Robust Occupant Detection Through Step-Induced Floor Vibration by Incorporating Structural Characteristics

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5 authors, including:

Mostafa Mirshekari
Carnegie Mellon University

Shijia Pan
Carnegie Mellon University

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Mike Lam[1], Mostafa Mirshekari[1], Shijia Pan[2], Pei Zhang[2] and Hae Young Noh[1]

[1]Department of Civil and Environmental Engineering, Carnegie Mellon University
5000 Forbes Avenue, Pittsburgh, PA 15213
[2]Department of Electrical and Computer Engineering, Carnegie Mellon University
Building 23, Moffett Field, CA 94035

Abstract

The objective of this paper is to present an occupant detection method through step-induced structural vibration. Occupant detection enables various smart building applications such as space/energy management. Ambient structural vibration monitoring provides a non-intrusive sensing approach to achieve that. The main challenges for structural vibration based occupant footstep detection include that 1) the ambient structural vibration noise may overwhelm the step-induced vibration and 2) there are various other impulse-like excitations that look similar to footstep excitations in the sensing environment (e.g., door closing, chair dragging, etc.), which increase the false alarm rate for occupant detection. To overcome these challenges, a two-stage step-induced signal detection algorithm is developed to 1) incorporate the structural characteristics by selecting the dominant frequencies of the structure to increase the signal-to-noise ratio in the vibration data and thus improve the detection performance and 2) perform footstep classification on detected events to distinguish step-induced floor vibrations from other impulse excitations. The method is validated experimentally in two different buildings with distinct structural properties and noise characteristics, Carnegie Mellon University (CMU) campus building and Vincentian Nursing Home deployments in Pittsburgh, PA. The occupant footstep detection F1 score shows up to 4X reduction in detection error compared to traditional thresholding method.

Keywords: Occupant Detection, Structural Vibration, Wavelet Analysis, One-Class Classification, Natural Frequency

1 Introduction

Accurately detecting occupants is an important starting point for successful analysis of occupant information. Occupant detection has extensive applications in smart infrastructures. For example, detecting occupants can help understand infrastructure utilization and thus improve maintenance schedule and management. Furthermore, the presence and number of occupants can aid HVAC control for energy management purpose.

Current indoor occupant detection makes use of several types of sensors, and each has its own benefits and limitations. The main sensor types include cameras, infrared (IR) sensors, radio frequency (RF) sensors, acoustic sensors, and vibration sensors [1, 2, 3, 4, 5, 6, 7, 8]. Cameras, IR sensors, and RF sensors require line-of-sights to capture occupants, which introduces difficulty in installation. RF sensors also face the multipath problem, which makes the sensing sensitive to the ambient environment. Acoustic sensors detect occupant presence by their talk or footstep sounds, however such methods are often sensitive to high ambient noise in the sensing environment. In addition, under some scenarios users do not want their images being captured in cameras and their conversations being recorded by microphones due to privacy reasons. The vibration sensors are used for pedestrian spatio-temporal information sensing [9, 10, 11], however the application's performance depends on the footsteps detection performance.

We use vibration sensors in this paper to detect occupants due to its non-intrusive deployment nature, which makes the system easy to install and maintain. The main idea of our method is to detect individual occupants through their footstep-induced vibration in the building structure. Challenges for occupant detection through ambient structural vibration sensing are mainly two folds: 1) the ambient structural vibration noise may overwhelm the step-induced vibration signals; and 2) various other impulse excitations in the environment generate vibration signals similar to step-induced signals, thus introduce false alarms (low precision) on footstep-induced vibration detection.

In this paper, we present an algorithm to detect occupants through step-induced floor vibration that takes those challenges into account. To address the first challenge, the signal is decomposed into specific components, which correspond to the natural frequencies of the structure. Vibration responses of a structure amplify near natural frequencies of the structure, which results in a higher signal-to-noise ratio (SNR) at these frequencies. Thus, focusing on the vibration signal components at natural frequencies allows higher recall rate for detection comparing to using the original signal. Wavelet analysis is used for decomposing the signal. To exclude non-step impulse excitations detected, the system runs a classification algorithm to determine whether the detected signals are induced by occupant footsteps.

The algorithm consists of two modules: structure characterization and occupant footstep detection. The structure characterization module is an offline component of the algorithm, which identifies the floor structure characteristics needed for subsequent modules. The occupant footstep detection module is an online component of the algorithm, which includes event detection and event classification. In the event detection module, various impulse-like events (footsteps or other excitations, such as ball dropping, door closing, crutches, etc.) are detected from the incoming signal. In the event classification module, the detected events are classified into step events or non-step events. The algorithm is validated in one of the Carnegie Mellon University (CMU) campus buildings and a nursing home in Pittsburgh, Vincentian Home, to show the detection algorithm performance in different structures with different usages. The CMU campus building is a 3-story reinforced concrete commercial building with offices, classrooms and lecture theatres. The Vincentian Home is a 3-story steel residential building with 60 elderly resident rooms. The results show up to 4X reduction in detection error compared to traditional thresholding method.

The main contributions of the paper are:

- We proposed a two-stage footstep detection algorithm that incorporates structural characteristics to increase detection performance.
- We present an algorithm that distinguishes footstep-induced signals from other detected impulse excitations signal to achieve occupant detection.
- We evaluated the algorithm with implementations at different buildings, including a commercial school building at CMU and a residential building at Vincentian Nursing Home.

The rest of the paper is structured as follows. Section 2 covers literature survey on techniques and background information related to the project. Sections 3 and 4 explain the developed algorithm and its evaluation, respectively. Finally, Section 5 describes future works, and Section 6 concludes the paper.

