Occupant Activity Level Estimation Using Floor Vibration

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UbiComp/ISWC'18 Adjunct, October 8–12, 2018, Singapore, Singapore
ACM 978-1-4503-5966-5/18/10.
https://doi.org/10.1145/3267305.3274184

Abstract

Occupant activity level information is essential in many smart home applications, such as energy management and elderly care. Various methods have been proposed for detecting occupant activities through vision-, acoustic-, or radio frequency-based methods. However, the visual-based methods function only when occupants are in the visual field, the acoustic-based methods are sensitive to noise, and the radio-based methods usually require occupants to carry receivers all the time. These requirements increase the difficulty of deployment and maintenance in typical indoor smart home scenarios.

To overcome these shortcomings, we propose a structural vibration-based approach. Specifically, we develop a system with sparse sensor configuration deployed in the floor to monitor the activity levels of different areas. Compared to vision- and acoustic-based methods, our method is not restricted by line-of-sight and less influenced by noise. Compared to the access control system (ground truth), our system enables finer grained activity level estimation with a comparable resolution. We evaluate our system in a real-world deployment in an office building and used the building access control as the ground truth system. Our system shows a correlation coefficient at 0.836 when compared to the ground truth systems.

Author Keywords

occupant activity estimation; structure vibration; area activity monitoring;

ACM Classification Keywords

C.3 [SPECIAL-PURPOSE AND APPLICATION-BASED SYSTEMS]: Real-time and embedded systems

Introduction

Occupant activity level, a.k.a. the utilization frequency of a designated area, can be widely used in many smart home applications such as energy management [12, 17, 10], customer traffic monitoring, and elderly care [1, 11, 8, 2]. Researchers have explored various methods to obtain this information from vision-based [7, 13], audio-based [15, 16], and radio-based sensing systems [9, 4]. Generally, these systems fall into two categories: device-based and device-free. With device-based approaches it is necessary for occupants to carry special devices to receive signals from transmitters. However, it is difficult to assume that all the occupants carry these devices, especially in shopping or hospital scenarios. On the other hand, device-free approaches, such as visual- and acoustic-based methods, often have certain sensing requirements (e.g. light-of-sight, and low ambient noise).

In this paper, we present a structural vibration-based occupant activity level estimation method. Since vibration signals travel far in solids, the coverage of each sensor is large, enabling sparse sensing configurations without the need to carry a device. A typical sensing range for footstep-induced floor vibration is between 3 and 10 meters (depending on the structural materials and layout). Although the sensing range is large in typical structures, the magnitude of the footstep-induced vibrations is often small as compared to the ambient vibration conditions due to the high stiffness of the floor structure, resulting in low signal-to-noise ratios (SNRs). Further, the structural conditions (and hence SNR), vary spatially, resulting in different response magnitudes in different areas of the sensing region. Therefore, we summarize the main challenges of this work as follows:

- Low signal-to-noise ratio (SNR) of occupant activity-induced vibrations due to the high stiffness of the floor structure.
- High variance of structural conditions causes different SNRs in different sensing areas.

To address these challenges, we observe that human activity typically has a pattern based on the time-of-day. Therefore, recorded floor vibrations vary with these patterns. Using this insight, we adaptively set our activity detection threshold based on the time of day and historical patterns, thus enabling a method that is robust to low SNR and that can adapt to different sensing configurations. The our major contributions of this paper are as follows:

- We present a device-free occupant activity level monitoring system through structural vibrations sensing.
- We utilize the prior knowledge that different sensing areas during a particular time (i.e., early morning) have similar activity levels to select thresholds of our activity detection algorithm.
- We deployed our system in an office building to verify the robustness of our system design through real-world experiments.

