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Enhanced Indoor Localization System based on Inertial Navigation

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Abstract

An algorithm for indoor localization of pedestrians using an improved Inertial Navigation system is presented for smartphone based applications. When using standard inertial navigation algorithm, errors in sensors due to random noise and bias result in a large drift from the actual location with time. Novel corrections are introduced for the basic system to increase the accuracy by counteracting the accumulation of this drift error, which are applied using a Kalman filter framework.

A generalized velocity model was applied to correct the walking velocity and the accuracy of the algorithm was investigated with three different velocity models which were derived from the actual velocity measured at the hip of walking person. Spatial constraints based on knowledge of indoor environment were applied to correct the walking direction. Analysis of absolute heading corrections from magnetic direction was performed . Results show that the proposed method with Gaussian velocity model achieves competitive accuracy with a 30% less variance over Step and Heading approach proving the accuracy and robustness of proposed method. We also investigated the frequency of applying corrections and found that a 4% corrections per step is required for improved accuracy.

The proposed method is applicable in indoor localization and tracking applications based on smart phone where traditional approaches such as GNSS suffers from many issues.

Keywords: Inertial Navigation, Step and Heading Systems

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List of Abbreviations

AOA	Angle Of Arrival
API	Application Programming Interface
ASCII	American Standard Code for Information Interchange
EKF	Extended Kalman Filter
FSM	Finite State Machine
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HTTP	Hyper Text Transfer Protocol
IoT	Internet of Things
INS	Inertial Navigation System
IMU	Inertial Measurement Unit
JSON	JavaScript Object Notation
MEMS	Microelectromechanical System
RFID	Radio Frequency Identification
REST	Representational State Transfer
SHS	Step and Heading System
SVM	Support Vector Machine
TDOA	Time Difference Of Arrival
TOA	Time Of Arrival
UKF	Unscented Kalman Filter
UART	Universal Asynchronous Receiver/Transmitter
ZUPT	Zero Velocity Update

Chapter 1

Introduction

1.1 Motivation

Computing devices are advancing rapidly with many emerging new technologies. High computing power and resources are now available in many day to day use devices. Smartphone is a popular device nowadays, which possesses high computing power, multitude of sensors and communication ability. Smartphone based applications are prominent in many industries and in general use.

Tracking and localization of things and people has been an active area of research during the last decade and it has applications in many areas. Most early solutions have been developed to solve specific localization problems in industries while many new technologies are emerging recently to provide localization as a universal general service. Smartphone based location inference plays a vital role in this application area, because of the ubiquity of an advanced computing device in a small and relatively cheap form factor. Smart phones are capable of outdoor navigation using popular technologies like GNSS. However, localization and tracking indoors have not been successful with these technologies due to signal propagation issues.

Indoor localization and tracking based on smartphone is the application area of research presented in this thesis. Although many technologies are currently available, accuracy and robustness of these applications need to be increased to an acceptable level in order to fulfil the general indoor location inference requirements. Indoor localization finds its applications in many areas as summarized below.

- Internet of Things (IoT)

  Location is a key context in IoT applications for providing the best possible service. Indoor localization provides the location context for IoT applications.

- Location based services

  Resource allocation based on indoor occupancy for efficiency and customized productive marketing/advertising.

- Support services

  Navigational services in unfamiliar indoor environments and services for disable individuals like visually impaired.

- Safety Applications

  Emergency rescue team collaboration and dynamic security implementations with situational awareness harness the indoor location inference.

- Military Applications

  Tracking of teams and things in harsh environments.

- Industrial Applications

  Tracking and navigation of robots and equipment

- Medical Care

  Health monitoring, patient care and emergency situations.

Variety of application areas and advancement of IoT proves the need of indoor localization solution with high accuracy and robustness.

Many approaches are proposed in available literature for smartphone based indoor localization. Figure 1.1 shows the classification of current approaches. Dead Reckoning approach calculates the displacement using inertial sensors initializing at a known position. Inertial Navigation Systems (INS) continuously calculate and track the position of the pedestrian using accelerometers and gyroscopes while Step and Heading Systems (SHS) estimate the location by counting number of steps taken multiplied by the step length.

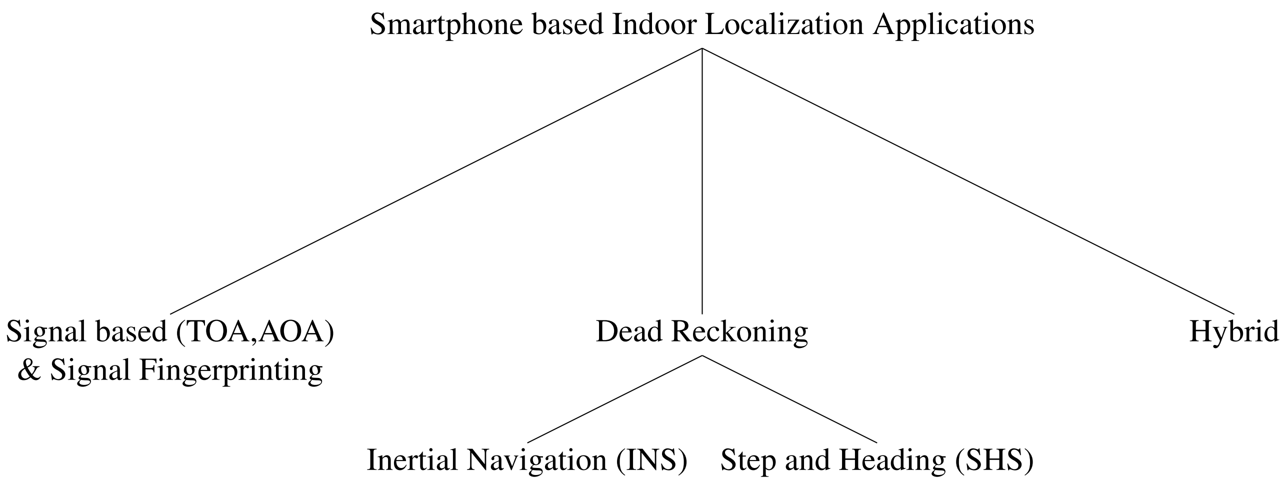


Figure 1.1: Classification of smartphone based indoor localization approaches.

An improved INS based dead reckoning approach for pedestrian localization is proposed in this thesis. Due to higher levels of errors in the low cost sensors available in smartphones, traditional INS results in a large amount of drift from actual location within few seconds. Corrections to walking velocity from a velocity model derived using actual velocity measurements and walking direction corrections from domain specific knowledge are employed to control the drift to improve upon current methods. A prototype system was developed to investigate the performance of proposed method. Results from several experiments on walks demonstrate the increased accuracy and robustness of this method over SHS which is currently popular in this application area.

1.2 Contributions

We propose an enhanced INS approach for localization which incorporates corrections based on a velocity model based on step detection together with applying spatial constraints derived from domain knowledge. These velocity and spatial constraints are incorporated via the measurement vector of a Kalman filter framework.

- Actual velocity at the hip of a pedestrian was measured using Hagisonic Stargazer system and these measurements were used to derive three velocity models. These models were then used to correct the position estimation. We evaluated the performance of these three velocity models as well as investigated the best rate of applying corrections based on these models.

- Walking direction also needs to be corrected frequently to reduce the drift. Simple domain specific features drawn from common indoor environment are used to impose spatial constraints on location estimation. Our experiments show the increased accuracy obtained by applying these spatial constraints based on domain knowledge.

- In order to correct walking direction, angle from magnetic north can be used. This angle can be calculated using magnetic field measurements of magnetic sensor. Analysis of calculated angle from magnetic field measurements in indoors along corridors was performed and it is observed that due to large local distortions, direct usage of this correction was limited in indoors.

1.3 Document Structure

This thesis presents the proposed method with the content organized as below.
Chapter 2 consists of the literature survey of indoor localization research area. It provides overview of current indoor localization attempts and highlights where the proposed system fits with existing pool of different technologies.
Chapter 3 introduces the proposed approach and describes the theoretical aspects of the proposed method. It includes a description of prototype system developed to investigate the effectiveness of the proposed method compared to classical SHS approach.
Chapter 4 presents comparison and performance results of proposed approach using various walking experiments. Accuracy of the proposed method and it's comparison to SHS approach is shown for a variety of experiments which includes different individuals, different paths and different devices.
Chapter 5 includes a critical analysis and suggested improvements for the proposed system along with a discussion of future research along this path.

Chapter 2

Background

Localization and tracking is becoming a key requirement in context aware applications as location is a key context. Global Navigation Satellite Systems (GNSS) is a mature technology for outdoor localization and tracking. Dispite of many attempts to increase accuracy and reliability, GNSS performs poorly in indoors because of high signal attenuation and multipath distortion. Many techniques have been proposed for indoor use to overcome limitations of GNSS.

This chapter includes a summary of outdoor and indoor localization and tracking techniques for location awareness of a person with a comprehensive analysis on dead reckoning systems. Section 2.1 and 2.2 describes the outdoor and indoor localization approaches respectively in general and section 2.3 focus on approaches which are specifically based on smartphone. Section 2.4 describes the basic strapdown inertial navigation algorithm.

2.1 Outdoor Localization and Tracking

Two main localization techniques for outdoor use are a) systems based on satellite signals which are called Global Navigation Satellite Systems (GNSS) and b) systems based on cellular network.

2.1.1 Global Navigation Satellite Systems

The most common and widely used outdoor localization system is based on signals from geostationery satellites and is known as GNSS (Global Navigation Satellite Systems). In the operation of this system, ground receiver device receives signals from 4 or more satellites which consists of synchronized time stamps. The distance from each satellite can be calculated deducting time stamp from the time of arrival. With the knowledge of satellites' location and distance to them, ground receiver location can be calculated geometrically using triangulation technique. In order to eliminate the need of time synchronization between ground receiver device and satellites, Time Difference of Arrival (TDOA) has been adapted to GNSS. In TDOA, distance is calculated based on the time difference between the signals from satellites instead of Time of Arrival (TOA).

Currently, several GNSS systems exist which are operated by different countries. Out of them, Global Positioning System (GPS) operated by USA and GLONASS (Global Navigation Satellite Systems) operated by Russia are widely used today. While both the GPS and GLONASS systems are operated by military authorities, a new civilian operated GNSS has been introduced as Galileo which is compatiple with GPS and GLONASS. This system has achieved full global coverage in 2011 and is operated by Czech Republic based European Global Navigation Satellite Systems Agency (GSA). Some regional satellite positioning systems such as Indian Regional Navigation Satellite System (IRNSS) by India and BeiDou Navigation Satellite System (BDS) by China have also emerged which may soon be deployed on a global scale.

Accuracy of these satellite based positioning systems directly depends on the received satellite signal strength which can vary bacause of environmental conditions like clouds and humidity and receiver environment (e.g urban areas). Current average accuracy is around 10 m and attempts are being made to improve this. Assisted GPS (A-GPS), Differential GPS (DGPS), and Wide Area Augmentation System (WAAS) can be given as examples which can achieve an accuracy up to 1-3 m [1].

2.1.2 Cellular Positioning Systems

Cellular systems are providing voice and data services to mobile phones using radio signals trasmitted and received from base stations which cover a specific area. So, triangulation can be applied with the known base station locations as with the satellite systems. TOA, TDOA and AOA approaches are used in triangulation using cellular base stations.
Accuracy level of this method alone is around 150 m and are mostly used to complement other technologies such as Assisted-GPS.

2.2 Indoor Localization and Tracking

Although GNSS has become the standard technology for outdoor localization and tracking, usabilibity of GNSS is severely limited in indoors because 1) attenuation of satellite signal received indoors is high and 2) signal conditions like multipath distortion are complex in indoors [2].
Many other approaches have been attempted to locate and track things indoors. Earliest indoor tracking applications include locating and tracking machinery and robots inside factories using highly specialized methods with distributed sensors. Although the accuracy is comparatively high in these applications, they are specialized applications which are not usable in general day to day use by localization applications.
Attempts have been made recently to perform indoor localization by utilizing existing infrastructure or environmental properties. Examples include indoor localization based on received signal strength fingerprints of radio signals (e.g. WiFi signals) and dead reckoning methods based on wearable inertial sensors. There are specialized complex applications which utilize image processing techniques to locate and track indoors which are mostly used with robot navigation. Although most techniques have been developed from the robot localization research area, significant complexities arise when it comes to tracking of pedestrians indoors [3].

- Only limited number of sensors can be used with pedestrians while robots can use high end sensors including laser range finders, cameras, etc.

- Robots posess limited number of different movements which are constrained while pedestrians move in ways that are not easily predictable.
- Robot localization occurs in a limited coverage area, while with pedestrians this is not the case.

With the widespread use of smartphones, indoor localization applications have become popular in general use inside malls, event locations etc. Smart phones are equipped with necessary resources to support location aware applications. Mobile Internet of Things (IoT) has also made indoor localization desirable, for its applications.
Indoor localization approaches can be classified mainly in to following 4 categories [4].

- Lateration and Angulation Systems
- Proximity systems
- Radio fingerprint systems
- Dead reckoning systems

2.2.1 Lateration and angulations systems

These systems calculate the distance from known locations to the mobile unit, which is being tracked, using signals between base station and mobile unit. Minimum of three base stations are required to calculate the distance in 2D while minimum of four is required for 3D localization. Based on the method of distance calculation, these systems can be divided in to three categories as Time of Arrival (TOA) based, Angle of Arrival (AOA) based, and Hybrid systems[5].
In this category of methods, different signals can be used to calculate the angle or time. Most systems use electromagnetic signals; specially in the unlicensed 2.4 GHz range. However, other signal types have also been used where the "Active Badge System" [6] uses infrared signals while "Active Bat System" [7] and "Cricket System" [8] uses ultrasound signals, all being lateration and angulation systems.
These systems may achieve an accuracy around 1m with ideal signal conditions such as Line of Sight. Requirement of radio base station installation and complex signal properties in indoors makes these systems not robust enough for indoor applications in general use.

