Poster
IPS: A Ubiquitous Indoor Positioning System

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Abstract. Although GPS has been considered a ubiquitous outdoor localization technology, we are still far from a similar technology for indoor environments. While a number of technologies have been proposed for indoor localization, such as WiFi and GSM-based techniques, they are isolated efforts that are way from a true ubiquitous localization system. A ubiquitous indoor positioning system is envisioned to be deployed on a large scale worldwide, with minimum overhead, to work with heterogeneous devices, and to allow users to roam seamlessly from indoor to outdoor environments.
We describe an architecture for the ubiquitous indoor positioning system (IPS)[1]. We then focus on the feasibility of automating the construction of a worldwide indoor floorplan and fingerprint database which, as we believe, is one of the main challenges that limit the existence of a ubiquitous IPS system. Our proof of concept uses a crowd-sourcing approach that leverages the embedded sensors in today's cell phones, such as accelerometers, compasses, and cameras, as a worldwide distributed floorplan generation tool. This includes constructing the floorplans and determining the areas of interest (corridors, offices, stairs, elevators, etc). The cloud computing concepts are also adopted for the processing and storage of the huge amount of data generated and requested by the system users. Our results show the ability of the system to construct an accurate floorplan and identify the area of interest with more than 90% accuracy.

Key words: Area of interest classification, Automatic floorplan construction, Ubiquitous indoor localization.

1 Introduction

Many indoor location determination technologies have been proposed over the years, including: infrared [1], ultrasonic, and radio frequency (RF) [2]. All these technologies provide varying levels of accuracy that can support different application needs. However, each of these technologies is designed to be deployed in

[1] More details can be reached at the project's web page `http://wrc.ejust.edu.eg/IPS.html`.

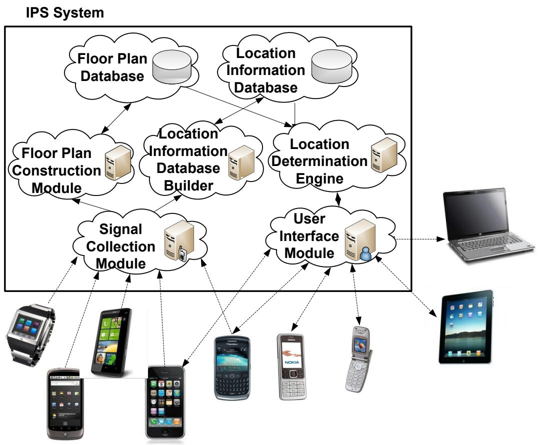

Fig. 1: The IPS system architecture.

a certain area, with known floorplans, and some of them require deployment of special hardware and/or require special calibration of the area of interest. We address the problem of realizing a ubiquitous indoor positioning system (IPS). Similar to the outdoor GPS, a ubiquitous indoor positioning system is envisioned to be deployed on a large scale worldwide, with minimum overhead, to work with heterogenous devices, and to allow users to roam seamlessly from indoor to outdoor environments. Such a system will enable a wide set of applications and provide a richer environment for location-aware social networking applications.

We believe that obtaining floorplans for virtually all buildings worldwide is the ***main challenge*** that limits the existence of a ubiquitous indoor localization system. As an example, although WiFi has been installed in a large number of buildings worldwide and WiFi localization can give meter accuracy [2], it cannot be leveraged as an IPS as there are no floorplans for all WiFi-enabled buildings. This can be due to the lack of building blueprints, as is the case in many developing countries, privacy issues, or to the fact that no one is willing to take the effort to submit the floorplan to a worldwide floorplan database. Even if someone submits the floorplan, there is still a manual effort required to process the floorplan to identify the areas of interest. In addition, constructing a WiFi signal fingerprint for a given area is an expensive, time consuming process that has to be repeated from tim to time to capture changes in the environment. In addition, a floorplan cannot be used for WiFi localization without constructing a fingerprint for the area of interest, which is a time consuming process. Updating the floorplan and the fingerprint is a task that has to be repeated from time to time to capture changes in the environment. Clearly, a true worldwide ubiquitous localization system has to overcome these hurdles.

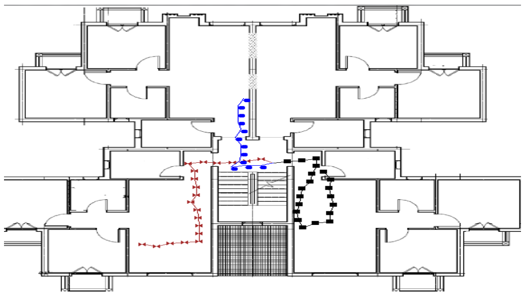

Fig. 2: An example of the different traces generated by the different users using the cell phones' inertial sensors.

