PARTICLE FILTER BASED INDOOR PEDESTRIAN LOCALIZATION USING MAGNETIC MAPS

A DISSERTATION
Submitted in partial fulfillment of
the requirements for the award of the degree
of
INTEGRATED DUAL DEGREE
in
COMPUTER SCIENCE AND ENGINEERING
(With Specialization in Information Technology)

By

PUTTA RAMAKANTH

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY, ROORKEE
ROORKEE-247 667 (INDIA)
JUNE, 2014

CANDIDATE'S DECLARATION

I hereby declare that the work, which is being presented in the dissertation entitled **"Particle filter based Indoor pedestrian localization using Magnetic maps"** towards the partial fulfilment of the requirements for the award of the degree of **Integrated Dual Degree in Computer Science & Engineering with specialization in Information Technology**, submitted in the Department of Computer Science and Engineering, Indian Institute of Technology Roorkee, Roorkee (India) is an authentic record of my own work carried out during the period from May 2013 to June 2014, under the guidance of **Dr.Manoj Misra**, Professor, Department of Computer Science and Engineering, Indian Institute of Technology Roorkee.

I have not submitted the matter embodied in this dissertation for the award of any other Degree or Diploma.

Date:

Place: Roorkee **(Putta Ramakanth)**

CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my knowledge and belief.

Date:

Place: Roorkee

Dr. Manoj Misra
Professor,
CSE Department,
IIT Roorkee, India

ACKNOWLEDGEMENTS

I would like to express my heartfelt gratitude to my guide and mentor, Dr. Manoj Misra, Professor, Department of Computer Science and Engineering, IIT Roorkee for his trust in my work, his able guidance, for being a regular source of inspiration and insightful advices. Without his constant support, this work would not have been in its present form. His wisdom, knowledge and commitment to the highest standards inspired and motivated me. He has been very generous in providing the necessary resources to carry out my research. He is an inspiring teacher, a great advisor, and most importantly a nice person.

I am thankful to the staff of computer lab, department of Computer Science and Engineering, IIT Roorkee for providing me the resources used in this research, and also to the staff of MGCL library, IIT Roorkee for allowing me to conduct the experiments in the library space. I am greatly indebted to all my friends, who have graciously applied themselves to the task of helping me with ample moral supports and valuable suggestions.

On a personal note, I am very thankful to my parents for their constant support, care, love and belief in me. They have been a constant inspiration for me to work hard and seek perfection.

(Putta Ramakanth)

ABSTRACT

Indoor localization has become an active topic of research because of its importance to the pervasive computing applications. Automatic indoor navigation systems, location based services such as advertising, intelligent information systems, animation, surveying, augmented reality have several applications of indoor localization. smart-phones provide us the opportunity to localize users in indoor environments as GPS signals are not effective in indoor environments. The smart-phone inertial sensors are extensively used in indoor localization systems. The inertial sensors are affected by magnetic perturbations, gyro drift and hand movements and do not provide accurate measurements. Hence, along with inertial sensors other information available in indoors is used for localization. Wi-Fi based fingerprinting are studied and combined with the inertial sensors in many recent studies as a low cost technique. But, Wi-Fi maps change frequently with time. Their mean localization accuracies are in the range of 1-2 m.

The Earth's magnetic field is corrupted by big steel structures in indoor environments. The studies show that the indoor magnetic maps are stable over time. Recent studies have focused on using magnetic maps and inertial sensors together. In this thesis, we use magnetic maps (magnitude & vector), inertial sensors, indoor maps together to improve the accuracy of localization. We have developed a smart-phone application to evaluate the performance of these different techniques. In addition, we have used a more accurate indoor orientation estimation method available in literature in our implementation. Our system has a mean accuracy of 0.75 m – 0.95 m. We present a comparison of the different approaches proposed in this dissertation. We compare our results with the earlier published approaches.

Table of Contents

CANDIDATE'S DECLARATION i
CERTIFICATE i
ACKNOWLEDGEMENTS ii
ABSTRACT iii
Table of Contents iv
List of Figures vi
List of Tables vii
List of Acronyms viii
1. Introduction 1
1.1 Motivation and Overview 1
1.2 Problem statement 3
1.3 Organization of thesis 3
2. Back Ground 4
2.1 Classification of Indoor localization systems 4
2.1.1 Infrastructure based or Absolute localization systems 4
2.1.2 Inertial sensors based or Relative localization systems 4
2.1.3 Probabilistic approaches for Indoor localization systems 4
2.2 Indoor localization Techniques and Terminology 5
2.3 Applications 7
3. Literature Review 9
3.1 Outdoor Localization 9
3.2 Indoor Localization 9
3.2.1 Infrastructure based Indoor localization systems 10
3.2.2 Inertial sensors based Indoor localization systems 11
3.2.3 Magnetic field based Indoor localization systems 15
3.2.4 Other Indoor localization systems 17
3.3 Major Challenges 18
3.4 Research Gaps 19
4. Proposed Approaches 21
4.1 Components & Methods 21

4.2 Motivation for using Magnetic map 23
4.3 Application Architecture 24
4.4 Proposed Approaches 25
4.4.1 Particle filter using Magnetic Field (Magnitude) 25
4.4.2 Particle filter using Magnetic Field (Vector) 27
4.4.3 Particle filter using Magnetic Field (Magnitude + Indoor Map) 27
4.4.4 Particle filter using Magnetic Field (Vector + Indoor Map) 28
4.5 Algorithm 28
5. Implementation Details 33
5.1 Magnetic field map construction 33
5.2 Magnetic field map properties 34
5.3 Using the Magnetic map in Algorithm 38
5.4 Step detection and step length estimation 38
5.5 Heading direction estimation [31, 32] 40
5.6 High level overview of Indoor localization application [9] 42
6. Experiments & Results 43
6.1 Experimental set up 43
6.2 Experiment test bed 43
6.3 Experiment test paths 43
6.4 Experiments conducted 46
6.5 Results & Analysis 47
7. Conclusions & Future Work 59
7. 1 Conclusions 59
7. 2 Future Work 59
Bibliography 60

List of Figures

Figure 4.1: High level overview of application architecture 24
Figure 4.2: Particle Filtering Algorithm using Magnetic maps and INS [26] 30
Figure 4.3: Move Method used in Particle Filtering Method 31
Figure 4.4: Convert Method used in Particle Filtering Method. 31
Figure 4.5: Resample Method used in Particle Filtering Method [26] 32
Figure 5.1: Comparison of magnetic field readings a) x-axis, b) y-axis, c) z-axis, d) magnitudes collected with east and west orientations of the smart-phone. x-axis is in (μT) 35
Figure 5.2: a) Comparison of magnetic field magnitudes of all gird locations for east direction of smart-phone collected on different days of the month, y-axis has location index,b) Histogram distribution of magnetic field magnitudes of west directed smart-phone based magnetic map 36
Figure 5.3: Test area magnetic map (west) visualization using grid data based interpolation 37
Figure 5.4: Orientation estimated (degrees) for repeated rectangular test walks in the test 37
Figure 5.5: Step detection and Step length estimation procedure [9] 40
Figure 6.1: a) Smart-phone, Nexus S b) pathway 5 c) wooden trolley used during offline database construction d) pathway 3 e) pathway 4 44
Figure 6.2: a) lay out of the test area with the grid points and the book shelves b) Bit map image of the indoor map used in the application c) test path 1 c) test path 2 e) test path 3 45
Figure 6.3: Plots of probability(importance weight) vs. sense_noise (μT) for different values of ||z|-|k|| in equation (4.3). In figure, ||z|-|k|| = 1 μT , 2 μT , 3 μT , 4 μT , 5 μT , 6 μT , 7 μT , 8 μT , 9 μT for 9 plots 53
Figure 6.4: Comparison of cumulative distribution functions for M, V, MM, VM approaches 53
Figure 6.5: Estimated paths for test path-1 for, sense_noise = 3.5 μT 54
Figure 6.6: Estimated paths for test path-2 for sense_noise = 3.5 μT 55
Figure 6.7: Estimated paths for test path-3 for sense_noise = 3.5 μT 56
Figure 6.8: Histogram distribution of all the test paths localization errors 57, 58

List of Tables

Table 5.1: Hierarchy of the application implementation procedures 42
Table 6.1: Comparison of our results with similar approaches used in literature 49
Table 6.2: Mean localization error (in m) of proposed approaches for three test paths for two sense_noise values 2.5 μT, 3.5 μT 51

List of Acronyms

Acronyms	Description
GPS	Global Positioning System
PDA	Personal Digital Assistant
SLAM	Simultaneous Localization And Mapping
MEMS	Micro Electro Mechanical Systems
INS	Inertial Navigation System
Wi-Fi	Local area wireless technology
RSSI	Received Signal Strength Indicator
AHRS	Attitude and Heading Reference System
UWB	Ultra Wide Band
TOA	Time Of Arrival
TDoA	Time Difference of Arrival
LDPL	Log Distance Path Loss model
SVM	Support Vector Machine
DTW	Dynamic Time Warping
kNN	k Nearest Neighbours Algorithm
NLOS	Non Line of Sight
WLAN	Wireless Local Area Network
NFC	Near Field Communication
RFID	Radio-frequency identification
EZ	Algorithm proposed in Indoor localization without pain [7]
Zee	Algorithm proposed in Zero effort crowd sourcing [10]
UnLoc	Algorithm proposed in Unsupervised indoor localization[33]
SLM	Seed Land Marks
OLM	Organic Land Marks
ZUPT	Zero Velocity Update
GDA	Gradient Descent Algorithm
API	Application Programming Interface
QR code	Quick Response Code

1. Introduction

1.1 Motivation and Overview

In recent years, smart-phones, tablets, personal digital assistants (PDAs) with high processing ability and embedded low cost inertial sensors have dominated the consumer market. These devices integrate the technology into our daily life. Various pervasive computing applications like GPS enabled Maps, high definition games, voice / video calls over phone, social network applications, e-book readers, live streaming on phones etc., are widely in use.

Future pervasive computing applications that offer location based services especially in the shopping malls, office buildings, health care centres, conferences, rescue operations, museums etc., will be based on the accurate location estimation approaches in indoor environments. Though various outdoor positioning and tracking algorithms like GPS have been widely useful, they are not applicable in indoor environments.

Various techniques have been explored and tested to improve indoor localization accuracy. Some of them are triangulation techniques [1-5,11,15], Wi-Fi fingerprinting techniques [6-12], infrastructure based techniques , inertial sensor navigation systems [9,10,12,13,16,17, 18,21,24,25,29,33] , probabilistic approaches such as particle filter [26], SLAM techniques of robotics [13,14]. Wi-Fi fingerprinting was widely accepted as the suitable way of indoor localization as it uses existing Wi-Fi infrastructure indoors without needing extra cost or deployment time. Now-a-days, MEMS sensors (like accelerometer, gyroscope and magnetometer) are available in most of the smart-phones in the consumer market. These sensors can be used to track the movements of the user. The indoor localization systems using inertial sensors only are termed as inertial navigation system (INS).

In principle, the distance can be estimated by integrating the accelerometer readings. But due to the sensor inefficiencies, the estimated distances are widely erroneous. The human locomotion or gait motion is periodic in nature that involves the periodic movements up and down during the forward or backward motion. This results in periodic repetitions of peaks on the z-axis accelerometer readings. Thus steps can be counted. Based upon the placement of smart-phone, hand held, front pant pocket, back pant pocket, handbag, talking on phone the accelerometer readings will be different. Different algorithms are used to count the steps independent of the placement of the smart-phone [28]. The stride lengths of the user on each step may not be the same. The stride lengths are estimated based upon the accelerometer readings [30], demographics of the user, frequency of steps [25] etc.

To estimate the location of the user using inertial sensors and other available information indoors probabilistic approaches are employed. Particle filters [26] use measurements and motion model together to estimate the correct location of the user in the pre-learned environment. The inertial sensors based dead reckoning work good for short paths but with longer paths the location error will be increasing. Hence, inertial positioning systems use floor maps [10, 25], Wi-Fi RSSI fingerprints [9,10,12], magnetic fingerprints[16,17,18,21,24], Wi-Fi or magnetic land marks [29, 33], other signals to assist in localizing the user using the particle filter. Inertial navigation systems using Wi-Fi fingerprints to improve localization accuracy are implemented in many papers [9, 10, 12]. Many new approaches in this area have been tested and explored in the recent years. The RF fingerprinting technique needs to train the database with the RF fingerprint values and corresponding locations ahead of time, this is a time consuming and effort some job. This is also termed as War-driving. To avoid this, systems are developed to automatically collect the indoor RF fingerprints using crowd sourcing from users [10, 33, 29]. This crowd-sourcing is run in the background without disturbing the user.

We present indoor localization system using magnetic maps, indoor maps and inertial sensors for hand held smart-phones in indoor environments. We use gradient descent optimization technique based AHRS [31, 32] algorithm to counter heading error due to magnetic perturbations. Our implementation is tested in a test area in the central library, IIT Roorkee that has similar environment as many commercial buildings. The user walked in the test area with the smart-phone in the hand along the pre-marked test paths among the book shelves to estimate the accuracy of the system. The performance of four different proposed approaches using magnetic maps (magnitude or vector) with or without indoor map are evaluated. This is the first work to use indoor maps and magnetic maps together along with inertial sensors as far as we have known. We have achieved mean localization accuracy in the range of 0.75 m – 0.95 m for the four approaches considering the general zig–zag path scenarios in the indoor environments. Several earlier works have only tested their systems in corridors or for linear paths and circular paths.

1.2 Problem statement

We aim at developing a general purpose and low-cost indoor localization system for smart-phone held in hand along the moving direction. We aim at using indoor maps, magnetic maps and inertial sensors together for this purpose. The key objectives of this dissertation are

1. Implement the hand held smart-phone inertial sensors based pedestrian indoor localization system using magnetic map vector or magnitude information.
2. Integrate the indoor map information to improve the localization accuracy
3. Use accurate and reliable orientation estimation [31, 32] for indoor environments to improve localization accuracy so that the system is usable in indoor spaces along with corridors.

1.3 Organization of thesis

This thesis is organized as the following chapters

Chapter 1 explains the motivation for taking up smart-phone based pedestrian indoor localization as the thesis topic and also explains the aim and objective of this thesis.

Chapter 2 gives the back ground for understanding the indoor localization techniques. We discuss the applications of indoor localization systems.

Chapter 3 presents the related work of indoor localization techniques in the literature and explains the infrastructure, inertial sensors based and magnetic field based indoor localization related research in the recent years.

Chapter 4 explains application architecture, our proposed approaches and the algorithmic details. Different algorithms using indoor maps and magnetic maps are discussed in depth.

Chapter 5 presents implementation details like magnetic map construction, magnetic map properties, step detection, step length estimation, orientation estimation, and high level overview of the application.

Chapter 6 explains the experiments done in the test area using our smart-phone application and discusses results of our experiments. It compares and discusses improvements over the existing research literature.

Chapter 7 provides conclusions achieved from our experiments and research and suggests future research that can improve on our implementation

2. Back Ground

2.1 Classification of Indoor localization systems

2.1.1 Infrastructure based or Absolute localization systems

Localization is the problem of finding target’s (pedestrian or robot or vehicle) co-ordinates relative to the environment assuming we have map of the environment [27]. Outdoor Localization is done using long range GPS signals. But GPS is not effective for indoor localization. Short range wireless technologies such as UWB and Wi-Fi (WLAN) are used for indoor localization. These are termed as Infrastructure based localization systems as they need costly and widely deployed infrastructure. They are also called Absolute localization systems as they use triangulation methods or fingerprinting methods.

2.1.2 Inertial sensors based or Relative localization systems

A different technology was being used for navigation from decades in ships, air-crafts and space-crafts [27]. They use heavy inertial measurement equipment to estimate the ships movements and thereby take proper actions to control the path being taken. With the development of micro electro mechanical sensor (MEMS) devices, several low grade inexpensive small MEMS sensors became available. These Inertial sensors are used in robots and human navigation. The three important inertial sensors used for navigation are accelerometers, gyroscopes and magnetometers. These systems are called Relative localization systems as they sequentially update the current position from previous position by using the motion model.

2.1.3 Probabilistic approaches for Indoor localization systems

Both the absolute and relative localization systems do not provide accurate location. Indoor environments have information such as pathways, staircases, lifts, walls etc., and magnetic field variations, light density variations, visual information etc. that can be used in localization. As localization may involve the loss of the correct location information and has to again arrive at the correct location, it needs some good algorithms. The probabilistic approaches are found to be most suitable for localization purposes [26]. These approaches are probabilistic density estimation problems that predict the posterior distribution of the possible locations using the available data.

The data used is of two types, momentary sensor data and sensor data during change of state, For example, momentary sensor data will contain light intensity, magnetic field characteristics, Wi-Fi RSSI signals, FM RSSI signals and other information sensed at a moment. The latter includes all the motion related sensor data such as distance moved, direction of movement, altitude change information. These data are used together using the probabilistic algorithms such as Kalman Filter [34], Particle Filter [26] etc., These algorithms need intense computational resources.

The availability of smart-phones with high computational power now-a-days enables the possibility of low cost and low infrastructure indoor localization systems using the above algorithms and embedded sensors in the smart-phones. There has been an exponential growth of sales in the smart-phone market and all the smart-phones are equipped with the inertial sensors, Wi-Fi interfaces, Bluetooth interfaces, Light sensors, FM antennas and many other sensors. We use a smart-phone and a pre-stored Magnetic field map database of the environment and pre-stored indoor map as our test set up. We use the particle filter to integrate the inertial sensors and the building information in the form of magnetic map and indoor map together in our localization system.

2.2 Indoor localization Techniques and Terminology

TOA

Time Of Arrival (TOA) is the time taken by a signal to reach from transmitter to a receiver. TOA of a signal can be used to find the distance between the mobile station and known beacons (anchor) in the indoor environments, provided the mobile stations, beacons are time synchronized. Infrared signals [15], ultrasonic signals [3, 5], UWB signals [1, 2] etc., based systems use the TOA and the velocity of those signals to find the relative distance from pre known beacon locations. The key dis-advantage of this method is the transmitters and receivers should be time synchronized before-hand with high precision for accurate localization.

TDoA

TDoA is an improvement over TOA, as it involves the difference of the time of arrivals at two static beacons from the mobile station. The beacons should be time synchronized. This method is used to localize the mobile station based upon the distances from three or more known beacons. The difference of TOA of two sub stations will remove the time offset between beacon and mobile station from calculations.

Triangulation or Multilateration

Triangulation is a positioning method used to find the location of a mobile node when its relative distances from three or more static nodes are available. Triangulation method uses TOA, TDOA techniques for distance estimation from known anchor nodes. RSS can also be used to estimate the distance based on the log-distance path loss (LDPL) model. UWB signals, infra-red signals, ultra sound signals etc., use this method.

RSSI (Received Signal Strength Indicator)

The cellular systems transmit radio frequency (GSM) signals from the base station (antennas) to the mobile station or vice-versa. The signals transmitted have power associated with them. The power of the signal fades as it travels away from the antennas. When the signals reach the mobile station, the signal strength measured at the mobile station is termed as RSSI. This phenomenon of power loss during transmission of radio signals over large distances is called large scale fading. The signal strength decreases exponentially with distance from the antenna during signal transmission in open spaces. The small scale fading of radio signals due to multipath effect is also predominant. It is because of multiple reflections of the radio signals in the indoor environments before reaching the mobile station. Only the large scale fading is considered in Wi-Fi RSSI based Indoor localization systems. Wi-Fi RSSI based triangulation methods, Wi-Fi RSSI fingerprinting based methods are the most popular techniques in the literature.

Fingerprinting

Fingerprint is the vector or scalar value of a signal at a location. Fingerprinting involves an offline and an online phase. In the offline phase, signal fingerprints at various locations of the test area are collected and stored in the database. In the online phase, user measures the signal fingerprint at a location and matches the measured fingerprint with the stored fingerprints in the database. The matching algorithms like k-nearest neighbour (k-NN), support vector machines (SVM), neural networks, probabilistic matching, Dynamic Time Warping [22], fuzzy logic etc., are generally used.

Particle Filter

Kalman Filter and grid based bayesian estimation methods are probabilistic solutions to estimation problems where some strict assumptions hold. Particle filter is a more general form of these filters after some approximations. It can be applied to several estimation problems and have lower computational requirements.