2.2.2 Proximity systems

Instead of calculating the exact location, proximity systems output the proximity of a mobile node to a base station. These systems can be implemented with low cost. Depending on the application requirements, proximity systems provide an economical system. Bluetooth based systems and RFID tag employed systems [9] are common in this category of approaches.
But the accuracy of these systems is typically at room level which is more than 10 m. Other approaches can achieve more accuracy which is required for a indoor localization application.

2.2.3 Signal fingerprinting systems

In fingerprinting methods, measurements of particular property of an interested signal are surveyed for different points in the interested area. These measurements are then stored along with the actual location and is called the radio/signal map. Once this offline process is complete, location of the mobile station is estimated online by matching the current measurement from the mobile station with the radio map. With the assumptions of signal property having significant differences along the interested area and they do not change significantly with time, these systems can perform with higher accuracy for indoor applications.
Fingerprinting method is widely used in general indoor localization and tracking applications. Popular "Accuware Indoors' [10]', "Indoor Atlas" [11], and "Google Indoors" [12] commercial mobile applications are implemented using fingerprinting on WiFi and cellular network signals.
The RADAR system, which can be identified as the first of this attempts in year 2000, used a proprietary wireless technology in 2.4 GHz frequency range and used the received signal strength (RSS) as the mapping signal property [13]. WiFi Radio signal is used in most applications nowadays because of it's ubiquitous availability indoors which makes the system implementable without additional infrastructure. Use of nearest neighbour and k-nearest neighbour empirical algorithms are suggested to find the best match from the radio map for the current reading by the authors of RADAR system.
Improvements have been proposed for the accuracy of fingerprinting systems built from the basic idea of radio fingerprinting as below.

- Use of advanced signal properties for fingerprinting
- Use of other signal types for the fingerprinting
- Use of advanced methods to find the best match
- Increase the map building efficiency

Fingerprinting methods can achieve an accuracy around 5 m. However these systems need to have a radio map built before use and it need to be updated whenever radio base stations change. These reasons makes it less suitable for indoor localization applications in general.

2.2.4 Dead Reckoning systems

Objects can be tracked by calculating the displacement from a known location using motion parameters like acceleration, velocity and direction. This method is named as “Dead Reckoning” and commonly used in tracking of ships and robots. Usage of this approach in tracking walking users indoors or outdoors is termed Pedestrian Dead Reckoning (PDR).
With the development of MEMS (Micromachined electromechanical sensors) technology, low cost and miniaturized accelerometers and gyroscopes became widely available. Early dead reckonning based indoor localization systems used MEMS IMU (Inertial Measurement Units) by placing it in foot, thigh or hip level.
Pedestrian dead reckoning approaches can be devided in to two categories: Inertial Navigation Systems (INS) and Step and Heading Systems (SHS) [4].

Inertial Navigation Systems (INS)

These sytems continuosly track the location of a sensor with reference to an initial point in space. Acceleration and gyroscope sensors which measure the acceleration and rotaion velocity respectively are commonly used where the second integral of acceleration yeilds the distance and first integral of rotation velocity yeilds the direction.
When the sensor is rigidly attached to the sensor body, this method is called strapdown INS. Although the strapdown INS should yeild the actual displacement from the known location theoretically, errors due to random noise and bias in MEMS IMU readings result in a large

drift from the actual location with time. Hence, external correction are employed to correct the drift normally.

The "Navshoe" system introduced by Foxlin is a dead reckoning INS solution with a shoe mounted IMU which employs Zero Velocity Updates (ZUPTs) as the main correction to control the drift [14]. As introduced by Foxlin, complementary Kalman filter is commonly used in these INS based tracking applications to apply the external corrections [14]. This filter allows the tracking of error and applying a correction to the measurement. In addition, Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) have been used with non-linear motion models in calculating the position. A basic generic strapdown INS system is shown in figure 2.1.

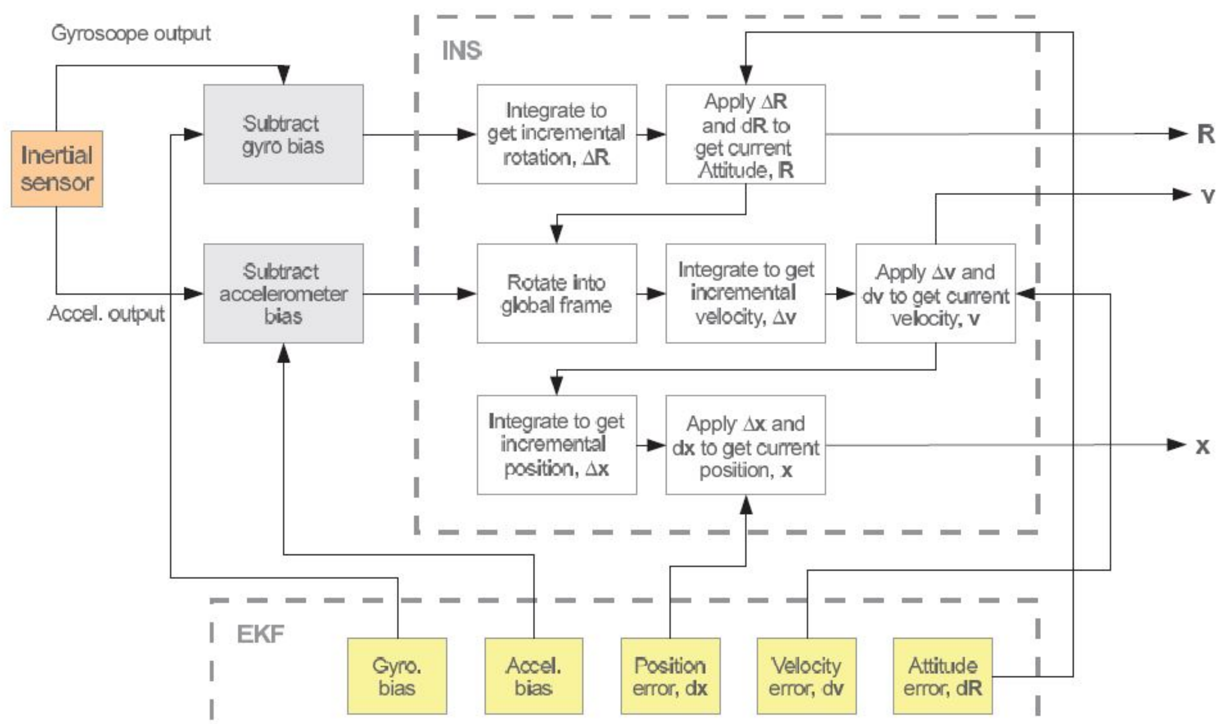


Figure 2.1: Common INS solution architecture with complementary Kalman filter for drift correction [4].

When the sensor is placed in upper parts of the body rather than on foot, different solutions have been suggested. Lo et al. suggests using two sensors, one on upper body which is used

to calculate the distance and heading while the other sensor on lower foot which is used for corrections [15]. Basically when the foot is straight (Pitch of the lower sensor is zero) velocity of the upper sensor is updated using the angular velocity of the lower sensor which is called a W-UPT (Walking update).
Kinematic model based walking speed calculation approaches have been suggested by Hu et al. for waist mounted inertial sensors which can be used for INS dead reckoning [16] [17].

Step and Heading Systems (SHS)

SHS systems totally depend on the walking movement of pedestrians which is a major form of human locamotion.
In walking motion, humans lift one foot and then move it forward in front of other foot, leaning on that foot. This process is repeated alternatively with each foot in order to move forward. In the analysis of the walking pattern, few definitions are essential.
"Gait Cycle" is defined as heel strike to next heel strike of the same foot. This cycle goes through two main phases known as "Swing" and "Stance". From heel contact to the next toe off is called "stance phase" and the foot is in contact with the floor and stationary in this phase. The "swing phase" is from the toe off to the next heel contact and foot is in air in this phase. The actual movement in forward direction happens in the swing phase [18]. This analysis is further shown in figure 2.2 for clarity.

Pattern of human walking cycle is same for all normal humans where parameters can be different based on some factors like gender, height, and weight. Normally "stance" phase occupies 60% of the gait cycle.
SHS systems detects steps and estimate the step length using the inertial sensors mounted on foot or upper parts of the body. Most fitness bands currently in the market uses this approach and is only applicable for walking/running users. It follows basic steps below.

- Detect the completion of a step
- Estimate the length of the step
- Estimate the step heading direction

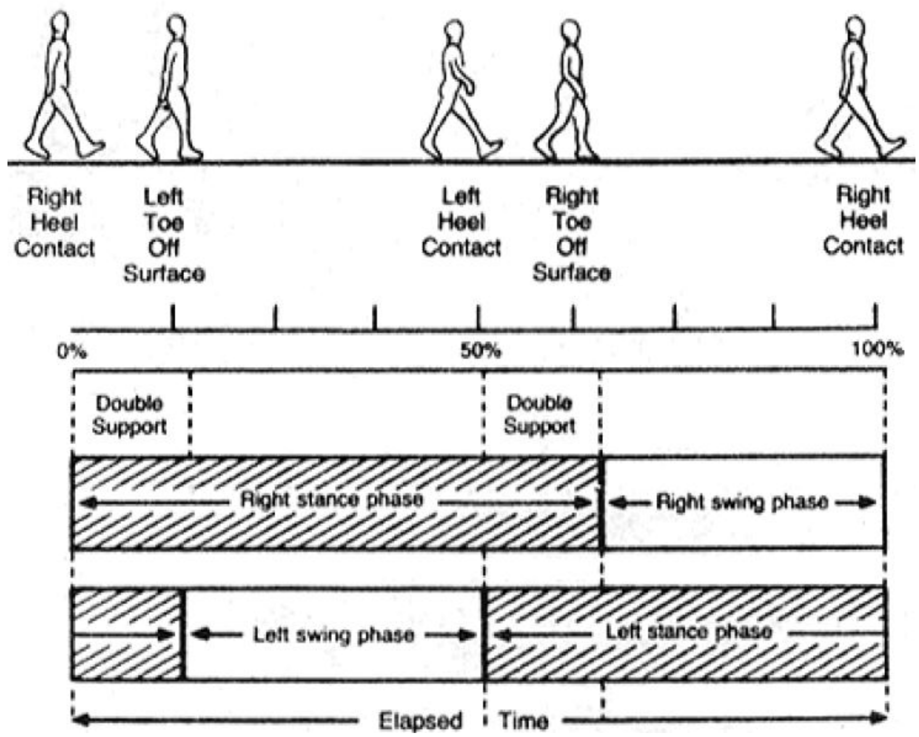


Figure 2.2: Analysis of different phases of human gait cycle [18].

- Project the step distance in to the heading direction
- Repeat above steps for the next step

Hence, the SHS requires algorithms or methods for two major tasks: 1) step detection 2) step length estimation.

Step Detection When the sensor is attached to the body, step events can be detected using the variations in readings produced by walking pattern. Acceleration signal or gyroscope signal is commonly used in this process. Clear identification of the subset of data which belongs to each step is needed in localization applications instead of just counting the number of step events. Thus, many methods employ the periodicity of the signals in ambulatory motion.
A raw acceleration signal in the walking direction for 10 steps is shown in the figure 2.3 from a hip mounted sensor.

Main approaches for step detection are, 1) Local Variance 2) Zero Crossings and 3) Finite state machine technique.

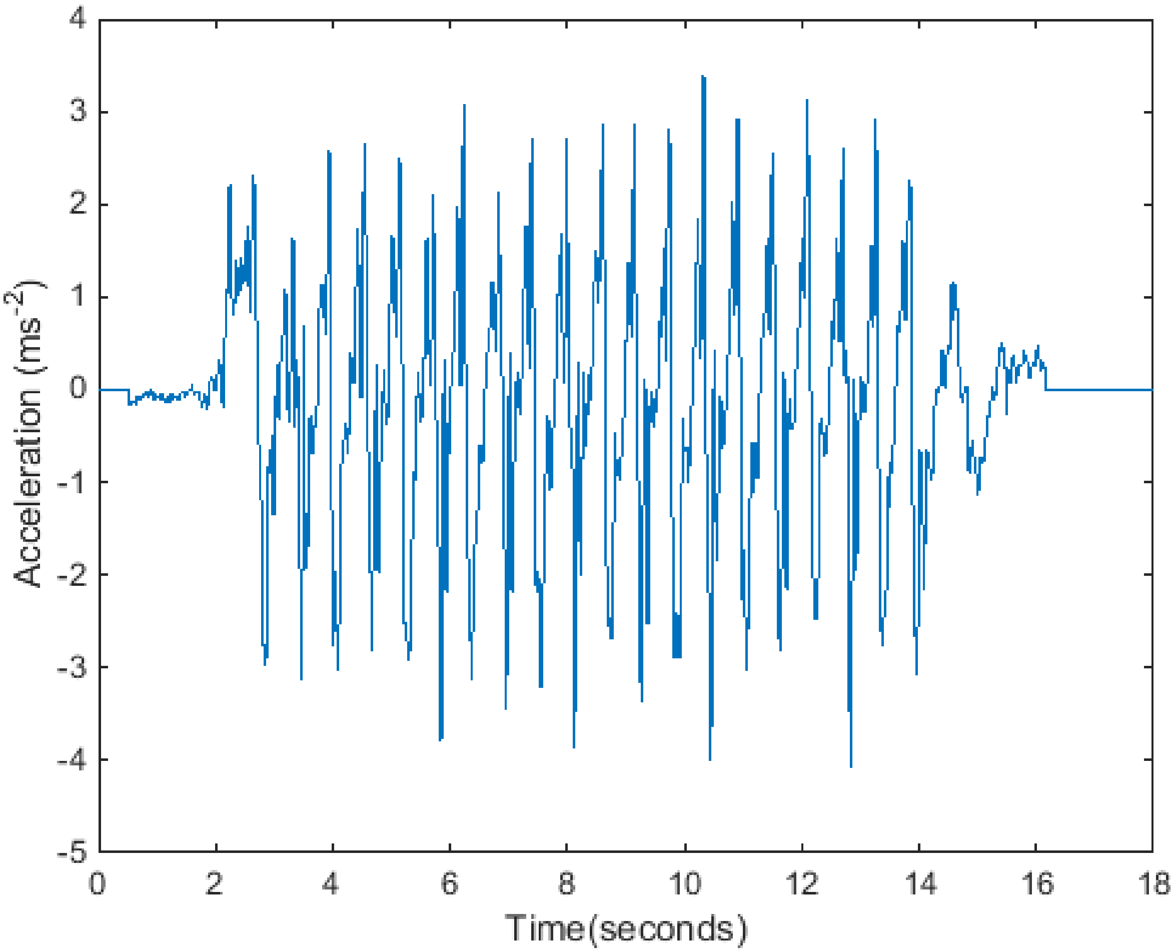


Figure 2.3: Raw acceleration signal on walking direction for a walk with 10 steps from a hip level sensor.

