RETHINKING INDOOR LOCALIZATION SOLUTIONS TOWARDS THE FUTURE OF MOBILE LOCATION-BASED SERVICES

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ABSTRACT:

Satellite navigation systems with GNSS-enabled devices, such as smartphones, car navigation systems, have changed the way users travel in outdoor environment. GNSS is generally not well suited for indoor location and navigation because of two reasons: First, GNSS does not provide a high level of accuracy although indoor applications need higher accuracies. Secondly, poor coverage of satellite signals for indoor environments decreases its accuracy. So rather than using GNSS satellites within closed environments, existing indoor navigation solutions rely heavily on installed sensor networks. There is a high demand for accurate positioning in wireless networks in GNSS-denied environments. However, current wireless indoor positioning systems cannot satisfy the challenging needs of indoor location-aware applications. Nevertheless, access to a user's location indoors is increasingly important in the development of context-aware applications that increases business efficiency. In this study, how can the current wireless location sensing systems be tailored and integrated for specific applications, like smart cities/grids/buildings/cars and IoT applications, in GNSS-deprived areas.

1. MOTIVATION

The advances in localization based technologies and the increasing importance of ubiquitous computing and context-dependent information have led to a growing business interest in location-based applications and services, such as locating or real-time tracking of physical belongings inside buildings accurately (Farid et al., 2013). Hence, the demand for indoor localization services has become a key prerequisite in some markets.

Positioning systems are used for determining the position and they can be categorized depending on the target environment as either indoor, outdoor, or mixed type (Farid et al., 2013).

Global Navigation Satellite System (GNSS) is one of the most successful positioning systems in outdoor environments. However, GNSS satellite signals are obstructed by the presence of obstacles in the line of sight (LoS) between the satellite and the receiver in closed structures, which makes the GNSS unsuitable for indoor location estimation and indoor navigation due to the high attenuation of GNSS signals across enclosing materials, resulting in non-negligible positioning errors. Although, one manages receive the GNSS signal inside a closed environment, like buildings, the signal strength is not sufficient enough and remains a limiting factor for the performance of GNSS within indoor environments.

In recent years, numerous different systems are developed for indoor localization in many end-user applications by aiming to provide the highest accuracy at least cost in order to eliminate GNSS deficiencies in GNSS-deprived areas. These systems differ in respect to accuracy, coverage, frequency of location updates, and cost of installation and maintenance. Among these solutions, radio-based localization systems surpass the others.

Radio Frequency (RF)-based technologies are commonly used in location systems because of some advantages; for example, radio waves can penetrate through obstacles like building walls and human bodies easily. Due to this, the positioning system in RF based has a larger coverage area and needs less hardware comparing to other systems. (Farid et al., 2013)

In comparison with outdoor environments, sensing location information within indoor environments requires a higher precision and is a more challenging task in part (Alarifi et al., 2016) because of severe multipath, low probability for availability of LoS path, and specific site parameters such as floor layout, moving objects, numerous reflecting surfaces, and disperse signals (Liu et al., 2007).

Wireless location sensing systems are used in the numerous real-world application areas since wireless information access is now widely available. However, none of the existing technologies can meet the challenging demands of indoor localization, tracking targets of interest, mapping environment, navigation of the user and location-aware applications since there is a great diversity in the accuracy, range, availability and costs of indoor positioning systems.

A central problem in location-aware computing is the determination of physical location. Indoor localization typically relies on measuring a collection of RF signals in conjunction with positioning algorithms corresponding to different measuring principle. Once the readers, such as Access Points (APs), beacons, are positioned at fixed locations in a given environment, the location of the receiver, such as nodes, tags, is determined by analyzing the various aspects of the communications between readers and mobile devices (receivers). There are many kinds of indoor sensors and each sensor has its own advantages and disadvantage. Table 1 briefly compares the current indoor localization technologies. After determining the distance between readers and mobile clients, the next step is to estimate the position of the node within the given area. Several computation methods are available and the choice of a method depends on the application requirements. Table 2 compares the positioning methods in general and the methods of determining location of mobile devices are given as follow:

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1. Model-based
    1.1. Proximity Detection
    1.2. Triangulation
        1.2.1. Direction-based (Angulation)
            1.2.1.1. Angle-based
                1.2.1.1.1. Angle of Arrival (AoA)
        1.2.2. Distance/Range-based (Lateration)
            1.2.2.1. Time-based
                1.2.2.1.1. Time of Arrival (ToA)
                1.2.2.1.2. Time Difference of Arrival (TDoA)
                1.2.2.1.3. Round Trip Time (RTT)
            1.2.2.2. Phase-based
            1.2.2.3. Signal Attenuation-based
2. Scene Analysis
    2.1. Fingerprinting
    2.2. Map Matching
3. Dead Reckoning

At first glance, it is easy to observe that indoor localization and mapping are very different from outdoor counterpart because of the complex nature of indoor environments. For instance, positioning systems used outdoor and indoor can vary, positioning systems used in different buildings can vary, beacons/access points used in different parts of the same building can vary. Hence, it is needed to combine measurements from different signal sources even in the same location and detect a particular region of a building to trigger a particular positioning service.