The rest of this paper is organized as follows. Section ”**Indoor Activity Monitoring System**” illustrates the main units of

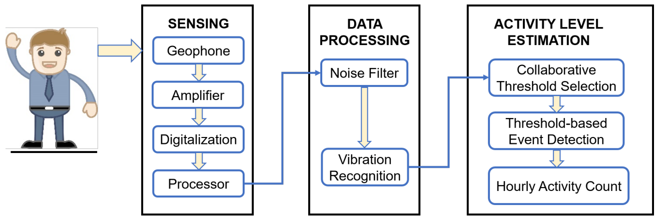


Figure 1: System architecture. The sensing module records vibration signals on the floor. The data processing module extracts vibration signals from background noise and utilizes the cross-correlation method to recognize occupant activity vibration signals. The activity level estimation module utilize a threshold-based algorithm to detect the occupant activity event.

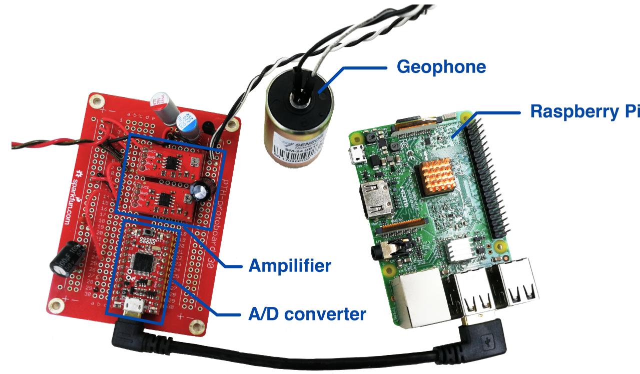


Figure 2: A sensing unit consists of a geophone sensor, an amplifier module, an ADC, and a processor (Raspberry Pi).

our system. Section "**Evaluation and Analysis**" introduces the performance of our system and analyzes occupant activity from both temporal aspect and spatial aspects. Finally, we conclude the paper.

Indoor Activity Monitoring System

Our system mainly consists of three modules: 1) sensing, 2) data processing, and 3) activity level estimation, as shown in Figure 1. The sensing module captures the vibration signal of the floor, and sends the corresponding digital signal to the server. The data processing module reduces the ambient noise to increase the SNR and conducts occupant induced vibration recognition through a cross-correlation-based method. The activity level estimation module counts the detected occupant activity through a threshold-based method. Due to the structural variation, different sensors deployed in different areas have different SNR and sensitivity to the same type of occupant activities. Therefore, the system automatically calibrates their thresholds using heuristic rules.

Sensing

Each sensing unit contains four main components, a geophone, an amplifier, an analog to digital converter (ADC), and a processor. An example of the sensing unit is shown in Figure 2.

First, the geophone captures vibration signals on the floor and generates an analog signal. Next, the amplifier improves the analog signal's resolution. The amplitude of the signal is determined by the occupant activity and the distance between the Geophone and the occupant. However, due to structural vibration reduction design, skyscrapers with concrete floors often result to a low amplitude of the vibration signals caused by occupant activities [**?**] (e.g. walking or opening/closing doors). Therefore, the amplifier module is added to enlarge vibration signals and increase signal resolution. Then, the ADC digitizes the amplified signal. Finally, the processor collects the digital signal and communicates with the server to synchronize timestamps, upload data, and report sensing unit states. To enable large scale occupant activities level monitoring in a real-world scenario, multiple sensing units are deployed in different areas. These sensors are synchronized to millisecond level to ensure temporal comparison analysis.

Data processing

The data processing module aims to filter noise and recognize the impulsive vibration signals. To filter noise, we utilize the Wiener filter (a linear, time-invariant filter) to decrease the interference of background noise. To recognize the impulsive vibration signals, we adopt a cross-correlation-based method which extracts signals that are similar to the representative signals.

Noise filtering

Due to the high stiffness of the floor structure, one of the primary research challenges of our work is the low SNR of the occupant-induced vibration signals. To address this challenge, we analyzed the measured background noise and discovered that it was mainly from the circuit and was an additional noise that fits a Gaussian distribution. Therefore, we applied the Wiener filter to remove the background noise. The Wiener filter minimizes the mean square error (MSE) between the noise signal and the target signal, and has a significant effect of filtering additional noise [3, 5].

