FLoc: Device-free Passive Indoor Localization in Complex Environments

Wenqiang Chen*,Maoning Guan†,Lu Wang*, Rukhsana Ruby*, and Kaishun Wu*

*College of Computer Science and Software Engineering, Shenzhen University
†College of Information Engineering, Shenzhen University

***Abstract*—Localization in complex indoor environments with RF signal is a challenging task. Via this technique, the signal is easily affected by obstacles and environmental noise due to the broadcast nature of RF signal transmission. In this paper, we observe that seismic signal is more oriented than the RF signal, and thus is more suitable for localization in an complex indoor environment with obstacles. Motivated by this observation, we propose a device-free passive indoor localization system, namely Floc, that can fight against environmental impact and achieve high localization accuracy. FLoc is composed of three modules, which are sensing module that collects seismic signal from footsteps, footstep detection module that remove the environmental impact and recover the clean footsteps, and localization module that leverages seismic signal from footsteps for positioning. We implement FLoc on credit-card sized single-board computer Raspberry Pi equipped with geophones. To verify the effectiveness of our system, we conduct extensive experiments for different scenario in a complex indoor environment with the area of 6×8 square meter. The experimental results demonstrates that Floc can achieve up to 7cm localiztion accuracy on average, and can outperform the existing acoustic signal-based localization techniques.**

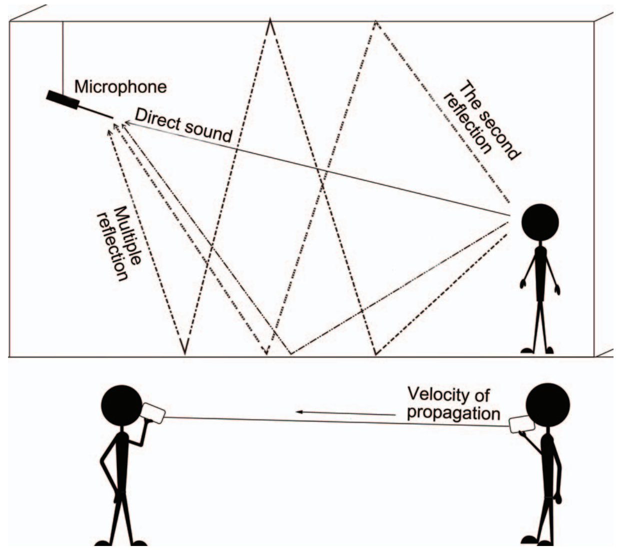

Fig. 1. Multipath propagation of sample acoustic signal.

I. Introduction

Indoor localization is currently a cutting-edge research topic because of its huge market value. Extensive research has been carried out in this direction. Till now, numerous technologies, such as infrared, Bluetooth, Computer Vision, RFID, WiFi, ZigBee, Ultra Wide Band (UWB), etc. are used to address this problem. Among these technologies, UWB and infrared have the highest positioning precision. However, UWB has high cost and infrared technology has blocking issue. Cameras cannot be applied in intelligent home environments because of privacy issues. Consequently, RF signaling technology is the most popular at this point. However, the transmission of RF signal is broadcast by nature, and the receiver receives the signal after multiple reflection in 3D space. As shown in the top half of Fig. 1, a human voice is received by a microphone from different paths at different time instants.

As shown in the top half of Fig. 1, a human voice is received by a microphone from different paths at different time instants. Our objective is only to use the solid path in the middle to calculate the distance. The other paths cause a great deal of error in positioning accuracy. This phenomenon is named as multipath effect. In order to mitigate the multipath effect, most of the existing positioning technologies require an open experimental environment without obstacles. In reality, in any indoor environment, there are many obstacles, such as tables, chairs, etc. These obstacles not only bring the multipath effect in signal propagation, but also are the source of extreme power consumption. We observe that the acoustic signal transmits information through a single path via the vibration of the cord, as shown in the bottom part of Fig. 1. There is no multipath effect in this case. The sound of footsteps spread along the ground, and travels farther than the original distance through the air[1]. These signals are not reflected in the 3D space but along the ground. Furthermore, they are not affected by objects in the space. They propagate only in the ground with low multipath effect, and can incur high positioning accuracy in complex environments with many obstacles.