Indoor location applications have varying accuracy needs. The type of venue determines the type of location applications and hence the accuracy needs. The type of user (consumer, enterprise, public) determines the type of location application and deployment model even in the same venue.
Since the ecosystem of indoor positioning systems are very large subject and indoor positioning opens up a market for many players, the following research topics are worth considering:

- How to deploy sensors to improve the positioning accuracy
- How to extend the positioning range
- How to combine different wireless positioning systems, in terms of positioning technologies and/or positioning algorithms, with other technologies such as inertial, ultrasound, vision sensors (as sensor fusion)
- How to integrate indoor and outdoor positioning system
- How to evaluate the proposed models by researchers and companies

In the context of this study, while trying to answer the questions above, how indoor location sensing technologies can be integrated with smart cities, context-aware applications, IoT applications that will be expressed. It is needed to emphasize that what can be expected from indoor positioning in a highly dynamic and diverse real-world environment? To handle all these issues, indoor positioning and navigation applications need an indoor localization framework and figure 1 displays the components of proposed indoor localization framework in this study.

2. POSTIONING ALGORITHMS

For indoor environments, it is difficult to find a LoS channel between the transmitter and the receiver. Radio propagation in such environments would suffer from multipath effect. The time and angle of an arrival signal would be affected by the multipath effect; thus, the accuracy of estimated location could be decreased. An alternative approach is to estimate the distance of the mobile unit from some set of measuring units, using the attenuation of emitted signal strength. Signal attenuation-based (or Received Signal Strength (RSS)-based) methods attempt to calculate the signal path loss due to propagation. (Liu et al., 2007)

IEEE Standard 802.11 for Wireless Local Area Networks (WLAN) defines Received Signal Strength Indication (RSSI) as the determination of the propagation distance between the reader and the unknown node by measuring the signal's degree of attenuation. Mobile device receives the RSSI from beacon nodes on the WLAN. The RSSI is decreased exponentially as the distance from AP increased, and this can be expressed by a path loss model (Farid et al., 2013). Since the strength is inversely correlated with the distance from the AP to the receiver, the distance travelled by the packets can thus be estimated.

One solution is measuring the signal strength and estimating position using trilateration, i.e., trilateration of RSS-based ranges. To estimate the distance between two stations, first of all, the RSSI is needed to be converted from the difference between the transmitted signal strength and the received signal strength into distance value through an appropriate indoor path loss model, for instance free space path loss given in the following formula (1 and 2). Thereafter, the distance estimation can be achieved by generating circles around each non-collocated, non-collinear transmitters and the receiver must be at the position where the circles from each transmitter coincide or by using the Extended Kalman Filter to compute the position of the mobile device on the basis of distance estimates, and finally updates the location estimation using least square estimation or residual weighted least square algorithm.

$$\text{PathLoss}_{\text{dB}} = 10\,\log_{10}\left(\frac{4\pi \text{ x Distance}}{\text{Wavelength}}\right)^2 \quad (1)$$

$$\text{Power}_{\text{RECEIVER}}(\text{PR}) = \text{Power}_{\text{TRANSMITTER}}(\text{PT}) - \text{PathLoss}_{\text{dB}}$$

$$\text{Distance (d)} = 10^{\frac{\frac{PT}{10} - PR - 10\,log10\left(\frac{4\,\pi}{Wavelength}\right)}{20\ \mu}} \quad (2)$$

Due to severe multipath fading and shadowing present in the indoor environment, RSS-based models do not always work. The problem with such an approach is that the signal strength is a poor indicator of a distance. If signal strength is low, either the mobile device is far from the reader or there is an obstacle between the reader and the node. Another solution to solve this problem is fingerprinting matching. As displayed in figure 2, the location method of fingerprinting first collects features (fingerprints) of a scene and stores the set of signal strengths in a fingerprint database. Then, if a device wants to determine its location, it can compare the set of currently measurable signal strengths to the fingerprint database (a priori location fingerprints), and the closest match is assumed to be close to the current location.

