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Conference Paper · September 2016

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Abstract. Pervasive and ubiquity computing are expected to expand the development of new business oriented mobile applications. Knowing the exact physical location of the wireless devices is crucial for providing awareness of these applications. Many algorithms have been proposed for wireless localization, but most of them are designed for outdoor localization by using Global Positioning System (GPS) signals. In indoor environments, the GPS is not available, which makes localizations not trivial. This paper surveys state-of-the-art attempts toward efficient indoor localization for smartphones. We define a taxonomy used for better classification of the algorithms. Furthermore, we describe the characteristics of modern indoor positioning systems, as well as the challenges associated with the localization techniques. Finally, we provide real experiments using different smartphone models in order to discover typical problems that occur when signal strength is used as a range measurement technique in indoor localization systems.

Keywords: indoor localization · taxonomy · smartphone · RSSI

1 Introduction

With the flourish of smartphone market and context-aware computing, knowing the exact location of the mobile peers is an inevitable requirement. Analyzing the current positioning infrastructure identifies a gap between the lower technology layer and the upper application layer. This gap needs to be bridged in order to allow development of new service-oriented architectures for mobile devices that will foster business oriented mobile applications.

The well-known American Global Positioning System (GPS) and its cohorts (Russian GLONASS, Chinese Compass or European Galileo) don't provide indoor positioning [1]. The main limitations of these systems are the inability to measure the signal indoor, as well as the huge error in altitude (ranging from 10m to 25m), which makes them inappropriate for everyday purposes. On the other side, the algorithmic-based solutions for indoor localization (using distance calculation between the peers) usually suffer from the lack of accuracy, mainly due to inappropriate calibration of the measuring devices. Other drawback of such systems is their design which is optimized toward particular infrastructure, making their reusability unachievable. The moving objects inside the building cause reflection, diffraction or absorption of the radio signals, that makes these algorithms prone to errors due to multipath phenomenon. Additionally, many other characteristics of the indoor environments should be considered, like temperature and humidity variations, orientation of the antenna, furniture rearrangements, presence of human beings, etc.

With the rapid growth of location-enabled applications and indoor mapping information, the potential mass market opportunity for high-accuracy indoor positioning is huge. Still, the current evolution of indoor location enabled applications and services are only at the beginning. As the technologies continue to improve with better and more accurate positioning performances, new and more exciting applications will be developed to service and entertain the mass consumer markets.

The most common uses of indoor localization include:

- Locating People, Places, and Things Indoors
- Coordinating Joint Activities
- Augmented Reality Gaming
- Monitoring and Tracking People and Things

This paper aims to review the current state-of-the-art indoor positioning systems (IPS) for smart devices (mobile phones and tablets). Section 2 reflects to the current taxonomy of IPS. Section 3 presents a brief survey of some of the most popular commercial approaches used nowadays. The characteristics of modern IPS are described in Section 4. Challenges associated with the localization techniques are covered in Section 5. Section 6 reflects to the problems that we identified when deploying real experiments for measuring radio signal strengths, which is a very common technique for distance measurement in modern IPS. Finally, we conclude this paper in Section 7.

2 Taxonomy of IPS

Many different technical terms with identical or slightly different meanings are frequently used in the literature to define the process of determining a location. Among them, positioning and localization are used almost interchangeable.

As nouns, location and position are synonyms. However, location is more commonly used for a particular point or place in a physical space, while position is more general term of a place or location.

Hence, positioning is used to define object/person position, or/and to emphasize a change in the position, i.e. when object/person has been moved to a new location. On the other side, localization is mostly used for describing the process of position determination in wireless sensor networks, carried out in an ad-hoc and cooperative manner. In this context, there is a requirement for topological correctness of the nodes locations, which are also known as relative locations.

Nodes in the network with a priori known location are referred to as anchor or beacon nodes. Anchor node is usually used when the node is stationary in wireless sensor networks community. Other terms are also found in the literature, like Hotspot, Access Points (AP) or Base Stations (BS).

There are many classifications of IPS, regarding different criteria. In this section, we will briefly discuss the most common characteristics that distinguish the IPS.