Now, the question is, *how we can get the signal propagation along the floor?* If we use the microphone on the floor, the received sound wave is greatly affected by sound noise (e.g., human speech). On the other hand, seismic signals extracted from the floor are weak and have very little usage. A seismograph is too expensive and accelerometer cannot detect the sensitively of seismic signal effectively. Furthermore, modern buildings are constantly in vibration. These vibrations affect the shape of the footstep signals. Typically,

[1]In ancient China, people used to put their ears close to the ground to monitor distant hoofs of horses

978-1-4673-8999-0/17/$31.00 ©2017 IEEE

the footstep-induced seismic signal has low signal-to-noise ratio (SNR) especially when the pedestrians walk far away from the geophone. Again, the way to do the segmentation for detecting footsteps is not straightforward. Another challenge is, if there are some noise pulses, such as the fall of chairs, how we can distinguish the noise pulses from footstep pulses.

To address the aforementioned challenges, we design a low-cost but high-sampling rate-based seismic wave detection system using geophone of the Raspberry Pi, which can successfully detect footstep-induced floor seismic signal in an indoor environment. Then, through the spectrum analysis, we design a butterworth highpass filter to reduce the background noise and improve SNR of seismic signal. From the collected denoised data, at first, the authors in [3] use a training-based learning model to detect the origin of footsteps. Then, we observe the characteristics of pedestrian walk, and build a walking **S**peed based adaptive **W**eight **I**ncrement **M**odel (SWIM) to detect footsteps with higher accuracy without training.

After the detection of footsteps, we estimate the resultant time delay and use the time-difference-of-arrival (TDOA)-based algorithm for the localization of the corresponding footsteps. We conduct extensive experiments to verify the effectiveness of our system. The results verify that it is possible to exploit the seismic signal of footsteps for indoor localization. Our SWIM can remove environmental noise (signals other than from footsteps) effectively and can detect footsteps 97% of time. Moreover, the positioning accuracy can be achieved up to 7cm on average.

The rest of the paper is organized as follows. First, we review the existing works related to this paper in Section 2. Followed by the description of basic components, in Section 3, we describe the mechanism of the system in detail. We evaluate the performance of our proposed system in Section 4. Finally, Section 5 concludes the paper.

II. Related Work

There were many works have been done on indoor localization using wireless signals.

In the context of this paper, there are many works appeared in the literature. For example, Wu et al. [4-7] uses channel state information (CSI) of wireless signal for indoor positioning, Zhang et al. [8]localized pedestrians using WiFi signal, and Liu et al. [9] used acoustic signal to localize objects in indoor environments. The technologies of these works are based on either received signal strength indicator (RSSI) of wireless signal or time-to-speed ranging concept, such as time of arrival (TOA). However, geometry-based positioning technique is highly susceptible to indoor obstructions. Typically, in a complex environment with many obstacles, positioning accuracy is low using wireless signal. We use footstep-induced seismic along the floor to transmit signal, via which a high positioning accuracy can be achieved even in an environment with full of obstacles.

Fingerprint-based indoor positioning technology [10] can determine the positioning information of a room equipped with many fixed obstacles. However, with this technology, the change of experimental environments leads to high positioning error. Camera positioning technology is limited by privacy issue, especially in the smart homes. On the other hand, UWB positioning technology is very expensive. Unlike these existing technologies, our FLoc system is free from obstructions and is adaptive to any indoor environment. Moreover, there is no privacy related issues and the cost is very low.

