Demo: Acoustic Sensing Based Indoor Floor Plan Construction Using Smartphones

Bing Zhou[1], Mohammed Elbadry[2], Ruipeng Gao[3], Fan Ye[1]
[1]Department of Electrical and Computer Engineering, Stony Brook University
[2]Department of Computer Science, Stony Brook University
[3]School of Software Engineering, Beijing Jiaotong University
{bing.zhou,mohammed.salah,fan.ye}@stonybrook.edu
rpgao@bjtu.edu.cn

ABSTRACT

This demo presents *BatMapper*, an acoustics sensing technology for fast, fine-grained and low cost floor plan construction. BatMapper operates by emitting sound signal and capturing its reflections by two microphones on smartphones. We develop robust probabilistic echo-object association and outlier removal algorithms to identify the correspondence between distances and objects, thus the geometry of corridors. We compensate minute hand sway movements to identify small surface recessions, thus detecting doors automatically. Additionally, we leverage structure cues in indoor environments for user trace calibration. The demo will enable any person to hold the smartphone and walk along a corridor to map the corridor shape and detect doors in real-time.

CCS CONCEPTS

• Networks → Location based services; **• Human-centered computing → Mobile computing**; **Smartphones**;

KEYWORDS

Acoustic Sensing; Indoor Floor Plans; Smartphones

1 INTRODUCTION

Online digital maps (e.g., Google Maps) have provided great convenience for location based services (LBS) outdoors such as finding nearby point-of-interests (POIs) and navigation. However, for indoor environments, such maps are extremely scarce and unavailable in most buildings. This has become a huge obstacle to pervasive indoor LBS.

Accurate, scalable indoor floor plan construction at low costs is urgently needed. Autonomous robots equipped with high precision special sensors (e.g., laser rangers [6], depth cameras [4], sonars [7]) can produce high quality maps. However, the high manufacturing costs, operational and logistic obstacles make it difficult to deploy robots in large quantities. Recently some work [2, 3] have leveraged crowdsourced data (e.g., WiFi, inertial, images) from commodity mobile devices to achieve scalability. However, they require large amounts of data to combat inevitable errors and noises in crowdsourcing, hence expensive total efforts and long data collection times. Those using images also face common limitations in vision techniques: dark/changed lighting, blurry images, glass walls, and restrictions on photo-taking due to privacy concerns.

In this demo, we present BatMapper, a novel acoustic sensing based system for accurate floor plan construction using commodity smartphones. Unlike inertial [1] or Wi-Fi [5] data that are inherently noisy, acoustics is capable of producing very accurate (e.g., cm-level) distance measurements. Unlike images [3], its performance is not affected by lighting conditions or transparent objects, nor does it cause privacy concerns. A single person can finish the measurements of a floor in a few minutes, eliminating the long time needed to crowdsource large amounts of data from many users.

2 OVERVIEW

BatMapper leverages three sensing modalities: acoustic, gyroscope and accelerometer for fast, accurate floor plan construction. The user walks along corridors while holding the phone, which keeps emitting and recording sound signals. It detects sound reflections (i.e., echoes) and measures their distances/amplitudes, from which relative positions of objects (e.g., walls) are inferred, and combined with user traces for floor plans.

Acoustic Ranging. The acoustic ranging module in BatMapper consists of sound emitting, sound recording by two microphones, and a series of signal processing steps to produce distance/amplitude measurements for echo candidates in both microphones (Figure 1). The received signals will go through Butterworth bandpass filters for the bottom/top microphone to remove background noise. Without such filtering, weak reflections can be buried in the noise. This step is critical for collecting data in noisy environments. Next we cross-correlate the signal with its respective pulse, a common technique that produces a peak for each echo, and obtain the upper envelop for the signal. Then we chop the envelop into segments of small time windows of $35ms$, each containing echoes from one pulse only. The first peak will always be the direct sound from the speaker to the microphone, and it has the highest amplitude. It will be used as the starting point. By measuring the time between the sound emission and echo reception, a series of ranging candidates to nearby objects are estimated.

Echo-Object Association. The ranging candidates are inherently noisy due to cluttered objects, multi-surface reflections, and lack direction information. *Echo-object association*, detecting which echo thus distance corresponds to which object (e.g., walls), is critical.

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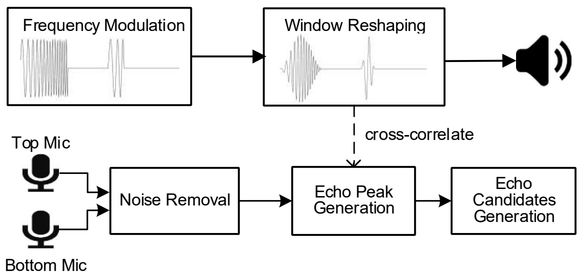

Figure 1: A particular sound signal and multiple signal processing steps produce echo candidates.

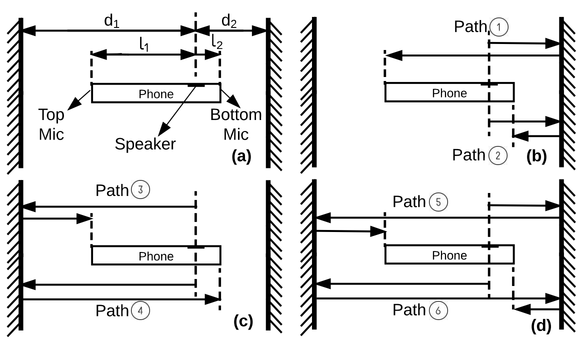

Figure 2: Position of speaker and microphones on the phone, and sound travelling paths of strong echoes in corridor.

