Seamless Outdoors-Indoors Localization Solutions on Smartphones: Implementation and Challenges

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The demand for more sophisticated Location Based Services (LBS) in terms of applications variety and accuracy is tripling every year since the emergence of the smartphone few years ago. Equally, smartphone manufacturers are mounting several wireless communication and localization technologies, inertial sensors as well as powerful processing capability to cater for such LBS applications. Hybrid of some wireless technologies is needed to provide seamless localization solutions and to improve accuracy, to reduce time to fix, and to reduce power consumption. The review of localization techniques/technologies of this emerging field is therefore important. This paper reviews the recent research-oriented and commercial localization solutions on smartphones. The focus of this paper is on the implementation challenges associated with utilizing these positioning solutions on Android-based smartphones. Furthermore, taxonomy of smartphone-location techniques is highlighted with a special focus on the detail of each technique and their hybridization. The comparative study of the paper compares the indoor localization techniques based on the accuracy, the utilized wireless technology, overhead and the used localization technique. The pursuit for achieving ubiquitous localization outdoors and indoors for critical LBS applications such as security and safety shall dominate future research efforts.

• **Networks~Network services** • **Information systems~Location based services** • **Human-centered computing~Smartphones**

Additional Key Words and Phrases: Smartphones localization; LBS, Localization techniques and technologies; Smartphone measurements error, localization challenges

ACM Reference Format:

Halgurd S. Maghdid, Ihsan Alshahib Lami, Kayhan Zrar Ghafoor, and Jaime Lloret 2015. Seamless Outdoors-Indoors Localization Solutions on Smartphones: Implementation and Challenges. ACM Comput. Surv. 9, 4, Article (October 2015), 37 pages.
DOI:http://dx.doi.org/10.1145/0000000.0000000

1. INTRODUCTION

The first generation of localization solutions of mobile handsets was focused on achieving the requirements of the Federal Communications Commission-Enhanced 911 (FCC-E911) authorization, and they were network based. Angle-of-arrival (AOA)

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DOI:http://dx.doi.org/10.1145/0000000.0000000

and time-based were some of the localization techniques deployed by some of the cellular networks at the time (Caffery & Stuber, 1998).

The second generation of localization solutions was focused on vehicle navigation. They incorporated Global Positioning System (GPS) receivers and added data via the cellular network and/or assistance from inertial sensors such as accelerometers and gyroscope sensors (De Angelis, Baruffa, & Cacopardi, 2012).

Some of these solutions have included a rough initial position obtained from WiFi access points (WAPs) available in the vicinity of these handsets/navigators. This provision is based on pre-surveyed WAPs in most built-up areas (where the WAPs location is stored in a central Internet server, e.g. solutions by Ekahau and Skyhook). Such implementations have formed the third generation of localization solutions (Gallagher, Li, Kealy, & Dempster, 2009).

Current solutions attempt to mix multi-GNSS signals (GPS plus GLONASS) with cellular, wireless fidelity (WiFi), Bluetooth (BT), as well as embedded sensors (and including future technologies such as Ultra-Wide Band "UWB" (Hui, Lei, & Yuanfei, 2010)) to offer accurate position of smartphones anywhere anytime. Typically, these solutions are focused on locating smartphones indoors to satisfy LBS requirements, thus attempting to offer seamless outdoors-indoors positioning.

Smartphones, as well as recent tablets and laptops, are becoming very important to our communication, localization and information needs. These are mainly driven by smartphones based mobile services/applications (Butler, 2011). Examples of the new LBS on smartphones do attempt to: 1) help the user navigate outdoors and indoors of large buildings, such as hospitals; 2) track the user for security via telematics; 3) assist the user to find the nearest restaurant, bus stop, coffee shop, and/or other point-of-interest (POI) information (Priyanka Shah, 2012). The most recent LBS applications which are interested by smartphones-users within different scenarios and categories are showed in Table I.

These LBS applications on smartphones are arising as current and/or next-generation 'killer apps' (Yun, Haejung and Han, Dongho and Lee, Choong C, 2013). However, such LBS applications are restricted due to the weaknesses or limited signal reception when the smartphone is indoors (Ryoo, Kim, & Das, 2012). For instance, GPS technology can be used to locate smartphones accurately and provide accurate time, when outdoors. However, this capability is degraded in urban areas or when indoors.

In another vain, onboard smartphone wireless transceivers and sensors have been used as an alternative to define smartphone location (based on some calibration algorithms) especially in situations when GPS signals do not exist (B. Li & Rizos, 2010). But, the position information of reference-stations, localization protocols and cost are the main challenges to offer seamless smartphone positioning.

The aim of paper is to survey on recent localization solutions that can be implemented on smartphone. In addition, the uniqueness of this survey is to present the main technical/practical implementation challenges which are associated with utilizing smartphone localization technologies/solutions, such as received signals' parameters measurements, wireless devices' firmware/API modification, deploy new HW equipments, and/or build up reference-location database with Internet connection. This literature survey is also examining commercial localization solutions available on smartphones in terms of their limitations and performances.

Table I. LBS applications on smartphones in different categories (Strout, Aaron and Schneider, Mike, 2011), (Anuar, Faiz and Gretzel, Ulrike, 2011), (Lopez-de-Ipina, Diego and Klein, Bernhard and Guggenmos, Christian and Perez, Jorge and Gil, Guillermo, 2011).

LBS Categories	Scenarios	Applications on Actual-smartphones
Marketing	Shopping centres advertise for their items using location information of LBS-users	Shop Kick
Emergency	LBS-users call the emergency response agency in fire, stolen and abnormal situations	911 in US and 112 in EU via nearest public safety answering point (PSAP)
Geotagging	Finding location of touristic services using geotagged images	GeoRSS
Tracking	LBS-users can track on smartphones exact location of the bus to be sure about the path and the schedule	PDX Bus
Navigation	LBS-users can location information and Map information to navigate through the path of the trip to a specific destination	Google Places
Mobile Location-Based Gaming	Treasure hunts (e.g. GeoSocial and Geocaching)	SCVNGR
Location Based Social Media	LBS-users use their location information to keep their relation via Facebook and/or Twitter	Gowalla, Loopt, Facebook Place, Foursquare
Sports	Real-time route of outdoor sport activity via smartphones using Google Maps and sharing that data with a social networks	Nike+, Run Keeper, Endomondo
Billing	Using location information to charge LBS-users, when they access a particular services	On-Board Units
POI	Discovering nearest cafes, restaurants, petrol stations as well as real-time traffic information	OpenTable, Fandango, Vouchercloud, NearbyFeed

In fact, there are many surveys (e.g. (Dardari, D. and Closas, P. and Djuric, P.M., 2015), (Harle, 2013), (Partyka, 2012), (Mautz, 2009), (Bensky, 2008), (Roxin, Gaber, Wack, & Nait-Sidi-Moh, 2007), (Boukerche, Azzedine and Oliveira, Horacio ABF and Nakamura, Eduardo F and Loureiro, Antonio AF, 2007) and (Liu, Darabi, Banerjee, & Liu, 2007)) on localization system, a late survey needs to completely revealing insight into the new emerging localization systems with their limitations and challenges. Authors in (Dardari, D. and Closas, P. and Djuric, P.M., 2015), surveyed indoor wireless tracking of mobile nodes from a signal processing perspective as well as discussed the main sources of error that are present in indoor environments. R. Harle in (Harle, 2013) developed taxonomy of modern pedestrian-dead-reckonings (PDRs) as well as compared different PDR techniques/schemes with applying statistical filtering. Also, the authors in (Partyka, 2012) reviewed available indoor positioning solution on smartphones in terms of accuracy and diversity. However, these surveys don't provide the detailed and experimental measurements of the emerging localization techniques/technologies. In addition, discussions on smartphone-LBS applications are not fully developed without the investigation of recent localization schemes/algorithms and their limitations that will impact of the overall localization solutions.

The rest of this paper is structured as follows: section 2 reviews few localization solutions surveys and highlights the main attributes which are used to compare/evaluate them. Section 3 details out the localization techniques and their practical challenges during the implantation on an Android-based smartphone, while Section 4 reviews onboard smartphone technologies with their measurement source errors. Section 5 explains the implementation of existing localization solutions on smartphones and discusses the main challenges to offer seamless outdoors-indoors positioning. Finally, Section 6 concludes this review as well as highlights the work planned for our future research.

2. RELATED WORK

Most of LBS applications that are based on existing wireless technologies included in smartphones need accurate outdoors as well as indoors location. Thus, they need a seamless positioning service. However, there is no such seamless solution yet due to the limitations of the existing wireless technologies included in smartphones, albeit many researches have been conducted to achieve it. The review of localization solutions/techniques of this emerging field is therefore important. This review provides a useful analysis and presents a roadmap to seamless localization solution and their implementation challenges.

A classification scheme to compare various indoors and outdoors localization solutions should be centered on accuracy, cost, coverage and overheads (hardware "HW" and software "SW") as well as indoors issues such as the multipath effect caused by the interior structure, moving objects blocking/reflecting signals amongst others (Hightower & Borriello, 2001). Most of the localization criteria are continuously revised as advances are made. Recent revisions for smartphones include aggressive power consumption, seamless positioning, more reliable implementations, and better accuracy. For example, phase II of FCC/E-911 rules now requires cellular network operators to provide the location of all smartphone emergency callers to an accuracy of about 50m horizontally and 3-4m vertically for 67% of emergency calls (previously was 125m accuracy only) (Fayaz, 2013).

Since the GNSS technologies do not offer accurate positioning when smartphones are in urban area or indoors, embedded smartphones wireless technologies are used as alternative to offer localization. Therefore, many algorithms focus on addressing localization issues associated with offering ubiquitous positioning in pervasive environments (Roxin, Gaber, Wack, & Nait-Sidi-Moh, 2007). Such algorithms include location-fingerprinting, time-difference-of-arrival (TDOA) and enhanced observed-time-difference (E-OTD) are used in Long Term Evolution (LTE). These algorithms have been used to offer accurate positioning, but at the same time they also present some challenges such as the need of deploying new additional HW.

The performance of indoor localization solutions in a real implementation has been observed in different levels of quality according to the localization area, HW components, complexity, and robustness (Liu, Darabi, Banerjee, & Liu, 2007). For example, in unblocked signal and/or open area, indoors localization solutions based on the fingerprinting method achieves good accuracy while the accuracy is degraded in dense areas. The solution based on cellular technologies is possible if more basestations (BSs) (i.e. additional HW) are available in the localization area (e.g. around a building). Also, a balance between accuracy and complexity must be considered carefully when a localization solution is chosen for different localization applications (e.g. LBS applications or for emergency applications). The localization solution is not robust if it is based on single wireless technology (Boukerche, Azzedine and Oliveira, Horacio ABF and Nakamura, Eduardo F and Loureiro, Antonio AF, 2008), because in some scenarios/environments the single wireless technology signals might not be available. Many integrated multiple-technologies have been developed to overcome these restrictions, especially on smartphones. For example, 1) integrated GPS-WiFi-Cellular to extend localization coverage, 2) hybrid GNSS signals with other wireless/sensor technologies such as: Bluetooth, Near Field Communication (NFC), audio sensors and inertial sensors to achieve good accuracy and to reduce time/space complexity (Partyka, 2012).

The complexities of the indoors structure (including moving objects, open/close spaces, multi floors, and dynamic changing structure of the indoors components like rooms, walls, and stairs) make more challenges to implement localization schemes. The challenges are: 1) obtaining high location accuracy, 2) huge cost due to pre-installed infrastructures, 3) as well as, most of the schemes suffers from the wireless signal multipath and interference problem (Mautz, 2009).

Capabilities and drawbacks of smartphones localization solutions depend on the onboard technologies that have been used in the solutions. Location of smartphones based on cellular technology is calculated in short time, wide coverage, within low cost, but the accuracy is limited. However, with more cellular BSs in the dense urban area, more accurate smartphones location would be achieved. While the location accuracy based on satellite technology (e.g. GPS) in such density area is degraded due to multipath issue and few numbers of satellite vehicles (SVs) in the sky are available (Waadt, Bruck, & Jung, 2009).

The literature survey for this research focuses on newly developed smartphones localization solutions and presents revised smartphone LBS user demands including seamless positioning, reliable solution, short time-to-first-fix (TTFF), and reasonable accuracy for both indoors **and** outdoors.

3. LOCALIZATION TECHNIQUES

Location information provides an important role in most current smartphones' services including traffic information for navigation and POI information for routing/planning and emergency calls. Localization techniques (including AOA, received signal strength (RSS), Cell-ID/Proximity, time-based localization, map-matching (MM) technique, and dead reckoning) have been developed to achieve these services (Bensky, 2008). Mainly, such services need high quality of performance from the localization solutions. Combination of different location techniques is possible to make a powerful localization solution including reasonable accuracy, short time to define smartphones' location and low battery power consumption.

Figure 1 displays the taxonomy of such techniques as well as shows new combined localization techniques including: time-of-arrival (TOA) & dead reckoning (DR) (Mariakakis, Alex and Sen, Souvik and Lee, Jeongkeun and Kim, Kyu-Han, 2014), RSS-Fingerprinting & TOA (Koenig, Schmidt, & Hoene, 2011), MM & DR and Proximity (Woodman & Harle, 2008) & RSS-radio propagation model (Park & Park, 2011).

The detailed of these techniques-implementation in the next subsections with their requirements/limitations and their ability are presented.

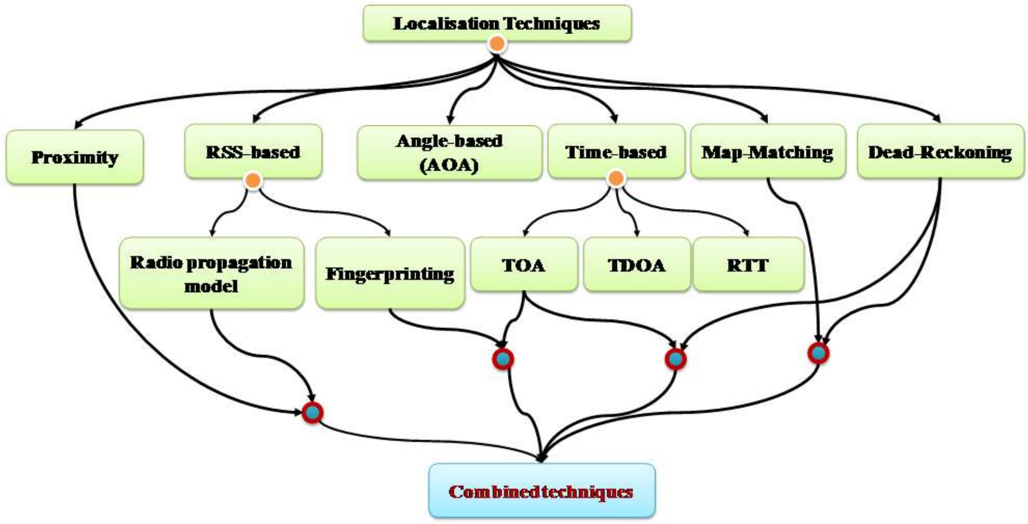

Fig. 1. Taxonomy of smartphone-localization techniques.