2.1 Ranging techniques

Regarding ranging techniques, algorithms can be divides on proximity-based and distance-based. When distance measurement is needed, the following ranging techniques are very common: Received Signal Strength Indicator (RSSI) used in lateration and centroid-based techniques, Angle of Arrival (AoA) used in angulation-based techniques, Time of Arrival (ToA) and Time Difference of Arrival (TDoA) [2].

2.2 Infrastructure-based vs. Infrastructure free (Infrastructure less)

Most techniques used for localization, apart from smartphone presence, require additional infrastructure (Wi-Fi, Access Points, etc.) that will provide additional data to the algorithm. This infrastructure is usually present in most of the buildings where IPS aims to operate (shopping malls, airports, student campus, etc.). On the other hand, there are research efforts toward development of infrastructure free algorithms, although still very limited.

2.3 Fingerprinting vs model-based techniques

Fingerprinting technique is based on creation of a collection of pre-measured signal strengths for all access points in a particular location, known as radiomap. Fingerprinting involves a site survey process in which RSSI measurements (known as RSS fingerprints) are collected and stored at every location of an interested area. In the next phase, a new user interested to obtain its own location has to send the current RSS fingerprint, so the localization algorithm can retrieve the database in order to find the best fingerprint match. However, site survey is time-consuming and labor-intensive task, that is vulnerable to environmental changes, like furniture rearrangement. On the other hand, model-based techniques use physical properties of the signal propagation. They require the positions of the access points, radio propagation model and a map of the environment.

3 Popular commercial approaches

In the recent years, number of companies (often startups) presented their commercial solutions. Many of these solutions mimic GPS by using Bluetooth, Wi-Fi or similar radio devices.

Arguably, the most popular indoor positioning system at the moment is Apple iBeacon [3]. The system uses Bluetooth low energy (BLE) device that broadcasts (advertise) its unique identification number to the surrounding area. Many companies use the same or comparable technology to achieve similar results. Indoo.rs [4], an Austrian company, offers a palette of different positioning technologies, including iBeacon, Wi-Fi Fingerprinting and utilization of different mobile sensors, that allows accurate and uninterrupted indoor positioning. Chipolo [5] uses BLE beacons in a form of a key ring tag that allow pinpointing any lost or misplaced item. Navizon [6] combines Wi-Fi and BLE tags with Wi-Fi fingerprints database to deliver precise and continuous positioning to a mobile user. Estimote Inc. [7] creates a platform for context and location retrieval, with their own BLE stickers, beacons and mobile software solution. This digital platform can be used in homes, museums, stores, restaurants or similar places where location-tagging is needed. Wifarer [8] uses existing Wi-Fi infrastructure or their own beacons to track user movement, providing turn-by-turn indoor navigation or location-aware content and services. Aisle411 [9] offers a technology that allows retail store customers to locate desired products. Many other companies offer similar solutions. AngelList [10], a US website that brings together startups and angel investors, lists 58 companies in its "Indoor Positioning Startups" category.

Google Maps for Android began introducing 2D floor plans of shopping malls, airports, and other large commercial areas, which tracks the user via Wi-Fi, using hotspots as beacons. Nokia is performing indoor localization using Bluetooth technology for actual 3D models of the buildings. Both Google and Nokia rely on well-known triangulation techniques.

Although the BLE or Wi-Fi beacon approach is the most common, there are also other solutions, usually specialized for specific purposes. Australian company Locata [11] uses custom GPS-like terrestrial network that allows successful outdoor or indoor positioning. Rosum (acquired by TruePosition [12]) offers the technology that enables usage of the television signals for outdoor and indoor positioning. Both technologies are described as a supplement to the GPS system. Skyhook Wireless[3], also recently acquired by TruePosition [12], is another positioning company and location provider for Apple, Samsung, Sony and Mapquest. Skyhook maintains a global database of Wi-Fi access points and IP addresses, offering their hybrid positioning system on different platforms. Microsoft Research's Mobile Indoor Localization [14] explores the potential of mobile inertial sensors (accelerometer and magnetometer) for indoor positioning. Their solution does not require additional infrastructure, like Wi-Fi or BLE beacons, except for the indoor map. Artemis Networks is developing the technology pCell [15], which promises to dramatically increase the efficiency of mobile networks and provide 100% of theoretical bandwidth for each user in the network.