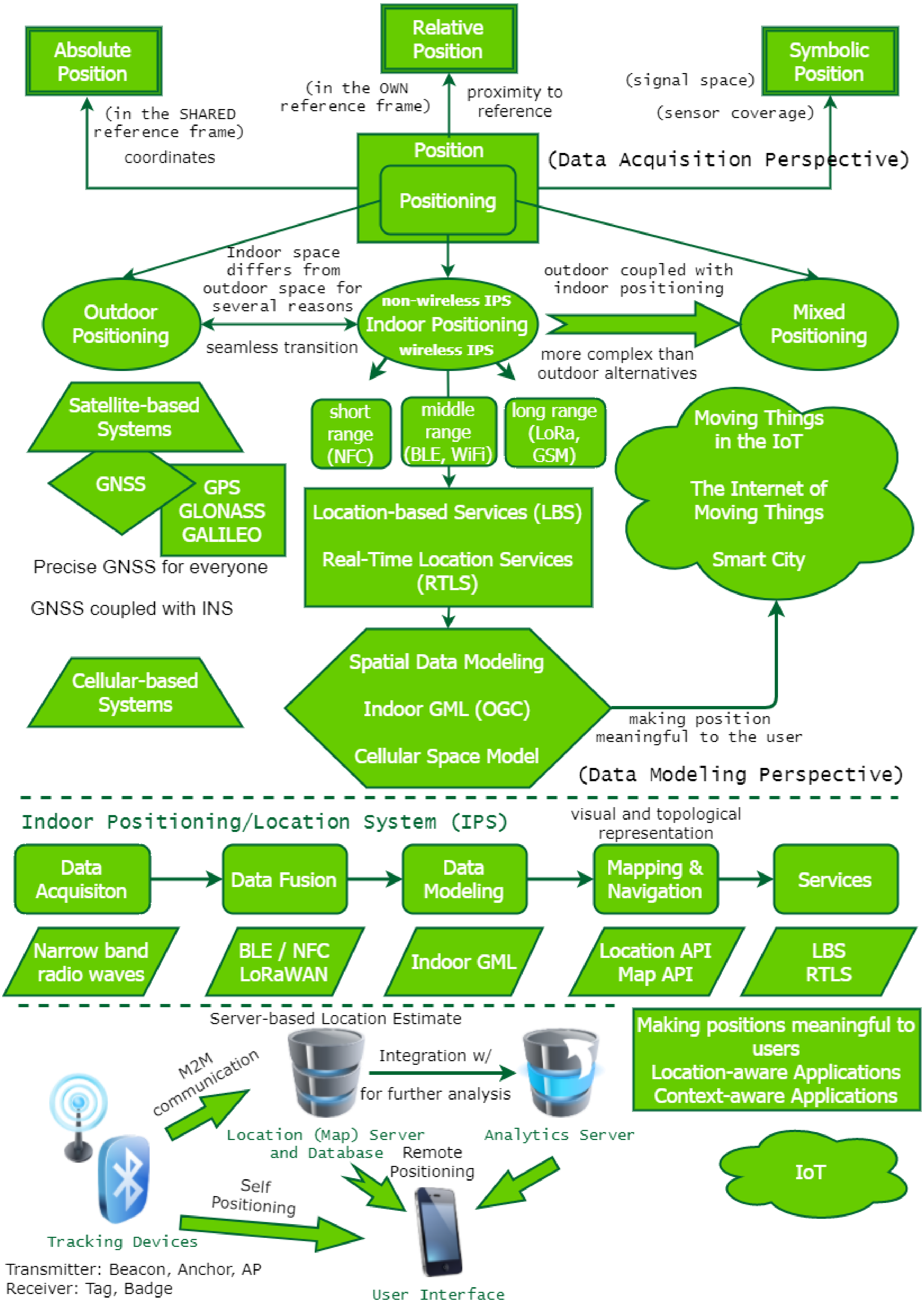

Figure 1. Positioning and Indoor Localization Framework

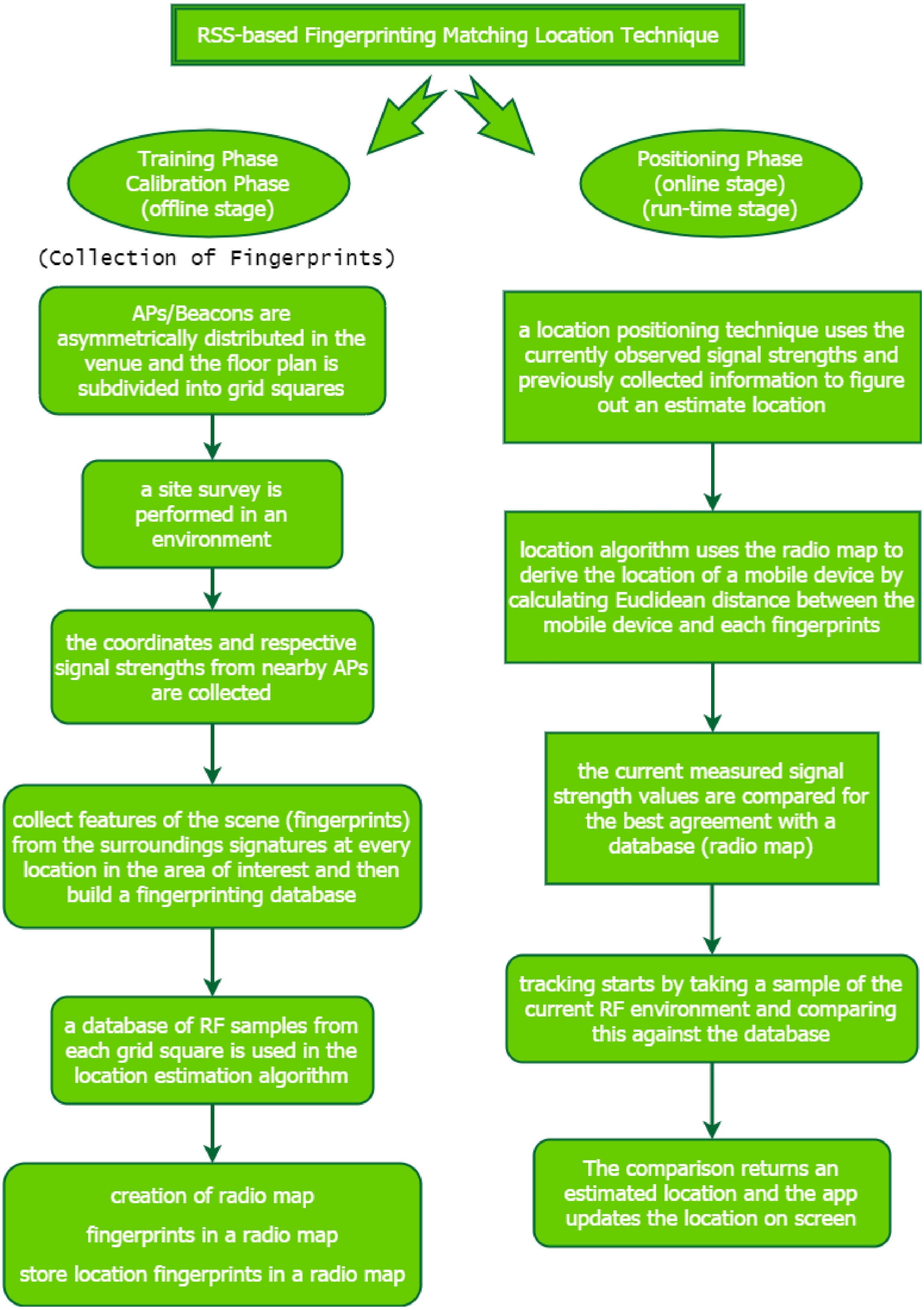

Figure 2. Fingerprinting Matching Technique Workflow

Existing Indoor Positioning and Navigation Technologies

Signal Type	Strength	Weakness	Opportunity	Threads	Range (Coverage)	Accuracy (Location Error)
Non-Wireless Technologies						
Vision **(Camera) (Network of Cameras)**	Resolution down to a few centimetres with up to 120 frames per second	1.) Direct LoS is needed 2.) LoS communication computationally expensive 3.) Need to integrate large network of cameras 4.) Computationally more expensive than trilateration	Hybrid positioning with wireless beacons			High Accuracy
Inertial Systems (motion sensors)	Provides motion information	Dead reckoning: The positional calculation errors increase cumulatively when the calculation of the new position is based on the previous DR position.	Potentially can reduce use of the radio			
Wireless Technologies						
Infared (IR-based)	1.) small, lightweight devices 2.) easy to carry out 3.) Precise indoor positioning determination (good accuracy inside the block) 4.) LoS communication between transmitter and receiver without interference from strong light sources 5.) no invasion of multipath	1.) LoS communication 2.) In a closed environment can easily be blocked by objects 3.) Short range detection since cannot emit through walls 4.) interference from fluorescent light and sunlight 5.) security and privacy issues 6.) expensive system hardware and maintenance cost				1m-2m
Laser	Phase difference or Time of Flight	LoS communication				
LED Lights (LiFi)	Visible Light Communication (VLC)		Light-based WiFi		<8m	<50cm
Sound (Ultrasound) (Mechanical Wave) (audible)	1.) accuracy (in centimeters) 2.) no invasion of multipath	1.) LoS communication 2.) needs many ceiling mounted ultrasonic detectors which are expensive to install 3.) unable to penetrate walls but reflects off most of the indoor obstructions 4.) sensitive to environmental (suffers a lot of interference from reflected ultrasound signals				3cm-1m

		propagated around by other sources such as the collision of metals)				
Indoor GPS (Satellite-based)	Independent from local infrastructure and worldwide coverage (satellite based positioning)	1.) Low acuracy 2.) Needs new infrastructure (expensive) 3.) High power consumption 4.) Multipath	1.) Pseudolites 2.) A-GPS 3.) IMES	very high power consumption		5m-20m
