INDOOR LOCALIZATION USING SMARTPHONES: APPROACHES, ISSUES, AND CHALLENGES

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ABSTRACT

LEE JOSEPH EASSON: Indoor Localization Using Smartphones: Approaches, Issues, and Challenges
(Under the direction of Dr. Feng Wang)

Localization has gained priority in an increasingly inter-connected world. The majority of industries and sectors require some means of tracking the location of objects and/or people anywhere on the Earth, whether indoors or outdoors. GPS is an already-implemented and viable solution for outdoor localization. However, indoor localization is more challenging to implement and thus has become a broad area of research. Despite the challenges of tracking location in places where satellite GPS signals are unreliable or unreachable (i.e. within a building or structure), there has been considerable progress made in indoor localization research. Although current indoor localization technology can achieve certain accuracy, they usually requires extra equipment and thus can be too cumbersome and/or expensive for common purposes. A relatively new field of indoor localization research involves using the sensors built into smartphones to triangulate a user's position within a structure. This eliminates the requirement for extra cumbersome sensors or accessories. This honors thesis surveys the current sphere of smartphone-based indoor localization research, analyzing the state-of-the-art approaches, their benefits and drawbacks. A test-bed is also developed to facilitate the evaluation of each method mentioned in this thesis.

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1 Introduction

The need to track the location of people and objects has gained increased importance in the modern world. Every sector from military to commerce to health-care has great demands for tracking the location of personnel or objects. In the military, it is necessary to keep track of where soldiers are located when they are out on a mission [9]. In health-care it is necessary to keep track of where patients are located in a hospital in case something goes wrong and doctors need to be of assistance to a particular patient. In commerce, determining delivery locations and tracking deliveries and delivery vehicles is vital [14]. Technology has been developed over the years that is designed to constantly record and update the tracked location (i.e. latitude and longitude, or x- and y-coordinates on a plane), orientation, and direction of motion of objects.

In general, there are two types of localization demands: outdoor and indoor. Outdoor localization has a wide variety of uses in many industries. For instance, outdoor localization is used heavily in the transportation industry as a means of navigation for vehicles, aircraft, and ships as well as for pedestrians. The Global Positioning System (GPS) can triangulate the position of an object anywhere on the Earth — until the object enters a building. Because GPS relies on reception of satellite signals, triangulating position within a building or structure using GPS is ineffective, as satellite signals can be easily blocked by ceilings and walls [10]. Because of this, it is necessary to use indoor localization to track objects within buildings or places where GPS satellite signals are not well received.

Indoor localization has the potential to provide a multitude of benefits to a variety of situations. Firefighters and emergency responders need to keep track of personnel and equipment even the midst of fire, smoke, and confusion. However, within a burning building, GPS signals are obscured. With an indoor localization sensor attached to each firefighter and piece of equipment, the fire chief is able to know where they are in a building and can determine whether or not they are in danger. A similar utilization can be applied to other professional fields such as park management (e.g. keep track of hikers on trails within thick forest canopy) and health-care (e.g. keep track of hospital patients or elderly nursing home residents).

Because of the beneficial potential of Indoor Localization, it has become a topic of research for many network engineers. A large body or research has been dedicated to indoor localization and many research teams have proposed different approaches to creating practical indoor localization systems with good reliability and accuracy.

However, despite that technology for indoor localization exists, much of it is either expensive, cumbersome, impractical, or less accurate. Recently, a new research direction has been proposed that uses smartphones as indoor localization tracking devices. This thesis explores the current state of smartphone-based indoor localization research, analyzes the benefits and limitations of each approach, and makes discussions and insights striving to identify the appropriate strategy for optimally utilizing the smartphone's sensor suite.

2 Background

2.1 The Need for Localization

Since the beginning of human existence, the need to keep track of things has been an important need. Whether on land, sea, or air, humans have needed determine and track the location of both people and objects, and have invented several ways to do so, including maps, compasses, astrolabes, and sextants [3].

This need for localization has lasted into modern times, and has even gained increased importance. Every sector from military to commerce to health-care to emergency response requires a means of locating personnel and objects. In the military, it is important to keep track of where soldiers are located when they are out on a mission. In commerce, it is required to track the routes and locations of packages and deliverable goods anywhere on planet earth. In health-care it is necessary to keep track of where patients are located in a hospital in case something goes wrong and doctors need to be of assistance to a particular patient. In emergency response, it is important to trace the quickest route to direct ambulances, firetrucks, or police cars to the site of the emergency.

Because of the modern need for localization, humans have derived dozens of technologies, systems, and software designed to pinpoint location, track position and motion, and provide remote direction.

2.2 Outdoor Localization

Outdoor localization is the process of pinpointing the position, including location (X and Y coordinates), altitude, orientation, and direction of motion. Some of the most effective and widely used means for outdoor localization include Radio Detection and Ranging (RADAR), Long Range Navigation (LORAN), and Global Navigation Satellite System (GNSS), the most common of which is the Global Positioning System (GPS) [3] [14]. GPS is one of the most widely used outdoor localization methods due to its high accuracy (up to 10 meters [5]) and adaptability making it useful for many situations. GPS is a system consisting of three parts: a network of 24 artificial satellites, a corresponding network of ground stations, and receivers (e.g. a smartphone GPS app) [17]. The satellites orbit earth at an altitude of 20,000 km (13,000 miles) and are relatively stationary at all times making them reliable points of localization similar to stars in constellations [18]. Using a process called trilateration, at least three satellites are used to triangulate the position of the receiver as shown in figure 1 [19].

The ground stations are used to ensure that the GPS satellites are in the appropriate positions of their orbits in order to ensure that the triangulation is accurate [17].

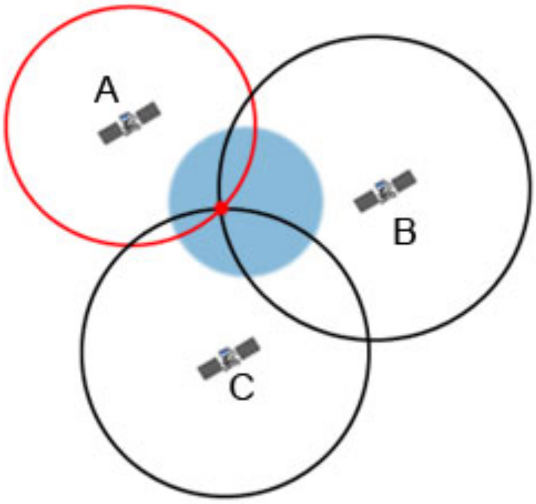


Figure 1: Trilateration using GPS satellites [19]

Because of these properties, GPS is excellent for tracking the location of objects anywhere on earth — unless the object is inside a structure. The major flaw with GPS and other outdoor localization systems is that they fail to function normally when tracking objects whose location is obscured by building walls, layers of earth, dense vegetation, or heavy atmospheric interference. Because of this flaw, a system designed to track personnel and objects that are within buildings, underground, or covered by a thick forest canopy is incredibly necessary. For cases such as these, an alternate means of localization is needed: Indoor Localization.

2.3 Indoor Localization

As opposed to outdoor localization, indoor localization is the process of pinpointing position, including location (X and Y coordinates), altitude, orientation, and direction of motion for an object located within a structure or any other location where GPS signals cannot be well received. Because of the need to track the location of personnel and objects when GPS is not a viable option, indoor localization has become an active research topic. Because of the amount of research on indoor localization, several pieces of indoor localization technology have been developed that are designed to overcome the limitations of GPS.

A relatively new area of research in indoor localization involves using a smartphone as a means to track location in a manner similar to a GPS app. One may wonder, since technology for indoor localization exists, why smartphone-based indoor localization is necessary. Much of the currently existing indoor localization technology is incredibly accurate, such as the indoor localization system using

Rao Blackwellized particle filter (RBPF) as presented in the *Chinese Journal of Aeronautics* with an error below 1.2 meters [12] and some systems like the Cricket indoor localization system are accurate down to the centimeter [3]! Despite great accuracy, there are downsides to both of these systems that make smartphone-based localization a relatively more viable option.

In particular, both the RBPF setup and the Cricket Indoor Localization system mandate the use of external sensors in order to be fully functional. The RBPF system requires a foot-mounted Microstrain inertial sensor in addition to a Samsung Galaxy tablet [12], and the Cricket indoor localization system requires that an ultrasonic sensor be placed in every room [3]. The cost of the foot-mounted inertial sensor with the relative cumbersomeness of a tablet for the RBPF setup, and the cost of installing and maintaining an array of ultrasound sensors for the Cricket system can make these setups either expensive, inconvenient, or both for enterprises despite their great accuracy [3] [12].

Currently, some of the most accurate indoor localization systems address the needs of the military and first responders. However, the current consensus in indoor localization research for military purposes is to use a multi-sensor fusion (i.e. system consisting of an array of sensors working in harmony) in order to achieve maximum accuracy. These sensors include GPS receivers, inertial sensors, radios, magnetometers, barometers, altimeters, ultrasonic sensors, Doppler radars, and imaging sensors all placed in a Body Area Network (BAN) on the soldier [9]. Although designed to be as lightweight and efficient as possible, the array of sensors dramatically increases the cost of these indoor localization systems and would be impractical and cumbersome for civilian use.

Some smartphone-based indoor localization setups are designed in such a way that requires additional sensors attached to the smartphone. External sensors for indoor localization can include ultrawideband radios and ultrasonic sensors, among others, that can be attached using the external ports on the smartphone or wirelessly using Bluetooth, BLE, and/or WiFi. Because of the cost of the extra components, indoor localization systems that use external sensors are more expensive and complex than systems that function with native sensors [14] and thus, this thesis avoids discussion of indoor localization systems that mandate the use of external sensors in order to achieve accurate localization, even if they do utilize a smartphone. The indoor localization systems discussed in this thesis will be referred to as smartphone-only indoor localization systems.

Smartphone-based indoor localization systems that use the sensors natively built into the smartphone, do not require any external sensor, and are accurate to a reasonable degree could prove to be highly effective and cost-efficient for a variety of purposes. The next section will detail two of the most compelling advantages of smartphone-based indoor localization system and provide a brief discussion on the sensor suite within a modern smartphone and how each sensor can be utilized for a smartphone-based indoor localization system.

2.4 Smartphone-only Indoor Localization

2.4.1 Benefits

2.4.1.1 Ubiquity In modern times, it is uncommon for someone to be without a smartphone. In almost every first-world country, the average middle class citizen is bound to own at least one smartphone which they carry with them at all times for the purposes of work, communication, and/or entertainment. This makes smartphone-based indoor localization great for emergency situations, because people will always have a means of emergency notification and navigation to the nearest safety exit even if they happen to be in a private location such as the restroom.

2.4.1.2 Convenience Many of the previously mentioned indoor localization systems all require the use of external sensors to a certain degree — some require only one extra sensor, while some require an array of sensors. A smartphone-based indoor localization system that does not require any additional sensors to be attached to a smartphone is incredibly convenient for most users. If the process of becoming a user of an indoor localization system is as simple as downloading an app that reads data from the smartphone's native sensors, many more people will find it easy to implement onto their devices (incredibly important in emergency situations). Finally, because people paid money for and claim ownership of their smartphones, they will feel compelled to take care of their devices. If an indoor localization system mandated that everyone attach sensors to their body and/or carry an electronic device that was handed to them, they will feel less compelled to take care of it and will not care very much if one of the devices malfunctions.

