TRACKINDOORS: REAL-TIME INFRASTRUCTURE-LESS INDOOR TRACKING USING HYBRID APPROACH

by

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I dedicate this thesis to my parents Mr. Arjun Palamakula and Mrs. Hemalatha Palamakula for their immense support throughout my life. I hope this achievement will complete the dream that you had for me long ago when you chose to give me the best education you could.

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ABSTRACT

The ability to locate and track humans or objects indoors and outdoors is becoming increasingly important in today's world of applications. The positioning accuracy and reliability outdoors is very well handled by the Global positioning system (GPS). However, GPS has very poor accuracy in indoor environments due to obstruction in the line of sight (LOS) of satellites. Most of the services require seamless positioning capabilities throughout all environments which made indoor localization a widespread field of study. In this thesis, a real-time hybrid approach is proposed to locate and track people indoors.

The main objective of this thesis is to design and develop a hybrid indoor tracking system called TrackIndoors. Our hybrid approach uses Wi-Fi and smart-phone sensors together to track and locate the position of people in the indoor environments. A real time android application is developed and it consists of three components: trilateration, fingerprinting and sensor fusion. The Kalman-filter based prediction is used to produce better tracking results. The performance of the proposed system was evaluated through experimental analysis. Results of our hybrid approach shows that the system is able to locate and track a person with high-precision and low cost.

LIST OF ABBREVIATIONS USED

API	Application Programming Interface
APs	Access Points
BLE	Bluetooth Low Energy
BSSID	Basic Service Set Identifier
dBm	decibel milliwatt
GPS	Global positioning system
INS	Inertial Navigation System
IR	Infra-Red
LBS	Location Based Services
MAC	Medium Access Control
MEMS	Micro Electro Mechanical Sensor
NFC	Near Field Communication
RF	Radio frequency
RFID	Radio frequency Identification
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
SSID	Service Set Identifier
TOA	Time of Arrival
UWB	Ultra Wide Band
WLAN	Wireless Local Area Network
WSN	Wireless Sensor Network
XML	Extensible Markup language

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CHAPTER 1 INTRODUCTION

1.1 Overview of Localization

Localization is defined as a process of determining the location of an object or a person in an environment either indoors or outdoors. As we dig into history, many specialized tools have been developed to help and provide more accurate localization. Global Positioning System (GPS [1] is currently used in all vehicular systems like cars, ships, and aeroplanes. This system helps in navigating across the globe over the roads, seas and sky. GPS is an outdoor localization technology [2] and is able to produce very accurate positioning. It depends on line of sight (LOS of satellites; therefore, it can accurately position the objects in outdoor environments. GPS is not reliable [3] in indoors due to obstruction of LOS caused by multi-path interference, building roofs and walls. Indoor positioning and navigation has become the hot topic in today's localization based research. Till today the research in this area [4] includes various technological approaches such as Infrared (IR), Ultra wide-band (UWB) [5], Wi-Fi[6],Blue-tooth low energy (BLE)[7], Zig-Bee [8], Near field communication (NFC) [9], Radio-frequency identification (RFID), Wireless sensor networks (WSN), magnetic field fingerprinting, image processing. This thesis mainly focuses on infrastructure-less technologies for indoor localization. A hy-brid approach is proposed to produce better accuracy. In this chapter, we present motivation of study, then we describe the overview of the proposed system and finally an outline of the thesis.

1.2 Motivation

We spend most of our time in indoor spaces like offices,universities,shopping malls, hospitals, airports, commercial buildings,transit stations, etc. When we are in these spaces most of us must have come across the scenario where we spend a lot of time in locating services and looking for directions to reach desired location indoors. Similar scenario in outdoors is solved by GPS but it fails in indoors. Indoor tracking would help us in providing services that are offered by GPS outdoors. Location based services(LBS holds considerably a high attention due to its requirement in various indoor locations. The development of indoor location tracking technologies is influenced by several advantages offered by LBS. The main objective of this thesis is to address the problems in indoor localization and come up with a solution which is infrastructure-less, cost effective and reliable accuracy. This thesis uses hybrid approach to overcome the disadvantages of an individual technology.

1.3 System overview

The main objective of this thesis is to propose a feasible indoor tracking system that is capable of tracking position of people inside the buildings at a low cost. This objective is achieved by integrating two different technologies that are Wi-Fi and smart-phone integrated sensors. Wi-Fi is freely available in most of commercial buildings, hospitals, universities, airports and transit sta-tions. Sensors used in our approach are accelerometers, magnetometers and gyroscopes which are available in most of the smart-phones that we use today. Much work has been done on Wi-Fi localization among which RADAR [10], [11] is very first Wi-Fi signal-strength based indoor positioning system. It proved that RF fingerprinting and environmental identification with the help of Wireless Local Area Network hardware will be used to track user or mobile device's lo-cation within buildings, thereby enabling indoor location-aware applications. In RADAR [11], three Wi-Fi base stations are infrastructure nodes. The mobile nodes measure signal-strength in DBm and patterns are matched to locate mobile nodes in the Wi-Fi environment.

Radio channels indoors are variable and unpredictable due to different multi-path shadowing effects, which are caused by reflection, refraction and scattering from walls, roofs, and other obstacles of the indoor environment. Wi-Fi localization is mainly based on two approaches deterministic and stochastic. The deterministic approach involves fingerprinting of received signal strength. In this approach Received Signal Strength(RSS) readings of the test environment are taken first and stored in a database;and this phase is known as Offline phase. In the Online phase, the user with Wi-Fi enabled device is tracked by comparing the RSS val-ues of an unknown location to that of the RSS stored in database. The Stochastic approach imposes a probabilistic model on RSS and posterior distribution is found.

Among these two approaches the most commonly used in indoor localization is deterministic; because the proba-bilistic approaches are not reliable, the probability of finding distance based on signal strength is completely unpredictable due to variant nature of signal-strength that would produce huge errors in predicting indoor locations. Though fingerprinting is popular approach in the field of indoor localization it has limitations due to time variant nature of signal-strength and signal attenuation.

Our proposed approach in this thesis mainly focuses on reducing the error rate involved in using Wi-Fi technology alone for indoor localization. The proposed system uses hybrid approach with multi-phase localization using infrastructure-free technologies such as Wi-Fi and MEMS (Micro-Electro-Mechanical System [2]. The proposed approach uses improved fingerprinting methods along with Enhanced RSS trilateration and Sensor fusion. Complimentary filters were used to remove the noise from the sensor data and Kalman-filter filter predicts the location of user based on sensor and Wi-Fi data. The performance of the proposed approach is evaluated by building real-time android application. The application is tested in the test area which is fully covered with existing Wi-Fi infrastructure and the results obtained were evaluated. The detailed system overview is presented in Chapter 3.

1.4 Outline

This thesis is organized into the following sections. Chapter 2 provides literature review in which various indoor tracking systems are discussed. Chapter 3 explains the system design of proposed hybrid approach. Chapter 4 provides the implementation of the proposed approach. In Chapter 5, the results and analysis of the proposed approach is discussed. Chapter 6 includes conclusion and future work.

CHAPTER 2 LITERATURE REVIEW

Indoor localization has remained a hot research topic over the past few years. Many different research groups have been trying to find the solution to locate the position of a person within indoor environments using various methods and technologies. This chapter explains the work which has been done in the field of indoor localization and points out the merits/de-merits of the existing systems.

2.1 Global Positioning System (GPS

The Global Positioning System (GPS [1] is a navigation system which can provide location information in all weather conditions,anywhere on or near earth. GPS receivers can determine latitude,longitude and altitude with high degree on accuracy. GPS is able to locate any GPS enabled receiver device. GPS was developed by US military and to make it work successfully, there are 29 satellites revolving around the earth among which 24 are used for the process of trilateration and 5 satellites are spare. GPS satellites constantly broadcasts two pieces of information which includes its own location and current atomic clock. The electromagnetic waves are transmitted from GPS satellites which are received by GPS enabled devices on the earth.

GPS is successful outdoor positioning system. However, the obstruction of line of site to the satellite signals in indoor environment makes it unfeasible in indoors. The signals from satellites are scattered and attenuated by walls, roofs, other object in indoor environment. In order to overcome the limitation of GPS SnapTrack [12], a Qualcom company came up with A-GPS which was called as Assisted Global Positioning System. It was wireless assisted GPS and was able to produce accuracy of about 5-50m.SuperSense was another approach proposed by Atmel and U-blox. Locata [3] an Australian company came up with system which consists of beacons that penetrate through walls. Locata receivers were used instead of GPS receivers. The accuracy levels were quite good as in outdoors but involves huge deployment of Locata receivers which is not possible in real-time. Therefore, the indoor positioning based research was needed and various indoor positioning approaches were proposed.

2.2 Overview of Indoor Technologies

In the literature [4], [13]–[15], Indoor localization employs a wide range of technological approaches like infrared *(IR),* ultra-wide band *(UWB*), wireless fidelity *(Wi-Fi),* Bluetooth low energy *(BLE),* Zig-Bee, Near Field Communication *(NFC)*, Radio frequency Identification and detection *(RFID),*Wireless Sensor Networks *(WSN),* Radio Frequency *(RF)* , inertial sensors, magnetic sensors, image processing, etc. Among all the technologies, ultra-wide band (UWB) signals, Infra-Red(IR), Radio Frequency (RF), proximity sensors and ultrasound systems can localize accurately. But the all these approaches require separate hardware setups which would increase the deployment cost that makes it unfeasible.

2.2.1 Infrared positioning system (IR

The first indoor location sensing system using Active Badge is developed by AT&T Cambridge[5]. In Figure 1 Active Badge [5] is an infrared beacon worn by a person which emits a unique code identifier for every 15 secs. Every location inside the building is covered by network of IR sensors which picks the signals emitted from the Active Badge. A centralized server was maintained to extract this data from fixed IR sensors and this data was used to track the location of a person wearing active badge.

IR radiations cannot penetrate through solid surfaces like walls which made it to use in the office building for tracking employee moments.

2.2.2 Ultrasonic positioning system

Another indoor location tracking system developed by AT&T Cambridge using an ultrasonic tracking technology which provided a better and more accurate indoor positioning than the previous Active Badges. Ultrasonic tags identified as “bats” were used to track object or person [16]. These bats emitted periodic ultrasonic signals to receivers mounted across the ceiling. The ultrasonic receivers were mount all over the ceilings of the test environment and the signals from bat were received to produce position related data. This data was used to localize person or object, See Figure 2.2. The deployment of this system is not easy since it uses large number of receivers and placing those receivers on ceiling is not an easy task.

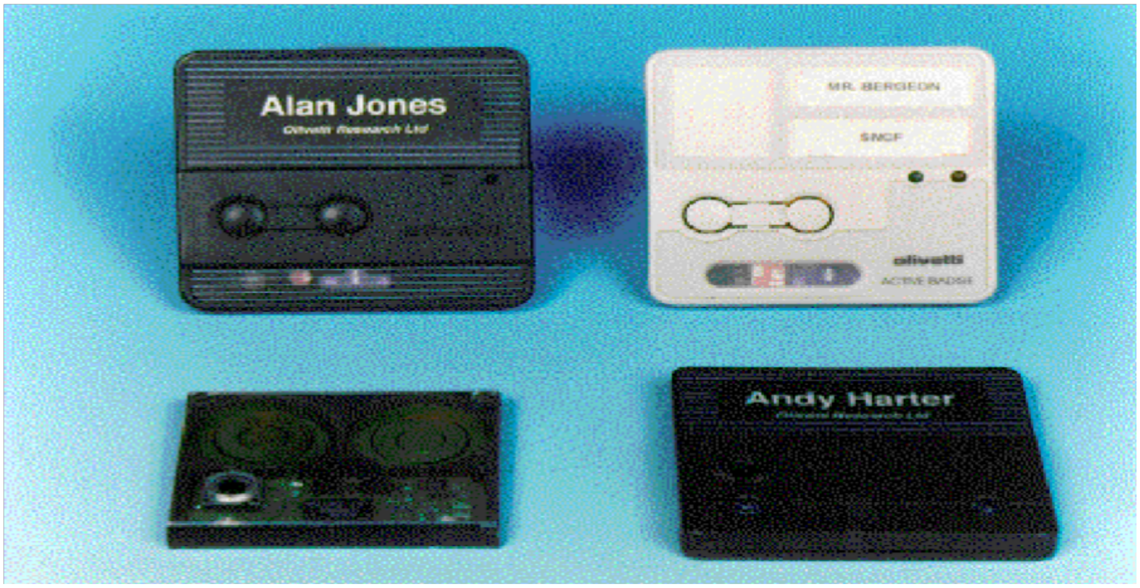

Figure 2.1: Active badge

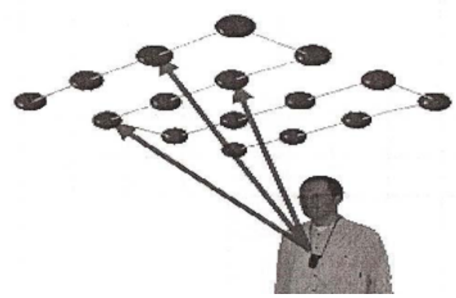

Figure 2.2: Active Bats

CRICKET [17] and "Distributed Object Locating System for Physical Space Internetworking" (DOLPHIN) [18], [19] are another location tracking systems that used ultrasonic beacons in localizing the object or a person.

2.2.3 Radio Frequency Identification (RFID

The RFID systems use Radio Frequency (RF for data transfers. The advantages of this technology are non-contact and non-line of site nature of the system. RFID can track the objects to which tags are attached. It is commonly used in assets tracking, inventory tracking, patient tracking, etc. Some of the popular RFID localization systems are SPOT ON [20] and LANDMARC [21], they manage 3D location sensing based on RSSI. Tags are developed such that they measure RSSI to calculate inter distance between Reader and sender tag.

2.2.4 Near Field Communication (NFC

Near field communication[9], [22] can also be used indoor for localization. Hammadi et al. 2012 [7] Proposed system which used NFC tags and QR scanner to localize inside the buildings, this system was able to locate user position on scanning QR codes or tapping NFC tags which were placed in known and readily accessible locations of buildings. On scanning the user would know the exact position and navigate to desired location by scanning through various points that are distributed inside the building. The problems in this kind of approach is user has to physically tap every time when he wants to know the location, this is time consuming and requires monitoring of tags and QR code all the time which is impractical when it comes to large scale implementation.