2 Literature Survey

Many footstep detection algorithms consist of feature extraction using signal processing and detection using machine learning. Proposed features for detecting human footstep excitations, based on which domain of the signal they are analyzing, can be classified into three categories: time, frequency, and time-frequency domain analysis. Some of the features defined using a time domain approach include auto-regressive models[12, 13], auto-correlation functions[14], and kurtosis [15, 16]. However, underlying structure, surrounding noise, and the non-stationary property of footstep signal bring inconsistency to the waveform in time domain and makes robust footstep signal detection difficult. Features defined using a frequency domain approach mainly include spectrum of the signals [17]. The main shortcoming of frequency domain based features is their unsuitability for dealing with non-stationary transient excitations such as footstep-induced vibration signals. Finally, some of the features defined using a time-frequency domain approach include the wavelet energy [18], PWV distribution assisted Renyi entropy (PWVD-RE) [19], and wavelet packet node energy (WPNE) [20]. The advantage of using time-frequency based features is their ability to deal with non-stationary signals (e.g., footsteps, seismic waves, impact loads)[18, 21, 22, 23, 24]. Thus, we use wavelet analysis for floor characterization and event detection, as discussed in section 3.

For classification, we investigate the cases in which there are only one class samples (positive class) available for training. Outlier detection with one-class classification (OCC) has been developed in machine learning community

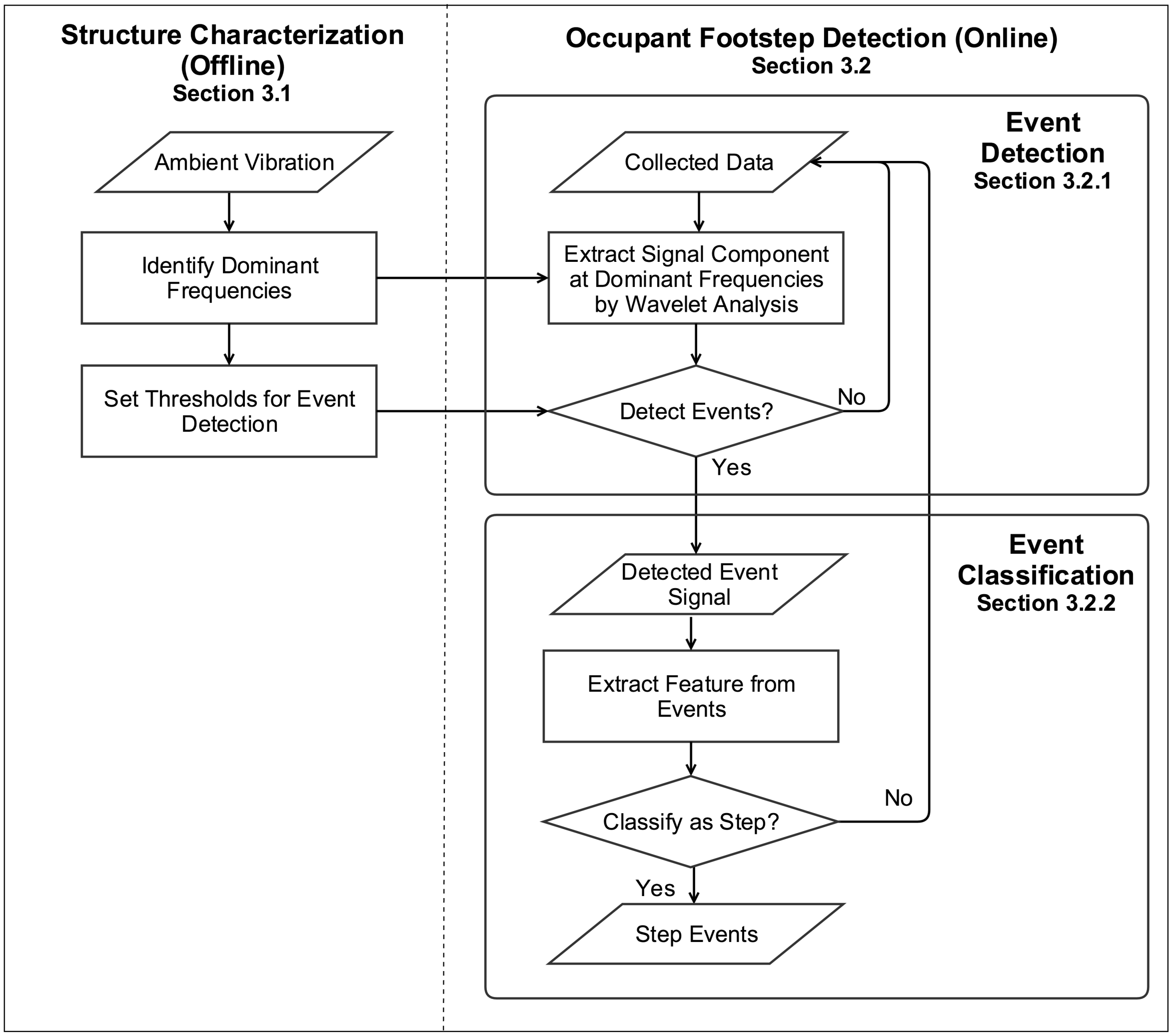
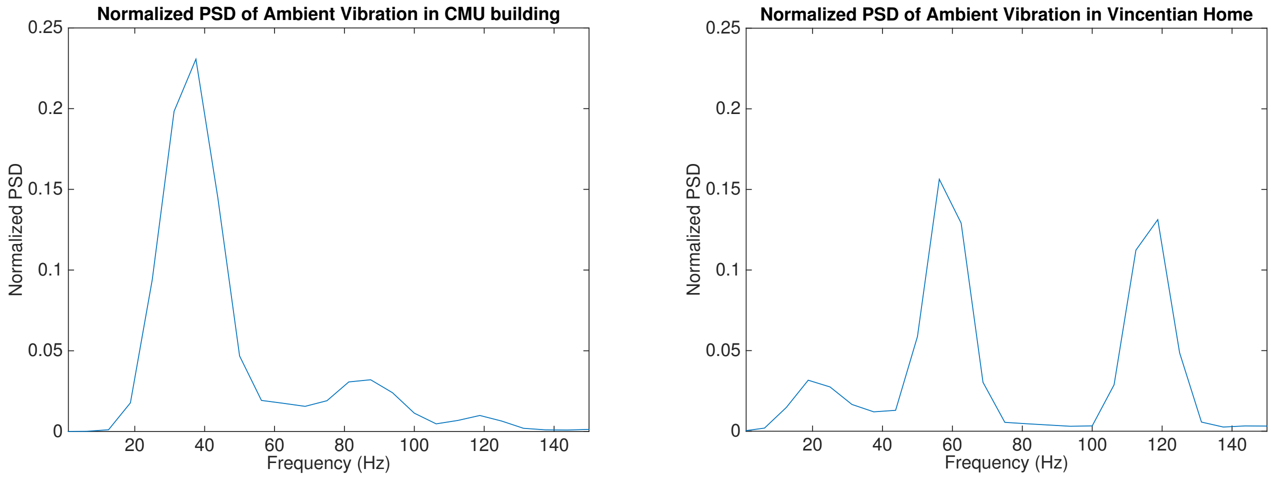