There are some prior works that detect footsteps and locate them in military outdoor environments [11][12]. These works basically track intruders through the detection of footsteps, and locate them at the border. However, the footstep-induced soil vibration in outdoor environments is entirely different from footstep-induced floor vibration in indoor environments. Moreover, the vibration of modern buildings have great noise, such as electric appliance vibration. Pan et al. [2][3] is the first one to address the localization problem with geophones in indoor environments. They used the training method to detect footsteps, while we use a mathematical tool for footstep detection without training and with high recognition rate. This year, Woolard et al. [1] also tried to solve indoor localization problems using floor vibration. However, in this work, they used an accelerometer mounted below the floor. The accuracy of accelerometers is so low that they can only use hammers to simulate footsteps for achieving high accuracy. Based on geophones, we design a sensitive vibration acquisition system for footsteps, and obtain high positioning accuracy.

III. Description of the System

In this section, we first provide the overview of the system. Then, we will provide the detailed description of its component modules, such as denoising, footstep detection and calibration modules.

A. System Overview

From the viewpoint of mechanics, footsteps travel down the ground through the obstacles to vibration detectors. Our system, Floc is able to collect footsteps vibration in indoor environments with many obstacles. However, typically, seismic signal is very weak. In fact, seismic signals of modern buildings are added as additional noise to footstep-induced seismic signal. In addition, after collecting the signal, we need to apply the signal segmentation to extract the pulses of footstep vibration. Moreover, noise information needs to be removed from the collected signal. For example, if there are chairs or other objects fall off the floor to stimulate vibration as noise, it is difficult to determine the vibration pulse associated with footsteps. Consequently, how to filter out the non-footstep noise vibration is another challenge.

In order to obtain weak vibration signal, we design a sensing module using a geophone. We use a low-cost raspberry controller to connect with geophone. Operational amplifiers are used to amplify weak vibration signals to facilitate detection, and then convert the analog signals to digital signals through the analog-to-digital converter (ADC). In order to detect the footstep-induced seismic signal, the traditional techniques use

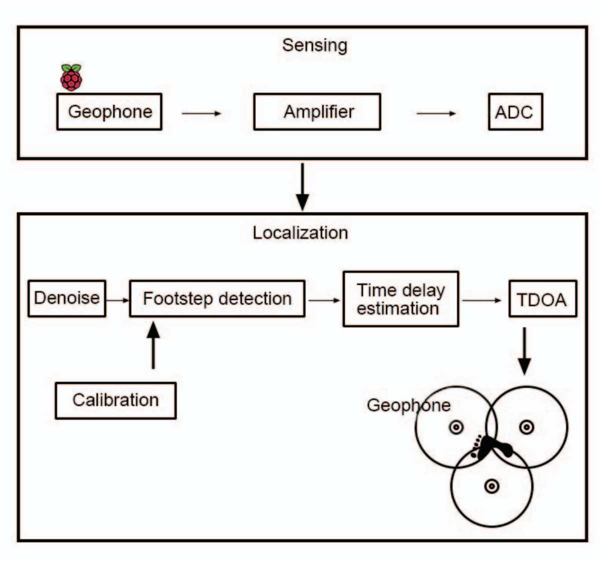

Fig. 2. An architectural overview of FLoc.

machine learning models to distinguish footsteps from non-footstep related events (e.g., the fall of chairs). Before building our system, we observe people walking at uniform speed over a period of time, and discover that the interval between footsteps is the same. Based on this feature, we build SWIM. This model can detect footsteps accurately, and is resilient to environmental other non-footstep related noise.

As shown in Fig. 2, FLoc is mainly composed of Sensing and Localization modules. For the sensing module, we develop a low-cost Raspberry Pi controller to achieve high sampling rate, select the geophone to act as a vibration sensor, operational amplifiers to amplify the weak vibration of footsteps, and then use ADC to enlarge voltage signal and convert it to digital signal and pass it to Raspberry Pi.

In the localization module, we first apply denoising scheme, and then use SWIM to detect and identify the footsteps, filter out high energy bursty noise, such as the fall of chairs, tables, etc. Finally, we estimate the time delay and localize the corresponding footsteps using a TDOA-based algorithm. To improve the footsteps detection accuracy, we further adopt the calibration of SWIM.