Particle filter uses point mass representation of probability densities called as samples or particles. When large number of particles are used then the probability density will be closer to the continuous probability density function (pdf). It constructs posterior probability density function of state, using the noisy sensor measurements, motion measurements and other information. Sensor measurements are available at discrete times. The posterior probability density function constructed can be used to find the optimal state estimate. Particle filter has low computational and memory requirements as it sequentially processes the received data and just keeps the knowledge of current state and previous state information. It is called recursive filter or sequential monte carlo filter.

Particle filter keeps track of the dynamic state probabilistically. It works using two probabilistic models together, namely measurement model and motion model. The sequential processing in particle filter involves two steps alternatively, prediction step and update step. Prediction step uses the motion model, movements between one state to another state to find the new posterior pdf. Due to the noisy nature of motion model, the posterior pdf spreads. In update step, using the latest measurements and measurement model, the posterior pdf is modified to become more accurate. Essentially, Particle filter uses bayes theorem based equations during the prediction and update phases.

2.3 Applications

In the smart-phone era of computing, several applications of indoor localization are emerging. With the future developments in ubiquitous computing and pervasive computing, several applications are yet to be identified. Some applications that are of high importance at present are:

Location Based Services

Indoor localization enables context dependent notifications to the user. The cinemas, concerts, events in the near-by locations can be notified automatically. Navigation in indoor environments to a store or a product location will be possible. Navigation of user in museums, railway stations, bus stations, shopping malls, conferences are some applications. Smart-phone can provide distance or proximity based notifications. The user statistics in shopping malls and museums can be used by the shop owners or organizers of the events.

Asset tracking

Products in ware houses, personal items in home environments, mechanical equipment in workshops or manufacturing houses can be located quickly and with minimum energy, resources using localization systems.

Elderly or Patient care or Visually impaired people

Location of the elderly in homes or patients in hospitals can be known at emergency situations such as fall detection. The patient can be monitored by using the localization system remotely. The localization systems can help the medical care systems a lot by automating several processes. There are no prominent systems that are used to guide the visually impaired people efficiently in indoor environments or outdoor environments. The localization system needs highly accurate estimation to be able to guide the visually challenged people through the pathways avoiding obstacles.

First Responder systems

Fire fighters or Rescuers need to know their surroundings in the rescue operations. At present, there are no good localization systems that can work during rescue operations.

Miscellaneous Applications

Police can use the localization systems to track the police dogs during the crime scenes. Stolen products can be recovered. Alert systems can be activated when some person equipped with localization systems is moving away from some restricted area. Medical studies also have various applications of localization. Location aware social networks can be developed. Location aware advertising would be benefitted.

Indoor localization has several applications in engineering too. It can be used while surveying the indoor spaces. Animated films need accurate localization to capture the movements of the actors. Worker safety in the under mines and mechanical industry can be ensured using localization systems and computerized monitoring of the environments. Smart homes can make use of the user location to automate several actions.

3. Literature Review

Outdoor Localization systems such as GPS are extensively available and are integrated into smart-phones and vehicular navigation systems. Smart-phones use embedded GPS receivers to find the user location. GPS is used for vehicular navigation to guide the vehicle drivers by automatically showing the route to the destination. GPS finds the location with an accuracy of 7 m in suitable outdoor environments. This accuracy is not sufficient for some real world applications like Google self-driving cars, Guidance systems for visually impaired, Engineering applications, location based services in museums, shopping malls etc.,. GPS do not work in indoor environments due to signal non line of sight (NLOS) and signal reflection (multipath effect).

The current day localization systems are still in capable of achieving localization accuracies of less than 1 m in the indoor environments at low cost. Sensor technology has seen several advancements in the past decade. The embedded sensors are used in indoor localization systems along with other signals of opportunity such as Wi-Fi, Bluetooth, Magnetic field signals. Efficient and accurate localization systems are being developed using the fusion of these sensors and signals. Literature review of various indoor localization techniques is presented in the next sections.

3.1 Outdoor Localization

Localization is primarily addressed using GPS satellites over the last four decades. GPS uses a constellation of satellites. The user needs distance estimates from any four or more GPS satellites that are in line of sight from user location. The receiver available with the user will calculate the position of the user using these distances and the satellites details. The time interval of the signal propagation between the satellites and the receiver is used to find their relative distance. GPS works optimally in clear sky environments. The presence of sky scrapers or buildings in urban environments affects the signal propagation and results in degradation of location estimation. In the clear sky environments, GPS satellites provide a localization accuracy of 7 m [27]. GPS cannot be used in indoor environments due to the multipath effects and non-availability of line of sight signals to the satellites.

3.2 Indoor Localization

Indoor Localization has been a topic of active research in the recent years. In the past two decades, several indoor localization systems were developed using different signals of opportunity such as infrared signals, radio frequency (RF) signals, UWB signals, acoustic signals, visible light, ultra-sound signals, blue-tooth signals, Near field Communication (NFC). UWB has been a signal of interest for accurate positioning and tracking [1, 2], but it needs costly infrastructure. As Wi-Fi infrastructure is widely available already, Wi-Fi is used by several authors as a low cost reliable indoor localization system. Mautz et.al. [35] presented an extensive survey of current indoor localization technologies explored in the past two decades.

3.2.1 Infrastructure based Indoor localization systems

Infrared signals, Ultra-Sonic signals, Ultra Wide Band (UWB) signals

Active Badge system [15] is an earliest indoor localization system. It uses infrared signals based tags and receivers. It consists of active badges that emit short IR pulses with unique codes. These badges were given to the people who need to be localized. Several IR receivers are deployed in the building and are connected over a network. But the disadvantage of this system is it needs lot of active badges and IR receiver sensors to make this system work. This system is not scalable. The localization accuracy is in the range of 6m, which is room level localization accuracy.

Ultrasonic signals were used in the Active bat system [5] and Cricket indoor localization [3] systems. These signals have speed of the order of 343 m/s in air and are short range signals as they are affected by the environmental noise. RF signals and ultra sound signals are transmitted from transmitter to receiver at the same time. The difference in arrival times is used to calculate the relative distance between transmitter and receiver. The RF signals travel at speed of light and hence take negligible time to reach the receiver. Ultrasonic systems are highly accurate up to 3 cm but needs high amount of infrastructure in form of beacons, data cables and receivers even for small areas and hence are not scalable.

Ultra Wide band signals [1, 2] is a high cost technology that offers good localization accuracy. UWB are used in commercial localization systems. UWB systems do not suffer multipath effects like other systems and can penetrate through glasses, walls etc., The number of beacons are considerably less than other technologies mentioned earlier. Triangulation method is used to localize using UWB signals.

RFID is a technology that has wide applications in the present day. It is also used for the indoor localization. They work with a range of 1-2m. LANDMARC have used RFID. The disadvantage of RFID is it needs deployment of new infrastructure and large number of tags.

Radio Frequency (Wi-Fi)

Different radio frequency signals based commercial systems are Wi-Fi, Cellular systems and Bluetooth. Wi-Fi is widely deployed in urban environments across the world. Its range is typically 3-30m. RADAR [12], an earlier fingerprinting based indoor localization system is based upon Wi-Fi. Its accuracy is about 2-3m. It uses fingerprinting technique instead of TOA, TDoA, and AOA techniques. It calculates the euclidean distance between the measured fingerprint and the stored fingerprints in the database and returns the location with the smallest euclidean distance as the estimate. Its key limitations are

1. Wi-Fi signals are affected by the user’s orientation, multipath effects, and with time.
2. The construction of Radio map (off line phase) is labour intensive.

The later systems tried to optimize the fingerprinting method. RADAR uses a deterministic method of RSSI matching. Horus [6] uses a probabilistic method of fingerprint matching with large number of samples at each location. The highest likelihood location is responded as the estimated location. Horus has achieved localization error of less than 2.1 m in 90% cases.

Received Signal Strength (RSSI) modelling is used to avoid the manual construction of radio map, but the signal strength models are too complex to model due to multipath effects and small scale fading. They also result in degradation of localization accuracy. EZ localization system [7] uses the signal strength models and achieves median localization accuracies of 2 m and 7 m in small and large test areas respectively.

Crowd-sourcing is used to involve user in constructing maps automatically. The RSSI values measured by the users were used to construct the radio map without disturbing the user. A partial RSSI fingerprint database can be provided initially to the system

3.2.2 Inertial sensors based Indoor localization systems

The Advent of Micro Electro Mechanical Systems (MEMS) technology has resulted in embedded sensors like accelerometers, gyroscopes, magnetometers on the chip. The low cost inertial sensors are not reliable due to their low accuracy. Wi-Fi fingerprints and INS [9, 10, 12] were used together to improve the accuracy of indoor localization. Some other researchers used indoor maps [9, 10, 25], magnetic signatures [29, 33], magnetic maps [16, 17, 18, 21, 24], light intensity, FM signals [8] and acoustic signals together with INS.

Inertial sensors based navigation is a topic of active research in the literature. Dead Reckoning algorithms are used in various papers [9,10,11,13,16,17,18,21,24,25,33]. Brajdic et.al. [28] presented and evaluated step detection algorithms and step length models used in the literature. We have chosen peak valley based step detection [9, 25] and acceleration based step length model [30]

The key challenges faced while using inertial sensors in the indoors is the orientation estimation. There are deviations in orientation estimates from ground truth due to the magnetic perturbations caused by building, elevators, steel bars and electrical equipment. We use an efficient orientation detection system presented by Madgwick et.al. [31] and Comotti et. al., [32]. It is a general purpose orientation estimation algorithm. It is computationally efficient than and presents similar accuracy as Kalman filter based orientation estimation.

Several localization applications using inertial sensors have made use of other available information in the indoor environments. Some key research efforts in the recent literature are summarized below:

Zee: Indoor maps, INS, Wi-Fi Crowd sourcing

Zee [10] employs an inertial sensors based navigation system, particle filter algorithm using indoor maps and Wi-Fi based initial location estimation. Zee crowd sources the training dataset of Wi-Fi fingerprints without explicit input from the users. Zee runs on the user's smart-phone as a client. Initially, Zee assumes the user's location is unknown, i.e., the particle filter assumes the user can be anywhere initially over the floor plan. As the user walks Zee constructs the path based on INS readings. It eliminates those possibilities of user's location on floor-plan that violates the constraints such as walls. Finally, Zee converges to the user's location after some time. Through-out the walk, the scanned Wi-Fi readings are time-stamped, and annotated with respective locations as soon as they are found using backward propagation. Though this is fine, the number of particles initially processed is too high due to uncertainty of position, to avoid this Zee initializes the user's location using previous Wi-Fi measurements trained to the system. As, the time passes the Wi-Fi measurements accumulated will become larger and a user can localize using only Wi-Fi based localization. Zee is able to localize the user to an accuracy of 1m after 120-140 steps with turns in the path. The average localization accuracy of Zee is 1-2 m. When Heading Offset of the building is known, the convergence of location was shown to be still faster at about 80 steps. When initial location is known, there was an initial high error due to stride length estimation. Zee is compared with the Wi-Fi only localization systems using the Wi-Fi measurements collected. Zee Horus/Zee EZ are able to achieve 50% error and 80% error of 1.2 m and 2.3 m respectively highly comparable to manual training data to Horus/EZ.

UnLoc: INS, Wi-Fi, Magnetic signatures, landmarks

Unsupervised Indoor localization [33] also achieves zero effort indoor localization based upon SLAM and inherent landmarks in indoor environments. It uses a learning algorithm for learning the landmarks and then used them to localize the user in addition to dead reckoning. Unsupervised localization is an extension of outdoor dead-reckoning using periodic GPS corrections to indoors. It uses activity recognition to determine landmarks for dead reckoning correction. It employs Wi-Fi subspaces to distinguish landmarks in different locations. UnLoc dead-reckons the user from a known location and localizes the identified signatures (landmarks). As more users provide the location estimates of landmarks they become more accurate. Key types of landmarks are Seed Landmarks (SLM) i.e., entrance, stairs, elevator, escalator, that provide distinct signatures in human motion traces identifiable from maps and Organic Landmarks (OLM) that offer magnetic signatures, Wi-Fi signatures that localize to a small area reproducibly. Dead reckoning while using these land marks offers a special feature, its error will be seeing tooth-shaped due to periodic corrections by the landmarks,

Magnetometer readings are affected by the magnetic and electric deflections indoors, but gyroscope appears unaffected. Hence gyroscope readings are integrated to provide the relative angular displacement. But, as we do-not know the initial direction of motion there is a bias in the estimates. To counter this, UnLoc uses the landmarks passed over a period of time to estimate the bias. UnLoc claims to have used the gyroscope readings for the first time for dead reckoning heading estimation in the literature. UnLoc has found out SLM's with high accuracy of order of 99.5%. OLM's are found to be widely distributed across the test location and have shown stable signatures on different days. UnLoc can correct the paths by tracing back during offline applications (not needing immediate location information). UnLoc offers an average error of 1.15 m in offline case and 1.69 m in online case.

Accurate and Reliable indoor localization system: INS, Indoor Maps

Fan Li et.al.,[25] implements dead reckoning technique using only smart-phone inertial sensors and floor map and not using any other infrastructure like Wi-Fi. They have developed a method that was giving an accuracy of 1.5 - 2 m. They developed a particle filter based personalization algorithm to model the stride lengths of users. A step detection model using DTW based step periodicity detection is developed in their work. A heading inference system based upon gyroscope and magnetometer that works independent of the placement of phone is also proposed by them. The filtered acceleration signal trace is monitored to find peaks and troughs. Thresholds were used to detect false peaks and troughs. They use DTW to exploit periodicity of human walk. A series of peaks are assumed as steps $\{S_1, S_2, S_3, \ldots . S_{n-2}, S_{n-1}, S_n\}$ and then DTW measure among alternate steps, say $S_{i-2}\ and\ S_i$ is found, if the DTW measure is less than a threshold, then the adjacent peaks are similar and hence they are actual real steps. . It found out that there is a linear relation among step length and walking frequency. Thus the equation is $L_g = a * f + b$, where a and b are specific to each user. The system works using the step model and step frequency and heading estimation on each step. These data are fed to the particle filter. Particle filter here is based on location co-ordinates x, y, and personalization model parameters a, b. Each particle represents its location and corresponding step model using the following equations

$$x(t+1) = x(t) + (l(t) + \delta l(t)) \cos\ (\theta(t) + \delta\theta(t)) \tag{3.1}$$

$$y(t+1) = y(t) + (l(t) + \delta l(t)) \sin\ (\theta(t) + \delta\theta(t)) \tag{3.2}$$

$$P_{(a,b)} = (a + \delta_a, b + \delta_b) \quad \text{and} \quad \mathbf{x} = \{(x, y)\ , P_{(a,b)}\} \tag{3.3}$$

where l(t) , θ(t) are lengths and heading estimations from the step model and the readings. **x** is the random variable. The other δ terms are gaussian noise terms. P is the personalization model that is updated through the course of time.

Walkie-Markie: Wi-Fi land marks, INS, Crowd sourcing

SLAM is used to simultaneously localize the robot and map the locality. In a similar manner, Walkie-Markie [29] tries to map the indoor pathways i.e., frequently travelled paths in a building just using some Wi-Fi landmarks and the user's trajectories. It does not need any map of the building but, just needs the Wi-Fi infrastructure to be available. The system depends on crowd sourcing for collecting the trajectories. The dead reckoning solutions used earlier have the drawback of drift in the user location over time due to errors and difficulty in estimating the stride lengths for different users accurately. The Wi-Fi finger printing is used widely in early experiments, But due to the Wi-Fi signal fluctuations over time and different days, months, and on heterogeneous devices these are not stable metrics. Walkie - Markie uses Wi-Fi land marks, based on the trends of Wi-Fi RSS but not absolute Wi-Fi RSS. Thus the landmarks are more stable. Walkie - Markie also uses the various trajectories to extrapolate the paths among these identified landmarks to construct the pathway. They use a map embedding algorithm, Arturia that constructs maps with Wi-Fi landmarks and trajectories. Wi-Fi mark detection is done on the mobile client itself using a 9- point weight window to smooth the RSS curve and then taking derivatives of the smoothed RSS curve. If the trend change is above a threshold then the peak RSS during the transition is selected as Wi-Fi mark. The displacement is calculated using the stride length estimation using frequency model with parameters specified. The direction change is estimated using the gyroscope at large when magnetometer shows a large change. Walkie-Markie has generated visually close path ways to the ground truth paths. The pathways constructed had a maximum discrepancy of 2.8 m and 90% error of 1.8 m. The mean localization error of Walkie-Markie is 1.65m and 90% error of 2.9m.

3.2.3 Magnetic field based Indoor localization systems

Recently, the adoption of Magnetic maps in Indoor localization systems has got significant attention as the magnetic maps are stable over time, unlike Wi-Fi maps which change with time quickly due to multipath effects.

One of the earliest contributions using magnetic maps was by Haverinen et.al, [18, 21] who have used a commercial IMU sensor unit and a circular robot to evaluate magnetic field based robot localization. They have also tested pedestrian localization. They have used a 1D - magnetic map along a corridor instead of 2D- magnetic map. The authors have achieved an accuracy of 0.1 - 0.7 m mean accuracy for robot localization and 3.3 m mean accuracy for pedestrian localization. Later, they have conducted experiments in underground mines of Finland [21], where magnetic field properties are more predominant. The paper achieved a better accuracy of 1.2 -1.44 m mean accuracy for wheel encoded odometry based localization just using magnetic field maps and inertial sensors. These results show that robot localization is possible in underground mines too.

Chung et.al, [19] have further studied the magnetic field properties in indoor environments. They have collected magnetic fingerprints along the corridor and used the nearest neighbour matching to find the location. They have shown that 72% of times, the matching based estimate have a distance error less than 1 m. They have achieved a mean accuracy of 4.7 m in location estimation just using NN matching algorithm without using any dead reckoning.

Kim et.al. [16] have used smart-phones for localization using magnetic fields in particle filtering algorithm and inertial sensors. This is the first smart-phone based magnetic localization system. They have implemented particle filtering algorithm using the magnetic maps of corridors collected for forward and backward motion. They have used the corner fixes, to reset the location at corners, using turn detection. The knowledge of corridors directions is used in their algorithm as moving direction instead of actual heading from the Smart-phone. Instead of using fixed moving directions, we have used corrected orientation estimates based on AHRS algorithm [31, 32].Thus our approach is applicable to indoor spaces also. Kim et.al. have used only magnetic field magnitude, Instead, we have used vector magnetic field, Indoor Maps + Vector, Indoor Maps + Magnitude in our implementation and compared the algorithms. They have achieved mean error of 1.12 m for the corridors. Thus, our system can be used in the indoor spaces also along with corridors.

Gozick et.al., [22] have tested Dynamic Time warping algorithm for matching the time series of the magnetic field data signatures during walk, with already collected pathway's magnetic field signatures. They localized the user with an accuracy of 2-3 m of localization. A distance of about 3m is needed to be travelled for arriving at the correct location.

Grand et.al, [17] have used the 3-axis magnetic field vector in the particle filtering algorithm. The authors have developed a method for constructing the indoor magnetic map based on the smart-phone readings collected for rectangular path walks in the indoors. They construct the map using a numerical optimization method. The authors have done the computer based experiments using actual smart-phone readings collected during a straight line path and a circular path without the knowledge of initial location. They have localized the estimate within 0.7 m from ground truth for the straight line path and within 1.2 m from ground truth for a circular path.

Frassl et.al. [24] have used foot mounted inertial sensors and high resolution magnetic maps to develop robot and pedestrian localization systems in the indoor spaces. They have implemented the particle filter algorithm using magnetic maps (magnitude or vector or horizontal and vertical components). They have achieved localization accuracies of the order of 10 cm for each of these methods for pedestrian and robot localization. They have used magnetic maps of resolutions 10 cm and 20 cm in their experiments. They have used kalman filter based orientation estimation methods. These systems are different from our work in many ways, our system uses indoor maps and magnetic maps together. We implement a pedestrian localization system for hand held smart-phones instead of foot mounted inertial sensors. The magnetic maps we have generated have a resolution of around 60 cm and consume less time and resources to construct.