2.4.2 Smartphone Sensor Suite

The modern smartphone comes equipped with an entire suite of sensors that can be utilized for indoor localization purposes. The sensors described in this thesis are shown in figure 2 and described in next sections listed in order from most useful to least useful for the purposes of indoor localization. The ordered list of sensors is show below.

- Accelerometer, Gyroscope, Magnetometer
- WiFi
- Bluetooth
- Cellular Radio
- GPS
- Camera
- Microphone
- Proximity Sensors

- Ambient Light Sensors
- Temperature Sensors

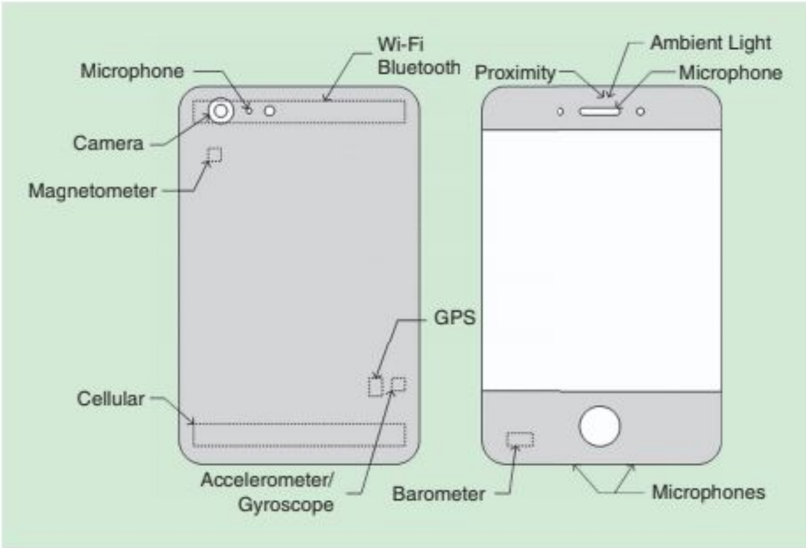


Figure 2: Sensor suite built into a modern smartphone [14]

2.4.3 Accelerometer, Gyroscope, and Magnetometer

Two of the key sensors for indoor localization built into a modern smartphone are the accelerometer and the gyroscope. The accelerometer is used to detect relative motion based on acceleration. This is especially useful for indoor localization because it is possible to calculate velocity and distance by integrating acceleration.

Small acceleration detection errors can easily accumulate and cause larger errors if not dealt with. The gyroscope is used in conjunction with the accelerometer to calculate and provide angular acceleration data relative to the positional acceleration data. Angular data is used to derive the Euler angles pitch, roll, and yaw. Similar to the accelerometer, small cumulative errors in angular acceleration can lead to large errors and heavily flawed calculations. The smartphone's magnetometer can be used as a means to re-calibrate angular position by calculating angular position relative to magnetic north. The magnetometer can itself also be used as a means of localization. Other sources of magnetism such as electrical wiring and metals can introduce errors caused by noise, but they can be used to determine location within a building (see Magnetic Fingerprinting). The combined data provided by a system that utilizes both an accelerometer and a gyroscope is called 6 Degrees-of-Freedom (6 DoF) data. Adding magnetometer data to a 6 DoF system is known as a 9 DoF system [14].

2.4.4 WiFi

Because of their ubiquity and range of WiFi, its signal strength is becoming a popular means for indoor localization. WiFi beacons can be set up and used as a means to triangulate and calculate a user's location within a structure by analyzing the strength of the WiFi signal. Although it has been proven effective, no WiFi localization-based smartphones have been released to the market as of yet [14].

2.4.5 Bluetooth

Similar to WiFi and Cellular Radio, Bluetooth can be used as a means of localization, albeit possessing the shortest range of the three. Bluetooth Low Energy (BLE) is an alternative form of Bluetooth that is better suited for indoor localization purposes due to its lower power usage and bandwidth. Both Bluetooth and BLE experience the same drawbacks as cellular radio and WiFi [14].

2.4.6 Cellular Radio

Providing a means of indoor position relative to a cell tower or base station is where the cellular radio in a smartphone comes into play. This sensor plays a key role in indoor localization systems that utilize RSSI (Received Signal Strength Indicator) Fingerprinting. Cellular signals can experience interference when penetrating walls, floors, or ceiling, so the RSSI often varies greatly in strength. Because cell towers and base stations are often located far away from a structure, the localization accuracy can vary greatly (anywhere from 50 to 100 meters) despite the relatively high range of cellular radio signals [14].

2.4.7 GPS

Although GPS is what indoor localization ultimately attempts to function without, it can still make use of GPS. GPS can still be used for situations such as when the user is standing next to a window or on a balcony. It can also act as a reference point for calibration when the user enters a building [14].

2.4.8 Camera

Identifying key features of the interior of a building using the high-resolution camera built in to a smartphone is another means of indoor localization. The drawbacks to using the camera are the fact that the camera must be exposed (as opposed to in the user's pocket), the rear-facing camera (i.e. the one that faces towards the user) has lower resolution than the front-facing camera, image processing is a highly-intensive process that require a lot of computational power and overhead, and the camera does not function well in dim or dark environments [14].

2.4.9 Microphone

The microphones built into a smartphone are great for determining location based on ambient sounds. A fingerprinting approach involving a system containing an array of beacons that each produce a unique frequency of sound can be used to accurately determine user location within a structure. However, the microphones in modern smartphones are optimized to register speech as opposed to ambient sounds and sound detection is greatly hindered if the smartphone rests in a user's pocket or bag [14].

2.4.10 Proximity Sensors

Recent models of smartphones have built-in proximity sensors designed to detect the presence of a face or a hand motion. The limited range of this sensor, however, severely limits its use and therefore can only be used in specialized situations [14].

2.4.11 Ambient Light Sensors

Smartphones have an ambient light sensor that detects the magnitude of ambient light and adjusts the phone's screen brightness accordingly. Although some system have made use of this sensor (see SurroundSense), its usefulness is only marginal. The time of day can affect the sensor greatly and produce noise, but artificial light sources can be installed to overcome this problem [14].

2.4.12 Temperature Sensors

The temperature sensor in a smartphone can also prove to useful for some indoor localization systems, but is highly limited and can be greatly affected by body temperature. Because most smartphones are constantly in contact with the user's body (either in the hand or in the pocket), much like the proximity sensor, this sensor can only be used in very specialized systems [14].

3 Smartphone-only Indoor Localization

Indoor localization systems that make use of smartphones have a lot of potential due to their cost, convenience, and portability. Making an indoor localization system that simply uses an app on a smartphone without requiring any external sensors or attachments at the expense of pinpoint accuracy costs much less than a highly-accurate localization that requires extra sensors. Smartphone-based indoor localization systems are also convenient because nearly every individual carries a smartphone with them at all times and is therefore great for emergency and evacuation situations (after all, people will even carry their smartphones to private areas like the restroom). Smartphones are portable by their design, so an indoor localization system that takes advantage of portability could easily be useful to the average person. This paper will survey the sensor suite within a modern smartphone, describe the challenges of designing an smartphone-based indoor localization system, and cover several methods for smartphone-based indoor localization, including both systems that take advantage of an individual method and system that take advantage of multiple methods (i.e. hybrid methods).

3.1 Challenges

Despite the bounty of research on smartphone-based indoor localization, the concept itself is not without flaw. There are several issues to consider when determining which indoor localization suits a particular need or situation the best. The next several section will list the common issues of smartphone-based indoor localization and examine how they affect/diminish the quality or usefulness of an indoor localization system. The ordered list of challenges is shown below.

- Cost
- Setup
- Sensor Error
- Power
- Memory Processing
- 3D Localization

3.1.1 Cost

Although some smartphone-only indoor localization methods avoid using external sensors *that attach to the smartphone*, many of them require additional remote sensors and beacons that can greatly increase the cost of an indoor localization system. For this reason, many research teams focus on the development of smartphone-based indoor localization systems that do not require the installation of beacons, emitters, or sensors in order to fully function. One example of cost reduction is to determine and install the minimum amount of beacons necessary using models and optimizations to determine best placement [14].

3.1.2 Setup

Many indoor localization systems require an initial setup procedure, such as those seen in the LearnLoc framework [11], SurroundSense [5], and many other fingerprinting-based systems. Often, dramatic changes to the environment will require the setup procedure to be run again, which can come at the cost of time and resources. Indoor localization systems that use crowd-sourced mapping or fingerprinting, on-the-fly fingerprinting, or map learning have proven to be useful for minimizing the cost of setup procedures [13].

3.1.3 Sensor Error

Smartphone sensors such as the magnetometer are incredibly prone to interference, especially when in the proximity of metals, electromagnets, or electronics. Noise produced from interference can lead to error in calculations. RF signals are prone to noise, environmental interference, and multipath errors. Localization methods that use inertia-based localization (e.g. pedestrian dead reckoning) are the best workaround for sensor error because their measurements rely on the physical movement of the user rather than propagated signals, but even they have their problems including irregular movements, error accumulation, and drift. Later we will see that calibration and filtering approaches (e.g. Kalman filtering) are the best counter to for sensor error [10].

3.1.4 Power

Battery lifetime is a primary concern for both smartphone users and the designers of indoor localization systems. Frequent, intensive calculations and use of sensors can quickly drain the battery power of the current suite of commercially-available smartphones. Different systems have different power requirements, and even the most power intensive system try to mitigate their battery usage (e.g. the LearnLoc framework, in which the initial calculations of the training phase are done on a remote server rather than the smartphone [11]) [14].

3.1.5 Memory and Processing

Some indoor localization methods, such as LearnLoc, require image processing, machine learning, map matching, or signal processing. These methods require high processing and memory usage, which limits their full usage on resource-conservative smartphones and can reduce battery life and service quality [14].

3.1.6 3D Localization

A challenge for many indoor localization systems is the accurate localization of a user in 3D space. Many indoor localization system, some of which are presented in this thesis, make satisfactory use of indoor localization on a 2D space. The introduction of a third dimension introduces more complex calculations and interesting edge cases that must be worked around. For instance, in a pedestrian dead reckoning system, the localization fails to work if the user enters an elevator [8] [14], which, in a multi-story building, is quite common. For this case, there would need to be some workaround that allows the indoor localization system to detect when the user enters an elevator on one floor and exits the elevator on a different floor.

3.2 Individual Methods

This section surveys several individual methods and/or algorithms for determining the location, direction of motion, and orientation of an object located within a building. Each method is presented with one or more examples of an indoor localization system that uses the method either in isolation or with an emphasis on it. Figure 3 shows a diagram of the individual methods discussed in the next sections and how they are categorized in relation to one another.

