

Silent Whistle: Effective Indoor Positioning with Assistance from Acoustic Sensing on Smartphones

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Abstract—Indoor positioning systems provide location information without the ability to use GPS. Indoor positioning faces challenges of accuracies and pervasiveness. In this paper, we present SilentWhistle, a mobile system that incorporates acoustic information and motion traces on smartphones to locate users. SilentWhistle does not expose the identity of a mobile device as does Bluetooth or WiFi communications. By detecting and filtering the received audio frequencies, we encode the frequencies to location information. When users encounter each other or related beacons, by measuring the relation between sound strength and distance, the initial location information obtained by dead reckoning can be enhanced by triangulations transferred from sound strength. Centralized and distributed models of SilentWhistle can avoid the spreading of incorrect location messages. Our case studies agree on SilentWhistle is capable of obtaining location with error of less than 1.25m.

I. INTRODUCTION

Indoor positioning systems enable a wide variety of mobile/pervasive services, such as indoor navigation systems, virtual reality, and other location-based applications [10], [12], [1]. Indoor positioning systems using mobile devices face challenges from the following aspects:

Accuracy: Each localization system cannot avoid distance errors because of various interferences. Although some indoor localization systems (such as SpotFi [6] and ArrayTrack [16]) can achieve the accuracy with 30-50cm, extra or special devices are required.

Pervasiveness: They should be convenient for the users of common mobile devices to detect their locations by leveraging WiFi, Bluetooth, and acceleration components. In addition, the users of these systems should not require extra efforts to obtain their locations, such as taking photos or long-term data training in a certain scenario [1], [7], [13], [9], [11].

Deployment: Ideal indoor positions systems should depend upon the devices existing in indoor environments or the portal devices of users. Modifying hardware and long-term data training may limit the further developments [6], [14], [9], [8].

Privacy: Although some indoor positioning systems are able to achieve accuracy within 1 meter, the IP/MAC addresses and other identifiers are often exposed to other users. These systems are easy to track and face various privacy problems [16], [6], [8].

If the above challenges can be solved, indoor positioning systems can be applied as a pervasive service for all users of mobile devices. Unfortunately, to the best of our knowledge, no existing system can satisfy the four conditions. RSSI systems such as RADAR [2] are easy to deploy, but their ranges of errors

are beyond 1 meter. Some indoor localization systems such as ArrayTrack and SpotFi can reduce the distance deviation within 40cm, but they need a special hardware (Intel 5300 NIC) or modified hardwares to support the system deployment. Some indoor localization approaches are based on inertial sensing information, however, the accumulative errors and data fusion procedure are still challenging. Additionally, most current indoor localization systems can be tracked by the exposed identifiers.

Smartphone based indoor positioning are rapidly developing. By using crowd sourcing and opportunistic sensing approaches, some do not rely on the pre-deployed scenarios. However, once the mobile devices turn on their WiFi or Bluetooth adapters or other hardware to communicate, the non-reliable information might be shared between devices. If these information includes deviated location, the localization accuracy will be reduced. In addition, the time to scan and build connections is significant. Sometimes, when samples are collected by mobile devices, the users of devices move to other locations. Therefore, this leads to our conjecture: *Can we provide a passive indoor localization system with real time and fault tolerance features based on the daily uses of smartphones?*

In this paper we propose SilentWhistle, a light-weight indoor positioning approach that leverages acoustic sensing and dead reckoning to obtain the users' locations. SilentWhistle improves its performance in terms of accuracy, pervasiveness, and deployment without any hardware modifications of smartphones. We use the accelerometers on smart devices to generate the motion traces of users initially. Considering the accumulative errors of motion traces, our goal is to employ acoustic sensors on smartphones to enhance the positioning accuracy. In fact, translating this idea-sketch into a prototype still faces a variety of challenges: (1) even if acoustic sensors can detect the sounds in an indoor environment, how do we use the acoustic information that humans cannot hear to locate the users' positions accurately? (2) how do we deploy the system just using smartphones without extra devices? (3) how does the system filter incorrect location messages when they conduct Machine-to-Machine (M2M) communications? (4) SilentWhistle needs to reduce the noise caused by background noise and some exceptional samples from accelerometers. This paper addresses these problems step by step and evaluates the system by real scenario studies. Our extensive evaluation results indicate the accuracy range of SilentWhistle can achieve 0.88-1.24m.