Vibration recognition

The challenge faced by impulsive vibration recognition is the variation of different structures. Apart from occupant induced vibration signals, which are mostly impulsive, other ambient vibrations can also be detected by our system. For example, when a metro train passes by the building, it induces a high-amplitude vibration signal on the floor, which would interfere with the recognition of occupant-activity vibration. We utilize a cross-correlation method to recognize occupant activity signal by comparing the investigated signal to a representative signal. To address the structural response variation, we collaboratively select representative signals for each sensor. The insight used here is that we compute the average length of a few labeled vibration signals from different sensors, and design an algorithm to recognize vibration signals.

Activity Level Estimation

To integrate and compare data from different sensing units deployed in multiple areas, the activity detection at each area needs to be comparable. In real-world deployments, the structural responses varies at different locations, which leads to different sensitivity at different areas, i.e., the same activity may generate vibration response of different signal energy in different areas. Therefore, for each sensor, the system selects detected events that have a signal energy larger than a threshold (Collaborative Threshold Selection) as area occupant activity (Threshold-based Event Detection) and update the hourly activity count of the sensing area accordingly (Hourly Activity Count). We will explain the Collaborative Threshold Selection in detail in the rest of the section.

Collaborative Threshold Selection

To guarantee that each sensing unit has a similar sensitivity, we adjust the sensitivity of each sensing unit by selecting different thresholds in the vibration detection. We assume that in the office building, each monitoring area has the same activity strength from 12:01 AM to 5:00 AM. The justification for this assumption is that, during this time period every day, most occupants are not at work, except for a small number of security patrols. Therefore, we utilize the vibration signal magnitude during this time as our threshold for detecting occupant activity at each sensor. To accomplish this, we select a threshold that results in the same number of detected activities for each sensor during

Figure 3: Deployed sensing unit example: For safety reason, sensing unit is installed underneath the floor, and covered with a steel plate. The geophone sensor is fixed on the floor to ensure a stable connection.

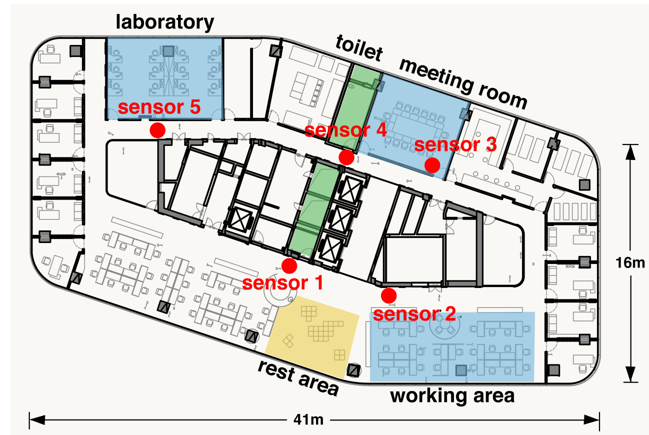


Figure 4: Sensing unit deployment: five sensing units are deployed on the 15th floor to monitor designated area usages, including: a rest area, a working area, a meeting room, a restroom, and a laboratory.

the unoccupied time between 12:01 AM and 5:00 AM.

Evaluation and Analysis

For system design evaluation, we deployed our system on the 15th floor of an office building and collected the floor vibration signals across four weeks. The investigated floor includes meeting rooms, working areas, and laboratories. Everyone needs to pass an access control system using their RFID badges to enter the monitored area. The access control records can be used to infer the information of occupant activity level. Therefore, we select the number of times that access control is activated every hour as the ground truth of the area activity level.

We analyze four-week results from both spatial and temporal aspects to infer the occupant activity information. In the temporal aspect, we can observe hour-level occupant activity events, such as occupants taking breaks and starting to work. Additionally, work patterns of workday and weekends are observed in the results, which are analyzed in the Analysis Section. Then, by comparing different sensing unit results, we can obtain the distribution of occupant activity level in different areas.