FM Radio (frequency-division multiple access : FDMA)	1.) low cost 2.) indoor and outdoor coverage 3.) less susceptible to objects 4.) Signal is strong; due to this, it covers large area		It is widely available across the globe especially in most households and in cars			2m-4m
Radio Frequency Identification (RFID)	1.) one way wireless communication 2.) no need LoS contact 3.) (passive RFID) low price of tags, no battery required in tag 4.) (active RFID) low price of reader, tag does require battery, battery life expected to be used to 1-3 years	1.) Needs new infrastructure 2.) response time is high 3.) high cost of the active RFID tags, which does not provide a cost efficient solution			passive RFID (3 m or less), active RFID (100m or more) (tens of meters)	1m-2m
Wireless Local Area Network **(WLAN)** **Wireless Fidelity (Wi-Fi)** **(IEEE 802.11x)**	1.) cost-effective solution (no costly requirement of infrastructure and hardware) (locate the position of almost every WiFi compatible device without installing extra software or manipulating the hardwares) 2.) Able to leverage and reuse existing and widely available WLAN infrastructure (unlike UWB, BLE) which eases deployment and maintenance 3.) specialist equipment is not required to provide location information 4.) WiFi signals are able to penetrate walls 5.) LoS is not required	1.) signal attenuation of the static environment like wall, movement of furniture and doors 2.) (initial deployment is expensive) heavy setup costs in laying the foundation for WiFi position tracking 3.) WiFi APs may be unreliable, inconvenient, and poorly placed for the situation at hand 4.) multipath susceptibel slightly 5.) power consumption is very high	1.) the most widespread approach for indoor localization 2.) the advantages of widespread use of Wi-Fi networks (WiFi is everywhere) (universal)	needs to have power supplier	<150m	1m-5m (experiment) 5m-15m (real world)
Bluetooth Low Energy (BLE) (IEEE 802.15)	1.) high security, low cost, low power, and small size 2.) Lightweight communication between devices 3.) peer-to-peer messaging 4.) Data transfer speed is high	1.) Beacons need to be installed once and checked regularly for battery levels 2.) requres many beacons 3.) in each location finding, it runs the device discovery procedure (due to this, it	Bluetooth 5.0: Up to 2x bandwidth of Bluetooth 4.2 with low energy, Up to 4x range of Bluetooth 4.2 with low energy		<300m	1m-5m (experiment) about 5m (real world)