The rest of paper is organized as follows. Section 2

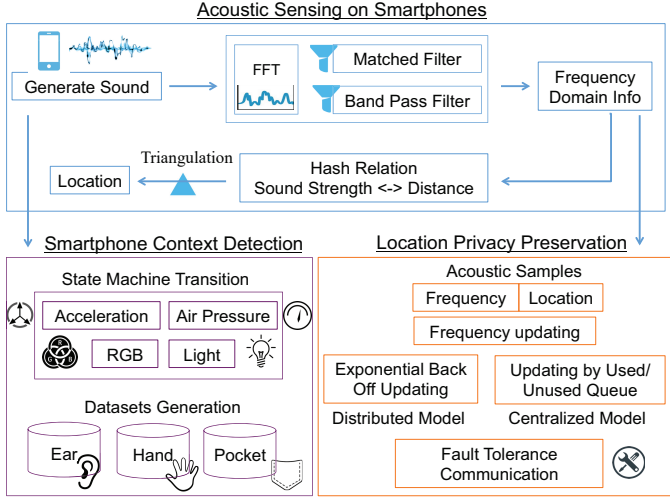


Fig. 1: The framework of SilentWhistle.

provides some preliminary techniques. The system design of SilentWhistle is introduced in section 3 in detail. We implement, evaluate, and discuss SilentWhistle in section 4. Conclusions are presented in section 5.

II. PRELIMINARIES

Dead reckoning is a simple and established idea: modern smartphones are equipped with accelerometers. By computing the moving distance in each time slot by obtained accelerations, the motion traces of users can be generated. As illustrated in equation (1), the symbol g is the earth gravity, a_x , a_y and a_z refer to the acceleration received on the three axes. By the obtained acceleration in each period, the movement distance of a mobile device in time period n is based on the equation (1). The parameters of v_{n-1} and a_{n-1} refer to the velocity and acceleration from the previous time period. t_n refers to the time length of the current period. S_n refers to the vector of movement distance in the current period. In addition, we leverage sensors (accelerometer, magnetometer, and gyroscope) on the smart device to estimate the user's step length and obtain heading direction [4].

Considering that noisy sensors accumulate errors over time (such as when users type on the screen or swing hands that hold smartphones), some systems leverage beacons to reset the location of mobile devices when users cross any of the beacons [15].

$$\vec{a} = (a_x, a_y, a_z - g), \vec{S}_n - \vec{S}_{n-1} = \frac{1}{2} \vec{a}_{n-1} t_n^2 + \vec{v}_{n-1} t_n \quad (1)$$

In this paper, we introduce a practical method to calibrate the deviations of dead reckoning. We analyze the Average Speed of user's Movements (ASM). For certain users, the average speed has a temporal correlation in different time slots. Namely, when people carry mobile devices, the average speed of users in a certain time slot is related to the average speeds of previous time slots and following time slots. According to this phenomenon, for every t time slots, 1) we curve fit the average speed values as the linear function and 2) predict the range of average speed for the $t+1$ time slot based on the historical information. When the obtained average speed in $t+1$ time slot is out of the estimated range, the accelerations will be disposed. The accelerations in $t+1$ time slot will be replaced by the accepted accelerations in the closest time slot.

A. Mapping between Sound Strength and Distance

Sound intensity is defined as the sound power per unit area. The sound intensity from a point source of sound will obey the inverse square law as formula (2). P refers to the source power. $4\pi r^2$ is the sphere area. I is the sound intensity. Therefore, the sound intensity is highly related to the distance between the source of sound and the sound receiver.

$$I = P / 4\pi r^2 \quad (2)$$

The most common approach to sound intensity measurement is to use the decibel scale.

III. DESIGN OF SILENTWHISTLE

A. Overview of SilentWhistle

As shown in Fig. 1, our system contains the following main parts:

(1) The sender smartphone generates the sound at approximately 20KHZ (people cannot hear). The receiver smartphone can obtain the sound strength with corresponding sound frequencies. We leverage FFT to transfer the time-domain signal to sequential-domain signal and filter the noises by a band-pass filter and matched filter.