Experiment Setup

We deployed several sensing units on the 15th floor for the building. As shown in Figure 3, sensing units were deployed underneath the floor to prevent tampering and prevent tripping hazards. The sensing units are provided with 24-hour power supply and Ethernet connection. To ensure full coupling of the geophone and the structure, geophones are fixed to the concrete floor with an adhesive. The amplification values are determined empirically based on observed responses in each sensing region. A Raspberry Pi is used

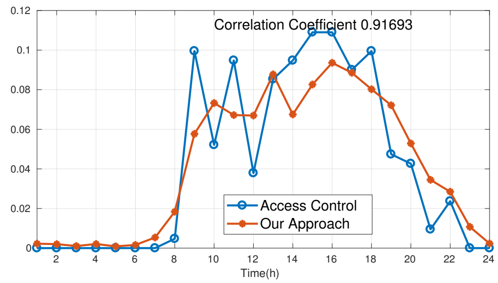


Figure 5: One sensor's results compared with the access control record in a typical day. The y-axis is normalized with the sum of the 24-hour record

as the processor of sensing unit, collecting data from ADC and sending it to the server.

As shown in Figure 4, we deployed several sensing units in high traffic areas, while ensuring full coverage of the main corridors and maintaining a sparse configuration. Areas covered with the deployed sensors include: a meeting room, working area(s), and laboratories.

Evaluation of Occupant Activity Estimation

We evaluated our system performance by comparing its performance to access control records over a one week period. Figure 5 shows a sensing unit's results compared with the access control record. We use the correlation coefficient to measure the similarity between the ground truth (access control record) and the activity estimation per hour from our system. As shown in Table 1, the correlation coefficient is in the range of $[0.807, 0.877]$ on workday, while in the range of $[0.737, 0.772]$ on weekend, indicating different occupant activity patterns on workdays and weekends.

Analysis

We analyze the occupant activity level from two dimensions – spatial and temporal: 1) temporal variations in a single sensor across a 24-hour time period, and 2) hourly spacial activity level variations across the sensor network.

Temporal Aspect

We compare the number of hourly activity detected by a sensor throughout a day. We plot the average number of detected occupant activities an hour in Figure 6, where the blue solid line shows the results from weekdays, and the red solid line shows the results from weekends. Compared to weekends, the average occupant activity level on a workday between 8 AM and 10 PM is about twice as high as that of the weekend; which reflects the attendance of the students. On the other hand, on a workday, occupant activity levels decrease after 7 PM, but in weekend occupant activity decreases after 5 PM, from which we can infer that those persons who do work on weekends tend to work shorter hours and leave earlier than on a weekday.

Figure 7 shows four weeks of activity-level estimates from Sensor 4. In this figure, ”Day 1” is a Saturday, each data point represents one day during the observation period. From these results, it is clear that activity level is significantly higher on weekdays as compared to weekends. In addition, activity level decreased on a holiday, when it is likely that not many people were working. From these results, we can infer that fewer people are working on weekends and holidays as compared to normal weekdays.

Spatial Aspect

Also, experimental results verify that our system can precisely reflect the spatial information of occupant activity level. Figure 4 shows the sensor placement and monitoring regions, which include a rest area, working area, meeting room, restroom, and laboratory. In Figure 8, comparing dif-

	Mon.	*Tues.*	*Wed.*	*Thur.*	*Fri.*	*Sat.*	*Sun.*
Correlation coefficient	0.834	0.832	0.852	0.807	0.877	0.772	0.737

Table 1: The hour-level correlation coefficient between our approach and the access control (ground truth) record.

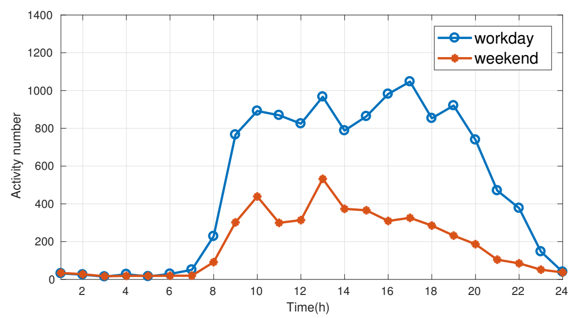


Figure 6: This figure shows the hour-level differences of occupant activity level on workdays and weekends. On a workday, occupant activity decreases after 7 PM. However, on a weekend day, occupant activity decreases after 5 PM. We can infer that most occupants tend to leave earlier on weekends.

