Smart Home Monitoring System via Footstep-Induced Vibrations

Fangyu Li, Jose Clemente, Maria Valero, Zion Tse, Sheng Li, and WenZhan Song

Abstract—**Instead of using traditional intrusive surveillance technologies such as cameras or body sensors, we propose a smart home system sensing the footstep-induced vibrations to feature the same functions which can be used for the assisted-living purpose. Based on distributed sensing and processing units, we adopt a distributed computing approach to preprocess the time-series data, recognize footstep signals, and extract vibration features locally. Through communications over the sensor networks, our system is capable to estimate the occupancy via counting the number of occupants. Besides, based on the multicomponent seismometer sensing system, we propose a novel indoor footstep localization method called angle constrained time difference of arrivals relying on both angle and arrival information of the recorded waveforms. According to separated pedestrian locations, different trajectories of multiple people can be tracked. From the location-tracking history, the resident's daily activities and social interactions can be inferred. In our experiments, the proposed system obtains promising results. Specifically, the location error is 0.14 m with a 0.11 m standard deviation. And the multipeople identification accuracy is above 87.83%.**

Index Terms—**Footstep, localization, occupancy estimation, seismometer, trajectory tracking.**

I. Introduction

SMART home technologies help to evaluate the physical and emotional health through one's physical movement signatures and the social interactions [1]–[7], e.g., elderly in-home assistance [8], and cognitive health assessment [9]. Taking advantage of human–system interactions, the cyber-physical system (CPS) with pervasive and ubiquitous computing capability can be leveraged to transform a regular indoor space into a multisensory, autonomous "smart" environment [10]–[12].

However, the privacy violation issue and indoor obstacles reduce the applicability scope of the home monitoring systems. Whereas, human footsteps induce the floor vibrations, which can be detected to characterize physical conditions of the pedestrian as well as analyze the indoor trajectory pattern to further infer the psychological status [13]–[15]. Vibration signals do not carry sensitive information and are not obstructed by indoor obstacles, so vibration-based smart home system is very promising. There have been some vibration-based indoor applications [16], [17], where people identification function is included, but there was no trajectory tracking. Also, Pan *et al.* [16], [18] used vibration sensors, but their system was not distributed CPS. Instead, a centralized way was adopted, which means all data need to be transmitted to a central processing computer. Zhang *et al.*, [19] measured structural vibrations, but sensors in their experiments were not easily installed.

Smart home systems rely on sensing human activities. Related indoor sensing studies typically use vision, radio frequency (RF), mobile, and acoustic methods [20]. However, specific sensing conditions and location rules are required according to methodology assumptions, including line-of-sight, high sensor density, carrying wearable devices, and so on. In contrary, vibration-based methods provide easy-to-install sparse sensing, which can be embedded to an Internet of Things (IoT) smart building system [21]–[26]. Since not all traditional techniques are suitable for vibration data from seismometers, we need to develop a novel location method which considers the acoustic wave properties and given instruments.

Thus, we propose to use "smart" seismometer units to detect footstep vibrations, and then extract features corresponding to unique walking and gait patterns [16], [19]. Keeping generality and avoiding violating privacy, we do not ask for the identity registration, and the number of pedestrians is adequate for occupancy estimation [27]. This is similar to the speaker count problem, which estimates the number of speakers participating in a conversation [28]. With no prior information about speakers, machine learning techniques [29] can solve the problem. Based on the location information, the trajectory can be estimated, which can be used to interpret one's behavior patterns, and determine when multiple people are interacting [30]. Social interaction and personal activity pattern can be analyzed. Thus, the proposed system can be used for the assisted-living purpose, especially for elderly people who live alone.

In this article, based on footstep-induced vibrations, a smart home system shown in Fig. 1 is proposed, which embeds footstep detection, occupancy estimation, localization, and trajectory tracking functions. The little-explored sensor technology—vibration sensors, i.e., seismometers, is adopted. Based on smart IoT sensors, the proposed system achieves real-time calculation, processing, online occupancy estimation, and trajectory tracking. Following are the main contributions of this article.

1) We propose a novel vibration-based smart indoor monitoring mechanism. There is no existing system to implement

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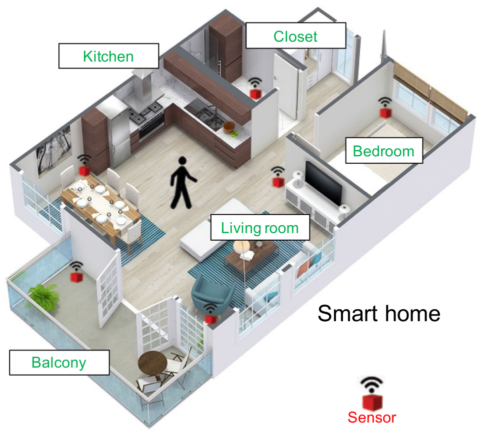

Fig. 1. Proposed smart home system detects human footsteps, locates walking positions and tracks trajectory.

our comprehensive tasks, including footstep detection, occupancy estimation, location, and trajectory tracking.