2.2.5 Bluetooth low Energy (BLE

Bluetooth is a wireless technology which is used between two or more devices to communicate over short distances. It is a wireless,inexpensive technology. Since Bluetooth is available in majority of smart-phones today this technique is gaining popularity as Wi-Fi. Class1.0 Bluetooth supports a maximum transfer speed of 1 megabits per second (Mbps),while class 2.0 Bluetooth can manage up to 3 Mbps, Bluetooth class 2.0 can have maximum communication distance of up to 10 meters. Bluetooth class 4.0 offers better range and very low energy consumption. Faragher et al. 2014 [23] claimed that fingerprinting approach of BLE is more accurate than Wi-Fi fingerprinting. This positioning system must deploy BLE beacons around the area of localization and fingerprint maps are taken which are stored in database and compared to that of fingerprints of localization phase.

2.3 Wireless local area networks (WLAN)

RADAR [10], [11] ,developed by Paramvir Bahl and N. Padmanabhan, was the first Wireless Local Area Network (WLAN) based indoor positioning system. This approach had an error of 2.94 meters using nearest neighbor algorithm. The accuracy was improved by reducing error distance of 2.37 meters on employing Viterbi algorithm which outperformed nearest neighbor in signal space (NNSS .

The Wi-Fi standard provides great possibilities for indoor localization both in public and corporate areas. There are some advantages compared to other positioning techniques is that the range of typical wireless products, like Wi-Fi AP's is limited (30m and thus AP's needs to be placed in relatively short intervals. The Wi-Fi infrastructure is ubiquitous and readily available at many places making Wi-Fi based localization popular. Currently 9 out of 10 smartphones are capable of communicating over Wi-Fi and the deployment of applications is easy and read-ily available for a large amount of users in platforms like Android. One of the disadvantages is that indoor environments are always complex, which require harder modeling methods for better accuracy. Various methods of Wi-Fi based indoor localization given in the following subsections.

2.3.1 Fingerprinting

The fingerprinting based methods [24]–[29] are used to localize the user in wireless area networks. Fingerprinting localization approach consists of two-steps the training phase (Offline) and the localization phase (Online). In the training phase, the fingerprint map of the environment is built which consists of MAC address and RSS of APs. The map is consisting of the unique parameter at every reference points within the environment. In the localization phase, the RSS values of the user are recorded and compared to the values that are stored in the database during training phase [24], [30]. The location of user is estimated based on the best match between the user's current RSS value and training database values. Fingerprint based localization produces relatively better localization accuracy when compared to other Wi-Fi localization.

2.3.2 Received signal strength indication (RSSI

Wi-Fi runs by having routers broadcast radio signal which is received by smart devices such as phones, tablets, laptops etc. Measuring the signal strength [31], [32] from each AP can be used to gives a rough indication of the distance to the AP. On trilateration of multiple AP's, the position of user's device in the vicinity can be calculated using RSSI one can estimate the position of target based on AP's. The AP's are considered as reference points and by estimation of distance user location is determined.

$RSSI = -KlogD + A$

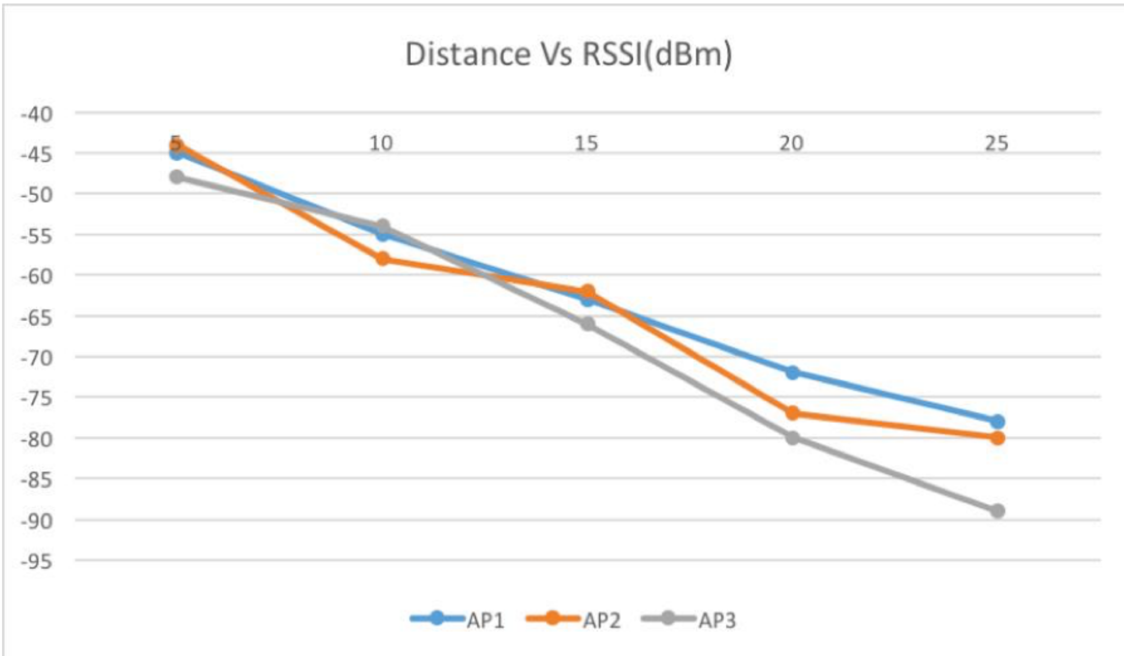

Figure 2.3: Distance vs RSSI

2.3.3 Trilateration

The strength of signal is used to estimate the user's distance from three AP's. The estimated distance is used to generate circle's around the AP's and the point where three circles intersect is considered to be the user's current location. Though it can estimate user's current location this technique is error prone since the Wi-Fi signals are variable, the factors such as walls, roofs, number of people, objects inside the building makes Wi-Fi signal variable [25]. Trilateration [33] can produce unique results only when the distance is correctly estimated. Which is challenging to estimate accurate distance therefore this technique cannot be used alone for the localization. Several techniques were proposed to address this issue. Researchers used distance which was obtained after averaging distance between receiver and transmitter. After about 300 estimations the results were close to the actual result.

Various algorithms were proposed to improve trilateration among those spherical trilateration

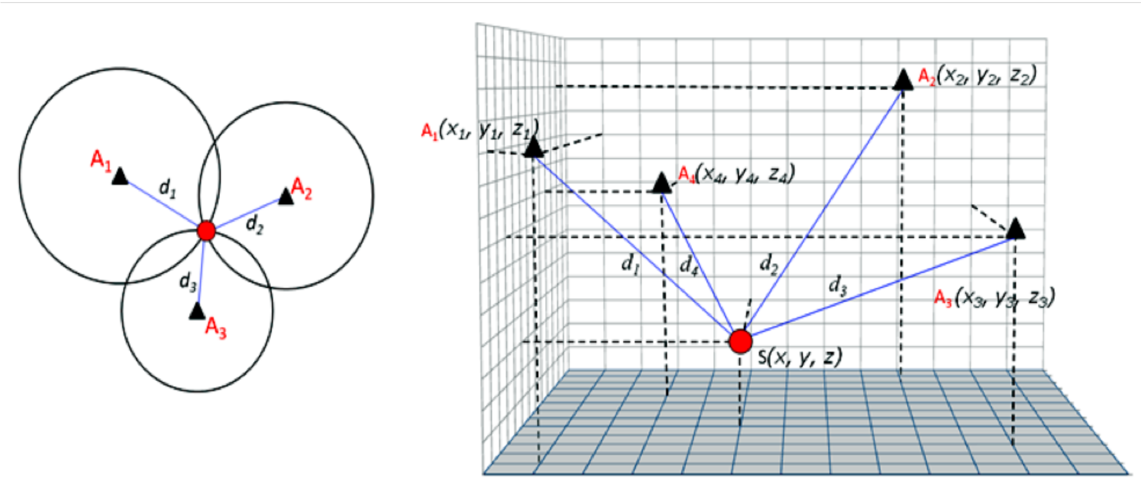

Figure 2.4: 2D and 3D Trilateration; Source:[33]

was popular.

Spherical trilateration

In this estimation of user's location is done when the position of AP's and the distance between device and AP's is known.

Let 'n' be the number of Access Points their position is represented by (x_1, y_1, z_1), (x_2, y_2, z_2), ..(x_n, y_n, z_n).

Let r1, r2, r3 be the distance and (x_u, y_u, z_u) be the users location.

The algorithm calculates actual position using

$$U_i = (X_u - X_i)^2 + (Y_u - Y_i)^2 + (Z_u - Z_i)^2 \tag{2.1}$$

2.3.4 Medium Access Control (MAC

Receiving a signal with a MAC address from an AP's indicates that the receiving device is within approximately 30 m range, depending on building structure, power of transmitted signal and effectiveness of a receiving antenna. It can be used to pinpoint a device to a certain area. Furthermore, to improve the positioning multiple AP's are to be used.

trilateration.png trilateration.bb

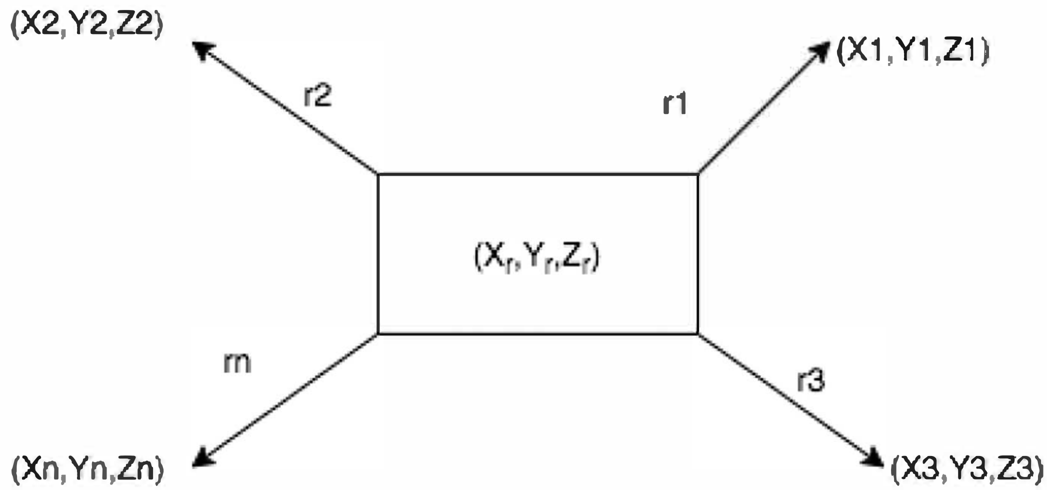

Figure 2.5: Spherical trilateration

2.3.5 Time of Arrival (TOA)

In this approach the time taken by a message from when it was sent from transmitter and received by device may be used to compute the distances between the AP's and the device. But it needs AP's and the measuring device to be synchronized, the time difference is usually very short (□ 3 seconds per meter). However, in indoor environments, time synchronization needs to be precise.

2.3.6 Time Difference of Arrival (TDOA)

It is a measurement of the time difference between signals arriving from different AP's is used to determine the position, when all the available AP's are synchronized, this requires the similar kind of synchronization as the *Time of Arrival* method.

2.3.7 Round Trip Time (RTT)

The measurement of time taken by a message to travel to the AP and back again called as the round trip time. This method eliminates the need of synchronized APs, as there is only one device used in the time measurement the need for synchronization is eliminated, the time from when an AP receives a message and it sends the response has to be known. This technique can be used for positioning the receiving device can be AP or positioning device.

In trilateration signal decays as the distance between transmitter and mobile device increases due to wall attenuation. Therefore, fingerprinting localization technique produces better results than trilateration [34].

2.4 Sensors

The common sensors that are available in today's smart-phones are the accelerometer, the gy-roscope and the magnetometer. A very brief description of how they work, advantages and disadvantages and their use in position estimation. A more in-depth description of the sensors and about their biases and drifts can be found in [35], [36].

2.4.1 Accelerometer

An accelerometer is a sensor which can measure an acceleration (m/s^2 along one or more axes. An accelerometer at rest on the Earth's surface measures an acceleration of $g = 9.81 m/s^2$ and an accelerometer in free space will measure zero acceleration. Now a day, most accelerometers measures acceleration along 3 orthogonal axes, thus giving information about the three dimensional acceleration. We know that every object that is at rest on the Earth experiences the acceleration associated with gravity which poses a problem when using the accelerometer, since the gravity is always there in the measurements. Managing this problem by keeping the accelerometer fixed in reference to the Earth's coordinate system by making gravity as a constant bias along a certain direction, which can be easy to subtract. A case where the accelerometer changes its orientation compared to the Earth's coordinate system. Accelerometer could be used to estimate a position by integrating its output twice with respect to time. Practically, it is hard as the gravity needs to be accurately subtracted from the measurements if not to introduce a large positioning error. If just 1 % of gravity is in the measurements would introduce an error of 500 m over 100 secs further, the sensors present in today's smart-phones suffer from various biases and drifts. This error needs to be corrected otherwise that would lead to huge positioning in accuracy.

2.4.2 Magnetometer

By the use of a magnetometer, the problem of knowing initial heading can be solved. It measures the magnetic field strength in each of the phone's three coordinate directions. Therefore, using the known electromagnetic field produced by the Earth's core, it is possible to find the phone's heading. In theory the magnetometer along with a known phone's orientation in reference to the Earth's coordinate system could be used to give an accurate estimation of the user's direction of heading. It is possible in environments where the electromagnetic field is strong. i.e., outdoors. In indoor environments however, the fields from electronic devices and elements (metals, pipes etc. produce their own magnetic fields which would produce wrong headings. The fingerprinting strategy for signal strength can be used to characterize the magnetic field strengths in an indoor environment. These measurements can then be used to find the true heading, but this approach lacks generality as measurements at each location are needed. In order to increase the positioning accuracy, all the above discussed technologies can be combined or used with different technologies such as Bluetooth low energy(BLE, NFC, RFID etc.

2.4.3 Gyroscope

A gyroscope measures the angular velocities around each of its axes. Most gyroscopes use three orthogonal axes giving measurements of the angular velocities in the form of ω= (ωx ωy ωz). A gyro normally consists of a spinning machine or disc mounted in every gimbal, a pivoted support that permits the disc to rotate freely over all 3 axes. This construction permits the disc to stay Associate in Nursing virtually mounted position in regard to the mounting platform's motion. However, this can be some reasonably huge devices cannot match electronic devices. The electronic devices use MEMS gyroscopes which are designed into a more portable form and it can measure angular velocities. Set of angular velocities measured with a time difference of Δt, the angular change θ, this can be computed using numerical integration. According to the trapezoidal rule [37], It can be applied to each of the gyroscope axis, with which estimation of how the gyroscope is turning and its orientation in 3 dimensions.