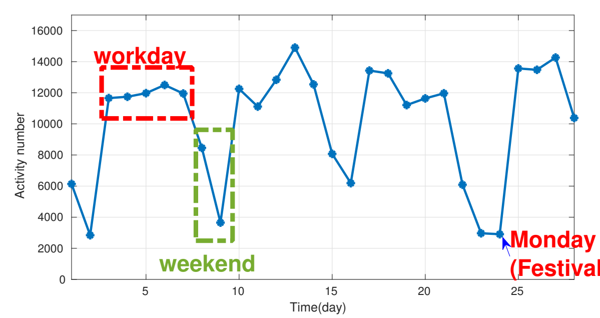


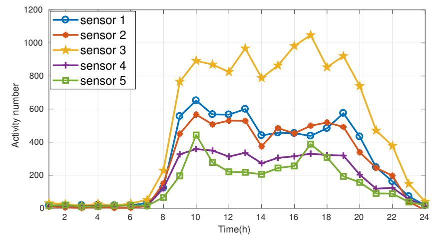
Figure 7: Detected activity level for one sensor across a 4-week monitoring period. Note the significant decrease in activity associated with weekends and holidays.

ferent area's activity levels on workdays and weekends, the meeting room is the most active area, and the activity on workdays is significantly higher than other areas. The activity of working areas and rest areas is similar during the workday, and the activity of laboratory and restroom is lower than the working and rest areas. Each area of activity has a decrease from 1 PM to 2 PM on the workday. This is likely due to the observation that most most occupants take a nap following lunch that lasts from 1 PM to 2 PM; causing a low occupant activity level during that time period.

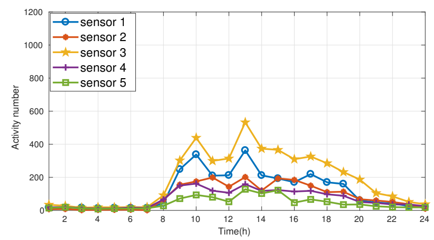
Figure 9 shows the daily activity number in each area across the four weeks that were monitored. From these results, we can observe that the most active area is the meeting room, and the least active area is the laboratory.

Conclusion

We introduced a device-free occupant activity level estimation approach using floor vibrations. We overcame system challenges of low signal-to-noise ratio (SNR) of occupant activity-induced vibrations and high variance of structural conditions causing different SNRs in different sensing areas by developing a noise-adaptive activity-level detection approach. Through a real-world deployment of our system, our approach achieved a high correlation with access



(a) Area activity on workday.



(b) Area activity on weekend.

Figure 8: Occupant activity level in the 5 sensing areas across a typical 24 hour period.

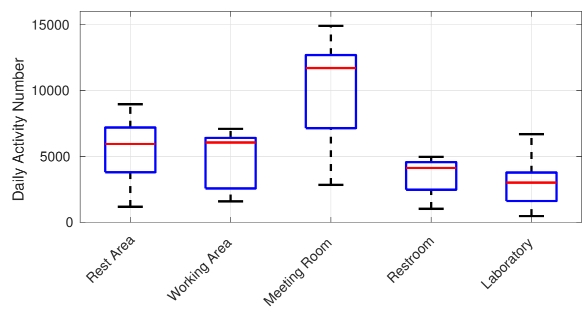


Figure 9: Distribution of occupant activity levels for each sensing area across the 4 week monitoring period.

control (ground truth) record. The correlation coefficient is in the range of $[0.807, 0.877]$ on the workday, while in the range of $[0.737, 0.772]$ on the weekends.

Acknowledgements

This research was partially supported by NSF (funding number CNS-1149611 and CMMI-1653550), Google, and Intel. Thanks for the support of Tsinghua-Berkeley Shenzhen Institute. The views and conclusions contained here are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed implied, of CMU, NSF, or the U.S. Government or any of its agencies.

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