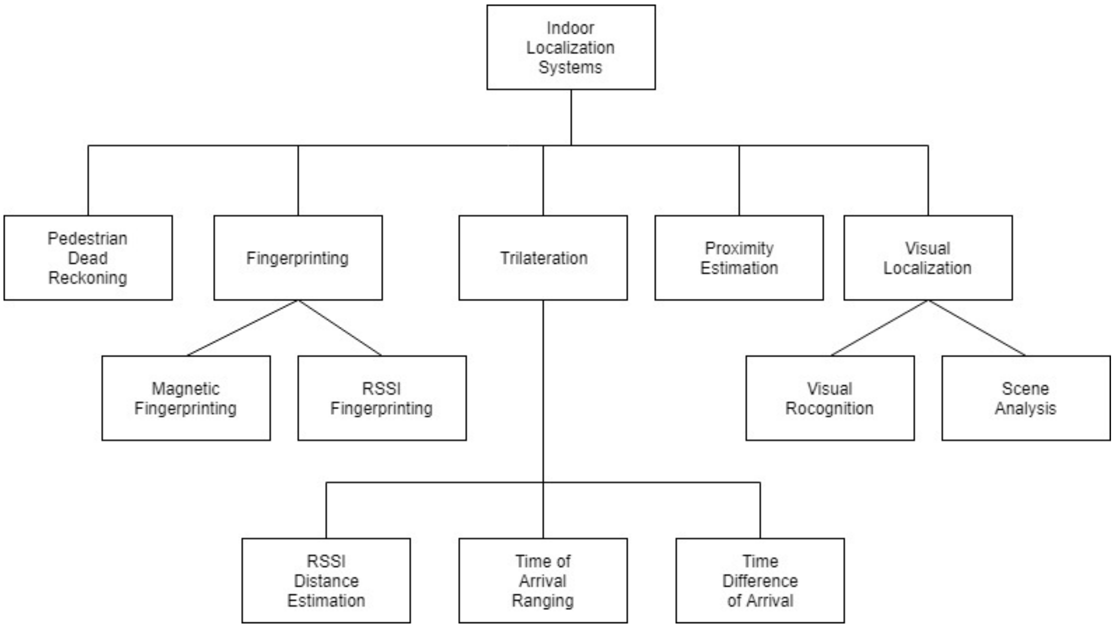


Figure 3: Diagram of Indoor Localization Techniques

3.2.1 Dead Reckoning

Dead Reckoning [6] is a statistical technique in which previously recorded data is used to estimate current data, as demonstrated in figure 4. In the case of indoor localization, dead reckoning uses previous location data in order to predict the target's current location. There are several dead reckoning techniques currently used for indoor localization. The most common method is Pedometer-based Dead Reckoning, also called Pedestrian Dead Reckoning (PDR) in which a person's steps are detected and recorded along with stride-length measures in order to estimate where a person is within a given structure. PDR has been shown to demonstrate sufficient accuracy for many indoor localization systems, which is why it is the standard dead reckoning method for indoor localization [4].

FootPath [8] is a self-contained map-based indoor localization system designed for smartphones that uses step detection and dead reckoning by way of sequence alignment algorithms borrowed from bioinformatics [8].

Indoor localization for FootPath involves five steps, as described in Figure 5. First, FootPath gathers map data using an open-source mapping software. Second, the user uses his/her smartphone to

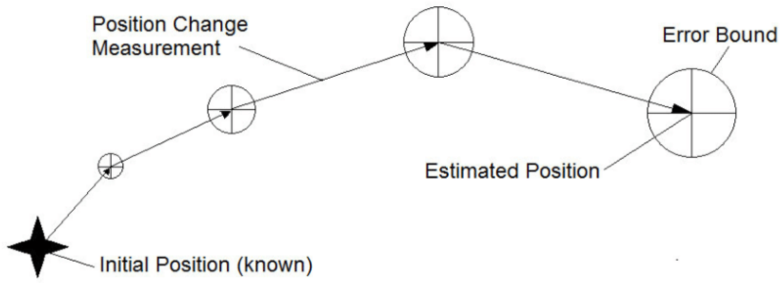


Figure 4: Dead Reckoning [6]

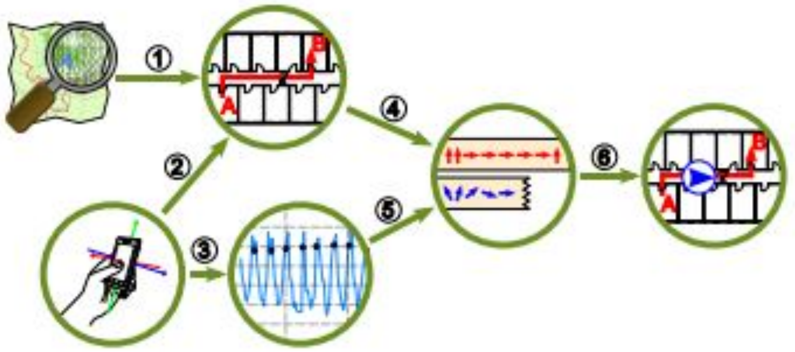


Figure 5: Overview of FootPath [8]

pinpoint a starting location and a final destination, after which the smartphone app traces the best route. Once the path has been traced, FootPath begins step detection using the smartphone's accelerometer and compass. The FootPath software recognizes a step when the detected acceleration is at least $12m/s^2$ within a window of 165ms (which allows for about five samples) with a timeout of 333ms. A graph showing the filtered accelerations and detected steps with respect to time (ms) used in FootPath is shown in see Figure 6.

After a step is detected, FootPath immediately begins the path matching algorithm. There are two possible path matching algorithms for FootPath, *first fit* and *best fit* [8].

The *first fit* algorithm assumes that the user's current step heading will match directly with the user's expected direction. A step heading α_i is said to be matching with current direction β_j if the angle between them is less than 42^o. First fit will operate in *direct matching mode* if the current step heading with the expected direction , and *lookahead matching mode* if the current step heading does not match the expected direction for more than five consecutive steps.

The *best fit* algorithm is more complex than *first fit*, but allows for more accurate matching of step heading and expected direction. Best fit utilizes a sequence matching algorithm commonly used in bioinformatics that uses pattern matching with an map of expected patterns as demonstrated below.

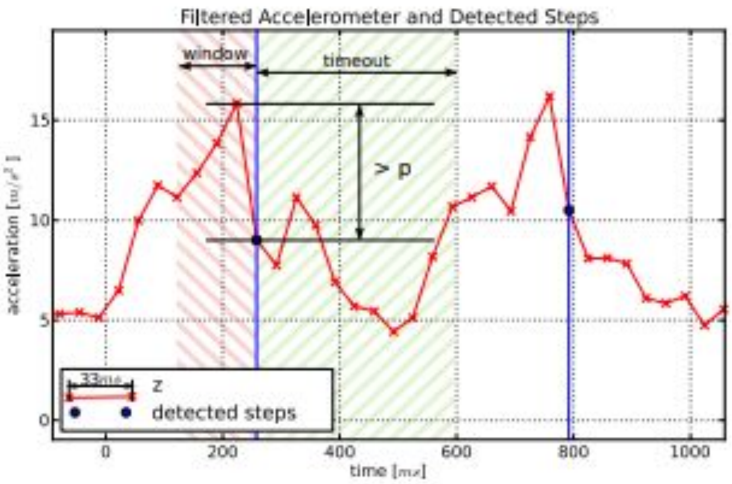


Figure 6: Experimental Setup for FootPath - Step Detection [8]

$$score(\alpha,\beta) = \begin{cases} 0.0 & \text{if } \sphericalangle(\alpha,\beta) \leq 45° \\ 1.0 & \text{if } 45° < \sphericalangle(\alpha,\beta) \leq 90° \\ 2.0 & \text{if } 90° < \sphericalangle(\alpha,\beta) \leq 120° \\ 10.0 & \text{else} \end{cases}$$

Using a dynamic programming approach with the matrix $D(i,j)$, the expected position along a pathway can be calculated using the pos_j formula:

$$\begin{aligned} D(i,j) = min\{&D(i-1,j-1) + score(M(i),S(j)), \\ &D(i-1,j) + score(M(i),S(j-1)) + 1.5, \\ &D(i,j-1) + score(M(i-1),S(j)) + 1.5\} \end{aligned}$$

$$pos_j = argmin(D(i,j))$$

The formula only worries about pos_j because $D(\_,j)$ only depends on $D(\_,j-1)$ allowing for fast and efficient calculation.

Discussion: It is worth noting that because dead reckoning is a category of mathematical techniques rather than a single method. Different indoor localization systems that use dead reckoning may use different mathematical techniques. While FootPath uses a combination of string pattern matching and recursion to estimate user location, the LearnLoc Framework, a hybrid indoor localization system that combines pedestrian dead reckoning along with other methods (see section of LearnLoc Framework), uses trigonometric formulas for location calculation.

With the current suite of sensors built into the modern smartphone, along with high refresh and sampling rates, pedestrian dead reckoning systems like FootPath would be an excellent strategy for smartphone-based indoor localization. Because pedestrian dead reckoning systems only rely on inertial measurements (i.e. readings from the accelerometer and gyroscope), they do not require the installation of additional devices like WiFi beacons.

However, a downside to pedestrian dead reckoning is that calculations of distance are commonly inconsistent and can lead to additive inconsistencies in stride length calculations (i.e. some strides are shorter and some are longer, even with the same person). A second, and crippling, downside is that because pedometer-based dead reckoning depends on step detection, it fails when a person enters a vehicle or uses a device that substitutes for walking (i.e. elevator, wheelchair, escalator).

3.2.2 Fingerprinting

Fingerprinting is a localization and/or mapping technique involving the gathering of data from several wireless sensors or radios placed at various spatial points. There are two steps involved in the fingerprinting process: an initial setup, and a real-time recording. In the initial setup, selected locations are marked with a unique ID or signature (i.e. a fingerprint, hence the name of the process). During the real time recording, location data is gathered continuously and compared relative to the fingerprinted locations. As the user navigates through a building where fingerprints placed strategically throughout, the indoor localization system will estimate user location based on which fingerprint has the highest received signal strength from the user. To give an example, a floor of an office building has two fingerprints, one in the conference room and one in the manager's office. If an employee logged into the fingerprinting-based indoor localization system is walking toward the manager's office, the office fingerprint will have an (increasingly) higher signal strength than the conference room fingerprint. Thus, the system determines that the employee is located in the vicinity of the manager's office. There are two commonly used methods for fingerprinting: magnetic and RSSI.

3.2.2.1 Magnetic Fingerprinting Magnetic fingerprinting is an indoor localization fingerprinting method that utilizes the magnetometer in smartphones by detecting sources of magnetic noise such as electronics, metals, and electrical wiring. By observing and classifying the magnetic noise produced by each source, the magnetometer in a smartphone can give a good approximation of where a person is within a building.

IndoorAtlas [16] is a company that specializes in developing indoor localization systems using geomagnetic mapping and tracking. In a partnership with Yahoo!, IndoorAtlas created a fingerprinting-based indoor localization system to create indoor maps for buildings in Japan. The system uses the compass built into a modern smartphone in conjunction with several geomagnetic "fingerprints" that are unique to each building. According to Ben Frederick's article [16], "the earth generates a magnetic field, and each structure erected on the earth carries its own magnetic signature that can be detected through a phone's sensors". According to Dan Patton, the CCO (Chief Commercial Officer) at IndoorAtlas, scalability is a limiting factor for many hardware-based indoor localization systems. Maintaining beacons and WiFi routers can become expensive and time-consuming and would require specialized personnel to keep them in working order. The cost of equipment for many hardware-based localization systems is often prohibitive for many companies. The IndoorAtlas system, on the other hand, seeks to take a software-based approach to indoor localization that allows for customers to customize the system to suit their needs (e.g. manage data and location-based services using a mobile application). The system, according to Patton, is accurate within one to two meters and works in three dimensions because each floor of a building has its own unique magnetic fingerprint.

