# Demonstrating CrowdInside: A System for the Automatic Construction of Indoor Floor-plans

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***Abstract*—The existence of a worldwide indoor floor-plans database can lead to significant growth in pervasive computing, especially for indoor environments. In this demonstration, we show *CrowdInside*: a crowdsourcing-based system for the automatic construction of buildings floor-plans. *CrowdInside* leverages the smart phones sensors that are ubiquitously available with humans who use a building to automatically and transparently construct accurate motion traces. *CrowdInside* processes the collected motion traces from different visitors of a building to detect its overall floor-plan shape as well as higher level semantics such as number of rooms, their shapes and locations, and corridors shapes along with a variety of points of interest in the environment. The goal of this demo is to show how the accurate motion traces are constructed as well as how the building floor-plan can be automatically generated.**

***Keywords*-Automatic floor-plans construction; crowdsourcing; mobile computing.**

## I. BACKGROUND

During the last decade, there has been a rapid growth in location based applications, including location-enabled social networking, direction finding, and advertisement. This has been driven by the flourishing of smart phones and mobile devices, location determination technologies, and wireless Internet connectivity. A key requirement to many of these location-based applications is the availability of a map to display the user location on. This map can be a street map, in case of outdoor applications, or a floor-plan, in case of indoor applications. Traditionally, outdoor location-based services providers, such as Google Maps, Bing Maps, FourSquare, etc, provide outdoor street maps for almost all regions around the globe. However, the indoor equivalent floor-plans are currently very limited, affecting the ubiquity and spread of indoor location-based applications. Recently, a number of commercial systems for indoor direction finding have started to emerge, e.g. Point Inside and Micello Indoor Maps. In late 2011, Google Maps started to provide detailed floor-plans for a few malls and airports in the U.S. and Japan. Nevertheless, all these systems depend on **manually** building the floor plan. Manual addition/editing of all buildings floor-plans around the world requires an enormous cost and effort which may be unaffordable. In addition, keeping these floor-plans up to date is another challenge.

## II. RESEARCH CONTRIBUTION

In this demo, we introduce *CrowdInside* [1] as a automatic floor-plan construction system. *CrowdInside* leverages the ubiquity of smart phones to infer information about the building floor-plan along with other semantic information. In particular, today's smart phones have an array of sensors, e.g. inertial sensors (accelerometers, compasses, and gyroscopes), that can be used to construct traces of movement in a transparent manner to the users. People walking in their homes, offices, and even visitors collect these traces and send them for processing by *CrowdInside*. Using this crowdsourcing approach, *CrowdInside* can provide the general layout of a building, identify the rooms and corridor locations and shapes, along with identifying other points of interest, such as elevators, stairs, and escalators.

*CrowdInside*, however, has to address a number of challenges including handling the smart phones noisy sensors, estimating the positions of points of interests in the building, detecting rooms and corridors shapes.

In summary, CrowdInside leverages the smart phones sensors in a crowdsourcing approach to automatically estimate the indoor floor-plans for virtually any building around the globe. It is based on a novel technique for constructing accurate indoor user traces based on the noisy inertial sensors in todays commodity smart phones. It can also detect the different points of interest inside the building (elevators, stairs, and escalators) with high accuracy based on users activity recognition. In addition, it leverages these points to reduce the error in the generated traces. Finally, it uses a novel technique to automatically construct a detailed floor plan, including the rooms and corridors shapes as well as the overall building layout using computational geometry techniques.