Figure 1: Algorithm flowchart

for this purpose[25]. OCC aims to build classifier when negative class is not available, is poorly sampled or not well defined [26]. Our objective of classification is to separate the excitations induced by steps from other excitations. However, we do not know all the possible non-step excitations. There could be unexpected excitations which are not collected in the signal library for training the classifier in database-based approaches. In our case, OCC allows us to train the classifier just by footstep signals. Major OCC algorithms are based on one-class ensembles, neural networks, decision trees, nearest neighbors, and Bayesian classifiers [26]. Among them, One-class SVM (OSVM) has been extensively studied and widely applied with various parameter estimation methods [26, 27, 28, 29, 30]. Researchers have used it for fall detection [31], intrusion detection [32], machine fault detection [33], document classification [34], sound classification [35] and extraction of brain tumor from MR images [36]. We use the OSVM algorithm in this paper to map the data into the feature space using the radial basis function kernel and then to classify with maximum margin[37].

3 Occupant Detection Algorithm Using Structural Characteristics

The proposed algorithm detects occupants through detecting general events and then classifying footsteps from other excitations. To do this it has an *offline* component which characterizes the structure and an *online* component which performs footstep detection incorporating the structure characteristics.



(a) CMU Campus Testing Location

(b) Vincentian Home Testing Location

Figure 2: Normalized PSD of ambient vibration in two different buildings

Figure 1 shows the components of the system. Ambient floor vibration signal captured contains both events that we like to measure (e.g., footsteps, door closing, objects dropping, etc.), as well as noise that we do not want to measure (i.e., all signals other than events). These signals are propagated through the unique building structure and is absorbed at different rates. Therefore, in the offline component, ambient vibration noise is analyzed to characterize this process in order to improve signal to noise ratio for subsequent modules. This structure characterization procedure is described in Section 3.1.

Then, with that characterization, the online component detects occupants through two modules, 1) event detection and 2) event classification. Event detection is performed to distinguish event signals from the noise signals by thresholding on the signal component at dominant structural frequencies base on the offline module. We detail this approach in Section 3.2.1. If an event is detected, event classification then classifies the resulting event as a step event (an occupant is detected) or a non-step event. We describe this approach in Section 3.2.2.

3.1 Structure Characterization

Structure characterization is necessary to improve the signal quality thus increasing the signal to noise ratio of the events. Using the fact that the vibration is amplified near natural frequencies, this module identifies the dominant vibration frequencies from collected floor ambient vibration data and then set threshold for Event Detection.

The algorithm first *identifies dominant frequencies* of the unique building structure that can potentially be used to better identify events. It does this by first finding the percentage of energy contribution at each frequency of the ambient vibration signal captured when minimal footsteps or other excitations are present. This is accomplished by computing the normalized power spectrum density (PSD). Then the algorithm applies peak picking [38] on the normalized PSD to obtain the dominant frequencies of the structural vibration. These dominant frequencies are important to the analysis because these frequencies include the natural frequencies of the structure. Vibration at natural frequencies is amplified and footsteps far away from sensor will have a higher chance to be detected if they have frequency components at the natural frequencies. Fourier transform, instead of time-frequency domain analysis, is used here because the background signal is relatively stationary, thus inspecting the Fourier transform is sufficient to provide insights on structural characteristics while being computationally more efficient than time-frequency analysis. Figure 2 shows normalized PSDs in two different buildings which show different values of dominant frequencies, confirming the need of structure characterization.