3.1 Cell-ID or Proximity technique

Proximity, cell of original (COO), or cell identification (Cell-ID) technique is a simple localization technique. It refers to define location of a smartphone as being within radio pseudoranges of a BS. Thus, the smartphone is known to be within the area around that BS location. Therefore, the issue here is that the accuracy of the defined smartphone location is based on the radio coverage (i.e. cell size) of the BSs. For example, in cellular networks the cell size lies between 2 Km to 20 Km (Roxin, Gaber, Wack, & Nait-Sidi-Moh, 2007).

Certainly now in urban area the cell size is reduced to only tens of meters. Additionally, this technique has been used in WiFi networks, since the cell size of these networks is much smaller than the one in cellular network. However, the accuracy of this technique in WiFi networks depends on the effective signal propagation pseudoranges as well as the density and distribution of WAPs (Mok, 2010). Several solutions have been proposed for this technique to improve location accuracy, especially for cellular technology, (as illustrated in Figure 2) including:

- Providing cell sector,
- Providing cell ID with time advance (Cell-ID + TA), and
- Providing cell-ID with max signal strength value.

In cell sector: the cell is divided into sectors, such as by using directional base station antennas with 120' beam width antenna. In such cases, the obtained location accuracy of smartphones can more narrowed by taking only the coverage of the received-signal sector. Also, further improved accuracy can be achieved by reading more signal-received measurements either based on timing (i.e. measuring round-trip-time “RTT” of the received signal) or based on strength of the received signals (i.e. RSS measurements).

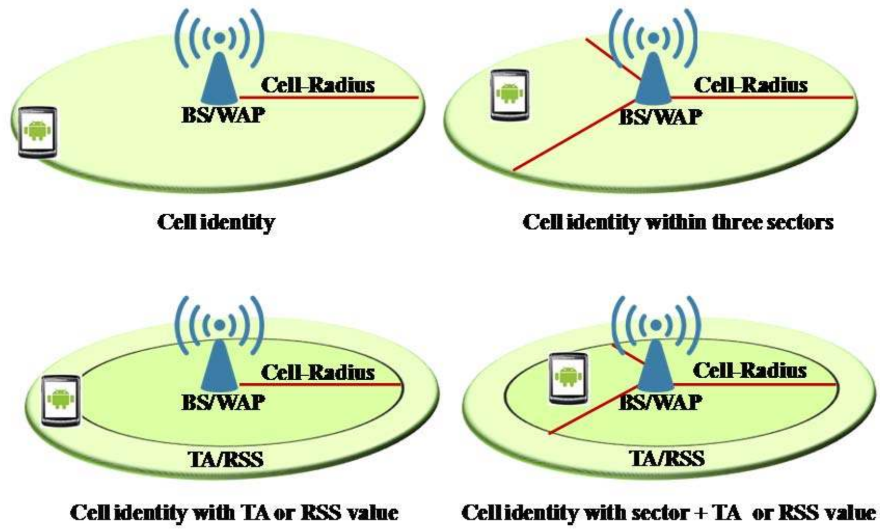

Fig. 2. Proximity technique.

Practically, this technique is the easiest technique to implement on smartphones as well as it takes short time and consumes low power to locate smartphones. However, the accuracy of this technique is not enough for major smartphone LBS applications, especially when indoors.

3.2 RSS-based technique

To estimate smartphone's location based on RSS technique, two methods have been used:

1) Pseudoranges measurement method (Park & Park, 2011): This method is based on known radio propagation analytic relationship. It employs trilateration to find smartphone location from the estimated pseudoranges between a smartphone and multiple BSs/WAPs, as it can be seen in Figure 3. Practically estimating the path loss exponent, signal propagation parameters, and environmental conditional are the main challenges to measure the pseudoranges between the smartphone and the BSs/WAPs (Wu, Yinfeng and Li, Ligong and Ren, Yongji and Yi, Kefu and Yu, Ning, 2014). To estimate the pseudorange between the smartphones and BSs/WAPs, equation (1) should be utilized.

$$p_i = p_0 * 10^{\left(\frac{RSS_{i0} - RSS_i}{10 * \eta_i}\right)} \quad (1)$$

Where p_i is the pseudorange between smartphones and BSs/WAPs, p_0 is the estimated calibrated pseudorange at zero distance, RSS_{i0} measured signal stength value for the p_0 , RSS_i is the measured signal strength for the received BSs/WAPs signals, and η_i is the calculated/calibrated path loss exponent for the received BSs/WAPs signals.

In addition, inaccuracy of measuring RSS values in a localization solution is due to:

— HW implementation (approximately ±4dBm varies),
— Mathematical methods to calculate the RSS values,
— Other working systems in the same band (i.e. interference issue),

— Moving objects (e.g. human moving) in buildings, and
— Fixed and/or movable obstacles.

Certainly, many dynamic models have been proposed to mitigate these inaccuracies, which are more accurate than the traditional static model such as in (Elbes, Mohammed and Al-Fuqaha, Ala and Anan, Muhammad, 2013). But still these models are not appropriate for most LBS applications, especially when high location accuracy is demanded.

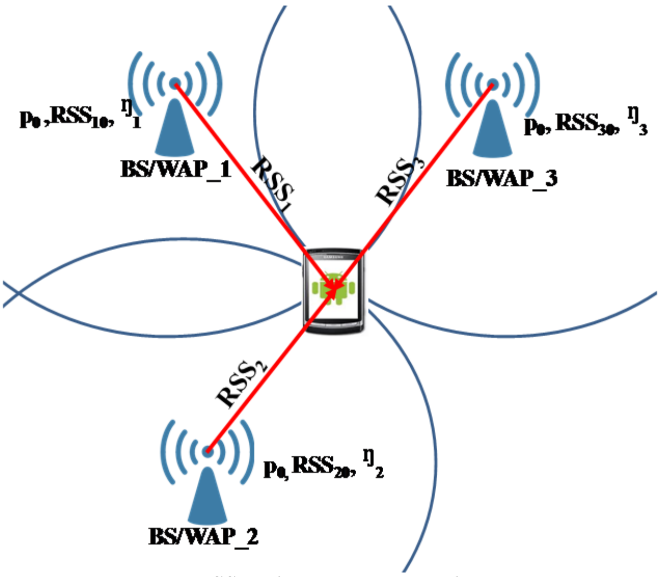

Fig. 3. RSS-Radio propagation technique.

2) The second method, RSS-fingerprinting, is based on searching for pre-stored RSS values of BSs in a database (Lymberopoulos, Dimitrios and Liu, Jie and Yang, Xue and Choudhury, Romit Roy and Handziski, Vlado and Sen, Souvik, 2015). In this method, offline and online stages should be performed to calculate smartphones location. These stages with their localization process are displayed in Figure 4.

In the offline stage, a radio map (i.e. the database) for signals' strength of the major BSs in different points (i.e. reference points) around an area should be recorded.

Then in online stage, a matching process between real-time RSS and the recorded of the pre-defined radio map is involved to estimate smartphone's location.

The accuracy of this method is based on actual path loss at points near the smartphone. Thus, unknown factors of multipath and shadowing are bypass and affect only minimally on the smartphone location estimation. However, practically, this method has many challenges including:

— This method is for a specific building or area (site-dependent),
— It takes a long time due to connect with the Internet and searching in the location database/server and then sends back the result of location calculation for the users,

— This method also deduces huge cost to make the radio map. I.e. this method needs to use dedicated HW and re-calibration of the BSs/WAPs location, since the environment of the area may be changed over time.

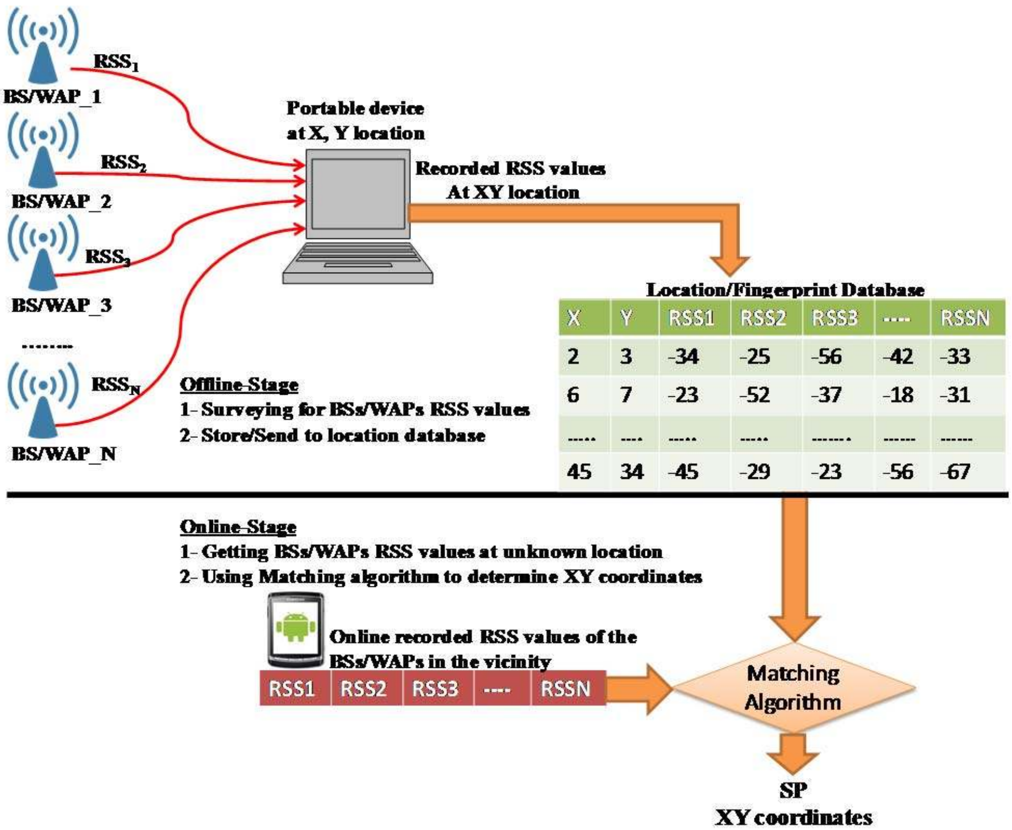

Fig. 4. Smartphone's location determinations via RSS-Fingerprinting technique.

3.3 AOA technique

In AOA technique, pseudo-ranges and location are found by performing triangulation (Niculescu & Nath, 2004). The location of a smartphone can be computed when: the angles of arrival of the received signals from the smartphone by two or more BS/WAPs are defined (as shown in Figure 5) and distance between the two BSs/WAPs is known. Such smartphone location definition for 2D coordinates is expressed in equation (2):

$$(x_i - x_{sp})\, sin(\theta_i) = (y_i - y_{sp}) cos(\theta_i) \qquad (2)$$

Where x_i *and* $x_i$are XY coordinate values of BS/WAPs positions, $\theta_i$is the arrival angles for the received WAPs signals and x_{sp} & y_{sp} are XY coordinate values of the smartphone location.

To be more specific, location determination from numerous distance measurements is known as Lateration, while angulations allude to the use of heading or angle measurements respect to known reference position to define a smartphone's location. However, the main factors that effect on angles measuring are:

— Varying of signal-to-noise-ratio (SNR),
— Modulation technique of the transmitted and/or received signals,

— Moving the smartphone, and
— Reflecting surfaces near the Line-of-Sight (LOS) path of the received signals.

Technically, AOA technique needs to deploy array-antennas to find out the angles of the received signals (Sen, Souvik and Lee, Jeongkeun and Kim, Kyu-Han and Congdon, Paul, 2013). Practically, due to requiring these special antennas and then incurs large cost, this technique is rarely applicable to locate smartphones.

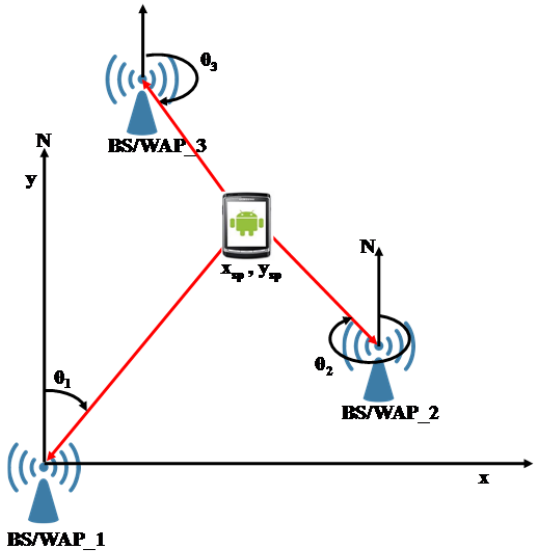

Fig. 5. AOA technique with three angle measurements.

3.4 Time-based technique

Time-based localization techniques measure signal's propagation time, which is called time-of-flight 'TOF', to estimate pseudoranges between smartphone and multiple BSs/WAPs/anchors (De Oliveira, Horacio Antonio Braga Fernandes and Boukerche, Azzedine and Nakamura, Eduardo Freire and Loureiro, Antonio Alfredo Ferreira, 2009). TOA, RTT and TDOA are the common techniques for pseudoranges estimation (Kim, Lee, & Park, 2008).

TDOA calculates location of smartphone from only differences of the measured arrival times on pairs of BSs/WAPs' signals, as expressed in equation (3) and employs hyperbolic process.

$$\begin{aligned} \Delta t_{12} &= t_1 - t_2 \\ \Delta t_{13} &= t_1 - t_3 \\ \Delta t_{23} &= t_2 - t_3 \\ \Delta p_{ij} &= \Delta t_{ij} * c \end{aligned} \tag{3}$$

Where t_i is the time measured of the received BSs/WAPs signals, Δt_{ij} is the differences of the two received of BSs/WAPs signals, $\Delta p_{ij}$is the estimated difference of the pseudoranges and c is the speed of light.

While TOA first measures the time of the arrived signals and subtract by the transmitted time of the signals to estimate pseudoranges, as express in equation (4), then it employs trilateration to find smartphone location from the estimated pseudoranges between the smartphone and the BSs. The process of TOA and TDOA are illustrated in Figure 6.

$$TOF_i = T_i - t_i \quad (4)$$
$$p_i = TOF_i * c$$

Where p_i is the estimated pseudoranges between smartphones and BSs/WAPs, TOF_i is the calculated propagated time of the received BSs/WAPs signals, T_i & t_i are the received and transmitted time of the signals, and c is again speed of light. Note: at least one extra BS/WAP/anchor is required for TDOA per dimension compared to TOA.

