# Final Report of CSIT 6910A Indoor Localization leveraging Heterogeneous crowdsensing data

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## Introduction

This report summarizes a variety of approaches to the study of indoor localization from different perspectives in four papers, all of which approach the study of indoor localization and zoning in an efficient and inexpensive manner. Most of them are based on the traditional RSS fingerprint technique, but novel in their use of different clustering methods to classify indoor areas. The reading of these papers has provided me with the knowledge and theoretical foundation for the next semester's implement work.

This report will then be organized as follows, I will give a brief overview of the four papers in section 2, discuss specifically the differences in their research methods, specifically in terms of the automatic acquisition of information, the amount of manual annotation required, and the depth of research in section 3. and in section 4 I will present my own thoughts of the future work base on the details of the implement in future’s work.

## Overview

### 2.1 Paper #1

***CrowdInside: Automatic Construction of Indoor Floorplans (SIGSPATIAL’ 12)[[1]](#endnote-1)***

This paper introduces a crowdsourcing-based system for the automatic construction of buildings floorplans named “CrowdInside”. In this paper they address the problem of low GPS signals and inaccurate localization of mobile phones indoors. Instead of using RSS fingerprint for indoor user localization, they provide a highly accurate technique for estimating points of interest (or anchor points) in the environment (e.g. building entrances, lifts, stairs and escalators) based on mobile phone inertial sensors.

Specifically, the CrowdInside can be divided into four steps:

1. Using samples from different users to estimate the building entrance location.
2. Using inertial sensors to record acceleration, which is used to separating elevators, escalators, and stairs from other patterns such as normal walking and being stationary. And these elevators, escalators, and stairs are used as indoor anchor point.
3. Using a traditional localization technique often used in navigation, which is called “dead-reckoning based approach”, while the accumulation of error can be resetted the accumulation by leveraging the detected anchor points in step(2).
4. Employs classification techniques to separate corridors from rooms and further apply clustering techniques to separate the rooms from each other and identify the rooms shapes using computational geometry techniques.

Figure 1 shows the system architecture of CrowdInside.

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Figure 1. CrowdInside system architecture

### 2.2 Paper #2

***Smartphones Based Crowdsourcing for Indoor Localization[[2]](#endnote-2)(TMC’ 15)***

This paper proposes a wireless indoor localization approach named LiFS. The key idea of LiFS is connect previously independent radio fingerprints under certain semantics by human motion, LiFS transforming the localization problem from 2D floor plan to a high dimension fingerprint space and introduces new prospective techniques for automatic labeling.

The working process of LiFS consists of two phases: training and operating, and Figure 2 shows the system architecture of LiFS.

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Figure 2. LiFS system architecture

The major output of training phase is a fingerprint database in which an RSS fingerprint and its corresponding location are associated. The fingerprint database is further used in operating phase to process location requests.

In training phase, there are three steps:

1. Transforming floor plan to stress-free floor plan, which puts real locations in a floor plan into a high dimension space by multidimensional scaling.
2. Creating fingerprint space, Multidimensional Scaling is used to create a high dimension space, in which fingerprints are represented by points, and their mutual distances are preserved.
3. Mapping fingerprints to real locations. In fingerprint database, fingerprints are associated with their collecting locations (i.e., fingerprints are labeled with locations). Such associations are achieved by mapping fingerprint space (fingerprints) to stress-free floor plan (locations).

In operating phase. When a location query comes, usually an RSS fingerprint sent by a user, LiFS takes it as a keyword and searches the fingerprint database, the operating phase can be divided into two steps:

1. Using the nearest neighbor algorithm to predict the position: a fingerprint f is collected at the same location as f’, if f’ is the most similar to f in the fingerprint database.
2. Using continuous trajectory matching scheme to reduce the localization error caused by the fingerprint ambiguity for mobile users. In this scheme, a user’s location is estimated based on his/her moving trajectory, instead of one single RSS report, by measuring successive RSSs and the accompanying mobility information when a user is moving.