We propose robust algorithms for echo-object association to derive geometries of corridors: a *probabilistic evidence accumulation* wall-distance association algorithm computes probabilities of echoes bouncing off different surfaces using relationships among various distances. Figure 2 shows a phone held perpendicular to both sidewalls in a corridor, and reflection paths of strong echoes received by microphones. In Figure 2(a), d_1, d_2 are distances from the speaker to the left/right wall (the width of corridor $d = d_1 + d_2$); l_1 and l_2 are the constant distances from speaker to the two microphones (the length of the phone $l = l_1 + l_2$). Certain distance relationships can be derived, such as echoes bounced from the same side wall have a certain difference (Figure 2(b&c)), and the multipath (Figure 2(d)) reflects the corridor width. Depending on how close these constraints are met, we assign probabilities for each echo candidate whether it's from left or right side walls.

A *recursive outlier removal* further eliminates residual incorrect associations caused by cluttered/moving objects. A *sway compensation* technique is designed to extract and compensate hand sway during walking and its disturbance to distance, thus small surface recessions caused by doors ($\sim 10cm$) are reliably identified and door locations detected. Distinct patterns in inertial and acoustics are combined to classify corridors, corners, open spaces and cluttered areas. Refer to [8] for further details.

User Trace Construction. We construct user's walking trace through step counting and orientation estimation from inertial sensors. However, the accumulation error with dead-reckoning from inertial sensors is a well known problem. Thus, several techniques are developed to suppress such errors: i) we minimize user's manipulation while walking; ii) we estimate orientation from sensor fusion instead of gyroscope only; iii) structure cues of indoor environments are leveraged to calibrate the orientation drifts.

First, BatMapper just requires the user to hold the phone and walk along a corridor. It does not require the user to take pictures every now and then, which involves a lot of phone rotations, thus introducing more errors in orientation estimation and step detection. Second, for more robust orientation measurement, we use the composite sensor game-rotation-vector in smart phones that leverages accelerometer and gyroscope, which proves to be more reliable than integrating gyroscope data for orientation. Finally, to combat the accumulation error, we leverage the structure cues (e.g., straight corridor, right-angle corners) in buildings for orientation calibration. As the user is supposed to walk along corridors, and make turns at corners, we detect major orientation changes instead of using instantaneous inertial sensor readings. That is, we "lock" the orientation to a constant value when there's no obvious rotation detected (e.g., the user is walking along a straight corridor). When the user makes turns, we detect such large orientation changes. If the orientation change is close to right-angle within a certain threshold, it will be calibrated to right-angle automatically. The trace is further calibrated when a walking loop closure is available to compensate step length error.

Figure 3: User interface of BatMapper demo application on Android.

3 DEMO SETUP

A demo application on Android devices is developed for real-time mapping. Figure 3 shows the user interface and a sample corridor map. The constructed map sample is on the left, the red dotted line represents user's walking trace, and black lines are corridor walls with door locations marked as yellow segments. The camera view on the right side leverages computer vision techniques for straight corridor detection, which is used for map refinement.

Our demo setup just requires a smartphone and indoor environment (i.e., a long corridor) for experiment. Due to acoustic sensing range limitations, our demo is capable to produce reliable results in buildings with a reasonable corridor width(i.e., <3m, office building, hotel), but not those with extreme wide corridors (e.g., shopping malls). The demo will generate the corridor shape with door locations marked in real-time as the user walks along the corridor.

We may need a table to set our laptop (plus a monitor, if available) to show our off-line map generation from collected data. We also need a place to hang the poster and AC power for laptop. Setup is expected to be done within 10 minutes.

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REFERENCES

[1] Moustafa Alzantot and Moustafa Youssef. 2012. Crowdinside: automatic construction of indoor floorplans. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems*. ACM, 99–108.

[2] Jiang Dong, Yu Xiao, Marius Noreikis, Zhonghong Ou, and Antti Ylä-Jääski. 2015. imoon: Using smartphones for image-based indoor navigation. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems*. ACM, 85–97.

[3] Ruipeng Gao, Mingmin Zhao, Tao Ye, Fan Ye, Yizhou Wang, Kaigui Bian, Tao Wang, and Xiaoming Li. 2014. Jigsaw: Indoor floor plan reconstruction via mobile crowdsensing. In *Proceedings of the 20th annual international conference on Mobile computing and networking*. ACM, 249–260.

[4] Kourosh Khoshelham and Sander Oude Elberink. 2012. Accuracy and resolution of kinect depth data for indoor mapping applications. *Sensors* 12, 2 (2012), 1437–1454.

[5] Hongbo Liu, Yu Gan, Jie Yang, Simon Sidhom, Yan Wang, Yingying Chen, and Fan Ye. [n. d.]. Push the limit of WiFi based localization for smartphones. In *ACM Mobicom 2012*.

[6] Hartmut Surmann, Andreas Nüchter, and Joachim Hertzberg. 2003. An autonomous mobile robot with a 3D laser range finder for 3D exploration and digitalization of indoor environments. *Robotics and Autonomous Systems* 45, 3 (2003), 181–198.

[7] Juan D Tardós, José Neira, Paul M Newman, and John J Leonard. 2002. Robust mapping and localization in indoor environments using sonar data. *The International Journal of Robotics Research* 21, 4 (2002), 311–330.

[8] Bing Zhou, Mohammed Elbadry, Ruipeng Gao, and Fan Ye. 2017. BatMapper: Acoustic Sensing Based Indoor Floor Plan Construction Using Smartphones. In *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services*. ACM, 42–55.