		significantly increases the localization latency and power consumption as well)				
Ultra Wide Band **(UWB)**	1.) (low power consumption) UWB tags consume less power than conventional RF tags 2.) UWB provides a high accuracy positioning (many times more accurate than today's positioning technologies (WiFi, BLE, RFID or GPS) 3.) UWB location exploits the characteristics of time synchronization of UWB communication to achieve very high indoor location accuracy 4.) Short-pulse waveforms permit an accurate determination of the precise TOA 5.) high level of multipath resolution 6.) UWB the signal passes easily through walls, equipment and clothing 7.) does not interfere with most of the existing radio systems	1.) needs new infrastructure 2.) UWB hardware is expensive, making it costly for wide-scale use 3.) metallic and liquid materials cause UWB signal interference 4.) UWB technology may affect GPS and aircraft navigation radio equipment and can also cause interference to the existing systems that operates in the ultra wide spectrum				few cm 5cm-20cm
ANT/ANT+ (IEEE 802.15.4)	1.) ultra low power 2.) specifically designed for wireless sensor networks 3.) easy to use with low system cost		ANT+ is a set of mutually agreed upon definitions for what the information sent over ANT represents	"		
Near Field Communi-cation (NFC) **(IEEE 802.15.4)** **(touchable)**	1.) the highest accuracy, because when a user touches a tag, the exact location is retrieved immediately 2.) security and privacy 3.) low cost 4.) NFC tags are passive components that do not contain any batteries hence these do not require replacement with respect to power failure	1.) not an inherent capability of most mobile devices 2.) position is determined by touching the mobile device to the NFC tags 3.) communication over short range 4.) Real time positioning cannot be provided in NFC Internal system. The DR method is used by NFC Internal to calculate an approximate location when the user is moving between Location Tags, and fixed positioning will be performed immediately after the user touches to the next tag.	1.) the majority of smartphone manufacturers have started to adopt NFC 2.) payment technology in their products as a "de facto standard"	If the density of placed tags is low with respect to the user traffic, queues may occur in front of many tags. Additionally, queues will possibly occur in front of Location Tags located a certain key places such as elevators. To prevent queues in such places, redundant tags can be deployed so that a visitor can use another spare tag if another user is already using the other tag.	10 cm or less (between 0 and a few cm)	Highest Accuracy

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Cellular-based (GSM/CDMA)	1.) outdoor and indoor positioning	1.) Not very high accuracy the accuracy is higher in densely covered areas (e.g, urban places) and much lower in rural environments 2.) accuracy depends on the cell size				(outdoor) 50-200m (indoor) <5m
Femtocell **(4G LTE small cells)**	rich signal strength information	small cells have limited range (comparable to the typical WiFi AP coverage)	they could be used, in combination with indoor radio technologies, as inputs to a localization system			
LPWAN LoRa / LoRaWAN	1.) low power, long range wireless communication technology 2.) low cost, low power Internet of Things (IoT) networks 3.) GPS-free geolocation technology (Network-based Geolocation) 4.) works both outdoors and indoors		1. LoRa (LoRa Alliance) 2. NB-IoT (Vodafone and Huawei) 3. Sigfox		(outdoor) 15km, (indoor) 3km	10m-100m
ZigBee	1.) It is mainly designed for applications which require low-power consumption but do not require large data throughput 2.) Low data transmission rate 3.) Nodes are mostly asleep	open to interference from a wide range of signal types using the same frequency which can disrupt radio communication because it operates in the unlicensed ISM bands			20-30m	3m-5m

Table 1: Existing indoor localization technologies

Comparison of Indoor Localization Methods

Methods	Advantages	Disadvantages
Proximity Detection (Connectivity Based Positioning)	relatively simple to implement	provides symbolic relative location information
Angle of Arrival (AoA) Direction of Arrival	1.) no time synchronization between measuring units is required 2.) NLoS propagation of signals	1.) affected by multipath effect, thus degrade the accuracy 2.) requires additional antennas (directional antennae or with an array of antennae to measure the angles which increase the cost of the system 3.) For accurate positioning, the angle measurements need to be accurate, but not easy

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Time of Arrival (ToA)	1.) high accurate technique used in indoor environment which can filter out multipath effects 2.) the one-way propagation time is measured	1.) all transmitters and receivers in the system have to be precisely synchronized 2.) affected by multipath effect, thus, the accuracy of estimated location could be decreased 3.) For time delay measurement, an additional server will be needed which will increase the cost of the system 4.) increased delay can also be propagated by a denser environment, in terms of more people.
Time Difference of Arrival (TDoA)	1.) when implemented correctly is an accurate method	1.) affected by multipath effect, thus, the accuracy of estimated location could be decreased 2.) less used method due to the precision required with synchronization of clocks of the devices within the system 3.) needs an infrastructure support
Round Trip Time (RTT) Time of Flight (ToF) Round-Trip Time of Flight (RToF)	1.) solves the problem of synchronization to some extent (according to ToA)	1.) range measurements to multiple devices that need to be carried out consecutively which may cause precarious latencies for applications where devices move quickly 2.) affected by multipath effect, thus, the accuracy of estimated location could be decreased
RSS-based Signal Attenuation-Based	1.) One of the most commonly implemented techniques, due its practicality, low cost and availability 2.) Uses properties of the received signal, with RSSI being the most widely used signal-related feature	1.) RSS inversely proportional to square of distance 2.) need to calculate the signal path loss due to propagation, can be energy inefficient and path loss models vary widely with venue 3.) This method can only be possible with radio signals
Received Signal Phase Phase of Arrival	Needs an LoS signal path, otherwise it will cause more errors for the indoor environment	Ambiguous carrier phase measurements to overcome
Fingerprinting	1.) no time synchronization necessary between the stations 2.) use of maps is an efficient alternative to the installation of additional hardware	1.) Lower level of accuracy 2.) Fingerprinting does not need geometric surveys 3.) Site surveying time consuming and labor intensive 4.) RSS could be affected by diffraction, reflection, and scattering in the propagation indoor environments 5.) RSS changes in variations due to time 6.) To maintain the positioning accuracy, the calibration process should be periodically repeated to a recalculation of the predefined signal strength map.
Dead Reckoning	1.) provides very accurate directional information 2.) very widely applied	1.) the inaccuracy of the process is cumulative 2.) the deviation in the position fix grows with time