### Paper #3

***Hallway based Automatic Indoor Floorplan Construction using Room Fingerprints[[3]](#endnote-3)(Ubicomp’ 13)***

In this paper, they propose an automatic indoor floorplan construction system, using the following main components.

• Propose a room adjacency graph construction algorithm that identifies the adjacency of rooms and constructs a room adjacency graph that is robust to the spatial bias of room fingerprints and Wi-Fi noise

• Propose a hallway layout learning algorithm that determines the room arrangement along each hallway, e.g., room sizes and orders, using crowd-based motion sensing on smartphones; and

• Propose a force directed dilation algorithm that adjusts the individual room structures globally to improve floorplan accuracy.

The Figure 3 shows the details of the automatic Indoor Floorplan.

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Figure 3. LiFS system architecture

### Paper #4

***ARIEL: automatic wi-fi based room fingerprinting for indoor localization[[4]](#endnote-4)( Ubicomp’ 12)***

This paper presents a room localization system that automatically learns room fingerprints based on occupants’ indoor movements named *ARIEL*. *ARIEL* consist of three parts:

1. A zone-based clustering algorithm that accurately identifies in-room occupancy “hotspot(s)” using Wi-Fi signatures.
2. A motion-based clustering algorithm to identify inter-zone correlation, thereby distinguishing different rooms.
3. An energy-efficient motion detection algorithm to minimize the noise of Wi-Fi signatures.

ARIEL supports automatic indoor fingerprinting and room location using collaborative Wi-Fi signature analysis based on a personal mobile phone carried by the occupant. Figure 3 illustrates the architecture of the entire system, which consists of mobile phone side and server side components.

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Figure 4. ARIEL system architecture

On the mobile phone side, ARIEL performs the following operations.

• The run-time Wi-Fi signal vectors observed by each mobile phone are collected and delivered to the server to support room fingerprinting and room localization.

• The Wi-Fi signal vector stream is further annotated with motion data from build-in accelerometer, i.e., either collected when the occupant is in motion or stationary.

• Each mobile phone also maintains a local database storing the fingerprints of the rooms that the user has visited before, which serves as a local cache, enabling run-time on-device room localization without engaging the server.

• A system software module provides room localization APIs to support high-level applications & services.

On the server side, ARIEL performs room fingerprinting and localization through an incremental process:

• Given the streams of Wi-Fi signal vectors and the corresponding motion information collected from mobile phones, ARIEL uses the zone-based clustering algorithm to incrementally identify in-room occupancy hotspot(s), or zone(s). Meanwhile, inter-zone correlations are identified by the motion-based clustering algorithm, then zones belonging to the same room are merged into a new cluster. Each cluster is assigned a room ID and the Wi-Fi signal vectors in the cluster form the room fingerprint.

• Using the n-gram augmented Bayesian room localization method, run-time room localization services are then offered to the occupants. A room fingerprint database maintains room IDs, room fingerprints, and the converted room fingerprints (n-gram AP subsequences and corresponding probabilities). The converted room fingerprints are selectively synchronized to each user’s mobile phone based on the user’s room visit history and predicted room visits in the future.

## Comparison

### 3.1 Paper #1

***CrowdInside: Automatic Construction of Indoor Floorplans (SIGSPATIAL’ 12)***

The advantages of Paper #1 *CrowdInside*:

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Figure 5. Effect of using anchor points to reset the error in dead-reckoning

1. In terms of the **data used**, CrowdInside is so unique that it does not use RSS fingerprint data, but only acceleration data collected by internal sensors in smartphones to localize indoor position.
2. In terms of the **indoor localization method**, the method is simple and clever, guaranteeing a certain degree of accuracy. Because of the poor GPS data signal of cell phones indoors, they first used the location of the lost GPS signal of cell phones as the location of doors in the building, and then used the acceleration characteristics of different areas to locate the location of elevators, escalators, stairs and other anchor points, using the dead-reckoning based approach usually used in navigation, and the location of anchor points to correct the position deduced by the method, results are showed in Figure 5.
3. In terms of **method of identifying rooms as well as corridors**, the paper uses alpha-shape(a family of piecewise linear simple curves in the Euclidean plane associated with the shape of a finite set of points) to get the shape of the whole building first. Secondly they segment the trace of individual user and classify corridors and rooms base on (1) Average time spent per step in the segment; (2) Segment length; (3) Neighbor traces density. Finally the paper use a DBSCAN clustering algorithm to identify every single room and corridor, and the alpha-shape is used again to estimate the shape of room or corridor again after that.

