Theme Article

# Area Occupancy Counting Through Sparse Structural Vibration Sensing

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***Abstract*—This paper presents an indoor area occupancy counting system utilizing the ambient structural vibration induced by pedestrian footsteps. Our system achieves 99.55% accuracy in pedestrian footsteps detection, 0.2 people mean estimation error in pedestrian traffic estimation, and 0.2 area occupant activity estimation error in real-world uncontrolled experiments.**

**Ubiquitous area occupancy** information acquisition is essential for smart building applications such as energy/space management and market research. Sensing methods to obtain this information mainly fall into two categories: infrastructure-based sensing[1–5] and mobile-based sensing.[6,7] Mobile-based sensing requires occupants to carry or wear a device, therefore limiting their applications in many scenarios such as elderly and child monitoring. On the other hand, infrastructure-based techniques refer to passive sensing methods that do not require the monitored subject to carry a sensing device, which is a better fit to our sensing goal. However, these techniques, such as surveillance cameras and motion sensors on doorways, often have sensing requirements, such as line-of-sight and dense deployment at designated areas/positions.

To overcome these limitations, footstep-induced structural vibration is introduced for occupancy monitoring.[8,9] The main intuition behind structural vibration-based sensing is that when people walk, their footstep striking results in structural vibrations, which are perceived by sensors. The vibration signals caused by multiple people can be utilized to count and track them. By measuring structural vibrations, this approach enables sparse sensing and does not require occupants to carry devices. However, prior vibration-based approaches either focus on one person or in a limited space in the building, which may not reflect the scenario in real-world applications where multiple people might simultaneously walk between rooms and hallways.

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In this paper, we present a structural vibration-based occupancy estimation system, which obtains occupancy information for multiple people across various rooms. For this purpose, the main challenges are 1) sensitivity of the footstep-induced vibration signals to spatial structure changes (e.g., reduction in amplitude when the person walks in a room and signal gets obstructed by the wall), and 2) complexity of signal mixture when multiple people walk simultaneously in the sensing range.

To address these challenges, we estimate the traffic count through characterizing the signal mixture for different traffic conditions and then utilize the traffic count and heuristics about structural properties and human walking patterns to track occupancy across rooms. Specifically, we 1) estimate the number of people walking in the sensing range using the signal mixture characteristics, 2) utilize the known building layout, general walking patterns, and structural characteristics to track pedestrians when they walk along the hallway and enter rooms, and 3) estimate the overall occupancy of different areas of a building based on the updates of the detected occupancy change events.

The contributions of this work include

- We present a footstep-induced structural vibration-based occupancy estimation method.
- We consider vibration wave properties to handle a variety of signal mixture scenarios.
- We evaluate the system with real-world experiment datasets.

## PHYSICAL BACKGROUND

To understand our method for room occupancy counting, this section explores how structural vibration waves are affected by the building layout and how we can use the wave properties to estimate the number of occupants in a location.

### Floor Vibration Wave Propagation

When a foot strikes the floor, its impact generates a dynamic response in the floor structure in the form of structural vibrations. In occupancy monitoring applications, we leverage two critical insights regarding wave propagation: 1) the vibration signal energy/amplitude is inversely proportional to the distance between the vibration sensor and the footstep location (the footstep-sensor distance),[8,10] and 2) vibration wave propagation is affected by changes in the underlying structure (e.g., floor beams, voids, etc.).[9,11]

The first insight enables relative location tracking and allows walking directions estimation in the sensing area. With a known sensor location, we can infer the position and trajectory of occupants by observing a steady increase or decrease in the vibration signal amplitude/energy. Furthermore, with a series of vibration sensors in a network, we can observe when an occupant approaches one sensor and becomes increasingly far from another.

With the second insight, we utilize the known sensor locations and building floor plan information to determine when occupants enter and exit a sensing area. We observe that the distance/amplitude relationship from the first insight changes significantly when an occupant moves from one area into another. Figure 1 shows an example of the structural response through balldrops in a residential townhouse.[8] In this scenario, the observed vibration signal energy is significantly greater in the hallway (where the sensor was located), and then reduces for excitations located in the adjacent rooms. Therefore, by observing the general walking trend for occupants in a space, we can determine when they move into various rooms in the building by monitoring abrupt changes to the distance/amplitude relationship.