- Local Variance method

  This method was first suggested by Seco et al. [19]. Basic idea behind this method is the use of change of the variance in the acceleration during "swing" and "stance" phases which can be segmented by applying thresholds. The algorithm is described in four steps.

  - Compute the magnitude of the acceleration
  - Compute the variance of the acceleration using a predefined window size.
  - Two threshold are selected as: 1) Higher threshold to detect the "swing" and 2)

Lower threshold to define the "stance"

- Movement from "swing" to "stance" by crossing the thresholds is detected as the end of step and a step is counted.

- Zero Crossings method

  This method was first suggested by Beauregard et al. [20]. A deceleration is observed in the swing phase of each step which is followed by a acceleration because of the swing phase of the other foot. This behavior is utilized in this method, where a step is detected by a positive-going zero acceleration. Low pass filtering of the acceleration signal is recommended before detection to remove the high frequency noise which may interfere with the zero-crossing detection.

- Finite State Machine

  Suggested by Alzantot et al., this method tries to match the specific pattern of the step acceleration signal to states and define a step as the trasition between those states [21]. State transition is enabled by selecting four different threshold values as shown in figure 2.4 for one complete step.

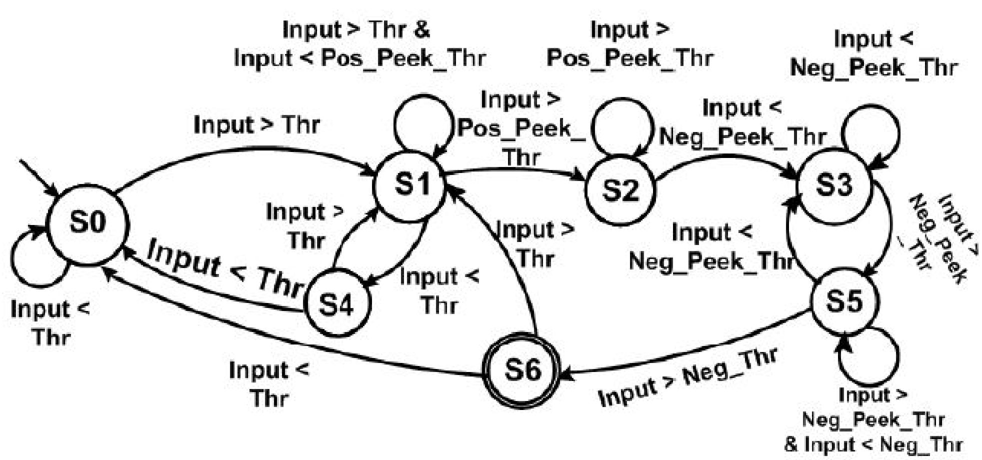


Figure 2.4: State transition for one step in FSM step detection method suggested by Alzantot et al. [21].

S0 and S6 denote the stationary and end of step states respectively. Other states are used as intermediate states to navigate thorugh the step acceleration signal to ensure a full step detection. When acceleration magnitude exceeds the threshold (Thr), state transfers from S0 to S1 by indicating a possible start of a step. Then the acceleration magnitude goes through positive peak threshold (Pos_Peak_Thr), negative peak threshold (Neg_Peak_Thr) and negative threshold (Neg_Thr) in that oder transferring between S2, S3, S5, and S6. The transition from S5 to S6 is detected as the end of the step and a step is counted.

The movement through the states guarantees that the acceleration signal passed thorugh the positive and negative peaks to complete a step which is the pattern observed in the acceleration signal. This method does not need any filtering before processing.

A simplified version with four states has been used in a smartphone localization application and it is shown in figure 2.5 [2].

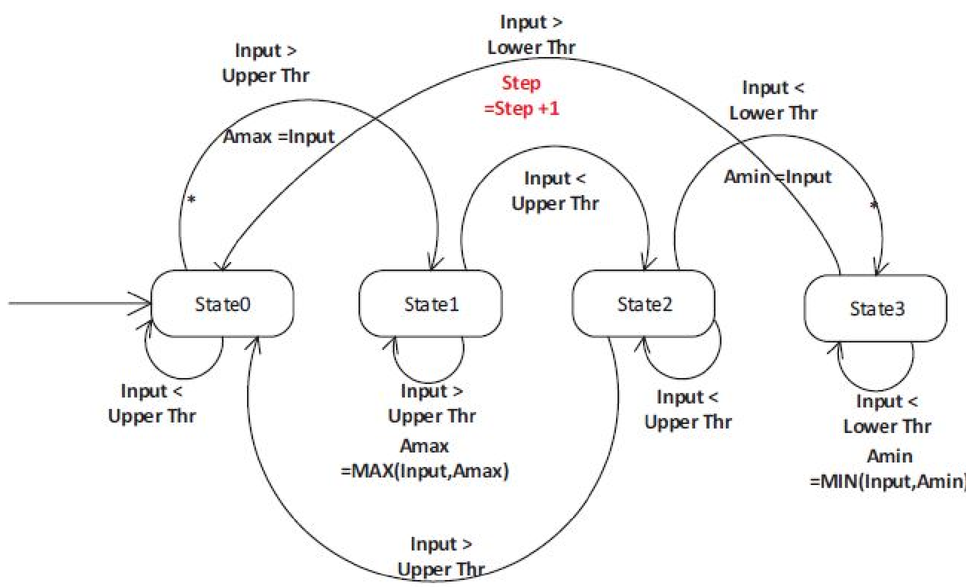


Figure 2.5: Simplified state transition for one step in FSM step detection method suggested by Do et al. [2].

Step Length Estimation Early SHS based implementations have assumed the average step length as constant for each individual. The implementation by Constandache et al. uses a fixed step size calculated from the height and weight of the person [22].

The step length is not a constant for each individual which can change from person to person depending on the pace and placement of the foot on floor, so that a dynamic approach to estimate the step length is required [23]. Several methods have been suggested to use acceleration signal to dynamically determine the step length for each step. These attempts can be categorized in to two as below.

- Equation based approaches

  These methods find the numerical relationship between the properties of the acceleration signal and the step length. Three main methods can be identified which utilize different statistical properties of the acceleration signal.

  - Weinberg Method

    The relationship can be presented by equation 2.1 which depends on the maximum and minimum acceleration values during a step which are denoted by A_{max} and A_{min} respectively [24].

    $$L = K\sqrt[4]{(A_{max} - A_{min})} \tag{2.1}$$

    The method has been emperically validated for the accuracy and use of a adaptive approach to calculate the K constant is recommended.

  - Scarlet Method

    Scarlet suggests using equation 2.2 after analysing the behavior of acceletation with the pace of walking [25]. This equation uses average, maximum and minimum acceleration values of a step which are denoted by A_{avg}, A_{max} and A_{min} respectively. The constant K must be estimated experimentally.

    $$L = K\frac{(A_{avg} - A_{min})}{(A_{max} - A_{min})} \tag{2.2}$$

  - Kim Method

    Equation 2.3 is used in this method, which has been found experimentally based on walking tests [26]. It uses the correlation of step length to the average acceleration of a step which is denoted by A_{avg}.

$$L = K \sqrt[3]{A_{avg}} \tag{2.3}$$

- Machine learning approaches

  Methods in this category estimate the step length through a learning process using machine learning approaches instead of finding the numerical relationship between the acceleration signal and the step length. Neural networks are employed with the input of some features selected from the acceleration signal and the output is the step length. Common input features selected are maximum, minimum, average, and variance of acceleration signal of one step as well as step duration.

  Beauregard et al. used a neural network with 10 nodes in single hidden layer to estimate the step length after detecting steps using zero crossings method in a head mounted sensor system [20]. Alzantotot et al. used a multi class Support Vector Machine (SVM) classifier along with FSM step detection to achieve better results than applications which use fixed step length in calculations [21].

2.3 Smartphone based Tracking

Smart phones allow voice, data, and video communication through cellular or data networks. Upgraded from mobile phones, smartphones are equipped with more services and pheripherals with a high processing power and storage. Smartphones run proprietary or open source operating systems and allow using phone resources and pheripherals through Application Programming Interface (API) for applications. Most of the smartphones nowadays are equipped with inertial sensors like accelerometers and gyroscopes, environmental sensors like thermometers and magnetometers, GNSS receivers like GPS receivers and cameras in addition to communication interfaces like 3G/4G cellular, WiFi, Bluetooth and Infrared. These additional resources combined with different communication options has paved the way for context aware applications using smart phones.

Indoor localization and tracking applications has become a major application in smartphone as

a standalone navigation and in providing location context for other location based applications. Availability of high processing power and memory, different communication technologies and inertial sensors have made it feasible to develop diverse indoor positioning approaches based on smart phones.
A survey done by Subbbu et al. with visitors to a mall, shows that most people still do not believe and accept an application to navigate inside buildings. This suggests that a robust system with more accuracy is still a pressing need for general users [27].
In analysis of different approaches suggested for indoor localization, accuracy is a major measurement metric which can be of two forms as below [27].

- Relative accuracy

  Applicable to fingerprinting methods and is defined as the percentage number of test fingerprints correctly classified.

- Average error

  Applicable in dead reckonning systems and is defined as average distance between the actual location and the estimated location as a percentage of total distance travelled.

When comparing different indoor tracking applications, accuracy alone may not be enough since the accuracy comes at the cost of many other factors. So, the following additional criteria should also be considered.

- Power consumption

  Battery life of the smartphone is a major concern and hence the power consumption of the tracking application need to be as low as possible. Number of sensors and pheripharals used, frequency of accessing them and the processing power requirements contribute towards the battery usage of the application.

- Processing power

  Applications designed for smart phones need to be minimized in processing and memory usage, since smart phones are constrained on those resources. Hence, the algorithms should be simple enough to be accomodated by the limited processing and memory available. Most applications which employ offline processing should ideally be implemented on the phone itself or with minimum interactions with external servers because of the security and privacy issues.

- Infrastructure requirement
  Indoor tracking applications need to be implemented without any additional infrastructure requirements or by utilizing the existing infrastructure as much as possible for it to be affordable for general use. Although location is a major context in mobile IoT applications, investing heavily on the infrastructure requirements for location inference rather than the application itself may not provide the best value [28].

Smartphone based approaches for indoor localization and tracking can be categorized as Fingerprinting and Dead Reckoning.

2.3.1 Fingerprinting

Signal fingerprinting can be considered as the most popular and widely used approach with smart phones. The inclusion of wide range of wireless technologies and sensors in smartphones has made it possible to use a variety of signals and properties in fingerprinting methods.
WiFi radio signal based fingerprinting is the most widely used approach up to date. This is because of the availability WiFi coverage now in most indoor environments. The "ARIEL" system is a sucessful smartphone fingerprinting application using WiFi signals with room level accuracy [29]. The radio map building process has been crowdsourced by analysing the occupancy and user movements.
In contrast, Tarzia et al. proposes the fingerprinting based on acoustic background sound with the target of achieving room level accuracy and shows that it performs better than WiFi fingerprinting in distinguishing rooms, specially with adjacent rooms [30]. This system does not require any infrastructure for the operation which is another advantage.
The "Skyloc" system proposed by Varshavsky et al. is another variant which employs fingerprinting based on cellular signals and achieves floor level accuracy in high rise buildings [31].
The "SurroundSense" system proposed by Azizyan et al. uses ambience fingerprinting to achieve a logical localization rather than fine physical cordinates [32]. They suggest using color, WiFi, sound, and light as ambience parameters to be used in generating the fingerprint-

ing database. Although the accuracy results achieved are competitive, power consumption and computing effort needed by the use of many sensors and pheripherals questions the efficiency of the approach.

By utilizing the uniqueness of the magnetic field distribution inside buildings due to pillars, elevators, the “Locate Me” system builds a fingerprinting map based on magnetic field strenth sensed using smart phone magnetic field sensor [33]. They have targeted fine tuned localization rather than room level and achieved 2-6 m accuracy. The independence from any infrastructure is also an advantage of this system.

From the applications, it can be observed that accuracy levels of fingerprinting methods are low compared to other methods since most of them attempt to achieve room level coarse localizations for application use rather than fine tuned physical location.

2.3.2 Dead Reckoning

Dead reckoning systems implemented on smart phones try to achieve better accuracy than that provided by fingerprinting methods.

While moving, smartphone can be in pocket, bag, or in hand being used. As such, the orientation of the phone is a major concern which directly affects the calculations in dead reckoning methods. Most applications assumes the location of the phone to be fixed for strapdown inertial navigation while some applications try to accomodate more phone positions and orientations.

Dead reckoning systems with smart phones can also be analyzed based on the two categories: INS and SHS.

Inertial Navigation Systems

Measurement errors are inevitable in smartphone sensors so that an external correction is required to correct the drift in INS approach. In a smartphone application, the sensors need to be placed around hip area. Since a hip mounted smartphone does not come to a complete stop in the “stance” phase, ZUPT method yeilds unacceptable levels of errors when applied in this scenario.