2) We propose an innovative location method, which is based on the additional information extracted from triaxial seismometers that have not been used in the smart home applications yet.
3) A novel occupation estimation technique is developed, which is based on unsupervised machine learning method without any prior information.
4) The footstep trajectory for single and multiple people can be obtained, which has the potential to infer the person's physical condition and analyze social interactions.

II. System and Algorithm Design

We propose an end-to-end system, whose flow chart is shown in Fig. 2. Here, we discuss key steps one by one. At the end of this section, the system architecture is also described.

A. Sensing

From the mechanics' viewpoint, footstep energy travels through the floor media to vibration sensors. Using networked seismometers attached on the floor, we record footstep vibration signals. We use a sensitive seismometer to collect vibration data. The three-channel (triaxial) seismometer has a 1000 Hz sampling rate with an 8 Hz corner frequency. Unlike the previous work using single component seismometers [31], [32], not only the vertical vibration but also horizontal vibrations are obtained by our triaxial seismometers. The three-channel recorded data respect to movements on directions north (N), east (E), and vertical (Z), which enable us to propose an innovative indoor location approach, whose details are discussed in Section II-D. The seismometer is installed in a corner on the floor and sensors form a sparse mesh network.[1] A low-cost single-board Raspberry Pi is employed to record data, apply computation tasks locally and communicate with other units. Raspberry Pi receives data from the seismometer and saves raw data to a local database, which will be discussed in Section II-F. The online data collection is 24/7 continuous. To process data in real time and obtain accurate location results, the sensor synchronization is important, which is done by global positioning system (GPS) just one time when the system starts.

[1]User datagram protocol (UDP) is used in our system to establish a low-latency and loss-tolerating mesh network.

B. Footstep Detection

To extract footstep signals from the background for analysis, we first need to remove noises from recorded data. Then a footstep isolation step is implemented to isolate footsteps.

1) Preprocessing: The building is constantly shaking and generates background vibration noises to the interested footstep vibration. Besides, the air conditioners (AC) and other appliances also generate vibrations. Unlike the simple environment noise in [32], which can be removed using a highpass filter, our background noise is not limited at a given frequency range. Therefore, to improve the signal-to-noise ratio (SNR), we need to remove the background noise adaptively. A wavelet denoising technique is applied to recorded data to suppress nonstationary noises. However, instead of using a fixed threshold [20], we adopt a relative threshold according to the signal strength. Fig. 3(a) shows a raw data example. It is clear that our background noise is not band limited, so a simple bandpass or highpass filter can not generate satisfying filtering results. The time domain denoising result based on the wavelet thresholding method is shown in Fig. 3(b).

2) Footstep Detection and Isolation: After denoising, we apply a signal segmentation step to extract footstep vibrations, which means we need to recognize a footstep-induced signal from the background. Considering the complexity and efficiency, we adopt a change point detection algorithm based on the second-order statistics, short time average over long time average method, which is usually applied in the seismic event detection [33], [34]. Fig. 4(b) shows footstep isolation results, where the signals between blue (onset) and pink (ending) bars are recognized footstep vibrations.

C. Occupancy Estimation

The occupancy estimation means to count the number of occupants over a given time period. First, our system extracts features of footstep events. Then a machine learning clustering model is generated to estimate the occupancy. Traditional person identification projects used supervised machine learning models, such as support vector machine (SVM) and its derivations [16], [31]. Since occupants are not registered, we propose to use a clustering method to estimate the number of walking people rather than who is walking. In addition, instead of using a supervised model, such as k-nearest neighbor classier [35], we use an unsupervised model to enhance the system versatility, so no supervision information is needed.

1) Feature Extraction: To characterize footstep signatures, features should be extracted [36], [37]. Vibrations and sound pressure responses of human footsteps in buildings can be broadband and frequency-dependent [38]. Different vibration signatures from different walking styles have been studied [39].

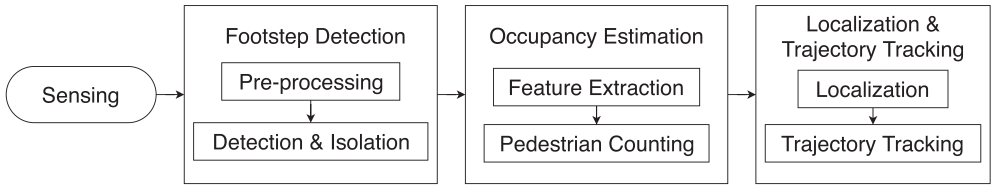

Fig. 2. Proposed system includes sensing, footstep detection, occupancy estimation, location and trajectory tracking. The whole system is introduced in detail in Section II. The smart sensor properties are mentioned in Section II-A. Signal processing methods used in the footstep detection are discussed in Section II-B. Machine learning details about occupancy estimation are covered in Section II-C. The proposed indoor location and trajectory tracking methods are discussed in Sections II-D and II-E.