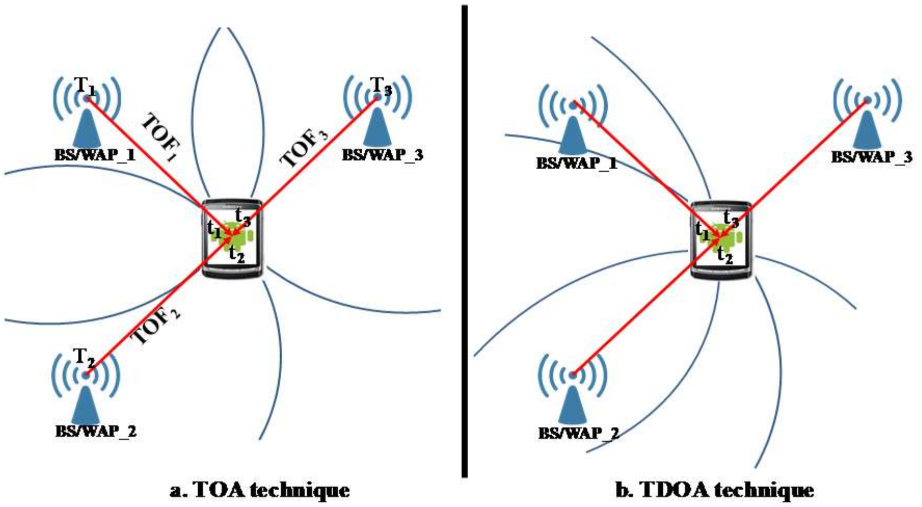

Fig. 6. TOA and TDOA for smartphone's location determinations.

Clock-time synchronization is required among the smartphone and BSs in TOA, while synchronization is only required among BSs/WAPs/anchors' clocks in TDOA. A way to do this clock synchronization is to use signal transmission between smartphones and BSs/WAPs/anchors. Beacon signals is a proper one, since it is a continuous or periodic transmission that facilitates timing synchronization or position measurements between the smartphones and BSs. However, for the clock synchronization, wireless devices' clocks such WAPs and cellular BSs clocks are cheap and inaccurate (1 µsec in time error is equivalent to 300 meters in position error) (Günther & Hoene, 2005), therefore, high quality reference-time in nanosecond resolution is needed to synchronize such clocks.

RTT estimates the spent time of the transmitted signal travelling from the smartphone to the BSs/WAPs and back, as expressed in equation (5).

$$RTT_i = (t_{i2} - t_{i1}) + (t_{i4} - t_{i3})$$
$$TOF_i = (RTT_i/2) - \Delta t_i \quad (5)$$
$$p_i = TOF_i * c$$

Where RTT_i is the estimated round trip time for each received BSs/WAPs signals, t_{i1}& t_{i4} are measured time of the transmitted and received signals (via the smartphone) respectively, while t_{i2}& t_{i3} are measured time of the received and transmitted signals via BSs/WAPs respectively, Δt_i is the delay time of the packets/signals processing through receiving and transmitting signals, and c is the speed of light. To calculate smartphones location, RTT techniques employs trilateration process, as shown in Figure 7.

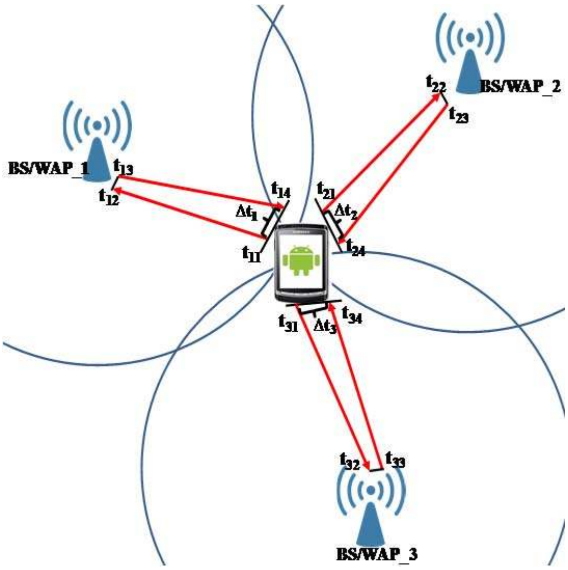

Fig. 7. RTT for smartphone's location determinations.

In TOA, calculating the delay is by using both smartphones and BSs/WAPs clocks, while in RTT, it uses only the clock of the smartphone to record the transmitting and arrival times. Because of this advantage, RTT avoids the necessity of clock synchronization between the smartphones and BSs/WAPs to some extent. The drawback of this method, however, is that the range measurements are needed to be carried out from multiple BSs/WAPs consecutively which will cause precarious latencies for LBS applications where smartphones move quickly. Furthermore, this method makes huge traffic-load on the network due to exchange large number of frames between the smartphones and the BS/WAPs.

Several factors are existing which extremely influence on time-based techniques and then affect on localization accuracy. These factors include:

- Non-Line-of-Sight (NLOS) and multipath issue (Wibowo, Klepal, & Pesch, 2009),
- Inaccuracy of existing chipset-clocks on BSs/WAPs (Lee, Lin, Chin, & Yar, 2010),
- Radio-signal coverage of BSs/WAPs (Jaime Lloret, Jesus Tomas, Alejandro Canovas, Irene Bellver, 10 May 2011),
- Time-source functions for timestamping (Mock, Frings, Nett, & Trikaliotis, 2000) and
- Taking time measurements at different network stack layers and OS interrupt handling time delay (Ciurana, Lopez, & Barcelo-Arroyo, 2009),

To mitigate the impact of these factors, practically, statistical/filter processes or some calibration/compensate algorithms are needed to estimate accurate pseudoranges between smartphone and BSs/WAPs and then to define smartphone location.

3.5 Map-Matching technique

Map-Matching (MM) technique is based on the theory of machine learning algorithms (e.g. pattern recognition/matching) which combines map with the measured smartphone's location observations to obtain the real position of smartphones in 2D or 3D coordinates.

Many solutions on the smartphones available to utilize mapping technique including GNSS, simultaneous localization and mapping (SLAM) solution, and WiFi-SLAM solution. This technique could be combined with time-based, RSS-based and DR techniques. Actually, this technique is mostly used in order to increase the accuracy of the localization solutions (Gallagher, Wise, Li, Dempster, Rizos, & Ramsey-Stewart, 2012). However, the main drawback of this technique, especially when indoors, is to build and maintain huge knowledge of the buildings' layout.

3.6 Dead reckoning

This localization technique is based on utilizing onboard smartphones inertial sensors including gyroscope, accelerometer, and magnetometer sensors. The DR technique uses: gyroscope for angular velocity, accelerometer sensor for acceleration, and magnetometer sensor for magnetic fields. To locate smartphones, using DR technique, calibrate these inertial sensors and an initial reference-point are required. This technique is highly smooth and stable, but its performance degrades quickly over time due to the accumulated measurement noise of sensors causing cumulative positioning error (Woodman & Harle, 2008).

Figure 8 shows a typical smartphone's dead-reckoning prototype model to compensate and to reduce both drift and sensor noise using dedicated filtering algorithms (e.g. Kalman Filter).

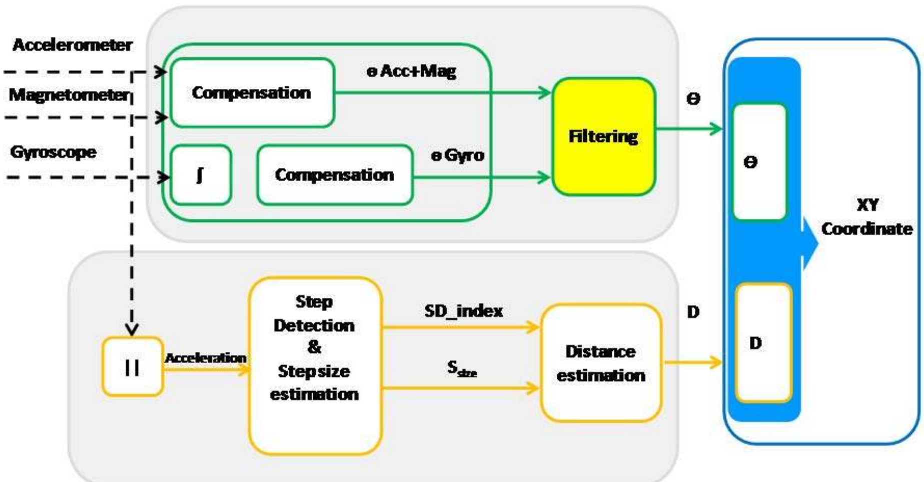

Fig. 8. A DR-prototype model for smartphone localization solutions

The figure also shows how the model utilizes inertial sensors to measure both distances and heading and then how use these measurement to calculate smartphone's location. To calculate smartphone position based on DR technique, equation (6) should be utilized.

$$X_i = X_{i-1} + d_i * \cos(\theta_i) \quad (6)$$
$$Y_i = Y_{i-1} + d_i * \sin(\theta_i)$$

Where X_i & Y_i are the estimated XY coordinate values of smartphone position, d_i is the calculated distance using the accelerometer measurements and θ_i is the estimated heading of the smartphone via gyroscope measurements.

3.7 Combined localization techniques

In order to improve the location accuracy, to reduce measurement records, short time to locate, and then to reduce battery-power consumption, a hybrid localization techniques is needed (Jaime Lloret, Jesus Tomás, Miguel Garcia, Alejandro Cánovas, 2009).

The combination technique is not only to make powerful localization solution, but it is also to reduce the number of reference positions to involve the smartphone location estimation. For example, combining TOA and DR techniques has been used to hybrid the range and the heading of the smartphone only with a single WAP (Mariakakis, Alex and Sen, Souvik and Lee, Jeongkeun and Kim, Kyu-Han, 2014). In this hybrid approach TOA is used to measure the range between the WAP and the smartphone in two different locations and it uses DR to estimate the heading as well as the distance-displacement between the two different locations.

The combined technique, as it is shown in Figure 9, has the following achievements:

— Obtaining better accuracy than DR (when it is used as a standalone technique) and
— It needs only a single WAP to contribute smartphone location calculation in compare with TOA technique alone that needs three WAPs as reference positions.

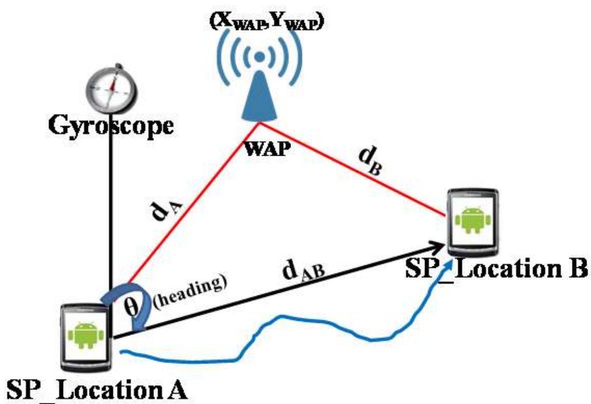

Fig. 9. Using TOA and DR techniques to construct a triangle between a smartphone and a WAP.

4. ONBOARD SMARTPHONES TECHNOLOGIES FOR LOCALIZATION

The increasing technologies such as: GNSS (including GPS and GLONASS) receivers as well as cellular (e.g. LTE), NFC, WiFi, Bluetooth transceivers, inertial sensors on smartphones makes possible to more powerful positioning with smartphones in different circumstances. Figure 10 illustrates these technologies in standalone and in combined hybrid solution. In fact, some of these technologies are not originally intended for positioning functionality such as: Cellular, WiFi, and Bluetooth. But, the reading form of transmitted/received radio signals of these technologies in somehow can be utilized for localization purposes. In addition, each individual technology has its own advantages and limitations in terms of availability and robustness (Boukerche, Azzedine and Oliveira, Horacio ABF and Nakamura, Eduardo F and Loureiro, Antonio AF, 2008). Therefore, in this section, we are going to show the ability and the imperfections of the localization measurements via these technologies.

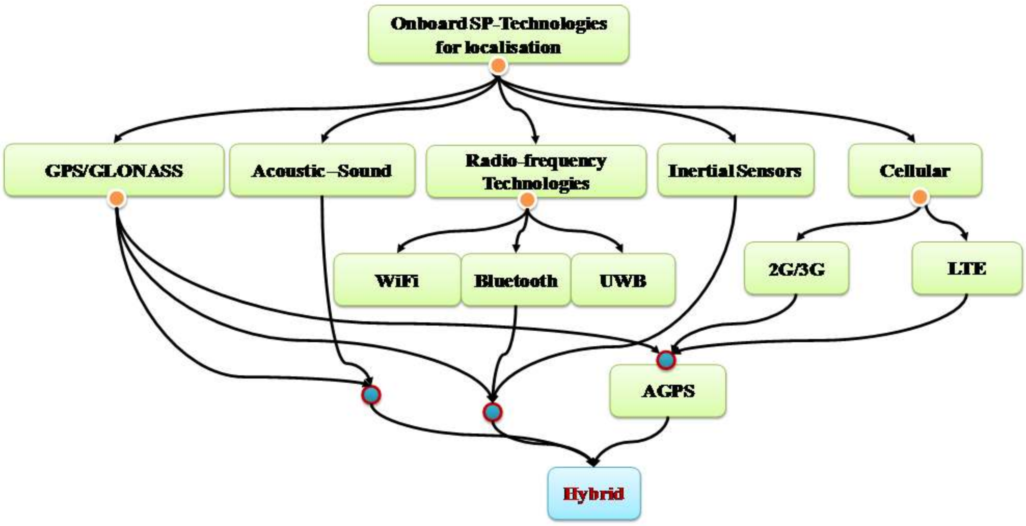

Fig. 10. Taxonomy of technologies for smartphone localization

4.1 Cellular technologies

Cellular technologies rely on a group of BSs, with the radio coverage at different sizes. Historically, the localization solutions of mobile handsets were focused on achieving the requirements of the FCC-E911 mandate, and they were Cellular-Network based. Cell-ID, AOA, TOA, TDOA and E-OTD were some of the localization techniques deployed by some of the cellular networks at the time (Deng Zhongliang and Yu Yanpei and Yuan Xie and Wan Neng and Yang Lei, 2013). In addition, nowadays with existing LTE technology on smartphone, a new protocol, known as secure-user-plane-location (SUPL) is included to provide secure smartphone positioning (Farid, Zahid and Nordin, Rosdiadee and Ismail, Mahamod, 2013).