B. Denoising

The architecture of modern buildings is constantly shaking and drives the vibration of floors and walls. These default vibrations in indoor environments cause background noise to the original footsteps vibration. Therefore, in order to improve the SNR, we apply the Fourier transform over the background noise and footstep-induced seismic signal, and observe the frequency distribution. The main component of the background noise exhibits a Gaussian distribution at low frequencies. The frequency of footsteps are mainly concentrated in the low-frequency domain. We first remove the direct current (DC) component of the footstep signal. In order to minimize the noise without affecting the composition of footsteps, we design a Butterworth highpass filter and access the signal beyond 63Hz frequency.

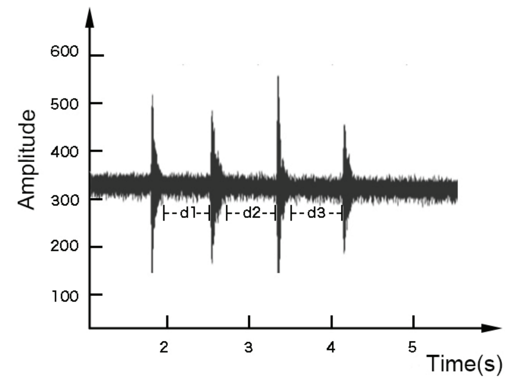

Fig. 3. The proof of uniform footstep interval.

C. Footstep Detection

In order to localize footsteps, we apply segmentation on each footstep-induced seismic signal. However, the footstep-induced seismic signal is very weak, especially when the footsteps are far away from a geophone and the SNR of footsteps is very low. While applying the segmentation, we inevitably cut some of the noise pulse out which is similar to the footstep pulse. This means that once the segmentation is done, we need to recognize whether it is a footstep-induced signal or not. The traditional methods cut these signals out, and apply training-based classification models to identify footsteps [3]. In our case, we use a training-free mathematical tool to achieve better recognition accuracy. We observe that if the pedestrians do not change walking speed frequently and randomly, there is a series of continuous uniform footsteps because of their uniform walking speed. The gap between one footstep and the following footstep is often fixed. As shown in Fig. 3, the footstep interval $d1$ is approximately equal to $d2$ and $d3$.

Using this observation, and combining the short-term energy-based dual-threshold endpoint detection method, we design a walking speed-based adaptive weight increment model, namely SWIM, to identify footsteps. First, a two-threshold endpoint detection method based on short-term energy is used. A short-term energy is shown as

$$En = \sum_{m=-\infty}^{\infty} [x(m).w(n-m)]^2. \quad (1)$$

We apply segmentation on the initial signal, which is basically noise component. We set the lowest threshold value as the maximum value of the noise and set the highest threshold value as half of the maximum footstep energy. The entire endpoint detection time can be divided into four segments, which are quiet, transition, voice segment and endpoint. The endpoint detection program uses a variable, namely Status, to indicate the current state. Two parameters, such as the longest silent length and the shortest voice length are set as well. In the quiet section, if the short-term energy exceeds the lowest threshold, the program starts marking the starting point and enters into the transition section. In the transition section, if the short-term energy dropped below the lowest threshold, the program cannot be sure about the voice segment. If the length is more than the maximum quiet length, the program returns to the quiet state. If the transition section exceeds the highest threshold value, the program convinces into the voice segment. If the length of the final segment is less than the minimum voice length, it is considered to be noise and discarded. We cut the end points of the first footstep and label them as x_0 and x'_0. In the similar manner, we cut out the second footstep and we obtain the corresponding endpoints x_1 and x'_1. Let subtract x_1 from x'_0, we can obtain the footstep interval, sampling point $d1$ in Fig. 3. Let denote all endpoints and the corresponding footstep intervals as x_i, $x'_i(i \geq 1)$, d_{i+1} $(i \geq 0)$. Combining the energy-based dual-threshold endpoint detection method and the footstep interval di, we can assign weights to them and calculate the new endpoints y_i, $y'_i(i \geq 2)$.