The pocket navigation system proposed by Diaz et al. uses a MEMS IMU in a pant pocket

[34]. Basically, they suggests a system where position of the sensor is tracked in a kalman filter with corrections from a SHS system. Additional corrections named Zero Acceleration Assumption (ZAA) update and Magnetic update have been suggested. ZAA updates the roll and pitch using gravity when the acceleration is almost zero (when below a threshold) i.e. when stationery. Magnetic update corrects the direction using magnetic field sensor when no magnetic disturbances are found. Accuracy around 5 m have been achieved with limited number of experiments in this method. Proposed method in this thesis can achieve higher accuracy on flat surfaces which is demonstrated with higher number of diverse experiments.

Step and Heading Systems

Since a smartphone can be placed in different places on the body other than on foot, SHS method has mostly been adopted in dead reckoning approaches using a smartphone.

The Finite State Machine (FSM) approach has been initially introduced for smartphone applications [21]. Authors have experimented Local Variance and Zero Crossing methods to compare with the new approach and found better results with FSM in smart phones.

Different smartphone applications have used different combinations of step detection and step length estimation. SHS approach is currently the dominating approach in smartphone based dead reckoning applications [21] [2] [35] [23] [22].

To compare the accuracy of the proposed system, a SHS based system proposed by Scarlet was implemented [25]. Detection of steps involved in this implementation was also used in application of corrections in proposed INS based system.

Out of the available step detection methods, FSM method was selected in this experiment [21]. This algorithm has been proven to be more accurate when used with a smartphone. Acceleration along the walking direction was selected as the signal for thresholding instead of the vertical component. This selection was done after the observation of both components, where the vertical displacement acceleration component showed more variations and noise due to shake, which made it difficult to be used in the detection using FSM approach.

To calculate the step length, the method proposed by Scarlet was used [25].

2.4 Strapdown INS

Basic idea behind INS is to calculate the displacement vector of an object by double integration of the measured acceleration vector of a sensor attached to the object. Location of the object relative to ground is required as the final output. Hence this frame of reference is called "Navigation Frame".

Mechanical sensors are always integrated in to a device and these systems can be devided in to two categories based on how these sensors are attached to the device [36].

- Stable Platform Systems

  In these systems, sensors are mounted in the device in such a way that, device orientation does not affect the orientation of the sensors i.e. the sensor readings are on Navigation frame. They typically employ a gimballed, gyro-stabilized platform.

- Strapdown Systems

  In these systems, sensors are mounted rigidly on to the device. So, the sensor readings are relative to the device which is called "Local Frame".

INS applications widely use strapdown systems because of low complexity and cost [36]. In this approach, orientation of the sensor device is used to transform the local frame readings to navigation frame readings while calculating the orientation by the integration of angular velocities from the gyroscope sensor.

Basic steps of strapdown INS are summarized below which is further illustrated in figure 2.6.

1. Initialize starting position and heading direction

2. Read accelerometer and gyroscope sensor data from the device

3. Calculate the orientation matrix using the angles derived from integration of rotational velocity from the gyroscope sensor

4. Transform the accelerator sensor data from local frame in to navigation frame using the orientation matrix

5. Integrate navigation frame acceleration twice to get the displacement

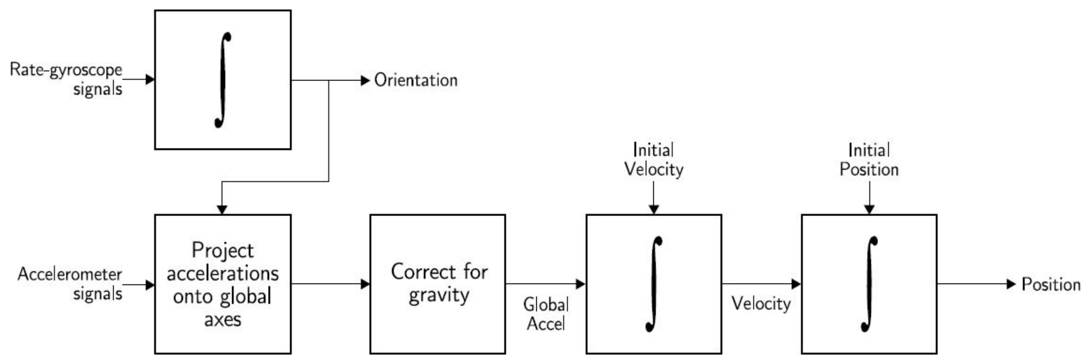


Figure 2.6: Basic strapdown INS algorithm [36].

Due to bias and random errors present in sensor readings, calculated distance deviates from the actual distance exponentially within few seconds. In order to correct that, zero velocity updates have been employed in the foot mounted inertial sensor scenario when the foot is in the “stance” phase. Rather than directly resetting the velocity to zero, the error is maintained as the state in Kalman filter and correction is applied as a measurement to the filter. This is known as the complementary Kalman filter application.

Chapter 3

Methodology

When a smart phone is used for indoor localization, phone location is typically around the hip area and fingerprinting approaches and SHS based dead reckoning systems are most common [4]. In this thesis, an INS based dead reckoning approach with corrections from a velocity model and domain knowledge is proposed. Further developments define and integrate a knowledge model for generalized application of corrections. The error drift is maintained in a complementary Kalman filter and it is used for the application of corrections.

Experiments were performed by collecting sensor data from a smartphone carried by a walking user. Then the collected data was used in proposed INS based algorithm to recreate the path travelled by the user. Actual walking velocity model, required for corrections, was derived using data collected from an advanced localization system carried by an user in different set of walks. Difference between the actual path and the calculated path was used in analyzing the error.

Section 3.1 describes the methodology used for the derivation of actual velocity models and section 3.2 presents the description of proposed Kalman filter framework based INS system. Section 3.3 describes the corrections introduced to basic INS system to control the drift which were integrated in to a 'Knowledge Model'. A prototype system with the proposed method was developed to perform experiments for analysis and technical details of this prototype system are inlcuded in Appendix A.

3.1 Development of Velocity Models

External measurements from a hip level velocity model is employed as the main correction to minimize the walking distance drift. Hagisonic Stargazer system, which is an indoor localization system used in robotics was used to measure the actual walking velocity. This system consists of an infrared projector, an infrared camera and a processing unit and estimates the location by applying advanced image processing techniques on aquired images of passive labels fixed on the ceiling. Details of the Stargazer system is included in Appendix A.
Primary output of the velocity measurement node is the actual position of the Stargazer sensor. The position signal along each axis was differentiated to calculate the velocity along each axis. Central approximation differentiation was used in this differentiation which uses equations 3.1 where n, T, X, Y, V_x, and V_y denotes measurement number, time of measurement, X axis distance, Y axis distance, velocity along X axis, and velocity along Y axis respectively.

$$\begin{aligned} V_x(n) &= \frac{(X_{n+1} - X_{n-1})}{(T_{n+1} - T_{n-1})} \\ V_y(n) &= \frac{(Y_{n+1} - Y_{n-1})}{(T_{n+1} - T_{n-1})} \end{aligned} \tag{3.1}$$

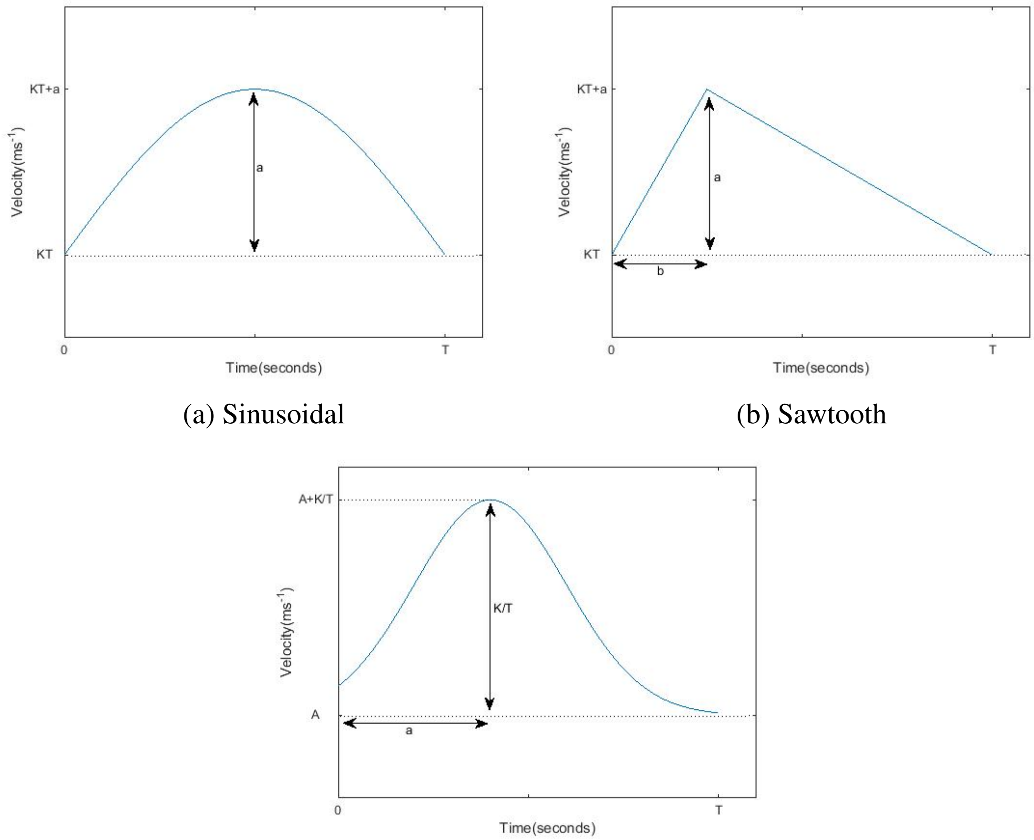
Resultant vector magnitude was obtained as the walking velocity of the user where V is the final walking velocity.

$$V(n) = \sqrt{V_x(n)^2 + V_y(n)^2} \tag{3.2}$$

It was observed that in the map mode, measurements sent by the device were sometimes delayed. This may happen due to the heavy processing involved within the Stargazer system when moving between two passive labels. In order to have equally spaced veclocity readings from the device, missing sample values were obtained using linear interpolation. In the derivation of velocity model, following two signals were compared.

- Actual velocity signal
- The velocity curve obtained by integration of acceleration signal

Three models derived from Gaussian, Sinusoidal and Trapezoidal functions were evaluated in this experiment and they are demonstrated in figure 3.1. The derived model parameters were optimized for each individual and measurements from the model were used for the corrections. Actual velocity measurements using Stargazer device was only used for derivation of these velocity models.



(a) Sinusoidal

(b) Sawtooth

(c) Gaussian

Figure 3.1: Graphical representation of three velocity models

Gaussian Model

This model is shown in equation 3.3 where T is the step period, A is the velocity shift, K is a constant and a is the mean fraction constant which changes the peak velocity point. The variance σ was defined as a fraction of the step period in order to maintain the shape of the velocity curve across steps. E.g. $\sigma = b * T$ where b is the step fraction constant.

$$V(t) = A + \frac{K}{T} \exp^{\frac{-(t-aT)^2}{2\sigma^2}} \tag{3.3}$$

Sinusoidal Model

This model is shown in equation 3.4, where T is the step period, a is the amplitude and K is the shift scale factor which are constants.

$$V(t) = K * T + a * sin(\frac{2\pi t}{2T}) \tag{3.4}$$

Sawtooth Model

Sawtooth model is shown in equation 3.5, where T is the step period, a is the amplitude, K is the shift scale factor and b is the width which defines the peak point in the signal.

$$V(t) = K * T + a * sawtooth(2\pi t, b) \tag{3.5}$$

3.2 Proposed INS system

Overall flow of the proposed INS based approach is shown in figure 3.2.

Sensor readings normally include a constant bias error which can be removed based on a precalcualted value. Low pass filtering is performed on sensor measurements signal to remove the random high frequency components. In our system, low pass filtering was only performed on gyroscope signal to identify domain specific spatial constraints. These tasks are performed in the preprocessing step after capturing sensor readings. Then the strapdown INS method is used to calculate the position using acceleration and gyroscope sensor readings. In order to correct the drift in strapdown INS, proposed corrections are applied. Corrections are gathered in a knowledge model, which calculates the correction values and corresponding time of application to the strapdown INS system and corrections are performed on the position calculated by INS system when available.

When a smartphone is carried at hip level, it does not necessarily become stationary in “stance” phase as the hip is moving while the hip is moving. Hence ZUPTs are not appropriate to correct the drift. Correction of walking direction velocity component using a velocity model is proposed in this thesis to maintain the drift at an acceptable level. A Modified strapdown INS approach summarized below was used in experiments in this thesis.

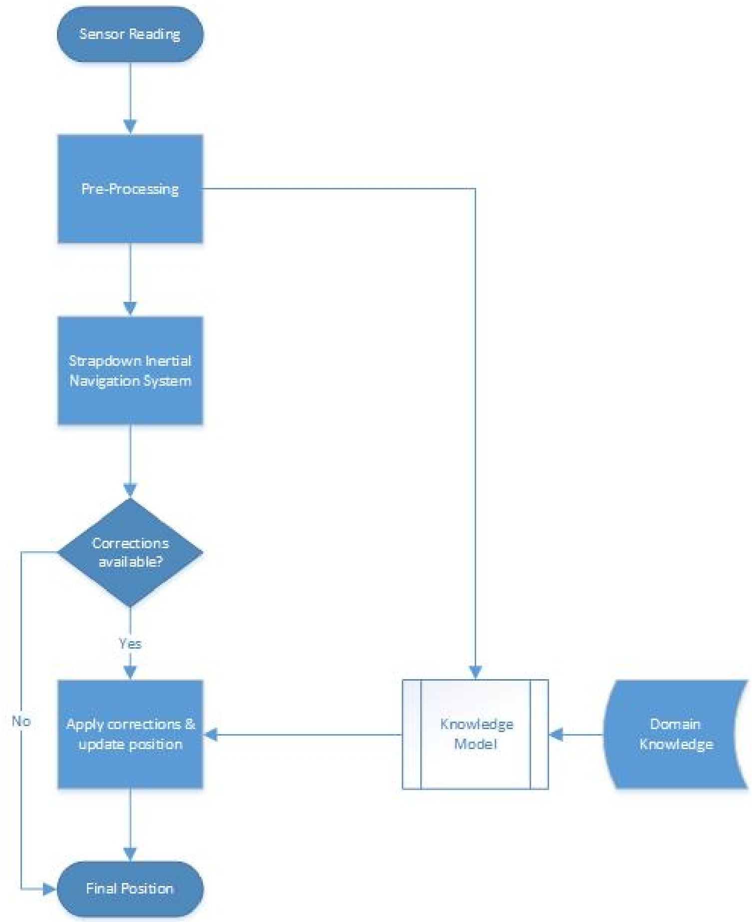


Figure 3.2: Flow of the proposed INS based system.