3.2.2.2 RSSI Fingerprinting RSSI fingerprinting is similar to magnetic fingerprinting with the difference being the detection of received RF signals by the smartphone's built-in radio. As of now, this is one of the most popular techniques for indoor localization, particularly when used in conjunction with WiFi RF signals. By categorizing RF fingerprints throughout a building or structure, the radio sensor in a smartphone can give a good approximation of a user's location within a structure. RADAR is an example of RSSI Fingerprinting that uses WiFi RSSI fingerprinting with Euclidean distance measurement [2].

Discussion: Fingerprinting is widely used in indoor localization because of it's accuracy. When many fingerprints are placed throughout a structure, and indoor localization system can pinpoint the location of a user down to a few meters. Although a limitation of fingerprinting systems is that many of them require an initial setup phase in order to place fingerprints, both magnetic and RSSI fingerprinting can use pre-installed beacons as fingerprints. For magnetic fingerprinting, in-built metals and electrical wiring can act as fingerprints, and for RSSI fingerprinting, WiFi access points (APs) can be used as fingerprints.

The biggest limitation fingerprinting is that the smartphone's magnetometer and radio sensors are prone to error and interference. The introduction of new sources of magnetic noise, including other cell phones, and radio interference can vastly affect the localization calculations of fingerprinting indoor localization systems.

3.2.3 Trilateration

Trilateration involves triangulating a user's location using distance estimations between the smartphone and two or more external RF beacons. When using the distance estimations from more than three beacons, it is possible to calculate a three-dimensional position for the user. The three means of trilateration-based indoor localization are RSSI distance estimation, Time of Arrival (ToA) ranging, and Time Difference of Arrival (TDoA) [14].

3.2.3.1 RSSI Distance Estimation Similar to RSSI fingerprinting, RSSI can also be used for distance estimation and in-turn the triangulation of a user's indoor location based on RSSI distance calculations. The RSSI value changes proportionally with the distance from the RF signal origin and therefore can be used to estimate distance from the source. The EZ localization algorithm is one of the earliest and most effective examples of RSSI distance estimation [7].

The EZ localization algorithm attempts a bold innovation: *an indoor localization system that does not require any preliminary setup.* Many indoor localization systems, especially fingerprinting-based, require an initial setup step to gather enough data in order to accurately determine location. EZ works under the assumption that a building will have WiFi, but the location of the access points (APs) is unknown. The EZ localization system involves the user's smartphone recording Received Signal Strength (RSS) measurements and transferring them to a remote server where the EZ localization algorithm performs localization calculations from the received data. The key way the EZ system seeks to bypass a lengthy setup process is to assume that all locations within a building, even when unknown, will abide by the laws of wireless propagation and uses genetic algorithms based off those assumptions to calculate location [7].

The distances between a set of APs and their corresponding mobile devices can be determined from the RSS values using the equations:

$$d_{ij} = \sqrt{(x_j - c_i)^T (x_j - c_i)}$$

$$p_{ij} = P_i - 10\gamma_i log d_{ij} + R$$

The equation for d_{ij} corresponds to the distance between the *jth* mobile device and the *ith* AP, calculated using the 2D vectors x_j and c_i. The equation for p_{ij} refers to the RSS amount from the *ith* AP at a distance of one meter. P_i is the received signal strength from the ith AP and R is a random variable designed to mimic the variations in RSS due to obstructions, noise, and multipath effects. γ_i refers to the fall rate of the RSS when in proximity of the *ith* AP. The higher the value of γ_i, the more the RSS decreases with distance and vice versa [7].

Discussion: The EZ localization system has two major limitations: selecting the correct APs, and selecting a subset of locations. Some buildings can have an astounding number of WiFi access points. In fact, during one of the experimentations with the EZ system, the experimenters at the Microsoft research lab in India detected 160 APs *on a single office floor.* The system even suffered the dividing wall problem [5] when they realized that some of the APs belonged to a neighboring office building. Some APs were even configured with multiples SSIDs! Running the localization algorithm using all of those access points could become extremely taxing on the system, so designing the system so that it only receives signals from the most optimal APs was a necessity [7].

In order to effectively train the EZ system, RSS signals need to be received from a healthy variety of locations across an indoor space. Data gathered from a single user who traverses most of the entire space or data gathered from a large group of people spread out over the indoor space are both ideal. The challenge is to determine, given a large amount of data, how do we determine a subset of "useful" locations. The Microsoft research team who developed the EZ system also developed an algorithm called *LocSelect* which is designed to select a subset of locations based on the overlap of RSS information throughout the indoor space [7]. In comparison to random selection of locations, the *LocSelect* algorithm provided significantly less location error (in meters) as shown in figure 7

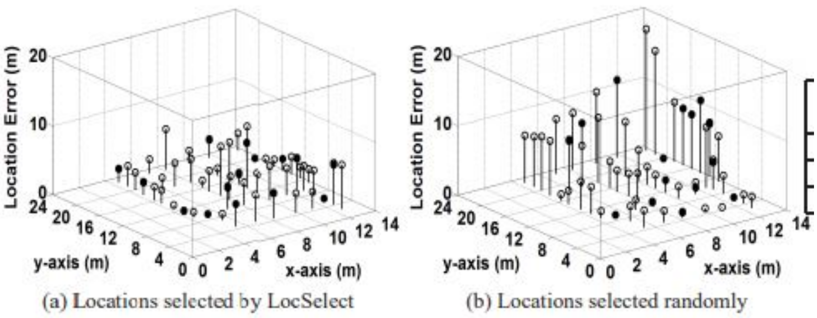


Figure 7: Comparison of Location Error (meters): *LocSelect* vs. Random Placement

3.2.3.2 Time of Arrival (ToA) and Time Difference of Arrival (TDoA) Ranging Another way of determining location using trilateration is to measure the time it takes for a signal to travel from RF source to receiver. This can be achieved in two different ways: Time of Arrival (ToA) and Time Difference of Arrival (TDoA) [14].

ToA ranging involves the smartphone sending a signal to an access point and estimating distance based on the round trip time (RTT) of the signal. Time Difference of Arrival (TDoA), also known as Multilateration involves the smartphone sending multiple signals to two or more access points and estimating distance based on the difference in the RTT of the signal from each point. For both ToA and TDoA, an alternate method is to do the reverse by having the fixed points simultaneously send a signal to the smartphone and calculate location based on the difference in time each of the signals is received by the smartphone [14].

Discussion: Because trilateration-based indoor localization systems calculate user location based on the RSS or ToA from multiple access points simultaneously, they tend to be more accurate than their corresponding fingerprinting-based systems.

However, trilateration methods are highly error-prone due to RF interference and multipath effects (a phenomenon that occurs when a receiver receives duplicate signals at different times [22]). A way to circumvent these errors is to use the magnitude (see Proximity Estimation) of a received signal instead of the estimated distance, but this has its own set of possible errors including including reflections, echo, and object interference.

For both ToA and TDoA, the sensors in a smartphone are not built to calculate the timing of a received signal to the degree of accuracy needed for ranging, so this option is not very viable unless employed with external sensors or beacons. Modern smartphones also do not include radios designed for multilateration by default and therefore would mandate the use of external sensors or beacons.

3.2.4 Proximity Estimation

The most basic form of localization that makes use of RF beacons, proximity estimation involves estimating the user's location based on the position of the beacon with the highest signal strength. Proximity estimation is useful for indoor localization systems where only rough estimates of position are needed instead of accuracy and minimal error. Similar to multilateration, this method can be accomplished with acoustic beacons, but is limited by the fact that smartphone microphones are designed to detect frequencies within the audible or near-audible range or hearing. Therefore, frequencies that are unique enough to be detected and differentiated but not distracting to humans and animals is a challenge [14].

Aruba [20], an HP enterprise company, has devised a "Blue Dot" approach to proximity estimation-based indoor localization. The Blue Dot approach is not as intensive as other indoor localization systems in that instead of using intensive calculations to output a user's location, the Blue Dot setup simply detects if a user is in the proximity of a beacon (usually a Bluetooth beacon), which indicates that the user is in an area of interest. This system was designed with marketing and advertisement in mind. Many commercial vendors have adopted the Blue Dot system as a way to send promotions and advertisements to potential customers.

Discussion: Because proximity estimation-based indoor localization systems are excellent when only rough estimates are needed, they are poor for situations when accurate localization is needed. Therefore, situations that require accurate localization, such as those in military and emergency response, will not find a proximity estimation-based solution viable.

3.2.5 Visual Localization

Using the smartphone's camera to read input from data sources is the basis of visual localization. In order for this method to be effective, the camera must be constantly exposed and free of any obstructions between it and the data source. This localization method could potentially be used for Augmented Reality (AR) purposes because of its relative ease of implementation and the necessity to keep the camera exposed while playing the AR game.

3.2.5.1 Visual Recognition Using environmental objects as unique visual cues is one way to utilize the smartphone camera for indoor localization purposes. As an example, the company ByteLight [15] planted a series of LEDs throughout a building that each transmitted a unique coded pulse. The camera could register the pulse generated by an LED to indicate where the user is located within the building.

ByteLight has implemented a visual recognition-based indoor localization system that uses Light Emitting Diodes (LEDs) for localization. Using a technique known as Visible Light Communication (VLC), the ByteLight system calculates location based on LEDs that give off a unique pulse installed in light fixtures. These pulses are undetectable to the human eye (the pulses are hundreds of hertz), but are very detectable to a smartphone's camera. By detecting nearby LEDs, reading the unique pulse, and performing client-side calculations, the ByteLight system can provide accurate localization in an indoor environment. A demonstration of the VLC system is shown in figure 8.

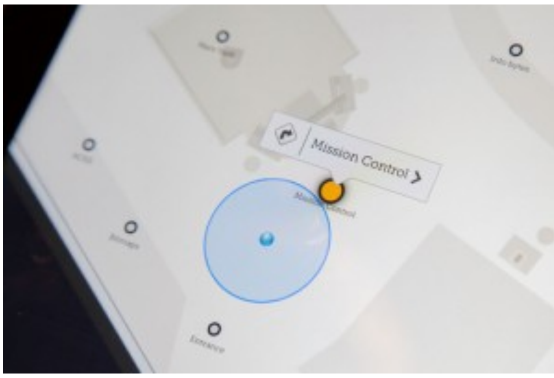


Figure 8: Visual Light Communication (VLC) system developed by ByteLight [15]

Discussion: One of the greatest benefits of VLC indoor localization systems is that, because they do not rely on WiFi, the system functions well even if the user is not connected to WiFi or the wireless internet is down. However, the VLC system invented by ByteLight does have its limitations. The unique LEDs that the ByteLight system relies on have to be installed in a buildings lighting system and, if the building already uses LEDs, the pre-existing LEDs cannot be retrofitted to work with the ByteLight VLC system. For companies that have yet to upgrade to an LED lighting system, however, VLC systems could be a fairly easy-to-implement means of indoor localization.