(2) A smartphone can generate its own trace by dead reckoning. However, there still exist distance deviations. Based on the obtained sound strength and pre-trained relation, we transfer the sound strength to distance and use triangulation to reduce the errors caused by dead reckoning.

(3) Our approach proposes two types of frequency assignment methods: 1) a centralized model exchanges the frequencies by a cloud server. 2) a distributed model exchanges the frequencies by device to device and uses an exponential back off algorithm. By broadcasting acoustic information, SilentWhistle has the property of fault tolerance by avoiding to accept some incorrect location messages.

B. Sound Generation and Detection

M2M communication is a common mechanism for crowd sensing. However, common communications methods are not satisfactory. WiFi and Bluetooth need a long time to broadcast and build connections between discovered devices. When mobile devices broadcast their information, the identifiers are exposed to other devices. Moreover, since the information shared between devices are often not reliable, it may cause serious errors for the computational results of the whole communication system. Therefore, a new communication channel on a smartphone for crowd sensing is required.

Most modern smartphones are able to generate sound from 20HZ to 22KHZ. The sound between 18KHZ and 22KHZ can not be heard by most adults. Therefore, the sound generators in SilentWhistle produce the source of sounds with frequencies from 18KHZ to 22KHZ. Namely, the users of SilentWhistle can leverage such sound to communicate and not suffer from the hearable noises.

If one smartphone generates the sound with a certain frequency (18KHZ and 22KHZ), another smartphone can detect such sound by its microphone. The Fast Fourier Transform (FFT) resolves a time waveform into its sinusoidal components. The FFT takes a block of time-domain data and returns the frequency spectrum of the data.

C. Filter of Acoustic Information

Considering that we choose the frequency from 18KHZ to 22KHZ on a smartphone, we need to avoid the background noises and other potential noises.

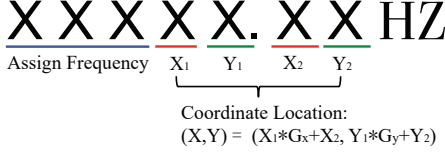


Fig. 2: The format of frequency message.

For reducing the background noises, we choose a band-pass filter. A band-pass filter [5] passes frequencies within a certain range and rejects frequencies out of that range. In our design, we filter the sound that are out of the range between 18KHZ and 22KHZ.

In addition, we further filter the background noises and other potential noises by a matched filter. A matched filter [3] is obtained by correlating a known signal, or template, with an unknown signal to detect the presence of the template in the unknown signal. In SilentWhistle, we can detect the sound source from other devices in the range between 18KHZ to 22KHZ. Once a smartphone can detect that the sound's strength is greater than a threshold and the frequency range is between 18KHZ to 22KHZ, we set the detected frequency as the "matched" value, and filter the values that are not matched.

D. Leveraging Triangulation for Improving Localization

Since dead reckoning is not enough to provide satisfactory location information, we adopt triangulation to further locate a user's position by knowing other detected devices' locations and sound strength: each smartphone computes its own position by dead reckoning initially, and then shares it with nearby smartphones by M2M communication. Furthermore, the signal strengths of multiple radios are used on smartphones to estimate distances between the devices. When individual smartphones may provide some positioning (possibly inaccurate) information, opportunities of accuracy improvement occur when several smartphones cooperate and share position information. Accuracy may improve as multiple iterations of information sharing and computations are made.

E. Format of SilentWhistle Message

As shown in Fig. 2, the last four digits present the location of a mobile device. The three leading digits are assigned frequencies by our system. Once an other user's smartphone detects the sender's frequencies by FFT, the sender's location information can also be obtained by the receiver. This procedure is similar to encoding and decoding: for a certain indoor room, we can transfer the map into a matrix. First, we cut the map into $X_1 \times Y_1$ grids. The number of grids on length side is X_1 , the number of grids on width is Y_1 . For each grid, we further cut them into sub-grids. X_2 refers the number of sub-grids that is on the length side of a defined grid. Y_2 refers the number of sub-grids that is on the width side of a defined grid. When we adopt a decimal system, G_x and G_y refer to 10.