In determining the direction of movement using gyroscope there are few problems as it only measures how the angles change over time, the direction at the start of the navigation must be known and the orientation needs to be kept fixed in reference to the movement. Furthermore, the gyroscope also suffers from drifts and biases resulting in a heading error. Hence, gyroscope needs to be calibrated to avoid biases and drifts.

2.5 Related Works

Xiao [37] developed a stochastic approach based on fininte state machine which utilized wi-fi fingerprinting and INS to track current location of user. Although it produced better accuracy, but at the cost of complexity in the deployment of the system. Korenberg [30] tried to combine Wi-Fi fingerprinting and INS data. however, the sensor data was collected from IMU mounted on shoe which added complexity in the deployment. Himloc [38] was another hybrid approach that used Wi-Fi fingerprinting and inertial sensors. The particle filter was used in combining Wi-Fi and INS data. In order to use this system, the knowledge about the map was needed.

Zee [39] was another hybrid approach in which Wi-Fi and INS were used for the localization of indoor environment. Berkovich developed hybrid positioning which was able to produce 1-2m accuracy but at the cost of high energy. The system used complex algorithm which utilized high energy resources. Herrera [40] used particle filter to combine PDR and WCL. Chai [41] used PDR, Wi-Fi, and Barometer all three technologies were integrated. The real time use of algorithm was limited. Jin [28] proposed nearest neighbor selection algorithm for real time fingerprinting along with INS. Ubejd [42] proposed hybrid approach with sensor fusion and wifi technologies. In this approach the results from sensor was not completely filtered and which had low accuracy. The proposed approach was a hybrid with improved accuracy which made use of INS and Wi-Fi.

Table 2.1: Comparision of different positioning systems

System	Outdoors	Indoors	Accuracy	Signal & Technologies	Cost
GPS[1]	✓		1-5m	TOA, trilateration	High
Active Badge[5]		✓	7m	IR, trilateration	Moderate
Active Bat [16]		✓	9m	Ultrasound, trilateration	Moderate
Cricket[17]		✓	2m	Ultrasound, trilateration	Low
Dolphin[18], [19]		✓	2m	Trilateration, Ultrasound	Moderate
UWB [43]		✓	10m	RF, TOA	Moderate
SPOTON [20]		✓	Room	RF, RSS,	Low
LANDMARC [21]		✓	50m	RF, Triangulation	Moderate
RADAR [10], [44]		✓	2-3m	RSS triangulation	Moderate
COMPASS [45]		✓	1.65m	WLAN, Fingerprint	Low
EKAHAU[46]		✓	1m	WLAN, RSSI	Low
UBISENSE[47]		✓	Tens of cm	UWB, TDOA, AOA	High

CHAPTER 3 SYSTEM DESIGN

This chapter outlines the technologies in the design of TrackIndoors. Our system design uses hybrid approach which consists of Wi-Fi and sensor data in order to increase overall accuracy of the system. This chapter explains main components of our design in detail.

3.1 Wi-Fi

Wi-Fi is a wireless technology that uses radio waves providing high speed Internet connections. Wi-Fi is a common name for the IEEE 802.11x standard. A Wi-Fi enabled device such as a smart-phones, pc's, video players, tablets etc. are connected to Internet through AP's. A commu-nication across a wireless network is a two-way communication. A device's adapter converts data into radio signals and the signals are transmitted through antenna, wireless router receives the signal, decodes it and then it sends the information to the Internet using Ethernet connec-tion. Every wireless router or AP broadcasts a signal that is received by devices in range of 100 m. The receiving devices have the capability of measuring signal strength. This strength is mea-sured as Received Signal Strength indicator (RSSI). Wi-Fi enabled smart-phones running over android operating system are capable of obtaining RSSI of AP's. Andoid's wifimanager API allows us to record signal strengths of AP's.The proposed system uses RSSI based positioning along with sensor fusion to produce better accuracy.

3.2 RSSI Localization Techniques

The RSSI based localization algorithms which were used are Weighted center trilateration and RSSI improved Fingerprinting.

3.2.1 Weighted Centroid Trilateration

Trilateration [48] uses Wi-Fi signal strength, signal frequency, MAC-address and real coor-dinates of AP's in the site. The signal strength received by target device is used as distance estimation between AP's and mobile devices. Trilateration needs at least 3 or more AP's. The signal strength of AP's is exponentially decreased with distance.

The weigthed centroid trilateration consists of two phases:

- Estimation phase
- Location phase

Estimation Phase: The distance between wireless device and each access point (AP) is estimated based on the strength of signal.

$$RSSI = 10log(Receivedstrengthinmilliwatts) \tag{3.1}$$

RSSI is measured in dBm. The path loss model can be given as

$$PL = PL_{ref} + 10 * n * log_{10}(d) \tag{3.2}$$

PL is the signal attenuation between two locations; n is an attenuation factor which varies with environment;PL_ref is path loss calculated at far-field of antenna.

$$PL = P_t - P_r + Site_c + AP_c + T_c \tag{3.3}$$

P_t is transmitting power;

P_r is power received;

$Site_c$ is the constant which varies with structure of site;

AP_c is the constant which varies with different AP's configs;

T_c is the constant which varies with wireless antena of various devices.

The values of constants is selected by based on optimazation.

Location Estimation phase: The location of target device is predicted based on estimated distance from various AP's and their positions.

Let us assume there are 'K' APs and $(X_1, Y_1), (X_2, Y_2)....(X_k, Y_k)$ be the coordinates of 'K' APs.The estimated distances between target and APs be $d_1, d_2, d_3...d_k$

The distance estimation is presented through circles around the APs. The circle with 'AP' as center can be given by [X,Y,d], where (X,Y) are coordinates of APs and 'd' being the estimated distance between APs and target device. The location estimation can be achieved through following steps; *Step 1:* Consider any 3 APs with strong RSSI let us say p,q,r the three circles can be given as $[X_p, Y_p, d_p]$, $[X_q, Y_q, d_q]$,and $[X_r, Y_r, d_r]$.

Step 2: The circles intersects each other at various points, Suppose intersecting points forms a polygon ACBD with triangles ACD,CBD,ACB and ABD and corresponding centroids $C_1, C_2, , C_3 and C_4$

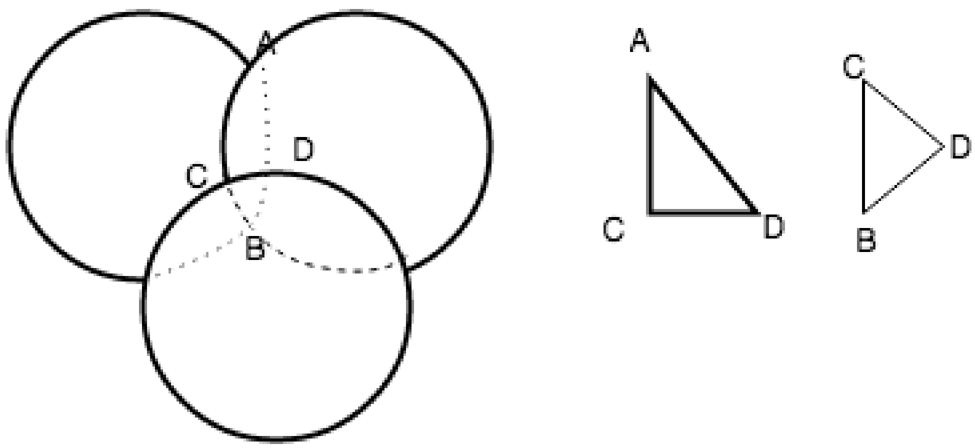

Figure 3.1: WCT Trilateration

Fig 3.1 shows three AP circles.

The weighted centroid of the triangle can be given as

$X_{c1}(X - coordinate) = \frac{X_A * W_A + X_E * W_E + X_F * W_F}{W_A + W_E + W_F}$

$Y_{c1}(Y - coordinate) = \frac{Y_A * W_A + Y_E * W_E + Y_F * W_F}{W_A + W_E + W_F}$

$$W_{ci} = \sum RSSI_{intersectingAPs} \tag{3.4}$$

The weighted centroid G can be given by

$$X_i = \sum \frac{X_{c_i} W_{c_i}}{W_{c_i}} \tag{3.5}$$

$$Y_i = \sum \frac{Y_{c_i} W_{c_i}}{W_{c_i}} \tag{3.6}$$

The weighted centroid of G_1 can be obtain from equation 3.4 and 3.5

$$(X_{G1}, Y_{G1}) = (\sum \frac{X_{c_1} W_{c_1}}{W_{c_1}}, \sum \frac{Y_{c_1} W_{c_1}}{W_{c_1}}) \tag{3.7}$$

Step 3: Repeat steps 1 and 2, if there are 'k' APs then the number of probable locations can be $k(k-1)2$. Finally Weighted centroid of all such locations say 'L' gives the most probable location.

Exceptional case : When no circles are coincided, choose 3 circle with strongest signal strength.

$$RSSI = (P_w * 10\frac{RSS}{20})^g \tag{3.8}$$

$P_w = referencepower; g = constant$

Trilateration technique used in this thesis is based on Weighted centroid algorithm. It works on calculating geometric centroid of all the measuring points. The RSS values are prioritized.

Trilateration based on RSS using weighted centroid algorithm is used in this work.

3.2.2 Fingerprinting

The fingerprinting based methods are used to localize the user in wireless area networks. Fingerprinting localization technique works in two-steps: the training phase (Offline) and the lo-calization phase (Online). In the training phase, the fingerprint map of the environment is built which consists of MAC address and RSS of APs. The map is consisting of the unique parame-ter at every reference points within the environment. In the localization phase, the RSS values of the user are recorded and compared to the values that are stored in the database during train-ing phase [24], [30]. The location of user is estimated based on the best match between the user's current RSS value and training database values. Fingerprint based localization produces relatively better localization accuracy when compared to other Wi-Fi localization. The RSSI database is known as a radio map.

Online Client:

- Measurement of signal strength from various Access points

- This information is mainly used to do the position estimation.
- The cost of deployment would be cost of managing client devices, profiling a site, build and maintenance of the model.

Offline

- Administering the signal strengths of the site.
- Monitoring the scanning devices.
- Cost of deployment would be cost of hardware and software used.

Though it produces better results it also has drawbacks, since it mainly depends on Wi-Fi signal strength which changes with time and environmental conditions of the location where fingerprints are taken. To overcome this problem "Double-peak Gaussian model" is adopted. It uses probability density function of RSSI which can be represented as

$$P(X) = (\frac{1}{\sqrt{2\pi\sigma}}) * e - (\frac{X - \mu^2}{2\delta}) \tag{3.9}$$

Where, $(\delta > 0)$ $X = variableoffunction$ $\mu = mean$ $\delta = Standarddeviation$

By using above approach the amount of work involved in building significant database can be reduced. The accuracy and reliability of fingerprint database is increased by using Gaussian arithmetic approach.

The procedure for fingerprint-based positioning using the proposed model is as follows, where steps 1 - 3 are data training phase and from steps 4 - 6 are the positioning phase:

Step-1: select the reference points (RPs), and then collect the RSSs from all APs at each RP.

Step-2: find the peaks values from RSSs using $P(X) = (\frac{1}{\sqrt{2\pi\sigma}}) * e - (\frac{X-\mu^2}{2\delta})$.

Step-3: Create the fingerprint database.

Step-4: RSSs are collected and outliers are removed. Calculate the probability distribution of received RSSs. The RSSs of estimated point (EP) which is obtained from trilateration is matched.

Step-5: Use the fingerprint database to calculate the probability density for the RSSs collected in the step 4.

Step-6: Estimate the user's location using the K weighted nearest neighbor (KWNN) algorithm.

KNN is a conventional algorithm used in Wi-Fi based positioning for fingerprinting. The location where fingerprinting and positioning is done will be referred as test site throughout the thesis. To improve the obtained result from fingerprinting it needs a different technology in order to compliment its limitations. Proposed method would solve this problem which can be explained in detail in coming sections.

3.3 Sensors

INS (Inertial Navigation System)[49] is an indoor navigation technique in which measurements from accelerometers,Magnetometer,and gyroscopes are used to track the position and orientation of a device. INS data is used in pointing position of device on a map relative to its previous position, orientation and velocity. The data from various sensors that is used in localization can be explained further in detail in section 3.5.

3.3.1 Accelerometer

An accelerometer is a sensor [50] which can measure an acceleration $\frac{m}{s}^2$ along one or more axes. Accelerometer measures the proper acceleration of the device. An accelerometer at rest on the Earth's surface measures an acceleration of $g = 9.81\frac{m}{s}^2$ and an accelerometer in free space will measure zero acceleration. Accelerometers measures acceleration by sensing amount of mass present on device when a force acts on it. A case where the accelerometer changes its orientation compared to the Earth's coordinate system. Accelerometer could be used to estimate a position by integrating its output twice with respect to time. Practically, it is hard as the gravity needs to be accurately subtracted from the measurements if not to introduce a large positioning error. If just 1 % of gravity is in the measurements would introduce an error of 500 m over 100 secs further, the sensors present in today's smart-phones suffer from various biases and drifts. These errors need to be corrected otherwise that would lead to huge positioning in accuracy.

3.3.2 Magnetometer

It measures the magnetic field strength in each of the phone's three coordinate directions. Therefore, using the known electromagnetic field produced by the Earth's core, it is possible to find the phone's heading. A magnetometer [50] is used to measure the direction of the magnetic field in its surrounding area. Magnetometers are basically of two types scalar and vector magnetometers. The scalar magnetometer measures the total strength of the magnetic field to which they are subjected and vector magnetometers are which have the capability to measure the component of the magnetic field in a particular direction, relative to the spatial orientation of the device [49].