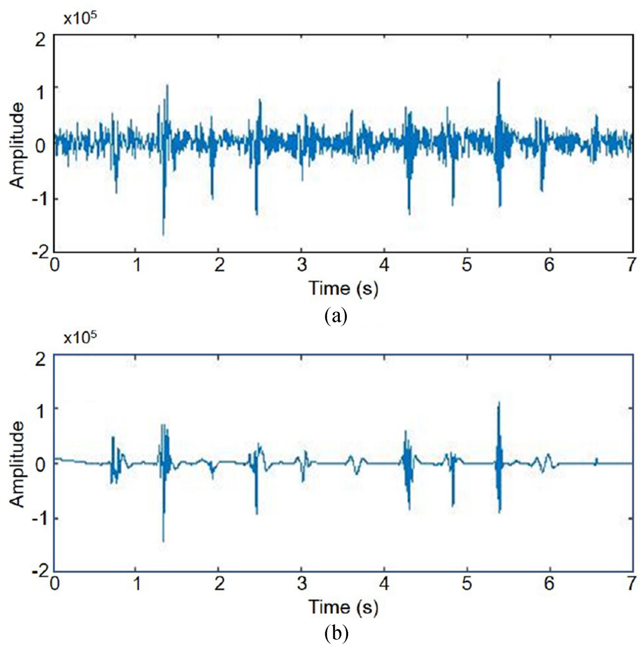

Fig. 3. (a) Raw data before denoising. (b) Signal after denoising in the time domain.

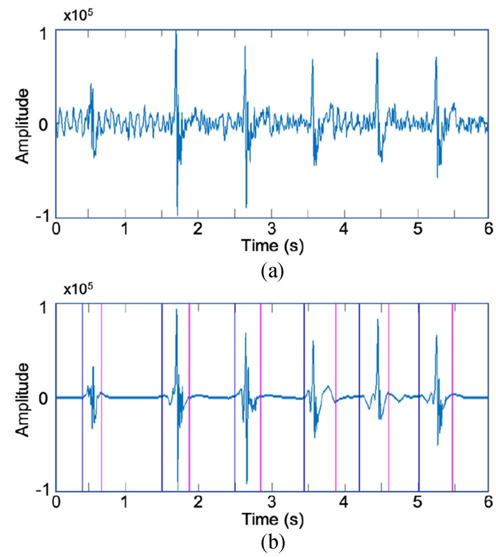

Fig. 4. Footstep isolation results. (a) Raw data. (b) Isolated footstep vibrations from the denoised data.

Footstep features include single footstep features [32], as well as gait features [40]. We compute features in both time and frequency domains, including:

1) time domain: event duration, maximum peak, standard deviation, location of maximum peak, entropy, three values before maximum peak, first three peak values, three values after maximum peak;
2) frequency domain: spectra, location of first three spectral peaks, centroid frequency, number of spectral peaks, first three peak values.

2) Counting via Clustering: We propose to use a clustering technique to estimate the number of occupants. Clustering techniques group similar objects, which are extracted footstep features in our article. The classic “k-means” method minimizes mean squared distances from all points to their respective cluster centers [41], but the “k” needs to be defined beforehand. In some prior work, a Markovian framework has also been used for occupancy estimation [42]. However, the computation cost is high for a real-time, online processing in IoT devices. In addition, to broaden the application range, no prior information should be assumed. Here, we use the density-based spatial clustering of applications with noise (DBSCAN) technique, which is a density-based clustering algorithm to group close sample points in the latent space [43]. DBSCAN starts with a random starting point that has not been clustered. If it contains sufficient neighboring points, a cluster is formed; otherwise, the point is labeled as noise.

D. Location

Location techniques require the prior knowledge of the vibration propagation speed and seismometer locations. Several units are needed to detect the event location. We incorporate four units to reduce the location error margin. To initialize the floor velocity map, we first repeatedly carry a hammer test to generate impulse signals. As we know the ground truth of the hammer location, based on the time differences among seismometers, the floor velocity can be estimated. From Fig. 5, the average floor velocity is around 400 m/s.

The typical location methods such as angle-of-arrival (AOA), time-of-arrival (TOA), time-difference-of-arrival (TDOA), Doppler shift frequency-difference-of-arrival (FDOA), or received signal strength (RSS), were mostly designed for RF

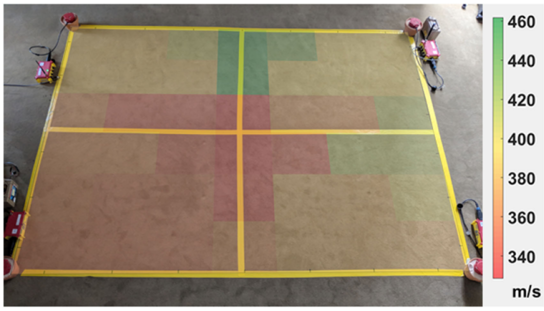

Fig. 5. Floor velocity model initialized by hammer tests.