4 Characteristics of modern IPS

In this section, we are going to describe the main characteristics that one modern IPS should have.

4.1 Hybrid location services

Since GPS fail to work well in indoor environments and Wi-Fi is not wide-spread to cover outdoor environments (except maybe in parts of the urban centers), there is an evident need for the IPS solutions to integrate different positioning techniques with different infrastructures, in order to switch seamlessly from indoor to outdoor environment and vice versa [16]. The solution should represent a hybrid location approach designed to choose and switch among multiple positioning technologies available at certain place and time during the user movement [17].

4.2 Cognitive positioning and sensing

As addition to aforementioned positioning technologies and techniques, sensors embedded in smartphones such as gyroscope, compass or camera can be used to enhance positioning [18]. In order to improve the accuracy of positioning service, concepts of sensor data fusion and cognitive positioning are lately introduced [19,20]. They are taking advantages of various positioning techniques and environmental information by combining them to determine location of the users, as well as to embed the intelligence of sensing and inferring human behavior and context.

4.3 Cooperative positioning

In certain situations, where access points cannot be manually positioned or located by a system administrator, cooperation between users becomes essential to unambiguously determine their positions [21]. In cooperative positioning, users exchange information about their position or other known data (such as number of visible satellites or computed position) with their neighbors in order to improve positioning accuracy [22, 23].

4.4 Real-time multiple object tracking

Tracking an object refers to the observation the sequence of positions or locations of certain object (called trajectory) [24]. However, tracking is not just repeated positioning. Since positioning error could be larger that distance between two sequential positions of the tracked object, obtaining meaningful trajectory could be non-trivial task. Parameters like orientation or altitude could enhance the accuracy of indoor tracking [25].

Another problem is tracking of multiple objects. Presence of more objects in space still represents a great challenge due to their interference which affects signal measurements and produces positioning errors [21]. Finally, to make such positioning system usable in practice and operable in real-time, algorithms should not be time-consuming and energy-consuming [26].

4.5 Map-matching

The result of the positioning process is useless without the corresponding map information. The desired result is usually symbolic coordinate that define the position in semantic terms such as room number or street name [17,24]. Map matching process could be useful in both ways: (1) as resulting information about the meaningful position and (2) as the contextual information to improve positioning accuracy. In [27], authors use map-matching, Wi-Fi and sensors to determine users' positions.

In contrary to outdoor maps, indoor maps are usually not available and have to be prepared in advance. This refers not only to the floor plans, but also to the plan of the spatial elements like furniture inside the rooms, which are usually exposed to rearrangements. In multifloor environments, 2D floor plan is usually not enough to match positions [28,29], which can cause additional problems.

We believe that map information is the missing point for rapid improvement of many IPS.

5 Challenges of IPS

As presented in the previous sections, there are plenty of methods and approaches for indoor positioning. Most of them represent appropriate solution to a specific problem domain. According to their properties and application needs, we address the following requirements that any indoor positioning system should strive to reach.

5.1 High position accuracy

Indoor environments require more accurate and more precise positioning than outdoor environments, as positions within close proximity could have completely different context (like exhibit in a museum). Some indoor technologies are highly precise such as ultrasound, with accuracy of up to several centimeters [30]. Due to its high cost, Wi-Fi, Bluetooth or infrared are more common. They have reported accuracy between 1 to 5 meters [31,22]. However, the accuracy achieved in practice ranges from 2 to 6m [32], which is not enough for many applications.

5.2 Minimal setup effort

Many positioning techniques require initialization or calibration, which can be time-consuming, complex and non-adaptive. One example is the process of creating a radiomap in a fingerprinting method [33,34]. Since radiomaps are "static" and cannot adapt to environment changes (e.g. people walking around the room, adding new piece of furniture), initialization should be repeated every time a significant change in environment occurs [33]. Apart from traditional site survey, many state-of- the-art approaches use crowdsourcing as a tool to avoid human labor for collecting initial fingerprints [35]. We claim that the positioning system should require as little setup effort as possible.