$$Y_i = M_{i-1}x_i + N_{i-1}d_{i-1}, \tag{2}$$

$$M_i + N_i = 1, \tag{3}$$

$$d_{i-1} = 0.8d_{i-2} + 0.2(\text{avg}(\sum_{i=1}^{i-3} di)), \tag{4}$$

$$M_{i-1} = (1/2)\hat{\ }i, \tag{5}$$

where M and N are weights and i is an incremental function whose step number is 1. Each segmentation is increased by 1. As mentioned previously, the walking trend of people is not absolutely uniform and the latest footstep interval can better predict the next footstep interval. Therefore, we choose exponential moving average (EMA) algorithm to compute di as we know that the more amount of movement towards the back, the more stable and reliable speed. Over the iterative process of EMA algorithm, the value of M decreases exponentially.

D. Calibration

The SWIM is developed based on the assumption that people walk in a constant speed. EMA algorithm allows people to gradually change the walking speed. However, when pedestrians suddenly make a significant change in walking speed, such as running from walking, the resultant segments generally cause significant bias. We learn from additive increase multiplicative decrease (AIMD) algorithm that when we suddenly change the walking speed, we let M and N return to their initial values and start to re-use the exponential growth model to assign M/N weights. In order to determine whether pedestrians' drastic change of walking speed resulting in segmentation errors, we introduce the vector $\vec{N}$. Typically, the stride of one person is not more than one meter. The footstep spacing is set to a vector $\vec{N}$, and if the module length is 1, we can obtain a reasonable positioning range. If the Euler distance between the predicted coordinate and the actual coordinate is greater than $\|\vec{N}\|$, the pedestrian is considered to

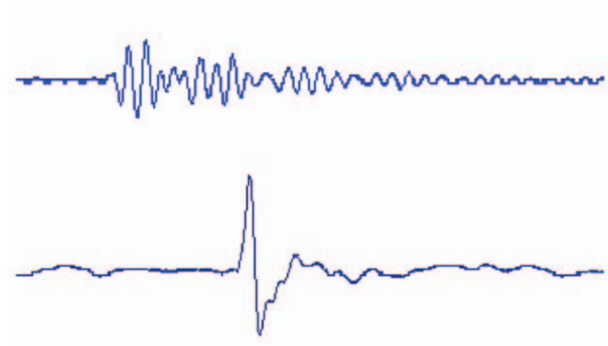

Fig. 4. A sample S-wave (top) and P-wave (bottom) when a desk is touched.

suddenly change the walking speed and we need to reassign the weights of M and N and restore their initial values.

IV. Experiments and Performance Evalution

In order to capture the vibration caused by footsteps, we have designed a low-cost high-sampling rate-based sensitive vibration acquisition device. Seismic signals can be collected using seismometers, geophones or accelerometers. Seismometers are mainly used to measure earthquakes, and expensive as well. The accelerometer is not sensitive to slight vibration. The geophone is cheap and has higher accuracy compared to accelerometer because of emerging hardware development in the recent years. The ground vibrations cut magnetic induction lines in the geophone and generate voltage. However, this voltage is very weak. In order to detect footsteps with as high SNR as possible throughout the experimental environment, we require highly sensitive vibration detection tool, and consequently an operational amplifier is used. To make the positioning accuracy higher, we need the highest possible sampling rate with a non-expensive sampling device. We choose to use the Raspberry Pi which is very cheap to sample, and use the BCM2835 library to ensure a stable sampling rate for up to 65KHz. The purchased Raspberry Pi did not have an ADC chip, and so we added an additional ADC.