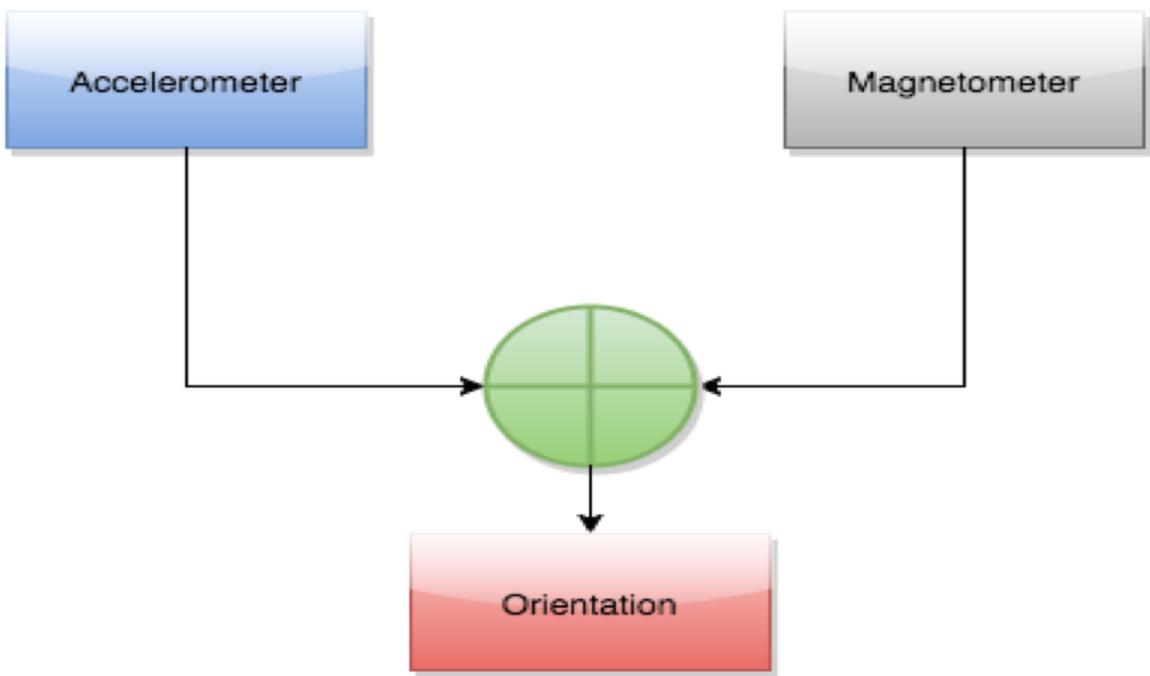

Figure 3.2: Device orientaion using accelerometer and magnetometer

3.3.3 Gyroscope

Gyroscope works on the principles of conservation of angular momentum. Gyroscope is a device used for measuring orientations. A conventional gyroscope consists of a spinning wheel which is mounted on two gimbals that allows it to rotate in all three different axes. MEMS gyroscopes contain vibrating elements to measure the Coriolis Effect. A single mass is driven to vibrate along a driver axis, when the gyroscope is rotated a secondary vibration is induced along the perpendicular sense axis due to the Coriolis force. The angular velocity can be calculated by measuring this secondary rotation. The Coriolis Effect states that reference frame rotating at angular velocity ω, a mass m moving with velocity v experiences a force [49].

$$Fc = -2m(w\times v) \tag{3.10}$$

The accelerometer and the magnetometer can measure acceleration and angle relative to the Earth, whereas gyroscope measures angular velocity relative to the body.

The three orthogonal axes when an object or device is rotated in a frame are yaw, pitch and roll. Single rotation matrix can be obtained through multiplying all the 3 rotations

along X axes can be given as

$$\text{R\_x} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha \\ 0 & \sin\alpha & \cos\alpha \end{pmatrix}$$

along Y axes can be given as

$$R_y = \begin{pmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ 0 & \sin\beta & \cos\beta \end{pmatrix}$$

along Z axes can be given as

$$R_z = \begin{pmatrix} \cos\gamma & -\sin\gamma & 0 \\ \sin\gamma & \cos\gamma & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$R(\alpha,\beta,\gamma)= \begin{pmatrix} \cos\gamma\cos\beta & \cos\gamma\sin\beta\sin\alpha-\sin\gamma\cos\alpha & \cos\gamma\sin\beta\cos\alpha+\sin\gamma\sin\alpha \\ \sin\gamma\cos\beta & \sin\gamma\sin\beta\sin\alpha+\cos\gamma\cos\alpha & \sin\gamma\sin\beta\cos\alpha-\cos\gamma\sin\alpha \\ -\sin\beta & \cos\beta\sin\alpha & \cos\beta\cos\alpha \end{pmatrix}$$

Figure 3.3: Device orientation [50]

3.4 Errors in sensors

Accelerometer: An accelerometer has important source of error which is the bias [51]. The bias of associate degree measuring system is that the offset of its sign from actuality worth in m/s2. A constant bias error of ε, once double integrated, causes a slip-up in position that grows quadratic with time. It is potential to estimate the bias by measuring the long run average of the accelerometer output once it's not undergoing any acceleration. If the error of bias is left uncorrected will limit the performance of the device.

$$S(t) = \varepsilon * (\frac{t^2}{2}) \tag{3.11}$$

where 't' is time of integration

Magnetometer: The two main sources of measuring errors are magnetic contamination within the device, errors within the measuring of the frequency and ferric (i.e. iron containing) material on the operator and within the instruments. If the sensor is rotated to take measurement that would accumulate additional errors.

Gyroscope: The bias of a gyro is that the typical output from the gyro once it isn't undergoing any rotation i.e. the offset of the output from real value. A continuing bias error of ε, once integrated, causes an angular error that grows linearly with time. The constant bias error of a gyro may be calculable by taking an extended term average of the gyro's output while it's not undergoing any rotation. Once the bias is understood it's trivial to catch up on it by merely subtracting the bias from the output. The other error arising in gyros is that the 'calibration error', it refers to errors within the scale factors, alignments, and linearity of the gyros. Such errors tend to provide errors that area unit solely determined while the device is popping. Such errors result in the buildup of further drift within the integrated signal, the magnitude of that is proportional to the speed and length of the motions [51].

3.5 Sensor Fusion

Sensor fusion [50] is the combination of sensor data derived from sensors of various sources such that it provides higher accuracy than just using sensors separately.

The accelerometer provides gravity vector pointing towards center of the earth where as magnetometer works as compass. The information from both the sensors is sufficient to calculate device orientation. But the sensor output from both the sensor is inaccurate. The magnetometer consists of lot of noise.

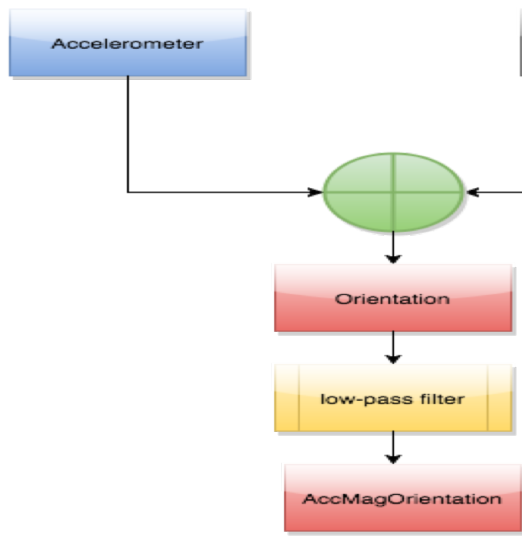

Figure 3.4: Structure of Low Pass filters in Accelerometer and Magnetometer

Gyroscope in the device has better accuracy when compared to other two sensors. Gyroscope gives angular rotation speeds for x, y and z axes. In order to get the actual orientation speed values, need to be integrated over the time.

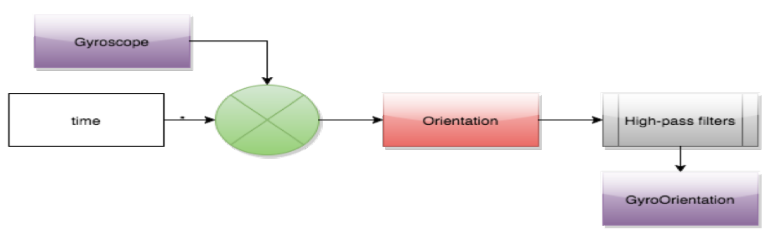

Figure 3.5: Structure of high pass filters in gyroscope

Let ω be the angular speed\$; $t = time$; $\omega * l = lastoutput$; $\omega * c = currentoutput$

Let the orientation be 'R'

$$R = (\omega * (t\omega * l) + \omega * (t\omega * c)) \tag{3.12}$$

The absolute orientation of device is calculated using $\sum R$.

During this process small errors can be introduced at each iteration which results in gyro drift. Therefore, sensor fusion is adopted in order to avoid both gyro drift and noisy orientation. Gyroscope output is applied for orientation changes in short interval. Magnetometer and Accelerometer data is used to support information over long period. Sensor fusion with com-plementary filter is low-pass filtering of magnetometer/ accelerometer and high-pass filtering of gyroscope data which produce better accuracy and reliable.

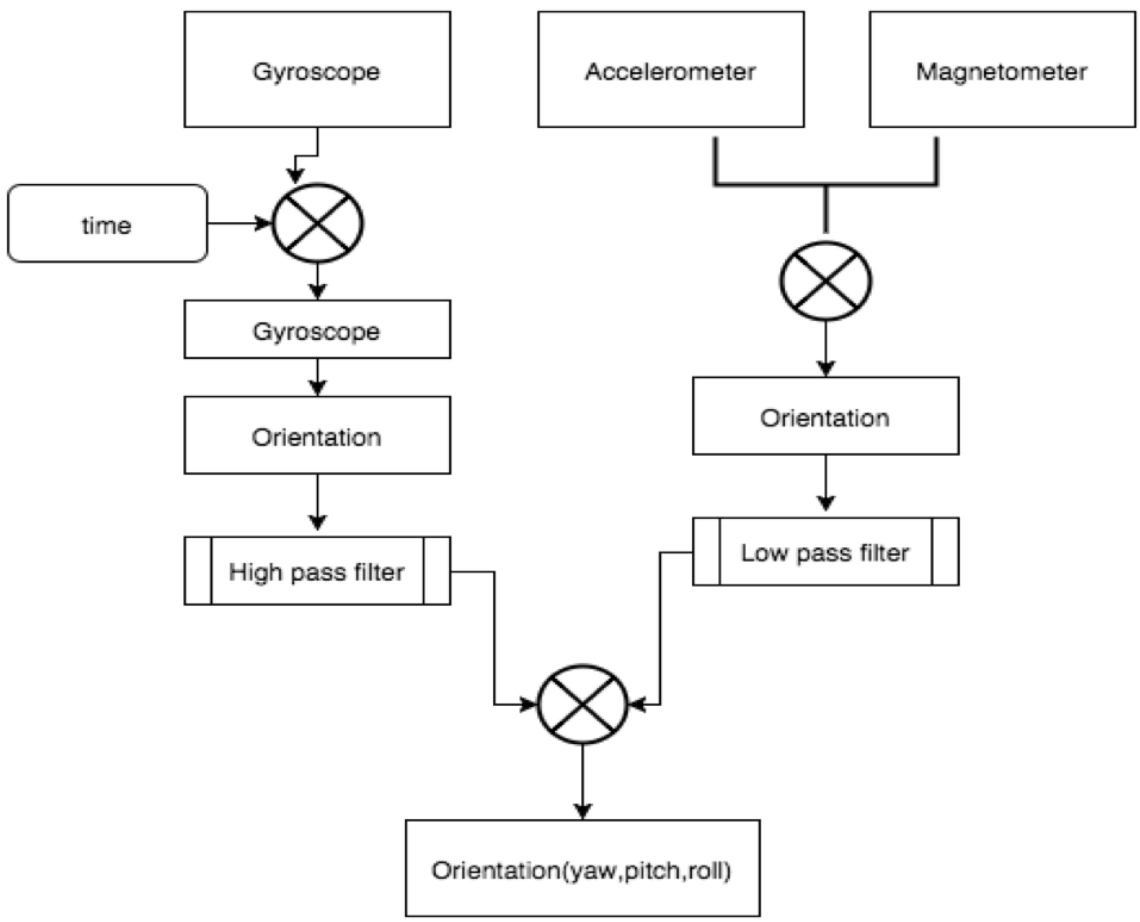

Figure 3.6: Sensor fusion

3.6 Kalman Filter

The equation of motion [52] can be given as

$$A^{|} = (A + Vt + \frac{1}{2}a(t^2)) \tag{3.13}$$

Where $A = position$

$V = Velocity$

$t = time$

$a = acceleration$

Let y_k be the coordinates of user and u_k be the input to the model

$$u_k = l_t(\sin\theta)t\cos\theta)^T \tag{3.14}$$

The state transition function can be given as

$$y_k = A(y_(k-1)) + Bu_k + Q \tag{3.15}$$

A, B are two identity matrix with Zero mean and covariance matrix 'Q'

The kalman filter applied to sensor fusion

$$y_(k|k-1) = Ay_{k-1} + Bu_k \tag{3.16}$$

Predicting

$$P_k = A(y_{k-1})(A^T) + Q \tag{3.17}$$

P_k is predicted state

Computing Kalman Gain

$$K = P_k(H^T)(HP_k(H^T) + R)^-1) \tag{3.18}$$

$$y_k = y_(k-1) + K(S_k - HY_{K-1}) \tag{3.19}$$

$$P_k = (I - KH)P_{k-1} \tag{3.20}$$

Where 'S_k'is sensor measurement, R is noise in the sensors measurements and H is the model Identity matrix.

The equation (3.14) is the output of kalman filter.

Let the coordinates from Fingerprinting be

$$F_K = \sum_{i=0}^{n}(X_i, Y_i) \tag{3.21}$$

When (3.16) is given as input instead of sensor measurement the output of the filter gives the desired position coordinates.

$$y_k = y_{k-1} + K(F_k - HY_{K-1}) \tag{3.22}$$

$$y_k = (X, Y) \tag{3.23}$$

Kalman filter is used to remove eliminate noise from the sensor and wi-fi measurements and provide optimal results.