### Floor Vibration Response Characteristics

Floor vibration monitoring systems are often considered linear, time-invariant systems, which indicate that each recorded vibration response can be viewed as a linear combination of the excitation sources at a given time.[9] Using this assumption, we infer that the scenario where multiple occupants are walking in the sensing area will generate a signal that varies from more impulsive (single person) to more similar to white noise (many people). As a result, we make two key observations: 1) signals with the same number of people walking (1 person vs. 1 person, 2 people vs. 2 people, etc.) will tend to have more similarity to each other, while those with

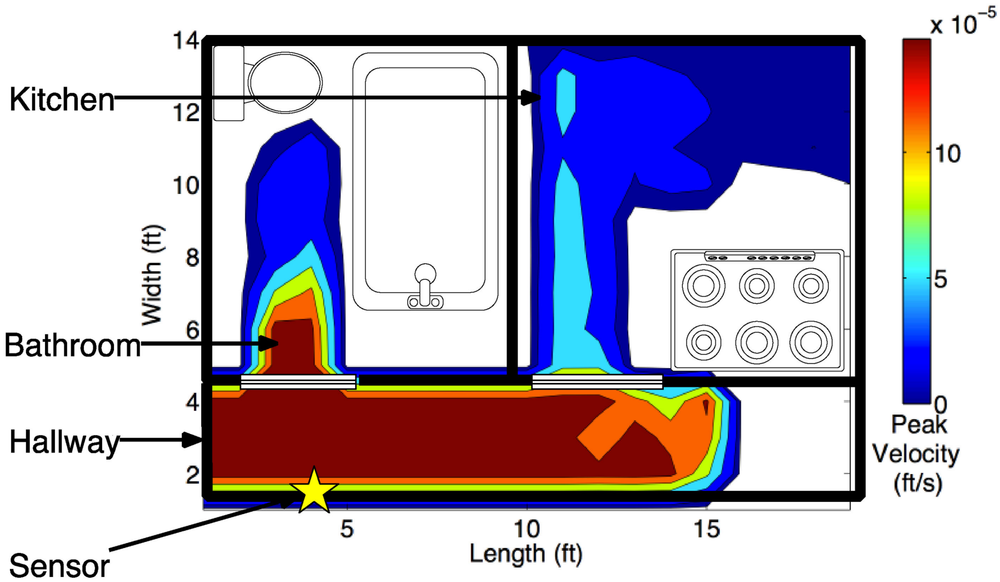


**Figure 1.** Heat map showing vibration signal energy in different regions in a residential townhouse. Note the sudden drop in energy between the hallway and adjacent rooms. Source: Shijia Pan, used with permission.[8]

different number of occupants (e.g., 1 person vs. 4 people) will tend to not be as similar, and 2) as the number of occupants increases towards the "white noise" condition, the signal randomness increases,[9] and the characteristics of the vibration waves can be distinguished by their increasing randomness. With an increasing number of impulses, the recorded vibration signal converges on the random, "mixed signal" case. By combining these two observations, our method can learn the differences in the signal caused by an increasing number of occupants and use that information to estimate the number of occupants in a given room.

## AREA OCCUPANCY COUNTING SYSTEM

The area occupancy counting system has three main modules: the sensing module, the intra-area detection, and the interarea decision making, as shown in Figure 2. The system first detects the floor vibration with the sensing modules that are placed on the floor. Then, for each sensing module, the signal is processed, which is referred to as intra-area detection. In the intra-area detection module, the system first detects the sliding windows that contain human activity events. Then, these detected events are segmented to indicate different activities. Finally, based on the segmented events, the system identifies the activities which are footsteps and focuses on tracking them. To obtain the overall occupancy count transfer between areas, the intra-area detection will use each single sensor data collaboratively to determine the walking direction and number of pedestrians and eventually estimate the traffic through each area.

### Sensing Module

The sensing module consists of a geophone sensor, an OpAmp, an ADC module, and an Arduino board with processor and communication functions, as shown in Figure 3. The sensing module is placed on the floor to detect floor vibrations induced by pedestrian footsteps in the sensing area.