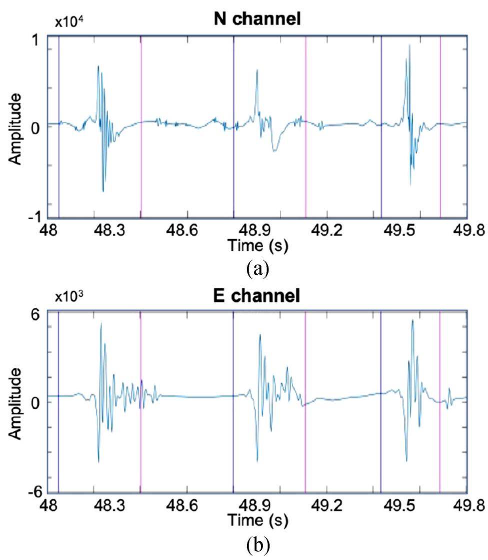

Fig. 6. Footstep vibrations recorded by the same seismometer but on two different channels. The waveform differences between the two axes can be used to determine the signal arrival direction.

or Wi-Fi signals with sensor arrays [20], [32], [44], [45]. In addition, different than radio wave propagation which can be disturbed by the obstructions in the space, footstep vibration signals propagate through the floor. So traditional RF and reflection-based location methods are not suitable for our system. Since we are using isolated seismometers instead of sensor array systems, typical beamforming techniques cannot be adopted too [20].

Based on isolated triaxial seismometers, we can obtain incident angles between footsteps and sensors. Then footstep location is determined through the intersection of a number of pairs of angle directions. For estimating the location of any entity in two dimensional (2-D), the method requires at least two known reference points (seismometer locations) and two angles (θ_1, θ_2), respectively. To obtain wave propagation angles, we take advantage of the triaxial seismometer. Received data have two orthogonal ground-motion records corresponding to the east and north components (noted E and N, respectively), as shown in Fig. 6. Configuration of a 2×2 covariance matrix over the two components is

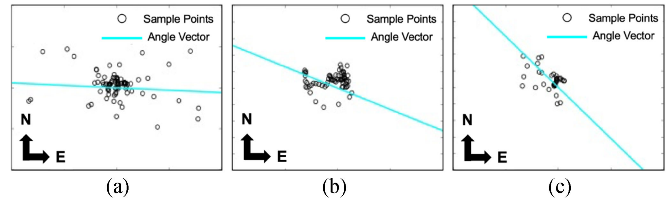

Fig. 7. Angles corresponding to the footsteps shown in Fig. 6.

$$\mathbf{C} = \begin{pmatrix} \mathrm{Cov}(E, E) & \mathrm{Cov}(E, N) \\ \mathrm{Cov}(N, E) & \mathrm{Cov}(N, N) \end{pmatrix} \tag{1}$$

where Cov($\bullet$) denotes the covariance. Eigenvectors of (1) form an orthogonal base, from which the wave orientation can be estimated. We organize eigenvalues so that $\lambda_1 \geq \lambda_2$ with U_i, $i = 1, 2$ as the eigenvector. Then, the wanted angle θ is the direction of U_1. Figs. 6 and 7 show three segmented footsteps and associated angles to the seismometer. As footstep locations are different when people are walking, relative angles are changing.

However, because of the uncertainty caused by the sensing system, the angle-based method would result in large location errors. So we propose an angle constrained time difference of arrivals (ATDOA) method, which is an optimization method to estimate a 2-D location vector

$$\underset{\mathbf{e}=(x,y)^T}{\operatorname{argmin}} \sum_{i=1}^{N} (\| \tau_i^{\mathbf{e}} - \tau_i \| + \lambda \| \theta_i^{\mathbf{e}} - \theta_i \|) \tag{2}$$

where $\mathbf{e} = (x, y)^T \in \mathbb{R}^2$ is the footstep location, $\mathbf{s_n} = [x_n, y_n]^T, n = 1, \ldots, N$ denote the coordinates of the N sensors, so $\min(\mathbf{s_m}[x_m]) \leq x \leq \max(\mathbf{s_m}[x_m])$, and $\min(\mathbf{s_m}[y_m]) \leq y \leq \max(\mathbf{s_m}[y_m])$. Every single node determines the footstep event arrival time and direction angle. $\tau_n = t_0 + \frac{d_n}{v}$ is the time difference of arrival for sensor $\mathbf{n}$, and it is composed for the time when the event starts $\mathbf{t_0}$ and the transmission time between the source and sensor $\mathbf{n}$. $d_n = \| \mathbf{e} - \mathbf{s_n} \| = \sqrt{(x - x_n)^2 + (y - y_n)^2}$, $n = 1, \ldots, N$, denotes the Euclidean distance between the source and sensor n. v is the propagation velocity matrix obtained from the calibration process. We eliminate the assumption of constant speed [45] due to the propagation velocity value is not constant. $\theta(\cdot)$ denotes the arrival angle. $\tau_i^{\mathbf{e}}$ and $\theta_i^{\mathbf{e}}$ are the estimated arrival time and angle of location $\mathbf{e} = (x, y)^T$. Fig. 8 shows a sketch of our ATDOA footstep location algorithm.

E. Trajectory Tracking

To track multiple people, we implement the trajectory tracking via three steps. Footstep separation, location, and interference removal. Assume our system receives a sequence of detected footsteps, $\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_k$, located at position $\mathbf{e}_k$ with a time stamp, t_k. We use $\mathbf{f}_k = f(\mathbf{f}_{k-1}, \boldsymbol{u}_k) + \mathbf{w}_k$ and $\mathbf{e}_k = h(\mathbf{f}_k) + \boldsymbol{v}_k$ to denote the transition and observation equations, respectively, where $\boldsymbol{u}_k$ is the control vector, $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ are the process and observation noises which are both assumed to be zero mean.