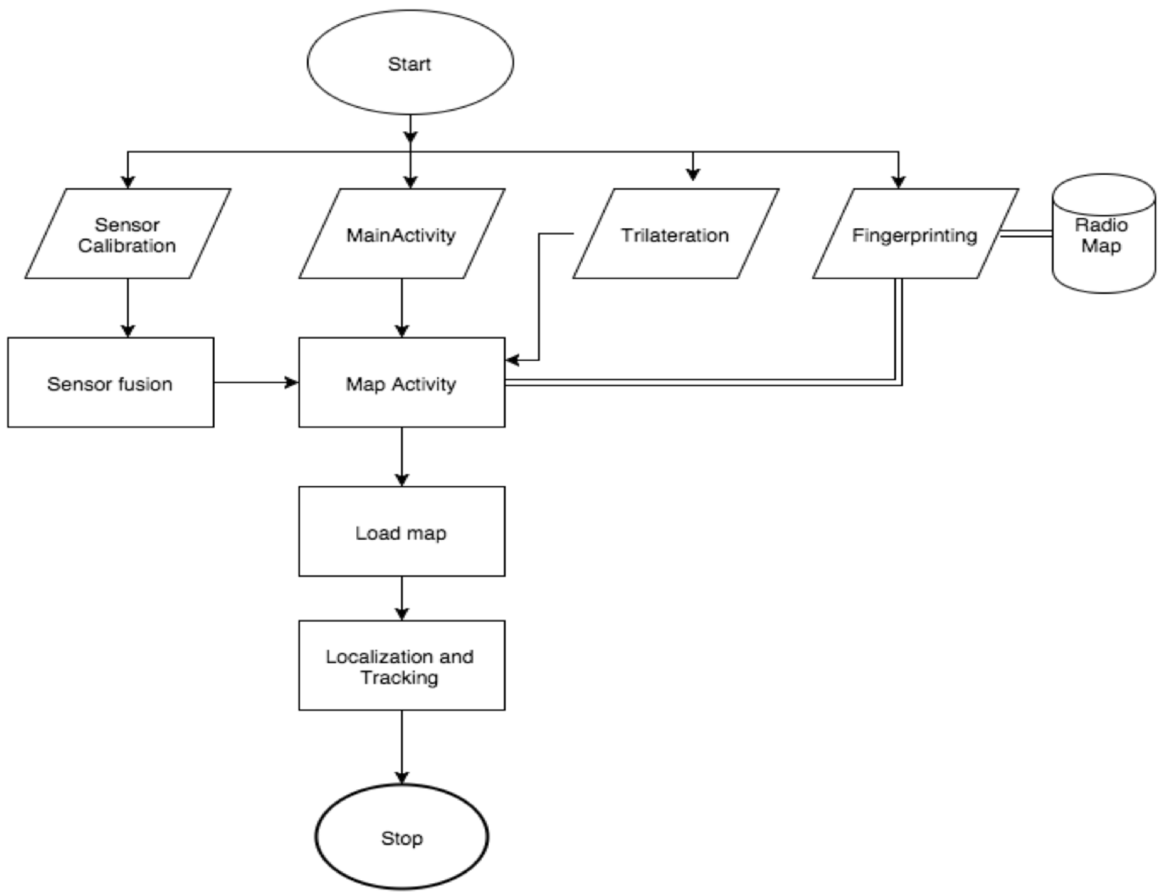

Figure 3.7: Application flow

CHAPTER 4 IMPLEMENTATION

This chapter describes the implementation of the thesis. Very first the preliminaries of the system are discussed and later the implementation of real-time application is discussed. Eclipse and Android Studio are the two integrated development environments (IDEs) for Android Application development.

Eclipse (ADT Bundle) Eclipse was the first freely accessible IDE for Android and has been in use subsequent to 2008. Past cycles needed a convoluted setup process that included downloading numerous pieces and integrating them together. Presently, with the presence of ADT Bundle, the procedure is much less demanding. All that you need to develop an Android application in Eclipse is in one helpful group configured to get you up and running in under five minutes.

Android Studio Android studio is Google's official IDE of application development, it's a spin-off of popular Java IDE IntelliJ. Android Studio provides new unified build system called Gradle, it provides utmost flexibility in development process. Since it is well integrated system which keeps development process easy and manageable.

4.1 Android OS

Android [53] is an open-source platform for mobile phones which is developed and managed by Google Inc. It incorporates operating system, middle-ware and key applications. As of late it has turned into the world's most utilized platform for smart phones. The inexorably high prevalence together with the actuality of being an open-source venture has given the platform a vast group of designers and developers. The following characteristics gives the reason for choosing Android as the development environment for this thesis when compared to other mobile platform like IOS, Symbian or Windows OS.

Android is a Linux-based software stack, it is divided in six sections and five different layers which can be explained in detail below:

Application layer: Application layer is the top most layer of the software stack which is accessible to end user. User can find all the Android application at the top layer. Applications which are readily installed on this layer, for example Contacts Books, Browser, Games etc. There are many default applications that can run simultaneously and are written in android based Java language.

Application framework: The product system used implement the standard structure of an application for the Android OS. The Application Framework layer gives numerous more high-level services to applications as Java classes. Application engineers are permitted to make utilization of these services in their applications. Following are the key services provided by Android framework

Activity Manager: This framework Controls all aspects of the application life-cycle and activity stack.

Content Providers: This allows applications to publish and share data with other activities or/and applications.

View System: This help in providing extensible set of views used to create application user interfaces.

Notifications Manager: It allows applications to display alerts and notifications to the user.

Package Manager: It provides application a package level abstraction.

Telephone Manager: It enables services related to telephone over android smart-phone.

Resource Manager: It provides access to embedded resources such as drawable for storing images that are used in app, user interface layouts, Strings, color codes etc.

Location Manager: This provides Location Based Services by enabling GPS over phone.

Sensor Manager: This class is used to access different sensors over phone like accelerometer, gyroscope, compass, magnetometer etc.

Bluetooth Manager: This provides services related to Bluetooth in an application such as Bluetooth fingerprinting etc.

Wi-Fi Manager: This provides services related to Wi-Fi in an application such as Wi-Fi fingerprinting which includes signal strength, MAC address etc.

Libraries: This is the third layer from the base. On Linux kernel over hardware layer there is a set of libraries which includes Surface Manager, Media framework, SQLite database which is a used for storage and sharing the application data, OpenGL, Web Kit and libraries needed to play, record audio and video, SSL libraries that are responsible for Internet security etc.

Android runtime: The Android runtime has two components in which first a set of core libraries which provides most of the functionality in the Java core libraries, and second is the virtual machine Dalvik which works like an interpreter between the application side and the working framework. This is the third area of the structural engineering and accessible on the third layer from the base. This segment gives a key segment called Dalvik Virtual Machine which is a sort of Java Virtual Machine extraordinarily outlined and enhanced for Android. The Dalvik VM makes utilization of Linux center components like memory administration and multi-threading, which is natural in the Java dialect. The Dalvik VM empowers each Android application to keep running in its own particular procedure, with its own occasion of the Dalvik virtual machine. The Android runtime additionally gives an arrangement of center libraries which empower Android application designers to compose Android applications utilizing standard Java programming dialect.

Hardware Abstraction layer: The android hardware abstraction layer handles hardware components like sound, camera, GPS, sensor integration, Graphics etc.

The kernel: Android operating system uses this Linux based kernel for its device drivers, memory management, process management and networking.
At the base of the layers is Linux this gives a level of deliberation between the device drivers and it contains all the fundamental equipment drivers like camera, keypad, display and so forth. Additionally, the Linux handles every one of the things for example, systems administration and a limitless cluster of device drivers, which makes the interfacing to hardware components very easy.

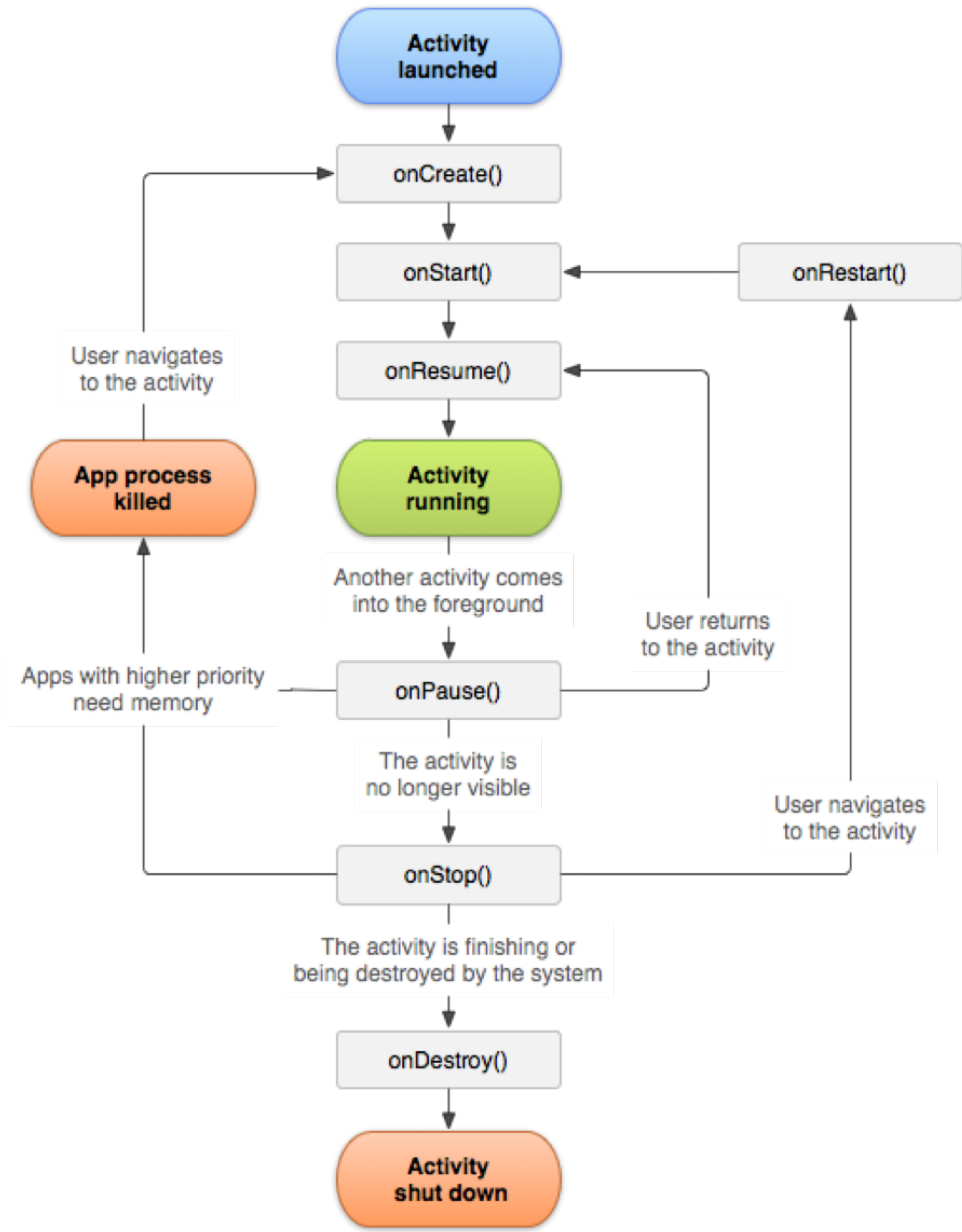

Figure 4.1: Activity life cycle [53]

4.2 Tools and technologies

Table 4.1: Tools and Technologies

Programming language(s)	Java
UI	XML
SDK	Android lollipop(5.0)
Build Tool version	21.1.2
Devices	Nexus 5 Samsung S4 Samsung S3
Deployment platform	Android
Libraries	Graph View Ormlite-android-4.40
Development Tool	Android Studio

Android provides WifiManager class by extending its services we can get the characteristic of Wi-Fi like its mac address, SSID, RSSI, Frequency and capabilities. This class uses following Methods

- OnCreate ()
- OnClick ()
- OnDestroy ()
- OnStop ()
- OnUpdate ()

SensorscanActivity.java ()

- Collects sensor data from accelerometer, magnetometer, gyroscope.
- Sensor values are stored in database

protected void onCreate(Bundle savedInstanceState){ super.onCreate(savedInstanceState);

log.debug(“created sensors activity”);

sManager = (SensorManager) getSystemService(SENSOR_SERVICE);

```
acc = sensorManager.getDefaultSensor(Sensor.TYPE_ACCELEROMETER);
gyro = sensorManager.getDefaultSensor(Sensor.TYPE_GYROSCOPE);
mag =sensorManager.getDefaultSensor(Sensor.TYPE_MAGNETIC_FIELD);
}
SensorfusionActivity ()
```

- Low pass filters applied to accelerometer and magnetometer values
- High pass filters applied to gyroscope values.
- Filtered values are used to determine the device orientation

4.3 Design overview

The proposed system provides indoor positioning through hybrid approach, users can locate and can track themselves indoors. The localization techniques such as Wi-Fi Localization and Sensor-Fusion were used in our approach and best possible outcome is obtained through improved fingerprinting and trilateration algorithms along with sensor-fusion. First, the system performs localization based on trilateration and sensor-fusion, rough positioning which is obtained using trilateration and sensor-fusion is provided as input to the fingerprinting algorithm. The fingerprinting matching is made simple and fast since the matching is performed based two parameters the coarse coordinate from trilateration and signal strength at the point which produces better results when compared to normal fingerprinting which just considers signal strength as a parameter while pattern matching. Therefore, the proposed hybrid approach can lower the complexity of fingerprinting and produce better results.

4.4 System Architecture

The system consists of two modules to process application the mobile device they are: Wi-Fi Scan,Sensor Manager Using the Sensor API, sensor data from three sensors (accelerometer, magnetometer and gyroscope) will be taken. The yaw, pitch and roll of the mobile device is obtained from Sensor API,using the Wifimanager API, the RSSI, frequency and MAC address of each of the Wi-Fi AP's is stored. The approximate location and the roll, pitch and yaw of the mobile device after sensor fusion is used to locate the position of user on map. The position estimation can be further improved by feeding this location results to the fingerprinting algorithm, thus an improved location of user can be pointed onto the map.