3.2.5.2 Scene Analysis Visual localization is not simply limited to LEDs; environmental objects and unique landmarks could also be used for indoor localization purposes. By identifying landmarks and measuring their perceived position, size, and orientation, the camera can estimate user location based on these environmental cues. This process is remarkably similar to how the human eyes registers environmental objects and makes judgments and calculations on distance, size, and orientation based on perception.

Discussion: Unlike visual recognition, scene analysis relies on pre-existing environment cues. Therefore, no infrastructure such as WiFi beacons or LEDs has to installed. Copious amounts of visual input, however, need to be fed into a machine learning system in order for this method to be effective enough for practical indoor localization purposes.

3.2.6 Comparison and Supplementary Techniques

Table 1 shows a summary of the individual indoor localization methods. Each method is given a rating in relation to each of the challenges presented earlier. For Cost, Setup, Sensor Error, and Resources, each method is given a rating of Low, Medium or High depending on quantity (e.g. estimate of cost). The 3D Localization column is given a rating of Poor, Average, or Good depending on the quality of how well a certain method can perform indoor localization calculations in a 3D space.

Some other techniques are not directly useable in the previously discussed indoor localization methods, but nonetheless can greatly improve their accuracy and speed if available [10]. The three most common supplementary techniques for indoor localization are map matching, particle filtering, and Kalman filtering.

3.2.6.1 Map Matching By matching received indoor localization data with a large data set of maps, accuracy of the indoor localization data can be greatly improved. By comparing indoor localization data with a set of maps, it becomes quite easy to detect errors in localization and pathing. Because people will take a path throughout a building that almost always corresponds with the floor layout of the building, any detected errors in pathing are extremely apparent. FoothPath collects accelerometer and magnetometer data and combines it with map data gathered through OpenStreetMap in order to improve overall accuracy [8].

3.2.6.2 Particle Filtering Particle filters are an extended form of map matching that assumes the notion that the mobile user's position abides by the natural laws of physics and any unnatural accelerations or locations are considered erroneous. Essentially, particles filtering involves representing as many possible points of location as possible and then eliminating any point that defies the laws of physics. Any remaining particles are deemed to be the array of possible locations within a building that the mobile user can occupy [12].

Individual Method Comparison					
Method	**Cost**	**Setup**	**Sensor Error**	**Resources**	**3D Localization**
Dead Reckoning	Low	Low	Medium	Medium	Poor
Magnetic Fingerprinting	Low	Low-Medium	High	Medium	Average
RSSI Fingerprinting	High	High	Medium	Medium	Good
RSSI Distance Estimation	Medium	Medium-High	Medium	High	Good
Time of Arrival Ranging	Medium	Medium-High	Medium	High	Good
Time Distance of Arrival Ranging	Medium	Medium-High	Medium	High	Good
Proximity Estimation	Medium	Medium	Low	Low	Average-Good
Visual Recognition	Medium	Medium	High	High	Average
Scene Analysis	Low	Low	High	High	Poor-Average

Table 1: Individual Method Comparison

3.2.6.3 Kalman Filtering Kalman filtering [10] is an algorithmic process that involves continuous input of data, filtering noise from the data, and the calculation of estimated variables with noise removed. Because noise is constantly being filtered out of equations, systems that make calculations using Kalman filtering tend to be more accurate than those without. An indoor localization study at the University of Freiburg [10] used this method in conjunction with an inertial measurement unit (IMU) in order to continuously correct and calculate orientation data.

A diagram of the Kalman filter setup used is shown in Figure 9. Similarly to other individual meth-

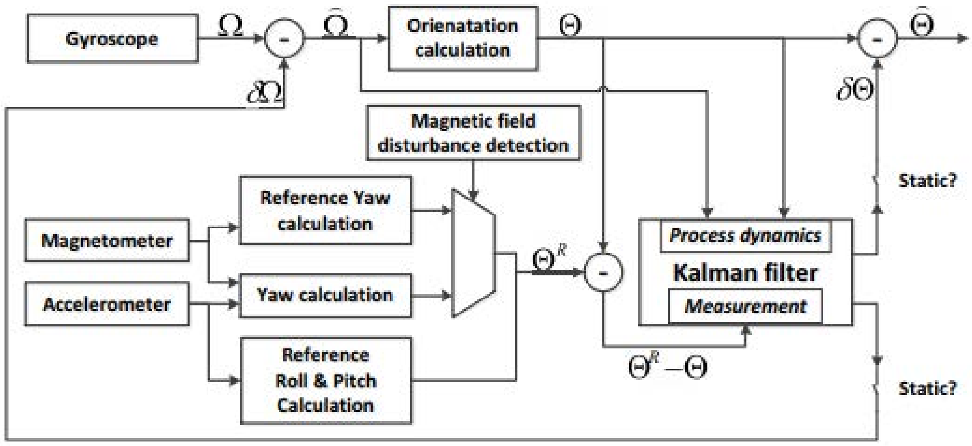


Figure 9: Kalman Filtering - Orientation Determination [10]

ods, orientation is determined with the smartphone's accelerometer, gyroscope, and magnetometer working together. With Kalman filtering, the noise produced by these devices is mitigated using a sequence of filters shown in the diagram, with Ω representing the raw gyroscope data, $\delta\Omega$ representing the bias error subtracted from Ω, $\hat{\Omega}$ representing the corrected gyroscope data, Θ representing the calculated orientation based on $\hat{\Omega}$, $\delta\Theta$ representing bias error subtracted from Θ, and $\hat{\Theta}$ representing corrected orientation calculation. The orientation is represented by the three Euler angles: Roll, Pitch, and Yaw (see Figure 10). The magnetometer is used to compare the calculated Euler Angles to a set of reference Euler Angles (based on magnetic North) and correct them accordingly. However, magnetic disturbance can affect the magnetometer, so a mechanism for detecting magnetic field disturbances is included in the filtering process.

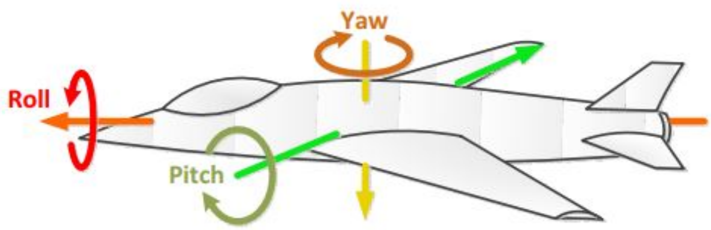


Figure 10: Euler Angles: Roll, Pitch, and Yaw [10]

Although the indoor localization setup at the University of Freiburg was used to calculate and correct orientation data, Kalman filtering can, theoretically, be used to calculate and correct any type of data needed. Because of its flexibility and effectiveness, it has become common method for combining data from multiple inputs sources for use in several hybrid indoor localization setups, as some of them will be discussed in the next session. The process of calculating and combining data based on input from multiple sensors using calculation and noise filtering is referred to as *sensor fusion* [14].

Kalman filtering is computationally intensive, however, so it is not wise to simply add a kalman filter to an indoor localization system without consideration of how system resources are budgeted.

3.3 Hybrid Methods

This section will survey several combined methods and/or algorithms for determining the location, direction of motion, and orientation of an object located within a building. Each method will be presented with an example of a indoor localization system that uses several of the previously mentioned individual methods in combination.

3.3.1 LearnLoc framework

The LearnLoc framework is a hybrid indoor localization system developed by a joint effort from Colorado State University and the Colorado School of Mines. The framework combines dead-reckoning and WiFi fingerprinting with several machine learning techniques for enhancement. With machine learning algorithms added to the system, LearnLoc can make use of effective mathematical and statistical calculations to help the system make better predictions of user location. The four core components of the LearnLoc framework are Step Detection, Inertial Navigation, WiFi fingerprinting, and machine learning enhancements [11].

3.3.1.1 Step Detection The LeanLoc framework, acceleration on the z-axis is used to detect a step. A low-pass filter is used to filter out only the major z-axis accelerations, in order to eliminate unwanted step detections in a manner similar to what FootPath [8] achieves [11].

3.3.1.2 Inertial Navigation Using inertial navigation (i.e. dead reckoning) is fundamental to the LearnLoc framework. It is used to determine the user's heading based on previous heading angle (in relation to magnetic north) and step detection. The heading angle is obtained by combining accelerometer, gyroscope, and magnetometer readings using Kalman filtering. Figure 11 shows how a new position is calculated [11]:

The equations for calculating the next user location, $L_{t+1}(x_{t+1}, y_{t+1})$, are:

$$x_{t+1} = x_t + d * cos(\Theta)$$

$$y_{t+1} = y_t + d * sin(\Theta)$$

3.3.1.3 WiFi Fingerprinting In order to utilize WiFi fingerprinting, LearnLoc uses IEEE 802.11 wireless signal strength standard and stores data including the Media Access Control (MAC) address of several WiFi access points (AP), the Received Signal Strength (RSSI), and the calculated location points

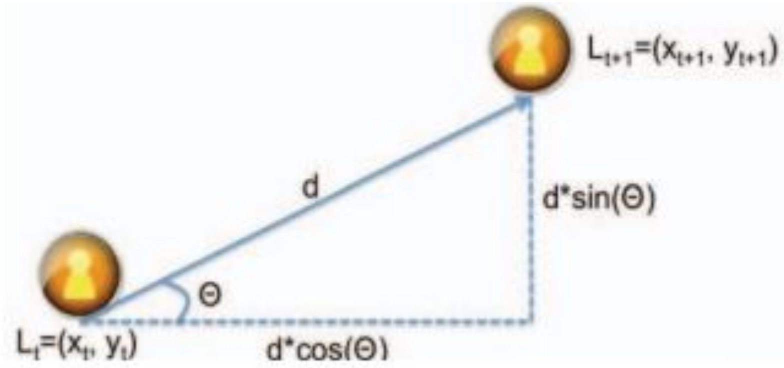


Figure 11: LearnLoc framework: Calculation of change in position [11]

in a tuple. A manual collection of fingerprint data with the mobile device is a required prerequisite step for this part of the system. The collected fingerprint data is inserted into a SQLite database that is later used for the machine learning algorithms (fingerprint data gathered regularly every three to four meters along the path proved most effective). To reduce noise and achieve better accuracy in fingerprinting, MAC addressed other those at at least j unique locations are filtered out.

3.3.1.4 Machine Learning The LearnLoc framework makes use of several common machine learning and data analysis techniques in order to improve prediction of indoor location based on previously gathered data. LearnLoc uses three learning algorithms to aid the previously mentioned indoor localization techniques: K-nearest neighbor (KNN), linear regression (LR), and non-linear reggression with neural networks (NL-NN).