With the analysis on the normalized PSD, the algorithm *sets thresholds to be used for online event detection* module by applying the wavelet analysis on the signals. Wavelet analysis is commonly used for analyzing non-stationary signals

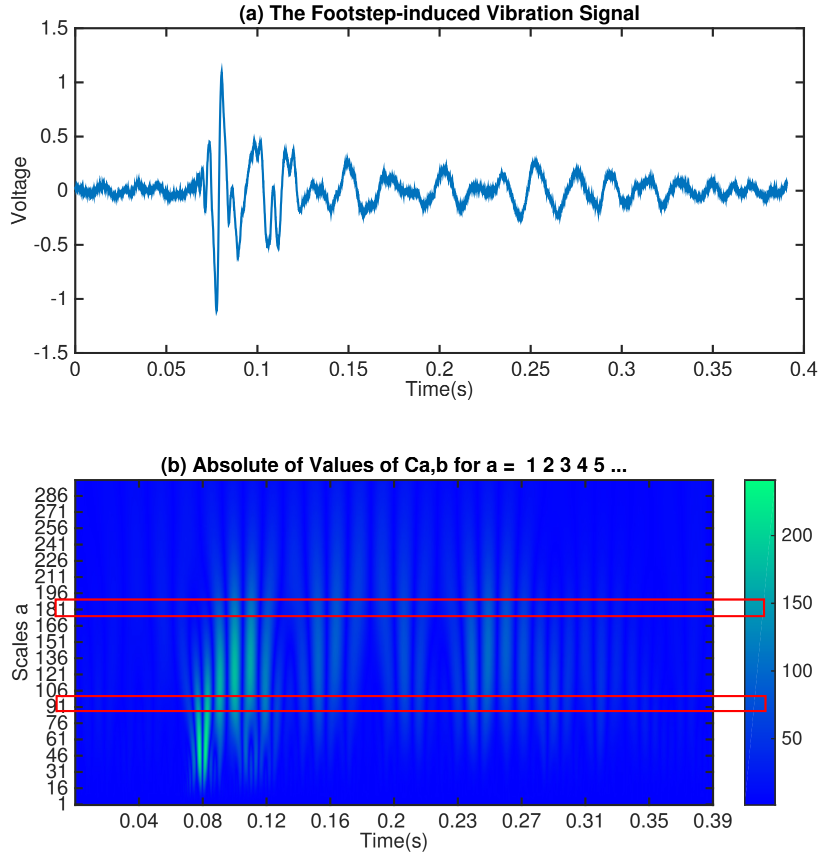


Figure 3: Wavelet analysis of a signal induced by a sequence of footsteps. (a) shows the step-induced signal, and (b) shows the CWT of the signal. The red boxes indicate the scales that correspond to dominant frequencies of floor vibration

(such as step-induced vibration signal). we used continuous wavelet transform (CWT) to measure the similarity between target signal and wavelet filter stretched to different extent (scale) at different time (shift). The choice of the wavelet filter is determined to be Mexican hat wavelet because of the resemblance between the footstep induced signal shape and a combination of the Mexican hat wavelet filters at different scales [39]. Figure 3 shows a sample footstep signal and its CWT output. The following equation explains the wavelet transform of function f, with wavelet filter ψ at different scales s, shift u and time t.

$$Wf(s,u) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{s}}\psi^*(\frac{t-u}{s})dt \tag{1}$$

ψ^* represents complex conjugate of ψ. To determine the threshold value for the signal component at dominant frequencies, the corresponding wavelet scales are computed, and CWT is performed at these scales. The output wavelet coefficient matrix is used to compute the thresholds for each scale. Assuming the ambient vibration noise is a Guassian noise, at each scale, one standard deviation above the mean $(\mu + \sigma)$ of the squared wavelet coefficients is set to be the threshold for that scale. The reason for using one standard deviation is that we only exclude noise with high certainty so that more possible events can be discovered and analyzed. More footsteps and noise will be detected and false alarm rate will increase at this stage because of the low threshold. However the false alarms will be filtered as non-step events in the event classification module.

The dominant frequencies and the thresholds are passed to occupant footstep detection module described in Section

3.2. Structural characterization module needs to be performed offline when the system is first deployed in a new structure.

3.2 Occupant Footstep Detection

The online component of the algorithm is responsible for detecting footsteps. It is a two-stage footstep detection algorithm which includes an event detection sub-module (that identifies all possible events) and an event classification sub-module (that determines if an event is a footstep). The online component continuously analyzes incoming vibration signals, detects possible events, and classifies footstep events from other excitations.

3.2.1 Event Detection

The goal of event detection module is to capture all possible events that can be footsteps as well as other excitations such as door closing. It obtains information such as dominant frequencies and thresholds for each corresponding frequency from structural characteristic module (Section 3.1). Since footstep signals are non-stationary, CWT is applied in this module to detect events. A lenient threshold value, $\mu + \sigma$, from offline component is adopted in order to detect more steps, as mentioned in Section 3.1. Therefore, some noise may be detected as an event and then classified as non-step event in event classification sub-module.

After converting dominant frequencies into wavelet scales of Mexican hat wavelet filter, CWT at these scales is performed on collected signal to obtain a matrix of wavelet coefficients. At each scale, the algorithm searches for possible events that have squared wavelet coefficients exceeding the threshold. If several dominant frequencies are found, event detection is performed at these frequencies (scales) simultaneously. The combination of scales allows more events to be detected, since the events may have different frequency contents and different events may exceed threshold in different dominant frequencies. If wavelet coefficients exceed thresholds at one or more frequencies, an event is said to be occurred.

3.2.2 Event Classification on Detected Events

In event classification module, detected events described earlier are classified into step events and non-step events.

The first step is to extract features from the detected events. PSD under 150 Hz is used as the main feature for classification in this paper because human footstep frequency range mostly lies in this range [2, 17, 40]. The frequency components contributing less than 1% of total signal energy are set to be 0 to reduce the noise effects in classification.

In the proposed algorithm, one-class SVM (OSVM) is adopted as the classification method since in real settings, the sources of excitations and noise are unknown a priori. Collection of training samples for all possible excitation sources is both time-consuming and inefficient. One-class classification using OSVM allows us to classify footsteps with only positive training samples (footstep signals).