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Figure 6. Construction of a detailed floorplan using multiple motion traces.

1. In term of the **work of label data**, researchers only need to match the reference objects such as building doors, elevators, escalators, etc. in the real scene with the anchor points identified by the above method and assign room IDs to each room in the final stage of room identification.

The disadvantages of Paper #1 *CrowdInside*:

1. Wi-Fi signals and AP MAC addresses are only used to distinguish different anchor points of the same kind, not to assist in improving the accuracy of predicting the user's location, which seems to be an oversight in the location methodology
2. There is some impracticality in determining the position of anchor points through the features of acceleration, and errors in the position of anchor points and so on will cause great errors in the work of user's indoor localization in later work.
3. The method of obtaining room and corridor shapes through segmented trajectories and density-based clustering is significantly less accurate when there are more segments, and the criteria for distinguishing corridors and rooms are not very clear, so it is easy to confuse corridors and rooms.

### 3.2 Paper #2

***Smartphones Based Crowdsourcing for Indoor Localization (TMC’ 15)***

The advantages of Paper #2:

1. In terms of the **data used**, there are two data sources: the first is the acceleration data collected by the smartphone's internal sensors, from which distance and location information can be obtained. The second is the Wi-Fi RSS fingerprint data collected by the smartphone.
2. In terms of the **indoor localization method**: the method reach a high accuracy by expanding the 2D floor plan of the building into a stress-free floor plan, the authors transform raw RSS data into fingerprint space, and by mapping the two spaces to each other, the user's location can be inferred from the RSS fingerprint data at a certain point, which inferred by the nearest neighbor algorithm and continuous trajectory matching scheme.
3. In terms of **method of identifying rooms as well as corridors:** through the stress-free floor plan, the different rooms are identified by classical k-mean clustering, where k is the number of rooms obtained from the real floor plan, and the remaining noise points are the corridors. The result is showed in Figure 8.

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Figure 8. Construction of a detailed floorplan using multiple motion traces.

The disadvantages of Paper #2 :

1. The k-mean clustering method used in distinguishing rooms from corridors does not significantly distinguish rooms from corridors, making the predicted range of rooms larger than the actual range of houses. The method used also fails to predict the shape of the house, which is determined by the simple mapping from stress-free floorplan to fingerprint space.
2. In term of the **work of label data**, The workload for data annotation in this thesis is large. First, the research method in this thesis is to predict the location of the user by the RSS fingerprint value of the user's current location by means of supervised learning, which requires a complete RSS fingerprint data collection in the research in the sample space. Second, in the part of distinguishing corridors from rooms, we need to know the number of rooms through the floor plan beforehand and then use the k-mean clustering algorithm to obtain the location of the rooms, which is very unintelligent, and in my opinion, the DBSCAN algorithm should be a better choice.

### Paper #3

***Hallway based Automatic Indoor Floorplan Construction using Room Fingerprints (Ubicomp’ 13)***

The advantages of Paper #3:

1. In terms of the **method of obtaining the adjacency between rooms:** creatively approximated by the value of the RSS fingerprint near the walls of adjacent rooms to obtain information on whether the rooms are adjacent or not.
2. In terms of the **method of obtaining the order between rooms:** the acceleration information collected by the phone is used to obtain the user's trajectory, and then the Wi-Fi RSS fingerprint collected during the user's movement on this trajectory is compared with the RSS fingerprint feature value of each room, and the order of each room in space is determined.
3. In terms of the **method of obtaining the size of rooms:** Creatively using the force directed dilation method in mechanics, the similarity of RSS fingerprint values between two rooms is abstracted as a spring, and information about the size of the room is obtained by calculating the equilibrium state of the spring system when a room is adjacent to multiple rooms.