K-nearest neighbor [1] among the simplest of the data analysis algorithms used for either classification and regression. It is non-parametric, which assumes that similar inputs have similar outputs, and is referred to as lazy learning algorithm, which is an algorithm that only generalizes its data once a query is received (the opposite is an eager learning algorithm which attempts to make generalizations before a query is sent). LearnLoc uses the KNN classification algorithm, in which new samples are classified based on the *k* closest samples in the training set (i.e. the data pulled from the SQLite database). In order to determine the closest sample, LearnLoc uses Euclidean Distance *D* to calculate the distance between two points *a* and *b* as shown below:

$$D(a,b) = \sqrt{\sum_{i=1}^{n}(b_i - a_i)^2}$$

Repeated calculations are memory and CPU intensive, which is a problem for a system designed to be used on a spec-restrained device such as a smartphone. By using Euclidean distance to find the set of closest neighbors, thereby constraining the search-able nearest neighbor space to a subset of the closest nearest neighbors, the LearnLoc framework makes efficient use of memory and energy.

By restraining possible nearest neighbors to a small, manageable subset and using only the MAC addresses present at j unique locations using the WiFi fingerprinting approach previously mentioned, this algorithm is able to perform intensive calculations while not consuming too much memory or battery usage [11].

Linear regression algorithms are designed to record relationships between input and output variables. In the LearnLoc framework, these relationships are recorded in the initial training phase to be used for predictions in the testing phase. Linear regression outputs can either be linearly or non-linearly related to their inputs. LearnLoc works under the assumption that the inputs and outputs are in a linear relationship, which produced reasonable accuracy during its initial testing. In order to create a linear regression model, the input data has to be "fitted" using one of several regression analysis estimation functions (including linear, non-linear, ordinary, weighted, generalized, partial, etc.). The preferred regression analysis estimation method used for LearnLoc was Least Squares, an approach which fits a curve to a set of points by minimizing the sum of the squares of the offsets of each point from the curve. The formulas for the Least Squares approach are shown below:

$$y(x;w) = w_0 + \sum_{i=1}^{N} w_i x_i$$

$$w_{best} = argmin \sum_{n=1}^{N} (t_n - y(x_n;w))^2$$

The equation $y(x;w)$ is a weighted sum that calculates the output values y as a function of the inputs x and the weights w. The w_{best} formula is used in conjunction with the equation $y(x;w)$ in order to minimize error between the target values t_i and the output values $y(x_n;w)$ ($argmin$ returns the minimum value from the set of calculated weights).

Because linear regression is a computationally intensive process, these calculations are performed on a remote server during the training phase rather than the smartphone. The smartphone is used, however, to perform indoor location calculations in real time during the testing phase.

Neural Networks are models based on how the brain and the nervous system receive, learn, and process information. The artificial "neurons" of a neural network are called perceptrons, and each one has several inputs that are individually weighted [11]. The equation below shows how the weighted sum of all inputs x is calculated based on the weight of each perceptron, w_i, which can increase or decrease proportionally based on the value of the input x_i:

$$y = \sum_{i=1}^{n} w_i x_i + w_0$$

By using a non-linear neural network, LearnLoc is able to greatly improve location prediction accuracy [11]. LearnLoc uses a feedforward backpropagation approach in the training phase to determine the set of weight parameters. Once the neural network model is created, it is possible to calculate the output $y_i^{'}$ based on the current value of x_i and w_i by using a sigmoidal tangent function as shown below.

$$y_i^{'} = \frac{1}{1 + e^{w_i x_i}}$$

The graphs in Figures 12 and 13 show the average distance error and energy usage, respectively, for each each of the previously discussed machine learning algorithms.

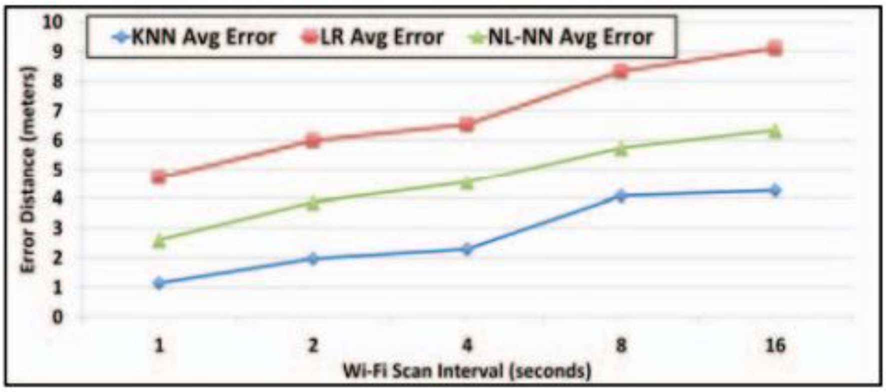


Figure 12: LearnLoc machine learning algorithms - Distance Error (m) [11]

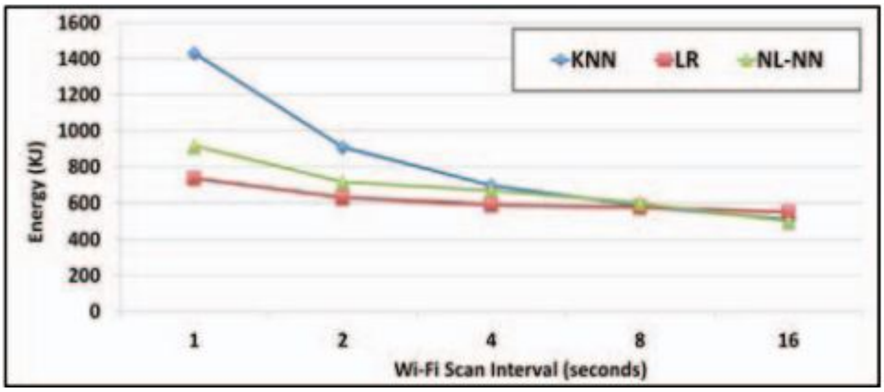


Figure 13: LearnLoc machine learning algorithms - Energy Usage (KJ) [11]

Discussion: By using dead reckoning and WiFi fingerprinting in conjuction with several machine learning techniques in order to provide error correction and make predictions on the user's current location, the LearnLoc framework proves to be an adept hybrid indoor localization system. Graph (a) in figure 14 shows that when any of the three machine learning algorithms is used in the LearnLoc framework, it produces significantly less distance error than similar indoor localization systems. However, graph (b) in figure 14 shows that energy consumption for the machine learning algorithms is still high in comparison to it's competitors, despite the offloading off calculations onto a remote server.

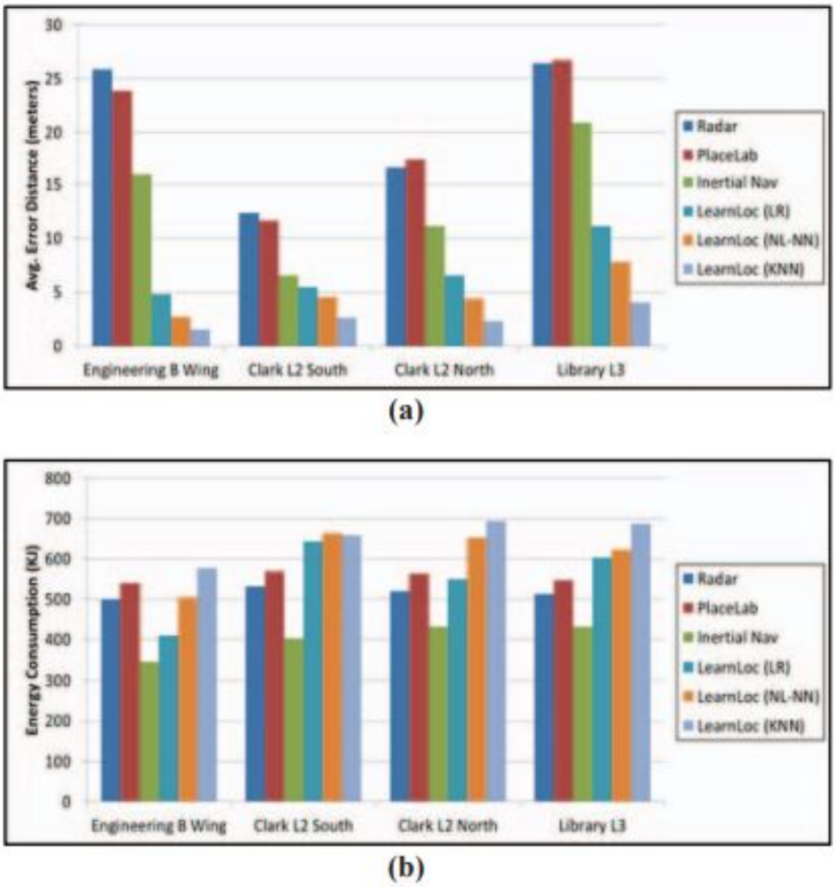


Figure 14: LearnLoc Results - (a) Average Error Distance (m) and (b) Energy Consumption (KJ) [11]

3.3.2 KAILOS

The KAist Indoor LOcalization System (KAILOS) [13] is a set of tools used for hybrid indoor localization system developed by the Korean Institute of Communications and Information Sciences. KAILOS makes use of an extended Viterbi algorithm (a dynamic programming algorithm designed to calculate the most likely path through a series of hidden states, called a Viterbi path) that makes localization calculations based on previously recorded data from WiFi fingerprints, magnetic fingerprints, and inertial sensors (gyroscope, compass, barometer).

In order to avoid time-consuming setup procedure in a manner similar to the EZ Localization algorithm, KAILOS is a set of various methods and tools that allow for volunteer registration of indoor maps and fingerprints of any building. These tools are available online on the KAILOS website (http://kailos.io). Examples of the tools and functionalities available on the KAILOS website, including building registration, indoor map construction, and fingerprint collection, are shown in Figure 15. With the cost of volunteer fingerprint collection being close to zero, the tools provide by KAILOS are incredibly beneficial.

The two main techniques used in KAILOS are a WiFi fingerprinting scheme called the Signal Fluc-

(a) Indoor map construction. (b) Fingerprint map construction.

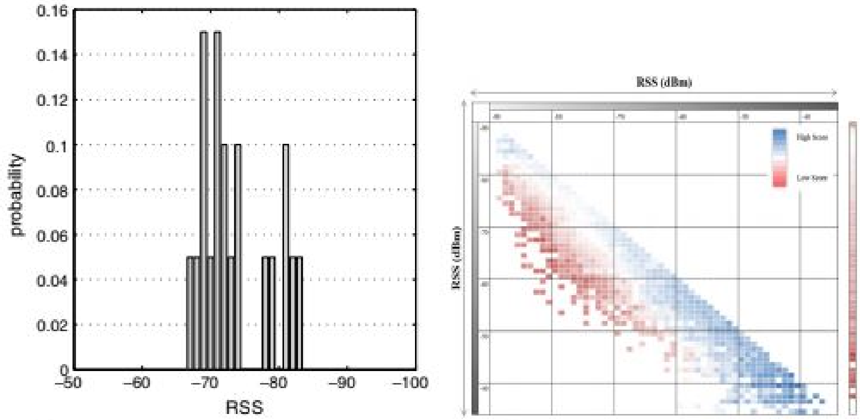
Figure 15: Tools available on the KAILOS website [13]

tuation Matrix (SFM), which is designed to optimize performance even when collected fingerprint data is sparse, and a sensor fusion that provides a framework for tracking user location [13].