F. How the acoustic information improves localization accuracies?

Initially, each smartphone can use dead reckoning to compute its own locations. Even if there exist some deviations on the smartphone, by analyzing the last four digits of a received acoustic message, the user can obtain the location of encountered devices. In the previous section, we introduced how users improve localization accuracy by sharing the

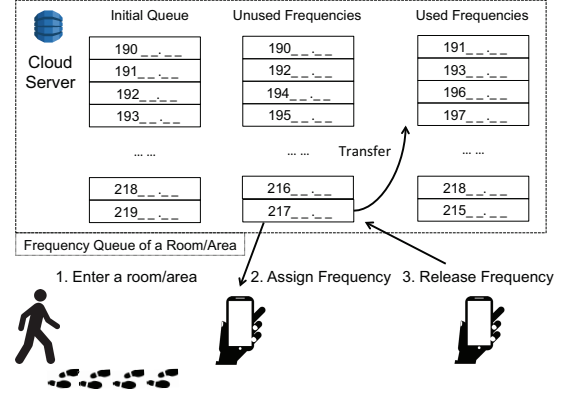


Fig. 3: The frequency assignment and releasing.

location information and do triangulation computation. Since the strength of sound can be detected by each device, we transfer the strength to distance by a hash map relation (distance - sound strength). We pre-trained these relations. In the experimental groups, we record the samples including the distance and sound strength information. Then, we use the average value in the normal distribution as the sound strength for a certain distance. All of these relations are stored in hash maps. Based on the estimated distance from sound strength, after running the triangulation approach many times, the errors of distance are eliminated effectively. The further results are demonstrated in the evaluation section.

G. Frequency Assignment

1) *Centralized Architecture*: In this section, we introduce two architectures to assign frequency ranges for smartphones. The central server of SilentWhistle stores two types of information. The first type is the real-time location of each smartphone. The smartphone will update its own location information and uploaded it to the central server continuously. The second type of information is the sound frequencies for each smartphone. As shown in Fig. 3, the initial frequency queue is stored on the cloud server. When a user enters a room, the last four digits can indicate the user is close to a entrance of a room/hallway, the server will assign a frequency to him/her immediately. The assigned sound frequency will be stored on the used queue. The remaining unused frequencies are stored in the unused list. Once the user leaves the room or turns off the acoustic sensing option, the assigned frequency will be released and go back to the unused queue.

2) *Distributed Architecture*: In practice, some indoor buildings do not include remote servers to support smartphones' location based services. We provide a mechanism to distribute localization tasks on the remote servers to users' smartphones. When a users enters a room, he/she can obtain initial position from a fixed beacon rather than by a cloud server deployed at the entrance. Then, the users of a distributed model have two functions: 1) computing its location by dead reckoning and 2) using triangulation to calibrate the localization errors. The users update the frequencies periodically. In each area/room, different users choose their frequencies from the previous frequencies tables that are stored in the smartphone rather than on the server. Sometimes, a user needs to change his/her frequencies when he leaves or enters a room. How to set the priority of items in the waiting table? We adopt an exponential back-off method to

achieve our goal. Exponential back-off is an algorithm that uses feedback to multiplicatively decrease the rate of some process in order to gradually find an acceptable rate. In our design, after k times of encountering, a random number of slot times between 0 and $2^k - 1$ is chosen. For the first encountering, each sender will wait 0 or 1 slot times. After the second encountering, the senders will wait anywhere from 0 to 3 slot times (inclusive). After the third encountering, the senders will wait anywhere from 0 to 7 slot times (inclusive), and so forth. As the number of retransmission attempts increases, the number of possibilities for delay increases exponentially. At the same time, the waiting list will be updated (sorted) based on the length of waiting time. Once a user hopes to change his frequency, he/she will choose the item with shortest waiting time on the table.