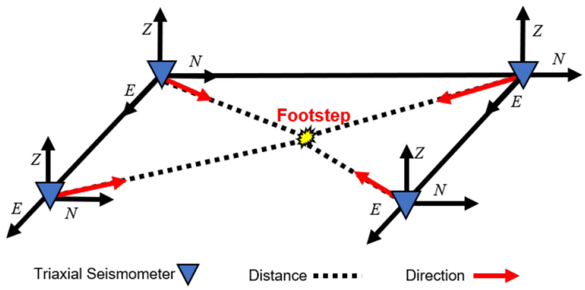

Fig. 8. Proposed ATDOA location method combines the advantages of time difference and angle-based methods.

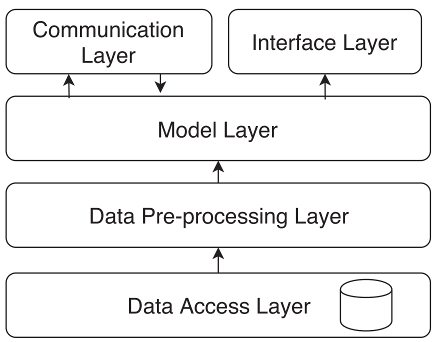

Fig. 9. Smart home monitoring system architecture. Data access layer includes access to a InfluxDB [47] database. Data preprocessing layer involves the background noise filtering and SNR improvement. The model layer manages algorithms for footstep detection, occupancy estimation, and localization and trajectory tracking. The communication layer includes the use of UDP protocol. The interface layer manages data visualization in Grafana tool [48].

The function f computes the predicted state from the previous estimate. The function h computes the predicted measurement from the predicted state. To overcome interferences of noise and uncertainty in location results, an extended Kalman filter (EKF) [46] is used to infer true underlying nonlinear pedestrian trajectories. Once the trajectory of a pedestrian is estimated, the trajectory map of one area can be obtained by stacking all trajectories from different people together.

F. System Architecture

The smart home monitoring system has been built on top of the layered architecture shown in Fig. 9. The "Data Access Layer" is composed by the sensing phase. The streaming data are stored inside each node. A database is used to save current data; however, to allow real-timing of the results, we employ a data buffer that sends information to the following layer for preprocessing. The buffer size can be configured in the system. In the "Data Preprocessing Layer" a background removal process is performed. Also, this layer applies data segmentation for footstep isolation. Once the events have been isolated, in the "Model Layer," the feature extraction algorithm extracts the features of the footstep signals locally. The "Model Layer" uses the "Communication Layer" to exchange features as well as footstep event arrival angles and time over the network. Note that after communication, the "Model Layer" can perform the multipeople separation and footstep location by using information of other nodes. The "Interface Layer" is in charge of showing results in real-time. Results include a mapping of the trajectory over a certain period of time.

Fig. 10. Three structural types and the sensors configuration for each of them.

III. Experiment and Evaluation

A. Experiment Setup

To measure its robustness, we evaluated system performances in three different types of floors with six participants. The three floor types and their configurations are shown in Fig. 10. The first structure is a carpeted-concrete floor from our lab. The second structure is a wooden-concrete floor from a living room of a residential house. The third structure corresponds to a carpeted wooden floor from a second-floor of a residential house. The total sample number is more than 1000.

B. Location and Trajectory Tracking Evaluation

To evaluate the location accuracy, we conducted experiments with footstep-induced vibration signals collected when people asked to step on the specific points. Fig. 11 shows the experiment setup and location results of ten footsteps at every point. The errors between the real and estimated locations from TDOA and ATDOA are measured. The average error of TDOA is 0.27 m with a standard deviation of 0.15 m, while those with ATDOA are 0.14 and 0.11 m, respectively. Note that our estimated location results from ATDOA are better.

Figs. 12 and 13 show a single person trajectory tracking example. One person is walking along a designed path in the testing area, and his footstep locations are recorded. It is clear that based on the relatively accurate location results and the EKF method, the footstep trajectory can be estimated.

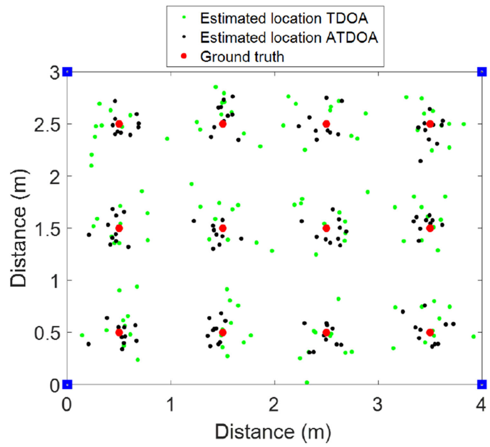

Fig. 11. Numerical experiments for location accuracy evaluation.

Fig. 12. Trajectory tracking experiment with a single person walking.