However, the obtained accuracy by cellular networks using above techniques is in the range of 20–200 meters, this is depend on the cell coverage and pseudorange measurements between the smartphones and the BSs. Generally, the accuracy is higher in urban areas and lower in rural environments (Cherian, Suma S and Rudrapatna, Ashok N, 2013). Also, for indoors, smartphone localization solutions based on cellular technology is conceivable if a large number of BSs are deployed around the buildings.

4.2 GNSS technology

The GNSS receiver, which is integrated on smartphones, is extensively used to obtain the smartphone position, when outdoors. GNSS receivers on smartphone have been developed with increasing performance and accuracy. GNSS systems provide accurate, continuous and world-wide, three dimension position, and velocity information to users with appropriate receiving equipments.

Taking GPS as an example, the GPS satellite constellation nominally maintains of at least 24 satellites, 95% of the time, arranged in 6 orbital planes with 4 satellites per plane. The satellites broadcast ranges codes and navigation data (ephemeris and Almanac data) on two frequencies using a technique called Code Division Multiple Access (CDMA). The two frequencies are L1 (1,575.42 MHz) and L2 (1,227.6 MHz). GPS uses the concept of TOA pseudoranging and trilateration to determine smartphone position (Lee, Jae-Eun and Lee, Sanguk, 2010).

Pseudoranging code enables the smartphone's receiver to determine transit time (propagation time) of the signal thereby determines the satellite-to-smartphone pseudorange. Navigation data provides the means for the receiver to determine the location of the satellite at the time of signal transmission. GPS receiver in a 3D mode three satellites and three distances are needed. The equal-distance trace to a fixed point is a sphere in a 3D case. Two spheres intersect to make a circle. This circle intersects another sphere to produce two points. In order to determine which point is the user position, one of the points is close to the earth's surface and the other one is in space. Since the user position is usually close to the surface of the earth, it can be uniquely determined (Kohtake, Morimoto, Kogure, & Manandhar, 2011).

However, the distance measured between the receiver and the satellite has a constant unknown bias, because the smartphone's clock usually is different from the satellites' clocks. In order to resolve this bias error one more satellite is required. Therefore, in order to find the smartphone position four satellites are needed. Despite the position error due to the clock time error, there are several other error sources which are affected on location accuracy such as: selective availability, DOP issue, ionospheric delays, tropospheric delays, multipath and receiver noise.

Furthermore, these receivers are presently ready to locate smartphones more accurately in signal-degraded environments than before. Following these achievements of GNSS-based services in outdoor applications, however, the challenge has shifted to the dense urban and/or indoor environment (Ryoo, Kim, & Das, 2012). For example, an experiment has been performed in near indoors (around a building) on two Android-based smartphones: Samsung Galaxy S2 and S3 mini, as it is shown in Figure 11, the accuracy of the obtained position for both smartphones sometimes is up to 20 meters. Therefore in such environments, techniques to improve location accuracy are needed such as MM technique. Figure 12 shows such kind of improvements, as it is observed; the accuracy is within 1 to 2 meters.

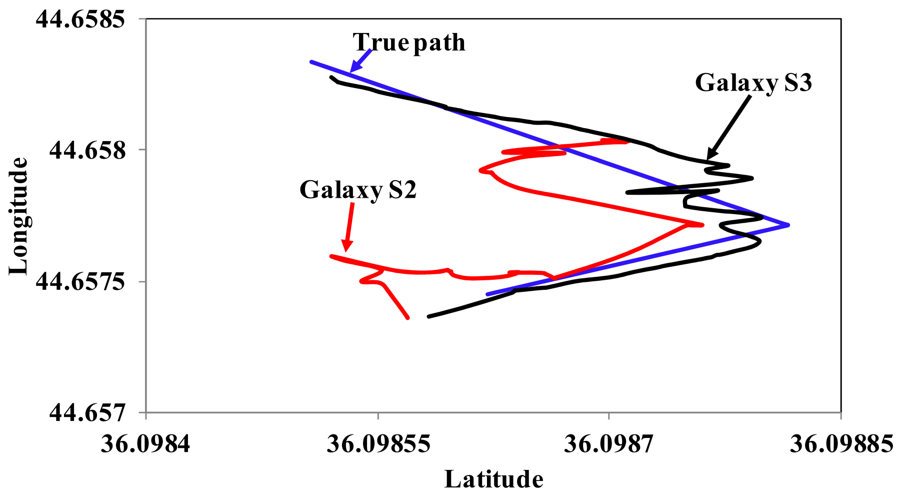

Fig. 11. Estimated location of two smartphones using only GNSS

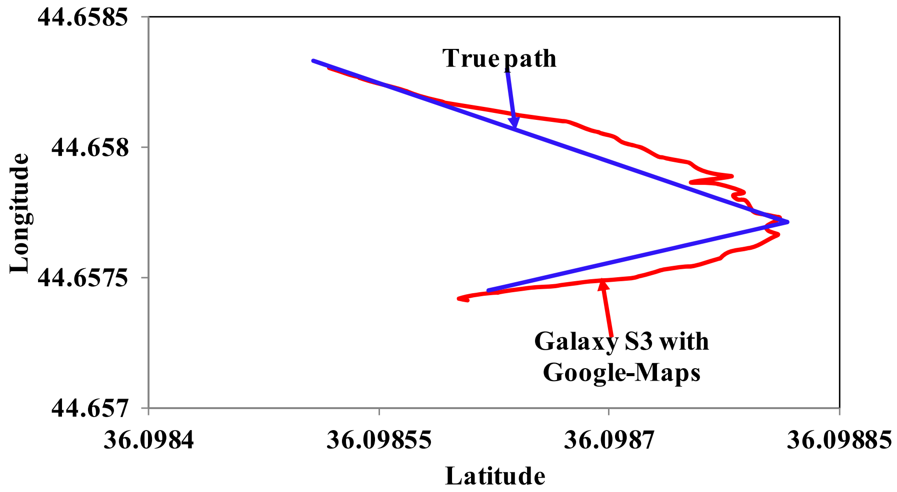

Fig. 12. Estimated location of a smartphone using GNSS and Google-Maps

Although, several attempts to enhance this technology by adjusting new infrastructures including Pseudolite (Lee, Jae-Eun and Lee, Sanguk, 2010), Locata (Rizos, Roberts, Barnes, & Gambale, 2010), indoors messaging system (IMES) (Kohtake, Morimoto, Kogure, & Manandhar, 2011) in the area of degraded GNSS signals, however, GNSS ability to locate indoors smartphones remains a substantial challenge which prevents accurate positioning seamlessly from outdoors to indoors (Jin, February 03, 2012). The detailed explanation of these solutions is included in section 5.

4.3 WiFi

The WiFi transceivers integrated on smartphones are not only for data communication, but they are also to estimate smartphones position. Mainly, the LBS

applications use this technology to define the smartphone position inside buildings, where the WiFi signals prevail. For example, a smartphone can calculate the TOF of WiFi signals coming from each WAPs distinguished through its MAC address, and assuming these WAPs' position are previously known. Based on these observations, the smartphone can perform a localization technique dynamically to report an estimation of the smartphone position. Specifically for WiFi time-based localization solution, however, due to existing inaccuracy clock source (clock drift and clock offset) for timing/TOF measurements on WAPs and onboard smartphone WiFi transceivers, pseudorange estimation based on the timing-measurements will not be accurate.
To demonstrate the clock drift and clock offset of a WAP in relative to a WiFi transceiver onboard smartphones, this research study conducted few trial experiments on actual smartphones. In a single experiment, for example, an HTC Android-based smartphone is used to collect the clocks measurements. Figure 13 shows the calculated clock drift and offset of a WAP in relative to a WiFi transceiver onboard smartphone. During the experiment, the smartphone's WiFi transceiver (Atheros-chipset model-6) is worked in monitor mode to receive WAPs beacons frames passively. The smartphone calculates the clock offset by timestamps for the received beacons and retrieves timestamp function values from the beacon frames. Then, to calculate the relative clock drift, the linear regression (based on linear-least-squares) method has been applied (using equation 7).

$$ClockOffset_i = a * NO\_Beacon_i + b \tag{7}$$

Where $ClockOffset$ is the clock difference between the WAP clock and WiFi-transceiver-MAC clock reading, a is the estimated slop (i.e. the estimated relative clock drift) and b is the intercept between both $ClockOffset$ and NO_Beacon values. The estimated clock drift by the regression method is 10 microseconds (forward).

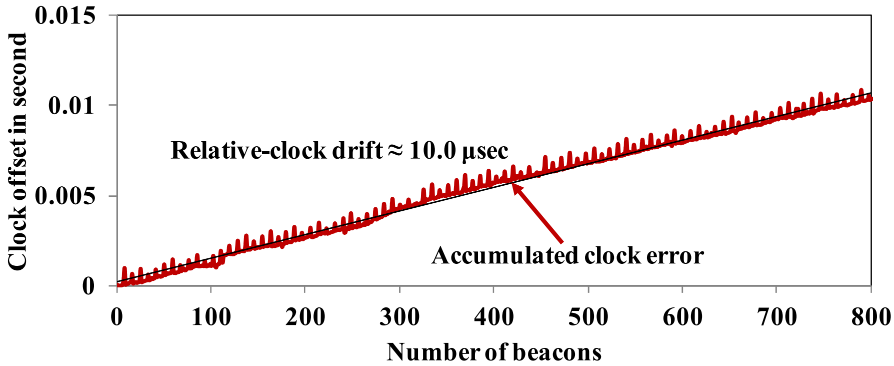

Fig. 13. Clock time different between a smartphone-WiFi transceiver and a WAP

It is observed that the clock error without any calibration or compensating algorithms is within microsecond's level which is produce huge positioning error (one microsecond error in clock measurements is equivalent to 300 meters in positioning error).

4.4 Bluetooth

Bluetooth has developed as a practical choice of indoors smartphone localization solutions and several indoor positioning systems relying on this technology (Subhan, Fazli and Hasbullah, Halabi and Rozyyev, Azat and Bakhsh, Sheikh Tahir, 2011). This is mainly because it has emerged as a low cost, low power consumption and bigger coverage range than traditional/classical Bluetooth classes.

The recent developed localization solution based Bluetooth is Bluetooth-Low-Energy Beaconing (BLE-iBeconing). With BLE, all its needed is to drop a few Bluetooth anchors around the area and then smartphones based on RSS measurements can detect these anchors. In this way, a localization solution using these measurements can successfully track smartphones location (Della Rosa, Francescantonio and Pelosi, Mauro and Nurmi, Jari, 2012). The main feature of BLE is that permits us to supply just enough contexts, while still being agile and portable. This peer to peer messaging opens up numerous potential outcomes, extending from LBS applications in shopping centers to emergency reaction circumstances.

However, during the research work we found out that RSS measurement has non-uniform shadowing which causes huge location error. To demonstrate this, few trial experiments are conducted on two Android-based smartphones types of Samsung Galaxy S3 mini. Figure 14 shows the average result of a three conducted trials to measure RSS values of the received smartphone BT-signals (as a BT-anchor or in Master mode) by other movable smartphone (in Slave mode) in the vicinity. Note: the enabled BT-transceivers on the smartphones are type of Bluetooth 4 version.

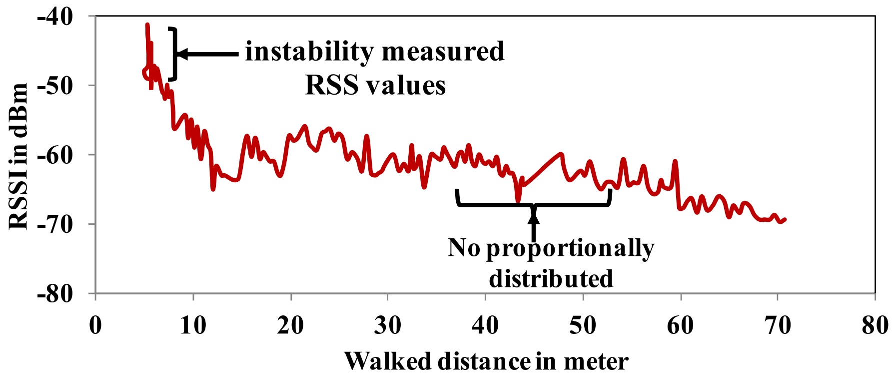

Fig. 14. RSS measurement values between two smartphones in different distances.

In the figure, it can be observed that the measured RSS values are instable, especially (when the Slave is near to the Master) and the measured RSS values are not proportionally distributed (when the Slave is far from the Master, i.e. weak RSS values do not contain valuable information). This inaccuracy makes huge location error, therefore any pseudorange measurements and/or location estimation based on RSS measurements will be not accurate.

4.5 Inertial sensors

Embedded inertial sensors on smartphone only give a relative location estimate with accuracy degrading over short run; therefore, they must be utilized together with other technologies including GNSS, WiFi, and Bluetooth to estimate absolute location and to get better accuracy (Yi Sun and Yubin Zhao and Schiller, J., 2014). Basically, a smartphone can read measurements from these sensors to locate users by performing DR technique. Accelerometer sensor to measure change of velocity (acceleration force), magnetometer sensor to measure magnetic field, and gyroscope to measure change of angles are the main inertial sensors that can used for smartphone positioning. However, accelerometer and magnetometer measurements are affected by sensors noises and interference issue (especially for indoors), while gyroscope measurements have huge drift over few seconds to estimate the heading (Xiao, Zhuoling and Wen, Hongkai and Markham, Andrew and Trigoni, Niki, 2015). To show these limitations, a set of trial experiments have been performed. Figure 15 displays an experimental-result of the inaccuracy of estimating heading via inertial sensors in compare with the true heading. Note: to run the experiment, we used Android-based smartphone type of Samsung Galaxy S3 mini to collect and to read the sensors' measurements, for 3000 samples. In this experiment, it can be noticed that these sensors are not accurate without calibration method to estimate heading due to fluctuation/accumulated drift for accelerometer & magnetometer and gyroscope sensors, respectively. In addition, in smartphone localization view, this inaccuracy of heading estimation induces huge positioning error.