H. Connectionless Model

Different from traditional M2M communication by Bluetooth or WiFi, SilentWhistle provides a method to enhance the localization accuracy by acoustic communication. As shown in Fig. 4, for tradition Bluetooth or WiFi communication, different devices have to build the connection to share the location information and RSSI. Namely, for some scenarios, when a smartphone of a normal user with obvious location deviation, once the device sends an incorrect location message to another user, it is difficult to distinguish it from the side of the other device when the location is in RSSI range. Since we use triangulation to localize users, the group of users' location accuracies will be reduced. In triangulation, users can compute its own position by the other two devices. Since one user (Alice) can receive the other two users' positions and RSSI (transferred to distance), the positions and distances can be abstracted as the centers and radii of two circles. The coordinates of the two centers are (x_1, y_1) and (x_2, y_2) . The radii are r_1 and r_2 . We assume the intersection is (x, y) . Then, we assume $x = r_1 \cos \Theta + x_1$ and $y = r_1 \sin \Theta + y_1$. In order to simplify the expressions of intersection, let $a = 2r_1(x_1 - x_2)$, $b = 2r_1(y_1 - y_2)$, $c = r_2^2 - r_1^2 - (x_1 - x_2)^2 - (y_1 - y_2)^2$. After solving the equations, we can obtain:

$$\Theta = ((q^2 - 4pr)^{1/2} - q)/2p \quad (3)$$

$$p = a^2 + b^2, q = -2ac, r = c^2 - b^2 \quad (4)$$

Therefore, if the value of x_1 and y_1 include some deviations, the final result of (x, y) will be changed.

Then, we need to compute the intersection as the estimated position of Alice. One user sends the location information that includes some errors. Such errors will be computed when we compute Alice's position (intersection of two circles). Therefore, when Alice uses the computation position by triangulation, it also includes certain errors.

In SilentWhistle, each user broadcasts its location information to other users. Once a user broadcasts incorrect location information, the other two users will share the information. Both of the users will check whether the received location message is in the radio range. Once a user confirms the location message is out of range, he/she will report this situation to the remote server. The remote server will forbid the suspicious device to broadcast its information. In the distributed model, he/she will dispose the location information broadcasting by the suspicious device and forward the ID of the suspicious device to the other users by the acoustic information. Therefore, our approach

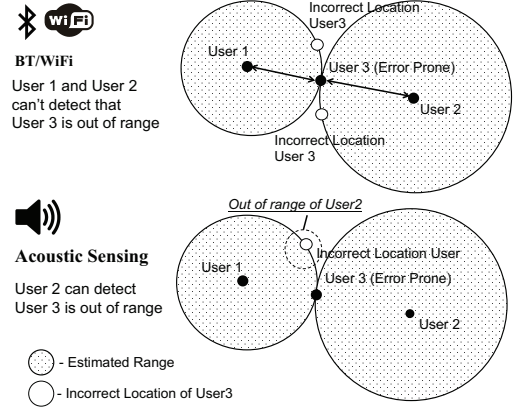


Fig. 4: The comparison between different connection models.

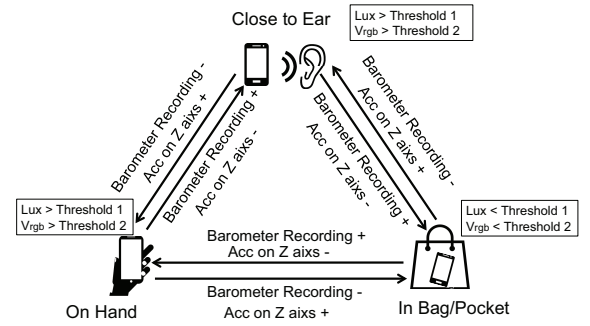


Fig. 5: The Contexts Transformation.

can further enhance the localization accuracy by using the connectionless communication model.

I. Smart Phone Context Detection

Considering that acoustic sensing information is used to enhance localization accuracies, we need to hold the smartphone in the hand or in an open area. In SilentWhistle, we propose an approach to distinguish three common states 1) close to ear, 2) in the pocket/bag, and 3) in the users' hands.

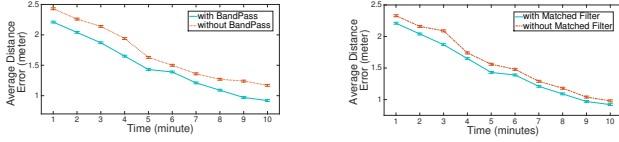
We build a state machine to describe the states on the smartphone. In the state machine, four types of information are leveraged: 1) the RGB color of picture captured from camera sensor; 2) the lumen from camera sensor; 3) the acceleration obtained on a smartphone; 4) air pressure recorded by a barometer.