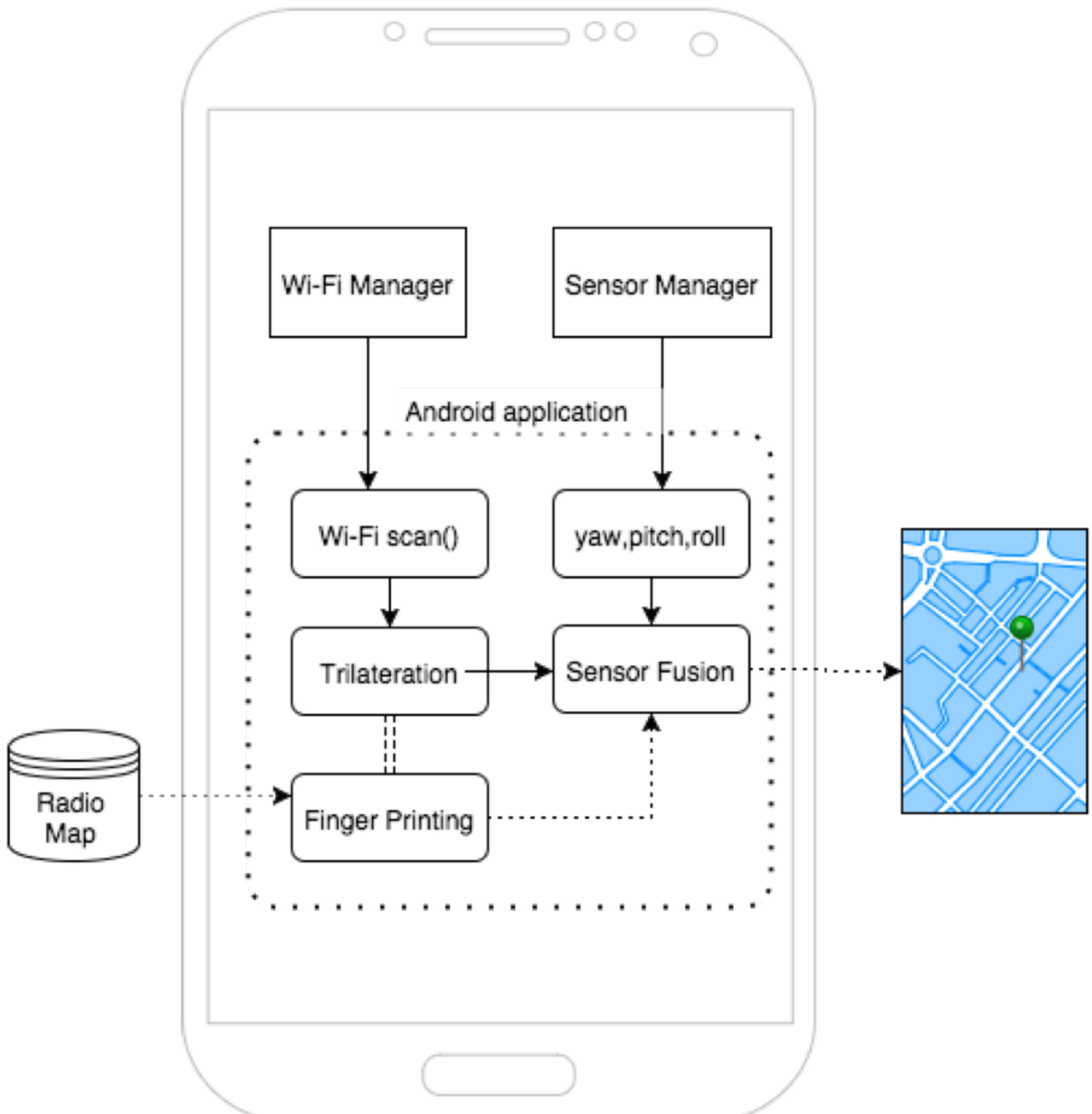

Figure 4.2: System architecture

4.5 Mobile Application

4.5.1 Wi-Fi Manager API

The mobile device is presumed to have Wi-Fi connection capabilities, with Wi-Fi turned on. Android uses its Wifimanager() class to scan all available connections it can detect. This information will contain the SSID (Service Set Identifier), BSSID (Basic Service Set Identifier) , RSSI (Received Signal Strength Indicator) and frequency . This module will select only the pre-defined SSIDs and plug their RSSIs into the Wi-Fi Localization algorithm as mentioned in the theoretical framework. The resulting coordinates values (x, y) would be used in the server side. Prior to deployment, the radio map which consists of RSSI of various reference points in the test environment is prepared and stored on internal storage of phone. This can be later used in fingerprinting module. The reference coordinates let us say (x, y) with some RSS in DBm is stored as radio map. where x represents the x-coordinate, and y represent the y-coordinate the plane.

4.5.2 Sensor API

In this module, the device makes use of Android's Sensor [54]. This API help in giving the yaw, pitch and roll values of the device's orientation. These values are then being processed through complementary filters. Prior to deployment, the device database holds information from the test environment. Some of these values would come from the Wi-Fi module and sensor module. Sensor module values are namely yaw, pitch and roll, where yaw represents the rotation of the device along z-axis, pitch represents the rotation of the device along y-axis, and roll represents the rotation of the device along x-axis.

4.5.3 ORMLite DB

ORMLite is an object relational mapping system [55] which provide light weight functionality for sending Java objects to SQL database without any overhead. It supports various databases using JDBC and also supports Sqlite with native calls to android OS database APIs. ORMLite libraries were used in successful data mapping from various sensors such as Wi-Fi, accelerometer, gyroscope, and magnetometer.

4.5.4 Methodology

Double-peak Gaussian Model for building Radio map is used. The radio map is further used in fingerprinting module. The Weighted Centroid algorithm was tested and provided better accuracy. It is fast and has low computational complexity which makes it easy to use on smartphones. Therefore, it was chosen as algorithm for trilateration. Our hybrid approach consists of Trilateration and improved fingerprinting [56] in combination of sensor fusion of accelerometer, magnetometer and gyroscope.

CHAPTER 5 EVALUATION AND RESULTS

In this chapter the results and the performance metrics of the proposed system are evaluated. This chapter presents the detailed experimental results, which were carried out on the 3rd floor of Computer Science building at the Dalhousie University. Chapter includes Application screens, experimental setup and evaluation and results.