Table 2: The comparison of spatial positioning algorithms

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In order to estimate the location of a device, fingerprinting-based positioning algorithms use pattern recognition techniques, which are either deterministic or probabilistic. Some instances of positioning algorithms are K-nearest-neighbor (KNN), weighted K-nearest neighbors, Naïve Bayes, artificial neural networks, Bayesian inference, Markov Chain Monte Carlo, support vector machine, WASP, or their combinations. (Chapre et al., 2013)

Fingerprinting accuracy performance depends on the number of base stations and the density of calibration points where the fingerprints are taken (Farid et al., 2013).

As expressed in table 2, each location estimation algorithm has unique advantages and disadvantages, hence, using more than one type of positioning algorithms at the same time could get better performance depends on the indoor environment and application type. Hybrid methods seem promising as they are more tolerant to external side effect of interference and reflection (Alarifi et al., 2016). For instance, the combination of fingerprinting matching and trilateration technique enhances the accuracy of the user position in an indoor environment. For an indoor positioning system, it is possible to use the signal phase method together with ToA/TDoA or RSS method to fine-tune the location positioning (Liu et al., 2007). Cook and his colleagues suggest using the position estimate generated by the trilateration algorithm as a characteristic of a location rather than an absolute position. They hope to use this “expected” position to recognize pre-known locations and are investigating the use of pattern matching techniques, such as Fuzzy Logic, to allow the system to associate live data with the stored results (Cook et al., 2005). The pedestrian dead reckoning (motion data from the smartphone) with position fixes (such as NFC tags) and the Simultaneous Localization and Mapping (SLAM) algorithm adapted for RF signal data (Mirowski et al., 2013). Google announced a new service to offer detailed indoor location positioning using its Tango 3D sensing computer vision technology, called Vision Positioning Service (VPS). VPS makes use of a Tango-enabled mapping system that uses augmented reality on phones and tablets to help navigate indoor locations.

3. RELIABLE LOCATION IN REAL-WORLD ENVIRONMENT

The majority of the existing research on indoor positioning centers around the improvement of positioning accuracy. However, currently there exists a limited understanding of how positioning algorithms proposed in research behave in real world settings, since many evaluations have been conducted on small data sets over short periods of deployment only or in small environments. This makes the related research strong but somewhat narrow focus on improving positioning accuracy, sometimes neglecting to evaluate other concerns which manifest in real-world deployments. There is missing a unanimous evaluation methodology appropriately reflecting criteria relevant in real-world use scenarios and their diversity. This leads to major challenges -and often disappointments- when implementing positioning methods in the hope of the promised accuracies. (Mathisen et al., 2016)

Radio signal propagation is highly dependent on a number of factors, such as attenuation across materials (or human presence), interference from other wireless devices, and various objects reflect or round corners refract signals – known as multipath signal propagation. This means that it is not easy to model the radio propagation in the indoor environment and, thus, the wireless indoor positioning technique is inherently inaccurate.

The prevalent limitation in using RSSI from a reader is the deviation of attenuation in the signal, which renders signal strength a measure hard to predict, as it changes chaotically and significantly with only small changes in position and tends to fluctuate over time (Mathisen et al., 2016). The RSS at a particular location and instant of time is average of the signal received through different paths (multipath effects) and it varies due to various in-path interferences. Therefore, it becomes crucial to determine the factors that affect RSS (Chapre et al., 2013).

In the indoor positioning literature, accuracy and precision are the most important concepts of the location. However, there is serious concern on reliability of the RSSI in fingerprinting. So far, many characteristic features of RSSI have not been thoroughly investigated in the literature. Many researchers have relied on the RSSI as signal information to determine objects location while ignoring the characteristic of RSSI. For instance, any physical barriers, such as materials or human presence, can drastically affect the signal travel time, potentially decreasing the accuracy and performance level of the systems.
The robustness of the indoor localization is related to the received signal and its strength. The factors, which causes of RSS variations, can be classified into the following areas (Chapre et al., 2013):

- Hardware
  - Orientation of the receiver, i.e. directionality of the antenna (bidirectional, omni-directional etc.)
  - Hardware quality: WLAN card, type of antenna

The RSSI fluctuations are quite significant even for a single hardware. In the case of multiple devices from different vendors are used, this variations will be amplified even further due to different sampling rates and quantization bins.

- Temporal
  - Need to analyze the time-variant nature of RSS in terms of its variation, distribution, nature and number of samples over time (time and duration of measurement).

Location signature captured at a location during the day time may not be same during night time. This difference in location signature may affect the localization accuracy, since it uses pre-stored radio-map. Therefore, it is important to determine the temporal variations of RSS.

- Interference
  - RF interference due to nearby devices operating is same or nearby radio channel radio channel (or other radio devices)
  - interference and noise originating from wired and wireless networks within the structures
  - Influenced by florescent lights, sunlight
- Human Presence
  - Presence, orientation, movement of human body and number of people around affects the RSSI

Human body that contains more than 50% water, absorbs the radio signals.