Each sensing area is covered by at least two sensors to collaboratively detect the scenarios when there are multiple people's footsteps mixed together.[9] The sensing area is defined based on the structural layout and the effective sensing range of the sensors in that structure. In the example shown in Figure 1, the hallway, bathroom, and kitchen are different areas because there is a structural element between these sensing areas.

The vibration sensor used here is Geophone SM-24, which has a sensitivity of 28.8 V/m/s. In

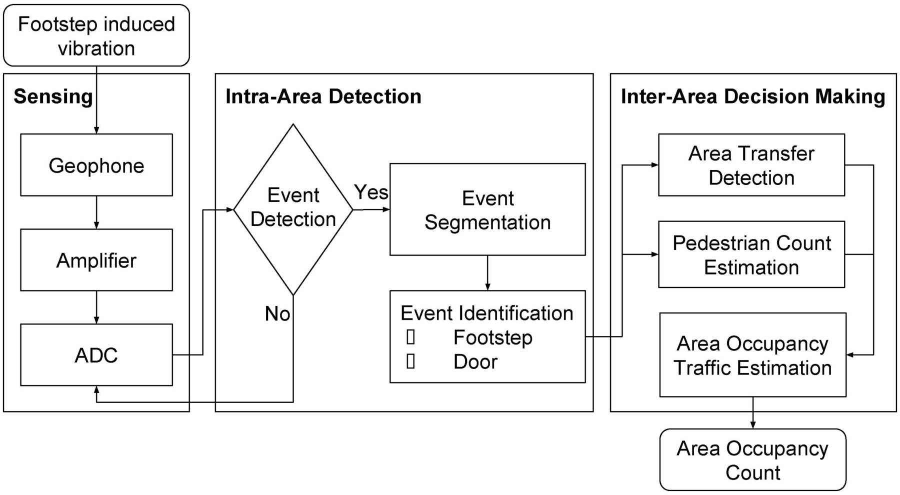


**Figure 2.** Indoor area occupancy count estimation system. The system mainly consists of three modules: the sensing module, the intra-area detection module, and the interarea decision-making module.

our prior works with this sensor, we have observed a sensing range on the order of 10–40 ft (3–12 m) depending on the floor construction. When first deployed, the sensing radius for the deployment structure can be easily obtained by conducting a brief walking experiment in the desired monitoring area, and sensor placement can be optimized based on the observed sensing range. The processor board used here is the WeMo D1 R2 Mini. It is an Arduino compatible board that supports Wi-Fi communication. However, the synchronization between sensing nodes is not guaranteed, which is also taken into consideration in our occupancy counting algorithm.

## Intra-Area Detection

For sensors within each sensing area, the event detection is conducted to extract the sliding windows that contain the events. Then, for the continuously detected windows, the peak detection is conducted to detect the potential impulse events. Next, events detected by each sensor are segmented based on their time-domain separation, indicating a continuous activity conducted by pedestrians. These segments then are analyzed to determine if it is a potential footstep signal, which is often multiple consecutive impulses, or door activity induced signal, which is more likely to be a single impulse signal.

**Event Detection** To detect the events, the sliding windows of the signal are compared to the noise signal through anomaly detection.[8,9] Figure 4(b) shows the detected sliding window from the raw signal shown in Figure 4(a). To handle the multiple people walking scenario, the detected event extracted is not required to have a fixed length.[9] However, to analyze the temporal information for various overlapping footstep-induced vibration signals, the onsets of each impulse are detected as peaks within a series of