According to the OSVM proposed by Schölkopf, the objective is to separate all data points from the origin in feature space and maximize the distance from the separating hyperplane to the origin [29, 37]. An important parameter for this method is the regularization parameter ν. It is the upper bound on the fraction of margin errors (outliers) and the lower bound of the fraction of support vectors relative to the total number of training examples. Trade-off between the power to identify other excitations and detecting footsteps is controlled by the ν parameter. A small value of ν will lead to a small number of outliers in training samples, while a large value of ν will lead to more outliers. Therefore, a smaller ν fits the training data well and classifies test samples closer to training samples as steps. It should have lower true positive rate and a high true negative rate. As ν increases, the true positive rate should increase and true negative rate should decrease. In this paper, ν is selected by searching through 0 to 1 at an interval of 0.01. The ν value achieving the best cross-validation result is adopted for the building. The dual expression to be minimized is shown in Equation2.

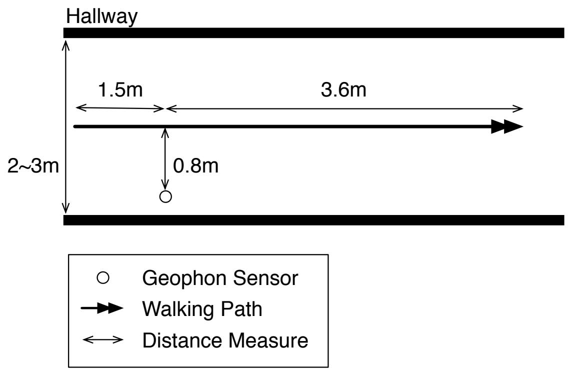


Figure 4: Experimental setup

$$0.5 \sum_{jk} \alpha_j \alpha_k G(x_j, x_k) \quad (2)$$

with respect to $\alpha_1, ...\alpha_n$, subject to $\sum \alpha_j = n\nu$ and $0 \leq \alpha_j \leq 1$ for all $j = 1, ...n$. G is the Gram matrix of which each element is defined by the inner product of the transformed predictors using a kernel function.

4 Evaluation

In order to evaluate the performance of the proposed algorithm on detecting and classifying footsteps from other impulse excitations, experiments were carried out in two buildings: CMU campus building and Vincentian Nursing Home. The CMU campus building is a 4-story concrete building with offices, classrooms, and lecture theatres. The Vincentian Home is a 3-story steel frame residential building housing 60 elderly residents. The event detection and classifier are trained and cross-validated for each building. Evaluation metrics adopted here are precision, recall rate, and F1 score. Section 4.1 covers the experiment details, and Section 4.2 covers the results and discussion.

4.1 Description of Experiments

Two sets of experiments are conducted for testing the algorithm under various excitation scenarios. The first dataset (dataset 1) is occupant step-induced structural vibration signals, collected with multiple people walking in one direction for about 5 meters under the scenario shown in Figure 4. The second dataset (dataset 2) is structural vibration signals induced by impulse-like excitations other than footsteps, within a 3.5 meter radius around the sensor. The impulses investigated here include objects dropping, chair dragging, and door closing from the CMU campus building, and walker hitting ground and wheelchair pushing from Vincentian Nursing Home. This dataset is combined with the first dataset to evaluate the event classification algorithm.

The structural characteristics of the floors in two test sites are different, which allows us to evaluate the robustness of algorithm for different structures. The test location in the CMU campus building is a concrete floor area on ground floor (referred to as CMU Testing Location). Testing in Vincentian Home includes carpeted concrete hallway on a metal deck (referred to as Vincentian Home Testing Location). These locations are hallways with the widths between 2 to 3 meters. The setup is shown in Figure 4. One geophone (SM-24) is used with a DAQ assistant to collect vibration signal at 25.6 kHz to explore wide frequency band [41]. 20 traces (7 steps each) of walking are collected at each testing location and 5 sets of each excitation mentioned above are collected.

4.2 Results and Discussion

The metrics used to evaluate the footstep detection rate include precision, recall rate, and the resulting F1 score. Traditional threshold method using time domain signal energy is compared as a baseline with the proposed algorithm[10]. The performance of the event detection module alone and the full two-stage footstep detection algorithm is evaluated. The recall rate (Equation 3) represents the ratio of the number of detected true footsteps to that of all true footsteps and is adopted here to validate the improvement of event detection rate of our algorithm compared to the baseline. The precision rate (Equation 4) represents the ratio of detected true footstep to that of all detected footsteps and is used to evaluate the event classification's false alarm elimination effects. The F1 score (Equation 5) is the overall performance metric on the algorithm's ability to detect step-induced signals. The results are presented in Figure 5 and each result will be discussed in the following subsections.

$$Recall = \frac{True\,Positives}{True\,Positives + False\,Negatives} \tag{3}$$

$$Precision = \frac{True\,Positives}{True\,Positives + False\,Positives} \tag{4}$$

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{5}$$

where True Positives mean the number of detected footstep events, False Positives mean the number of detected non-footstep events, and False Negatives mean the number of missed footstep events.

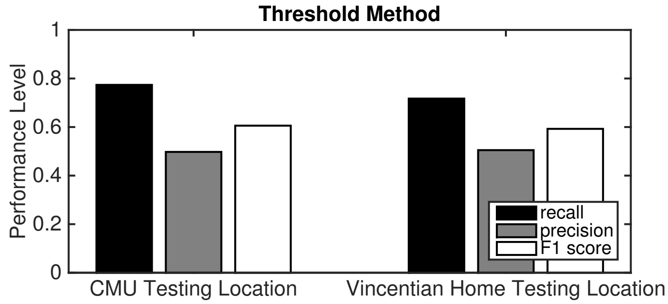
4.2.1 Baseline Method

Traditional threshold method is adopted as the baseline method to compare the performance with our detection algorithm [42, 43, 10]. The threshold method performs outlier detection by keeping track of surrounding ambient noise level. Events are detected whenever the measured signal has a energy level falling out of the $\mu + 3\sigma$ range, assuming the noise is modeled as Gaussian distribution with average of μ and standard deviation of σ. The algorithm keeps updating the Gaussian noise model when there is no event detected.