5.3 Easy usage/ Low complexity

Nowadays, smartphone users are accustomed to an unobtrusive and simple usage of mobile applications. Therefore, the positioning application should minimize additional user involvement. Techniques based on RSSI have privilege when comes to ease of usage. They don't require additional specialized software or hardware, eliminating the need for carrying any extra devices along.

5.4 Full coverage

Solutions for indoor localization usually use an existing infrastructure for positioning (like wireless network), since it is often available almost everywhere. Still, existing setups tend to leave some places out of reach of the signal. On the other hand, the coverage also depends on the methods used for positioning. For example, centroid-based algorithms cover the area of convex hull of devices, usually APs. On the other side, algorithms based on trilateration have better coverage.

In any case, positioning system should strive to reach global coverage or at least upgradeable coverage of certain space of interest.

5.5 Adaptive to the environment

The precision of signal measurements is affected by various factors like obstacles (such as walls or furniture, as well as people movements), equipment properties and environmental changes (such as temperature or humidity). Furthermore, very often indoor space is considered as 2D space, but common situations like positioning in multifloor buildings should be covered by the system as well [36][37].

5.6 Low power consumption

Most of the positioning systems cause an unacceptable energy cost. From users perspective side, it is not acceptable that smartphone battery will drain too fast because of IPS application [26]. Due to EU initiatives to implement energy-saving regulations, the need to reduce power consumption will be even more present in the future. Positioning system should strive to minimize additional power cost.

5.7 Low-cost

To be wide-used, the positioning system should minimize its cost. This requirement interlaces with requirements to be accurate and easy to use.

5.8 Scalability

By increasing number of nodes involved in localization, both network and user device could suffer from scalability problems. The main approach to this problem is distribution of measurement and calculation processes to more than one entity [38].

6 Lessons learned from experimental settings for localization

In order to identify typical problem and challenges associated with IPS, we set up three experiments in our faculty laboratory, which consist of measuring RSSI with smartphones and access points. Beside the standard problem of the signal variance due to the presence of obstacles, the difference between smartphones vendors and access points vendors yields to different RSSI values. Furthermore, RSSI measurements between two mobile phones in crowded scenarios are very dispersed and impossible to be fitted with any of common curve fitting methods.

6.1 Experiment 1

For the first experiment, we used two different smartphone models: Samsung Galaxy S4 and HTC Legend, and one access point (AP), models Air Pen express.

We recorded the RSSI measured by each smartphone to the Air pen express AP. The measurements were taken at distances of 0, 1, 2, 3 and 4 meters. The measurements were repeated three times for each distance and average value was taken.

The relationship between the RSSI value and the distance for the two mobile phones are shown in Fig. 1a. The difference between measures is nearly linear (around 8dBm).

6.2 Experiment 2

For the second experiment, we used two different access point models: Wireless pocket router and Air Pen express, and one smartphone device, model Samsung Galaxy S4. We recorded the measurements obtained by each access point to Samsung Galaxy S4, while the phone operated as hotspot. The measurements were taken at distances of 0, 1, 2, 3 and 4 meters between the phone and each access point.

Fig. 1b shows the relationship between the RSSI value and the distance for the two access points. Again, the difference between measures is nearly linear.

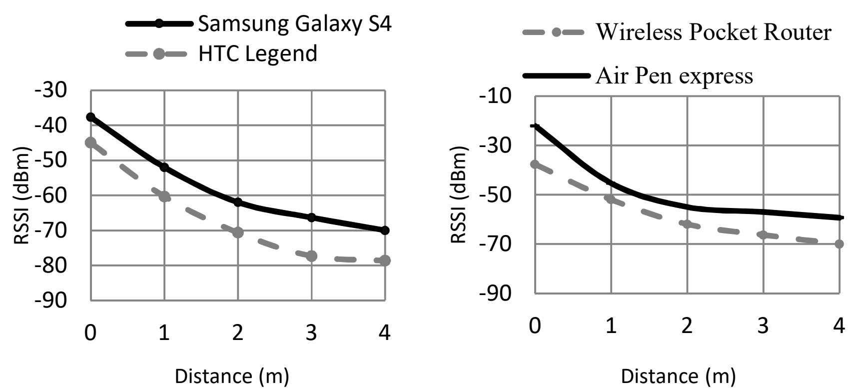
6.3 Experiment 3

For the third experiment, we generated five different scenarios. Two different scenarios are shown in Fig. 2.