3.2.4 Other Indoor localization systems

FM based Indoor Localization

FM radio signals in indoor environment were explored for fingerprinting by Yin Chen et.al [8] in large scale experimental testing. Though FM radio signals outdoors do not vary much at nearby locations, in indoors due to the building structure they show enough diversity. They are stable over time unlike Wi-Fi RSSI signals. FM and Wi-Fi signals are found to be complementary in nature and their localization errors are independent. FM signals are less affected by the presence of humans and their orientation.

FM RSSI is found to be a good indicator of room level localization better than SNR, Multipath, frequency offset alone. When FM RSSI and all the physical layer information are fingerprinted together then the accuracy is still better. Wi-Fi and FM RSSI are found to be independent in localization errors, as they result in different sets of localization errors, and combined they result in still higher localization accuracy. They further tried to find out the ideal number of FM stations to be included in each fingerprint. It also investigates the temporal variations of the FM fingerprints. The entire room level localization was done with 2-3 locations from each room of the test locations just to estimate the feasibility of FM signals for localization. For finer localization results, a test was done in an office building with 100 locations in a room FM fingerprinted, each location one foot away. The training data is used for test too, with one fingerprint removed form training data and testing for its location. The error was similar to 1ft in all the cases, while Wi-Fi RSSI was yielding an error of less than 10 ft. in 90% cases.

Foot mounted inertial sensors

FootSLAM [13] just uses inertial sensors mounted on foot of the pedestrian to track the pedestrian over a long time with small errors. This provides a bench mark for the smart-phone based inertial sensors performance in the future. This work lays out the foundation for proving that simultaneous location of pedestrians and building layout can be estimated jointly using just the inertial sensors measurements. The MEMS sensors that were being used in vehicular movement estimations are adapted to pedestrian tracking by the availability of low cost integrated MEMS sensors in smart-phones. FootSLAM [13] is an extension to FastSLAM [16] of robotics as applied to pedestrians. The FootSLAM algorithm is based upon assuming each position to be a hexagon and formulating the probabilities of moving over an edge e, based upon other constraints of human perception. FootSLAM with a hexagon radius of 0.5m was able to map the building paths with an accuracy of 1-3m.When the FootSLAM algorithm is using more than 10,000 particles it is able to achieve an accuracy of 2 m at the end points of a path.

Several other methods using electric light illumination in indoors, artificial magnetic field systems, computer vision based indoor localization systems are being explored by the researchers now-a-days. But these systems are either in-accurate or need costly infrastructure. Bluetooth can be used for localization with the development of Bluetooth 4.0 or Bluetooth low energy in the near future.

3.3 Major Challenges

Orientation estimation

The magnetometer readings are not accurate in the indoors due to magnetic deflections caused by electrical and metallic equipment. The initial orientation of the user is generally found using the magnetometer. Gyroscope is popular option for orientation estimation but they calculate the final orientation relative to the initial location. Gyroscopes also have the problem of gyro drift over time. Thus, orientation estimation of the user is the challenge that many localization systems face.

Step length estimation

Step length depends upon user demographics, frequency of walking steps, kind of foot wear, kind of floor walking upon. There are no accurate step length estimation algorithms. The error in step length adds to the total error during dead reckoning. As a result, the dead reckoning systems are inaccurate over longer walks.

Kidnapping problem

The localization systems suffer to converge back to the original location when they lose knowledge of their actual locations at any point of time. This problem is called kidnapping problem in localization. Several probabilistic methods are able to overcome this problem. But the algorithms like dead reckoning get deviated from the actual paths when the kidnapping problem occurs.

War driving

Fingerprinting is a popular technique used in multiple localization systems in the recent literature. But, construction of fingerprint database during offline phase is a cumbersome job and it needs lot of human efforts and time to construct the data base. This problem is called War driving.

Time dependency of maps

The fingerprint maps used in localization could be time dependent. For example. Wi-Fi maps are highly unstable over time and change frequently. Thus, these maps have to be updated frequently. Magnetic maps are found to be stable over time when the entire infrastructure in the surroundings remains the same over time. Thus magnetic maps constructed once can be used for long periods of time.

Infrastructure cost & Deployment

Localization systems have to be scalable and easily deployable. Several accurate localization systems need costly infrastructure. Their infrastructure is not readily available in the indoor environments for localization Thus deploying them in the indoor environments across the globe is a key problem facing many localization systems like UWB, Bluetooth 4.0, Camera, Ultrasound, Infrared signals.

3.4 Research Gaps

The research has focused on different techniques for indoor localization over the last two decades. Recent research been done in the area of magnetic field based indoor localization systems over the last five years. Some of the key research gaps found during literature review are:

a) Earlier studies have focused either on using magnetic maps or indoor maps along with inertial sensors for indoor localization. We used magnetic maps (magnitude or vector), inertial sensors and indoor maps together to improve the accuracy of smart-phone based indoor pedestrian localization. Magnetic maps are more stable than Wifi maps over time in indoors. They are also ambient in indoors.

b) Most of the earlier magnetic maps and smart-phone based approaches have been tested for the movement in a corridor except few like Grand et al. where circular paths have also been used for testing. We have tested the accuracy of our approach for real time zig-zag paths in indoor spaces by conducting several experiments.

c) There are no accurate and reliable electronic compass calibration techniques for smart-phone magnetometers to avoid the erroneous compass readings. These magnetometer errors are due to magnetic interferences of smart-phone battery material, manufacture material and other indoor magnetic perturbations.

d) There are very few studies that have focused upon the dependence of magnetic field observations on the smart-phone model and magnetometer manufacturer.

e) Construction of magnetic maps involves lot of time and resources, though there is one fast map generation technique proposed by Grand et al. [17], more general forms of magnetic map generation techniques are needed.

f) Simultaneous Localization and Mapping (SLAM) of the indoor environments using smart phone based magnetometers is not yet explored much by the researchers.

4. Proposed Approaches

Indoor localization is implemented using probabilistic approaches in the past decade by different researchers as its most appropriate solution. Particle filter is most popular probabilistic estimation approach. It consists of prediction-update step cycle. The prediction step uses the probabilistic motion model to modify the posterior probability density function of the location state. The update cycle uses the latest measurements in the measurement model to change the posterior pdf. The posterior pdf is used to find the most optimal location state. Many estimation problems were solved using particle filter approach in robotics, signal processing, artificial intelligence etc.

The Particle Filtering Algorithm shown in Fig 4.2 senses the magnetic field measurements. It uses a step motion model for particle movement in the map environment. Further details of the general particle filtering algorithm can be found in [26]. We have modified the algorithm to use Magnetic maps (magnitude or vector) with or without Indoor maps in our proposed approaches. Similar algorithms using magnetic maps (magnitude or vector) are found in [14, 17, 21, 24]. We have improved the previous implementations by using a more general and reliable orientation estimation AHRS algorithm presented in [31, 32]. The four approaches we have proposed, implemented, experimented and analysed in this dissertation are as below:

a) Magnetic map (magnitude)
b) Magnetic map (vector)
c) Magnetic map (magnitude) + Indoor map
d) Magnetic map (vector) + Indoor map

4.1 Components & Methods

Our system uses the inertial sensors to continuously log the user motion measurements, from 3-axis accelerometers, 3-axis gyroscope and 3-axis magnetometer. Lot of research has happened to understand the human activity [29] based upon the inertial sensor measurements. Step detection, turn detection, step length estimation, rotation measurement, walking, running, cycling, fall detection, lift motion, escalator motion and many other human activities can be predicted using the specific patterns in the sensor readings. Several algorithms have been used for step detection and step length estimation [29]. We use the peak valley based step detection [29, 10, 25] and an empirical formula [30] for calculating the approximate step length.

Gyroscope

Gyroscopes provide the accurate rotational measurements for sharp turns. Generally, integrating the gyroscope measurements at sharp turns gives us the turn angle. But as gyroscope gives small noisy measurements around zero when moving on a linear path, the non-zero noisy measurements when integrated, result in erroneous orientation calculation termed as gyro drift.

Accelerometer

Accelerometers sense the linear motion along all the 3-axis. The acceleration along z-axis of smart-phone (vertical to the screen of smart-phone) is a resultant of gravity as well as the vertical motion of the smart-phone while kept in hands of the user horizontally. The acceleration along y-axis of smart-phone is w.r.t motion along the direction of motion. The acceleration along x-axis is the side way motion while the human is moving ahead. Several algorithms [28] have shown that just using the z-axis measurements one can detect the steps. The stance, lift phases of steps are detected by the sinusoidal like patterns in z-axis acceleration. Zero update (ZUPT) [28, 9], peak valley based step detection [29, 9, 25] are key methods based on z-axis acceleration. Brajdic et.al. [28] presents all the methods used for step detection.

Accelerometers do not present the actual acceleration of the human, instead they present the acceleration detected by the smart-phone as a result of human motion and relative smart-phone motion. As a result, the accelerometer readings cannot be double integrated to provide the distance travelled. The other method we are using is step detection and step length estimation based upon empirical formulae [30]. An empirical formula relating the peak and valley acceleration values of a step to the step length provides a good approximation of the step length [30]. Other methods that use the height dependent step length estimation, step frequency dependent step models [25] also exist.

Magnetometer

Magnetometers provide the magnetic field detected as a 3-axial vector. This vector needs to point in the direction of geographic north as it represents the earth’s magnetic field. But due to the presence of electro-magnetic equipment and ferro-magnetic equipment, the earth’s magnetic field is corrupted with magnetic disturbances. In indoor environments these deflections are more than in the outdoor environments. Magnetometers are called electronic compasses. But they do not provide correct orientation due to magnetic disturbances in the indoor environments. Thus orientation estimation is a challenge in the indoor environments using the magnetometers, gyroscopes. We use an AHRS (Attitude and Heading Reference System) algorithm [31, 32] that implements Gradient Descent Algorithm (GDA) based optimization technique. It corrects the gyroscope based orientation estimated using the GDA for the gravity and magnetic field measurements. This orientation estimation technique runs continuously in the back ground using the magnetometer, gyroscope and accelerometer readings. We pick the orientation information at the moment when a step is detected by the system.

Dead Reckoning

Dead Reckoning is the simplest form of localization technique using just the inertial sensors. The user inputs the initial location co-ordinates to the Dead reckoning system. Then using the step length, orientation of movement the system updates the location relative to the previous location. The algorithm will accumulate distance and orientation error with number of steps, because of the in-efficient methodologies of the step length estimation and orientation estimation. This method is simple but inaccurate.

In the literature, several efforts were done to improve the step length estimation technique and develop kalman filter based orientation estimation [24], which is computationally very expensive but accurate. Some researchers integrated the dead reckoning technique with the Wi-Fi fingerprinting based localization techniques [9, 10, 12] and indoor maps [9, 10, 25]. Thus, reducing the growing error in dead reckoning system and correcting the deviated paths.

4.2 Motivation for using Magnetic map

Some key motivations for using magnetic maps along with inertial sensors are as follows:

a) Magnetic maps are more stable in indoor environments over long periods of time [23], unlike Wi-Fi signals which are time dependent and affected by the human presence [36]. Thus, we do not need to generate magnetic maps as frequently as Wi-Fi maps.
b) Magnetic field maps can be constructed for all indoor environments and do not need expensive or wide spread infrastructure. Thus, these signals can be used in implementing low cost commercial indoor localization system.
c) The magnetic field disturbances in the indoor environments are highly varying even in a small room due to the various building materials, book shelves, escalators, lifts, pillars in

the indoor environments. These magnetic anomalies can be used to improve localization accuracy, though they are responsible for incorrect orientation estimation of the user indoors.

4.3 Application Architecture

The Indoor localization application architecture is outlined in this section.

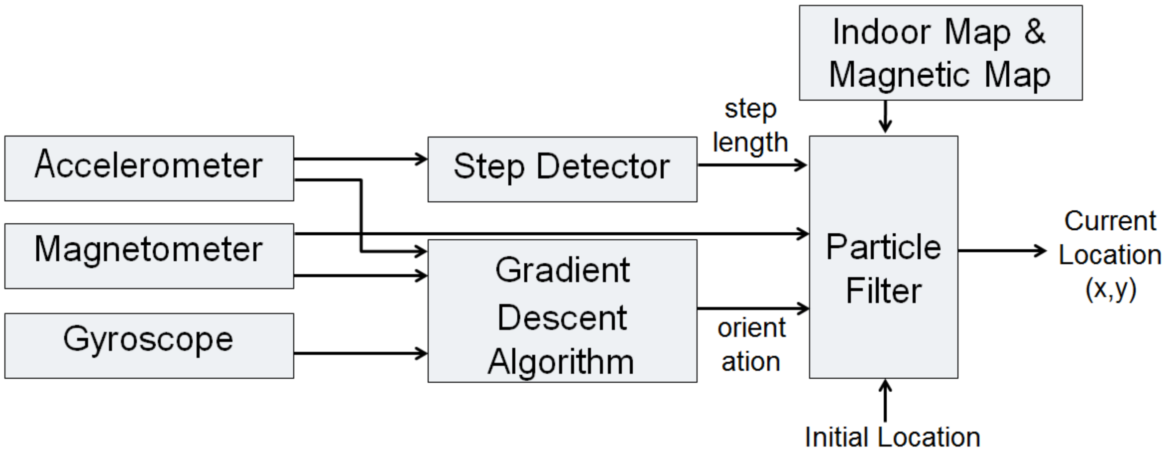


Fig 4.1. High level overview of application architecture

Sensors and Magnetic map

The application uses three sensors that are built-in to the smart-phones, These sensors are 3-axis accelerometer, 3-axis magnetometer, and 3-axis gyroscope. The measurements from these sensors are used by different components of the localization system. In the first two approaches (M, V), we use the pre-stored magnetic field measurements database (magnetic map). Magnetic map consists of location annotated magnetic field vector and magnitude measurements. In the latter two approaches (MM, VM), along with magnetic map we use the pre-constructed indoor map. Indoor map will be provided to the localization system in the form of bitmap image.

Step detection and Orientation estimation

Step detector and Step length estimation is done just using linear acceleration values obtained from Google's Android sensor API. Orientation estimation is done using AHRS algorithm [31, 32], which includes gyroscope based orientation estimation and gradient descent algorithm based optimization. This component uses the measurements from gyroscope, magnetometer (for magnetic field direction), and accelerometer (for gravity direction).

Particle Filter

The particle filter executes on each step detection. It uses the orientation estimated and step length estimated in the motion model to move the particles. It uses the magnetic field measurements at the current location in the measurement model to update the particle weights. Then resampling step [26] is done to select the most probable particles to be used on the next step detection and ignore the less probable particles. The measurement model can be implemented using the magnetic field measurements magnitude or vector readings. In the third and fourth approaches (MM, VM), we have also incorporated the indoor map information into the particle filter. Using indoor maps, we ignore the particles that collide with walls, or corners. Earlier researchers have used either magnetic maps [14, 17, 21, 24] or indoor maps [9, 10, 25] along with inertial sensors. But, there was no implementation combing all the three information sources together. We have improved our implementation by using a more reliable orientation estimation algorithm presented in [31, 32] so that our indoor localization system can be used in the corridors as well as rooms involving zig-zag motion, which is not tested or considered in the earlier research papers.

4.4 Proposed Approaches

4.4.1 Particle filter using Magnetic Field (Magnitude)

Particle filter uses inertial sensors based step detection procedure and orientation estimation method. We use magnetic field map pre-stored in the system, and interpolate the data available in the map to make the map continuous for implementation purposes. We made use of Bi-cubic Spline Interpolator function provided by apache common math API [39]. We use the magnetic field measured when the step is detected to update the weights of the particles. We need to interpolate the magnitude map of magnetic field east and west to form two interpolating functions that will be used during the measurement update equations.

The particles are moved using the dynamical equations (4.1, 4.2) in the prediction step, Step length is estimated from the accelerometer values as mentioned in previous sections. Rad_Angle is the orientation obtained from AHRS algorithm when the step is detected. These two values are corrupted by ‘d’ in range of [0, step noise) and ‘Ω’ in range of [0, turn noise) respectively and then used in dynamical equations. Each particle is moved by using dynamical equations (4.1, 4.2)

$$P.x' = P.x + (Step\_Length + d) * \sin (Rad\_Angle + \Omega) \qquad (4.1)$$

$$P.y' = P.y + (Step\_Length + d) * \cos (Rad\_Angle + \Omega) \qquad (4.2)$$

where ‘d’ is a normal gaussian noise of distance called step noise. ‘Ω’ is a normal gaussian noise of angle called turn noise. The step noise and turn noise together affects the spread of the particles on each step. The more the particle-spread, more area is searched in the map environment. step noise and turn noise are parameter values that affect the prediction step.

We update the importance weights of the particles by using the gaussian distribution based equation (4.3), used by several papers [16, 17, 18, 21, 24] with a similar form:

$$w_i = e^{\left[-\frac{1}{2}\left(\frac{|z|-|k_i|}{sense\_noise}\right)^2\right]} + 0.0001 \qquad (4.3)$$

where z is the magnetic field vector at current location measured on the new step, k_i is the magnetic field vector found by using the pre-stored magnetic map, corresponding to a particle p_i in the system and w_i is its importance weight k is the magnetic field vector. |x| means magnitude of vector x. The constant 0.0001 is added to the weight w_i to make particle weight non negligible, when value of update equation (4.3) is << 1. sense_noise is the parameter value used in particle filter to control the particle weight update equation and there by the performance of the system.

Resampling [26] is done after the update step. In this step, all the particles weights are normalized to sum to one. Now, a cumulative distribution function (cdf) of all the particle weights is constructed with the x-axis being the index of the particle and y-axis being the cdf value in the range [0,1). It is a discrete function with discrete x and y values. Now, random real numbers are generated between 0 and 1. The lowest index (x-value) is searched such that its cdf (y-value) is greater than this random number. The particle with this index is added to the new particle set. This process is continued N times. The same particle may be added more than once to the new particle set. Thus the particles with high particle weights are more probable to be present in the new particle set than the rest. This new particle set is used on the next step detection. This resampling process will select the good estimates of the location. The resampling can be done when a step is detected or when the cloud of particles has become too much close. In our approaches, we use SIR (sequential importance resampling) variant of particle filter, that is we resample the particles on every step detection.

At any point of time, we have a cloud of particles representing the posterior pdf of location. We use these particles to find the most optimal estimate of the location. Generally, weighted mean of particle's location co-ordinates is used as the location estimate. We use the geometrical median of the particle cloud as the location estimate.

Mean : $x' = \sum_{i=1}^{N} w_i * (p_i.x)$, $y' = \sum_{i=1}^{N} w_i * (p_i.y)$ (4.4)

Median : $x'' = \frac{1}{N}\sum_{i=1}^{N}(p_i.x)$, $y'' = \frac{1}{N}\sum_{i=1}^{N}(p_i.y)$ (4.5)

Where (x', y') is the weighted mean of the particles and (x'', y'') is the geometric median of the particle cloud.

4.4.2 *Particle filter using Magnetic Field (Vector)*

The vector form importance weight update equation used instead of equation (4.3) in this approach is

$$w_i = e^{\left[-\frac{1}{2}(z-k_i)^T R^{-1} (z-k_i)\right]} + 0.0001 \qquad (4.6)$$

where R is a covariance matrix, with its diagonal elements values as $sense\_noise^2$ and the rest of the matrix is zero. The rest of the variables have same meaning as in the equation (4.3). Here the operations in the equation (4.6) using R, z, k are matrix operations. The determinant value obtained after the matrix operations, is used in the equation (4.6) as the exponent.

We use magnetic field vector readings in this approach, hence we interpolate the x-axis, y-axis and z-axis readings in the pre-stored map separately into three interpolating functions for east and west respectively, totally six functions, that will be used during update step. This approach uses the same prediction step or dynamical equations as the magnitude based approach. All the other routines used in the magnitude based and vector based approach are the same.

4.4.3 *Particle filter using Magnetic Field (Magnitude + Indoor Map)*

Indoor maps are created as bitmap images by including the features of the building such as the walls, book shelves and other details. In our approach, we have created a bit map image showing the book shelves as red filled rectangles, and the boundary of the test area as a red outline. An example can be seen in section 6.3. We use Bitmap factory package of Android API to interpret this bitmap image in the android system.