- Environment
  - Building types and materials
  - obstacles (i.e., building geometry, walls, equipment), which reduce the propagation capability of electromagnetic waves
  - Building environment: Sample data gathering at different building complex parts (from a small office environment, to a large dynamic building complex)

Several factors can contribute to the enhancement of positioning performance. For example, the data is logged for four different orientations of the mobile device (east, west, north and south) (Chapre et al., 2013), the RSS values are to be averaged over a

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certain time interval up to several minutes at each fingerprint location.

4. INDOOR MAPPING AND BUILDING RADIO MAPS

The main challenge to the techniques based on location fingerprinting is sensitivity to environment changes such as object moving into the building (e.g., people, furniture), and RSS could be affected by diffraction, reflection, and scattering in the propagation indoor environments, which result in changes in signal propagation. To maintain the positioning accuracy, the calibration process should be periodically repeated to a recalculation of the predefined signal strength map. (Farid et al., 2013) (Liu et al., 2007)

Site survey of the training phase is performed generally by walking predefined routes at constant speed. The time and effort to manually collect signal fingerprints are often considered too costly in maintenance by stakeholders and vulnerable to environmental dynamics.

The challenging methods for automatically generating and updating signal coverage map within indoor environments are as follow:

- Indoor robotics method: Autonomous RF signal and venue mapping using indoor mobile robots
    - Wheeled robots can be impractical in some buildings or some locations in the building, such as staircases, elevators.
    - Unmanned Aerial Vehicles (UAVs) can be utilized
    - Mobile robot requires an Inertial Measurement Unit (IMU)
    - Involves deployment costs
- Crowdsourcing method: RF signal mapping using crowd-sourced pedestrian trajectories
    - Users will collect time stamped RF signals (such as WiFi, Bluetooth, small cell, UWB, NFC signals) based on inertial data while walking freely through a building at different speeds, taking care of their daily activities
    - Basically using only motion sensors available on a smartphone in the user's pocket
    - Wearable systems consisting of a color and depth (RGBD) camera, laser rangefinder can be utilized
- A calibration-free location algorithm

5. INDOOR SPATIAL DATA MODELING

Because of the unpredictable and complex nature of real world environments and depends on the application, accuracy requirements can be vary, for instance, some applications can ask this question any time "where is the user within a building?" Other applications do not need to know the location of the user at all times – it is only interested in when the user is in particular locations (Cook et al., 2005). The application which not need accurate position estimates, then, topological representation of the study area (based on a priori knowledge on the environment) may enhance the positioning/navigation/tracking performance. The use of a topological model can dramatically reduce the time required to train the localizer, while the resulting accuracy is still sufficient for many location-aware applications (Liu et al., 2007).

A user specifies the name or description of the destination on the graphical interface of the Location API, the location application/service first calculates the optimal route to the destination according to the user's preferences, for instance using elevators, stairs, and escalators to a different floor using shortest path algorithm based on the topological representation of the venue, then navigates the user to the destination point by giving real-time instructions.

There are two key issues in the indoor positioning and navigation modeling process: fast 2D/3D modeling and spatial model validity and accuracy problems.

Simultaneous Localization and Mapping (SLAM) has recently been extended to incorporate signal strength from WiFi in the so-called WiFiSLAM algorithm (URL 1).Another approaches WiFiGraphSLAM based on the extension to WiFi of the GraphSLAM algorithm and RFSLAM (SignalSLAM) based on the extension to RSS for WiFi and Bluetooth, and Reference Signal Received Power (RSRP) for small cells of the GraphSLAM algorithm (Mirowski et al., 2013).

Using a SLAM algorithm, like WiFiSLAM, SignalSLAM, floor plans and RF signal maps can be generated at the same time. Topologically-enhanced venue map encoded with thematic maps of RF signal fingerprints can be used as an indoor spatial data model for humans and robots.

6. INDOOR LOCALIZATION OF MOBILE ROBOTS

In recent years, there has been a rising demand in the use of multiple Unmanned Aerial Vehicles (UAVs) in indoor environments in various indoor applications such as exploration, search and rescue, time-sensitive medication or supplies delivery, manufacturing, indoor precision farming. For all these applications an imperative need for UAV autonomy is the ability to self-localization in the environment and to interaction with the environment. The challenge is to use radio based localization systems in GNSS-deprived environments for indoor localization of UAVs.

If the different scale of control of UAVs within an enclosed environment is categorized according to the required spatial resolution, it can be broadly generalized into two: micro-control and macro-control. In a closed environment, macro-control refers to the control of UAVs from one 3D point to another (i.e., its maneuverability across regions or chunks of space within the entire environment). If so, micro-control focuses more on the control around a point space of reference within a chunk of space and its maneuverability in the space around that point. For the macro-control a few meters of resolution is sufficient, on the other hand, a spatial resolution of less than one meter error is required for the micro-control. (Mui, 2014)

In order to improve the performance of indoor location and navigation of UAVs on-board sensors data, such as IMU, vision systems, laser rangefinders, can be fused data from radio-based indoor localization techniques, in particular, for macro-control considering its ease of integration across various environments. However, only using radio based localization is insufficient for micro-control of UAVs. The same approach is also valid for mobile wheeled robots, for instance, A robot moving through a doorway needs to be sure that it is going to make it through without bumping and damaging the sides of the door. Hence, meter-level location accuracy simply is not good enough for moving through a doorway.