5.1 User Interface screens

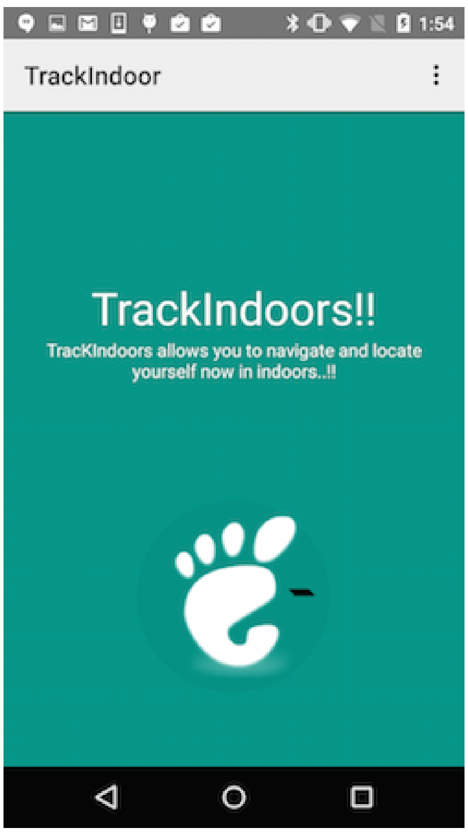

Figure 5.1: Welcome Screen

Figure 5.2: About Screen

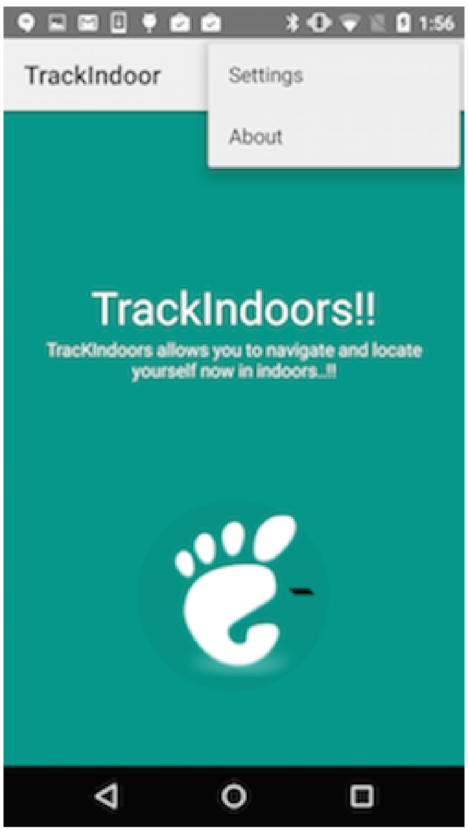

Figure 5.3: Main Menu

Figure 5.4: Settings options

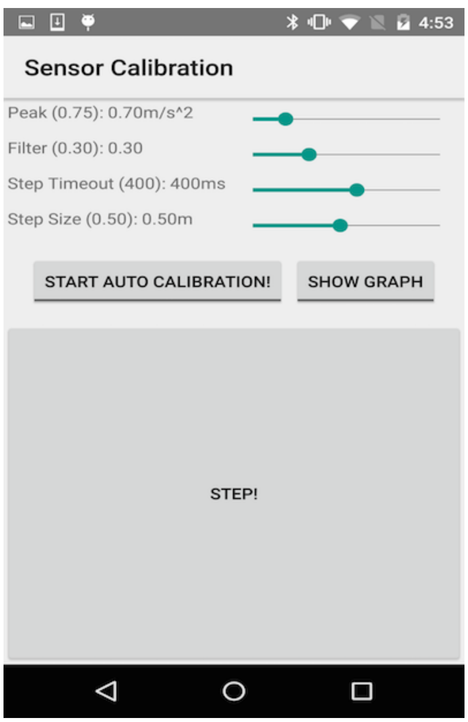

Figure 5.5: Sensor Calibration

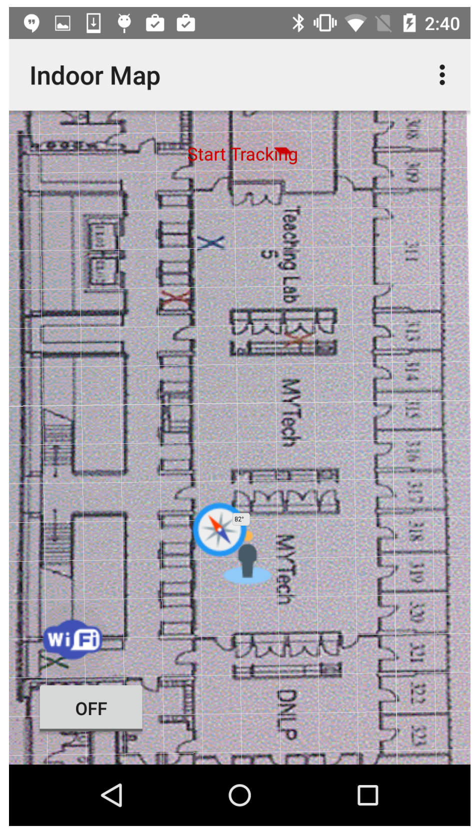

Figure 5.6: Indoor Map

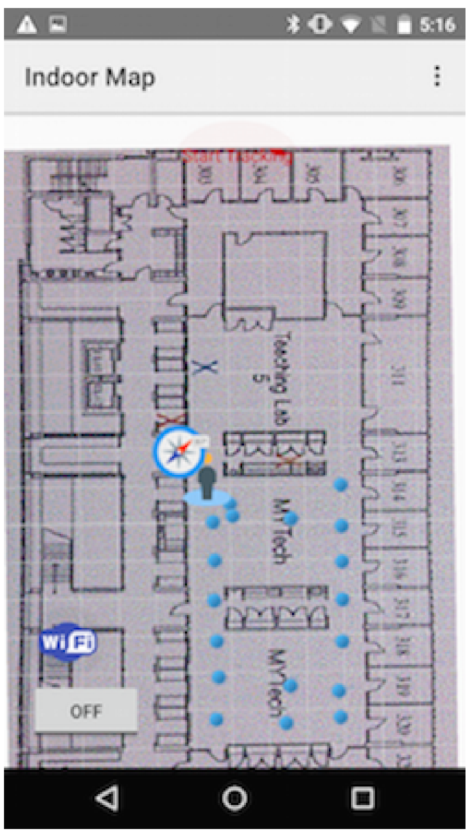

Figure 5.7: Fingerprinting

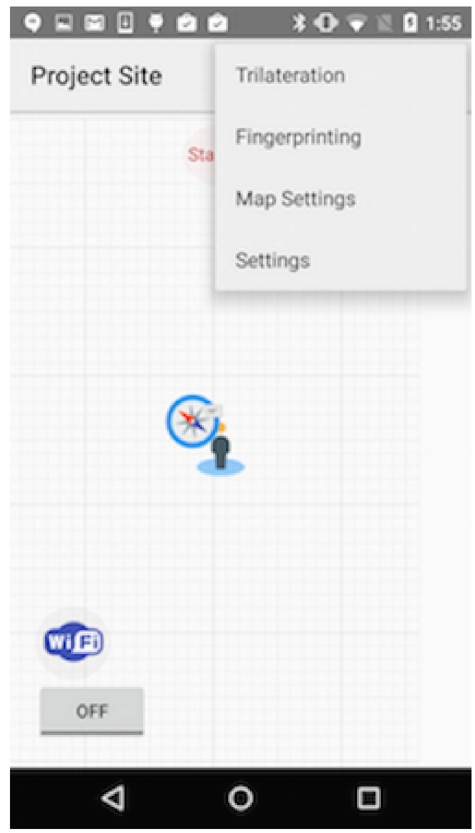

Figure 5.8: Map Activity options

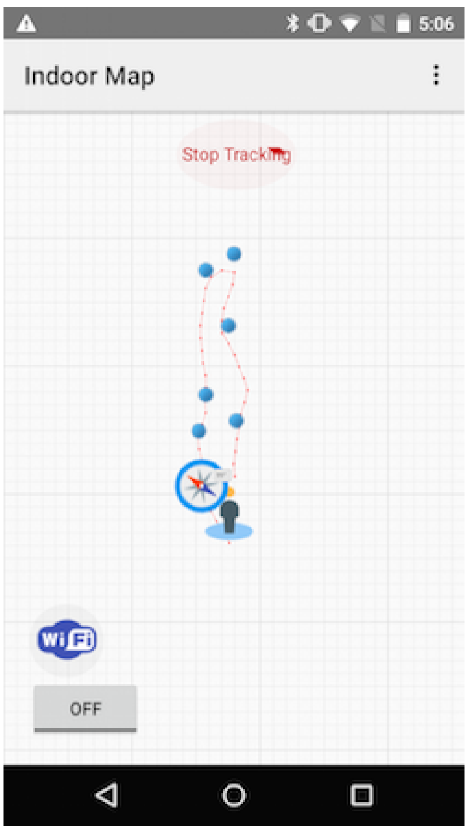

Figure 5.9: Tracking

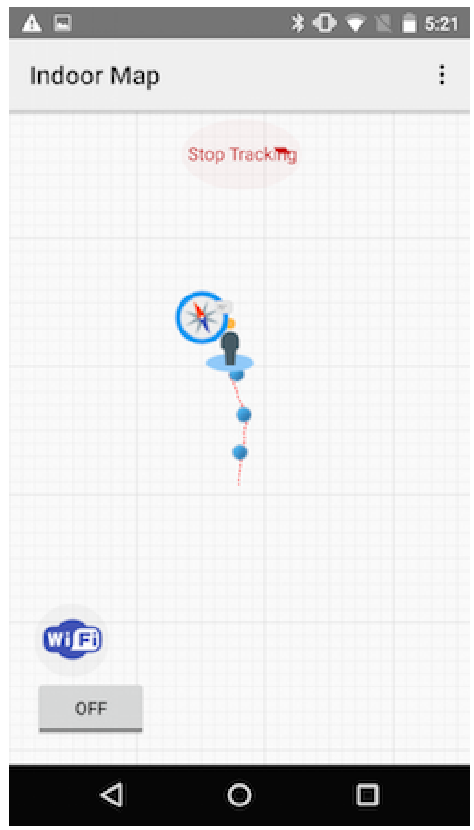

Figure 5.10: Indoor Tracking

5.2 Experimental Setup

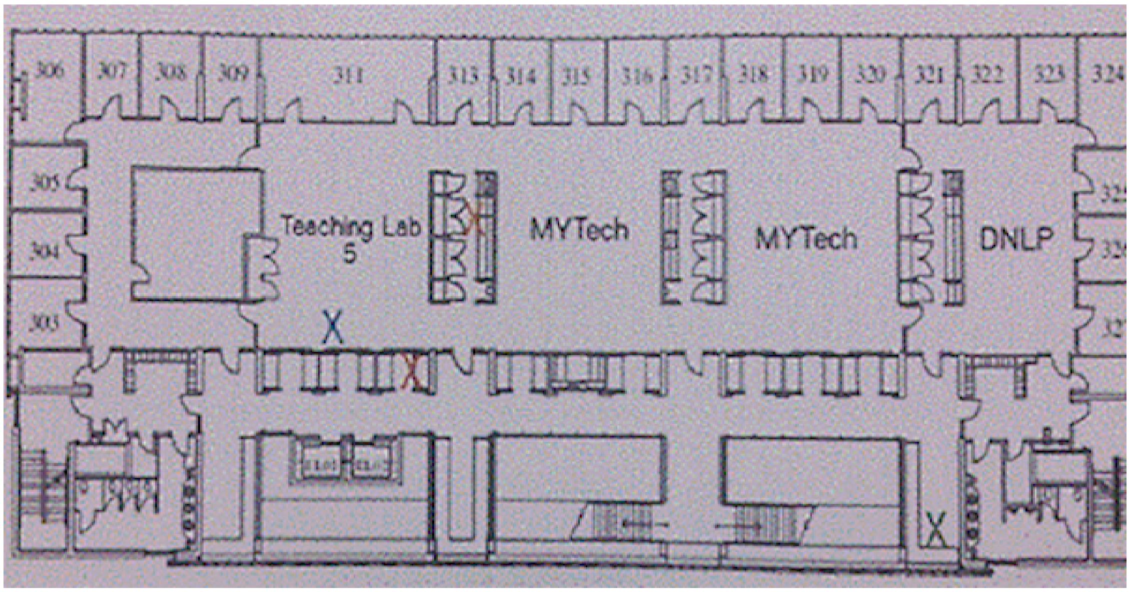

Figure 5.11: Test Environment

The proposed system was tested in the indoor environment of the Computer Science building at the Dalhousie University. The experimental results of the system were collected in the area of MyTech lab which is located on the 3rd floor of the building. The position of each APs was marked on to the map. The main objective of the thesis is to track a Wi-Fi enabled smartphone in the indoor environment by using the RSS and the Sensor data. When the application is started for the first time, it suggests the calibration of the sensors. Figure 5.1 shows the welcome screen of the application and figure 5.2 shows the about screen. Figure 5.5 shows a user is presented with a window where he/she can enter a threshold value for the step detection. This means that if the user taps the graph a bit too late or too early when making a step, the threshold value is the time interval within which the software searches for detected steps. The system then calculates the ideal settings for any device. There are various Android devices on the market currently and the sensor values may differ from device to device therefore calibration is needed. The device is calibrated to detect the number of steps. Then indoor map of the site is loaded and in order to find the distance traveled on map set the scale on measuring grid size. This is necessary so that the application can accordingly move the pointer when a step is detected. All other settings can be found in the menu options of 'Map Activity' which can be seen in figure 5.8.

Fingerprinting process is shown in figure 5.7 and the figure 5.9 presents indoor map activity where a user taps 'start tracking' button and is walks with a smart-phone in hand. The step detection algorithm tracks the position of user and Wi-Fi scanning activities are started in the background which uses weighted center algorithm and fingerprinting and the new position of a user is tracked onto the map. All the results were obtained from user holding a smart-phone in his/her hand in the test environment.

The Received Signal Strength is converted to distances using signal attenuation function. The noise caused by various environmental factors is removed using filters which enhances the usability and acceptability of the RSSI value as a parameter to estimate distance of APs from a smart-phone. In our experiment we used DAL-WPA network APs available on 3rd floor of computer science building.

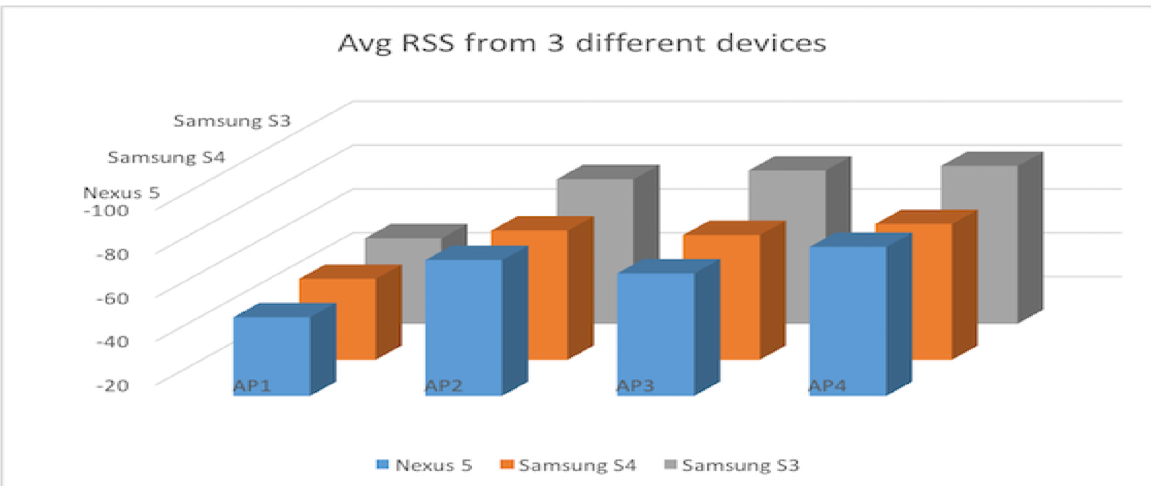

Figure 5.12: RSS values over different devices

We have collected RSS values in the indoor environment of MyTech lab using application. We stored the pair (distance, RSSI) for all the distinct locations with 1 feet distance intervals. We used the accelerometer, magnetometer and gyroscope sensors of the smart-phone to compute motion and direction from true north. The filtering of accelerometer sensor, mag-netometer sensor and gyroscope sensor data was done to compute proper heading direction. While walking the RSS from APs for each step detected was stored and processed. The exper-iment was continuous to evaluate it's accuracy, precision,complexity, robustness and cost. The evaluation and results of the system are discussed in the section 5.3.

5.3 Evaluation and Results

The evaluation of system can be done through various performance metrics they are as follows:

- Accuracy
- Precision
- Robustness
- Cost

5.3.1 Accuracy

The accuracy is defined as the ability of an indoor tracking system to locate and track in an indoor environment with the minimal error rate. The avg distance error of the system is calcu-lated based on the measurements of the distance error between estimated location and true loca-tion. The most important requirement for any system is its accuracy. The accuracy of the system was determined by testing a user walking with smart-phone in the area of MyTech lab. The dis-tance between initial position and final position pointer on map gives the distance error. Similar experiment was repeated and distance errors were obtained finally the avg distance error was calculated using equation 5.1.

$$\frac{Er_1 + Er_2 ... + E_n}{n} \tag{5.1}$$

The comparison of average distance error of various approaches is shown in figure 5.13.

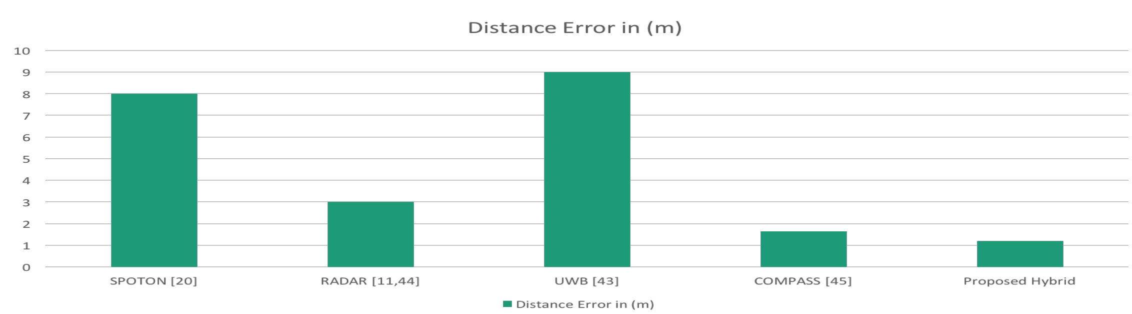

Figure 5.13: Accuracy

5.3.2 Precision

The precision is defined as the ability of an indoor tracking system to perform constantly with number of trials. The accuracy only measures the mean distance errors. Where as the precision of a system can be found by how a system performs over period of time with different number of trials. The results of the system over different trials were evaluated in order to measure its precision. In general sense the precision is measured based on how good is the application or a system when it is tested multiple times over various devices. The average distance error on various devices can be seen in figure 5.14.

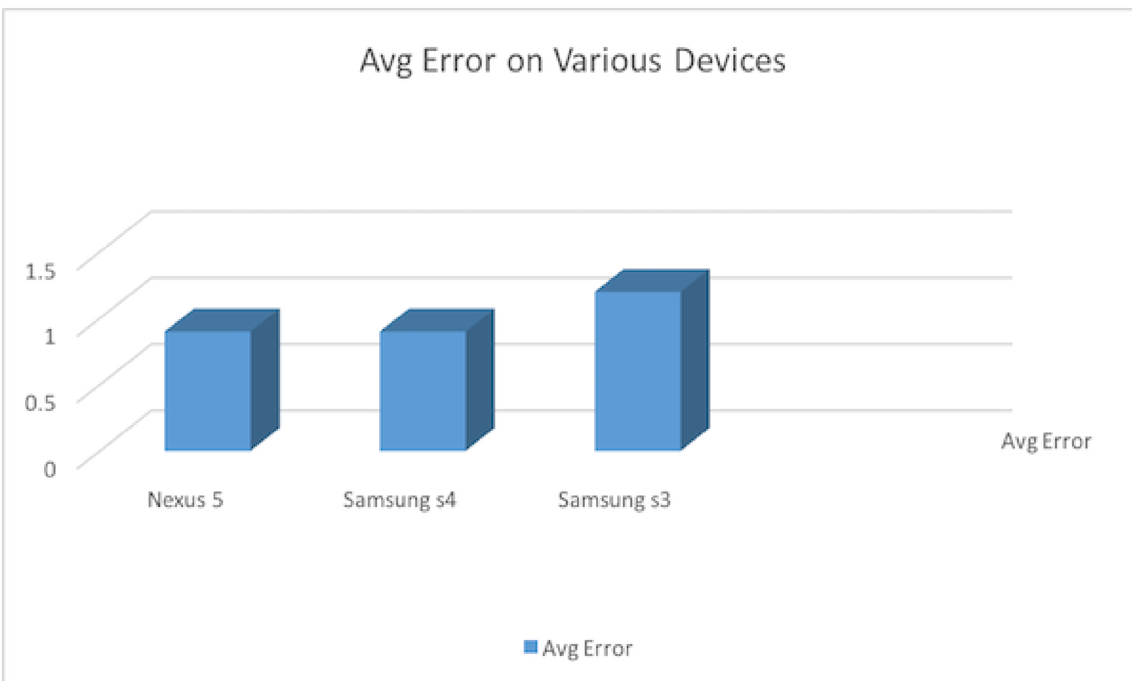

Figure 5.14: Precision

5.3.3 Robustness

The Robustness is defined as the ability of a indoor tracking system to perform in spite of a component failure. Robustness is the measure of tolerance, In other words how good a system can perform when there is sudden failure of software or hardware. The proposed approach is hybrid which makes the system robust. Which mean if one of the components of the system is failed, the other components keeps the application still running. The robustness of the system was tested by using trilateration alone later system was tested with only fingerprinting and sen-sor data. We can say that system performs even with single approach which makes it robust. The results of trilateration, fingerprinting and hybrid approach are plotted in the figure 5.15.

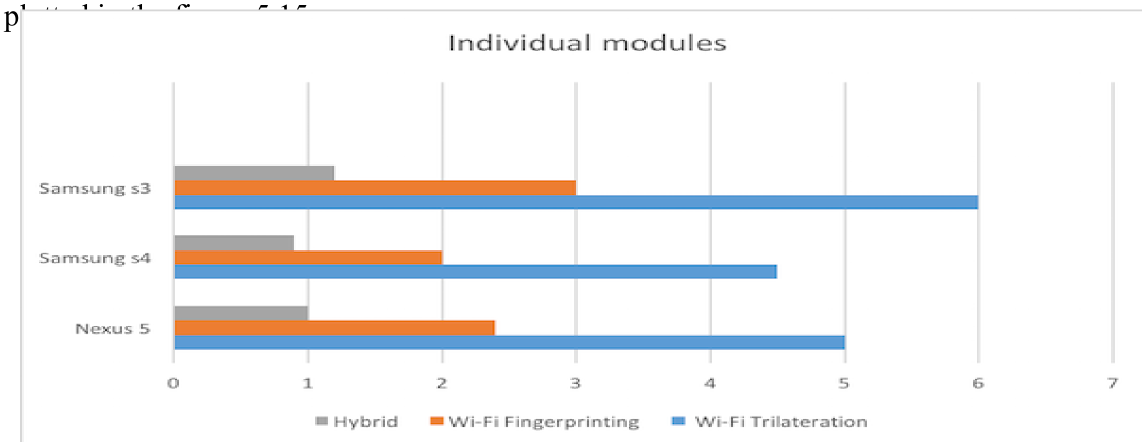

Figure 5.15: Robustness

5.3.4 Cost

The cost is defined as the ability of a system to perform without any external hardware require-ments. The implementation and deployment cost of a positioning system is also an important factor in deciding the performance of the system. Our approach leverages existing Wi-Fi in-frastructure and an Android smart-phone which cuts any extra cost. Therefore, we can say that the proposed system fulfill the final performance metric of indoor localization. The cost of the system was calculated based on the requirement of external hardware as our system doesn't require any specific hardware thereby it is infrastructure-less and inexpensive.