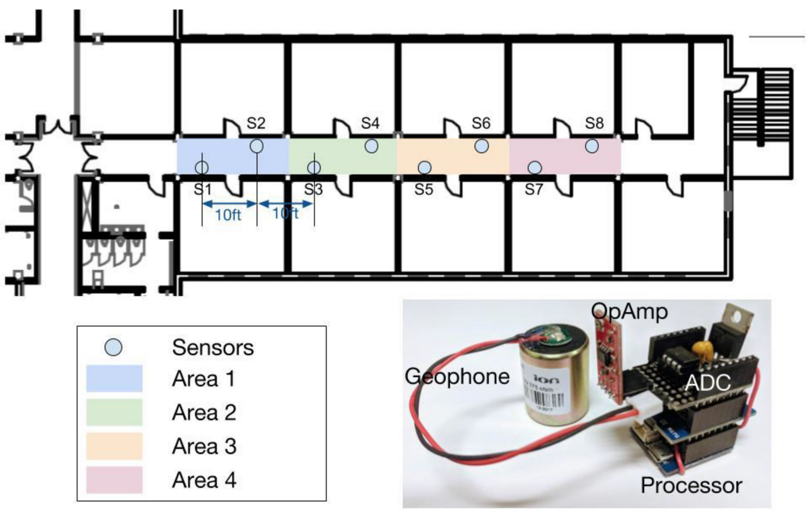


**Figure 3.** Sensor deployment and the floor plan. Lower right image shows the sensing node utilized for the uncontrolled experiments.

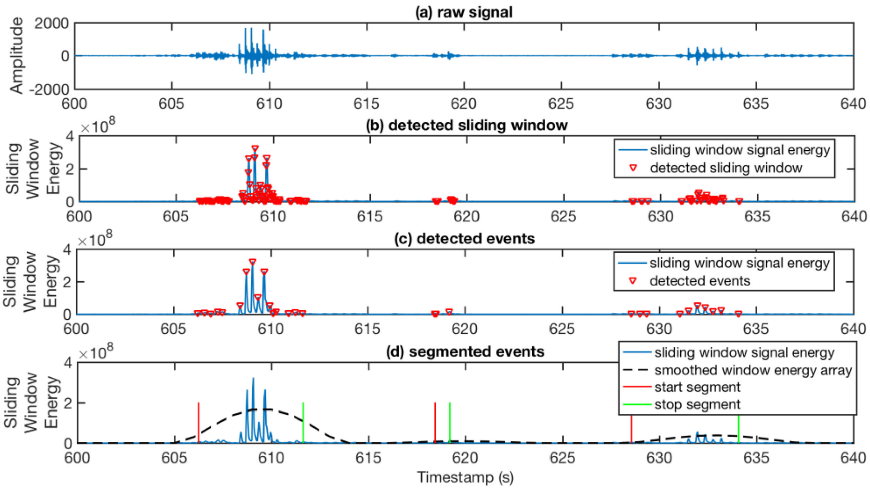


**Figure 4.** Intra-area detection.

consecutive detected sliding windows. Figure 4 (c) demonstrates the detected events from the detected sliding windows shown in Figure 4(b).

**Event Segmentation** The event segmentation is conducted based on the extracted peak that indicates the impulsive signal events, instead of the consecutive sliding windows. We consider a sequence of detected impulsive events with less than 2 s pause as one activity segment. The threshold (2 s) is selected based on 1) the potential structural variations causing false negative of the event detection, and 2) the observation that the natural step frequency of people is often higher than 1 Hz.[12] Figure 4(d) shows the segmented signal with a red line indicating the start of the segment and the green line indicating the end of the segment.

**Event Identification** To obtain the occupancy count, we consider segments that contain at least three consecutive detected impulsive events as a segment of footsteps. Specifically, we focus on the events from each footstep segment and their correlation in different sensors. For the identified events, the sliding window energy array of that segment is then smoothed, as shown in Figure 4(d), with the black dashed line. We consider the peak of this dashed line indicating the moment the person passes by the sensor.

### Interarea Decision Making

Once each sensor detects and segments impulsive events on their own, they make decisions on the occupancy traffic or counting collaboratively. First, for each detected segment, the neighboring area is investigated in a 10 s window before and after the passing point. If the neighboring sensor is in a separate sensing area, the peaking time (the time where the pedestrian is passing by the sensor) will be compared to determine the transfer between areas. On the other hand, if the neighboring sensor is in the same sensing area, the segment of the signals from these two sensors will be compared to determine the number of people walking together in the same sensing area.