We use the indoor map along with the magnetic map magnitudes in particle filter, to constrain the particle motion more. The free spaces in the indoor map are acceptable locations for the particles to exist. We also consider the case that any particle cannot move through a wall during the prediction step. Hence when a particle is moved we check whether it is colliding with the wall or not. Even though the final location of movement and initial location of the particle are acceptable, if there is an obstacle in between these locations when interpolated linearly, we ignore those particles.

We consider the particles which are valid only after the prediction step, to be used in update step and resampling. The number of particles may become less due to the generation of invalid particles on the prediction step. But after the resampling step, again N particles are available in the system. A peculiar case is when all the particles are invalid after the prediction step. In such a case, we will use the knowledge of the particles before prediction step, and move them a distance in the range [0, SD) in the direction ($\mathrm{Rad\_Angle} + \Omega'$), where Ω' is in the range of [-30°, 30°]. SD in our approach is set to 1m. This step is a recovery step.

$$x' = P.x + SD * \sin(\mathrm{Rad\_Angle} + \Omega') \quad (4.7)$$

$$x' = P.x + SD * \cos(\mathrm{Rad\_Angle} + \Omega') \quad (4.8)$$

4.4.4 Particle filter using Magnetic Field (Vector + Indoor Map)

This approach is a hybrid of the magnetic field (Magnitude + Indoor Map) and magnetic field (Vector) approaches. It uses the routines used in these two approaches. It generates the interpolation functions for each of x, y, z-axis east and west magnetic maps, to use during the vector update step. The particles which were invalid were ignored while doing the update step using the procedure explained in the (Magnitude + Indoor Map).

4.5 Algorithm

The particle filter uses a particle class, that provides the move method (motion model) and weight update method (measurement model). The particles are moved during prediction step using the Move method in fig 4.3. The Magnetic map is used to find the magnetic values at the particle's current location in the algorithm. These values are used by the measurement model to update the weights of the particles based on the equation (4.3, 4.6). In this way, the posterior pdf is modified by the measurement model and motion model.

Resample method of fig 4.5 is used to select the particles with high importance weights, and form the set of particles P after each step, this algorithm is called Sequential Importance Sampling (SIR) variant of Particle filtering algorithm [26] as it involves resampling after every step.

In Move Method (fig 4.3), x' and y' are variables used to temporarily store x and y values of the particles after applying dynamical equations. P' contains only the particles that are inside the map limits. 'd' is a normal Gaussian noise of distance called step noise. 'Ω' is a normal Gaussian noise of angle called turn noise. The step noise and turn noise together affects the spread of the particles during the process. The more the particles spread on each step, more area is searched for location estimate.

The Convert method (fig 4.4) uses the knowledge of the smart-phone orientation to choose from the magnetic maps (east and west) constructed using the smart-phone directed along east and west directions. This is needed because the magnetic field measurements collected at the same location are not the same for different smart-phone orientations. This is because of the smart-phone magnetometer offset along each of the axis that makes the readings biased. Magnetic maps for different directions were used in the paper [16] for the case of corridors. In paper [17], the authors have removed the magnetometer offset, after estimating the offset to a fixed vector using simple equations.

MEMS based sensors such as magnetometers, accelerometers and gyroscopes come embedded in the smart-phones. These sensors axes are aligned and the sensors are calibrated to give correct measurements. Unfortunately, these sensors still do not provide accurate measurements. Magnetometer when used at the same position to measure magnetic field, will provide different magnitudes for different smart-phone orientations. This behaviour is because of some offset (x-axis, y-axis, and z-axis) added to the measurements. The offset is caused due to the magnetic properties of the material (such as battery) used in the smart-phone manufacture. We map and use the magnetic field along the most possible user moving directions, in our case in a library book shelve space with smart-phone oriented along east and west directions when moving among the book shelves. Two separate magnetic maps are created using samples collected with smart-phone heading along both the directions at various uniformly distributed points in the test space. The appropriate magnetic map readings were used during localization in equation (4.3, 4.6), based upon the user's direction at any time as mentioned in the Convert function (Fig 4.4). In Particle Filtering Algorithm (Fig 4.2) the terms used are

- L is the variable that stores the user location estimate at any time. Initially, it is set to initial location of the user using First_Fix ( ) by scanning the QR code of initial location.
- P contains particles, where a particle contains its position (x, y) and importance weight w.

```
Input:      Sensor Events from Device Sensors
Output:     An estimate of location of the device at any time through the variable L
Algorithm:
begin
        L = First_Fix ( )
        P = N particles around L corrupted by Gaussian noise.
        M = Magnetic_Map ( )
        for each step_event from Sensors do
                z  =  Sense_MagneticField ( )
                P' = Move (P, Step_length, Rad_angle)        // P' contains inbound particles
                K =  Convert (P', M)
                P' = Gaussian (z, K, sense_noise)
                if  P' is not ϕ:
                        P = Resample (P')
                else:
                        P = Generate N inbound Particles from P in moving direction.
                end
                L = Mean (P)
        end
end
```

Fig 4.2 Particle Filtering Algorithm using Magnetic maps and INS [26]

- M is the interpolated magnetic map provided to the system as an input. M is generated by interpolating the discrete uniformly spaced magnetic field samples collected at grid points in the test bed beforehand.
- Step_Length and Rad_Angle acquired from step length estimation method and orientation estimation method on each step. Step_Length is estimated step length. Rad_Angle is estimated Orientation direction.
- *z* is the magnetic field vector collected at each step, with smart-phone held in the palm of the user along the direction of motion
- P' is a set of particles within map limits, after moving the particles in P using the step length and heading direction of a step.
- K contains the Magnetic field vectors of the particles in P' obtained from the map M.

```
Move ( P, Step_Length, Rad_Angle)
        for i = 1 to N
                x'  = P.x + (Step_Length + d)* sin (Rad_Angle + Ω)
                y' =  P.y + (Step_Length + d)* cos (Rad_Angle + Ω)
                if ( (x',y')  lies inside the boundary of magnetic map)
                        P'. append( Particle (x', y') )
        return P'
```

Fig 4.3 Move Method used in Particle Filtering Method

```
Convert( P , M )
        if ( Rad_Angle lies in [east + 90, east - 90] )
                H = Magnetic Map (east)
        else
                H = Magnetic Map (west)
        for i = 1 to N
                K[i] = Magnetic field at (P.x, P.y) in Magnetic Map H
        return K
```

Fig 4.4. Convert Method used in Particle Filtering Method.

```
Resample (P')
    Normalize_Weights (P')
    Initialize CDF: C_1 = 0
    for i = 1 to N
        Construct CDF: C_{i+1} = C_i + P'. w_i
    for i = 1 to N
        s = random (0, 1)
        index = Binary_Search(C, s)
        P''_i = P'_index
    return P''
```

Fig 4.5 Resample Method used in Particle Filtering Method [26]

5. Implementation Details

5.1 Magnetic field map construction

Location is assumed to be a point instead of an area in our indoor localization system. Magnetic samples are collected at the same point of position and averaged. Magnetic field samples at a location have a variance of around 1 μT, when we are measuring using a smart-phone kept static along a direction. Measurements at a location are different for different smart-phone orientations. This is because of the magnetometer offset error, that is added along the 3-axis. As we are using a smart-phone manufactured with embedded magnetometer, we cannot calibrate it with our routines to give correct readings. The manufacturer provides with a physical calibration technique [41] to avoid calibration errors the magnetometer. Magnetometer shall be calibrated once a day or after the smart-phone is switched on. The calibration method [41] is to swing the smart-phone keeping its screen horizontally and waving it in the form of '∞' in the horizontal plane five to six times.

In our experiments, all the measurements were collected using the smart-phone only. During the collection of measurements in offline phase, we have used a wooden trolley shown in fig 6.1(c). with a stack of books. The smart-phone is placed on the book stack of wooden trolley at a height of 1.2 m with its screen kept horizontally. Smart-phone y-axis is placed in two specific orientations (90 degrees, east and 270 degrees, west) to collect measurements at each location. In online phase while walking or standing, the user keeps the smart-phone in hand with its screen kept horizontally and its y-axis along the direction of motion. In our test area, the user will be moving along path ways among book shelves with the orientations (0 degrees, 90 degrees, 180 degrees, 270 degrees). But we are not using this information, in setting our orientation, instead we use a more general orientation estimation method [31, 32] that can be used in these path ways as well as the open space in indoors.

Smart-phone motion in the hand, or a different orientation of smart-phone in the hand of the user for example land scape, or reverse portrait etc., is beyond the scope of this study. The importance of using Magnetic field maps is that they are found to be stable over long periods of time, if the big electrical or ferrous equipment in an environment are not displaced too much. The measurements stored in our database as magnetic map and used during localization, are constructed by data logging of magnetic field measurements over a period of time at each grid location of the test area. 3-d Vectors of magnetic field are collected during the measurement time.

We have used the Android sensor manager API, Android Sensor Event Listener API [38] to access the sensors such as accelerometer, magnetometer and gyroscope. The sensors are polled frequently by the hard ware system, and whenever the sensor measurements are found they are returned to the system.

We have conducted our experiments in a book shelve space, in Central Library building, IIT Roorkee. This test area is marked with grid points, at the corners of rectangular grids, of size 0.56 m x 0.56 m each. A total of 405 uniformly spaced grid points were marked in our rectangular test area. We have mapped the space along five path ways among these book shelves along east and west directions by manually moving the wooden trolley between grid points and measuring the magnetic field using smart-phone. We have developed a smart-phone based data logging application to log the magnetic field readings for the specified amount of time (3 seconds) at each grid location. The data is logged over two days with time duration of around 8 hours. All the 405 grid points were traced with the smart-phone heading the west direction on first day evening. And the east direction based readings were collected on the next day morning. Some preliminary magnetic field maps were also constructed before the final magnetic map was constructed.

These preliminary magnetic maps were used while testing and debugging the localization system. When we compare the preliminary magnetic maps and the final magnetic map, we notice, the magnetic field maps are stable over a long period of time [23]. Fig 5.2 (a) shows the plot of two magnetic field magnitude readings collected with the smart-phone held along the east direction on different days of a month. This plot has magnetic field measurements (y-axis) at all the grid locations, location indices (x-axis). The old and new maps are same. This shows that the magnetic field is stable over long periods of time unlike the Wi-Fi signals.

5.2 Magnetic field map properties

Indoor Environments have ambient magnetic field distribution, that vary over small areas too, due to the magnetic fields of steel bars used in buildings, pillars, elevators, electric wirings, stair cases etc., The key component of indoor magnetic field is earth's magnetic field corrupted with indoor magnetic perturbations. Magnetic readings are unchanged in the different parts of the test system, even after several days of time [23]. This is due to the unchanged infrastructure arrangement and building environment over time. The general motion of people over the test space does not significantly affect the magnetic field distribution [23].

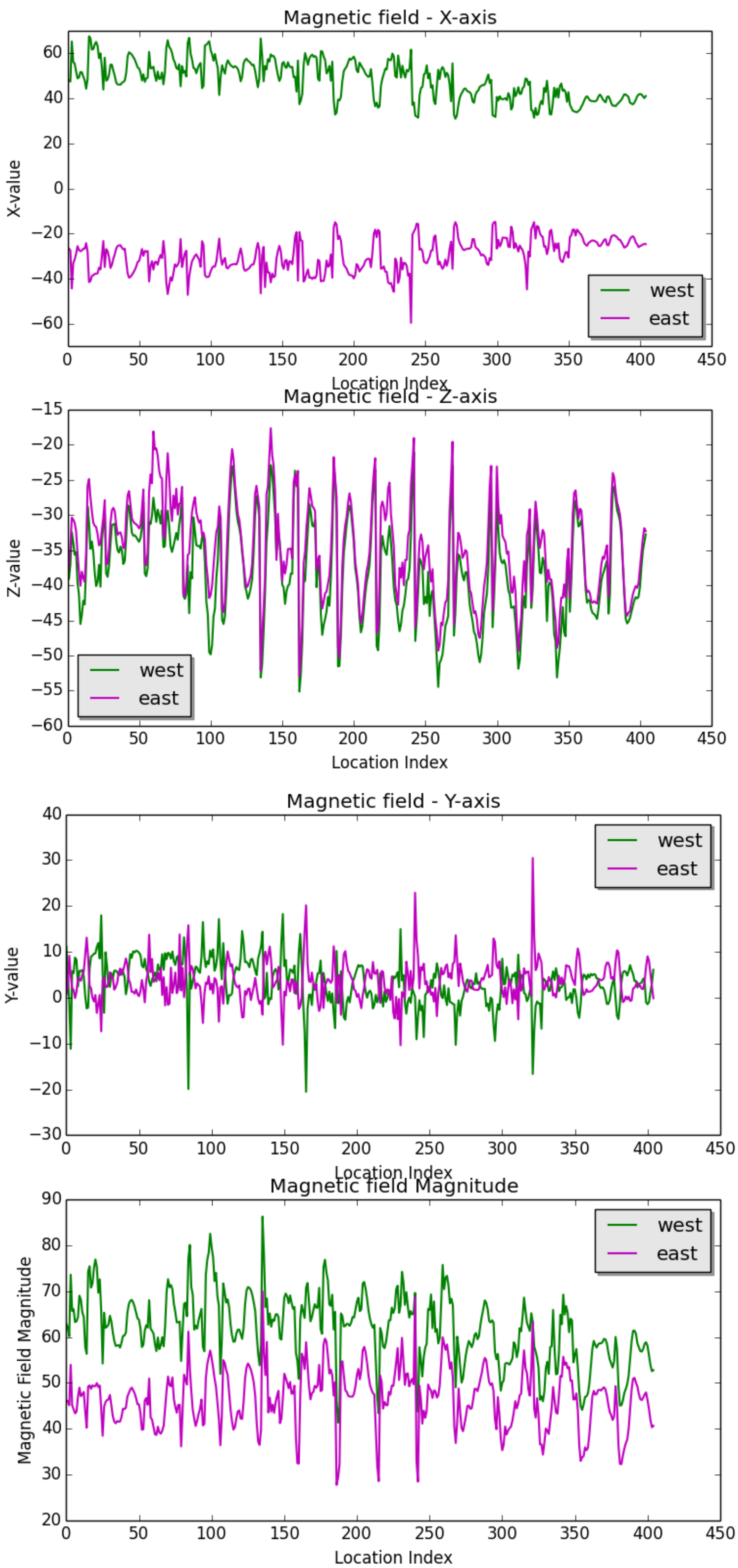
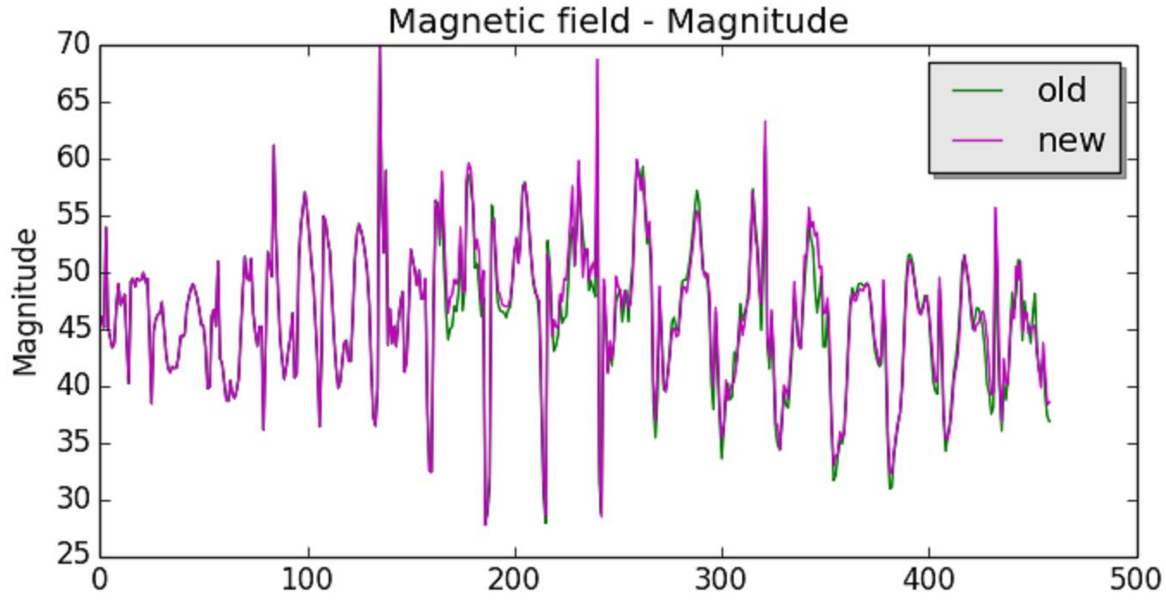


Fig 5.1. Comparison of magnetic field readings a) x-axis, b) y-axis, c) z-axis, d) magnitudes collected with east and west orientations of the smart-phone. x-axis is in (μT)



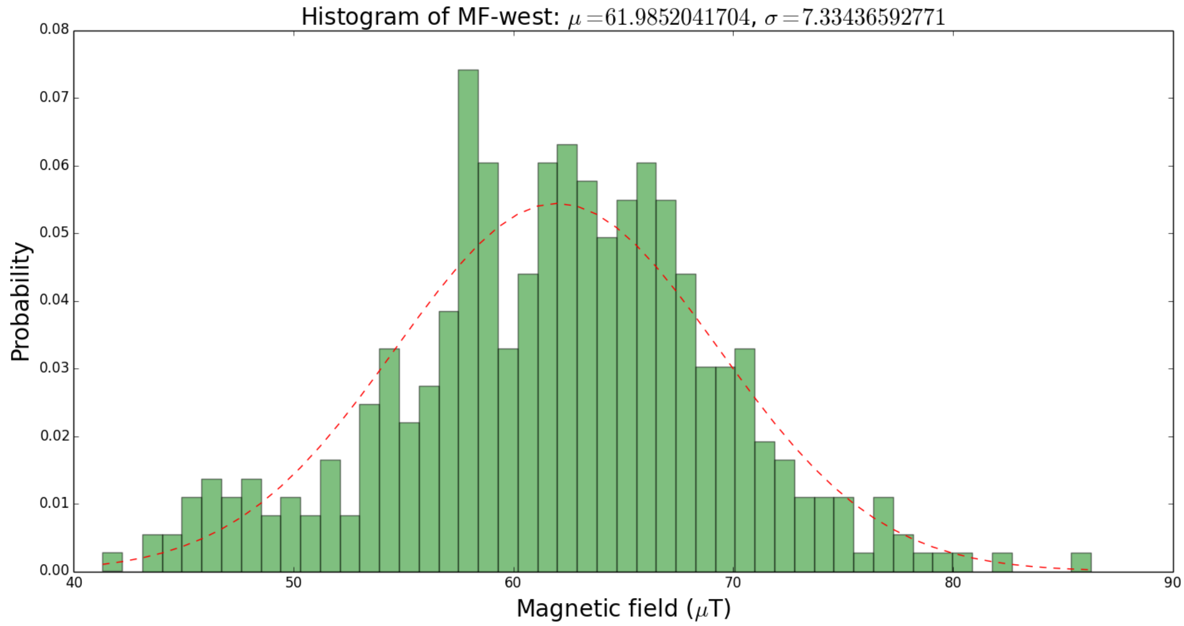


Fig 5.2 a) Comparison of magnetic field magnitudes of all gird locations for east direction of smart-phone collected on different days of the month, y-axis has location index b) Histogram distribution of magnetic field magnitudes of west directed smart-phone based magnetic map.