When a user of SilentWhistle changes the relative position of a smartphone, namely, if the states will be transferred, there are three types of conditions that should be satisfied: 1) the new states's RGB values and Lumen values should be greater than certain values. The values of RGB and lumen will be discussed in the evaluation sections; 2) before the state transition, the average change of acceleration on Z axis should be increased or decreased; and 3) the air pressure detected by barometers should be varied or decreased.

After distinguishing the three states of smartphones, as shown in Fig. 5, our system builds three separate datasets for three different states. Since our system uses the distance and sound strength relation to compute locations, the data from the dataset generated in the pocket/bag will not be used for triangulation because of interference. Additionally, considering the accelerations are obviously different when a smartphone is

TABLE I: The detections of in/out positions of smartphones

Truth / Detected	Pocket	Hand	Ear
Pocket	291	8	1
Hand	7	287	6
Ear	0	5	295



(a) Localization results comparison of bandpass filter. (b) Localization results comparison of matched filter.

Fig. 6: The evaluation results of filtering methods.

in the user's hand and the pocket, the dataset of in the hand will not be applied for dead reckoning.

IV. CASE STUDY AND EVALUATION

In this section, we attempt to answer two main questions:

- By applying SilentWhistle, what is the accuracy of indoor localization?
- How does acoustic information, phone context detection, and the coloring strategy help dead reckoning based indoor localization?

A. Experimental Setting

We build a prototype of SilentWhistle on the Android platform (version 5.0) and evaluate its performance on two types of smartphones (Samsung Galaxy S7 and Google Nexus 5). The smartphones are equipped with standard sensors that include accelerometers. The user's motion trace is computed by 5HZ. Initially, we focus on the case study in a single room. The size of the room is 20m × 6m. There are 4 users who walk freely in the room and turn on the sound generators on the smartphone. We set 4 initial frequencies: 19000.00HZ, 19500.00HZ, 20000.00HZ, 20500.00HZ. All four frequencies are stored in the unused queue.

In this section, we introduce the following metrics to measure our system:

1) Euclidean distance: measure the distance between the ground truth and estimated location;

2) p_{ij} value: as shown in formula (5), the parameter p_{ij} refers to the probability of obtaining the user i 's location on the side of user j via Bluetooth, WiFi or acoustic communications.

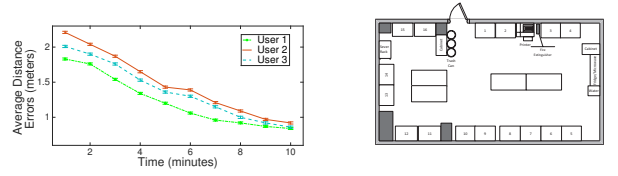
$$p_{ij} = \frac{\text{received samples including } i\text{'s location on } j \text{ side}}{i\text{'s broadcasting samples}} \quad (5)$$

B. Evaluation of Context Detection

Before we evaluate the localization performance, we focus on the Context Detection. Through applying our proposed approach, we test 300 cases on three volunteers. The results are shown in Table I. Based upon the detection results, we verify our proposed approach is able to distinguish the relative positions of smartphones effectively. Less than 10 samples are mis-analyzed.

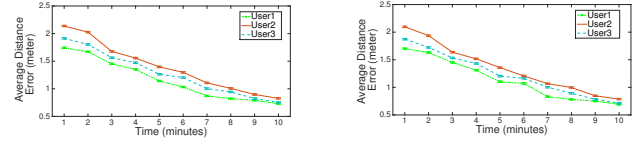
C. Evaluation of Noise Filters

In SilentWhistle, we adopt bandpass filters and matched filters. As shown in Fig. 6, both of the two filters are able to improve the localization accuracies.



(a) The average errors within 10 minutes (b) The layouts of eLANS lab

Fig. 7: The case study in a single room.



(a) The average errors with two beacons. (b) The average errors with four beacons.

Fig. 8: The case study in a single room with beacons.