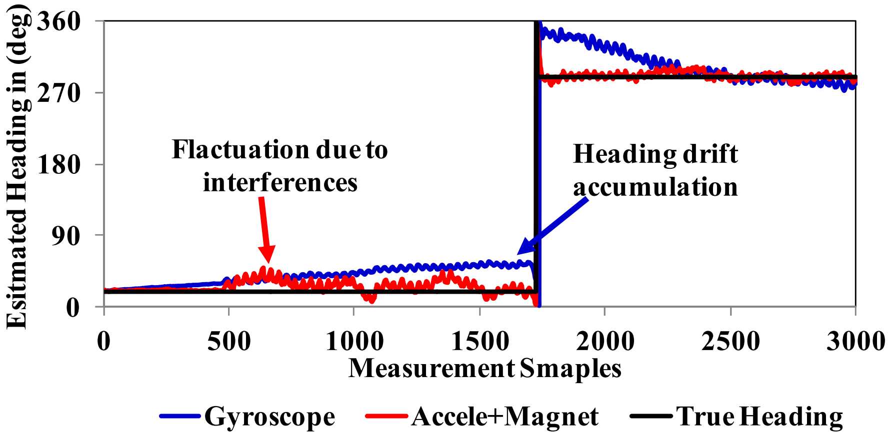

Fig. 15. Estimated heading through inertial sensors

5. SMARTPHONES LOCALIZATION SOLUTIONS

LBSs on smartphones adopt several solutions to ensure that location is achieved accurately and continuously. We adopted the following criteria to classify such solutions:

— Environments (indoors and outdoors)
— Standalone and hybrid solutions
— Satellite and terrestrial
— Unilateral and multilateral

In this research work, we attempt to classify the current trials and the improved localization solutions into: outdoors, indoors, and seamless outdoors-indoors. Additionally, practical challenges for implementing of the solutions and for new available commercial solutions are discussed.

5.1 Outdoors localization solutions

Cellular networks, GPS, and other GNSS technologies such as GLONASS are candidate solutions for smartphone outdoors localization (Roxin, Gaber, Wack, & Nait-Sidi-Moh, 2007). The onboard smartphones GNSS receivers can define their location within few meters. However, GNSS receivers: 1) consume more power, 2) provide inaccurate location, and 3) take long time to fix the smartphone, when indoors or in urban area, due to the availability of the GNSS weak signal and multipath issue (Pei, et al., 2011). Another factor of GNSS inaccuracy (or losing GNSS signal tracking) is due to GNSS jamming/interference (Paul Craven, Ronald Wong, Neal Fedora, and Paul Crampton). Vulnerable of GNSS signals from interference sources is due to received low GNSS signal strength. The interference sources do not necessarily need to be centered at the same frequency as the GNSS signals.

The promise of alternative solution for such cases is to use cellular network signals for positioning, as a GNSS backup solution or aid GNSS (e.g. A-GNSS) (Lim, Lee, & Cho, 2007). An example of A-GPS architecture is shown in Figure 16.

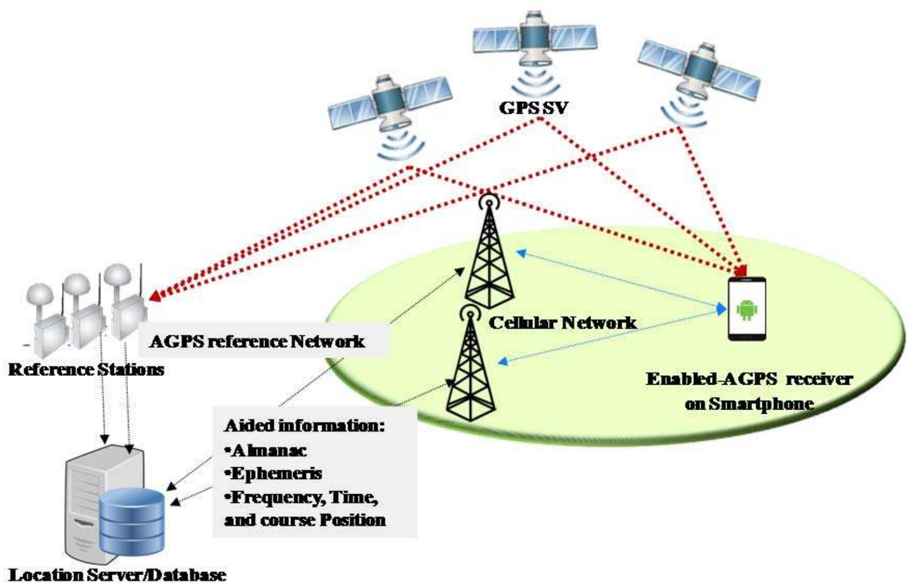

Fig. 16. AGPS overview-system architecture

Several solutions have been proposed to locate the smartphones through using only cellular signals based on different techniques. For example: cell identification (Cell-ID), RSS-based, AOA, TDOA, E-OTD and uplink-TDOA (U-TDOA) (Roxin, Gaber, Wack, & Nait-Sidi-Moh, 2007). Furthermore, these solutions could be classified into two major types of localization solutions: network-based solutions and handset-based solutions. Both localization solutions have different capabilities in terms of privacy, SW/HW upgrading, accuracy, and power consumption. These capabilities and performance parameters are evaluated and explained in Table II.

In addition, these solutions somehow are utilized as indoors or urbane localization solutions. However, since most of these solutions' accuracy is within tens of meters, as well as they are customized with special HW and take a huge cost (Adusei, Kyamakya, & Jobmann, 2002), therefore they are not utilized for most current smartphones LBS applications (Waadt, Bruck, & Jung, 2009).

Table II. Handset-based and network-based localization solutions

Handset-based location solution	Network-based location solution
It is more secure.	It is less secure than Handset-Based.
It doesn't affect the network capacity.	It uses facilities and resources of the network.
It is more accurate for location; it is not limited by the network to the number of measurements.	It depends on the requiring measurements to be improved for location accuracy.
It needs special SW and HW that must be incorporated together.	It doesn't require upgrading SW for the handsets (devices). Most legacy handset can receive services
It consumes the smartphone's battery power to carry out the positioning task.	It frees the handset of the power battery.
It participates in the positioning task, or the calculation is done by itself.	Network performs the positioning task without intervention by the smartphone (handset).
It is known as self-positioning solution.	It is known as remote positioning solution.

To evaluate the performance of these solutions, it can be noted, that if one solution has a good accuracy then it will take long time to fix and consequently consume more battery power such as GPS and A-GPS. In comparison, Cell-ID and Cell-ID + TA take short time to fix and low power consumption but have low accuracy. Additionally, some of these solutions could not be applicable transparently, due to having huge costs and function limitations such as U-TDOA and AOA, respectively.

Owing to the deployment of large number of WAPs in urban area, WiFi technology has been employed for such area as an alternative localization solution. Especially, when the cellular solutions are not accurate enough, or they are not applicable (Liu, Zhang, Quan, & Lin, 2010). However, in these situations WiFi-based solutions do not perform very well due to having multipath and NLOS signals which affect smartphones' location accuracy.

5.2 Indoors localization solutions

There is a huge demand on making reliable indoors positioning solutions, since people spend 80-90% of their time, and 70% of people calls & 80% of their data exchanging are occur when indoors (Kalliola, 2008). Recent commercial indoors localization solutions based on different technologies and techniques with their accuracy are listed in Table III. However, neither high performance nor wide-spread indoors localization solution is obtainable yet. This is due to wireless technologies limitations and the complexity indoors structure.

Although some of these solutions (e.g. WiFi-SLAM, Skyhook, and Ekahau) can achieve a reasonable accuracy (Faragher, R and Harle, R, 2013). But they need to deploy new HW; or they are using Internet to connect with reference-location database/server in order to calibrate the interest area and then to locate the smartphones (Miguel Garcia, Fernando Boronat, Jesus Tomás, Jaime Lloret, 2009). Furthermore, some of them are implemented on the smartphones (e.g. Sensewhere and Navizon), while some others are in process, i.e., they need more researching and solving practical issue (e.g. PlaceLab, ArrayTrack, and PinPoint).

Table III. Indoors localization solutions.

Solution name	Accuracy	Wireless Technology	Localization Technique	Overhead	Comments
ArrayTrack (Xiong & Jamieson, 2011)	Up to1m	WiFi	AOA	Needs to deploy a new WiFi directional antennas	It is good for LOS signals and for a small coverage
Ekahau (Gallagher, Li, Kealy, & Dempster, 2009)	5m-15m	WiFi	RSS	Clients need to calibrate and make the radio map for a specific area	An Internet connection is needed to reference the location-database
Skyhook (Gallagher, Li, Kealy, & Dempster, 2009)	10m-20m	WiFi	RSS	Solutions need to calibrate and make a radio map for a specific area	
Navizon (Zandbergen, 2009)	20m-40m	WiFi	RSS		
Place Lab (LaMarca, et al., 2005)	20m-40m	WiFi	Proximity and RSS		
Sensewhere (Sensewhere LTD, 2011)	Up to10m	WiFi and A-GPS	Proximity and RSS	No WAP surveying nor associated database	An Internet connection is needed to reference the location-database
Polaries (The Communications Security, March 14, 2013)	100-500m	RF technology	RSS-Fingerprinting	Survey RSS-values for a specific geographical area	
Qualcomm (The Communications Security, March 14, 2013)	50-400m	GPS and Cellular	AGPS/AFLT method as a hybrid solution	It doesn't need any additional or tailored HW during localization	It depends on the visibility GPS satellite vehicles (SV) in sky and cellular network conditions
NextNav (The Communications Security, March 14, 2013)	2-4m vertically and 50-150m horizontally	RF-technology (GPS-like signals)	TOA	Needs to deploy a special infrastructure in a geographical area	Special receiver should be connected with the smartphones
U-TDOA (Trueposition) (TruePosition, 2008)	Up to 50m	Cellular	TDOA	Needs to install Location Measurement Units (LMU) on the cell towers	SNR, number of cell towers, timestamp, and transmitter/receiver geometry condition are the main factors on the solution's accuracy
PinPoint (Youssef, Youssef, Rieger, Shankar, & Agrawala, 2006)	Up to 7m	WiFi	TOA (two-way measurements) and TDOA	Needs constant number of message exchanges between smartphone and WAPs or any other nodes	The accuracy is based on the accuracy of the clock rates (e.g. WiFi clock off-the-shelf is 40 MHz is ~ 25 ns). And the coverage in tens of meters.
Goodtry (Hoene & Willmann, 2008)	Up to 4m	WiFi	TOA (four way measurements)		
WiFi-SLAM (Huang, Millman, Quigley, Stavens, Thrun, & Aggarwal, 2011)	3m-5m	WiFi and Map	Mapping and RSS	Needs to upload the map of the buildings/area and calibrates WAPs' signals parameters	They need an internet connection to communicate with the system's location servers
GraphSLAM (Huang, Millman, Quigley, Stavens, Thrun, & Aggarwal, 2011)	4m-7m	MAP and Sensors	Mapping and DR	Needs to upload the map of the buildings/area and calibrates sensors	
Pseudolite (Mahiddin, Safie, Nadia, Safei, & Fadzli, 2012)	Sub-meter	Terrestrial replica of GNSS	TOA	They need to deploy new transmitters for (IMS) and transceivers for (Locata and Pseudolite)	They are GPS-like signals.
IMES (Kohtake, Morimoto, Kogure, & Manandhar, 2011)	Up to 10m		Proximity		
Locata (Rizos, Roberts, Barnes, & Gambale, 2010)	Sub-meter		TOA		

For indoors smartphones, most of the researches focused on technology to locate smartphones indoors as they have been located when outdoors and enable mapping, navigation, local search, sharing location, and other LBS. To achieve these services several solutions and researches have been proposed. For example, Pseudolite is as an alternative solution for GPS and used as an indoors technology to find the location of smartphones in sub meter accuracy (Mahiddin, Safie, Nadia, Safei, & Fadzli, 2012). However, it requires deploying ground-based transceivers which incurs huge cost. High quality of time synchronization, near-far problem, and multipath are the main challenges of the solution to locate the smartphones.
In a variety of localization solutions, an IMES and GPS receiver to provide indoors positioning solution has been proposed (Kohtake, Morimoto, Kogure, & Manandhar, 2011). The architecture of the IMES can be seen in Figure 17. Smartphones consume low battery power when IMES is used. However, obtained smartphones location performance by using this solution doesn't meet the LBS user's requirement, since IMES is based on proximity technique and it offers limited smartphone location accuracy. In addition for that, practically, a GPS receiver firmware modification is needed to implement IMES on the smartphones.

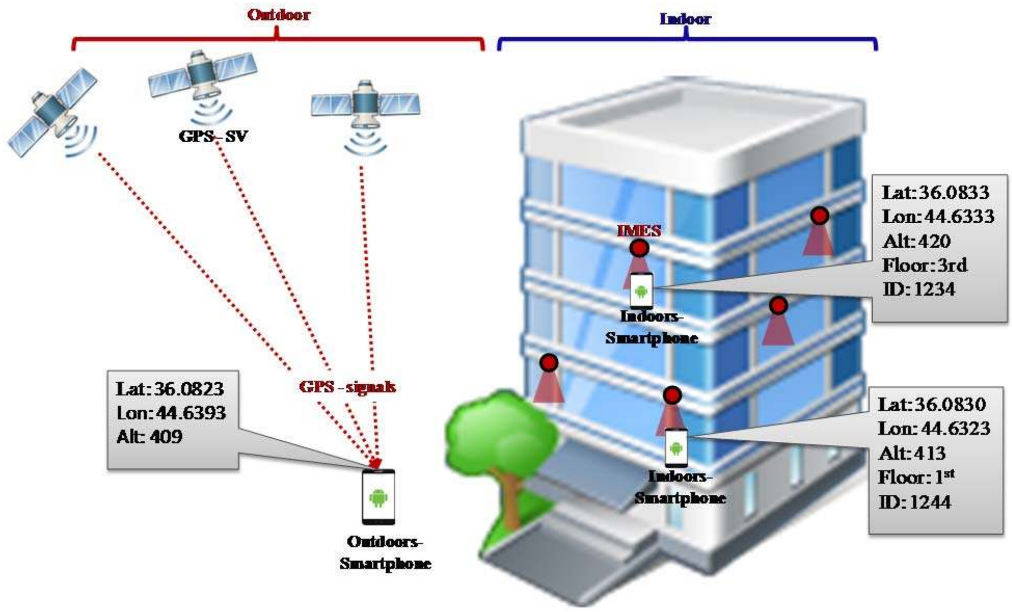

Fig. 17. Indoors and outdoors positioning using IMES and GPS

Locata system is another indoors solution (Rizos, Roberts, Barnes, & Gambale, 2010); it is able to replicate GPS/GNSS performance indoors, as it shown in Figure 18. Locata is GPS-like solution; it needs four transmitted signals to locate the smartphone as well as needs high quality clock synchronization to calculate accurate pseudoranges between the smartphones and Locata-transmitters.