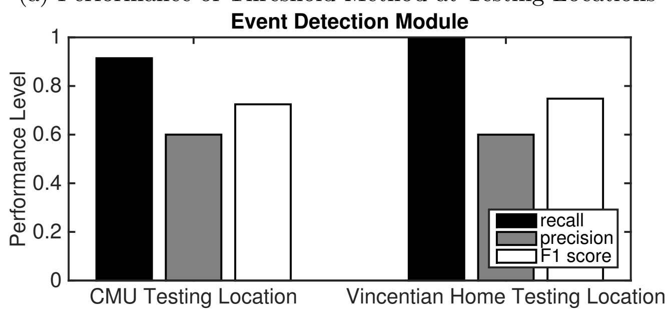
The results of applying the baseline method on all the data show the average of 0.75 recall rate, 0.50 precision, and 0.60 F1 score at the two test locations. Detailed breakdown of results for the two buildings are given in Table 1. The baseline method demonstrates low precision rate, i.e., high false alarm rate, because the events detected from dataset 2 cannot be distinguished as non-step events and therefore are false alarms. The recall rate of the baseline method is also relatively low. That is because when a footstep impulse is far away from the sensor or has a low amplitude, the step-induced vibration signal is then overwhelmed by the ambient noise and cannot be detected, therefore causing miss count. The baseline method fails to detect events under such condition due to the following factors: 1) noise amplitude varies in different locations, and when the signal-to-noise ratio is low, the detection may fail, and 2) the ambient vibration noise fail to meet the assumption of Gaussian noise model may lead to detection failure.

	CMU Testing Location	Vincentian Home Testing Location	Average
Recall	0.77	0.72	0.75
Precision	0.50	0.50	0.50
F1 Score	0.61	0.60	0.60

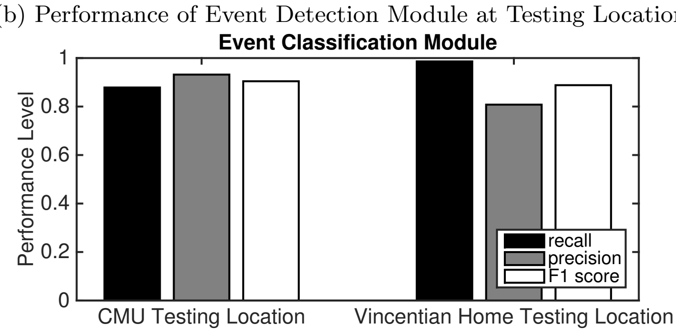
Table 1: Recall, precision, and F1 score for CMU and Vincentian Home testing locations using baseline method.



(a) Performance of Threshold Method at Testing Locations



(b) Performance of Event Detection Module at Testing Locations



(c) Performance of Event Classification Method at Testing Locations

Figure 5: Recall, Precision Rates and F1 score for Proposed Algorithm and Traditional Energy Threshold Based Method. The event detection module alone shows an up to 20% improvement on recall rate comparing to the baseline. The event classification module shows an additional 20% improvement on precision rate comparing to event detection module only case.

4.2.2 Event Detection Module

The event detection module aims to detect footsteps in time-frequency domain by incorporating structural characteristics. Analyzing signal component at dominant frequencies instead of the entire spectrum reduces the effect of surrounding ambient noise level on detection rate. The results of the event detection module show a higher recall rate and an improved precision rate, compared to the baseline method, as shown in Table 2. It shows approximately 10% and 20% improvement in precision and recall rates, respectively. The 20% improvement on recall rate suggests that our approach to investigate the signal component at dominant frequencies is able to discover more events and less sensitive to noise. The increase in precision rate in this case could be caused by the increase of the true positive cases. The average precision of applying the event detection module is at 0.60, due to the false alarms caused by the lack of the ability to classify between step events and non-step events. Therefore, such results indicate the need for classification module to classify detected excitations correctly.

	CMU Testing Location	Vincentian Home Testing Location	Average
Recall	0.91	0.99	0.95
Precision	0.60	0.60	0.60
F1 Score	0.72	0.75	0.74

Table 2: Recall, precision, and F1 score for CMU and Vincentian Home testing locations using event detection module.

4.2.3 Event Classification Module

Given that the event detection module alone cannot distinguish footstep events from other impulse-like excitation events, the event classification module aims to separate the footstep events using the normalized PSD.

The average of precision rate has reached 0.87 and the average recall rate is 0.93. More detailed results are shown in Table 3. There is a slight decrease in recall rate as compared to the event detection module, which is caused by mis-classification on the True Positive cases. The precision rate is improve by over 20%, due to the elimination of the non-step events through classification. Comparing with the baseline method, the detection algorithm shows an improvement of over 30% in precision and approximately 20% in recall rate, which translates to up to 4X reduction in detection error. This indicates that our footstep detection algorithm can detect events surrounded by ambient vibration noise and eliminate other impulse-like excitations as non-step events.

	CMU Testing Location	Vincentian Home Testing Location	Average
Recall	0.88	0.99	0.93
Precision	0.93	0.81	0.87
F1 Score	0.90	0.89	0.90

Table 3: Recall, precision, and F1 score for CMU and Vincentian Home testing locations using event detection and classification modules.