D. One room measurement by centralized model

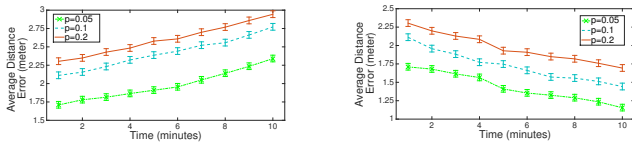
In the measurements in a certain room, 3 users walked and stopped freely for 10 minutes. Then, we repeated the case study 10 times. As shown in the Fig. 7, we conclude that 1) the accuracies of our approach can be achieved within 0.93 meters and 2) the accuracies are improved with the time increasing. Based on the initial step, we add four beacons that can communicate acoustic information. We repeat the previous experiment. After 10 minutes observation, Fig. 8 indicates the localization accuracy is further improved. Therefore, in our approach, more beacons in the proposed system can provide more opportunities to improve indoor localization accuracies.

E. Fault tolerance analysis in one room (centralized)

When we analyze the fault tolerance feature of the SilentWhistle, we specify that one user will send incorrect location information to the other two users. The distance between ground truth and sending incorrect location is 1 meter. Based on sensing the location information by Bluetooth or WiFi information, the average location accuracies of each users (user1, user2, and user3) are estimated as Fig. 9(a). In Fig. 9(a), we set the value of P as 0.05, 0.1, 0.2. The errors are difficult to reduce because of the connections. Then, by keeping the same experimental conditions, by using our approach (leveraging the acoustic information and turn off Bluetooth and WiFi adapters), as shown in Fig. 9(b), the broadcasting model without the connections outperforms. The sampling frequency of acoustic broadcasting is 10HZ. Namely, by cooperating with different smartphones' users, the incorrect location information can be reduced effectively in SilentWhistle.

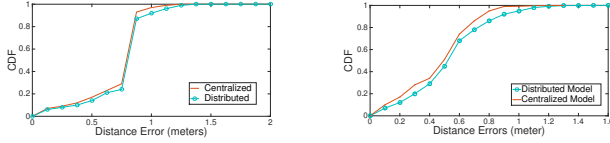
F. Fault tolerance analysis in one room (distributed)

The above analysis and evaluation are based on a centralized model. In our room observation, we use the exponential back-off algorithm for arranging the used list of frequencies. The length of each waiting slot is 10 seconds. When users enter the room, the initial position will be provided by an audio generator that is near the door. The relations between distance and sound strength are stored on each smartphone as hash tables. We keep the same experimental conditions as in the centralized evaluation. As shown in Fig. 10, the localization results by the distributed model are close to the centralized model by using SilentWhistle. Therefore, the fault tolerance



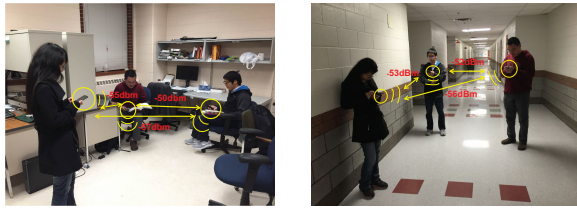
(a) Localization results by using connected model. (b) Localization results by using connectionless model.

Fig. 9: The case study by acoustic sensing channel.



(a) Average localization results by different models (10 minutes). (b) Average localization results by different models (30 minutes).

Fig. 10: The comparison between distributed model and centralized model.



(a) Room Measurement (b) Hallway Measurement

Fig. 11: Measurement in a building.

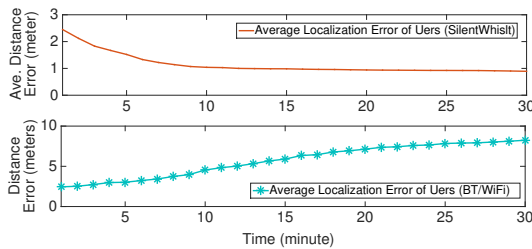


Fig. 12: Localization results in the multi-room scenario.

features in both centralized and distributed models are able to assist triangulation localization.