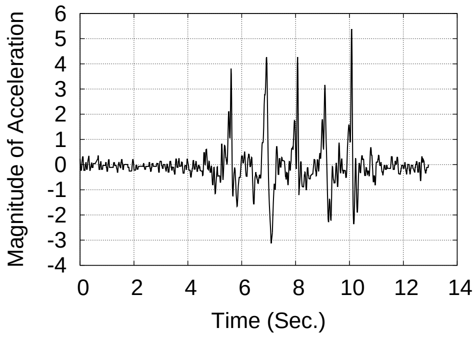

Fig. 3: The acceleration pattern for five steps.

2 System Design

The IPS system we envision is based on leveraging the cell phone as a ubiquitous computing device with a number of internal sensors, such as accelerometers, compasses, and cameras. The cloud computing concepts will be leveraged for the processing and storage of the huge amount of data generated and requested by the system users. Figure 1 gives an overview of an IPS system components. The system consists of five modules.

2.1 Raw Signal Collection Module

This module is responsible for collecting the data from the cell phones sensors. These sensors may produce different signals such as the acceleration, compass readings, gyroscope readings, WiFi information (signal strength and heard APs), GSM information (signal strength and nearby cell towers), camera images, sound signals, outdoor GPS signal, etc. Each signal is associated with a timestamp and is forwarded to other modules for processing.

2.2 FloorPlan Construction Module

This module takes the raw and processed sensor signals from the large number of users who use a building daily and fuse them to estimate the floorplan. It is also responsible for dynamically updating the floorplan. The estimated floorplans are stored in the cloud for later retrieval.

The first step in constructing the floorplan is to construct the user traces inside a building from the raw sensor data (Figure 2) by dead reckoning. To limit the growing error in location estimation using cheap noisy inertial sensors, we decided to track the users location by applying a step detection algorithm to identify the pattern of acceleration during a step. Figure 3 shows the acceleration pattern for five steps.

Once the user traces are constructed, the next step is to construct the floorplan and identify the areas of interest. Our technique is based on dividing the unknown floorplan area into blocks and classifying each block based on the traces that go through it (Figure 4). We have four different classes: Office, corridor, elevator, and stairs. We used the C4.5 tree-based classifier [3] to build a decision tree from a training set. We also use a bootstrap aggregation ensemble learning technique [4], this enables us to parallelize the technique, and hence becomes more suitable for the cloud.

2.3 Location Information Database Builder Module

This module is responsible for constructing the fingerprint database for the location determination system. It populates the fingerprint database, also stored in the cloud, based on the WiFi and GSM information it gets from the cell phones inside the building.

2.4 Location Estimation Engine

This module is responsible for estimating the user location based on the signals it receives in the user query. It consults the fingerprint generated by the Location Information Database Builder Module.

2.5 User Interface Module

This module is responsible for interacting with the system users. It receives a query from the users about their current location. This query may include a variety of sensor information, such as WiFi information, camera image, and other signals. The module then consults its location estimation engine and returns the current estimated user location and possibly the floorplan the user is currently located at.

3 Experiments and Results

As an example of a typical environment for the IPS, our experiment is conducted in a floor plan covering an area of $448m^2$ and covered with an 802.11 network. We have three different users carrying three android phones (two Nexus One phones and one Samsung Galaxy S phone). All phones have the same set of sensors: 3-axis accelerometer, 3-axis magnometer, WiFi and GSM information. Table 1 shows the confusion matrix of classification between different areas of interest inside a building. Although the GPS does not work indoors, we use it as a synchronization point to determine global reference points. In addition, even though the phones contain cameras and microphones, these are not used in our current testbed. Our system has been able to construct an accurate floorplan and identify the area of interest with more than 90% accuracy.

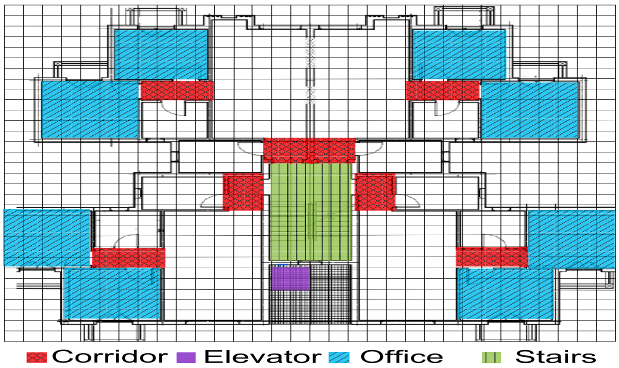

Fig. 4: The floorplan used in our evaluation divided into blocks. Note that the entire area is not highlighted for clarity.

	Predicted			
Actual	**Stairs**	**Corridor**	**Elevator**	**Office**
Stairs	478	23	0	0
Corridor	0	250	0	0
Elevator	0	0	46	0
Office	46	0	0	182

Table 1: The confusion matrix for the classifier

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