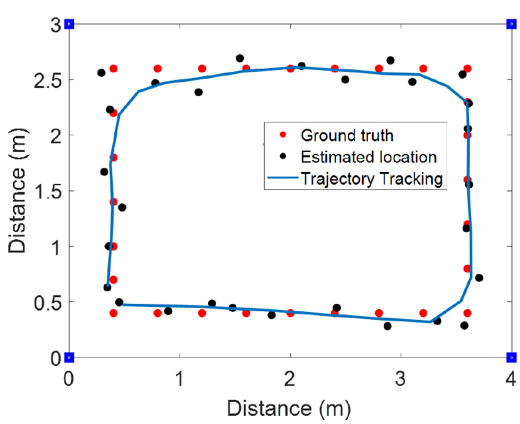

Fig. 13. Trajectory tracking results of the single person walking experiment.

C. Occupancy Estimation Evaluation

We only investigate the number of occupants from one to four, which is sufficient based on the research that shows that multiple people tend to walk in smaller units with less than four people [35]. Table I shows the clustering accuracy in our experiment. We group people from one to four, and record footsteps, then the unsupervised clustering method is used to estimate the cluster number. It is not surprising that we achieve the highest accuracy for the single person walking scenario. However, we did not expect the three people identification accuracy is higher than two people. The reasons could be related to the dataset, because we only have limited data, the hyper parameter selection is influenced by the existing people. Though four people identification accuracy is lower than in other cases, 87.83% is still a better result compared with the previous work [35].

TABLE I
OCCUPANCY ESTIMATION ACCURACY (MAXIMUM FOUR PEOPLE WALKING)

	1P	2P	3P	4P
Accuracy	92.06%	88.89%	89.79%	87.83%

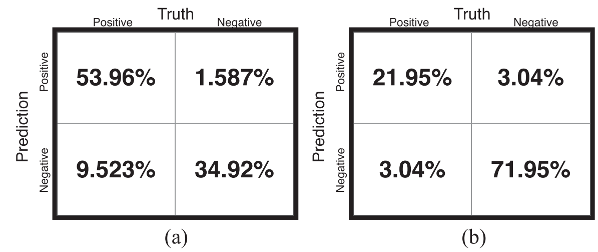

Fig. 14. Confusion matrices. (a) Two people walking. (b) Four people walking.

We further evaluate our clustering method to distinguish different footsteps with more metrics. In machine learning, a confusion matrix is a specific table layout that allows visualization of the performance of an algorithm [49]. In the confusion matrix, true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

The first metric gives the proportion of actual positive events that are correctly identified as positives by the classifier called Recall ($Re = \mathrm{TP}/(\mathrm{TP}+\mathrm{FN})$). Precision, the second metric, reflects the proportion of events classified as positive that are positive ($Pr = \mathrm{TP}/(\mathrm{TP}+\mathrm{FP})$). Fig. 14 shows the confusion matrices of two and four people walking scenarios, and other two scenarios can be easily inferred. For the two people walking scenario, $Re = 0.849$ and $Pr = 0.964$, while for the four people walking scenario, $Re = 0.878$ and $Pr = 0.878$. It is clear that our proposed method works well for occupancy estimation based on walking footstep separation.

IV. CONCLUSION

In this article we have presented a footstep vibration sensing system that monitors the indoor people walking activity. The system achieves sparse sensing with limited seismometers to cover an indoor monitoring area and utilizes key footstep signature features to conduct the occupancy estimation. A novel location method is proposed to obtain footstep locations. Furthermore, with estimated footstep locations, we evaluate the trajectory tracking. Our article suggests a smart environment system based on CPS and IoT devices has promises in physical condition analysis and social interaction assessment.

REFERENCES

[1] W. Li, Z. Chen, X. Gao, W. Liu, and J. Wang, "Multimodel framework for indoor localization under mobile edge computing environment," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4844–4853, Jun. 2019.

[2] T. S. Barger, D. E. Brown, and M. Alwan, "Health-status monitoring through analysis of behavioral patterns," *IEEE Trans. Syst., Man, Cybern.-Part A: Syst. Humans*, vol. 35, no. 1, pp. 22–27, Jan. 2005.

[3] M. R. Alam, M. B. Reaz, and M. A. Ali, "A review of smart homes—Past, present, and future," *IEEE Trans. Syst., Man, Cybern., Part C (Appl. Rev.)*, vol. 42, no. 6, pp. 1190–1203, Nov. 2012.

[4] N. K. Dhar, N. K. Verma, L. Behera, and M. M. Jamshidi, "On an integrated approach to networked climate control of a smart home," *IEEE Syst. J.*, vol. 12, no. 2, pp. 1317–1328, Jun. 2018.

[5] H.-H. Chang, W.-Y. Chiu, H. Sun, and C.-M. Chen, "User-centric multi-objective approach to privacy preservation and energy cost minimization in smart home," *IEEE Syst. J.*, vol. 13, no. 1, pp. 1030–1041, Mar. 2019.

[6] J. Wang, Z. Zhang, B. Li, S. Lee, and R. S. Sherratt, "An enhanced fall detection system for elderly person monitoring using consumer home networks," *IEEE Trans. Consum. Electron.*, vol. 60, no. 1, pp. 23–29, Feb. 2014.