Fig 5.1 shows the magnetic field vector readings x, y .z of all the 405 grid points collected in the form of a plot. In fig 5.1(a) we can observe that x -axis, y-axis east and west plots are mirror images of each other. This is because the smart-phone measures the same magnetic field along opposite directions in the *xy*-plane of the earth. But they are not exact mirror images. East x-axis values lie in the range [-40,-20] approximately, while west x-axis readings lie in the range [40, 60]. This is because of the addition of a constant magnetometer

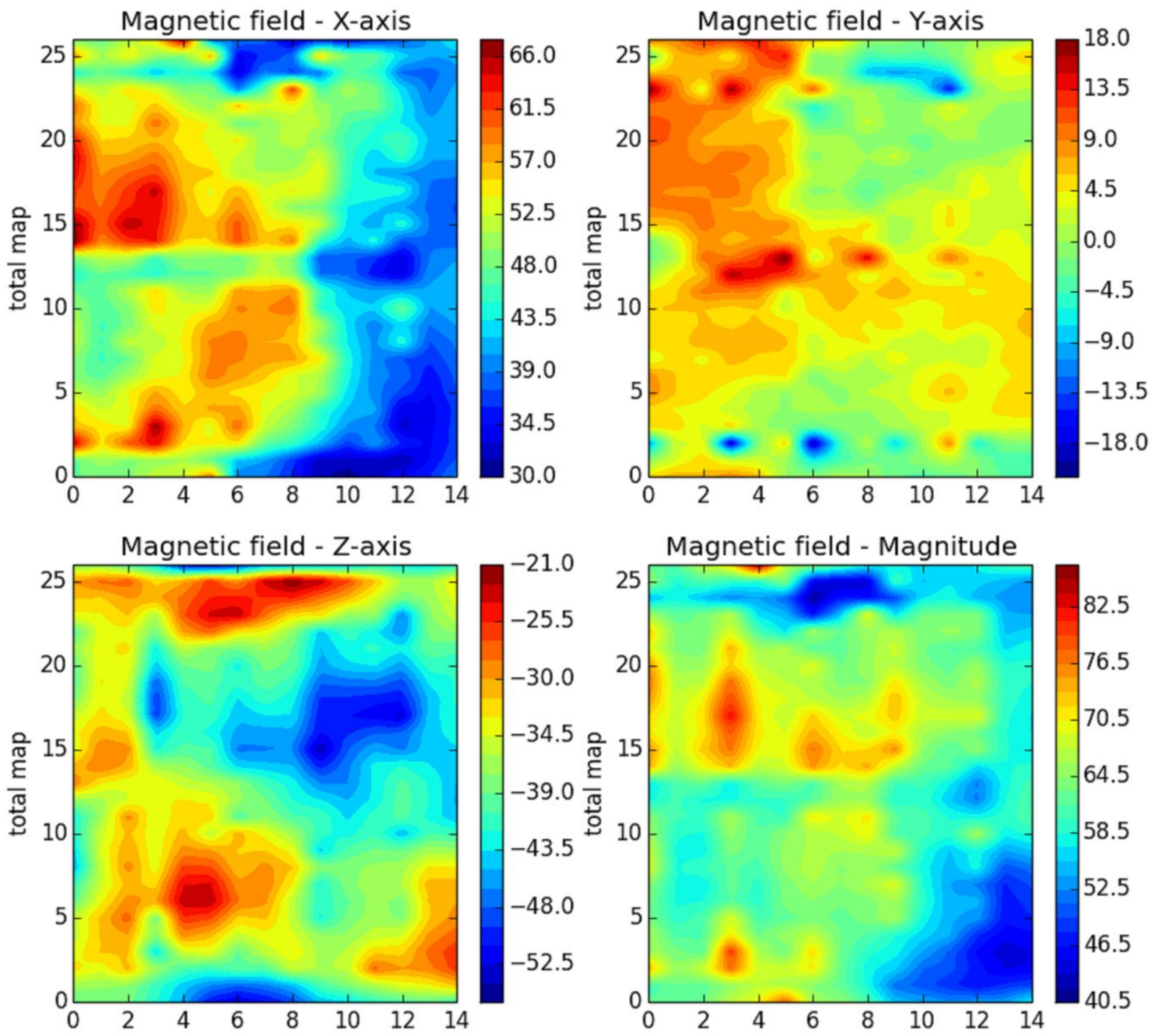


Fig 5.3 Test area magnetic map (west) visualisation using grid data based interpolation

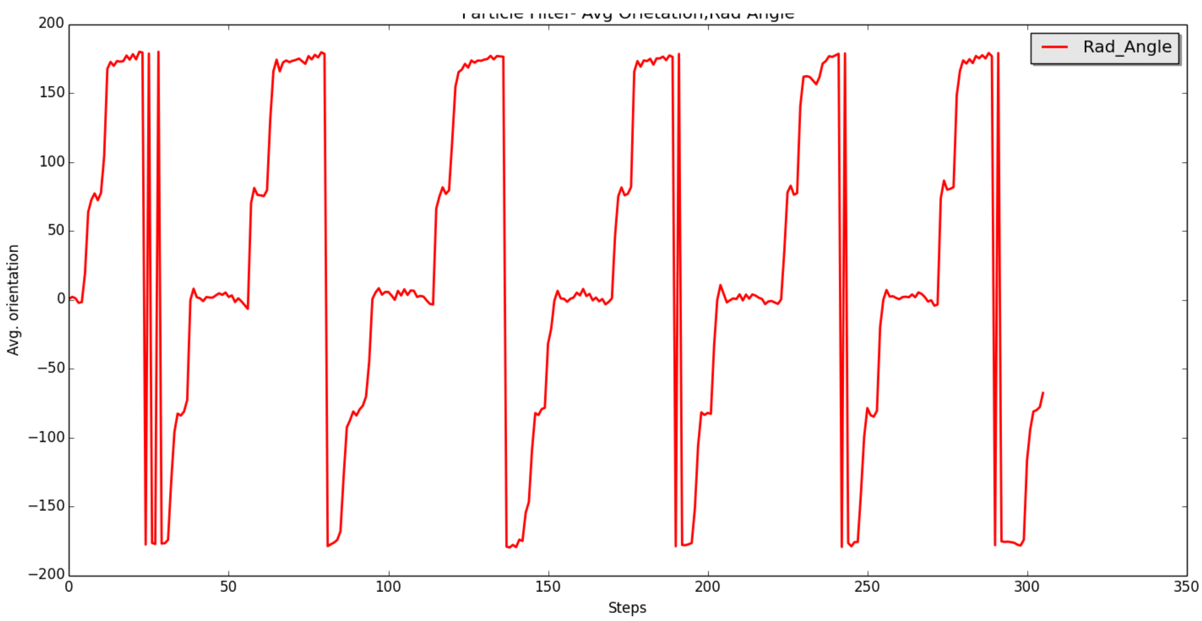


Fig 5.4. Orientation estimated (degrees) for repeated rectangular test walks in the test.

offset along, x-axis to the real magnetic field measurement in both the scenarios. This is predicted in the paper by Grand et.al. [17] also. But z-axis readings are the same for east and west directions in fig 5.1(c). The magnitudes for east and west maps (in fig 5.1(d)) differ by a constant value approximately because of this magnetometer offset. This cannot be eliminated completely from the system as the magnetometer is calibrated during its embedding into the smart-phone. And hence it cannot be changed. Even the offset is dependent upon the magnetic field strength in the environment. As the Ferro-magnetic parts of smart-phone may cause the magnetometer errors. The visualization of magnetic map (west) of the test area is shown in Fig 5.3. In fig 5.2(b), we have plotted the histogram distribution of magnetic field magnitude readings for magnetic map (west). It follows a gaussian distribution with the mean 61.95 μT and variance of 7.33 μT.

5.3 Using the Magnetic map in Algorithm

Magnetic maps contain the x, y, z–axis values and resultant magnitude corresponding to each location co-ordinates. A library of Bi-cubic spline interpolation [39] is used to interpolate the available magnetic field data to approximate the magnetic field at intermediate locations between grid points. We use the interpolator to interpolate the available magnetic field data to approximate the magnetic field at intermediate locations which is used in the weight update equation to find the magnetic field estimates corresponding to the particles location estimates. We have wrote a map generator routine, that is called from the application using java threads, so that the amount of load on the application is not high at the start of the application.

5.4 Step detection and step length estimation

Brajdic et.al. [28] have compared various step counting algorithms available in the literature. They have classified the algorithms into three categories, time domain, frequency domain, and feature extraction based. We developed a variant of time-domain peak valley hunting based step detection algorithm [9, 25, and 28]. The algorithm is presented in the fig 5.5. Noise filter [9] used to remove noisy accelerometer readings before applying the algorithm.

$$Noise\_Filter(a) = \begin{cases} 0 & if\ |a| \le Q \\ a & otherwise \end{cases} \tag{5.1}$$

where ‘a’ is the z-axis linear acceleration, and Q is the threshold used to remove noisy measurements that do not correspond to steps. In our experiments, we have set Q to be 1.3 m/s2. We search the noise filtered acceleration to find peaks and valleys, a peak or valley is a position when the derivative of the acceleration is zero but the acceleration is not zero. A step is detected when first a peak of acceleration is found.

We find the Amax, Amin as a part of this algorithm which are used to estimate the step length also. Amax and Amin correspond to the peak and valley accelerations of a step. Thus it is an efficient way of step counting and step length estimation. Humans can move at a limited speed. Thus we can neglect steps that are too close in time intervals. Based upon our experiments, we have constrained adjacent steps to be at least 100 ms apart to avoid any false positives. QR codes are generally used to provide quick user inputs to the Smart-phone. Our system uses the location QR codes for scanning the initial location or any other location during the path. We use the Empirical relationship [30] widely used in various papers [9, 10, 14, 33], for the step length.

$$step - size = C * \sqrt[4]{Amax - Amin} \qquad (5.2)$$

where C is a user-dependent constant, used to scale the steps to real world step lengths. We find the training constant C, for each user by asking them to walk along a short straight line path between 2 QR coded locations in the corridor. The Training constant C is obtained for each user by using the equation (5.3) also used in [9]

$$C = \frac{\sqrt{(x1-x2)^2+(y1-y2)^2}}{\sum_{i=1}^{stepCount} \sqrt[4]{Amax-Amin}} \qquad (5.3)$$

(x1, y1), (x2, y2) are the start and end positions of the training path. *Amax* and *Amin* are the acceleration values of the corresponding steps, *stepCount* is found using the algorithm shown in fig 5.5. fig 5.5 provides the flow chart of peak valley based step detection. The key steps of the algorithm are:

a) Sensing the acceleration values from smart-phone sensors

b) Filtering the noisy acceleration values that fall below a threshold Q

c) Detecting Peak or Valley from the readings and update the Amax and Amin accordingly.

d) Step length estimation using Amax and Amin

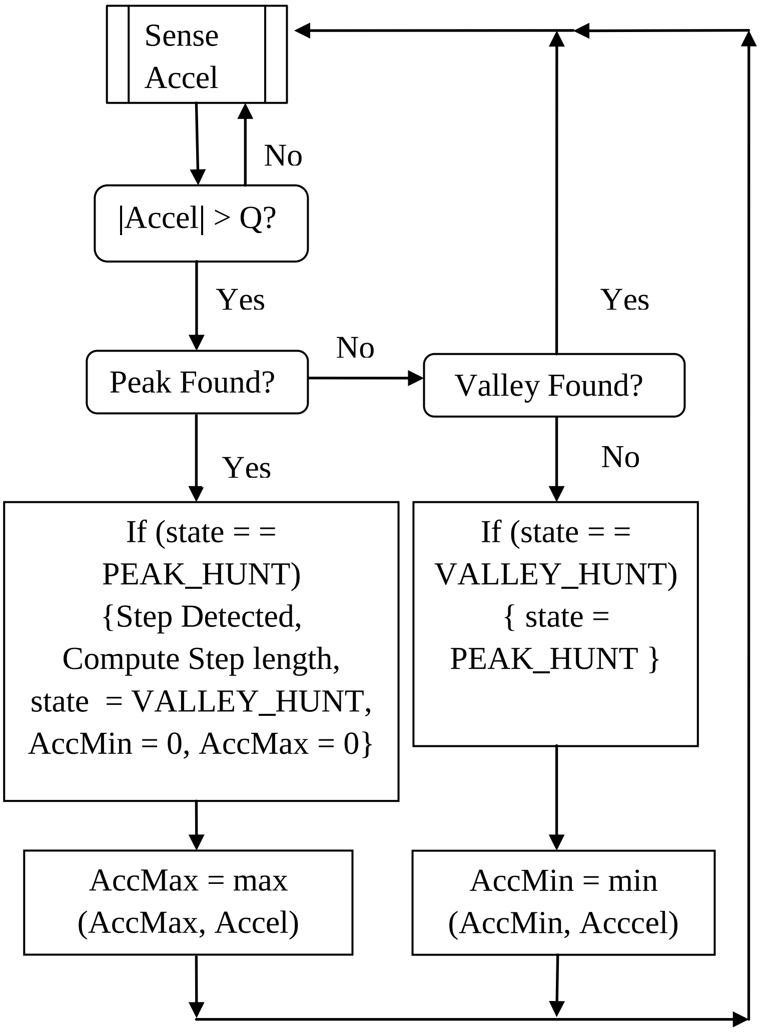


Fig 5.5 Step detection and Step length estimation procedure [9]

5.5 Heading direction estimation [31, 32]

Direction of movement (Heading Direction) is generally estimated using gyroscopes, magnetometers and accelerometers. Gyroscopes provide accurate results on turns, but add gyro drift over time. Magnetometers are affected by magnetic perturbations in the indoor environments. AHRS algorithm [31, 32] estimates the correct orientation by sensor fusion and using magnetic field and gravity directions in Gradient descent optimization. The algorithm presented by madgwick [31] and comotti [32] has two parts, as presented here

Orientation from gyroscope

The equations (5.4, 5.5, 5.6) uses the instantaneous angular velocity measurements *wx, wy, wz* and compute quaternion orientation Q of the smart-phone. This orientation is computed using just gyroscope measurements using equations (5.4, 5.5, 5.6) given in [31.32]

$$S_w = \begin{bmatrix} 0 & w_x & w_y & w_z \end{bmatrix} \quad (5.4)$$

$$\bar{Q}_{w,t} = \frac{1}{2} Qn_{est,t-1} \otimes S_{w,t} \quad (5.5)$$

$$Q_{w,t} = Qn_{est,t-1} + \bar{Q}_{w,t} * \triangle t \quad (5.6)$$

The step wise explanation of the equations is as below

a) Forming Quaternion of the gyroscope measurements w_x, w_y, w_z (in rad/s) in eqn (5.4) ,
b) Equation (5.5) finds the angular rate at time *t* relative to sensor frame from the gyroscope measurements and normalized orientation estimate of the smart-phone at time *t-1*.
c) Equation (5.6) estimates the orientation at time t in quaternion form by adding the angle change.

$\otimes$ is quaternion multiplication, Q is quaternion form of orientation estimate., Qn is Q normalized to unit length and $\bar{Q}$ is quaternion form of angular rate derivative.$\triangle t$ is the small interval of time between sensor events.

Orientation from vector observations

Gradient descent optimization [31, 32] is used to correct the gyroscope based orientation estimation computed using previous section. The earth's gravity direction and the earth's magnetic field direction in earth's frame are invariant at a position over time. The estimated gravity direction corrupted with acceleration in sensor frame and estimated magnetic field affected with the magnetic distortion in the sensor frame can be computed. If we know the earth's magnetic field direction at a place, we can use the measured magnetic field in sensor frame to obtain the orientation of sensor frame relative to earth frame which is the smart-phone orientation. Similarly, we can use the earth's gravity direction and the gravity direction in sensor frame to find the orientation. The optimization involves minimizing the objective function formulated in [31, 32]

The fig 5.4 shows the orientation estimated using the AHRS algorithm for a repeated rectangular test walk in the test area The long streaks of horizontal angle around 0 degrees and 180 degrees represents the motion along the pathways, the small streaks at 90 degrees and -90 degrees represents the transition paths between two pathways.

5.6 High level overview of Indoor localization application [9]

The hierarchy of our application can be divided into various levels as shown in the table 5.1. At the lowest level we have the QR code scanner for initialising the application initial location, map interpolator for loading and creating the interpolator functions, Training activity for setting the sense noise, turn noise, step noise, user specific training constant, acceleration threshold, AHRS algorithm to continuously estimate the correct orientation of the smart-phone, step detection to detect steps. The other routines that work along with the Google Android API are Sensor life cycle manager and HW sensor event listener, that controls the sensor event listening and communication of the sensor readings to the low level routines and high level routines. The actual algorithms are executed when a step is detected using the step length and orientation estimated and magnetic field measurement and magnetic map based estimates and indoor map. During implementation, we have used Android's Sensor Manager API, Sensor Event API [38], Apache's commons-math Java API [39], Java Matrix package (jama).

Table 5.1 Hierarchy of the application implementation procedures

PF – Magnitude (M) , PF – Vector (V) , PF- Magnitude + Map (MM), PF–Vector + Map (VM)	Implementation of Particle filtering algorithm for magnetic maps and indoor maps.
Sensor Life Cycle Manager	Pauses and Resumes sensors, informs about sensor calls to HW Sensor Event Listener
HW Sensor Event Listener	Listens to the Sensor Events and sends the sensor values to the Algorithm.
Map Interpolator AHRS Algorithm QR Code Scanner Training Activity Step Detection	Magnetic Map Interpolator, Gradient Descent based Orientation estimation, Location Scanner , Computes training constant C for each user. Implementation of Step Detection, Step Length Estimation

6. Experiments & Results

6.1 Experimental set up

Our system consists of a smart-phone, (Nexus S model, GT-I9020T) and pre-stored magnetic field map (east and west) for the test area and indoor map of the test area. The smart-phone runs Android operating system v 4.1.2, Jellybean. It has Samsung Exynos 3110 processor of 1000 MHz and RAM of 512 MB. It has a GPU and NAND memory of 16 GB. The different sensors embedded in the smart-phone and their details as shown by the Quick System Info PRO application are

1. KR3DM 3-axis Accelerometer
2. AK8973 3-axis Magnetic Field Sensor
3. K3G Gyroscope Sensor
4. Rotation Vector Sensor (Virtual Sensor by Google Inc. ver-3.0)
5. Linear Acceleration Sensor (Virtual Sensor by Google Inc. ver-3.0)
6. Corrected Gyroscope Sensor (Virtual Sensor by Google Inc. ver-1.0)

6.2 Experiment test bed

A library book shelve space as shown in fig. 6.1 (b, d, e) is chosen as a test bed for our experiments. The tests were conducted in the Mahatma Gandhi central library, IIT Roorkee. We have chosen a rectangular part shown in fig 6.1(a) of the library first floor book shelve area. The first floor consists of several book shelves and large rectangular pillars. Our test area consists of 8 book shelves and 5 pathways along them. The 5 path ways are parallel to each other. Adjacent pathways are separated by book shelve racks. The pathways are connected through gaps among book shelves. This test area is marked with grid points, at the corners of small rectangular grids, of size 0.56 m x 0.56 m each. A total of 405 uniformly spaced grid points were marked in our rectangular test area. We have mapped the magnetic field vector at grid points along five path ways among these book shelves along east and west directions by manually moving the wooden trolley shown in fig 6.1(c) mounted with smart-phone shown in fig 6.1 (a) using our data logging application.