5 Future Work

The future work related to footstep sensing can be vast. Particular to the topic covered in this paper we see two main directions for future work: improve robustness to noise and to structure variation. To improve the robustness to noise under different situations, we will explore more features in both time and frequency domains. We will also investigate the effects of different walking patterns and more factors affecting the wave propagation. Structural variation is another remaining challenge. Footstep-induced signals propagate through the floor structure to reach the sensor. Thus, structural characteristics affect the collected signal forms, which influences the detection algorithm performance. This leads to the need for separate calibration and training for each location. We plan to overcome this challenge through developing a structure independent features for footstep signal detection.

6 Conclusions

Detecting occupants can provide essential information for smart infrastructure applications. In this paper, we utilized human footstep induced floor vibration to detect occupants in buildings. The advantages of this approach includes non-intrusive nature, ease of setup and maintenance. The main challenges regarding the footstep detection using vibration sensors are: 1) the signal-to-noise ratio is often low, which result in high rate of missed detection. 2) it is possible to detect other impulse-like excitations instead of footsteps as the shape of the signals received is similar, especially in time domain. To overcome these challenges, we proposed a two-stage footstep detection algorithm, which by incorporating structural characteristics, is able to increase detection performance. The proposed algorithm involves structure characterization module and occupant footstep detection module. In structure characterization module, the dominant frequencies of the floor structure is obtained from ambient vibration. Occupant footstep detection module consists of two sub-modules: event detection and event classification. Event detection sub-module is carried out to detect events, which can potentially be footsteps or other impulse excitations, using the vibration signal components at floor dominant frequencies. The signal at the dominant frequencies is amplified higher than other frequencies, which leads to higher signal-to-noise ratio, and hence improves step detection accuracy. Then, event classification sub-module classifies the detected events into step events or non-step events. Two-stage footstep detection algorithm is used for footstep detection in two buildings with different structure and usage pattern. We validated our two-stage detection algorithm in both a Carnegie Mellon University building and Vincentian Nursing Home. The results show up to 50% improvement over the traditional threshold method, which also translates to up to 4X reduction in detection error.

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References

[1] Thiago Teixeira, Gershon Dublon, and Andreas Savvides. A survey of human-sensing: Methods for detecting presence, count, location, track, and identity.

[2] Alexander Ekimov and James M Sabatier. Vibration and sound signatures of human footsteps in buildingsa). *The Journal of the Acoustical Society of America*, 120(2):762–768, 2006.

[3] Xin Jin, Soumalya Sarkar, Asok Ray, Shalabh Gupta, and Thyagaraju Damarla. Target detection and classification using seismic and pir sensors. *Sensors Journal, IEEE*, 12(6):1709–1718, 2012.

[4] Zheng Sun, Shijia Pan, Yu-Chi Su, and Pei Zhang. Headio: Zero-configured heading acquisition for indoor mobile devices through multimodal context sensing. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, pages 33–42. ACM, 2013.

[5] Zheng Sun, Aveek Purohit, Kaifei Chen, Shijia Pan, Trevor Pering, and Pei Zhang. Pandaa: physical arrangement detection of networked devices through ambient-sound awareness. In *Proceedings of the 13th international conference on Ubiquitous computing*, pages 425–434. ACM, 2011.

[6] Zheng Sun, Aveek Purohit, Raja Bose, and Pei Zhang. Spartacus: spatially-aware interaction for mobile devices through energy-efficient audio sensing. In *Proceeding of the 11th annual international conference on Mobile systems, applications, and services*, pages 263–276. ACM, 2013.

[7] D. Sousa Nunes, Pei Zhang, and J. Sa Silva. A survey on human-in-the-loop applications towards an internet of all. *Communications Surveys Tutorials, IEEE*, 17(2):944–965, Secondquarter 2015.

[8] Amruta Purohit, Zheng Sun, Shijia Pan, and Pei Zhang. Sugartrail: Indoor navigation in retail environments without surveys and maps. In *Sensor, Mesh and Ad Hoc Communications and Networks (SECON), 2013 10th Annual IEEE Communications Society Conference on*, pages 300–308. IEEE, 2013.

[9] Mostafa Mirshekari, Shijia Pan, Adeola Bannis, Yan Pui Mike Lam, Pei Zhang, and Hae Young Noh. Step-level person localization through sparse sensing of structural vibration. In *Proceedings of the 14th International Conference on Information Processing in Sensor Networks*, pages 376–377. ACM, 2015.

[10] Shijia Pan, Amelie Bonde, Jie Jing, Lin Zhang, Pei Zhang, and Hae Young Noh. Boes: building occupancy estimation system using sparse ambient vibration monitoring. In *SPIE Smart Structures and Materials+ Nondestructive Evaluation and Health Monitoring*, pages 90611O–90611O. International Society for Optics and Photonics, 2014.

[11] Shijia Pan, Ningning Wang, Yuqiu Qian, Irem Velibeyoglu, Hae Young Noh, and Pei Zhang. Indoor person identification through footstep induced structural vibration. In *Proceedings of the 16th International Workshop on Mobile Computing Systems and Applications*, pages 81–86. ACM, 2015.

[12] Arun Subramanian, Kishan G Mehrotra, Chilukuri K Mohan, Pramod K Varshney, and Thyagaraju Damarla. Feature selection and occupancy classification using seismic sensors. In *Trends in Applied Intelligent Systems*, pages 605–614. Springer, 2010.

[13] Ross E Bland. *Acoustic and seismic signal processing for footstep detection*. PhD thesis, Massachusetts Institute of Technology, 2006.

[14] SA Alyamkin and SI Eremenko. Pedestrian detection algorithms based on an analysis of the autocorrelation function of a seismic signal. *Optoelectronics, Instrumentation and Data Processing*, 47(2):124–129, 2011.

[15] George P Succi, Daniel Clapp, Robert Gampert, and Gervasio Prado. Footstep detection and tracking. In *Aerospace/Defense Sensing, Simulation, and Controls*, pages 22–29. International Society for Optics and Photonics, 2001.