Localization methods that use Received Signal Strength (RSS) calculations and fingerprinting require gathering and sampling of fingerprints in order to be effective. The purpose of the SFM is to make predictions of location data even when the number of crowd-sourced fingerprints is low. The SFM ignores the subtle fluctuations in the distance distance between a user's location and an AP due to fluctuations in the receiving of signals by the smartphone's sensors and instead focuses on the probability of the fluctuation between the user's location and two RSS values. Because this kind of fluctuation can be observed between any two APs, a reliable SFM can be obtained even if there are only a few sparse fingerprints in the vicinity [13]. Figure 16 displays the difference between RSS and SFM radio maps.

On the RSS histogram, many of the bins are empty because there were not enough samples collected to produce an accurate calculation (only 20 samples were collected). The SFM, on the other hand, was able to fill in the missing cells using frequency measurements of the fluctuations. According to the authors of the KAILOS article, "an SFM can be regarded as a universal histogram of RSS values irrespective of locations and APs" [13]. The SFM calculates the probability of signal fluctuation based on the RSS i of an AP at location l using a log-odd probability formula as shown below, where j is the mean RSS of the AP l, $P(i,j)$ is the observed fluctuation of an RSS pair (i,j), and $P(i)P(j)$ is the expected fluctuation of the probability of the pair (i,j):

$$P(i|l) = log(\frac{P(i,j)}{P(i)P(j)})$$



(a) Histogram. (b) SFM.

Figure 16: Difference between RSS and SFM [13]

Using the SFM probability calculations, the Viterbi algorithm can be used to determine user location in conjunction with the inertial sensors in a smartphone (e.g. accelerometer, gyroscope). Inertial sensors are known to produce errors that can easily accumulate, so the extended Viterbi algorithm is used to mitigate the distribution of errors. Figure 17 demonstrates how the Viterbi algorithm allows for error compensation in the KAILOS system. The solid arrows represent the tracking results and the dotted arrows represent distance and orientation data provided by the inertial sensors. At steps t_0 , t_1, and t_2, error is filtered out from the tracking results, represented by the large gray circles, until step t_4 is reached where there is very little error present. At step t_4, the tracking algorithm can use the corrected probability distribution data as depicted by the dark circle.

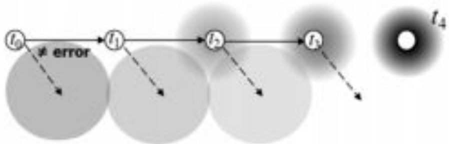


Figure 17: Probability calculation and error compensation using a Viterbi Algorithm [13]

Figure 18 shows a diagram of the KAILOS positioning framework including Viterbi tracking and the SFM. Detected inertial sensor readings (which produce transition probabilities) and WiFi signals (which are used to generate emission probabilities). The probabilities are fed into the Viterbi algorithm for error elimination and final location estimation. **Discussion:** KAILOS [13] and its use of crowd-sourced fingerprints and maps bypasses the requirement of pre-installed beacons, making it cost-effective. The Signal Fluctuation Matrix (SFM) is designed to ensure accurate location calculations even in areas with sparse fingerprints and the Viterbi is used as an effective means of inertial error correction. When all three tools are combined, KAILOS proves to be both an accurate and cost-effective indoor localization system.

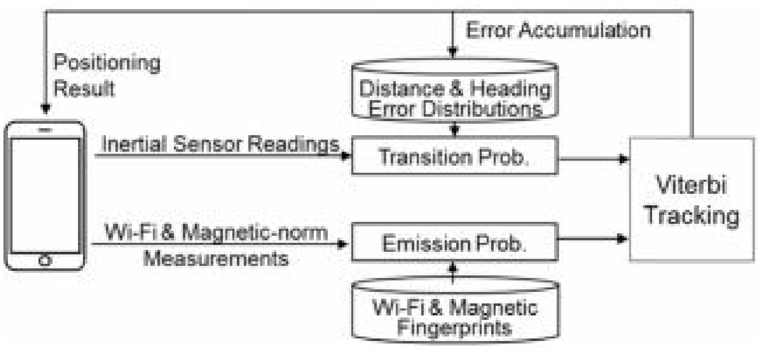


Figure 18: Sensor Fusion using a Viterbi Algorithm [13]

The greatest downside of KAILOS is accuracy. Crowd-sourced fingerprints will never be as accurate as meticulously-place fingerprints, which makes the KAILOS better suited for large-scale or remote buildings with plenty of crowd-sourced fingerprints available.

3.3.3 SurroundSense

SurroundSense [5] makes use of the more auxiliary smartphone sensors by using a fingerprinting approach based on ambient sounds, lighting, colors, and motion patterns. It also uses fingerprinting based on WiFi access points and geocentric solar magnetospheric coordinates (i.e. magnetic fingerprinting).

The SurroundSense system seeks to solve a very likely and feasible problem with both indoor and outdoor localization systems: localization errors caused by a *dividing wall*. As an example, let's say we have an indoor localization solution with an accuracy of 5 meters. If a user is either standing next to a dividing wall or has his/her phone placed next to the wall, the localization system may erroneously determine that the user's position is on the other side of the wall. As demonstrated in Figure 19, even though the user is sitting in the Starbucks, the indoor localization system has determined that he/she is actually located in the adjacent RadioShack.

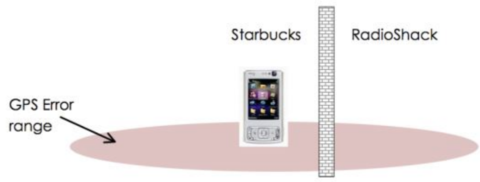


Figure 19: Localization error caused by a dividing wall [5]

Several indoor localization systems have made attempts to overcome this issue, and several have been successful. The Cricket indoor localization system [3], for instance, is one of the most noteworthy of these types of systems. Designed by Nissanka Bodhi Priyantha, a PhD student at Massachusetts

Institute of Technology in 2005, for her dissertation, Cricket dealt with the dividing wall problem by using a RSSI fingerprinting approach that uses both RF and ultrasound transmitters, the former used for measuring and calculating distance between the user and the transmitter, and the latter for producing a frequency unique to individual rooms.

Even though the design of the Cricket indoor localization system is effective and accurate, placing specialized transmitters in every room in a building is expensive and often unfeasible. SurroundSense seeks to overcome this problem by localizing based on properties inherent to individual rooms: ambient light and sound. The ambience (both light and sound) of a bookstore is different from a boutique, which is different from a pub (see Figure 20).

Figure 20: Difference in ambience in a bookstore, boutique, and pub [5]

The SurroundSense indoor localization process is divided into two parts: fingerprint generation and matching. The architecture of the SurroundSense system and the diagram of the fingerprinting and matching processed is shown in Figure 21. To generate fingerprints, the smartphone gathers ambience data, including the light, color, sounds, and WiFi signals unique to each room. It then processes the data automatically using the SurroundSense software and transmits to a remote server. The data is sent to the “fingerprint factory” where it is sorted by type (e.g. light, sound, color, accelerometer, WiFi radio, etc.). The sorted data is then distributed to each of their respective modules. These modules perform the respective action on their data types: color clustering for color, light extraction for light, sound filtering for sound, etc. Once sorted and processed, the data is placed into an “ambience fingerprint” in the form $< f_s, f_l, f_c, f_w, f_a >$ corresponding to sound, light, color, WiFi, and accelerometer respectively. This first fingerprint acts a “test fingerprint”. As a way to gather candidate fingerprints to compare to the test fingerprint and account for instances where WiFi is unavailable, the smartphone’s physical coordinates, L_{GSM}, are also recorded, which includes $< latitude, longitude >$. L_{GSM} is passed to geographical database, where the possible localization area is narrowed down to an area with a radial accuracy of 150 meters. All of the fingerprints of the shortlisted stores (called “candidate fingerprints”) within that 150 meter radius are sent through fingerprint processing and placed in a specialized tuple $F_i =< f_s^i, f_l^i, f_c^i, f_w^i, f_a^i >$.

In the matching part of the localization process, the matching/filtering module selects the candidate fingerprint that most closely matches the test fingerprint by comparing the set of candidate fingerprints to the test fingerprint. The matching/filtering module will eliminate some of the candidate fingerprints that are not likely to match with the test fingerprint (filtering) and return subsets of the candidate that are likely to match the test fingerprint. By using pairwise similarity (comparing a pair of values based off of a quantitative property, or by whether or not they are identical), the set of candidate fingerprints gradually gets smaller revealing the best possible candidates until the only remaining candidate is declared as matching the test fingerprint and thus the user's location.

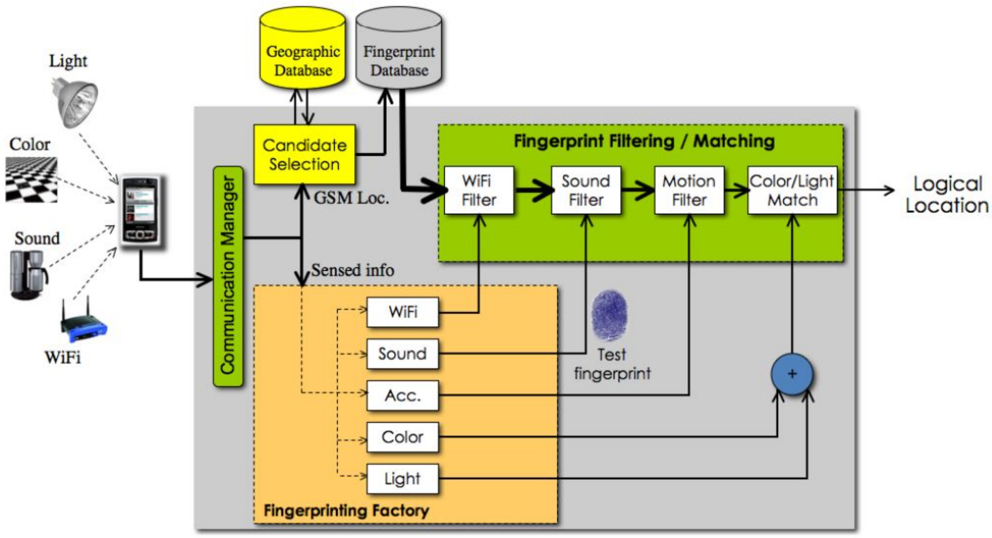


Figure 21: SurroundSense Architecture [5]

The SurroundSense system has definite advantages. The dividing wall problem is addressed by localizing based off the unique ambience of a particular location rather than localizing based on an arbitrary fingerprint. Because the system requires ambient light and sound data and only uses WiFi as a backup, localization using SurroundSense can work even in areas with weak or no WiFi signals. Finally, because the intensive fingerprint matching calculations are performed on a remote server, the user is able to use the system while conserving smartphone battery and processing power.

Despite its unique approach to indoor localization, SurroundSense is not without its limitations. Because the SurroundSense system uses the smartphone's camera and photosensors for localization, the smartphone must be exposed at all times. Normally, a smartphone spends most of its time in a pocket or handbag, but, with the rise of wearable smartphones, this may become less of a problem [5]. Another limitation is that the testing of the SurroundSense system did not account for a lot of normal customer behavior. The system was tested using two groups of students (four in total) at a shopping mall who had earlier fingerprinted every store within the mall. Effort was made to mimic normal customer behavior, but since none of the students had the intention of buying anything, the SurroundSense system failed to pickup certain important sounds such as the beep of a checkout counter. To make up for this, the students imitated the behavior of random customers from a distance including browsing a store shelf or walking through the aisles [5]. Even though this improved accuracy, the

SurroundSense system could not account for the wide variety of customer behavior and would need further improvement in order to do so.