[7] X. Gao, Z. Chen, S. Tang, Y. Zhang, and J. Li, "Adaptive weighted imbalance learning with application to abnormal activity recognition," *Neurocomputing*, vol. 173, pp. 1927–1935, 2016.

[8] F. Zhou, J. R. Jiao, S. Chen, and D. Zhang, "A case-driven ambient intelligence system for elderly in-home assistance applications," *IEEE Trans. Syst., Man, Cybern., Part C (Appl. Rev.)*, vol. 41, no. 2, pp. 179–189, Mar. 2011.

[9] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, "Automated cognitive health assessment using smart home monitoring of complex tasks," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 43, no. 6, pp. 1302–1313, 2013.

[10] C.-L. Wu and L.-C. Fu, "Design and realization of a framework for human–system interaction in smart homes," *IEEE Trans. Syst., Man, Cybern.-Part A: Syst. Humans*, vol. 42, no. 1, pp. 15–31, Jan. 2012.

[11] S. Zhou, M. Ke, and P. Luo, "Multi-camera transfer GAN for person re-identification," *J. Visual Commun. Image Representation*, vol. 59, pp. 393–400, 2019.

[12] S. He, K. Xie, K. Xie, C. Xu, and J. Wang, "Interference-aware multisource transmission in multiradio and multichannel wireless network," *IEEE Syst. J.*, vol. 13, no. 3, pp. 2507–2518, Sep. 2019.

[13] D. J. Cook, A. Crandall, G. Singla, and B. Thomas, "Detection of social interaction in smart spaces," *Cybern. Syst.: Int. J.*, vol. 41, no. 2, pp. 90–104, 2010.

[14] J. Clemente, W. Song, M. Valero, F. Li, and X. Li, "Indoor person identification and fall detection through non-intrusive floor seismic sensing," in *Proc. 5th IEEE Int. Conf. Smart Comput.*, Washington, DC, USA, 2019, pp. 417–424, doi: 10.1109/SMARTCOMP.2019.00081.

[15] Z. Chen *et al.*, "Unobtrusive sensing incremental social contexts using fuzzy class incremental learning," in *Proc. IEEE Int. Conf. Data Mining*, 2015, pp. 71–80.

[16] S. Pan, N. Wang, Y. Qian, I. Velibeyoglu, H. Y. Noh, and P. Zhang, "Indoor person identification through footstep induced structural vibration," in *Proc. 16th Int. Workshop Mobile Comput. Syst. Appl.*, 2015, pp. 81–86.

[17] J. Clemente, F. Li, M. Valero, and W. Song, "Smart seismic sensing for indoor fall detection, location, and notification," *IEEE J. Biomed. Health Inform.*, vol. 24, no. 2, pp. 524–532, Feb. 2020.

[18] S. Pan, K. Lyons, M. Mirshekari, H. Y. Noh, and P. Zhang, "Multiple pedestrian tracking through ambient structural vibration sensing," in *Proc. 14th ACM Conf. Embedded Netw. Sensor Syst.*, 2016, pp. 366–367.

[19] P. Zhang, H. Y. Noh, P. A. N. Shijia, N. Wang, A. Bonde, and M. Mirshekari, "Indoor identification of individuals through footstep induced structural vibration," U.S. Patent 15/544,928, Jan. 2018. [Online]. Available: https://patents.google.com/patent/US20180018509A1/en

[20] X. Tang, M.-C. Huang, and S. Mandal, "An "Internet of Ears" for crowd-aware smart buildings based on sparse sensor networks," in *IEEE SENSORS*, Glasgow, 2017, pp. 1–3, doi: 10.1109/ICSENS.2017.8234263.

[21] F. Zafari, I. Papapanagiotou, and K. Christidis, "Microlocation for Internet-of-Things-equipped smart buildings," *IEEE Internet Things J.*, vol. 3, no. 1, pp. 96–112, Feb. 2016.

[22] S. He, K. Xie, W. Chen, D. Zhang, and J. Wen, "Energy-aware routing for SWIPT in multi-hop energy-constrained wireless network," *IEEE Access*, vol. 6, pp. 17 996–18 008, Mar. 2018.

[23] Q. Tang, M. Xie, K. Yang, Y. Luo, D. Zhou, and Y. Song, "A decision function based smart charging and discharging strategy for electric vehicle in smart grid," *Mobile Netw. Appl.*, pp. 1–10, 2018. [Online]. Available: https://link.springer.com/article/10.1007/s11036-018-1049-4

[24] M. Lin, Q. Feng, J. Wang, J. Chen, B. Fu, and W. Li, "An improved FPT algorithm for almost forest deletion problem," *Inf. Process. Lett.*, vol. 136, pp. 30–36, 2018.

[25] Q. Tang, K. Yang, D. Zhou, Y. Luo, and F. Yu, "A real-time dynamic pricing algorithm for smart grid with unstable energy providers and malicious users," *IEEE Internet Things J.*, vol. 3, no. 4, pp. 554–562, Aug. 2016.

[26] X. Gao *et al.*, "Sparse online learning of image similarity," *ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 5, 2017, Art. no. 64.

[27] J. D. Poston, "ILoViT: Indoor localization via vibration tracking," Ph.D. dissertation, Virg. Tech, Blacksburg, VA, USA, 2018.