[16] Gökhan Koç and Korkut Yegin. Footstep and vehicle detection using slow and quick adaptive thresholds algorithm. *International Journal of Distributed Sensor Networks*, 2013, 2013.

[17] Kenneth M Houston and Daniel P McGaffigan. Spectrum analysis techniques for personnel detection using seismic sensors. In *AeroSense 2003*, pages 162–173. International Society for Optics and Photonics, 2003.

[18] Huai-Fei Xing, Fang Li, and Yu-Liang Liu. Wavelet denoising and feature extraction of seismic signal for footstep detection. In *Wavelet Analysis and Pattern Recognition, 2007. ICWAPR'07. International Conference on*, volume 1, pages 218–223. IEEE, 2007.

[19] Ripul Ghosh, Aparna Akula, Satish Kumar, and HK Sardana. Time–frequency analysis based robust vehicle detection using seismic sensor. *Journal of Sound and Vibration*, 346:424–434, 2015.

[20] Jingchang Huang, Qianwei Zhou, Xin Zhang, Enliang Song, Baoqing Li, and Xiaobing Yuan. Seismic target classification using a wavelet packet manifold in unattended ground sensors systems. *Sensors*, 13(7):8534–8550, 2013.

[21] Hae Young Noh, K Krishnan Nair, Dimitrios G Lignos, and Anne S Kiremidjian. Use of wavelet-based damage-sensitive features for structural damage diagnosis using strong motion data. *Journal of Structural Engineering*, 137(10):1215–1228, 2011.

[22] H Noh and AS Kiremidjian. On the use of wavelet coefficient energy for structural damage diagnosis. *Proc. the10th International Conference on Structural Safety and Reliability, Osaka, Japan*, 2009.

[23] Hae Young Noh, Dimitrios Lignos, Krishnan K Nair, and Anne S Kiremidjian. Application of wavelet based damage sensitive features for structural damage diagnosis. In *Proceedings of the 7th International Workshop on Structural Health Monitoring*, 2009.

[24] Tong-hua Ling and Xi-bing Li. Analysis of energy distributions of millisecond blast vibration signals using the wavelet packet method. *Chinese Journal of Rock Mechanics and Engineering*, 24(7):1117–1122, 2005.

[25] MJ David. Tax. one-class classification; concept-learning in the absence of counter-examples. *ASCI dissertation series*, 65, 2001.

[26] Shehroz S Khan and Michael G Madden. One-class classification: taxonomy of study and review of techniques. *The Knowledge Engineering Review*, 29(03):345–374, 2014.

[27] Shehroz S Khan and Michael G Madden. A survey of recent trends in one class classification. In *Artificial Intelligence and Cognitive Science*, pages 188–197. Springer, 2010.

[28] Chih-Chung Chang and Chih-Jen Lin. Training v-support vector classifiers: theory and algorithms. *Neural computation*, 13(9):2119–2147, 2001.

[29] Bernhard Schölkopf and John C Platt. Support vector method for novelty detection.

[30] David MJ Tax and Robert PW Duin. Support vector data description. *Machine learning*, 54(1):45–66, 2004.

[31] Stephen J Preece, John Y Goulermas, Laurence PJ Kenney, Dave Howard, Kenneth Meijer, and Robin Crompton. Activity identification using body-mounted sensorsa review of classification techniques. *Physiological measurement*, 30(4):R1, 2009.

[32] Kun-Lun Li, Hou-Kuan Huang, Sheng-Feng Tian, and Wei Xu. Improving one-class svm for anomaly detection. In *Machine Learning and Cybernetics, 2003 International Conference on*, volume 5, pages 3077–3081. IEEE, 2003.

[33] Hyun Joon Shin, Dong-Hwan Eom, and Sung-Shick Kim. One-class support vector machinesan application in machine fault detection and classification. *Computers & Industrial Engineering*, 48(2):395–408, 2005.

[34] Larry M Manevitz and Malik Yousef. One-class svms for document classification. *the Journal of machine Learning research*, 2:139–154, 2002.

[35] Asma Rabaoui, Manuel Davy, Stéphane Rossignol, Zied Lachiri, and Noureddine Ellouze. Improved one-class svm classifier for sounds classification. In *Advanced Video and Signal Based Surveillance, 2007. AVSS 2007. IEEE Conference on*, pages 117–122. IEEE, 2007.

[36] J Zhou, KL Chan, VFH Chong, and Shankar M Krishnan. Extraction of brain tumor from mr images using one-class support vector machine. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pages 6411–6414. IEEE, 2006.

[37] Bernhard Schölkopf, John C Platt, John Shawe-Taylor, Alex J Smola, and Robert C Williamson. Estimating the support of a high-dimensional distribution. *Neural computation*, 13(7):1443–1471, 2001.

[38] Output-only modal parameter identification of civil engineering structures. *Structural Engineering and Mechanics*, 17(3-4):429–444, 2004.

[39] Michael Edwards and Xianghua Xie. Footstep pressure signal analysis for human identification. In *Biomedical Engineering and Informatics (BMEI), 2014 7th International Conference on*, pages 307–312. IEEE, 2014.

[40] James M Sabatier and Alexander E Ekimov. A review of human signatures in urban environments using seismic and acoustic methods. In *Technologies for Homeland Security, 2008 IEEE Conference on*, pages 215–220. IEEE, 2008.

[41] I/O Sensor Nederland bv. *SM-24 Geophone Element*, 2006. P/N 1004117.

[42] Charu C Aggarwal. *Outlier analysis*. Springer Science & Business Media, 2013.

[43] Victoria J Hodge and Jim Austin. A survey of outlier detection methodologies. *Artificial Intelligence Review*, 22(2):85–126, 2004.