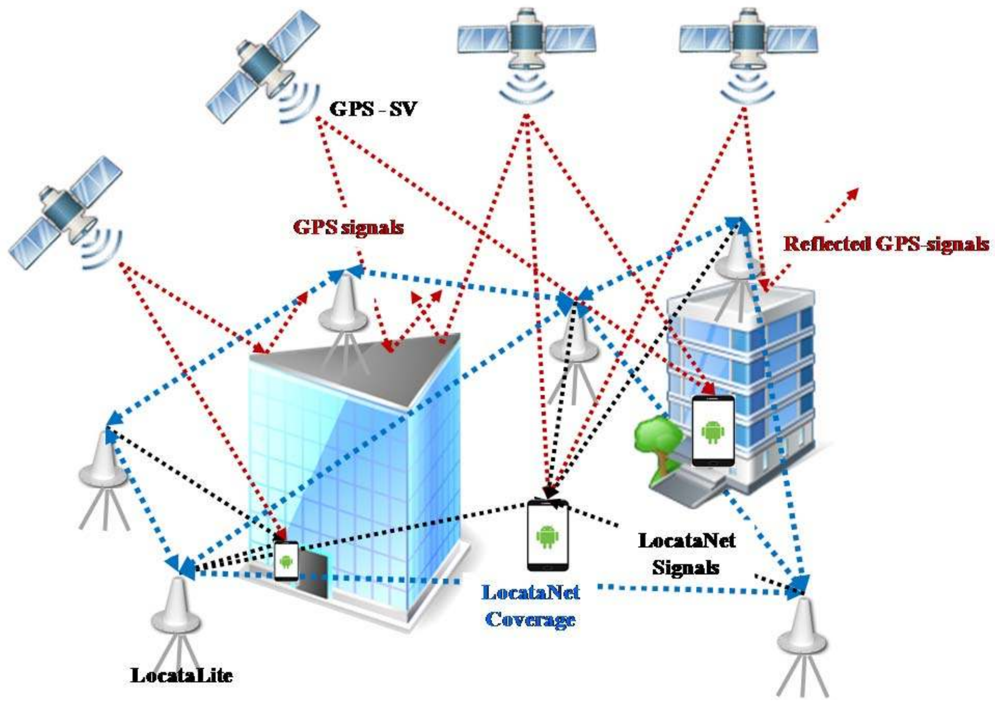

Fig. 18. Locata positioning architecture

All requirements and capabilities for IMES and Locata solutions are listed in Table IV. The main unique drawback of Pseudolite, Locata, and IMES is to establish new infrastructure to cover smartphones indoors for LBS application which is incur huge cost.

Table IV. Comparison on Locata and IMES solutions

IMES	Locata Solution
It does not need any synchronization.	Strong time synchronized ranging signals are needed.
It operates in GPS L1 band (with offset 8.2 kHz).	It works in the industrial, scientific and medical (ISM) band 2.4 – 2.4835 GHz.
It does not need any HW modification.	Needs equipped Locata receiver in smartphones.
The accuracy is up to 10 meters.	Position accuracy is in cm-level.
Application in deep indoors shopping builds and underground.	Applications are in open-cut mines, urban and even indoors locations.
Need a single transmitted signal and/or message to locate the smartphones.	Needs four transmitted signals to locate the smartphone.

Although WiFi technology is not planned or deployed for the purpose of localization, measuring WAPs signal-parameters provide the possibility of locating smartphones (Manodham, Loyola, & Miki, 2008). WiFi technology based on some calibration conditions shows better smartphone positioning accuracy when other localization technologies embedded smartphones cannot be utilized.

Many localization techniques such as: RSS-based, proximity, and time-based localization are likely being used to locate smartphones based on WiFi technology. However, due to having a lot of big obstacles indoors, most of the time the WAPs signals cannot penetrate the obstacles (i.e. multipath issue) (Zhao, Li, & Shi, 2010). Thus, such signals may reach smartphones by bypass deviation (i.e. NLOS), and then introduce large error on estimating pseudoranges and on location estimation.

Several researchers have been involved to mitigate this inaccuracy in measurements by using different statistical and/or mathematical models. For example, due to the fluctuation of WAPs signals, calibrating some parameters for these signals are examined in (Park & Park, 2011) including attenuation factor of the WAP signal and offset parameter of the RSS. The calibration algorithm has been proposed to improve the accuracy of pseudoranges measuring. However, the accuracy of measured pseudoranges is not adequate as well as the algorithm takes huge processing and then consequently more power consumption. In other study, RSS-fingerprinting method has achieved better accuracy in (Feng, Au, Valaee, & Tan, 2010), but the database generation, maintenance and extra HW cost are the main drawbacks of the method.

The other major approach in WiFi positioning solutions is to use time-based approach such as TOA, TDOA and RTT, which are more accurate than RSS technique, as it has been proved in (Koenig, Schmidt, & Hoene, 2011). However, all WiFi time-based localization solutions suffer from timestamps generation of the received and transmitted signals by using inaccurate local clocks, instability and limited of WAPs coverage (Lee, Lin, Chin, & Yar, 2010). Mainly, the current solutions based on time measuring ignore the use of accurate reference time for clock synchronization.

In order to improve the localization performance, a combination of RSS and TOA localization techniques based on WiFi technology is proposed in (Koenig, Schmidt, & Hoene, 2011). The combined approach has achieved higher location accuracy than the RSS technique and TOA technique. However, in most cases, statistical processing or calibration algorithms, again, are needed as a pre-processing step.

Another indoors localisation solution such as iBeaconing based on BT technology is released on Apple-iPhones and Android-based smartphones. This solution offers good smartphone-position accuracy based on the combined version of proximity and RSS techniques (Padilla, November 16, 2013). The position accuracy will be varied (up to 2 meters) based on the number of deployed BT-anchors in the vicinity. The main LBS-application based on this solution is starting from shopping to patient monitoring in hospitals. However, the incurring cost to install this solution on smartphones and deploying large number of the BT-sensors are the main limitations for indoors-smartphones solutions.

SLAM solutions using WiFi, inertial sensors and Map building information based on various localisation techniques, such as TOA, RSS, and DR, are reliable indoors localisation solutions, when Internet connection with smartphones is available to connect with the pre-defined radio-map/database of reference locations. GraphSLAM and WiFi-SLAM software are examples of such indoors-smartphone positioning solutions. Taking GraphSLAM as an example (Huang, Millman, Quigley, Stavens, Thrun, & Aggarwal, 2011), it fuses map buildings-information and inertial sensors readings to define indoors-smartphones position by performing statistical/mathematical filtering. The well-known example these filters are particle filter and Kalman filter. However, the achieved smartphones position accuracy within 4m – 7m is not dependable for most indoors LBSs.

On the whole, because the indoors environment are complex areas and the need of high location accuracy in smartphone LBS applications, current indoors localization solutions based on WiFi technology do not satisfy LBS users' requirements. Therefore, more researches and further work are needed to mitigate and to overcome these limitations.

5.3 Outdoors-Indoors seamless localization solutions

Outdoors to indoors seamless localization is a main user demand for most of the smartphones LBS application. However, wireless technologies available on smartphones do not provide continuous positioning due to their environmental limitations and their own low performance. The performance of current localization implementations and limitation on smartphones are shown in Table V.

To avoid technologies' environmental limitations and/or to provide outdoors-indoors seamless positioning, combining the technologies should be utilized into a single positioning solution (Koenig, Schmidt, & Hoene, 2011).

Table V. Performance of current localization implementations on smartphones

Technology	Time to fix	Accuracy	Coverage	Environments
GNSS	Quick fix, when outdoors	Up to 5m in clear sky.	World wide	Outdoors
WiFi	Quick fix, when Internet and location database are available.	Better accuracy when GNSS is worst, between 10m-25m.	Build up area	Urban/Indoors
Cellular	Quick fix, when communication with BSs is available.	25m-100m, wherever that there is cellular coverage.	Build up area	Urban/Indoors
Inertial sensors	Possible fixing, when the other technologies are not available.	Up to 5m, for short time since the last calibration (drift issue).	Build up area	Indoors

The combination usually could be based on taking the advantages/capabilities of the technologies and avoiding their limitations. Actually, such combination is not only to offer seamless positioning, it can provide other performance improvements including reduce smartphones' battery power consumption, reduce time to fix, maximize localization coverage, and improve location accuracy (Shafer & Chang, 2010).

However, all these performance improvements are not supplied in a single localization solution so far, as well as current localization solutions are normally tailor-made with specialized HW and they incur large cost. Note: to assure the cost level for each localization solutions, this research study produces Table VI. As shown in the table, the cost level is presented in different type of costs including: software (SW), hardware (HW), human resource (HR) and/or database (DB)/server.

Furthermore, for HW cost either installing expensive basestations such as in SUPL and using vehicles in Skyhook solution or deploying cheap sensors such for iBeaconing solution. In addition, current localization solutions might us a dedicated DB/server and Internet connection to report the smartphone location information or sometime the solutions need HR to do the survey or calibrating the installed localization-infrastructures such in Ekahau.

Table VI. Cost level for current localization solution.

Level	SW	HW		HR	DB/Server
		Cheap	Expensive		
Very-Low (VL)	√	X	X	X	X
Low	√	√	X	X	X
Medium	√	√	√	X	X
High	√	√	√	√	X
Very-High (VH)	√	√	√	√	√

In research community, many trials and simulations to provide such service have been conducted a few years ago. Table VII shows capability of these recent smartphone localization solutions.

Table VII. Seamless outdoors-indoors positioning solutions

Solution	Accuracy	Hybridising onboard technologies	Combined/standalone Localisation Technique	Cooperative	Cost (according to Table VI)	Pre-knowledge/ Pre-calibration
SILS (Ihsan Alshahib Lami, Halgurd S. Maghdid, Torben Kuseler, 2014)	2 – 3 meters	GNSS with WiFi, BT and inertial-sensors	TOA and DR	Yes	V-Low	No
WGCP (B. Li & Rizos, 2010)	Up to 19 meters	GNSS with WiFi	Standalone TOA	None	V-Low	No
WGIM (Mok, 2010)	Cell-ID size (e.g. 20 meters)	GNSS with WiFi	Cell-ID with RSSI	None	V-Low	No
DREAR (Torok, Agoston and Nagy, Akos and Kovats, Laszlo and Pach, Peter, 2014)	5 – 10 meters	Inertial-sensors with Internet	DR and Activity-style	Yes	Low	Yes
Infra-free (Iwase, T. and Shibasaki, R., 2013)	Up to 5 meters	GNSS with WiFi and INS	TOA and DR	Yes	Low	No
ADPS (Hassan & Khairulmizam, 2009)	Up to 7 meters	GNSS and INS	TOA and DR	None	Medium	Yes
CPSM (Taniuchi, Daisuke and Liu, Xiaopeng and Nakai, Daisuke and Maekawa, Takuya, 2015)	Up to 4 meters	WiFi with BT	Distance-based and RSSI-Fingerprinting	Yes	V-High	Yes
HCLSN (Ruijun Fu and Yunxing Ye and Pahlavan, K., 2012)	Up to 5 meters	GNSS with WiFi	TOA and RSSI-Fingerprinting	Yes	V-High	Yes
IGSC (Kaikai Liu and Qiuyuan Huang and Jiecong Wang and Xiaolin Li and Wu, D.O., 2013)	Up to 4 meters	GNSS and acoustic	Standalone TOA	Yes	V-High	Yes
SUPL (Rowe, Duffett-Smith, Jarvis, & Graube, 2008)	Up to 3 meters	GNSS with Cellular	Cell-ID, TDOA and TOA	None	V-High	No
WiFi-GPS (B. Li & Rizos, 2010)	2-10 meters	GNSS with WiFi	TOA and RSSI-Fingerprinting	None	V-High	Yes

For example, specifically to hybrid GNSS with WiFi technology: combining GPS technology with WiFi technology based on directional approach of WiFi RSS-Fingerprinting with GPS parameters has been proposed in (B. Li & Rizos, 2010). GPS parameters include Horizontal Dilution of Precision (HDOP), Code to Noise Ratio, and the number of satellite signals acquired. The combination scheme provides large reduction in computational burden, different coordinate systems to be used in different situations (latitude-longitude-altitude "LLA" for outdoors and XYZ for indoors), also provides intended blocks of RSS-location information to be selected from the database when necessary.

Combining GPS technology with WiFi technology based on directional approach of WiFi RSS-Fingerprinting with GPS parameters has been proposed in (B. Li & Rizos, 2010). The GPS parameters include code-to-noise-ratio, horizontal dilution-of-precision (HDOP) and the number of satellite-vehicles available. The combination scheme provides large reduction in computational burden, different coordinate systems to be used in different situations (e.g. LLA for outdoors, and XYZ for indoors), also provides intended blocks of RSS-location information to be selected from the database when necessary.

Seamless outdoors-indoors positioning service by integrating GPS with WiFi location fingerprinting in different handover solutions on smartphones has been involved in (Hansen, Wind, Jensen, & Thomsen, 2009). Different handover scenarios have been conducted including always use GPS, always use WiFi or use both technologies (i.e. combined) when the acquired singles for each of them are available. The performance of the scenarios has been evaluated regarding to location accuracy and battery-power consumption of the smartphones. The evaluation showed that combined scenario provides good location accuracy and consumes low batter power.

A solution that uses WiFi localization to supply a new kind of assisted-GPS (WiFi-Assisted-GPS) has been proposed in (Weyn & Schrooyen, 2008). The solution from a smartphone can be started by enabling GPS receiver and simultaneously records all received WAPs signal strengths in the vicinity and send all these recorded information to a reference-location server. This server then processes the required position based on the recorded WAPs RSS values and will send back GPS-ephemeris data to the smartphone. Then the smartphone can start with the estimated position retrieved by the server. Thus, the GPS signal search space is reduced in comparison with a normal GPS receiver. Therefore, the solution shall avoid the main drawbacks of GPS technology such as: long TTFF, huge power consumption and enabling smartphone positioning when not enough satellite-vehicles are visible.

4) Simulation experiments of a positioning scheme based on combined GPS and WiFi technologies using trilateration technique is conducted in (Zirari, Canalda, & Spies, 2010). The simulated scheme is to locate of GPS-enabled device if the number of available satellite-vehicles is not enough for positioning. Mathematically, the scheme is to compensate the set of the GPS-signal equations (which are less than four equations) by equations obtained from the received WAPs signals. The aim of the scheme is to provide better position anywhere, anytime and to ensure a seamless positioning.

5) A hybrid urban public WiFi with GPS positioning algorithm to provide reliable and to improve the accuracy of positional information in a knowledge-based logistics system (KLS) has been proposed in (Mok, 2010). The integrated solution provides full use of the already available public WiFi signals to support correct position of the

smartphones in real time when insufficient GPS data are available for correct and reliable position fixing.

These studies have been proposed to improve the location accuracy and to offer seamless positioning when GNSS signals are weak or numbers of visible GNSS signals are not enough for localization. However, the above solutions are tailored or customized solutions for some specialized scenarios. As well as accurate GPS parameters (e.g. time) for WiFi transceiver clock synchronization, traffic burden on WiFi networks, establishing special HW to survey the localization area, and cost for deploying the localization solutions have not been considered.