1. Initialize the starting position and heading direction.

2. Read sensor data from linear accelerometer, gravity sensor and gyroscope sensors

3. Calculate the orientation matrix from gravity sensor readings

4. Calculate the acceleration component in walking direction in the navigation frame

5. Calculate the rotational velocity along the vertical axis of navigation frame using the orientation matrix.

6. Double integrate the acceleration in walking direction to obtain the distance and project it on the direction obtained by integrating the vertical rotational velocity

In this modified approach, acceleration along the walking direction was used instead of the acceleration along three navigation frame axes and orientation was calculated using gravity sensor instead of the gyroscope output.
In mitigating the drift, corrections on walking velocity, angular velocity and walking distance were applied using the complementary kalman filter. All these corrections are grouped in to a "Knowledge Model" in this thesis.
The steps of calculating the orientation and application of corrections are discussed in detail in following sections.

3.2.1 Calculation of Orientation

Due to movement of the device while walking, the orientation of the phone may not align perfectly with the navigation frame. Furthermore, this offset may change while walking. Hence a transformation is needed to convert the readings in local frame in to the navigation frame. Local (phone) frame reference system and the navigation frame reference system, which were used, are shown in figure 3.3.

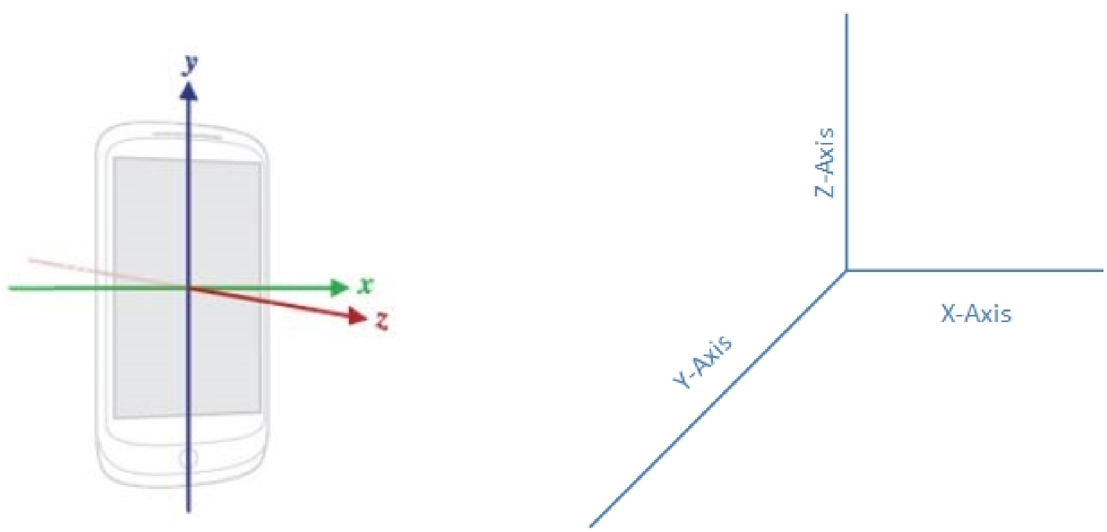


Figure 3.3: Local frame and Navigation frame reference systems used in this experiment

In geometry, orientation of an object in 3-dimentional cartesian system is described using the rotation angle along each axis, which are called Euler angles named Yaw, Pitch and Roll. Mathematical symbols and axis around which these angles are defined are summarized in table

3.1.

	Yaw	Roll	Pitch
Symbol	ψ	ϕ	θ
Axis	Z	Y	X

Table 3.1: Eular angle definitions

A rotation matrix, which defines the transform to the navigation frame for each specific angle is generated seperately. These individual matrices are then multiplied to make the orientation matrix, which transforms local frame to the navigation frame [37].
Individual rotation matrices are defined in equation 3.6 where R_θ,R_ψ and R_ϕ denotes the rotation matrix for pitch, yaw and roll respectively.

$$R_\theta = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta) & -\sin(\theta) \\ 0 & \sin(\theta) & \cos(\theta) \end{bmatrix}$$
$$R_\psi = \begin{bmatrix} \cos(\psi) & -\sin(\psi) & 0 \\ \sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3.6}$$
$$R_\phi = \begin{bmatrix} \cos(\phi) & 0 & -\sin(\phi) \\ 0 & 1 & 0 \\ \sin(\phi) & 0 & \cos(\phi) \end{bmatrix}$$

In order to calculate the Euler angles in orientation matrix, following equations are used where G_X, G_Y and G_Z represents gravity sensor readings along X, Y and Z axes respectively [34].

$$\tan(\phi) = \frac{G_X}{G_Z} \tag{3.7}$$

$$\tan(\theta) = \frac{G_Y}{\sqrt{G_X^2 + G_Z^2}} \tag{3.8}$$

When the phone is vertical, roll angle cannot be calcuated from gravity sensor readings. So roll was assumed to be zero in this experiment. Pitch angle was calculated using equation 3.9 extending the approach by Do-Xuan et al. [2] and assuming phone is placed vertical.

$$\sin(\psi) = \frac{G_Y}{\sqrt{G_X^2 + G_Y^2} + G_Z^2} \tag{3.9}$$

Since the roll angle assumption of zero makes the R_ϕ a identity matrix, orientation matrix in equation 3.10 was used to transform local frame vectors in to navigation frame. These vectors are acceleration and angular velocity vectors.

$$R = \begin{bmatrix} \cos(\psi) & -\sin(\psi)\cos(\theta) & \sin(\psi)\sin(\theta) \\ \sin(\psi) & \cos(\phi)\cos(\theta) & -\cos(\psi)\sin(\theta) \\ 0 & \sin(\theta) & \cos(\theta) \end{bmatrix} \tag{3.10}$$

3.2.2 Application of Corrections

Kalman filter was used to apply corrections in to the strapdown INS system. Kalman filter is a implementation of Bayesian filter, which is used to estimate state of a dynamic system based on noisy measurements of the system. It maintains the system state variables in a vector, estimate and update the state based on measurements. Kalman filter is described in detail in Appendix B. The steps and approach in this experiment to validate the proposed method was derived from the algorithm, used to apply ZUPTs in to foot mounted sensor INS system [38].

Actual state of the INS system in this experiment is defined in equation 3.11 where p,v,θ and ω denotes distance, velocity, heading angle and angular velocity.

$$x_t = \begin{bmatrix} p \\ v \\ \theta \\ \omega \end{bmatrix} \tag{3.11}$$

Kalman filter maintains the probability distribution of the error vector of INS system instead of actual vector in it's state (called Error-state or complementary Kalman filter). State is defined in equation 3.12 where δp, δv,$\delta\theta$ and $\delta\omega$ denotes distance, velocity, heading and angular velocity errors respectively and δx_t is the error-state vector at time t.

$$\delta x_t = \begin{bmatrix} \delta p \\ \delta v \\ \delta\theta \\ \delta\omega \end{bmatrix} \tag{3.12}$$

In this filter implementation, only linear velocity, angular velocity and distance along the walking direction were included in the error state.

Measurements from the sensors are received at a rate of 100 readings per second. The time difference between two samples, which is denoted as δt, is almost constant with a value of 0.01 seconds. With the receipt of every new measurement from the sensors, orientation matrix is updated and it is used to tranform the local frame vectors in to navigation frame. The acceleration along the walking direction is integrated once to get the velocity, and again velocity is integrated to get the distance. Then the angular velocity is integrated once to get the heading angle. In all these cases, the trapezoidal numerical integration was used.

In standard Kalman filter, with a receipt of new measurement, state is propagated to next state using equation 3.13 where F is called "State Transition Matrix" and Q is the process noise covariance.

$$\delta x_{t+\delta t} = F * \delta x_t + Q \tag{3.13}$$

Transition matrix used in this experiment is defined in equation 3.14

$$F = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \delta t & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & \delta t \end{bmatrix} \tag{3.14}$$

In this case, mean of the errors are always maintained at zero so that the state is always maintained at zero in this propagation stage. But the error covariance is propagated with the INS measurements using the standard kalman filter equation 3.15 where K is the error correlation matrix.

$$K_{t+\delta t} = F * K_t * F' + Q \tag{3.15}$$

When there is no external correction available, the above covariance update process continues propagating the error correlation forward. When an external measurement is available, error between current estimate and external measurement is calculated. The relation between measurement (Z) and state is defined using equation 3.16 and the Measurement matrix (H) as below where R is the measurement error covariance. Measurement vector contains a subset of the state variables which needs to be corrected, so that the dimention of the measurement matrix depends on the dimension of measurement vector. Equation 3.17 defines an example measurement matrix which is used to correct only the velocity and the heading angle of state.

$$Z_t = H * x_t + R \tag{3.16}$$

$$H = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{3.17}$$

Then, the error in estimated value by INS system, relative to the external measurement, can be calculated as below where Y is the error state measurement.

$$Y_t = Z_t - H * x_t \tag{3.18}$$

Y is the measurement applied to the kalman filter in actual correction steps. Standard Kalman filter equations in equation 3.19 are used to calculate Kalman Gain (G), update the error correlation matrix and get the new error state.

$$\begin{aligned} G &= K_t * H' * (H * K_t * H' + R)^{-1} \\ \delta x_{t+\delta t} &= G * Y \\ K_{t+\delta t} &= K_t - G * H * K_t \end{aligned} \tag{3.19}$$

Once the correction phase is completed, error values are transfered to the underlying INS as the final step in the filter. This corrects the position and velocity estimate using the errors calculated by kalman filter. Equation 3.20 is used in this case.

$$x_{t+\delta t} = x_t + \delta x_t \tag{3.20}$$

Results of basic INS approach and the improvement achieved by the application of corrections to the velocity in walking direction from the velocity model are presented in section 4.2.1 for experiments with straight walks.

3.3 Heading Direction Corrections

Spatial constraints based on domain knowledge was the primary direction correction applied in this thesis. Direction correction from magnetometer direction was also evaluated, but not applied due to high disturbances in magnetic sensor readings along indoor corridors.

3.3.1 Spatial constraints based on domain knowledge

Most indoor environments share common features in walking spaces. Rather than making use of indoor maps with complex algorithms, knowledge of the environment can be used by exploiting simple features in the environment. These features are converted to rules that constrain the movement of walking user and then applied as external corrections to the basic INS.
Straight corridors and square angle bends are two common features exploited as corrections in this experiment.

- Straight walks

  Moving average of angular velocity signal is calculated which outputs a low-pass filtered version of the signal. When the average angular velocity is below a threshold value, walking direction is considered to be the same (walking straight) and the direction is maintained unaltered.

- 90^0 angle turns

  Bends or turns in most indoor environments are 90^0 angle turns which can also be used in a simple correction; specially, in a navigation application. By selecting threshold values on average angular velocity and the turn time, and analysing the movement before and after the bend (i.e. if moving is straight before and after the bend), walking direction can be corrected to be 90^0 from the direction before the turn.

Improvements results by the application of these corrections are presented in the sections 4.2.2 and 4.2.3 for a series of walking experiements.

3.3.2 Compass direction

A magnetometer in a smart phone can be used as a compass when calibrated. Corrections based on this magnetometer direction is a common approach used in several applications.
Theoretically, the angle from North can be calculated using the magnetic field measurements along the earth surface which is X and Y axes in navigation frame. In this experiment, local frame magnetic measurement readings are transformed in to the navigation frame and then, equation 3.21 is used to calculate the angle from North where θ_M, M_x, and M_y are angle from North, navigation frame X and Y magnetic field measurements respectively.

$$\theta_M = \begin{cases} \frac{\pi}{2} - \arctan(\frac{M_y}{M_x}) & \text{if } M_x < 0 \\ \frac{3\pi}{2} - \arctan(\frac{M_y}{M_x}) & \text{if } M_x > 0 \\ \pi & \text{if } M_x = 0 \text{ and } M_y < 0 \\ 0 & \text{if } M_x = 0 \text{ and } M_y > 0 \end{cases} \tag{3.21}$$

Declination angle, which is the difference between magnetic north and true north, need to be added in order to get the actual angle. Since these experiments calculate the location with reference to the building, actual declination angle was not used.
Magnetic field strength and orientation are highly distorted indoors than in outdoors due to ferromagnetic materials and electric currents inside buildings [39]. Because of this,magnetometer reading does not provide a reliable source of correction. High distortion of magnetic field in indoors has been shown experimentally using “Magnetic Disturbances Detector” which avoids corrections at disturbed instances [34]. Analysis results of the magnetic field indoors for walking experiments are presented in section 4.2.2 under heading correction results.

Chapter 4

Results

Experiments were performed in two phases named: calibration phase and test phase. Walking data obtained in the calibration phase was used to find the optimized values for the necessary parameters and then they were used directly in test phase to calculate and compare the results. Variation of accuracy, with the amount of corrections in the proposed method was investigated. For this, 'Correction Percentage' was defined as the percentage of sensor reading samples per step at which corrections were applied and they were equally spaced for that step. Average error and standard deviation were selected as the final comparison metrics in test phase results.

4.1 Calibration phase

In the calibration phase, actual measurements using Stargazer and smart phone measurements for 15 straight walks of 15 m length were performed for each individual. This data was closely analyzed to find the best possible experimental values for the following variables.