6.3 Experiment test paths

We use three zig-zag paths as shown in fig 6.2 (c, d, e) in our experiments to evaluate each of the four approaches mentioned (M, V, MM, VM). The first test path starts at location (1, 0), moves through path way 1, after reaching (25, 0), turns right and moves into the adjacent path

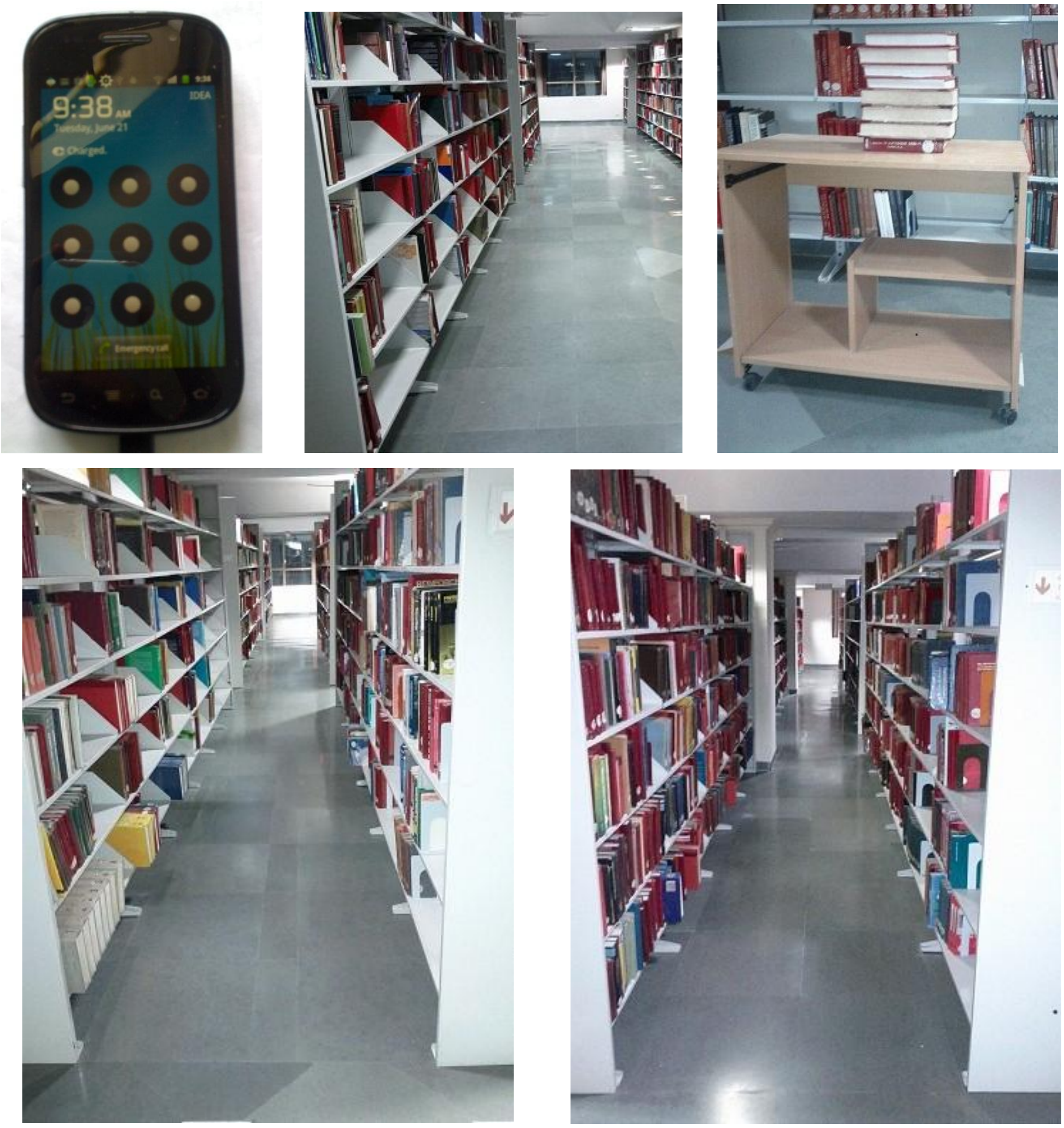


Fig 6.1 a) Smart-phone, Nexus S b) pathway 5 c) wooden trolley used during offline database construction d) pathway 3 e) pathway 4

way 2, reaching (2, 4) turns left, and moves into the adjacent path way 3, and so on. The second path is in the opposite direction of the first test path. It starts at the right most path way 5, and moves towards path way 1. The initial location is (13, 0).

The third path is a still more complex path, with more turns. In this path, the user will start from (1,0) , reaches (1,13) , turns right and moves into path way 2, and so on until he reaches path way 5, moves till (13,25) at the end of path way 5 and then turns left, and moves into path way 4. Thus it is a hybrid of first path and second path together with shorter path way traces.

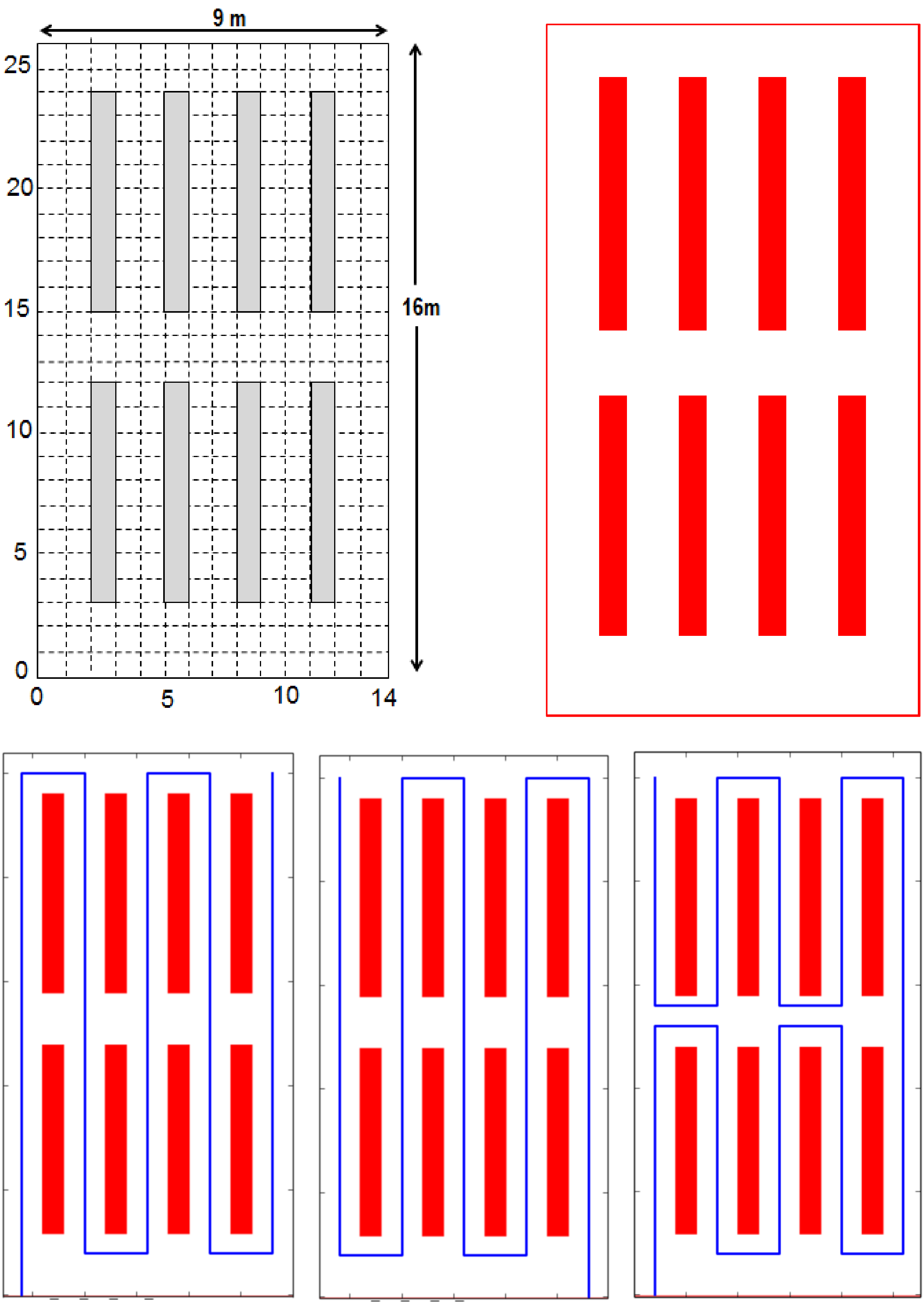


Fig 6.2 a) lay out of the test area with the grid points and the book shelves b) Bit map image of the indoor map used in the application c) test path 1 c) test path 2 e) test path 3.

6.4 Experiments conducted

We evaluate the performance of our system in a library test bed with an area of 9 m x 16 m, containing 8 book shelve racks on the first floor of the library. We have tested the performance of different implementations of the particle filtering algorithm using Magnetic maps and Indoor maps. The approaches we have tested are:

a) PF algorithm using Magnetic field magnitudes,

b) PF algorithm using Magnetic field vectors.

c) PF algorithm using Magnetic field magnitudes + Indoor map

d) PF algorithm using Magnetic field vectors + Indoor map.

Our application needs the user specific training constant C for empirical formula. Training constant is computed by conducting 5 test walks between two QR coded locations before the tests. The C values estimated on all the test walks were consistent for each specific user. The mean of these values is calculated. It is input manually using the slider in the Dead reckoning training activity.

The user uses the application to scan QR code of the initial location before starting the walk. The user waits for few seconds at the initial location with the smart-phone held in hand horizontally for AHRS algorithm (see Section-III (b)) to compute the initial orientation.

A user with a hand-held smart-phone (Samsung Nexus S) has walked along 3 test paths. The smart-phone is held in the hand along the direction of motion of the user, assuming it to be the most common placement by the user tracking his location in real life scenario. Sense Noise parameter plays a key role in the performance of the magnetic maps based Particle filtering algorithm. After several tests conducted we have fixed the other parameters (step noise, d in Fig(4.3) and turn noise Ω, in Fig (4.3) to 0.1 m and 10 degrees respectively). Sense noise of around 3-4 μT is found to give good results with our approaches.

The user has moved through the test paths 1, 2, 3 for each of the algorithms a, b, c, d with sense noise values 2.5 and 3.5 respectively. Totally 24 test case scenarios were considered for the analysis of the algorithms performance. More than one test walk for some test case scenario were performed. The mean localization accuracies of such test scenarios is the average of all the test walks of the same scenario. The results were tabulated in the Table 6.2. The paths taken involve zig-zag motions in between the book-shelve racks. Each test path is around 85 m long. Because of the system constraints, equal number of particles were not used in each of the algorithms. The number of particles used by each of the algorithm were mentioned in the Table 6.2. The varying particle count do not have much effect on the performance of the system, as above a threshold limit of particles, the particle filtering algorithm performance would be the same from literature. We have used at least 250 particles in each of the algorithm. The highest being 1700 particles, used in algorithm (a).

The application estimates and shows instantaneous position in real time to the user just using the smart-phone. The estimated paths during the walks are logged for analysis. We have marked the test path locations at equal intervals on the test bed. The user moves through the marked locations for each test path. We obtained the localization errors of the user position by finding distance between ground truth locations and corresponding location estimated. The localization error is computed as distance between median of particles cloud obtained by using eqn (5.5) and the ground truth location using the euclidean distance criterion.

6.5 Results & Analysis

Comparison with earlier works

Table 6.1 summarizes the earlier research works which have used magnetic field maps and particle filtering for localization in underground mines, office corridors, small room with linear path and circular path tests. It tabulates the various techniques used in each of the research paper, the test set up they have used, the results presented in each of the paper and some specific remarks about the methods or test scenarios used in those papers.

Kim et.al. and Grand et.al., have used hand held smart-phones in their localization systems. Kim et.al., have used indoor magnetic field magnitude and inertial sensors in the particle filter. They have avoided the orientation errors due to indoor magnetic perturbations, by using the pre-identified moving direction of the corridor in their localization system. Thus their work is applicable only for rectangular corridors. Grand et.al. have presented localization accuracy of 0.7 m for linear paths and 1.2 m for circular paths. They have used gyroscope based orientation estimation. They did not conducted real time localization experiments using the smart-phone, instead using the magnetic field readings collected during the walk, they have conducted computer based experiments.

Our work is different from the two of these works, as we have used magnetic maps and indoor maps together with inertial sensors for the first time in the literature. We have compared the four different approaches using indoor maps and magnetic maps which was not done in any other work. We have corrected the orientation errors in the indoor environments using the AHRS algorithm, which is computationally efficient and provides accurate and reliable orientation estimation. Kalman filter based orientation estimation is computationally expensive, though accurate and cannot be implemented for the smart-phone based indoor application.

Haverinen et.al. has used commercially available sensors for localization in the indoor environments and underground mines. They have used magnetic field magnitude and vector based particle filtering algorithm for robot localization in underground mine corridors when no initial location is known. Our work implements a smart-phone based pedestrian indoor localization using the smart-phone embedded in-accurate sensors for indoor spaces. We have used indoor maps together with magnetic maps to improve the localization accuracy. We assume that initial location is known. We conduct our experiments in indoor spaces, instead of just corridors.

Foot mounted inertial sensors based systems are highly costly, but provide accurate localization. We cannot compare our work with that by Frassl et.al. as they are using foot mounted inertial sensors. Our system used smart-phone held in hand of the user for localization.

Rai et.al. have developed Zero effort crowd sourcing indoor localization system, Zee. Zee uses indoor maps, Wi-Fi finger prints and inertial sensors. They have achieved a mean localization accuracy of 1-2 m. Their work is one of the popular works at the current time using Wi-Fi systems.

Table 6.1: Comparison of our results with similar approaches used in literature

Literature	Techniques	Test Setup	Results (Error)	Remarks
Kim, Seong-Eun, et al [16]	Particle filtering, Magnetic maps (Magnitude)	smart-phone implementation for corridors	1.12 m (mean) for CW 1.07 m (mean) for CCW	Fixed Moving directions of Corridors are used to avoid magnetic perturbations

Le Grand, Etienne et.al. [17]	Particle filtering, Magnetic maps (Vector)	Offline computer tests using Smart-phone readings	< 0.7 m for a straight line path, < 1.2 m for a circular path.	Results are for a straight line path and a circular path only
Haverinen et.al. [18,21]	Particle Filtering, Magnetic maps (Vector)	Commercial Sensors based tests in Underground mines.	1.44 m and 1.2 m (mean) for two different tests	The tests were not conducted with smart-phones.
Frassl, Martin, et al. [24]	Particle Filtering, Magnetic Maps, (magnitude, vector, two components)	Foot mounted inertial sensors, Magnetic maps (10 -20 cm resolution)	mean errors of 9.41 cm (M) 8.41cm(HV) 7.77 cm (V)	Foot mounted sensors are costly & do not have the constraints faced by smart-phone based localization.
Rai, Anshul, et al [11]	Particle Filtering, Wi-Fi and Indoor Maps	Smart-phone implementation for office (Indoors)	1-2 m (mean)	
Our Experiments	Particle filtering, Magnetic maps (V&M), Indoor Maps, GDA based Orientation correction	Smart-phone implementation for corridors as well as indoor spaces (library book shelve space).	0.93 m (M) 0.82 m (V) 0.93 m (MM) 0.74 m(MV)	Can be used in indoor spaces as well as corridors. Integrating Indoor maps and Magnetic maps together.

*M –Magnitude *V-Vector *MM – Magnitude + Indoor Map * MV – Vector + Indoor Map *HV – two component Vector *CW – Clock Wise paths *CCW – Counter Clock Wise paths

Results discussion

Table 6.2 presents the mean localization accuracies of our indoor localization system, for the three test paths shown in fig (6.2). We have chosen the optimal sense noise parameters for the experiments by conducting several experiments. Analytically, we have tried to understand how the sense_noise parameter affects the performance fo the system. Fig 6.3 shows the plots of probability (on y-axis) for various sense_noise values (on x-axis). $||z|-|k||$ in the update equation (4.3) is given values from 1 to 9, and corresponding plots are simulated and results are presented in the fig (6.3). Lets assume the magnetic field near by a location is with in a range of 3 μT from that locations magnetic field. Then $||z|-|k|| < 3$ μT for the different particles in the algorithm in fig 4.2. We can observe from the fig (6.3) plots $||z|-|k|| = 1$ μT, 2 μT, 3 μT, 4 μT, for the sense noise values band of 3-4 μT, the probabilities are high when $||z|-|k|| = 1$ μT and decreases when $||z|-|k||$ increases to 4 μT. Thus the 3-4 μT band of sense_noise values will be good to distinguish the real time mangetic fields around a location.

Table 6.2 summarizes the results of test walks for the different test paths. Some test paths are experimented for the same value of sense_noise more than one time. The mean localization accuracy of such experiments in the table 6.2 is the average of the localization accuracies obtained for all the test walks. The Average Mean localization accuracy in the last column of the table 6.2 is not the average of localization accuracies in the columns path 1, 2, 3. Instead it is the mean value of the all the localization accuracies for all the test walks conducted for that particular sense_noise value and particular approach.

We present the Cumulative distribution function of errors comparison for all the four approaches proposed in the fig 6.4 .From the figure, we observe that MagVector + Indoor Map (VM) performs the best among all, as it contains good magnetic map matching because of 3-axis vector and the particles that clash into book shelves are removed from the system on each step. MagVector (V) is the next best approach even without the indoor map correction. MagMagnitude + Indoor Map (MM) performs similar to MagVector (V) in performance. MagMagnitude (M) has the bad mean localization accuracy among all the four. In fig 6.4, the four approaches M, V, MM, VM have 50% localization errors of 0.79 m, 0.67 m, 0.74 m, 0.63 m respectively. Similarly, their 70% localization errors are 1.18 m, 1.09 m, 1.07 m, 0.88 m respectively. Their80% localization errors are 1.45 m, 1.50 m, 1.28 m, 1.06 m respectively.

Table 6.2: Mean localization error (in m) of proposed approaches for three test paths for two sense_noise values 2.5 µT, 3.5 µT

Particle Filtering Algorithm	Parameters used	Sense Noise Parameter Value	Mean Error, Path 1	Mean Error, Path 2	Mean Error, Path 3	Avg. Mean Error
PF- Magnitude	1700 particles, d = 0.1 m, Ω = 10 deg	2.5 µT	0.99 m	0.93 m	0.69 m	0.90 m
		3.5 µT	0.69 m	0.92 m	1.07 m	0.95 m
PF - Vector	750 particles, d = 0.1 m, Ω = 10 deg	2.5 µT	0.87 m	0.92 m	0.95 m	0.93 m
		3.5 µT	0.76 m	0.59 m	0.95 m	0.81 m
PF- Magnitude + Indoor Map	850 particles, d = 0.1 m, Ω = 10 deg	2.5 µT	1.04 m	0.87 m	0.92 m	0.94 m
		3.5 µT	0.82 m	0.75 m	1.00 m	0.81 m
PF - Vector + Indoor Map	250 particles, d = 0.1 m, Ω = 10 deg	2.5 µT	0.59 m	0.85 m	0.80 m	0.75 m
		3.5 µT	0.76 m	0.74 m	0.72 m	0.74 m

In figures 6.5, 6.6, 6.7, we show the estimated paths for the four approaches for test path 1, 2 and 3 respectively. In fig 6.5 (c, d), 6.6 (c, d), 6.7 (c, d) we can observe that the indoor map based localizations correct the deviating paths by removing the particles that collide with book shelves. We have achieved a mean localization accuracy of 0.75 - 0.95 m for various approaches implemented in this thesis. The localization errors for each of the four approaches are plotted in the form of histograms in figure 6.8. In fig 6.8, we can observe most of the localization errors are less than 1.5 m.

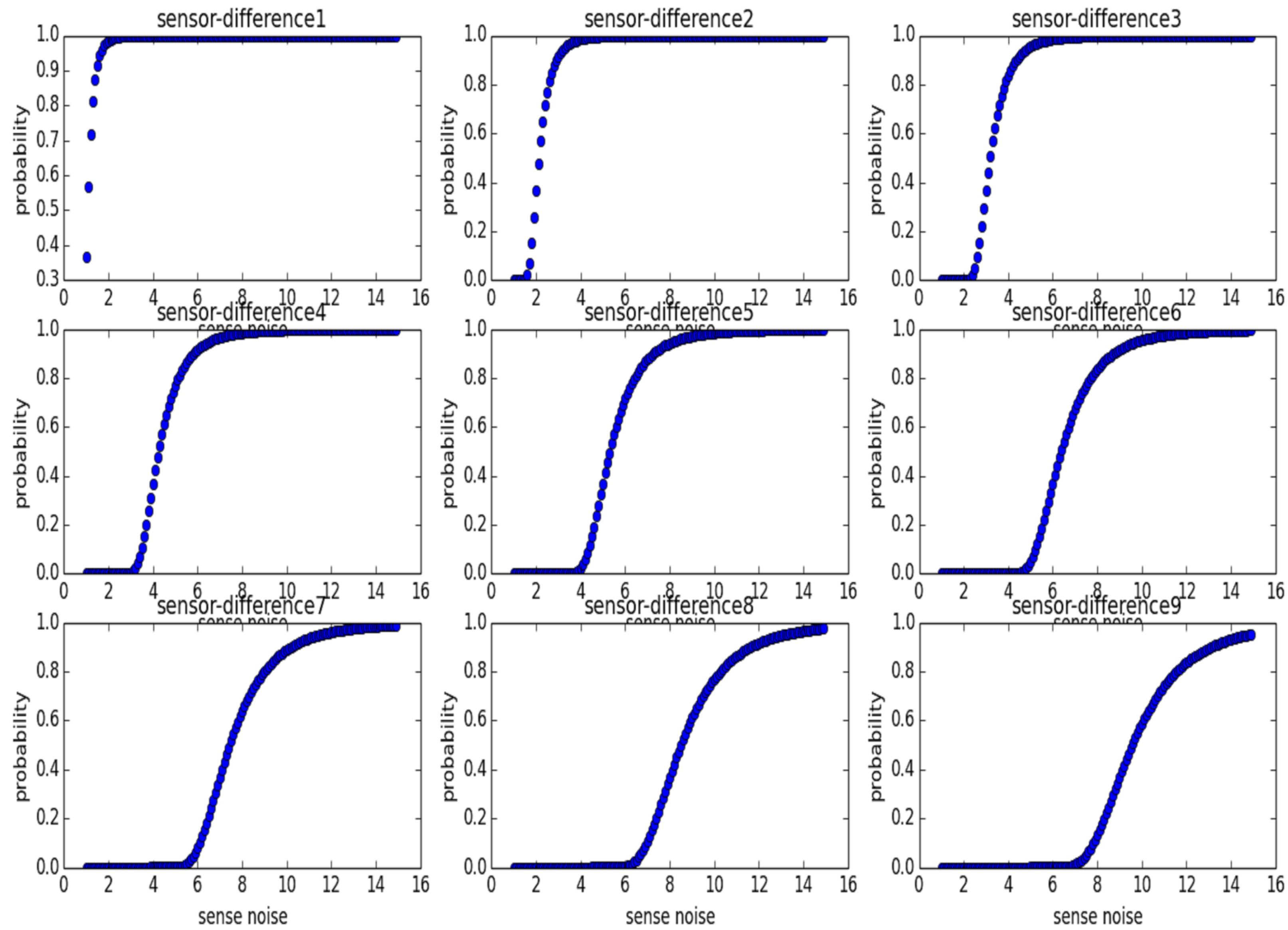


Fig 6.3 Plots of probability(importance weight) vs. sense_noise (μT) for different values of ||z|-|k|| in eqn (4.3).