In the experiment, the transverse wave (S-wave) geophones detects the seismic signal of the transverse wave vibration, the longitudinal wave (P-wave) geophones detect the seismic signal of longitudinal wave vibration. In order to observe the difference between the two types of detectors, we place the S-wave geophones and P-wave geophones on a desktop that has low-noise of vibration. To observe the difference of the received signal by two types of geophones, we touch the desktop lightly. The results of this event is shown in Fig. 4. The S-wave (top) is a series of continuous sine waves, while the P-wave (bottom) has an obvious peak which is good for calculating time delay. In addition, the signal energy of the P-wave geophone is significantly higher than that of the S-wave geophones, and P-wave geophones have a better SNR. Therefore, we choose the P-wave geophones.

Two experiments were designed to evaluate the sensing, denoising and localization performance of the system. The

Fig. 5. The experimental environment.

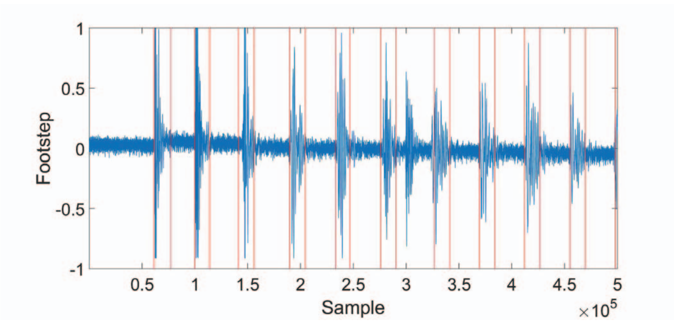

Fig. 6. A sample footstep detection process.

objective of the first experiment is basically to know how sensitive Floc system is and verify the performance of SWIM including its denoising scheme and recognition rate. The objective of the second one is to verify the overall performance of Floc system in terms of localization accuracy. As shown in Fig. 5, we conduct experiments in the Laboratory of Smart Sensing and Mobile Computing at Shenzhen University, China. The area of the environment is 6×8 square meter. Three people were involved in the experiments.

In the first experiment, we use a geophone. The participants walk towards a direction which is away from the geophone. Everyone walks 10 rounds and 10 footsteps in each round. Therefore, we collect a total of 30 samples and 300 steps of vibration. Then, we conduct the experiments again while adding noise (e.g., the fall of bottle) to the environment.

The performance of sensing module: Fig. 6 verifies the effectiveness of the sensing module. We see in the figure that each resultant pulse is obvious. This proves that the performance of sensing module is robust enough to detect the footstep-induced seismic signal even when the participants are far (e.g., 8m) away from the geophone.

The performance of denoising scheme: As shown in Fig. 6, the pulses in between two vertical lines are for the footsteps, and the seventh pulse is due to the fall of the bottle and there is no vertical lines beside it. Using SWIM, we successfully cut 10 footsteps. The seventh pulse with no vertical lines beside it is very similar to a footstep, however is a bursty noise.

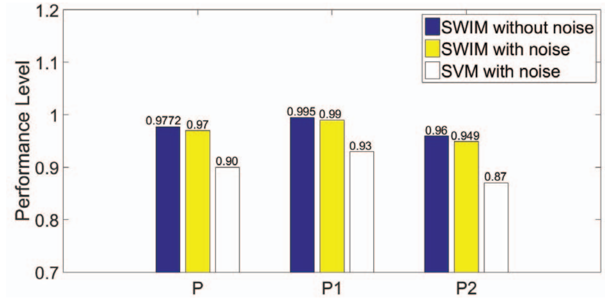

Fig. 7. The precision of SWIM and SVM.