- Four thresholds for the FSM step detection
- Constant K of the Scarlet method in step length estimation
- Parameters of velocity models

4.1.1 Thresholds for the FSM step detection

Total accuracy is directly affected by the number of steps in the walk for both INS and SHS techniques. Hence the accurate detection of steps is important in these applications. Acceleration signals acquired in this phase were analyzed individually for determination of threshold values, which were then averaged to reach the final values for the test phase. In this process, the lower positive threshold ("Thr" according to FSM algorithm) was carefully selected to be a lower value, since it mainly determines the start of a step. Detection and the threshold values are shown in figure 4.1 for a walk of 20 steps.

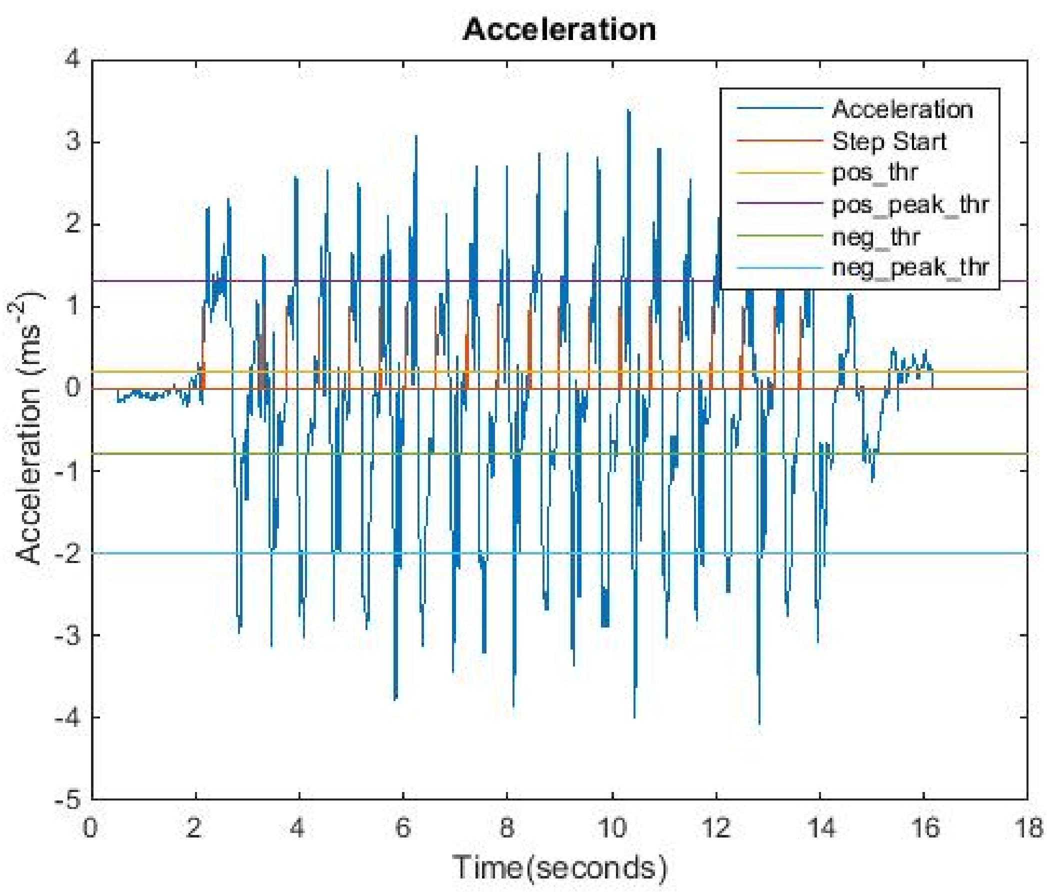


Figure 4.1: Detected steps by FSM algorithm with the acceleration signal and the threshold values for a walk with 20 steps

When the deduced thresholds were used in the FSM algorithm, overall step detection accuracy was 98.6% for the walks in this phase.

4.1.2 Step Length Estimation parameter

Constant K value in equation 2.2 for Scarlet step length estimation was calculated individually for the walks in this phase to minimize the distance error. These individual values were then averaged in reaching the fixed constant K for the test phase.

4.1.3 Velocity model parameters

Some parameters of velocity models were derived to match the shape of actual hip velocity and scaling parameters were selected to minimize the overall distance error of walks in the calibration phase afterwards.
Velocity shift, mean fraction constant and step fraction constant parameters of Gaussian model were selected as 0.9, 0.4 and 0.15 respectively to match the shape of the model velocity to actual velocity. Then the constant K was obtained by averaging the individual K values which minimized the position error of each walk in calibration phase.
In the Sinusoidal model, amplitude constant was used as 0.25 and shift scale factor was obtained as 1.29 experimentally in this phase.
In Sawtooth model, 0.2 for amplitude and 0.25 for width constant were used. Shift scale factor was obtained as 1.67 experimentally in initial phase.
Figure 4.2 shows an example velocity curve calculated from Stargazer measurements for a walk of 20 steps.

Due to practical way of holding the device while walking, stargazer system measures the hip level velocity on side of the body than in the middle, so that movement of left and right legs are felt differently. But in matching the model, a generalized curve was fitted.

4.2 Test Phase

Following experiments sets were performed in the test phase to find the accuracy of proposed approach using the parameters optimized in the calibration phase.

- Straight walk experiments
- Experiments along straight corridors with 90^0 angle bends

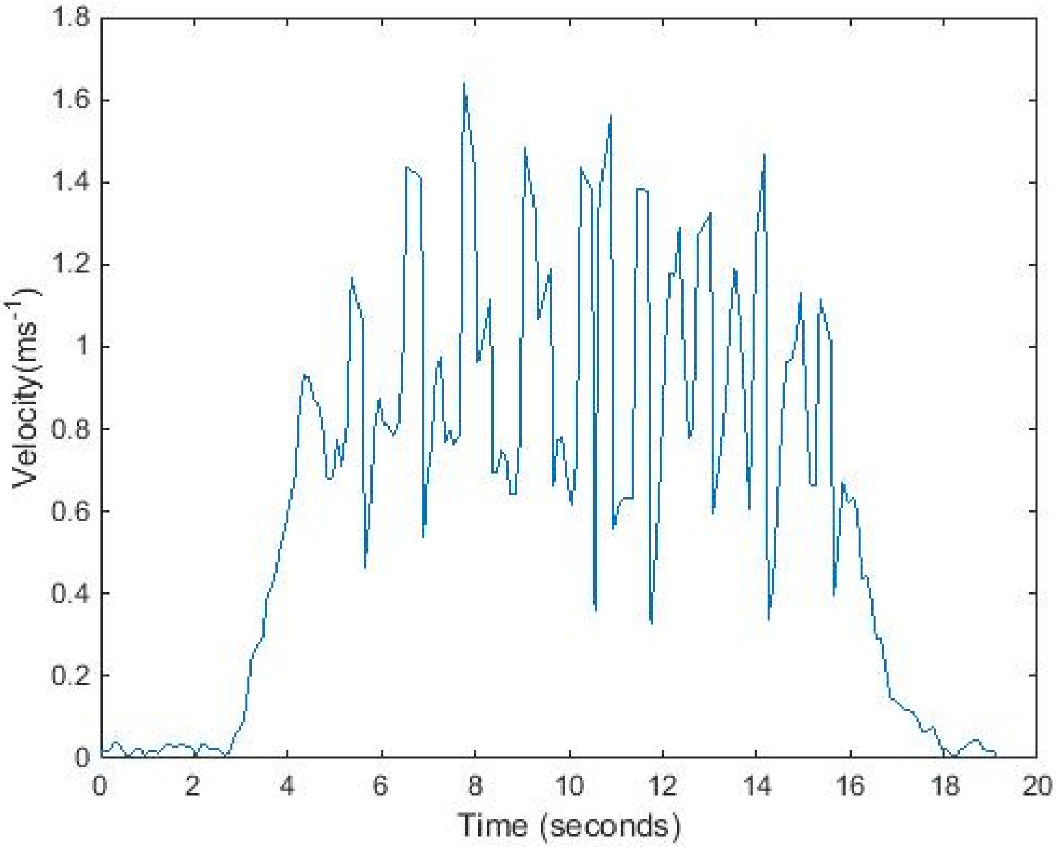


Figure 4.2: Actual velocity curve calculated from Stargazer measurements for a walk of 20 steps

Although most of the experiments were performed by the author, results by different individuals and different devices are also included to show the robustness of the proposed approach.

4.2.1 Velocity Correction

Feasibility of the distance correction based on actual velocity model and its performance compared to SHS method were first analyzed with straight walks. These straight walks were performed along one corridor for a distance of 40 m.

Because of bias and random errors of sensor units, it is common to have a large amount of drift within about one second with the basic strapdown INS. In this experiment, with the basic double integration of acceleration signal, an average error of 34.6m (±4.93m) for a 15m distance walk and an average error of 149.5m (±13.56m) for a 40m distance walk was observed. It was proposed to minimize this error by introducing an external correction derived from a velocity model. As expected, accuracy improved drastically when the correction was applied. Also the accuracy was high when applied with the complementary Kalman filter than the naive application. The average error was 1.8m (±0.69m) in Kalman filter application for Gaussian model where it was 2.1m (±0.95m) in naive application with a 10% correction percentage.

The velocity curve for a 15m walk is shown in figure 4.3. This shows how a large drift occurs in basic integration by the accumulation of small velocity errors which arise due to errors in acceleration readings. Then the velocity is aligned to a correct curve when corrections are applied. The position is also corrected along with the velocity correction based on the relation defined by Kalman filter transfer function.

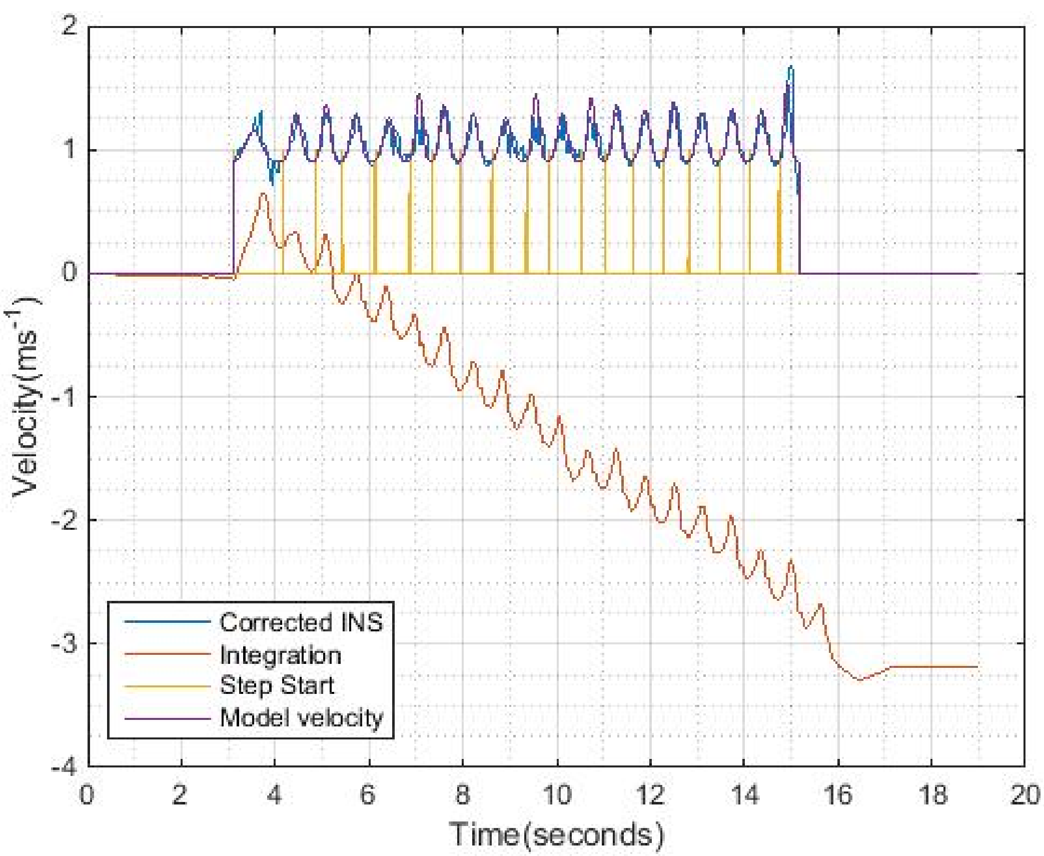


Figure 4.3: Estimated velocity for standard INS vs proposed method with corrections applied using Gaussian velocity model

Figure 4.4 shows the average accuracy and standard deviation values of INS with three different correction models and SHS method with the correction percentage of a step.