**Area Transfer Detection** The intuition of getting the pedestrian walking direction is that structural separations cause the signal to have significant decay when the pedestrians walk to the next sensing area. Therefore, the peaking timing for the sensing area the pedestrian passes by later will be later than that of the investigated sensor significantly. Since the synchronization of the system is at a second level, the interarea level instead of intra-area level direction estimation is more robust under the system setting.[8] Figure 5 shows an example of when a person walks from sensor 4 to sensor 1 direction. From Figures 5(a.1) to 5(d.1), we can see that the step signals are concentrated between 5 to 10 s for sensors 3 and 4, and this concentration shifts to sensors 1 and 2 between 10 and 15 s. This validates the selection of a 10 s window to investigate for each sensor's neighboring sensor as discussed.

**Pedestrian Count Estimation** For each detected area, the signal obtained by neighboring sensors will be compared to determine if there are multiple people walking at the same time in the area. The intuition behind the pedestrian counting is that for sensors in the same sensing area (i.e., no significant structural variation at the sensing points), the same impact induced signal will not be significantly altered through the propagation, which is discussed in "PHYSICAL BACKGROUND." When that happens, the features that describe the signal overlapping can be used to estimate the number of pedestrians walking in the area simultaneously.[9] The features are 1) normalized cross-correlation between spatio-different signals, 2) normalized cross-correlation between temporal-different signals, 3) signal duration, and 4) signal entropy.[9]

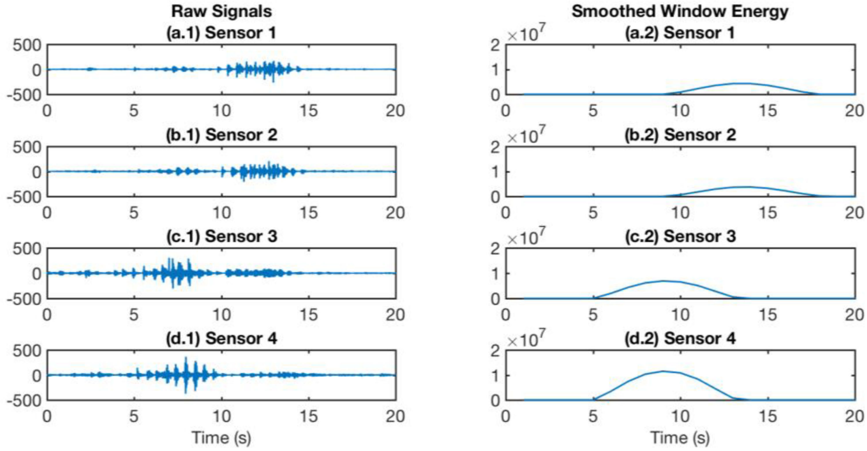


**Figure 5.** Inter-area decision making. An example of the signal detected by Sensor 1-4 when a person walks from Sensor 4 to Sensor 1.

**Occupancy Traffic Estimation and Updates** We use the detected count and direction to update the area occupancy count. For example, when there are multiple people's footsteps detected at one area and no transfer is detected at a different area, then the count of the person will stay in the sensing area until the transfer happens.

## OCCUPANCY TRACKING EVALUATION

To evaluate the module functionality as well as the system's overall performance, we conducted controlled and uncontrolled experiments. "Footstep Event Detection and Tracking Evaluation" and "Pedestrian Count Evaluation" will discuss the controlled experiments previously presented by Pan *et al.*, and "Uncontrolled Occupancy Tracking Evaluation" will present our uncontrolled occupancy tracking experiments.[8,9]

### Footstep Event Detection and Tracking Evaluation

To evaluate the performance of our footstep event detection algorithm, we conducted controlled experiments in two buildings under various experimental scenarios for a total of four evaluation datasets.[8] A total of three of the datasets were collected from Hamerschlag Hall at Carnegie Mellon University in Pittsburgh, PA, where the building is representative of a large-scale commercial building. The fourth dataset was collected in a residential townhouse. In each scenario, the geophone sensors were placed in the hallway for ease of access but can be placed in one or more of the rooms as desired for other deployments as long as the sensing coverage meets the requirements discussed in "Sensing Module." A summary of the datasets and experiments conducted is presented below.

**Footstep Event Detection** To evaluate our footstep detection system, we collected a series of human footstep data in the Hamerschlag Hall experimental location. For ground truth, we utilized predetermined step locations for the walking traces and manually recorded the step time (to ensure that detected steps are real steps). In the sensing area, three locations and trajectory directions were considered in our experiments.[8] For each location and trajectory, we recorded a total of ten walking traces.