Furthermore, integrating cellular networks with GPS technology could be applied to offer seamless positioning service. Using cellular signals, aiding information (like position information, time and frequency information) could be received from a server in the cellular network to enhance smartphones' GPS receivers (Lim, Lee, & Cho, 2007), when in harsh areas. For example, an Enhanced GPS (EGPS) and Aided-GPS (AGPS) are analyzed in (Rowe, Duffett-Smith, Jarvis, & Graube, 2008) to reduce the GPS signal search space by using cellular signal timing and consequently to reduce battery power consumption.

The other possible way to achieve seamless smartphone localization service is to use inertial sensors to aid GNSS technologies. These sensors are available on the smartphones, and using these sensors with GNSS technology for localization can offer seamless localization (Hassan & Khairulmizam, 2009) and smartphones' battery power saving (Oshin, Poslad, & Ma, 2012). However, using such sensors need calibration algorithms that are accurate for up to only few seconds.

In another vain, on-the-go smartphones based seamless outdoors-indoors localization is essential to realize the full potential of LBS application. Currently, most of the solutions to offer continue localization are based on cooperative strategy. Cooperative solution is to collect and to fuse several measurements from nodes of a network to obtain high localization accuracy and to offer seamless positioning (Miguel Garcia, Diana Bri, Jesus Tomas and Jaime Lloret, 2-25 September 2013).

Cooperation between smartphones, currently, is a new solution to improve location accuracy as well as to offer continuous and reliable localization solutions. A GNSS based cooperative location optimization scheme has been developed using a host server to fuse location coordinates supplied from onboard GNSS of any group of cooperative-smartphones to improve location accuracy (Kaikai Liu and Qiuyuan Huang and Jiecong Wang and Xiaolin Li and Wu, D.O., 2013). Then, pseudorange estimation between the group smartphones is calculated based on TOA technique using acoustic signal. The server then, as a final stage, receives these pseudoranges and uses a complex optimization model to obtain further location accuracy improvement, within 1.2 – 4 meters. Obviously this scheme has two main drawbacks, such as:

1) It needs to access a dedicated database/server to improve and share the location information among all these smartphones which acceptable as a small overhead.
2) Porting the task of the server into the smartphones will eliminate the overhead of this server and its associated wireless connectivity, but the optimization algorithm will take considerable resource and time that will drain the smartphones batteries.

Wi-Fi Positioning System (WPS)-Skyhook enabled smartphones can obtain WAPs location in any vicinity, as mentioned before. A group of such smartphones can then use these WAPs as reference point to locate themselves within a claimed 10-20 meters when indoors. An improved location can be achieved if a GNSS position from an outdoors smartphone is shared with this group of smartphones via WiFi connectivity. This can be achieved by applying "conditional prior probability" to improve the indoors-smartphone location via probability distribution of the set of shared information (WAPs pseudorange, GNSS location of the reference smartphones outdoors). For example, the "cooperative smartphones localization" algorithm in (Ruijun Fu and Yunxing Ye and Pahlavan, K., 2012) is based on four probabilistic methods namely: 1) Centroid method, 2) Nearest Neighbour method, 3) Kernel method and 4) WAPs density method. Both empirical and simulation results claims that the WAPs density method provided more accurate results than the others, since WAPs density provides a function to distinguish the overlapped or the common shared WAPs information between the outdoors smartphones and the indoors-smartphones. However, this location enhancement has resulted in 5 meters accuracy.

Also, an infrastructure independent cooperative indoor localization (i.e. on-the-go) using sensors onboard smartphones GNSS, inertial sensors such as accelerometer & magnetometer and WiFi has been implemented to locate indoors-smartphones to within 5 meters (Iwase, T. and Shibasaki, R., 2013). In this solution, a group of WiFi networked smartphones, when outdoors, start a calibration process where estimated heading error is calibrated by GNSS heading estimation, and where pseudoranges error between these smartphones is mitigated by detecting pedestrian-step trajectory using the onboard accelerometer. When indoor smartphones join this network, shared location information will help establish initial position and the heading calibration process of these indoor smartphones. Experimental results show that this cooperative solution can achieve location accuracy up to 5 meters, if number of smartphones is exceeds 40.

In another vain, to avoid the use of aided reference-positions and/or fixed devices such as WAPs and beacons, when indoors, DREAR (Torok, Agoston and Nagy, Akos and Kovats, Laszlo and Pach, Peter, 2014) proposes a new solution for indoors-smartphones localization using onboard sensors based on user-activities recognition. I.e. the solution is completely independent of using any infrastructures and offers low cost solution. DREAR uses DR techniques to locate any indoors-smartphones based on some pre-defined constraints such as user's motion-style, taking escalators and climbing stairs. This is important to mitigate the accumulated positioning error that caused by inertial sensors such as gyroscope. The solution is also follows to a client-server concept in which the coarse position based on DR is processed on client-side, while the refinement of the obtained position is performed on server-side using the defined constraints. The obtained results from a set of trials show that the achieved smartphone-position accuracy is within 5-10 meters.

Another collaborative indoors-smartphone-based solution using BT-RSS measurements between smartphones has been proposed in (Taniuchi, Daisuke and Liu, Xiaopeng and Nakai, Daisuke and Maekawa, Takuya, 2015) to improve indoors-smartphones location. In this solution, the indoors-smartphones, first, use the measured WAPs-RSS values to define their location via existing WiFi-Fingerprinting technique. Then in next step, the solution estimates pseudorange measurements between smartphones by using BT-RSS measurements values to narrow the accuracy of the achieved smartphones location. The process of location improvement is based on using force-directed-graph concept such as spring model. Different experiments in various indoors situations have been conducted to validate this solution. The high position accuracy that has been achieved is near to 4 meters.

Also, SILS (Ihsan Alshahib Lami, Halgurd S. Maghdid, Torben Kuseler, 2014)as a smart and/or cooperative localization solution provided on-the-go smartphones based seamless outdoors-indoors localization. This scheme works whereby participating smartphones in the vicinity, outdoors and indoors, form a Bluetooth network to: a) synchronise all reachable WAPs with GNSS time from outdoors smartphones (database of the time offsets of the various connected nodes are hosted on the smartphones), b) exchange and establish smartphones location and time-offsets based on available/reliable GNSS location from outdoors smartphones, and c) calculate approximate location of indoor-smartphones based on the proposed (SILS). i.e. SILS combines various measurements on-the-go of nodes formed network of smartphones based on BT to BT relative distances of all participating smartphones based on: 1) hop-synchronisation, 2) new Master-Slave role switching to minimize the distance error, 3) GNSS measured location of outdoors-smartphones, as well as 4) WAPs-smartphones triangulation estimates. Results obtained from actual trials of SLIS based on Android-smartphones network implementations for various indoors scenarios show that around 2-meters accuracy can be achieved when locating smartphones at various indoors situations.

These seamless localization solutions need further investigations to offer a robust, applicable and reliable solution. Furthermore, locating smartphones via these solutions are based on the estimation process, i.e. real complexity of indoors, obtaining high location accuracy, cost and traffic of the wireless networks are not considered.

These seamless localization solutions need further investigations to offer a robust and reliable solution. Furthermore, locating smartphones via these solutions are based on the estimation process, i.e., real complexity of indoors, obtaining high location accuracy, and traffic of the wireless networks are not considered.

6. CONCLUSION AND FUTURE PERSPECTIVE

Achieving accuracy of smartphones location in localization solutions is varying according to: environmental complexity, using localization techniques as a standalone or as a combined approach, HW or SW of the designed solutions, and estimating/calculating 'smartphones location' method.

Cellular, WiFi, Bluetooth or inertial-sensors based positioning systems have been proven to somewhat provide alternative solutions in GNSS-signal-denied areas to define smartphones location. However, limited coverage of WAPs/Bluetooth-anchors, no information of WAPs physical positions within a building, no access to API functions of important device data onboard smartphones, no WAPs localization protocol extensions, no synchronization between WAPs are some of the main challenges to design a spontaneous autonomous positioning solution with reliable accuracy at reasonable cost.

Existing localization techniques, such RSSI/fingerprinting techniques, do provide good performance (despite non-uniform shadowing problem) but at the expense of pre-installing dedicated infrastructure and therefore limited in LBS application. Other trilateration/pseudoranging-based approaches suffer from jitters, instability, coverage and dilution of precision issues. Finally, DR technique, especially when using low-cost inertial sensors such as accelerometer and gyroscope onboard smartphones, is highly smooth and stable, but their performance degrades quickly over time due to the accumulated measurement noise of sensors causing cumulative positioning error.

Various outdoors-indoors localization solutions for smartphone positioning are discussed, and the limitations as well as capabilities among them are addressed. Regardless of available localization approaches to mitigate the indoors positioning problems, current solutions do not offer seamless positioning from outdoors into indoors with high accuracy and at reasonable cost that significant LBS applications required. To achieve these, further researches is required to handle the challenges. The future trend of seamless outdoors-indoors positioning systems on smartphones is as follows:

1) Providing ideal platform to integrate HW and SW for GNSS with WiFi, Bluetooth, cellular and inertial sensors. I.e. hybrid multiple radio/sensor-reading sources into a single localization solution to offer seamless positioning,
2) Providing unconstrained and/or infrastructure-less localization solutions to reduce the cost and size,
3) Fusing of various localization algorithms/techniques to provide accurate localization solution. For example, fusing fingerprinting systems' measurements using artificial intelligent techniques or fusing measured relative-pseudoranges between smartphones (using TOA technique) and DR-technique measurements (distance-displacement and heading) of indoors smartphones by using Kalman filter. The fusion will be exploiting the advantages of each of these techniques while compensating for their limitations,
4) And providing cooperative (i.e. crowd sourcing) smartphones localization solution which will help smartphones among each other to define their positions accurately as well as offers on-the-go solution, anywhere and anytime.

ACKNOWLEDGMENTS

This research was sponsored by Koya University, Kurdistan Region-Iraq. The authors also would like to thank Dr. Ali Al-Sherbaz (from the University of Northampton-UK) and Dr. Naseer Al-Jawad (from the University of Buckingham-UK) for providing and improving the quality of this paper in terms of academic and technical writing.

REFERENCES

Adusei, I., Kyamakya, K., & Jobmann, K. (2002). Mobile positioning technologies in cellular networks: an evaluation of their performance metrics. MILCOM 2002. Proceedings, 2, pp. 1239-1244.

Anuar, Faiz and Gretzel, Ulrike. (2011). Privacy Concerns in the Context of Location-Based Services for Tourism. ENTER 2011 Conference, Innsbruck, Austria.

B. Li, A. G., & Rizos, C. (2010). Positioning in environments where GPS fails. (pp. 1-18). Sydney (Australia): FIG Congress.

Bensky, A. (2008). Wireless Positioning Technologies and Applications. 685 Canton Street, Norwood, MA 02062: ARTECH HOUSE, INC.

Boukerche, Azzedine and Oliveira, Horacio ABF and Nakamura, Eduardo F and Loureiro, Antonio AF. (2007). Localization systems for wireless sensor networks. wireless Communications, IEEE , 14 (6), 6--12.

Boukerche, Azzedine and Oliveira, Horacio ABF and Nakamura, Eduardo F and Loureiro, Antonio AF. (2008). Secure localization algorithms for wireless sensor networks. Communications Magazine, IEEE , 46 (4), 96--101.

Boukerche, Azzedine and Oliveira, Horacio ABF and Nakamura, Eduardo F and Loureiro, Antonio AF. (2008). Vehicular ad hoc networks: A new challenge for localization-based systems. Computer communications , 31 (12), 2838--2849.

Butler, M. (2011, JANUARY–MARCH). Android: Changing the Mobile Landscape. PERVASIVE computing .

Caffery, J., & Stuber, G. (1998). Overview of radiolocation in CDMA cellular systems. Communications Magazine, IEEE , 36 (4), 38-45.

Cherian, Suma S and Rudrapatna, Ashok N. (2013). LTE location technologies and delivery solutions. Bell Labs Technical Journal , 18 (2), 175--194.

Ciurana, M., Lopez, D., & Barcelo-Arroyo, F. (2009). SofTOA: Software ranging for TOA-based positioning of WLAN terminals. Location and Context Awareness , 207-221.

Dardari, D. and Closas, P. and Djuric, P.M. (2015). Indoor Tracking: Theory, Methods, and Technologies. IEEE Transactions on Vehicular Technology , 64 (4), 1263-1278.

De Angelis, G., Baruffa, G., & Cacopardi, S. (2012). GNSS/Cellular Hybrid Positioning System for Mobile Users in Urban Scenarios.

De Oliveira, Horacio Antonio Braga Fernandes and Boukerche, Azzedine and Nakamura, Eduardo Freire and Loureiro, Antonio Alfredo Ferreira. (2009). An efficient directed localization recursion protocol for wireless sensor networks. Computers, IEEE Transactions on , 58 (5), 677--691.

Della Rosa, Francescantonio and Pelosi, Mauro and Nurmi, Jari. (2012). Human-induced effects on rss ranging measurements for cooperative positioning. International Journal of Navigation and Observation , 13.

Deng Zhongliang and Yu Yanpei and Yuan Xie and Wan Neng and Yang Lei. (2013). Situation and development tendency of indoor positioning. Communications, China , 10 (3), 42-55.

Elbes, Mohammed and Al-Fuqaha, Ala and Anan, Muhammad. (2013). A precise indoor localization approach based on particle filter and dynamic exclusion techniques. Network Protocols and Algorithms , 5 (2), 50--71.

Faragher, R and Harle, R. (2013). SmartSLAM--an efficient smartphone indoor positioning system exploiting machine learning and opportunistic sensing. ION GNSS.

Farid, Zahid and Nordin, Rosdiadee and Ismail, Mahamod. (2013). Recent advances in wireless indoor localization techniques and system. Journal of Computer Networks and Communications , 12.

Fayaz, S. a. (2013). Location service for wireless network using improved RSS-based cellular localisation. International Journal of Electronics , 1-16.

Feng, C., Au, W., Valaee, S., & Tan, Z. (2010). Compressive sensing based positioning using RSS of WLAN access points. INFOCOM, 2010 Proceedings IEEE, (pp. 1-9).

Gallagher, T., Li, B., Kealy, A., & Dempster, A. (2009). Trials of commercial Wi-Fi positioning systems for indoor and urban canyons. IGNSS 2009 Symposium on GPS/GNSS.

Gallagher, T., Wise, E., Li, B., Dempster, A., Rizos, C., & Ramsey-Stewart, E. (2012). Indoor positioning system based on sensor fusion for the Blind and Visually Impaired. Indoor Positioning and Indoor Navigation (IPIN), 2012 International Conference on, (pp. 1-9).

Günther, A., & Hoene, C. (2005). Measuring round trip times to determine the distance between wlan nodes. in Proc. of Networking 2005 (pp. 768-779). Springer-Verlag.