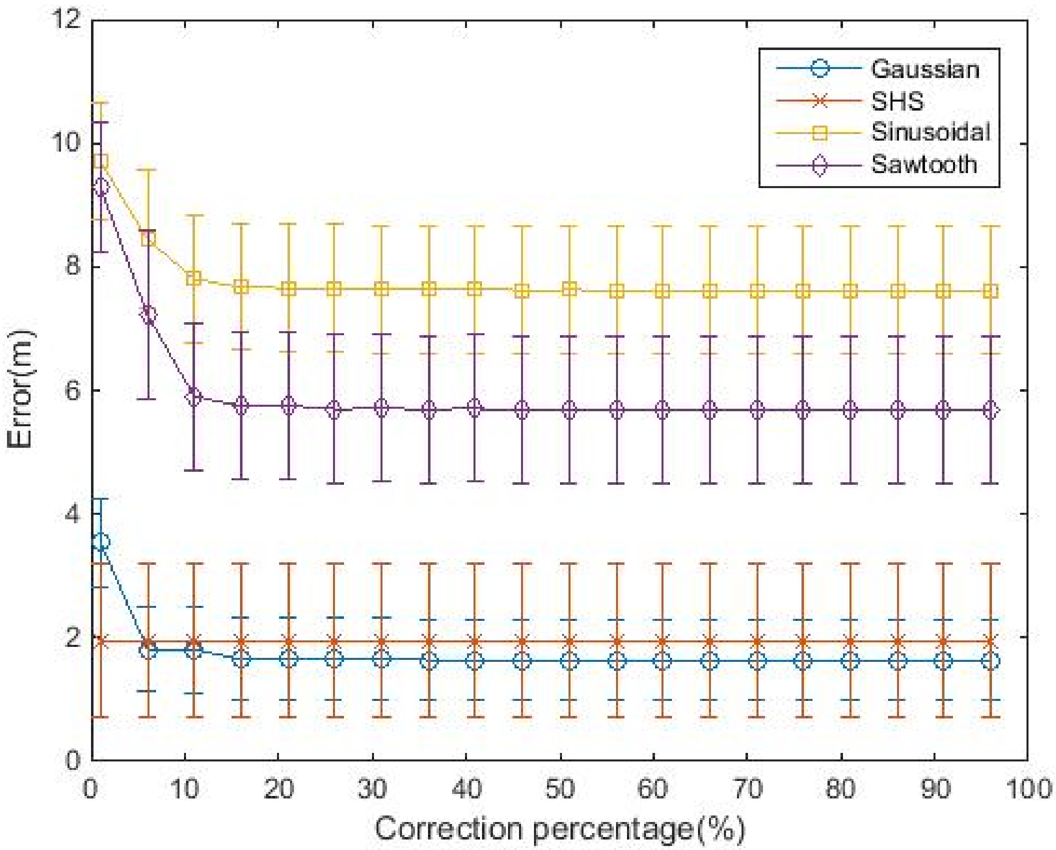


Figure 4.4: Comparison of SHS method and proposed method with three different models showing error vs correction percentage

Out of the three models, Gaussian model resulted in highest accuracy compared with others. We hypothesize that this is mainly due to its flexibility in matching the actual velocity curve by using the available parameters. From these results we observe that the proposed method with Gaussian model correction outperforms the SHS method with increased average accuracy and smaller standard deviation. The average error with 15% correction for 40m walk is 1.64.m (±0.66m) in proposed method with Gaussian while it is 1.94m (±1.24m) in SHS method. We can deduce that the proposed method is more robust than SHS as observed by the relatively small standard deviation in the proposed method. The accuracy variation with correction percentage shows that a minimum of 5% correction percentage is sufficient for improved accuracy and no significant improvement after 15%. Step detection accuracy was 98.7% in these experiments.

With the results from this experiment, we can deduce that the proposed INS system on smart phone with corrections improves upon the accuracy and robustness of the SHS method.

4.2.2 Heading Correction

Walks with turns along corridors were performed to find the feasibility and accuracy of proposed method with both distance and heading corrections.

20 walks on a corridor around the Thompson Engineering Building at Werstern was first considered in experiments containing turns. Corridors used in this experiments consisted of straight paths and 90^0 angle turns. Start and end points were the same where user walked back to the same point after walking for 124.36 m in about 120 seconds. In order to compare the accuracy of each method, two error measurements were calculated.

- Absolute error: Difference between actual end and calculated end
- Distance error: Difference in total distance travelled

Figure 4.5 shows the initial strapdown INS result along with the actual path taken. Because of accumulation of error present in the accelerometer and gyroscope, calculated path becomes highly deviated from the actual path. The absolute error in this was 485.6 m (±131.53 m) and the distance error was 1067.4 m (±248.5 m).

When only the distance correction based on Gaussian velocity model is applied for the velocity, error becomes relatively small. Paths generated by INS with Gaussian model correction and SHS are shown in figure 4.6.

Absolute error and distance error was 29.8 m (±6.6 m) and 9.1 m (±4.6 m) respectively for SHS while it was 29.0 m (± 6.6 m) and 8.8 m (±3.8 m) for INS with 4% correction percentage. Distance error comparison with the correction percentage is shown in figure 4.7.

The distribution of error with this 124 m length path shows a different distribution than the 39 m short straight walk. When the correction percentage exceeds 5%, error becomes relatively high. This is because of the velocity becoming too dependent on the velocity model rather than

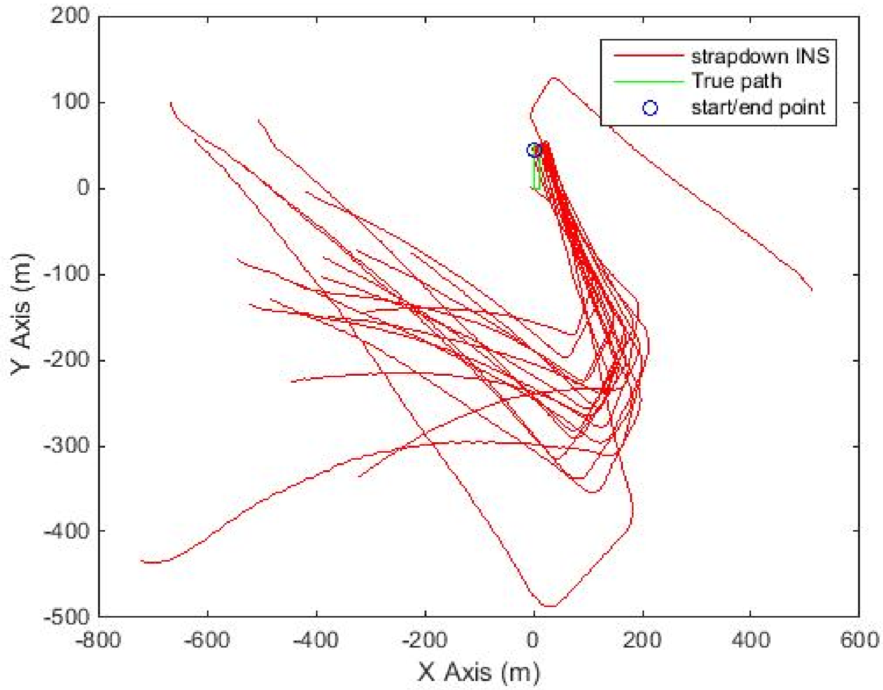


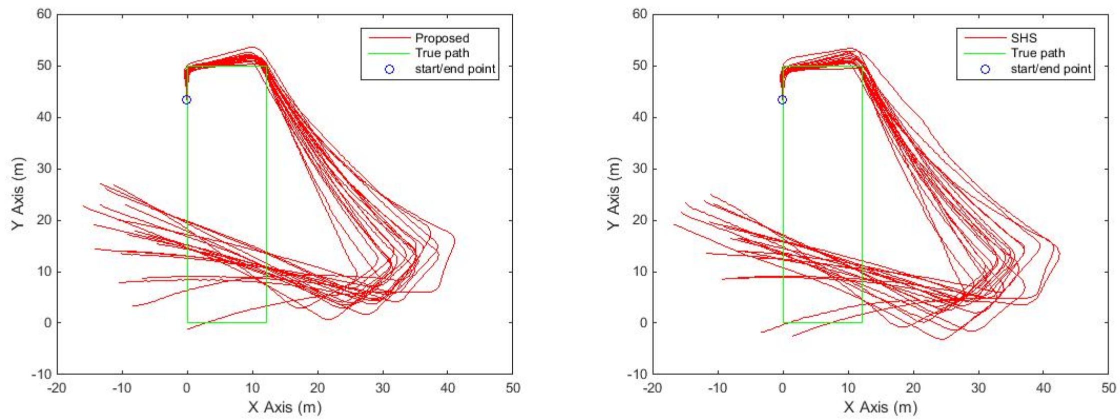
Figure 4.5: Paths estimated by basic strapdown INS along with the actual path

periodic corrections to keep the drift controlled. In particular, model can deviate from the actual velocity during turns. This was not considered when deriving the velocity model. But, standard deviation of the proposed method was always smaller when compared with the SHS method which shows the robustness of the method.

Distance error values for the three different velocity models for a correction percentage of 4% are shown in table 4.1 for comparison.

Method	Average error(m)	Standard Deviation(m)
Gaussian	8.88	3.82
Sinusoidal	18.12	10.14
Sawtooth	16.03	9.73
SHS	9.14	4.63

Table 4.1: Distance error comparison for INS with different models and SHS



(a) INS (b) SHS

Figure 4.6: Paths estimated by INS with Gaussian model distance correction and SHS method

Both corrections for velocity and heading were applied in to system as the next step. Absolute error was mainly used in comparison of performance of each correction method after the heading correction. In order to present a fair comparison, heading corrections were naively applied to SHS system too.

Magnetic Correction

Angle calculated from magnetic field measurements are shown in figure 4.8 for 20 walks along with the angle calculated by the gyroscope which shows the turns along the path.

Magnetic field measurements in the corridors of the building were highly irregular. Direct application of a correction based on magnetic field was not possible at this stage, since the measurements were affected by local distortions, this will require careful mapping of the magnetic field prior to using it as a source of correction.

Spatial constraints

Domain specific corrections were attempted for heading correction which resulted in improved accuracy for both INS and SHS. Improvements from these corrections were considerable as shown in table 4.2.

Figure 4.9 shows the paths determined after application of correction for 90^0 angle turns

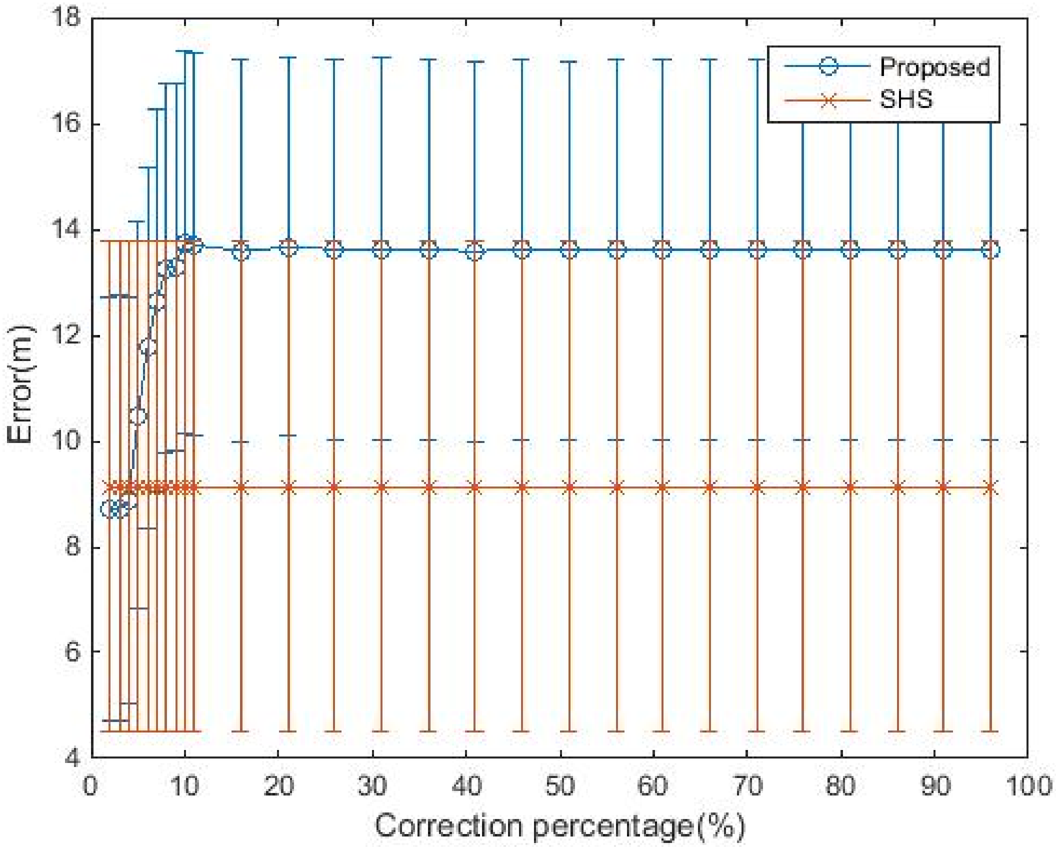


Figure 4.7: Comparison of SHS method and proposed method with Gaussian mdoel showing error vs correction percentage

for both INS and SHS.

Absolute error was 7.9 m (±4.9 m) for SHS while it was 7.8 m (±4.5 m) for INS after the application of this correction. Better results were observed with the proposed method in both average error and standard deviation compared to SHS approach.

If the angular velocity is below a threshold continuosly past a time interval (e.g. for three seconds), user was assumed to walk straight, hence a correction was applied to maintain the same walking direction. But, if the accumulated error in the heading direction at the point of application of this correction is large, it can further increase the drift, although it outputs a fine accurate path for some walks. The INS path with this correction is shown in figure 4.10 and a reduction in absolute error to 7.1 m (±3.3 m) was observed with the application of this correction.