Using this data, we evaluated the ability of our system to correctly identify footstep events. From the 30 walking traces recorded (3 trajectories $\times$ 10 traces each), our ground truth indicated a total of 660 footstep events. Of these 660 footstep events, we correctly identified 657 as footstep excitations, which indicate a 99.55% footstep detection accuracy.[8]

**Footstep Event Tracking** To evaluate our footstep event tracking system, we conducted controlled walking experiments with two occupants in a series of entering/exiting room scenarios.[8] We considered this additional testing area to validate the robustness of our system to different locations. The rooms adjacent to the hallway consisted of a carpeted room at the end of the hallway (room 1) and the building stairwell (room 2). Using these two rooms, we collected data for two change of occupancy scenarios: 1) one occupant walks into room 1, followed by a second occupant who walks into room 2, and 2) one occupant walks into room 2, immediately followed by a second occupant walking into room 2, and then one of the two occupants walks out of room 2. Each scenario was repeated 10 times for a total of 40 footstep traces where an occupant enters a room (2 occupants × 2 scenarios × 10 trials), and 10 traces where an occupant exits a room.

We used these 2 scenarios and 50 footstep traces to evaluate the accuracy of our system in detecting when an occupant enters a room, exits a room, and for real-time occupancy counting. Of the 40 walking traces where an occupant enters a room, our system correctly identified 38 of them, resulting in a 95% true-positive detection rate. For the ten walking traces where an occupant leaves a room, we observed an 80% true-positive rate. To evaluate the false-positive rate, we considered ten of the walking traces from the dataset in the detection evaluation above and found that our system experiences a 30% false-positive rate.

For real-time occupancy counting, we define a "success" as the instances where an occupancy change (entering or exiting a room) is detected at the correct step event time (i.e., there is not a time shift in the detected step).[8] Of the 20 walking traces considered, our system correctly identified the occupancy estimation for 17 of them, resulting in an 85% true-positive rate for occupancy counting.

### Pedestrian Count Evaluation

We evaluated the performance of our pedestrian count approach through experiments in various scenarios. Counting the pedestrians is performed through k-nearest neighbor classification with five traces for training and three traces for testing.[9] The most robust counting accuracies are for one and four people for which our approach results in 83.33% and 91.67%. One-person walking is mostly confused with the two-people walking case, which achieved 66.67% accuracy. This could be due to greater likelihood of synchronized walking. Three-people walking case, which is of a 33.33% accuracy, is confused with the four-people case often. Overall, the average counting estimation error is 0.2 people.

### Uncontrolled Occupancy Tracking Evaluation

For uncontrolled experiments, the metrics used to evaluate the area occupancy counting system are detection rate of human walking segmentation in each area and the area transfer direction detection rate percentage, and the area occupancy count error. The system is deployed in the hallway, as shown in Figure 3. The sensors are placed on the floor and powered through the battery packs. A Raspberry Pi is placed in the hallway as the hub for the data collection. A camera is used as the ground truth recording.

A total of eight sensors are placed in the hallway, as shown in Figure 3, where four sensing areas are covered by each pair of two sensors from left to right in the figure. The structural separations along the hallway are the beams that are aligned with the walls of the room separation; therefore, each sensing area is linked to two rooms.

The ground truth is manually labeled and aligned to the raw sensing signal. For each labeled activity segment, the ground truth provides the activity occurring area ID, the number of people in each area, and the detected event segmentation transferring between areas. For the event segmentation transferring, we evaluate the detection rate as the number of transfers accurately detected to the next area over the total number of transfers detected. For the rest of the evaluation, we analyze the aforementioned metrics for each sensing area. In total, 18 activity segments are labeled in a 15 min record.

For each sensor, when a series of impulsive signals is detected, we verify if it is a recorded event. The evaluation metric is the difference between the number of detected walking activity events and the actual number of events (i.e., ground truth). For areas 1 and 4, we achieve 0 activity event detection error. For area 2, we observe a mean error of 0 activity event, with standard deviation less than 1 activity event. For area 3, we observe missed detected activity events and have a mean detection error of 0.2 activity event, with standard deviation less than 1 activity event. To further explore area variations, a longer deployment (1–12 months) with a higher resolution ground truth system is needed in the future. The transfer direction detection for these 18 cases is 100% correct.