Therefore based on various performance metrics discussed above our proposed system is eval-uated and performs well with good results.

CHAPTER 6 CONCLUSION

6.1 Conclusion

In our research,we propose a real-time infrastructure-less indoor tracking system using hybrid approach. Our hybrid system uses existing infrastructure to track a position of a user in the indoor environment. The proposed system utilizes sensor data and Wi-Fi Received Signal Strength to determine location and provide indoor tracking efficiently.

The system was implemented on the Android platform. The application is not site specific and can be used in any indoor environment with basic Wi-Fi infrastructure. In order to evaluate the performance and effectiveness of the proposed indoor tracking system, an extensive experimental analysis was carried out by testing the application in the indoor space of the MyTech lab environment. The application is tested on various devices such as the Samsung S4, Samsung S3 and the Nexus 5.

Our test results indicated that the proposed hybrid system is able to achieve better accuracy when compared to the single approaches. Our hybrid system managed to track a person indoors with an average error of 1.2m. Furthermore, the proposed system helps in reducing the cost of indoor tracking significantly. In terms of the hardware deployment of the system, a great monetary cost is saved. Our approach mainly concentrates on infrastructure-less technologies hence the deployment and maintenance cost is almost zeroed. The proposed system satisfies the objectives of our research.

6.2 Future Work

The future work is always important for successful deployment of the system. The scope of the project can be extended by exploring other wireless technologies. Explore new API's which can further improve the navigation performance of the system. Further improvements in the effectiveness of the system by incorporating bluetooth needs to be explored in the future work.

BIBLIOGRAPHY

[1] "Global positioning system," *Wikipedia, the free encyclopedia*. 22-Sep-2015.

[2] M. S. Grewal, L. R. Weill, and A. P. Andrews, "Introduction," in *Global positioning systems, inertial navigation, and integration*, John Wiley & Sons, Inc., 2007, pp. 1–17.

[3] "Ten things you need to know about indoor positioning. Directions magazine." [Online]. Available: http://www.directionsmag.com/entry/10-things-you-need-to-know-about-indoor-positioning/324602. [Accessed: 24-Sep-2015].

[4] K. Al Nuaimi and H. Kamel, "A survey of indoor positioning systems and algorithms," in *Innovations in information technology (IIT), 2011 international conference on*, 2011, pp. 185–190.

[5] R. Want, A. Hopper, V. Falcão, and J. Gibbons, "The active badge location system," *ACM Trans Inf Syst*, vol. 10, no. 1, pp. 91–102, Jan. 1992.

[6] S. Zirari, P. Canalda, and F. Spies, "WiFi GPS based combined positioning algorithm," in *Wireless communications, networking and information security (WCNIS), 2010 IEEE international conference on*, 2010, pp. 684–688.

[7] O. Hammadi, A. Hebsi, M. Zemerly, and J. Ng, "Indoor localization and guidance using portable smartphones," in *2012 IEEE/WIC/ACM international conferences on web intelligence and intelligent agent technology (WI-IAT)*, 2012, vol. 3, pp. 337–341.

[8] F. Salim, M. Williams, N. Sony, M. Dela Pena, Y. Petrov, A. A. Saad, and B. Wu, "Visualization ofWireless Sensor Networks using ZigBee's Received Signal Strengthindicator (RSSI) for indoor localization and tracking," in *Pervasive computing and communications workshops (PERCOM workshops), 2014 IEEE international conference on*, 2014, pp. 575–580.

[9] E. Husni and S. Purwantoro, "Shopping application system with Near Field Communication (NFC) based on android," in *2012 international conference on system engineering and technology (ICSET)*, 2012, pp. 1–6.

[10] P. Bahl, V. N. Padmanabhan, and A. Balachandran, "Enhancements to the RADAR user location and tracking system," technical report, Microsoft Research, 2000.

[11] P. Bahl and V. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *IEEE INFOCOM 2000. nineteenth annual joint conference of the IEEE computer and communications societies. proceedings*, 2000, vol. 2, pp. 775–784 vol.2.

[12] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.*, vol. 37, no. 6, pp. 1067–1080, Nov. 2007.

[13] K. Zhang, H. Hu, W. Dai, Y. Shen, and M. Z. Win, "Indoor localization algorithm for smartphones," *ArXiv Prepr. ArXiv150307628*, 2015.

[14] Kun-Chan Lan and Wen-Yuah Shih, "Using smart-phones and floor plans for indoor location tracking," *IEEE Trans. Hum.-Mach. Syst.*, vol. 44, no. 2, pp. 211–221, Apr. 2014.

[15] S. Boonsriwai and A. Apavatjrut, "Indoor WIFI localization on mobile devices," in *2013 10th international conference on electrical engineering/Electronics, computer, telecommunications and information technology (ECTI-CON)*, 2013, pp. 1–5.

[16] M. Hazas and A. Hopper, "Broadband ultrasonic location systems for improved indoor positioning," *IEEE Trans. Mob. Comput.*, vol. 5, no. 5, pp. 536–547, May 2006.

[17] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in *Proceedings of the 6th annual international conference on mobile computing and networking*, 2000, pp. 32–43.

[18] Y. Fukuju, M. Minami, H. Morikawa, and T. Aoyama, "DOLPHIN: An autonomous indoor positioning system in ubiquitous computing environment," in *IEEE workshop on software technologies for future embedded systems, 2003*, 2003, pp. 53–56.

[19] M. Minami, Y. Fukuju, K. Hirasawa, S. Yokoyama, M. Mizumachi, H. Morikawa, and T. Aoyama, "DOLPHIN: A practical approach for implementing a fully distributed indoor ultrasonic positioning system," in *UbiComp 2004: Ubiquitous computing*, N. Davies, E. D. Mynatt, and I. Siio, Eds. Springer Berlin Heidelberg, 2004, pp. 347–365.

[20] J. Hightower, R. Want, and G. Borriello, "SpotON: An indoor 3D location sensing technology based on RF signal strength," *UW CSE 00-02-02 Univ. Wash. Dep. Comput. Sci. Eng. Seattle WA*, vol. 1, 2000.

[21] L. Ni, Y. Liu, Y. C. Lau, and A. Patil, "LANDMARC: Indoor location sensing using active RFID," in *Proceedings of the first IEEE international conference on pervasive computing and communications, 2003. (PerCom 2003), 2003, pp. 407–415*

[22] B. Ozdenizci, K. Ok, V. Coskun, and M. Aydin, “Development of an indoor navigation system using NFC technology,” in *2011 fourth international conference on information and computing (ICIC)*, 2011, pp. 11–14.

[23] R. Faragher and R. Harle, “Location fingerprinting with Bluetooth Low Energybeacons,” *IEEE J. Sel. Areas Commun.*, vol. PP, no. 99, pp. 1–1, 2015.

[24] M. Rodrigues, L. Vieira, and M. Campos, “Fingerprinting-based radio localization in indoor environments using multiple wireless technologies,” in *2011 IEEE 22nd international symposium on personal indoor and mobile radio communications (PIMRC)*, 2011, pp. 1203–1207.

[25] M. A. Bitew, R.-S. Hsiao, H.-P. Lin, and D.-B. Lin, “Hybrid indoor human localization system for addressing the issue of RSS variation in fingerprinting,” *Int. J. Distrib. Sens. Netw.*, vol. 2015, pp. 1–9, 2015.

[26] N. Le Dortz, F. Gain, and P. Zetterberg, “WiFi fingerprint indoor positioning system using probability distribution comparison,” in *2012 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, 2012, pp. 2301–2304.

[27] V. Moghtadaiee and A. Dempster, “WiFi fingerprinting signal strength error modeling for short distances,” in *2012 international conference on indoor positioning and indoor navigation (IPIN)*, 2012, pp. 1–6.

[28] Q. Chang, S. Van de Velde, W. Wang, Q. Li, H. Hou, and S. Heidi, “Wi-fi fingerprint positioning updated by pedestrian dead reckoning for mobile phone indoor localization,” in *China satellite navigation conference (CSNC) 2015 proceedings: Volume III*, vol. 342, J. Sun, J. Liu, S. Fan, and X. Lu, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015, pp. 729–739.

[29] S. Hossain, S. H. Ariffin, N. Fisal, C. K. Neng, N. A. Hassan, and L. Latiff, “Accuracy enhancement of fingerprint indoor positioning system,” 2012, pp. 600–605.

[30] M. M. Atia, M. J. Korenberg, A. Noureldin, M. M. Atia, M. J. Korenberg, and A. Noureldin, “Particle-filter-based WiFi-aided reduced inertial sensors navigation system for indoor environment,” Int. J. Navig. Obs. Int. J. Navig. Obs., vol. 2012, 2012, p. e753206, Jun. 2012.

[31] A. S. Paul and E. A. Wan, "RSSI-based indoor localization and tracking using sigma-point kalman smoothers," *IEEE J. Sel. Top. Signal Process.*, vol. 3, no. 5, pp. 860–873, Oct. 2009.

[32] M. O. Gani, C. OBrien, S. I. Ahamed, and R. O. Smith, "RSSI based indoor localization for smartphone using fixed and mobile wireless node," 2013, pp. 110–117.

[33] C.-Y. Shih and P. Marrón, "COLA: Complexity-reduced trilateration approach for 3D localization inWireless Sensor Networks," in *2010 fourth international conference on sensor technologies and applications (SENSORCOMM)*, 2010, pp. 24–32.

[34] S. Boonsriwai and A. Apavatjrut, "Indoor WIFI localization on mobile devices," in *2013 10th international conference on electrical engineering/Electronics, computer, telecommunications and information technology (ECTI-CON)*, 2013, pp. 1–5.

[35] A. S. Morris, *The essence of measurement*. Prentice Hall, 1996.

[36] J. P. Bentley, *Principles of measurement systems*, 4th ed. Harlow, England ; New York: Pearson Prentice Hall, 2005.

[37] W. Xiao, W. Ni, and Y. K. Toh, "Integrated wi-fi fingerprinting and inertial sensing for indoor positioning," in *2011 international conference on indoor positioning and indoor navigation (IPIN)*, 2011, pp. 1–6.

[38] V. Radu and M. Marina, "HiMLoc: Indoor smartphone localization via activity aware pedestrian dead reckoning with selective crowdsourced WiFi fingerprinting," in *2013 international conference on indoor positioning and indoor navigation (IPIN)*, 2013, pp. 1–10.

[39] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: Zero-effort crowdsourcing for indoor localization," in *Proceedings of the 18th annual international conference on mobile computing and networking*, 2012, pp. 293–304.

[40] J. Herrera, A. Hinkenjann, P. Ploger, and J. Maiero, "Robust indoor localization using optimal fusion filter for sensors and map layout information," in *2013 international conference on indoor positioning and indoor navigation (IPIN)*, 2013, pp. 1–8.

[41] W. Chai, C. Chen, E. Edwan, J. Zhang, and O. Loffeld, "2D/3D indoor navigation based on multi-sensor assisted pedestrian navigation in wi-fi environments," in *Ubiquitous positioning,indoor navigation, and location based service (UPINLBS), 2012, pp. 1–7.*

[42] U. Shala and A. Rodriguez, “Indoor positioning using sensor-fusion in android devices,” 2011.

[43] L. Yu, M. Laaraiedh, S. Avrillon, and B. Uguen, “Fingerprinting localization based on neural networks and ultra-wideband signals,” in *2011 IEEE international symposium on signal processing and information technology (ISSPIT)*, 2011, pp. 184–189.

[44] P. Bahl and V. Padmanabhan, “RADAR: An in-building RF-based user location and tracking system,” in *IEEE INFOCOM 2000. nineteenth annual joint conference of the IEEE computer and communications societies. proceedings*, 2000, vol. 2, pp. 775–784 vol.2.

[45] T. King, S. Kopf, T. Haenselmann, C. Lubberger, and W. Effelsberg, “COMPASS: A probabilistic indoor positioning system based on 802.11 and digital compasses,” in *Proceedings of the 1st international workshop on wireless network testbeds, experimental evaluation & characterization*, 2006, pp. 34–40.

[46] “Ekahau.” [Online]. Available: http://www.ekahau.com/wifidesign/blog/tag/wifi-training/.

[47] “Ubisense. Ubisense.” [Online]. Available: http://ubisense.net/en. [Accessed: 24-Sep-2015].

[48] N. K. Sharma, “A weighted center of mass based trilateration approach for locating wireless devices in indoor environment,” in *Proceedings of the 4th ACM international workshop on mobility management and wireless access*, 2006, pp. 112–115.

[49] F. Faisal, “Inertial navigation system.” [Online]. Available: http://faizan5422.blogspot.ca/. [Accessed: 25-Sep-2015].

[50] S. Ayub, A. Bahraminisaab, and B. Honary, “A sensor fusion method for smart phone orientation estimation,” in *Proceedings of the 13th annual post graduate symposium on the convergence of telecommunications, networking and broadcasting, liverpool*, 2012.

[51] O. J. Woodman, “An introduction to inertial navigation,” *Univ. Camb. Comput. Lab. Tech Rep UCAMCL-TR-696*, vol. 14, p. 15, 2007.

[52] G. F. Welch, “Kalman filter,” in *Computer vision*, K. Ikeuchi, Ed. Springer US, 2014, pp. 435–437.

[53] “Android developers.” [Online]. Available: http://developer.android.com/index.html.

[54] “Sensor manager.” [Online]. Available: http://developer.android.com/reference/android/hardware/SensorManager.html.

[55] “ORMLite.” [Online]. Available: http://ormlite.com/sqlite_java_android_orm.shtml.

[56] Z. Zheng, Y. Chen, T. He, F. Li, and D. Chen, “Weight-RSS: A calibration-free and robust method for WLAN-based indoor positioning,” *Int. J. Distrib. Sens. Netw.*, vol. 2015, pp. 1–7, 2015.