[28] C. Xu *et al.*, "Crowd++: Unsupervised speaker count with smartphones," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.*, Zurich, Switzerland, Sep. 2013, pp. 43–52, doi: 10.1145/2493432.2493435.

[29] A. Agneessens, I. Bisio, F. Lavagetto, M. Marchese, and A. Sciarrone, "Speaker count application for smartphone platforms," in *Proc. 5th IEEE Int. Symp. Wireless Pervasive Comput.*, 2010, pp. 361–366.

[30] H. Lee, J. W. Park, and A. S. Helal, "Estimation of indoor physical activity level based on footstep vibration signal measured by MEMS accelerometer in smart home environments," in *Proc. Mobile Entity Localization and Tracking in GPS-less Environnments*, R. Fuller and X. D. Koutsoukos, Eds. Berlin, Heidelberg: Springer, 2009, pp. 148–162.

[31] S. Pan *et al.*, "FootprintID: Indoor pedestrian identification through ambient structural vibration sensing," *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 1, no. 3, 2017, Art. no. 89.

[32] W. Chen, M. Guan, L. Wang, R. Ruby, and K. Wu, "FLoc: Device-free passive indoor localization in complex environments," in *Proc. IEEE Int. Conf. Commun.*, Paris, 2017, pp. 1–6, doi: 10.1109/ICC.2017.7997098.

[33] F. Li, J. Rich, K. J. Marfurt, and H. Zhou, "Automatic event detection on noisy microseismograms," *SEG Tech. Program Expanded Abstracts*, pp. 2363–2367, 2014.

[34] F. Li and W. Song, "Automatic arrival identification system for real-time microseismic event location," in *SEG Tech. Program Expanded Abstracts*, pp. 2934–2939, 2017.

[35] S. Pan, M. Mirshekari, P. Zhang, and H. Y. Noh, "Occupant traffic estimation through structural vibration sensing," *Proc. SPIE*, vol. 9803, 2016, Art. no. 980306.

[36] U. O. Ofoegbu, A. N. Iyer, R. E. Yantorno, and B. Y. Smolenski, "A speaker count system for telephone conversations," in *Proc. Int. Symp. Intell. Signal Process. Commun.*, 2006, pp. 331–334.

[37] P. Anghelescu, G. V. Iana, and I. Tramandan, "Human footstep detection using seismic sensors," in *Proc. 7th Int. Conf. Electron., Comput. Artif. Intell.*, 2015.

[38] A. Ekimov and J. M. Sabatier, "Vibration and sound signatures of human footsteps in buildings," *J. Acoustical Soc. Amer.*, vol. 118, no. 3, 2005.

[39] S. Pan, M. Mirshekari, H. Y. Noh, and P. Zhang, "Structural sensing system with networked dynamic sensing configuration," in *Proc. 14th Int. Conf. Inf. Process. Sensor Netw.*, Seattle, WA, USA, 2015, pp. 344–345, doi: 10.1145/2737095.2737147.

[40] R. Tibshirani, G. Walther, and T. Hastie, "Estimating the number of clusters in a data set via the gap statistic," *J. Roy. Statistical Soc.: Ser. B (Statistical Methodology)*, vol. 63, no. 2, pp. 411–423, 2001.

[41] C.-Y. Wee and R. Paramesran, "Measure of image sharpness using eigenvalues," *Inf. Sci.*, vol. 177, no. 12, pp. 2533–2552, 2007.

[42] V. L. Erickson and A. E. Cerpa, "Occupancy based demand response HVAC control strategy," in *Proc. 2nd ACM Workshop Embedded Sens. Syst. Energy-Efficiency Building*, 2010, pp. 7–12.

[43] M. Ester *et al.*, "A density-based algorithm for discovering clusters in large spatial databases with noise," in *Proc. 2nd Int. Conf. Knowl. Discovery and Data Mining*, vol. 96, no. 34, 1996, pp. 226–231.

[44] J. D. Poston, R. M. Buehrer, V. V. N. S. Malladi, A. G. Woolard, and P. A. Tarazaga, "Vibration sensing in smart buildings," in *Proc. Int. Conf. Indoor Positioning Indoor Navig.*, 2015.

[45] M. Mirshekari, S. Pan, P. Zhang, and H. Y. Noh, "Characterizing wave propagation to improve indoor step-level person localization using floor vibration," in *Proc. SPIE*, vol. 9803, 2016, Art. no. 980305.

[46] S. J. Julier and J. K. Uhlmann, "New extension of the kalman filter to nonlinear systems," in *Proc. SPIE*, vol. 3068, 1997, pp. 182–194.

[47] "InfluxDB - scalable datastore for metrics, events, and real-time analytics," [Online]. Available: https://www.influxdata.com/, Accessed on: Sep. 9, 2019.

[48] *Grafana*. (2018), Grafana Labs, [Online]. Available: https://grafana.com/, Accessed on: Sep. 9, 2019.

[49] Y. Shi, F. Li, T. Liu, F. R. Beyette, and W. Song, "Dynamic time-frequency feature extraction for brain activity recognition," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2018, pp. 3104–3107.