### A. System Architecture

Our system design is based on a crowdsourcing approach, where measurements from sensors embedded in mobile devices are collected from users moving naturally inside the buildings. The intuition behind this is that a large number of motion traces can provide an adequate description of the building's layout. Figure 2(a) shows an example for the motion traces collected from a number of users moving

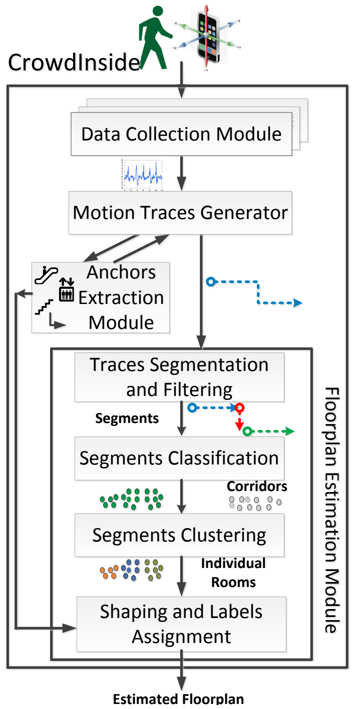



Figure 1. *CrowdInside* system architecture.

inside a building. As the number of traces increases, we get a better idea of the building layout. *CrowdInside* employs further processing to provide more semantic information, such as separating rooms and corridors, points of interest (such as elevators, stairs, escalators, etc).

Figure 1 shows our system architecture. The system consists of three main module: (a) the **Data Collection Module** is responsible for collecting measurements from users' devices, (b) the **Traces Generation Module** is responsible for generating accurate motion traces based on employing the points of interest for error resetting and (c) the **Floor-plan Estimation Module** that separates the corridors from the rooms and detects the rooms boundaries.

In the next two subsections, we give more details on the Motion Traces Generation module and the Automatic Floor-plan Construction module.

### *B. Motion Traces Generation*

In order to obtain accurate motion traces from users moving inside the building we employ the dead-reckoning approach described in [2] and its extensions for error resetting [3]. Each trace consists of a sequence of (time-stamp, location, and measured Wi-Fi RSSIs) tuples.

### *C. Automatic Floor-plan Construction*

Once accurate motion traces are collected from different users, the goal of this module is to estimate the building floor-plan. There are two levels of details that can be obtained: (1) the overall shape and (2) the room-corridors details.

*1) Overall Floor-plan Shape:* This level of detail provides a black and white occupancy map of the building. In particular, areas where users move represent walkable area (black) and areas free of users' traces represent blocked area (white).

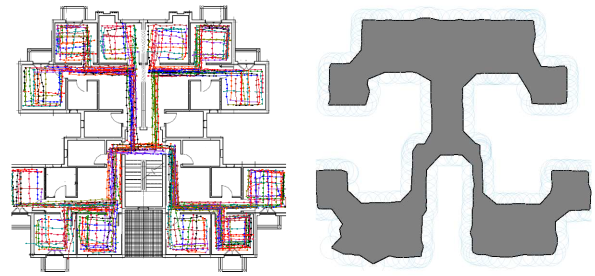
We have found that alpha shapes[4] (The $\alpha$-shape is a generalization of the concept of the convex hull (for $\alpha = 0$) can be effectively used to capture the building shape with high accuracy.

Figure 2(b) shows the $\alpha$-shape of the points corresponding to the traces in Figure 2(a).

*2) Detailed Floor-plan:* To further obtain more details about the building internals, we apply a number of processing steps on the collected traces to discover the distinct rooms, corridors, and room doors. These include traces segmentation and filtering, segments classification into rooms and corridors, segments clustering to obtain rooms boundaries, and final shaping and labeling.