One of the more interesting limitations that we noticed when examining the SurroundSense system was the testbed that was used in the article describing it. The system was tested on a Nokia N95 mobile phone, which was released in 2007 in the United States to be succeeded by the Nokia N96 in 2008. Given the fact that usage of Nokia phones has dramatically plummeted since the introduction of the iPhone in 2007 [21], the mobile phone tested with this system would not be a smartphone representative of the mass population.

3.3.4 Hybrid Method Comparison

All of the hybrid indoor localization systems attempt to solve a current issue with indoor localization systems and provide a unique approach in how to solve it. Table 2 displays a summary of the benefits and drawbacks of each of the previously discussed hybrid systems.

Hybrid Method Comparison		
Hybrid System	Benefits	Drawbacks
LearnLoc	• Machine learning algorithms help make better location calculations	• High energy consumption
KAILOS	• SFM makes accurate location calculations with sparse fingerprints • Viterbi algorithm can account for inertial sensor error	• Crowd-sourced fingerprints are often unreliable • Crowd-sourcing creates cost of accuracy
SurroundSense	• Works well without WiFi connection • Accounts for dividing wall problem	• Camera and photosensors need to be constantly exposed • System did not account for majority of customer behavior • System was tested on an outdated smartphone

Table 2: Hybrid Method Comparison

4 Further Discussion

This honors thesis is written in conjunction with a research project that we have been working on in which we design a system for indoor localization using senors built into a modern smartphone. Our design assumes that the University of Mississippi Oxford campus will be where the system is utilized. Our indoor localization system must be able to calculate position in 3D space because nearly all of the on-campus buildings are multi-story. The design should attempt to make use of what devices and resources are inherently available. In other words, our design should neither require the user to attach external devices to his/her smartphone, nor should the design require campus maintenance to install specialized beacons unless absolutely necessary. Finally, in the case that our system uses WiFi fingerprinting, our system should be able to function even if campus WiFi is down. There are five main components in the testbed for our system design: the client-side mobile app, the remote server, the real-time database, the remote client, and the web client. Each of these components and their relations are diagrammed in figure 22.

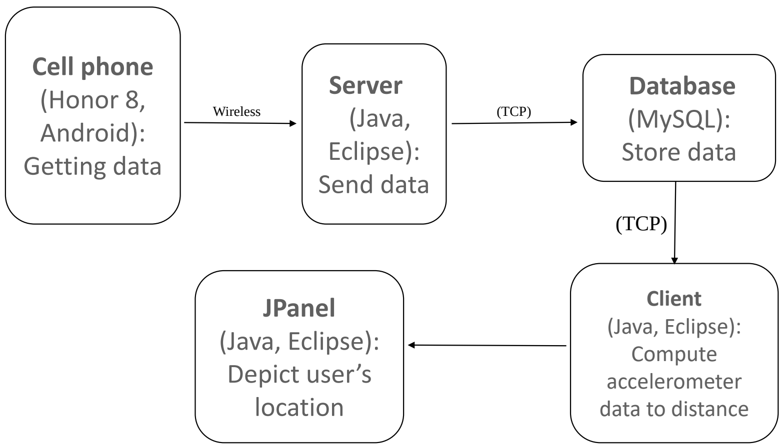


Figure 22: Diagram of our Indoor Localization System

The client-side app will read necessary data from the smart-phone, including accelerometer, gyroscope, and geo-sensor (including latitude, longitude, altitude, heading, and accuracy) data, as well as a time stamp. Further data collection can be added while the app development proceeds. The app will collect the data, package it, and transmit it to the remote server via a TCP (Transfer Control Protocol) connection every 20 milliseconds.

The server will collect the data from the buffer sent over the TCP connection and send it to the real-time database for storage. Having the real-time database will both allow us to store previously recorded data and help us better manage the stream of received data. The data stored in the database is then sent to the remote client, where the data fed into an indoor localization algorithm which outputs an X, Y, and Z coordinate as well as orientation. The coordinates and orientation will then be transmitted to the web client also via a TCP connection.

The web client provides a user-friendly 3D interface that allows a user to visualize where tracked objects are located within a structure. The client will use a graphical rendering framework designed for the web and will receive calculated localization data from the remote client.

4.1 Experimental Setup and Testbed Implementation

For testing purposes, our experimental setup assumes that the indoor testing environment is Weir Hall, the Computer Science and IT building on the UM campus that consists of two floors with almost identical floor plans and plenty of corridors and rooms to test the performance of our indoor localization design. The design will track user location in 3D in order to determine which floor the user is on as well as where the user is located spatially on their current floor.

The preferred mobile operating system (OS) for the client-side mobile app is Android 8.1, tested on an Honor 8 android smartphone. The server-side code is written in Java and uses TCP sockets to communication with the mobile app and web client. The web client uses JPanel as a simple display as of now, but will eventually use a 3D rendering framework such as WebGL to provide a user-friendly interface for our localization system.

Our current localization design uses a very basic form of pedestrian dead reckoning as shown in the formula:

$$\int a\,dt = v$$

with a representing the acceleration and dt being integration with respect to the current time-stamp t. By integrating a, a simple method of tracking the user's velocity can be achieved. This can be further expanded upon in future development by using a double integral to get velocity v and displacement x:

$$\int\int a\,dt\,dt = \int v\,dt = x$$

Although effective, this method in isolation would not make for a satisfactory indoor localization system due to drawbacks like sensor error and irregular user movement patterns, so other methods are needed to supplement our dead reckoning approach. The next section explores which previously-discussed indoor localization methods can be used in conjunction with our system in order to improve accuracy.

4.2 Potential Localization Methods for Our Localization Design

For the purposes of the experimental setup we have created, we now compare and contrast the methods previously discussed in this paper in order to determine which will be most effective to be integrated into our indoor localization design.

WiFi fingerprinting could potentially work as a correction method for our dead reckoning-based approach due to the fact that every building on campus, including Weir Hall, has access to WiFi with several routers in each building. The downside of using WiFi fingerprinting is that it becomes useless when the WiFi is down. Magnetic fingerprinting that localizes based on in-built sources of magnetism like wiring, metals, and electronic devices would work as a substitute barring any campus-wide power outages.

Trilateration would be a viable secondary methods for our design as long as some of the more intensive calculation can be done on a remote server instead of the smartphone. With the servers in Weir Hall, any mathematically complex setup processes could be performed on them which will save both battery and memory on the smartphone.

Proximity estimation would be the simplest secondary method if the application can be built to detect if the smartphone is within the proximity of a permanent, pre-installed beacon such a WiFi router. The downside to proximity estimation is accuracy since it forgoes complex calculations and instead uses simple proximity estimation.

Visual localization would probably be the least effective secondary method because the phone camera would always have to be exposed in order for it to work, and many students on campus carry their smartphones either in their purse, backpack, or pocket. The only possible niche that we could foresee visual localization being viable is for an augmented reality application in which students would points their phone cameras at objects.

Tables 3, 4, and 5 provide an analysis of how well each individual method would work in our current indoor localization design as well as possible hybrid setups, both dual and triple combinations. Each method or method combination is listed with its overall viability in our testbed (Bad, Medium, Good) and a brief explanation of why it would function well in our indoor localization design.

5 Conclusion and Future Work

Human civilization has greatly benefited from every advancement in localization. Indoor localization is a promising area of research that has the potential to benefit human society greatly. With the ability to determine and track the location of people and objects when GPS signals are unavailable — within a structure, underground or underwater, under dense forest canopy, etc. — the technological

Individual Method Consideration		
Method	Viability	Reason
Magnetic Fingerprinting	Medium	Plenty of magnetic sources in Weir Hall; highly prone to error
RSSI Fingerprinting	Good	Weir Hall has plenty of WiFi APs to utilize as fingerprints
RSSI Distance Estimation	Good	Similar to RSSI Fingerprinting; slightly resource intensive
Time of Arrival Ranging	Medium	Resource intensive; requires precise timing calculations
Time Difference of Arrival	Medium	Requires precise timing of multiple beacons
Proximity Estimation	Good	Simple approach; Weir Hall APs could be used as beacons
Visual Recognition	Bad	Visual cue setup required; smartphone camera must be exposed
Scene Analysis	Bad	Computationally intensive; copious amounts of machine learning needed; smartphone camera must be exposed

Table 3: Individual Method Consideration

Hybrid Method Consideration (Dual Combination)		
Method	Viability	Reason
Dead Reckoning and Fingerprinting (RSSI)	Good	Dead reckoning used for inertial measurements, fingerprinting for relative positioning
Dead Reckoning and Fingerprinting (Magnetic)	Medium	Similar to above approach, but higher possibility of sensor error
Dead Reckoning and Trilateration (RSSI Distance Estimation)	Good	Extension of combined DR and RSSI Fingerprinting
Dead Reckoning and Trilateration (ToA or TDoA)	Medium	Similar to above approach, but precise timing calculations are needed
Dead Reckoning and Proximity Estimation	Good	Inertial measurement combined with relative position; less accurate than with fingerprinting, but precise

Table 4: Hybrid Method Consideration (Dual Combination)

benefits are boundless. With indoor localization, autonomous vehicles have better pathing. Navigation and/or exploration through museums, amusement parks, hospitals, schools, and workplaces becomes greatly improved. Emergency response is streamlined and ever more effective. Vending,

Hybrid Method Consideration (Triple Combination)		
Method	Viability	Reason
Dead Reckoning, Fingerprinting, and Proximity Estimation	Good	Inertial measurements combined with 2 types of relative fingerprint localization
Dead Reckoning, Fingerprinting, and Trilateration (RSSI Distance Estimation)	Medium	Similar to above approach; incredibly computationally intensive
Dead Reckoning, Fingerprinting, and Trilateration (ToA or TDoA)	Medium	Similar to above approach; requires precise timing calculations; resource intensive
Dead Reckoning, Fingerprinting, and Filtering (MM, PF, or KF)	Good	Inertial measurements corrected with Kalman filtering; fingerprinting corrected with map matching or particle filtering

Table 5: Hybrid Method Consideration (Triple Combination)

advertising and marketing companies can utilize indoor localization technology to greatly improve customer experience. The possible benefits of indoor localization are limitless. When combined with the convenience, ubiquity, and ease-of-use of the smartphone, the power of indoor localization can aid the broadest audience possible.

There have been several advancements in the realm of research on smartphone-based indoor localization. Many of the systems discussed in this thesis offer a unique solution to the problem of determining indoor location using a smartphone either by combining existing methods or innovating on new methods. Although all of them offer a unique solution, none of them are flawless, and there are downsides to each, which makes smartphone-based localization an active area of research calling for further innovations, advancements, and improvements to be made in the near future.

Our indoor localization system will see improvements upon future developments including an enhanced localization algorithm, modifications to the client-side mobile app to allow for more reading of sensor data, and refinements on other system components including the database, remote server, and remote client. These improvements will allow for an incredibly refined and effective smartphone-only indoor localization system that could prove to be useful for the University of Mississippi, as well as other campuses, for campus navigation, special activities, and in case of an emergency situation.

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