In figure, ||z|-|k|| = 1 μT , 2 μT , 3 μT , 4 μT , 5 μT , 6 μT , 7 μT , 8 μT , 9 μT for 9 plots

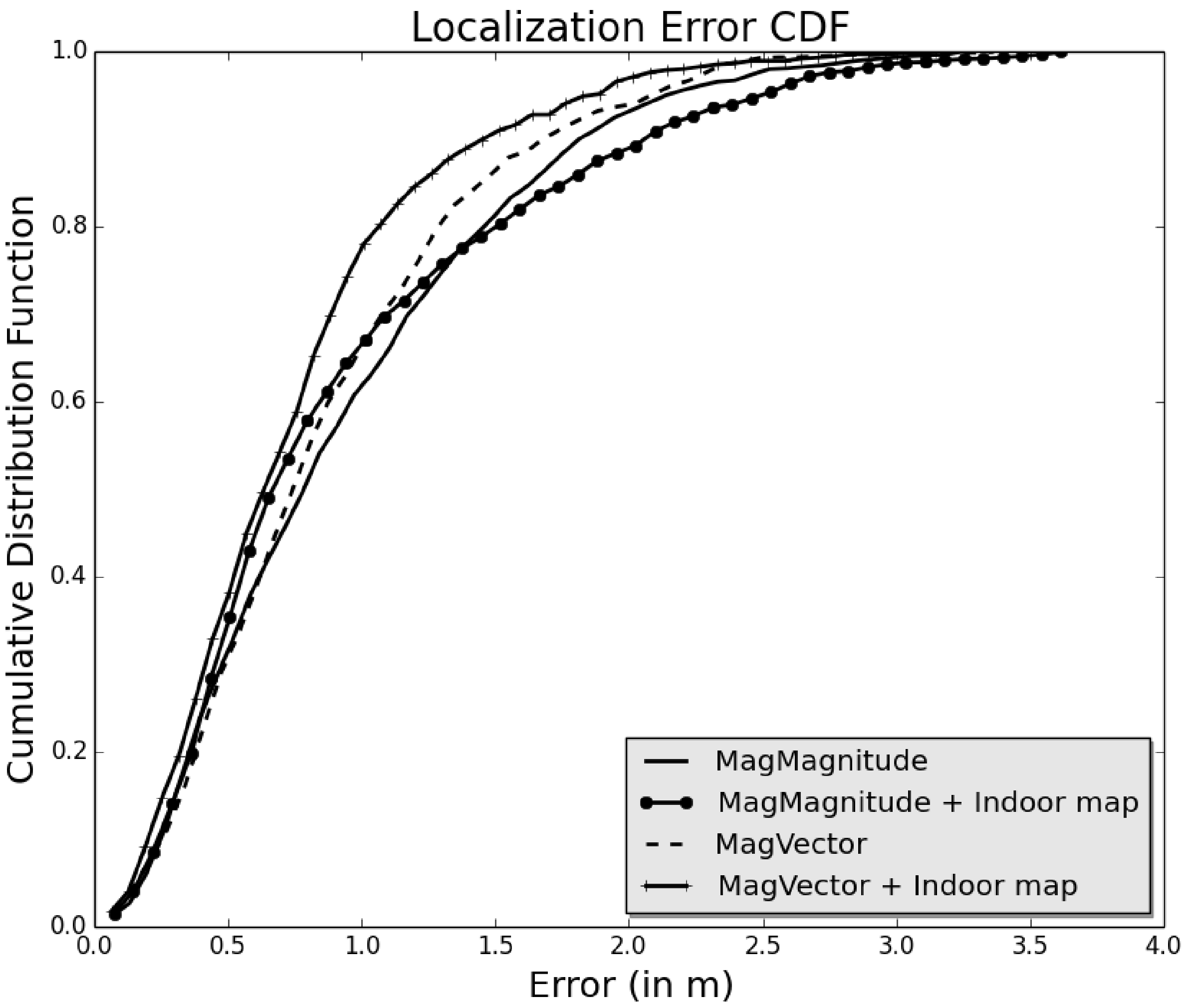
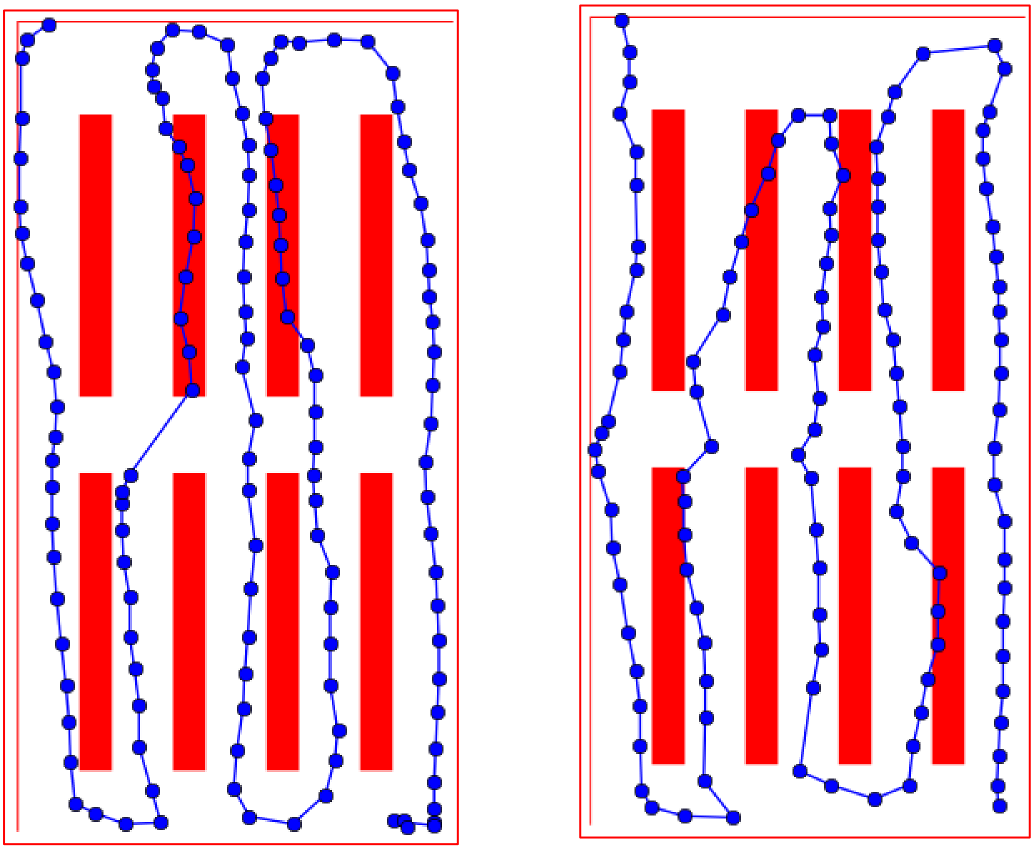
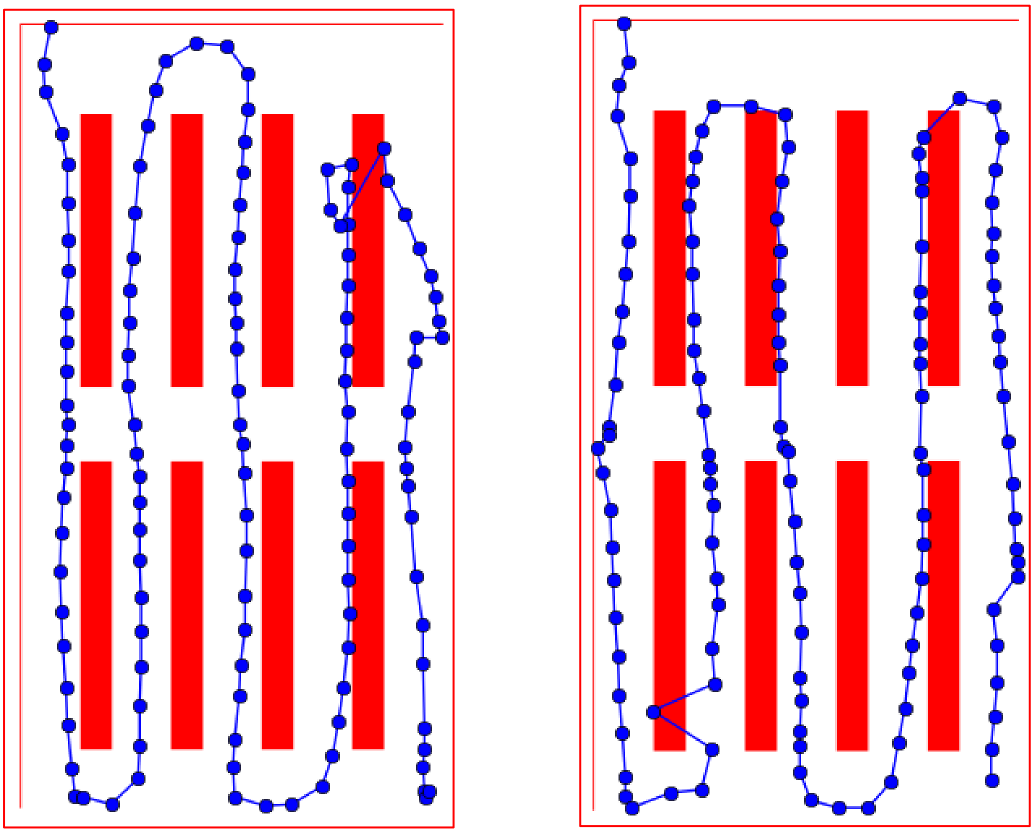


Fig 6.4 Comparison of cumulative distribution functions for M, V, MM, VM approaches

The figures 6.5. 6.6, 6.7 offer relative comparison of the performance of the different algorithms for each of the test paths. We can observe MM, VM have better performance for the test paths 1, 2. But in test path 3 sometimes the location is lost and paths are deviated due to the loss of particles during transiting from one path way to other near corners as seen in fig 6.7 (c,d). The histograms shown in the fig 6.8 show the relative distribution of all the localization errors for all the test walks for each of the four approaches M,V, MM,VM respectively and their average localization accuracies.

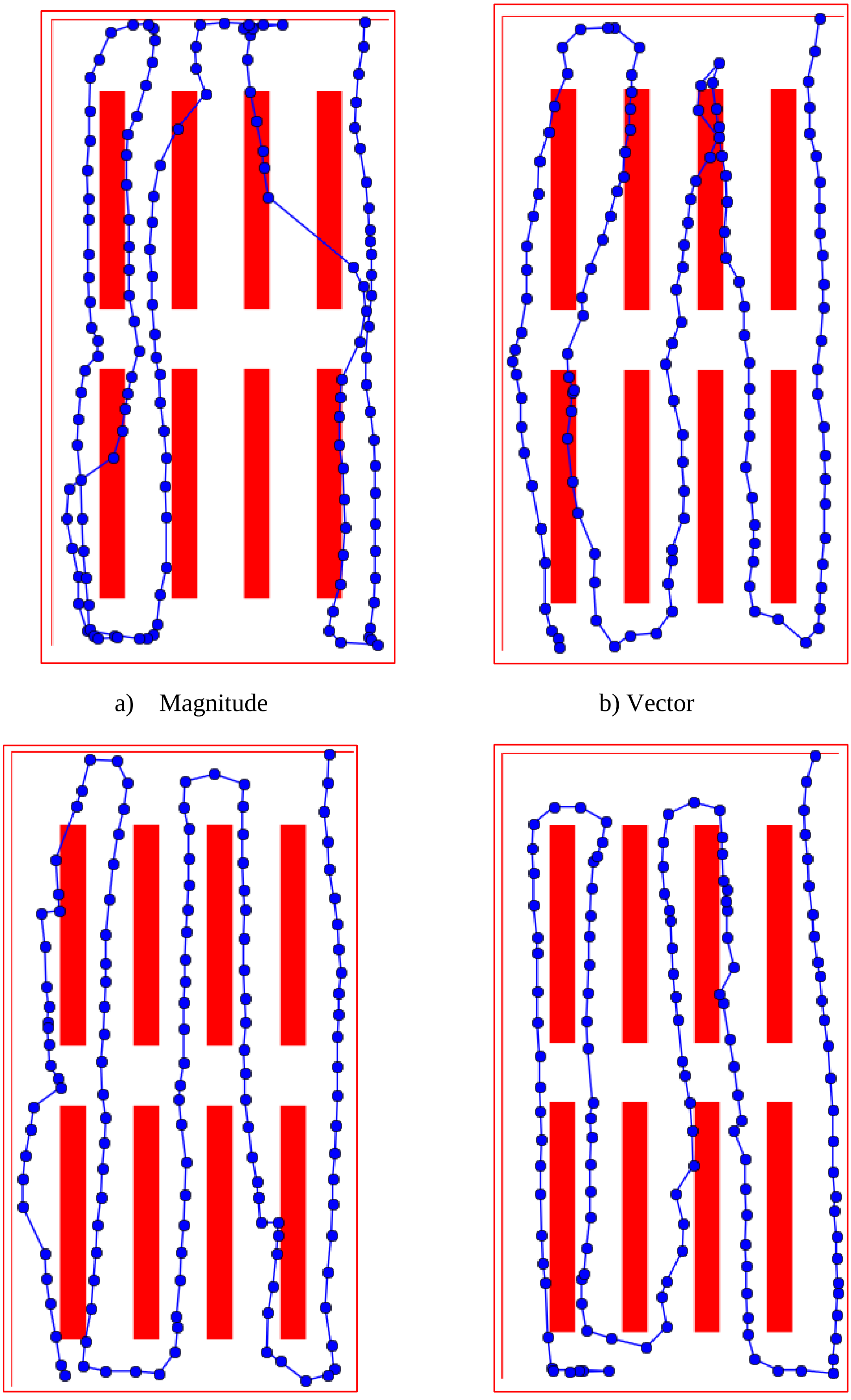


a) Magnitude b) Vector



c) Magnitude + Indoor Map d) Vector + Indoor Map

Fig 6.5 Estimated paths for test path-1 using various approaches using sense_noise = 3.5 μT



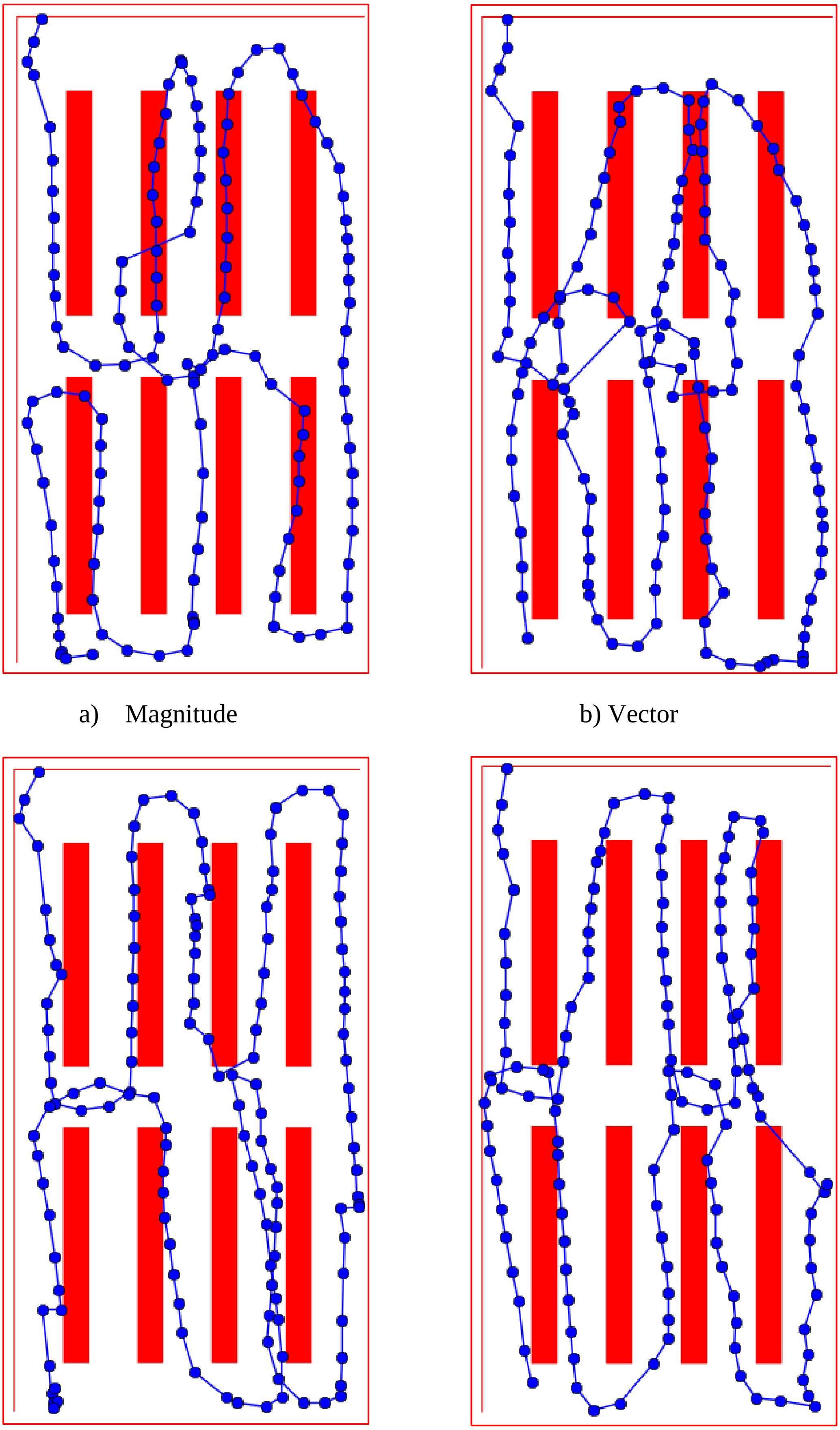
a) Magnitude

b) Vector

c) Magnitude + Indoor Map

d) Vector + Indoor Map

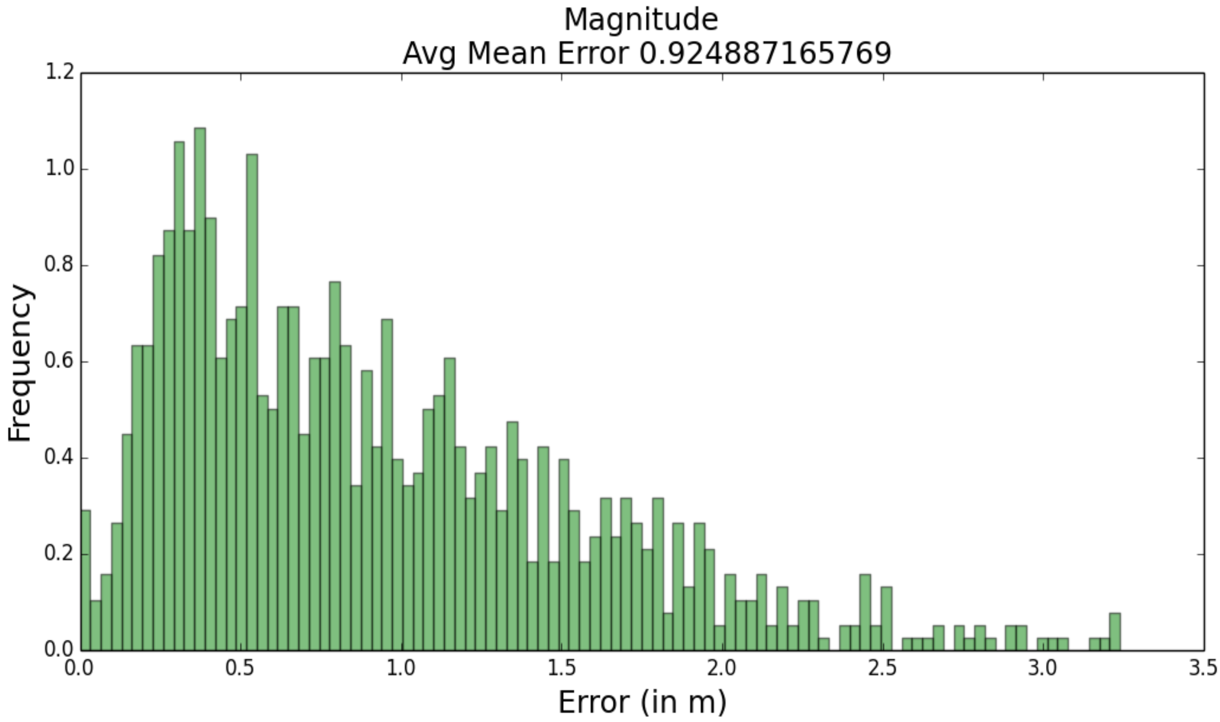
Fig 6.6 Estimated paths for test path-1 using various approaches using sense_noise = 3.5 μT