In each scenario, 6 persons where placed inside the room with size 7m x 8m. Each person has a smartphone. We use different smartphone models, i.e. four Samsung Galaxy S4, one Samsung Galaxy S3 and one HTC Legend. Smartphones were operating in normal mode and in hotspot mode.

We measured the RSSI between each two mobile phones, i.e. 30 measurements for each scenario. When a phone was in hotspot mode, all other phones measure the RSSI. The measurements were repeated twice (Series1 and Series2 on Fig. 3). Thus, we have collected 300 measurements.

The relationship between RSSI values and distances measured between mobile phones is shown in Fig. 3. As it can be seen, the measurements were much dispersed and inadequate for curve fitting.



(a) (b)

Fig. 1. (a) RSSI measurements of the smartphones toward Air pen express AP; (b) RSSI measurements of the APs toward Samsung Galaxy S4 smartphone

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(a)

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.	.	.	.	O3	O4	.	.
.	.	.	O2	.	.	.	.
.	.	.	.	O1	.	.	.
.	.	.	.	.	.	.	.

(b)

Fig. 2. Examples of the experimental setup for (a) sparse scenario and (b) crowded scenario

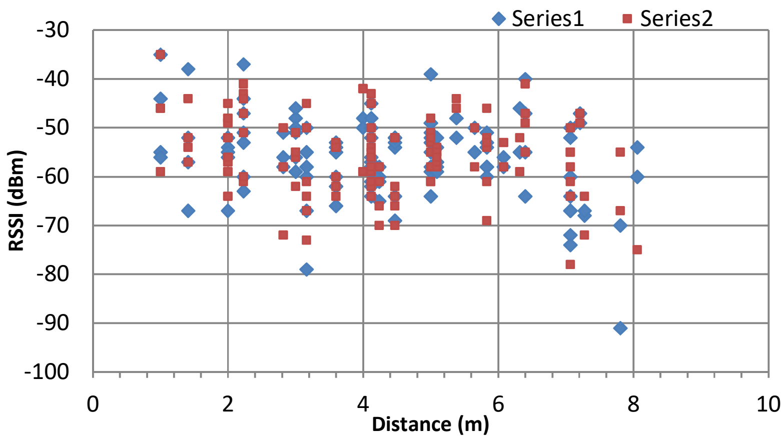

Fig. 3. Relationship between RSSI value and distance measured between mobile phone

Conclusion

In this paper, the current state of the rapidly developing indoor localization field was presented. With the growth of mobile computing market, including smartphones, tablet computers, and more recently smart watches, and the increase in the number of context-aware mobile applications, there is a rising need for high-precision indoor positioning solutions. In the recent years, we have witnessed a number of attempts from different companies (from startups to major ICT "players") to develop easy-to-use, robust and relatively cheap indoor localization systems. Different approaches were taken, from using custom setups, predefined and pre-measured fingerprinting maps, to systems that integrate into existing Wi-Fi or similar radio network. Still, all of these solutions impose some disadvantages, from setup complexity and price to the unsatisfactory precision, weak device support or inadequate software.

In this paper we briefly surveyed the most popular commercial IPS. We provided taxonomy to easily classify them. Additionally, we described the IPS characteristics and challenges. Through setting experimental test bed using smartphones and access points from different vendors, we showed that RSSI measurements are not adequate to provide accurate indoor positioning. Although the most popular localization methods at the moment seem to be the ones using WiFi or Bluetooth devices based on RSSI, there are many issues and challenges that need to be solved, before we could say they became a "de facto standard" in the indoor localization.

Acknowledgement. This work was partially financed by the Faculty of Computer Science and Engineering, Ss. Cyril and Methodius University in Skopje, Macedonia.

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