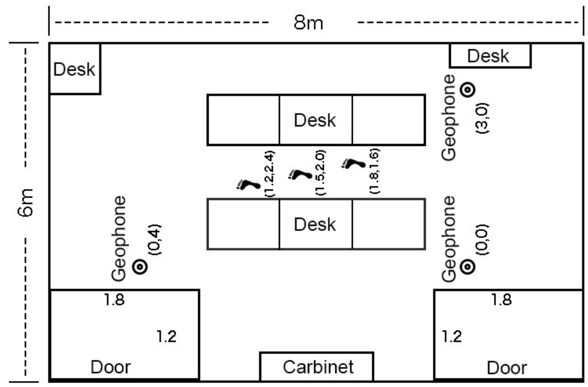

Fig. 8. The detailed coordinate of the experimental environment.

we manage to avoid it. This verifies the effectiveness of our denoising scheme. Let denote the true footsteps segmentation as TF, wrong footsteps as WF, missing footsteps as MF.

$$P1 = TF/(TF + MF), \tag{6}$$

$$P2 = TF/(TF + WF), \tag{7}$$

$$P = 2 * P1 * P2/(P1 + P2). \tag{8}$$

The performance of SWIM: As shown in Fig. 7, the precision of SWIM is about 97.72%, and the accuracy of support vector machine (SVM) is 90% [3]. The histogram shows that SWIM without training incurs significantly enhanced performance in terms of footstep detection compared with SVM model which needs training. Moreover, even after adding the bursty noise, the precision of SWIM remains the same compared with the noise-free case. This means that SWIM is resilient to environmental noise.

In the second experiment, the number and the identity of the participants are as same as the first one. Everyone walked 20 times, and there were 3 footsteps in each round. Fig. 8 shows this experimental environment. We apply TDOA-based technique over the known coordinates of all objects in this environment and the propagation velocity of vibration to calculate the coordinate of footsteps.

Accuracy of each footstep: To estimate the time delay, we subtract the reading of two geophones. From the subtracted results and the known coordinates of other objects, we obtain the coordinate of footsteps. Error is the Euler distance between

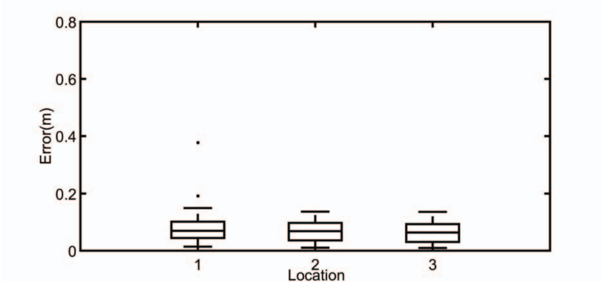

Fig. 9. Localization error of 3 footsteps.

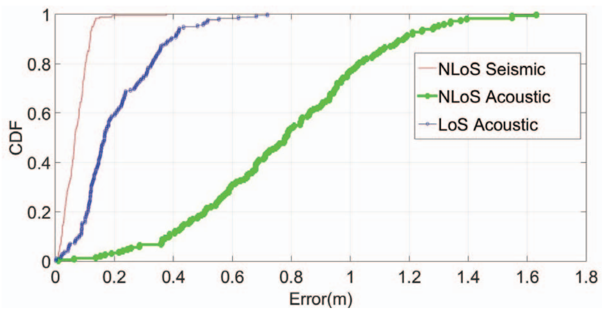

Fig. 10. The overall localization error.

the real and estimated coordinates. The localization error of three individual footsteps are shown in Fig. 9.

We then use the microphones to set up two controlled experiment scenarios. In the first experiment, we put the microphone on the ground and collect footsteps. This experiment is named as non-line-of-sight (NLoS) Acoustic. Then, we vacate the room to make it obstacle-free and repeat the experiment with the microphone. We label this experiment as line-of-sight (LoS) Acoustic. We compare the overall performance of these two types of experiments with the previously conducted experiments with our seismic-signal-based proposed system in Fig. 10.

Comparison between seismic and acoustic-based localization techniques: No matter the obstacles exist or not, the average positioning error using our footstep-induced seismic wave-based technique is 0.07m. Whereas, the average positioning error using acoustic wave-based technique is 0.78m and 0.21m for the cases when obstacles exist and when the environment is obstacle-free, respectively. It can be seen that under the influence of obstructions, the accuracy of seismic signal-based system is much higher than that of acoustic signal-based system. This is because obstacles enhance the reflection of acoustic signals and reduce the positioning accuracy. Furthermore, the positioning accuracy of seismic signal-based technique is higher than the case when LoS scenario is considered for the acoustic signal-based technique. This is because acoustic systems are easily effected by noise (e.g., human speech, transportation sound, etc.). In conclusion, these experiences prove that Floc can work effectively in a room with many obstacles and the resultant localization accuracy is very high.