G. Multi-room Scenario Measurement

We extend our evaluation from a single room to a multi-room scenario. We conduct the experiment as follows: as shown in Fig. 11, three users walk around the 2nd floor of the Engineering Building at Michigan State University. The scenario contains four rooms and three related hallways. We deployed beacons at each entrance/exit on the floor plan. We keep the same experimental conditions as the single room case. One user played the role of broadcasting the location information within 1 meter deviation in the whole procedure. As the control group illustrated in Fig. 12, by applying SilentWhistle for 30 minutes, we draw the conclusion: 1) the average indoor localization accuracy of SilentWhistle users can achieve 0.88 meter; 2) on the group using Bluetooth/WiFi connection approach, the distance deviations increase gradually. The average obtained location results are not satisfactory.

V. CONCLUSION

This paper proposed SilentWhistle, an accurate indoor localization system leveraging acoustic information and preserving the privacies of users effectively. Each use of SilentWhistle generates a sound that cannot be heard by people but can be detected by a smartphone. By using the relation between distance and sound strength, SilentWhistle uses triangulation to improve indoor localization accuracies from initial dead reckoning. Considering protecting the location privacy of user's devices, we change the sound frequencies of smartphone periodically. Based on the centralized model and the distributed model, the senders of obvious incorrect locations will be detected and disposed in our system.

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REFERENCES

- [1] Martin Azizyan and Romit Roy Choudhury. Surroundsense: mobile phone localization using ambient sound and light. *SIGMOBILE*, 13(1):69–72, 2009.
- [2] Paramvir Bahl and Venkata N Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *INFOCOM*, volume 2, pages 775–784. Ieee, 2000.
- [3] Ea-Ee Jan and James Flanagan. Sound capture from spatial volumes: Matched-filter processing of microphone arrays having randomly-distributed sensors. In *ICASSP*, volume 2, pages 917–920. IEEE, 1996.
- [4] Wonho Kang and Youngnam Han. Smartpdr: Smartphone-based pedestrian dead reckoning for indoor localization. *IEEE Sensors journal*, 15(5):2906–2916, 2015.
- [5] Fumihiko Kobayashi and Isamu Umio. Band pass filter, June 4 1991. US Patent 5,021,757.
- [6] Manikanta Kotaru, Kiran Joshi, Dinesh Bharadia, and Sachin Katti. Spotfi: Decimeter level localization using wifi. In *SIGCOMM*, pages 269–282. ACM, 2015.
- [7] Swarn Kumar, Stephanie Gil, Dina Katabi, and Daniela Rus. Accurate indoor localization with zero start-up cost. In *MobiCom*, pages 483–494. ACM, 2014.
- [8] Ye-Sheng Kuo, Pat Pannuto, Ko-Jen Hsiao, and Prabal Dutta. Luxapose: Indoor positioning with mobile phones and visible light. In *MobiCom*, page 447458. ACM, 2014.
- [9] Fan Li, Chunshui Zhao, Guanzhong Ding, Jian Gong, Chenxing Liu, and Feng Zhao. A reliable and accurate indoor localization method using phone inertial sensors. In *UbiComp*, pages 421–430. ACM, 2012.
- [10] Hui Liu, Houshang Darabi, Pat Banerjee, and Jing Liu. Survey of wireless indoor positioning techniques and systems. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 37(6):1067–1080, 2007.
- [11] Chen Qiu and Matt W Mutka. Cooperation among smartphones to improve indoor position information. In *WoWMoM*, pages 1–9. IEEE, 2015.
- [12] Chen Qiu and Matt W Mutka. iframe: Dynamic indoor map construction through automatic mobile sensing. In *PerCom*. IEEE, 2016.
- [13] Anshul Rai, Krishna Kant Chintalapudi, Venkata N Padmanabhan, and Rijurekha Sen. Zee: zero-effort crowdsourcing for indoor localization. In *MobiCom*, pages 293–304. ACM, 2012.
- [14] Yu-Chih Tung and Kang G Shin. Echotag: Accurate infrastructure-free indoor location tagging with smartphones. In *MobiCom*, pages 525–536. ACM, 2015.
- [15] He Wang, Souvik Sen, Ahmed Elgohary, Moustafa Farid, Moustafa Youssef, and Romit Roy Choudhury. No need to war-drive: unsupervised indoor localization. In *MobiSys*, pages 197–210. ACM, 2012.
- [16] Jie Xiong and Kyle Jamieson. Arraytrack: a fine-grained indoor location system. In *NSDI*, pages 71–84, 2013.