The disadvantages of Paper #3:

1. In term of the **work of label data**, the workload of label data is too large for RSS fingerprint labelled with different room IDs, in my opinion it is possible to first use the DBSCAN algorithm to automatically tag the RSS fingerprint feature values of different rooms. At the same time, it is necessary to mark the RSS fingerprint value in the form of a time stamp for each moment of the user's movement on the track and correspond it to the position in the track.
2. In terms of the **method of obtaining the order between rooms:** determining whether two rooms are adjacent by agreeing on the Wi-Fi RSS fingerprint values near the walls is unstable, firstly because the gap between the Wi-Fi RSS fingerprint values due to the walls becomes larger, and if there is a corridor between the rooms, then the two opposing rooms may also be determined to be adjacent, which can have a devastating effect on the final result.

### Paper #4

***ARIEL: automatic wi-fi based room fingerprinting for indoor localization (Ubicomp’ 12)***

Paper #3 and paper #4 are written by the same author, in my opinion paper #3 makes up for many of paper4's shortcomings.

The advantages of Paper #4:

1. In terms of the **zone-based clustering method to do room localization**, A noise reduction algorithm is added so that the distance between Wi-Fi sessions can be effectively distinguished.
2. In terms of the **Motion-based user localization**, assuming that the user's movement pattern is different in different rooms, we can obtain the user's movement pattern through the phone's internal sensors and add RSS fingerprint data to assist in localization to obtain the user's room ID.

The disadvantages of Paper #4:

1. In term of the **work of label data**, the Wi-Fi session needs to be artificially mapped to a specific room ID, and the user's acceleration data needs to be collected along with their RSS fingerprint value for each movement mode.
2. There is no way to get the floor plan of the building automatically, only to artificially match the Wi-Fi session of each room to the room
3. I am skeptical of the assumption that the movement patterns of people in different rooms are different. In my opinion, different people have different motion habits, and the motion patterns obtained by acceleration data alone can be used for location recognition, which is an unstable algorithm and the accuracy rate will not be high.

## 4 Future work

After reading four papers, I was very inspired by the approaches in these papers. Using smartphones to collect acceleration data as well as Wi-Fi RSS fingerprint data is crucial for indoor localization. In my opinion, the initial idea about IMPLEMENTATION is that a rough building plan can be obtained from the user's motion trajectory, which can be obtained using anchor point in paper #1 This trajectory can be obtained by means of anchor points in paper #1. In the step of identifying houses and corridors, we can use whether the user is moving or stationary to determine whether it is a corridor or a room and then cluster the Wi-Fi RSS fingerprint values of each room based on the DBSCAN algorithm to automatically obtain the number of rooms in the building. Finally, we can obtain the order and size of the rooms based on the room adjacency diagram and the force-directed dilation method in Paper #3, which enables an efficient and automatic way to obtain the floor plan of the building and locate the users based on their acceleration data and RSS fingerprint data, which greatly reduce the workload of human labelling.

## Acknowledge

I would like to thank Professor Chan for his careful guidance in this Independent Project, where I learned how to understand the work done by others in an efficient way, extract key information, and also learn how to present my work in the right way. His guidance not only gave me a deeper understanding in the field of localization, but also inspired my research. I would also like to thank my mentor Dr. Amy Liu for her guidance not only in the work process but also in my life, her gentle and patient answers to my questions, and I believe that after her postdoctoral work, she will be a very popular professor among her students!

1. https://dl.acm.org/doi/10.1145/2424321.2424335 [↑](#endnote-ref-1)
2. https://ieeexplore.ieee.org/document/6805641 [↑](#endnote-ref-2)
3. https://dl.acm.org/doi/10.1145/2493432.2493470 [↑](#endnote-ref-3)
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