V. Conclusion

We developed a sensitive seismic wave acquisition system that can detect weak vibrations of footsteps in an indoor environment with many obstacles. In order to detect the footstep-induced seismic signal and denoise the noise pulses, we combined their short-term energy and footstep intervals, and designed a training-free mathematical model SWIM for our Floc system. While considering diverse scenarios, extensive experiments have been conducted to verify the effectiveness of the system. The results verify that the footstep recognition rate is more than 97% on average. Furthermore, it is proved that the propagation of seismic signal along the ground under the obstacles can be used to localize footsteps with high accuracy.

VI. Acknowledgement

This research was supported in part by the China NSFC Grant 61472259, 61502313, Shenzhen Science and Technology Foundation (No. KQCX20150324160536457, JCYJ20150324141711621), Guangdong Talent Project 2014TQ01X238, 2015TX01X111 and GDUPS (2015).

References

[1] J. D. Poston, R. M. Buehrer, A. G. Woolard, and P. A. Tarazaga, “Indoor positioning from vibration localization in smart buildings.” in Proc. IEEE/ION PLANS. 2016: 366-372.

[2] 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 Smart Structures and Materials Nondestructive Evaluation and Health Monitoring. 2016: 980305-980305-11.

[3] M. Lam, M. Mirshekari, S. Pan, P. Zhang, and H. Y. Noh, “Robust occupant detection through step-induced floor vibration by incorporating structural characteristics.” Dynamics of Coupled Structures, Volume 4. 2016: 357-367.

[4] K. Wu, J. Xiao, Y. Yi, D. Chen, X. Luo, and L. M. Ni, “CSI-based indoor localization.” IEEE Trans. Parallel Distrib. Systems, 2013, 24(7): 1300-1309.

[5] J. Xiao, Y. Yi, L. Wang, H. Li, Z. Zhou, K. Wu, and L. M. Ni, “NomLoc: Calibration-free indoor localization with nomadic access points.”In Proc. IEEE ICDCS, 2014:587-596.

[6] K. Wu, J. Xiao, Y. Yi, M. Gao, and L. M. Ni, “Fila: Fine-grained indoor localization.” In Proc. IEEE INFOCOM, 2012:2210-2218.

[7] J. Xiao, K. Wu, Y. Yi, L. Wang, and L. M. Ni, “Pilot: Passive device-free indoor localization using channel state information.” In Proc. IEEE ICDCS, 2013:236-245.

[8] X. Li, S. Li, D. Zhang, J. Xiong, Y. Wang, and H. Mei, “Dynamic-MUSIC: accurate device-free indoor localization.” in Proc. ACM UbiComp, 2016: 196-207.

[9] W. Huang, Y. Xiong, X. Y. Li, H. Lin, X. Mao, P. Yang, Y. Liu, and X. Wang, “Swadloon: Direction Finding and Indoor Localization Using Acoustic Signal by Shaking Smartphones.” IEEE Trans. Mob. Comput. 14(10): 2145-2157 (2015)

[10] J. Xiao, K. Wu, Y. Yi, and L. M. Ni, “FIFS: Fine-grained indoor fingerprinting system.” In Proc. IEEE ICCCN, 2012:1-7.

[11] G. P. Succi, D. C. Gampert, and G.Prado, “Footstep detection and tracking.” in Proc. Aerospace/Defense Sensing, Simulation, and Controls. 2001: 22-29.

[12] A. Pakhomov, and T. Goldburt, “New seismic sensors for footstep detection and other military applications.” in Proc. Defense and Security. 2004: 463-468.