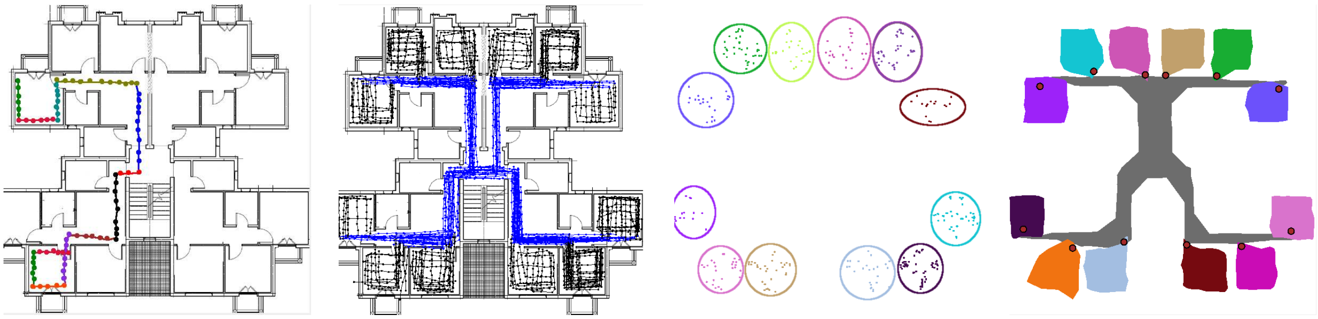
**Segmentation and filtering:** The first step in our approach is to break the continuous motion traces into segments. Segments are straight parts of the trace that are separated by either turns or pauses (periods of inactivities). In particular, consecutive segments are separated by significant changes in the direction of motion (we have chosen the threshold to be $45°$). The intuition is that a segment will be inside the same area (corridor/ room/ hall). Figure 3(a) shows how a sample trace has been broken into 10 segments (each segment shown in a different color). We also filter the segments by excluding short segments in terms of both time and/or distance as we found that those segments are not descriptive.

**Segments classification:** The goal of this module is to identify the type of each segment as one of two categories: corridors or rooms. We use a standard tree-based classifier using the following features : average time spent per step in the segment, segment length, neighbor traces density). The



(a) Collected traces (b) Shape of the building using $\alpha$-shapes

Figure 2. Construction of the overall building floor-plan from multiple motion traces (a). The grey area in subfigure (b) represents the estimated floor-plan shape.



(a) Breaking a trace into segments (b) Classified segments (blue corridors, black rooms) (c) Room clusters based on the center points of segments (d) Detailed estimated floor-plan

Figure 3. Construction of a detailed floor-plan using multiple motion traces.

result of classification is shown in Figure 3(b). Segments that are classified as "Corridors" are drawn in blue, whereas those classified as "Rooms" are shown in black.

**Segments clustering:** Once we identified the type of each segment (i.e. room or corridor), we apply a clustering algorithm on all segments of type "room" to find the number of rooms, their boundaries, and where they exist. We use a density-based clustering algorithm (DBSCAN) to group segments that lie close to each other into one cluster. To prevent segments from adjacent rooms to be grouped together and reduce the effect of the traces noise that may cross the walls between rooms, we use the center point of each segment for the clustering (rather than all the points in the segment). The similarity measure used for clustering is the distance between the location of **center points** and the similarity between the measured WiFi signals at these points. Figure 3(c) shows the clusters generated using the segments center points.

**Shaping:** To estimate the shape of rooms, we find the $\alpha$-shape of the points corresponding to all the segments that belong to each room separately (as generated by the clustering module). Similarly, to obtain the corridor shape, we find the $\alpha$-shape of the complete corridors point set. The final estimated floor-plan is shown in Figure 3(d) where different rooms are shown in different colors.

## III. Demonstration

In this demonstration, we show how *CrowdInside* can generate accurate motion traces and automatically construct an indoor floor-plan.

In our demo, we will provide the audience with android phones that they will hold while moving inside the conference venue to generate motion traces. The collected motion traces will be used to automate the process of indoor floor-plan construction. We will show how increasing the number of traces collected affects the accuracy of the generated map. We will also discuss the effects of changing different system parameters (e.g. clustering thresholds, the effect of employing WiFi RSSI for clustering, etc.) on the shape of the generated map.

## IV. Practical Setup

*CrowdInside* project is based on crowdsourcing. The system consists on two major parts: 1) A client mobile application running on user's mobile devices (We use Android devices) that records sensors measurements and sends them periodically to our central server. 1) *CrowdInside* server: a central processing server that aggregates and processes the collected sensors measurements from different users to output the floor-plan.

## V. Demo Requirements

The demo requirements are a number of Android mobile devices, a laptop to act as the central processing server, a table, power outlet and a wireless Internet connection. The presenter will provide the mobile devices and laptop required to do the demonstration.

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