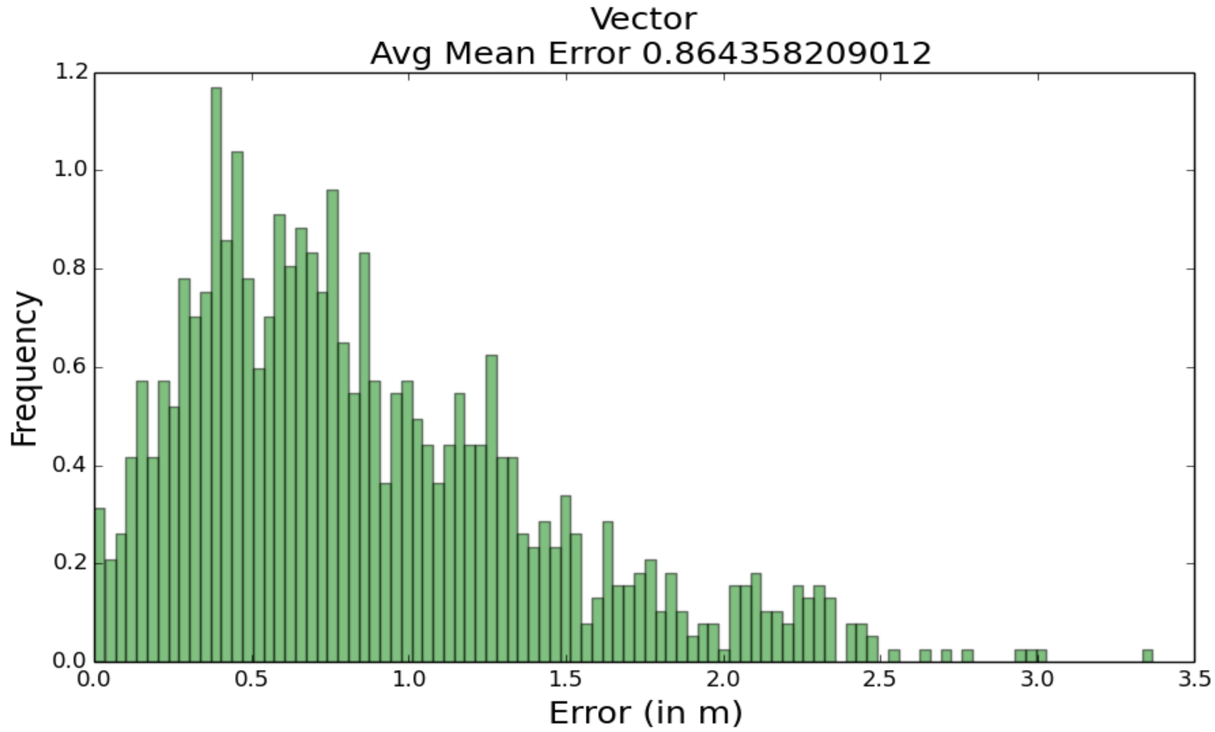
a) Magnitude b) Vector

c) Magnitude + Indoor Map d) Vector + Indoor Map

Fig 6.7 Estimated paths for test path-1 using various approaches using sense_noise = 3.5 μT

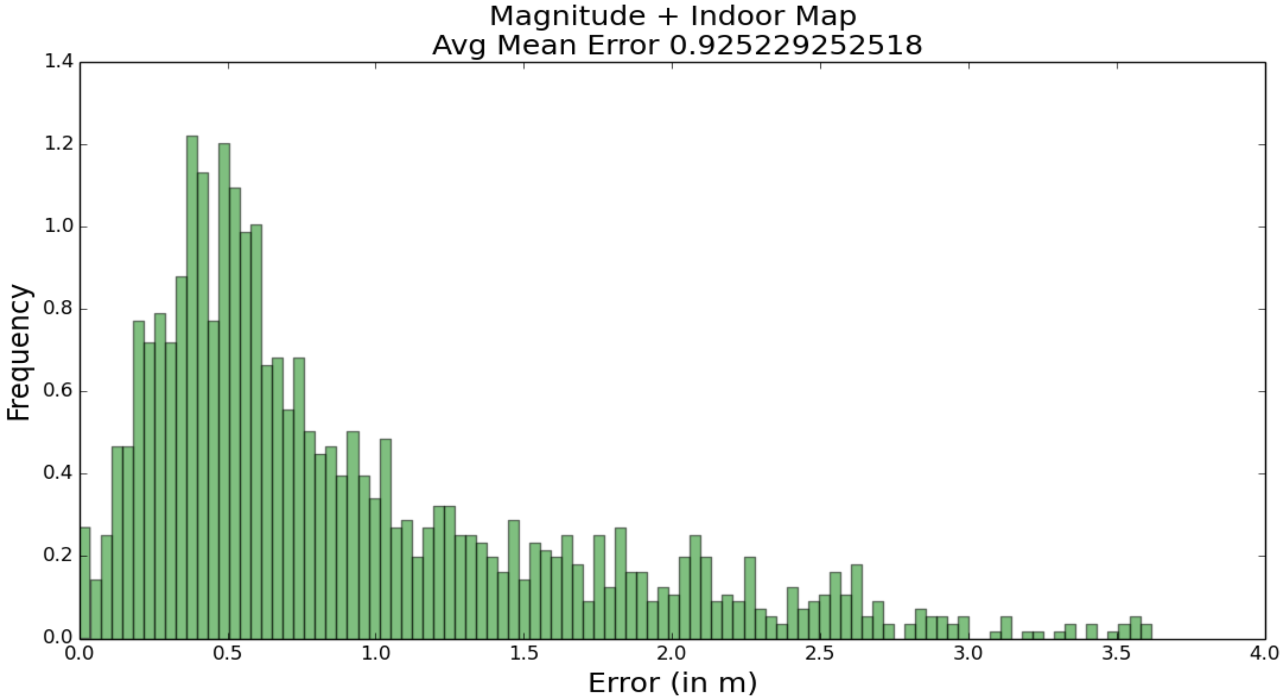


a) Magnitude

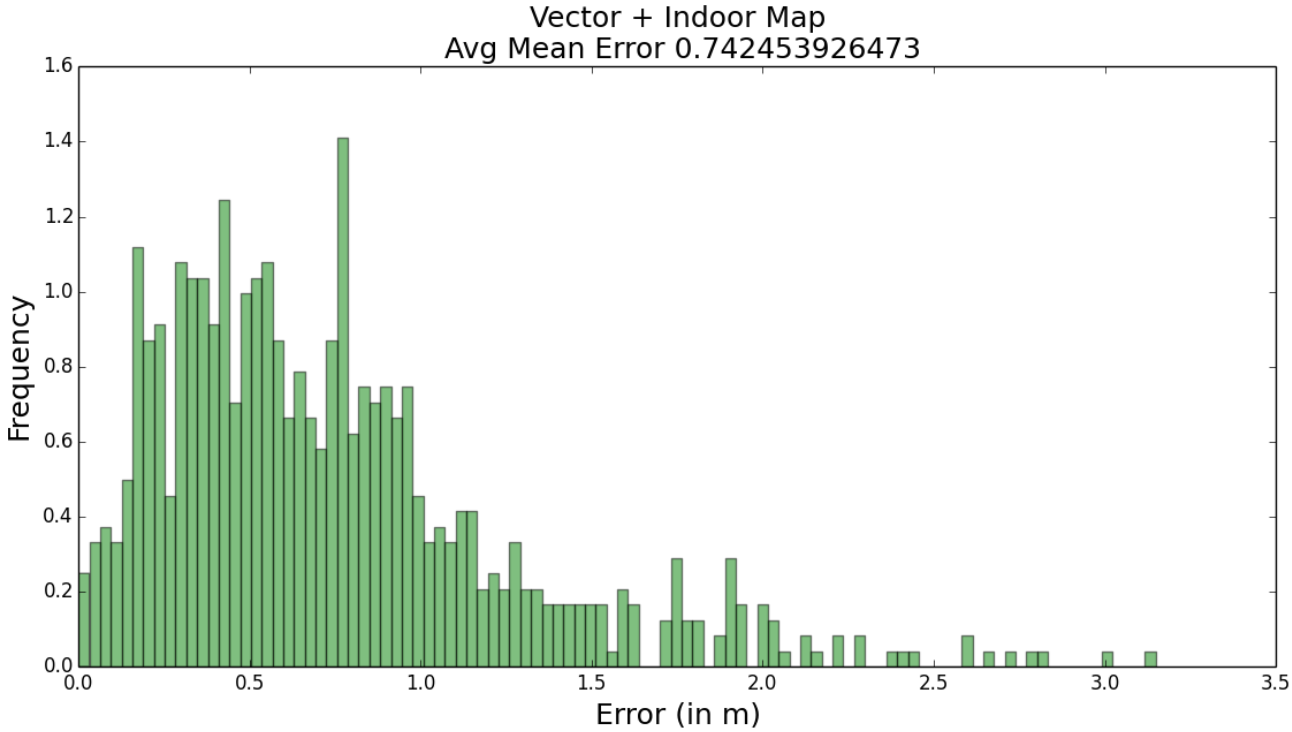


b) Vector

Fig 6.8 Histogram distribution of all the test paths localization errors for various approaches



c) Magnitude + Indoor Map



d) Vector + Indoor Map

Fig 6.8 Histogram distribution of all test paths localization errors for various approaches

7. Conclusions & Future Work

7. 1 Conclusions

Indoor localization systems need to localize the targets accurately with 0.1 – 0.5 m localization accuracies for many prominent real time location based applications. The general indoor localization systems should not depend upon high cost infrastructure and should be easily deployable. Pervasive applications in the future will depend upon these localization systems.

In this work we proposed to use the ambient information available indoors in the form of magnetic maps and indoor maps, along with inertial sensor on a smart phone. We proposed to develop a particle filter based pedestrian localization system using only the smart phone and the pre-stored magnetic maps and indoor maps. We have used accurate and general orientation estimation method, AHRS [31, 32] algorithm in our localization system. We have implemented four different approaches of localization using magnetic maps (magnitude and vector) and indoor maps.

We have conducted localization experiments in the indoor space (library) with book shelve racks. Several zig-zag paths were followed by the user with hand held smart-phone. The real time estimated paths were logged and their localization accuracies are evaluated. We have achieved mean localization accuracies of 0.75 – 0.95 m for the different approaches we have tested. Our implementation is more general and accurate than the previous magnetic map based indoor localization systems. We have improved the magnetic map based indoor localization systems using indoor maps. Magnetic field Vector + Indoor map based approach is found to be the performing better than the other three approaches.

7. 2 Future Work

Future work using the magnetic maps and indoor maps would include

- Testing and evaluating the performance of this implementation in different test areas such as corridors, open room.
- We have used a single smart-phone in our implementation so far. The performance dependence of the algorithm on the build and type of magnetometers on smart-phones has to be studied.
- We did not consider the motion of smart-phone in the hand of the user. Further advancements would include using placement and orientation independence of the smart-phone into localization.

Bibliography

[1] D. Davide et al., "Ranging with ultrawide bandwidth signals in multipath environments," *Proceedings of the IEEE 97.2*, pp. 404-426, 2009.

[2] J. Lien, M.Z.Win, H. Wymeersch, "Cooperative localization in wireless networks," *Proceedings of the IEEE 97.2*, pp. 427-450, 2009.

[3] N. B. Priyantha, "The cricket indoor location system," Massachusetts Institute of Technology, Cambridge, PhD Thesis 2005.

[4] L. M. Ni et al., "LANDMARC: indoor location sensing using active RFID," *Wireless networks*, vol. 10, no. 6, pp. 701 -710, 2004.

[5] A. Jones, A.Hopper, A. Ward, "A new location technique for the active office," *Personal Communications, IEEE*, vol. 4, no. 5, pp. 42-47, 1997.

[6] A. Agrawala, M. Youssef, "The Horus WLAN location determination system," in *Proceedings of the 3rd international conference on Mobile systems, applications, and services. ACM*, 2005.

[7] A. Padmanabha Iyer, V. N. Padmanabhan , K. Chintalapudi, "Indoor localization without the pain," in *Proceedings of the sixteenth annual international conference on Mobile computing and networking, ACM*, 2010.

[8] Y. Chen et al., "FM-based indoor localization," in *Proceedings of the 10th international conference on Mobile systems, applications, and services. ACM*, 2012.

[9] D. Kapoor, "Particle Filter Based Scheme for Indoor Tracking on an Android Smart-phone," Indian Institute of Technology, Roorkee, M.Tech Thesis 2011.

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

[11] V. N. Padmanabhan, P. Bahl, "RADAR: An in-building RF-based user location and tracking system," *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE* , vol. 2, pp. 775-784, 2000.

[12] H. Wang et al., "WLAN-based pedestrian tracking using particle filters and low-cost MEMS sensors," in *In Positioning, Navigation and Communication, 2007. WPNC'07*, pp. 1-7.

[13] P. Robertson M. Angermann, "FootSLAM: Pedestrian Simultaneous Localization and

Mapping Without Exteroceptive Sensors - Hitchhiking on Human Perception and Cognition," *Proceedings of the IEEE*, vol. 100, no. Special Centennial Issue, pp. 1840-1848, May 2012.

[14] S. E. Kim et al., "Indoor positioning system using geomagnetic anomalies for smart-phones," in *Indoor Positioning and Indoor Navigation (IPIN)*, 2012.

[15] R.Want et al., "The active badge location system," *ACM Transactions on Information Systems (TOIS)* , vol. 10, no. 1, pp. 91-102, 1992.

[16] M. Montemerlo et al., "FastSLAM: A factored solution to the simultaneous localization and mapping problem," *AAAI/IAAI*, pp. 593-598, July 2002.

[17] S. Thrun E. Le Grand, "3-Axis magnetic field mapping and fusion for indoor localization," in *Multisensor Fusion and Integration for Intelligent Systems (MFI), 2012 IEEE Conference on*, 2012, pp. 358-364.

[18] A. Kemppainen, J. Haverinen, "Global indoor self-localization based on the ambient magnetic field," *Robotics and Autonomous Systems*, vol. 57, no. 10, pp. 1028-1035, 2009.

[19] J. Chung et al., "Indoor location sensing using geo-magnetism," in *Proceedings of the 9th international conference on Mobile systems, applications, and services. ACM*, 2011.

[20] M. Angermann et al., "Characterization of the indoor magnetic field for applications in localization and mapping," in *International Conference on Indoor Positioning and Indoor Navigation Vol. 13*, 2012.

[21] A. Kemppainen, J. Haverinen, "A geomagnetic field based positioning technique for underground mines," in *Robotic and Sensors Environments (ROSE), 2011 IEEE International Symposium on*, 2011, pp. 7-12.

[22] B. Gozick, "Magnetic Maps for Indoor Navigation," *Instrumentation and Measurement, IEEE Transactions on*, vol. 60, no. 12, pp. 3883-3891, Dec 2011.

[23] B. Li et al., "How feasible is the use of magnetic field alone for indoor positioning?," in *Indoor Positioning and Indoor Navigation (IPIN), 2012 International Conference on*, Nov 2012, pp. 1-9.

[24] M. Frassl, "Magnetic maps of indoor environments for precise localization of legged and non-legged locomotion," in *In Intelligent Robots and Systems (IROS),IEEE/RSJ International Conference on* , 2013, pp. 913-920.

[25] Fan Li et al., "A reliable and accurate indoor localization method using phone inertial sensors," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, 2012,

pp. 421--430.

[26] M. S. Arulampalam et al., "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *Signal Processing, IEEE Transactions on*, vol. 50, no. 2, pp. 174 -188, 2002.

[27] P. D. Groves, *Principles of GNSS, inertial, and multisensor integrated navigation systems*.: Artech House, 2013.

[28] R. Harle, A. Brajdic, "Walk detection and step counting on unconstrained smart-phones," in *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, 2013, pp. 225 - 234.

[29] G. Shen et al., "Walkie-markie: indoor pathway mapping made easy," in *USENIX Association*, 2013, pp. 85 - 98.

[30] H. Weinberg, "Using the ADXL202 in pedometer and personal navigation applications," in *Analog Devices AN-602 application note*, 2002.

[31] S. Madgwick, "An efficient orientation filter for inertial and inertial/magnetic sensor arrays," *Report x-io and University of Bristol (UK)*, 2010.

[32] Mi. Ermidoro, D. Comotti. (2011, Mar 30) Angle Estimation using AHRS and Kalman Filter. [Online]. https://code.google.com/p/9dof-orientation-estimation/downloads/detail?name=AngleEstimationApp.zip&can=2&q=

[33] H. Wang et al., "No need to war-drive: unsupervised indoor localization," in *Proceedings of the 10th international conference on Mobile systems, applications, and services*, 2012, pp. 197 - 210.

[34] S. Thrun et al., *Probabilistic robotics*.: MIT Press, 2005.

[35] R. Mautz, "Indoor positioning technologies," Habil. ETH Zurich, , PhD. Thesis 2012.

[36] P. Krishnamurthy, K. Kaemarungsi, "Properties of indoor received signal strength for WLAN location fingerprinting," in *Mobile and Ubiquitous Systems: Networking and Services, 2004. MOBIQUITOUS 2004. The First Annual International Conference on*, 2004, pp. 14 -23.

[37] Google Inc. (2014, Jan) Android Developer Reference. [Online]. http://developer.android.com/reference/android/hardware/SensorManager.html

[38] Apache Inc. (2014, Feb) Apache Common Math API. [Online]. http://commons.apache.org/ proper/commons-math/download_math.cgi

[39] Python Inc. (2014, Jan) Mat Plot Library. [Online]. http://matplotlib.org/api/pyplot_summary.html

[40] D. Kapoor. (2011, Sep) wifilocator Application. [Online]. https://github.com/divyekapoor/wifilocator

[41] S-Cube Inc. (2014, Feb) Electronic Compass Calibration. [Online]. http://www.s3sensor.com/en/s3/calibration/