## DISCUSSION AND RELATED WORK

### Energy Efficiency Structural Vibration Sensing

The power supply used in our experiments is battery packs with capacities between 4400 and 10 000 mAh, which are sufficient for the data collection that is less than a day. However, compared to other low-power consumption design, the inevitable high sampling rate and amplification are the key power consumption source. In addition, for the wireless transmission-based data uploading, the communication is another key power consumption source. The power consumption can be reduced with adaptive sensing configuration to control the sampling rate and the communication. For example, for locations that do not have pedestrian all the time, the sensor can be awakened when the neighbor sensor detects people walking toward it.

### Sensing Methods Comparison

Various sensing approaches are utilized for occupancy estimation applications. These approaches belong to two main categories: 1) mobile-based sensing[6,7] and 2) infrastructure-based sensing.[1–5] We also compare the reported accuracy of these state-of-the-art systems here.

Mobile-based sensing methods utilize smart devices that people carry with them (e.g., smartphone, GPS, etc.) to detect the presence of people. Therefore, they require subjects to carry the sensing devices with them all the time (and hence are obtrusive). However, in many scenarios, it is often impractical to rely on the subjects to bring their devices and provide access.

Infrastructure-based sensing methods rely on passive sensors in the building and hence are not obtrusive. Some examples of infrastructure-based sensors are 1) vision-based sensors (98% accuracy),[1] 2) radio frequency (RF)-based sensors (70–90% accuracy),[2] 3) motion sensors (90% accuracy),[4] 4) pressure sensors (100% accuracy),[3] and 5) gas sensors (94% accuracy).[5] However, the application of these approaches is limited in some applications due to installment and deployment requirements. Vision-based sensors[1] are sensitive to indoor visual occlusions such as furniture and the columns. RF,[2] pressure,[3] and motion sensors[4] require dense sensing deployment for fine-grained occupancy estimation. Gas sensors,[5] which track the carbon dioxide concentration, are slow to respond to the changes in the occupancy.

### Vibration-Based Sensing

Researchers have introduced vibration-based sensing to overcome the limitations of the current approaches. The main intuition behind vibration-based sensing is that the footstep striking causes the floors to vibrate. These vibrations are received by the sensors and can be utilized for extracting information about the occupants. Some examples of occupant information extracted from the footstep-induced vibration are presence,[8,13,14] location,[15–17] identity,[12] and health-related balance.[10] Furthermore, the vibration-based sensing has been utilized for characterizing other interactions of indoor occupants.[18–20] Due to their applications, these works are generally focused on one occupant in the sensing range. However, focusing on one occupant for occupancy estimation application is an important limitation. In our previous work, we focused on estimating the number of people (one, two, or three people) in the sensing range.[9] However, this approach is useful for a limited sensing approach and becomes obsolete in a large sensing area. In this paper, we focus on developing a vibration-based occupancy estimation system, which is suitable for large sensing areas, which better represent real-life applications.

## CONCLUSION

In this paper, we present our work on an area occupancy counting system, which can be used in various smart building applications such as energy/space usage monitoring. We present our nonintrusive structural vibration-based sensing method to track the occupancy change from each area. We conducted both controlled and uncontrolled experiments to verify the system in school buildings. The system achieves 99.55% accuracy in footstep event detection and 0.2 people mean estimation error for multiple pedestrian counting in the controlled experiments. In the uncontrolled experiments, the system achieves an average of 0.2 area walking activity event detection rate with a less than 1 standard deviation and 100% for area transfer direction estimation.

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**Pei Zhang** is an Associate Research Professor with the Electrical and Computer Engineering Department, Carnegie Mellon University. His recent work focuses on model-based inference sensing in smart cities, including inferencing through vehicles (pollution, emergencies), humans (muscle activity), and buildings (occupant status). He received the Bachelor's degree from California Institute of Technology, in 2002, and the Ph.D. degree in electrical engineering from Princeton University, in 2008.