7. LOCATION AWARENESS & LOCATION-AWARE APPLICATIONS

Advances in the smartphones and the availability of equipment at affordable prices have increased in the popularity of Location Based Services (LBSs) over recent years. LBS is also an important component for a smart city. Central to such service is accurate positioning of users. While GNSS has been widely and successfully used for outdoor services, deploying indoor positioning technologies is still at its infancy. Indoor positioning technologies can be divided into two parts, one on client-based active localization and the other one on sensor-based passive tracking. With the location-based data collected, one can then conduct user analytics to under behaviors and offer timely and novel services. The ability for accessing to a user's location indoors is increasingly important in the development of context-aware applications that increase business efficiency (Cook et al., 2005).

Positioning and context information is becoming more important. In order to make user's position meaningful to the user, context information can be sent to the mobile user on the move at the right time and the right location, such as new events, offers, alerts in indoor environments are pushed to user. Location information can be also used to improve the quality of users' experience and to add value to existing services offered by wireless providers (Farid et al., 2013).

Innovative indoor location applications and services can be developed on top of positioning, which allows combining indoor positioning and navigation with the power of business analytics and provides (Geo)Location Intelligence. Some of them can be illustrated as follow:

- Zone-based Real-Time Location Services (RTLS) (Real time location tracking service of users and devices on a map)
- Real-time navigation inside large buildings
- Orientation of a user (visitors, traveler, etc.) in a new indoor environment and improvement of the quality of users' experience in museums, malls, campus, office buildings and transportation hubs (airport, train station, etc.)
- Automatic object location detection
- Event-based spatial monitoring service
- Tracking many user's locations, property, and statistics of traffic flow and detecting possible areas of higher revenue stream
- Optimization of the buildings due to most searched/visited destinations
- Producing temporal heat maps of the buildings which show most taken walking routes
- Indoor discovery pushed to user, for instance, showing the places on navigation path, personal recommendations can be performed based on use schedule, loyalty program, etc.
- Generating a Geofence area restrictions around some entity for push notification about the entrance and exit of an entity of interest, for instance, push notification when child/visitor moved zone

Internet of Things (IoT) is an emerging technology envisioned for the development of smart environments and context aware services. One of the enabling technologies is positioning, which can be simply understood as the estimation problem of object and user locations from radio signals. Especially, technologies like IoT or Wireless Sensor Networks rely on communication of devices over wireless networks. In these kinds of applications, devices need measurement of relative state of other devices in the network as well as environmental parameters. Relative distance between the devices is one of the important parameters to be measured. Machina Research estimates that 60% of IoT devices will use geolocation data, one-third of which will critically depend on it for their application.

Indoor positioning is not very useful without the availability of indoor maps since indoor maps help the user conceptualize her position. However, indoor maps are not standardized and each provider has their own API, such as Google Maps API (Google Indoor Maps), HERE Mobile SDK. Google Maps offers a floor plan generator (URL 2).

8. CONCLUSION

Recently, indoor and outdoor location-aware applications has been become increasingly widespread. Location information for outdoor applications is obtained from satellite and cellular-based technologies, such as GNSS, GSM. Although there are several systems for indoor localization, there is not a consensus on them like the outdoor. Besides there is a huge demand for low cost, low power consumption, low effort, low computational complexity, but efficient, more accurate and reliable indoor positioning/navigation systems in a large and diverse real-world environment.

As a result, this is study has proposed an indoor localization framework with the components of sensor technology, measurement techniques, positioning algorithms, location API, location-based services to provide fine-grain spatial information with low-latency and frequent updates.

The indoor localization framework allow users to locate assets/sensors, track devices/user's location, monitor sensors, detect geofences, navigate people/robots and manage location context.

Since the local positioning systems fail to work outdoors, whereas the GNSS-based positioning systems do not work inside buildings, the indoor localization framework supports seamless indoor and outdoor navigation and wayfinding.

Different prerequisites may require for different indoor applications/positioning problems. There is no 'one size fits all' solution since indoor location applications have varying accuracy needs. Type of venue, type of users affect selecting the right technology in a given use case. If the solution is leveraging existing wireless network infrastructure (e.g. Wi-Fi, cell towers, Zigbee) to locate objects, this solution avoids expensive and time-consuming deployment of infrastructure. If the solution requires new dedicated infrastructure deployment with a specific wireless system, the density of the sensors can be adjusted to the required positioning accuracy. Designing, implementing, deploying and utilizing indoor positioning solutions in real world environments and in different scenarios involve tradeoffs when selecting a specific system in a given use case. A wide variety of technology choices are possible for developing indoor positioning with different tradeoffs. For example, the one tradeoff is between complexity and accuracy, another one is that as the coverage area increases, the complexity becomes an important concern. In addition to those, there is a trade-off between coverage area and accuracy. The last tradeoff but not the end is between accuracy and cost.

The accuracy can be categorized into three different groups due to used wireless technology. First one is sub one meter accuracy (UWB), second is between 1 and 5 meters, in other word room-level (WiFi, BLE), the last one is above 5 meter (GNSS).

According to the framework, GNSS and Long Range Wide Area Network (LoRaWAN) can be used in smart city and smart grid applications, UWB or BLE with NFC can be used in smart buildings. For the smart cars, vehicle-to-vehicle and vehicle-to-infrastructure communication can be provided by means of IEEE 802.11p standard. The key difference between IEEE 802.11p and cellular connectivity pipes to the car is that there is a direct communication among 802.11p equipped devices, however, cellular based services rely on the presence of the network. Within indoor environments, available RF signals and motion sensors (IMU) can be used thorough an adaptation of the GraphSLAM technique.

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