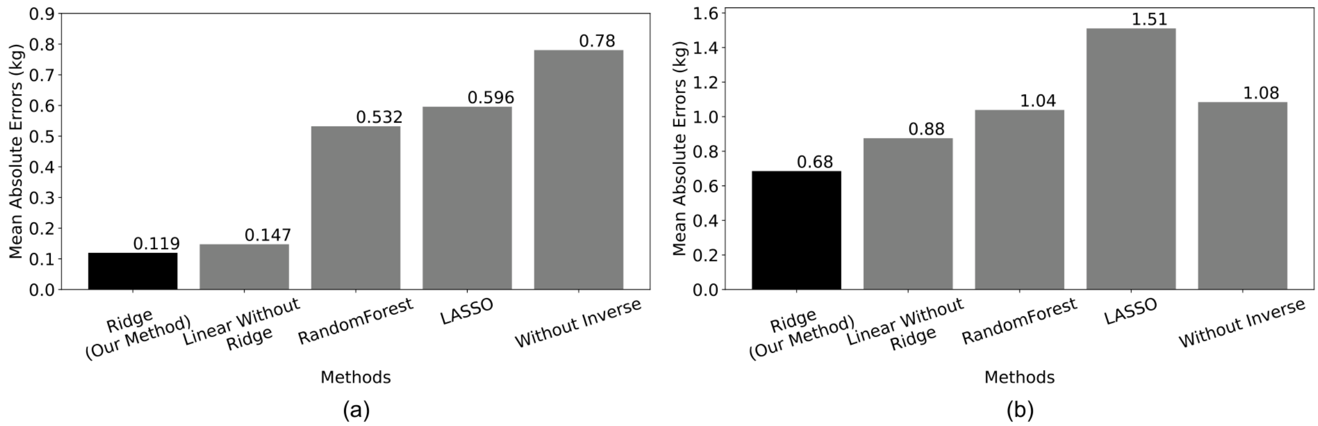

Fig. 6 Comparative Analysis of Regression Models for Weight Estimation. Our method (ridge regression), demonstrates superior performance over linear regression, random forest, and LASSO. Additionally, we evaluate the method that uses direct weight labeling for training ridge regression model ("Without Inverse"s). (a) Mean absolute estimation errors for stacked steel weight estimation. (b) Mean absolute estimation errors for human body weight estimation.

outperforms all other regression models in both the estimation of stacked steel weight and human body weight. Furthermore, in comparison to results obtained by linear regression without ridge regularization, our method achieves significant reductions in estimation error: 19% for the stacked steel weight estimation task and 22% for the human body weight estimation task. Given the linear relationship between the frequency spectrum and the reciprocal of the weight, we employ the inverse strategy which utilizes the reciprocal of the weight as labels during training. Compared to the estimation results which use the weights directly as labels in ridge linear regression, our method shows an error reduction of 84.7% for the stacked steel weight estimation task and 36.8% for the human body weight estimation task.

Conclusions

In summary, we develop a novel method for estimating human body weight using the speaker-excited bed structural vibrations. The main research challenge is the indirect and complex relationship between bed vibrations and body weight. To address this challenge, we model and formulate the inverse linear relationship between human body weight and the bed's frequency response based on both structural dynamics theories and empirical data. Guided by this analysis, we extract the frequency spectrum as a feature and develop a physics-informed machine-learning model for body weight estimation. We evaluate our method through laboratory experiments using a standard hospital bed. Our results demonstrate a mean absolute error of 0.119 kg (5.3% error rate) when estimating stacked weight and 0.68 kg (0.93% error rate) when estimating human body weight. This body weight estimation method provides a non-intrusive and cost-efficient method with minimal risk of harm for in-bed patients in clinical settings, thereby facilitating the development of more effective treatment plans.

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