Hansen, R., Wind, R., Jensen, C., & Thomsen, B. (2009). Seamless indoor/outdoor positioning handover for location-based services in Streamspin. Mobile Data Management: Systems, Services and Middleware, 2009. MDM'09. Tenth International Conference on, (pp. 267-272).

Harle, R. (2013). A Survey of Indoor Inertial Positioning Systems for Pedestrians. Communications Surveys Tutorials, IEEE , 15 (3), 1281-1293.

Hassan, A., & Khairulmizam, S. (2009). Integration of Global Positioning System and Inertial Navigation System with Different Sampling Rate Using Adaptive Neuro Fuzzy Inference System. Sci. J , 7, 98-106.

Hightower, J., & Borriello, G. (2001). Location systems for ubiquitous computing. Computer , 34 (8), 57-66.

Hoene, C., & Willmann, J. (2008). Four-way TOA and software-based trilateration of IEEE 802.11 devices. Personal, Indoor and Mobile Radio Communications, 2008. PIMRC 2008. IEEE 19th International Symposium on, (pp. 1-6).

Huang, J., Millman, D., Quigley, M., Stavens, D., Thrun, S., & Aggarwal, A. (2011). Efficient, generalized indoor wifi graphslam. Robotics and Automation (ICRA), 2011 IEEE International Conference on, (pp. 1038-1043).

Hui, L., Lei, Y., & Yuanfei, W. (2010). UWB, Multi-sensors and Wifi-Mesh based precision positioning for urban rail traffic. Ubiquitous Positioning Indoor Navigation and Location Based Service (UPINLBS), 2010, (pp. 1-8).

Ihsan Alshahib Lami, Halgurd S. Maghdid, Torben Kuseler. (2014). SILS: A Smart Indoors Localization Scheme Based on on-the-go Cooperative Smartphones Networks Using Onboard Bluetooth, WiFi and GNSS. Proceedings of the 27th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2014). Tampa, Florida.

Iwase, T. and Shibasaki, R. (2013). Infra-free indoor positioning using only smartphone sensors. Indoor Positioning and Indoor Navigation (IPIN), 2013 International Conference on.

Jaime Lloret, Jesus Tomas, Alejandro Canovas, Irene Bellver. (10 May 2011). A Geopositioning System Based on WiFi Networks. The Seventh International Conference on Networking and Services (ICNS 2011). Venecia (Italia).

Jaime Lloret, Jesus Tomás, Miguel Garcia, Alejandro Cánovas. (2009). A Hybrid Stochastic Approach for Self-Location of Wireless Sensors in Indoor Environments. Sensors , Vol. 9 (Issue 5), Pp. 3695-3712.

Jin, S. (February 03, 2012). Global Navigation Satellite Systems: Signal, Theory and Applications. InTech, Chapters published.

Kaikai Liu and Qiuyuan Huang and Jiecong Wang and Xiaolin Li and Wu, D.O. (2013). Improving GPS Service via Social Collaboration. Mobile Ad-Hoc and Sensor Systems (MASS), 2013 IEEE 10th International Conference on.

Kalliola, K. (2008). Bringing Navigation Indoors. The Way We Live Next .

Kim, J., Lee, J., & Park, C. (2008). A mitigation of line-of-sight by TDOA error modeling in wireless communication system. Control, Automation and Systems, 2008. ICCAS 2008. International Conference on, (pp. 1601-1605).

Koenig, S., Schmidt, M., & Hoene, C. (2011). Multipath mitigation for indoor localization based on IEEE 802.11 time-of-flight measurements. World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2011 IEEE International Symposium on a, (pp. 1-8).

Kohtake, N., Morimoto, S., Kogure, S., & Manandhar, D. (2011). Indoor and Outdoor Seamless Positioning using Indoor Messaging System and GPS. International Conference on Indoor Positioning and Indoor Navigation (IPIN).

LaMarca, A., Chawathe, Y., Consolvo, S., Hightower, J., Smith, I., Scott, J., et al. (2005). Place lab: Device positioning using radio beacons in the wild. Pervasive Computing , 301-306.

Lee, J., Lin, Z., Chin, P., & Yar, K. (2010). One way ranging time drift compensation for both synchronized and non-synchronized clocks. System Science and Engineering (ICSSE), 2010 International Conference on, (pp. 327-331).

Lee, Jae-Eun and Lee, Sanguk. (2010). Indoor initial positioning using single clock pseudolite system. Information and Communication Technology Convergence (ICTC), 2010 International Conference on, (pp. 575--578).

Lim, D., Lee, S., & Cho, D. (2007). Design of an assisted GPS receiver and its performance analysis. Circuits and Systems, 2007. ISCAS 2007. IEEE International Symposium on, (pp. 1742-1745).

Liu, H., Darabi, H., Banerjee, P., & Liu, J. (2007). Survey of Wireless Indoor Positioning Techniques and Systems. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on , 37 (6), 1067-1080.

Liu, X., Zhang, S., Quan, J., & Lin, X. (2010). The experimental analysis of outdoor positioning system based on fingerprint approach. Communication Technology (ICCT), 2010 12th IEEE International Conference on, (pp. 369-372).

Lopez-de-Ipina, Diego and Klein, Bernhard and Guggenmos, Christian and Perez, Jorge and Gil, Guillermo. (2011). User-Aware semantic location models for service provision. International Symposium on Ubiquitous Computing and Ambient Intelligence, Riviera Maya, Mexico.

Lymberopoulos, Dimitrios and Liu, Jie and Yang, Xue and Choudhury, Romit Roy and Handziski, Vlado and Sen, Souvik. (2015). A realistic evaluation and comparison of indoor location technologies: experiences and lessons learned. Proceedings of the 14th International Conference on Information Processing in Sensor Networks. ACM.

Mahiddin, N., Safie, N., Nadia, E., Safei, S., & Fadzli, E. (2012). INDOOR POSITION DETECTION USING WIFI AND TRILATERATION TECHNIQUE. The International Conference on Informatics and Applications (ICIA2012), (pp. 362-366).

Manodham, T., Loyola, L., & Miki, T. (2008). A novel wireless positioning system for seamless internet connectivity based on the WLAN infrastructure. Wireless Personal Communications , 44 (3), 295-309.

Mariakakis, Alex and Sen, Souvik and Lee, Jeongkeun and Kim, Kyu-Han. (2014). Single access point based indoor localization. Proc. of ACM MobiSys.

Mautz, R. (2009). The challenges of indoor environments and specification on some alternative positioning systems. Positioning, Navigation and Communication, 2009. WPNC 2009. 6th Workshop on, (pp. 29-36).

Miguel Garcia, Diana Bri, Jesus Tomas and Jaime Lloret. (2-25 September 2013). A Cooperative Decision Making Algorithm for Wireless Location Systems using Interlinking Data. 10th International Conference on Cooperative Design, Visualization and Engineering (CDVE 2013). Mallorca (España).

Miguel Garcia, Fernando Boronat, Jesus Tomás, Jaime Lloret. (2009). The Development of Two Systems for Indoor Wireless Sensors Self-location. Ad Hoc & Sensor Wireless Networks , Vol. 8 (Issue 3-4), Pp. 235-258.

Mock, M., Frings, R., Nett, E., & Trikaliotis, S. (2000). Clock synchronization for wireless local area networks. Real-Time Systems, 2000. Euromicro RTS 2000. 12th Euromicro Conference on, (pp. 183-

189).

Mok, E. (2010). Using outdoor public WiFi and GPS integrated method for position updating of knowledge-based logistics system in dense high rise urban environments. Supply Chain Management and Information Systems (SCMIS), 2010 8th International Conference on, (pp. 1-4).

Niculescu, D., & Nath, B. (2004). VOR base stations for indoor 802. 11 positioning. International Conference on Mobile Computing and Networking: Proceedings of the 10 th annual international conference on Mobile computing and networking, 26, pp. 58-69.

Oshin, T., Poslad, S., & Ma, A. (2012). Improving the Energy-Efficiency of GPS Based Location Sensing Smartphone Applications. Trust, Security and Privacy in Computing and Communications (TrustCom), 2012 IEEE 11th International Conference on, (pp. 1698-1705).

Padilla, R. (November 16, 2013). Apple Retail Stores to Integrate iBeacon Systems to Assist with Sales and Services. MacRumores .

Park, D., & Park, J. (2011). An Enhanced Ranging Scheme Using WiFi RSSI Measurements for Ubiquitous Location. Computers, Networks, Systems and Industrial Engineering (CNSI), 2011 First ACIS/JNU International Conference on, (pp. 296-301).

Partyka, J. (2012, 18 July). "A Look at Small Indoor Location Competitors. "A Look at Small Indoor Location Competitors .

Paul Craven, Ronald Wong, Neal Fedora, and Paul Crampton. Studying the Effects of Interference on GNSS Signals.

Pei, L., Chen, R., Liu, J., Liu, Z., Kuusniemi, H., Chen, Y., et al. (2011). Sensor assisted 3D personal navigation on a smart phone in GPS degraded environments. Geoinformatics, 2011 19th International Conference on, (pp. 1-6).

Priyanka Shah, R. G. (2012). Location Based Reminder Using GPS For Mobile (Android). ARPN Journal of Science and Technology , 2 (4), 377-380.

Rizos, C., Roberts, G., Barnes, J., & Gambale, N. (2010). Locata: A new high accuracy indoor positioning system. Proc. Int. Conf. on Indoor Positioning \& Indoor Navigation, Zurich, Switzerland, (pp. 15-17).

Rowe, R., Duffett-Smith, P., Jarvis, M., & Graube, N. (2008). Enhanced GPS: The tight integration of received cellular timing signals and GNSS receivers for ubiquitous positioning. Position, Location and Navigation Symposium, 2008 IEEE/ION, (pp. 838-845).

Roxin, A., Gaber, J., Wack, M., & Nait-Sidi-Moh, A. (2007). Survey of wireless geolocation techniques. Globecom Workshops, 2007 IEEE, (pp. 1-9).

Ruijun Fu and Yunxing Ye and Pahlavan, K. (2012). Heterogeneous cooperative localization for social networks with mobile devices. Personal Indoor and Mobile Radio Communications (PIMRC), 2012 IEEE 23rd International Symposium on.

Ryoo, J., Kim, H., & Das, S. (2012). Geo-fencing: Geographical-fencing based energy-aware proactive framework for mobile devices. Quality of Service (IWQoS), 2012 IEEE 20th International Workshop on, (pp. 1-9).

Sen, Souvik and Lee, Jeongkeun and Kim, Kyu-Han and Congdon, Paul. (2013). Avoiding multipath to revive inbuilding wifi localization. Proceeding of the 11th annual international conference on Mobile systems, applications, and services. ACM.

Sensewhere LTD. (2011). Indoor Location Technology Leaders.

Shafer, I., & Chang, M. L. (2010). Movement detection for power-efficient smartphone WLAN localization. Proceedings of the 13th ACM international conference on Modeling, analysis, and simulation of wireless and mobile systems (pp. 81-90). New York, NY, USA: ACM.

Strout, Aaron and Schneider, Mike. (2011). Location Based Marketing For Dummies. John Wiley & Sons.

Subhan, Fazli and Hasbullah, Halabi and Rozyyev, Azat and Bakhsh, Sheikh Tahir. (2011). Indoor positioning in bluetooth networks using fingerprinting and lateration approach. Information Science and Applications (ICISA), 2011 International Conference on.

Taniuchi, Daisuke and Liu, Xiaopeng and Nakai, Daisuke and Maekawa, Takuya. (2015). Spring Model Based Collaborative Indoor Position Estimation With Neighbor Mobile Devices. Selected Topics in Signal Processing, IEEE Journal of , 9 (2), 268--277.

The Communications Security, R. a. (March 14, 2013). Indoor Location Test Bed Report. E9-1-1 Location Accuracy.

Torok, Agoston and Nagy, Akos and Kovats, Laszlo and Pach, Peter. (2014). DREAR-Towards Infrastructure-Free Indoor Localization via Dead-Reckoning Enhanced with Activity Recognition. Next Generation Mobile Apps, Services and Technologies (NGMAST), 2014 Eighth International Conference on.

TruePosition. (2008, October). U-TDOA Enabling New Location-based Safety and Security Solutions. White Paper, USA .

Waadt, A., Bruck, G., & Jung, P. (2009). An overview of positioning systems and technologies. Applied Sciences in Biomedical and Communication Technologies, 2009. ISABEL 2009. 2nd International Symposium on, (pp. 1-5).

Weyn, M., & Schrooyen, F. (2008). A Wi-Fi Assisted GPS Positioning Concept. ECUMICT, Gent, Belgium .

Wibowo, S., Klepal, M., & Pesch, D. (2009). Time of Flight Ranging using Off-the-self IEEE802. 11 WiFi Tags. Proceedings of the International Conference on Positioning and Context-Awareness (PoCA'09).

Woodman, O., & Harle, R. (2008). Pedestrian localisation for indoor environments. Proceedings of the 10th international conference on Ubiquitous computing, (pp. 114-123).

Wu, Yinfeng and Li, Ligong and Ren, Yongji and Yi, Kefu and Yu, Ning. (2014). A RSSI Localization Algorithm and Implementation for Indoor Wireless Sensor Networks. Adhoc & Sensor Wireless Networks , 22 (2).

Xiao, Zhuoling and Wen, Hongkai and Markham, Andrew and Trigoni, Niki. (2015). Robust pedestrian dead reckoning (R-PDR) for arbitrary mobile device placement. nternational Conference on Indoor Positioning and Indoor Navigation. IEEE.

Xiong, J., & Jamieson, K. (2011). ArrayTrack: A Fine-Grained Indoor Location System. RN , 11, 19.

Yi Sun and Yubin Zhao and Schiller, J. (2014). An autonomic indoor positioning application based on smartphone. Wireless Communications and Networking Conference (WCNC), 2014 IEEE.

Youssef, M., Youssef, A., Rieger, C., Shankar, U., & Agrawala, A. (2006). Pinpoint: An asynchronous time-based location determination system. Proceedings of the 4th international conference on Mobile systems, applications and services, (pp. 165-176).

Yun, Haejung and Han, Dongho and Lee, Choong C. (2013). Understanding the Use of Location-Based Service Applications: Do Privacy Concerns Matter? Journal of Electronic Commerce Research , 14 (3), 215.

Zandbergen, P. (2009). Accuracy of iPhone locations: A comparison of assisted GPS, WiFi and cellular positioning. Transactions in GIS , 13 (s1), 5-25.

Zhao, Y., Li, M., & Shi, F. (2010). Indoor Radio Propagation Model Based on Dominant Path. Int'l J. of Communications, Network and System Sciences , 3 (3), 330-337.

Zirari, S., Canalda, P., & Spies, F. (2010). WiFi GPS based combined positioning algorithm. Wireless Communications, Networking and Information Security (WCNIS), 2010 IEEE International Conference on, (pp. 684-688).