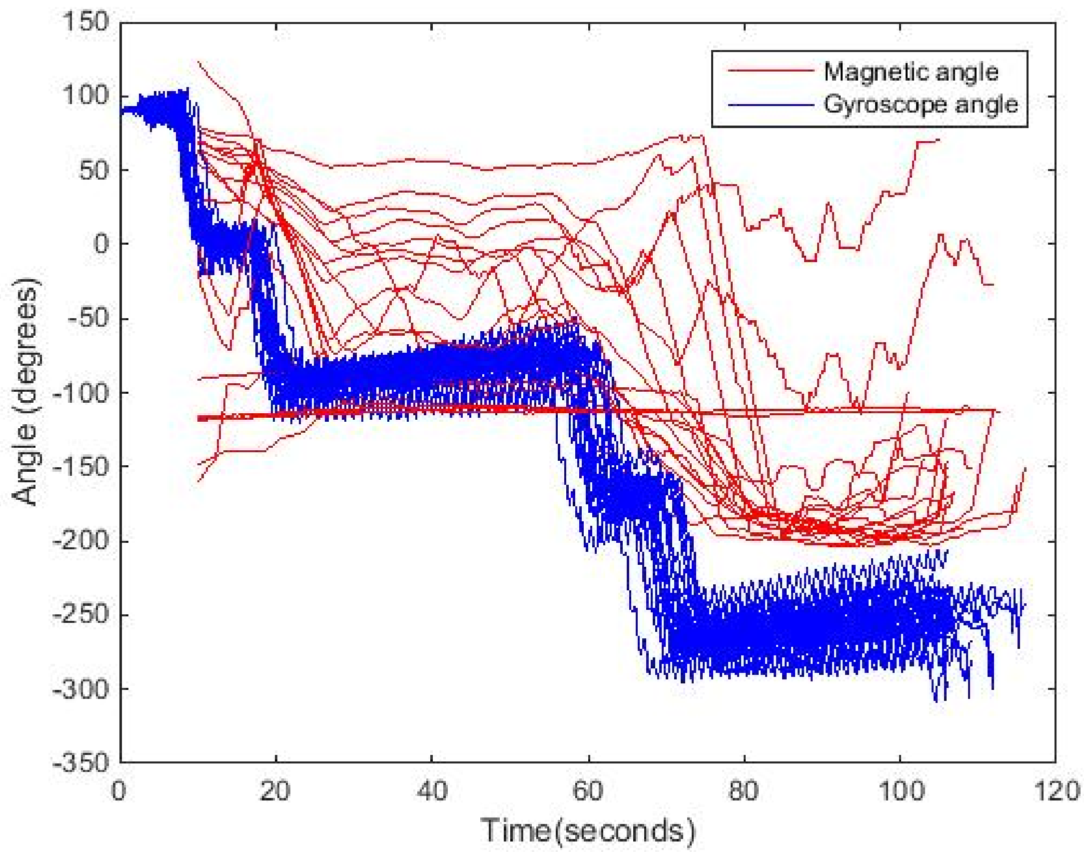


Figure 4.8: Low pass filtered angle calculated from magnetic field measurements along with the angle calculated by the gyroscope showing irregular measurements due to local distortions

Assuming a strict indoor environment with only 90^0 angle bends and straight corridors, more strict correction can be applied. Resultant paths with this correction are depicted in figure 4.11 and the absolute error was reduced to 3.3 m (±1.6 m)

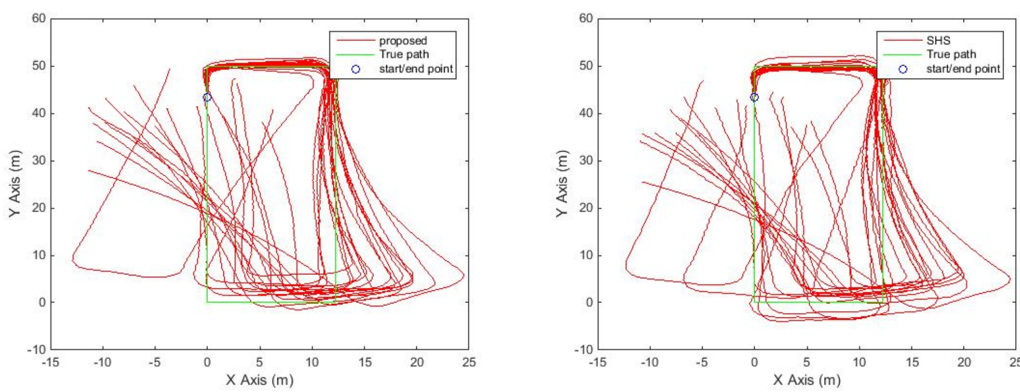
Absolute and distance error distribution with distance of the walk is shown in figure 4.12 for SHS and proposed method with corrections assuming strict indoor environment with only 90^0 angle bends and straight corridors.

Experiments of walks with combination of different indoor paths, different devices and different individuals were performed and analysis was done in proposed approach to show the robustness of the proposed approach. Three different example paths along with the calculated path is shown in figure 4.13.

Overall error percentage results are shown in figure 4.14 for comparison.

Correction	Average error(m)	Standard Deviation(m)
Velocity	29.0	6.6
velocity and 90^0 angle	7.8	4.5
velocity 90^0 angle straight	7.1	3.3
velocity strict 90^0 and straight	3.3	1.6

Table 4.2: Absolute error comparison with application of different heading corrections



(a) INS (b) SHS

Figure 4.9: Paths estimated by proposed and SHS method with the correction for 90^0 angle turn

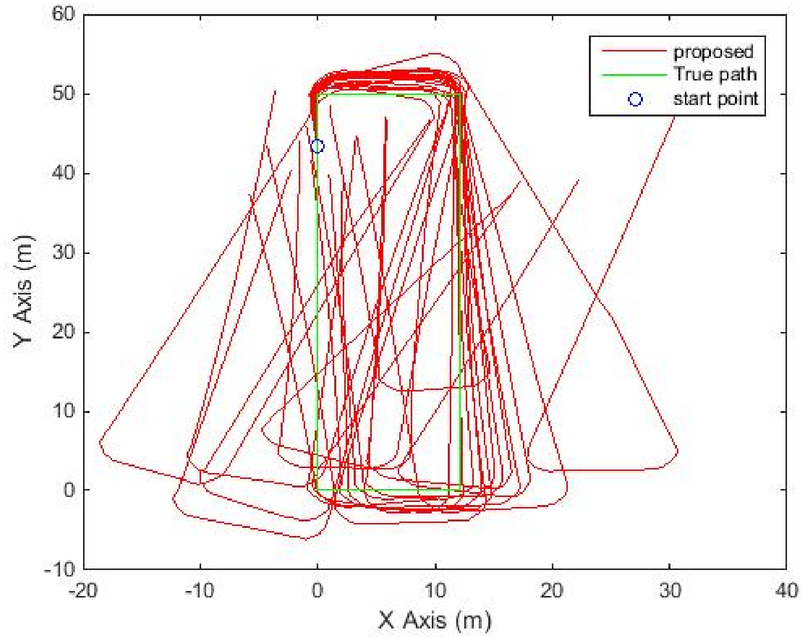


Figure 4.10: Paths estimated by proposed and SHS method with the corrections for 90^0 angle turns and straight walks

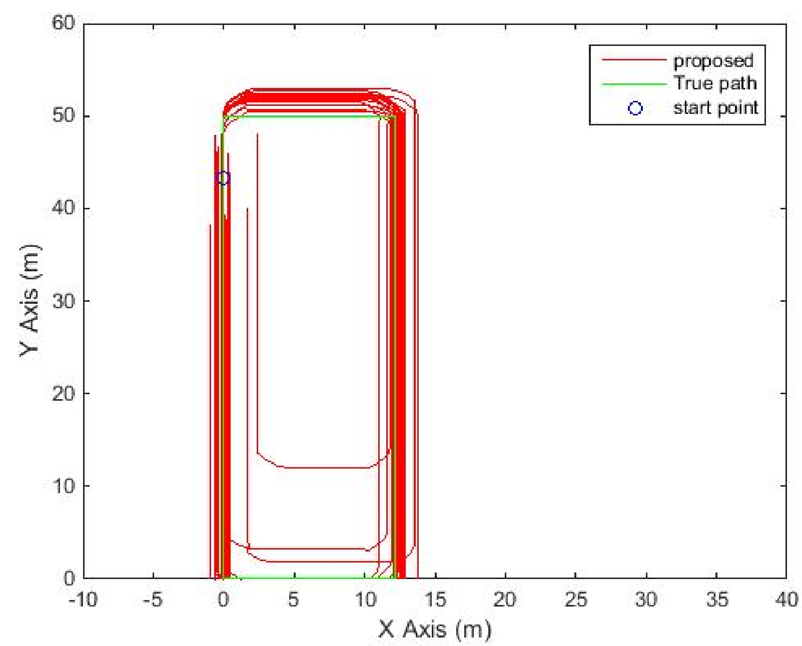
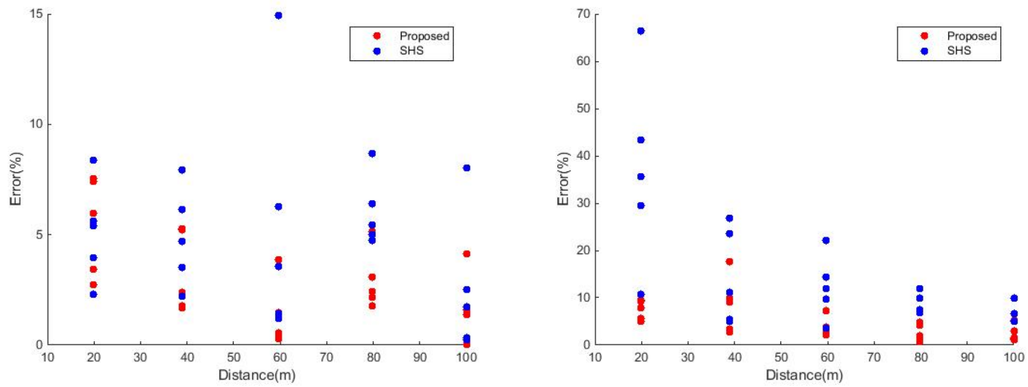


Figure 4.11: Paths estimated by proposed and SHS method with strict corrections for the 90^0 angle turn and straight walk only.



(a) Distance Error (b) Absolute Error

Figure 4.12: Absolute and distance error distribution with distance of the walk for SHS and proposed method with corrections assuming strict indoor environment

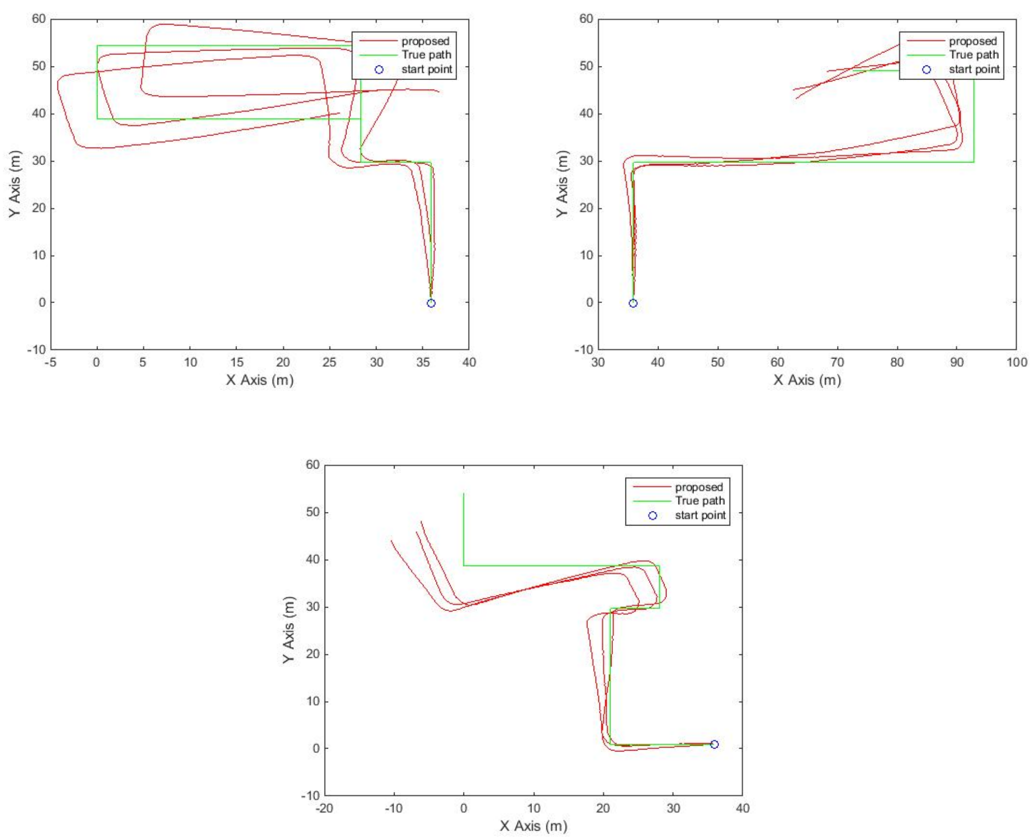


Figure 4.13: Paths estimated by proposed method for two different paths

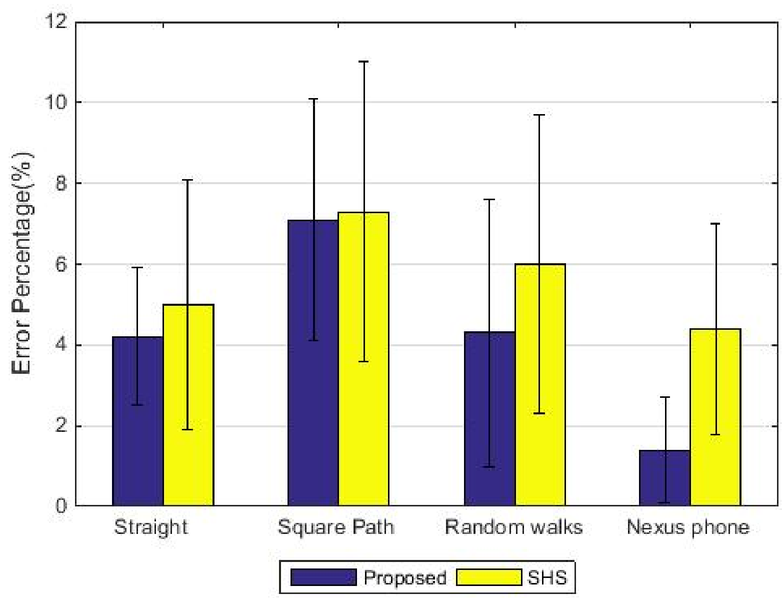


Figure 4.14: Distance error percentage for four different experiments of walks

Chapter 5

Discussion and Future Work

Indoor localization and tracking systems are currently an active research area because of its importance as a critical context in future context aware applications.
Current systems for smartphone based indoor tracking are dominated by fingerprinting systems and SHS based dead reckoning systems. Feasibility of INS based dead reckoning approach was explored in this thesis.
Competitive results were observed by the proposed INS based system compared to SHS approach. Error percentage was 4.3% (±3.3%) and 6.0% (±3.7%) for proposed and SHS respectively in experiments of walks consisted of different paths and individuals. Also it can be observed from figure 4.14 that proposed system resulted with smaller average error and standard deviation compared to SHS approach always in all experiment categories. A correction percentage less than 5% is required and sufficient for correction of velocity from the model for improved accuracy. Gaussian velocity model resulted in higher accuracy than other two models which is due to its flexibility in matching the actual velocity curve.
Although diverse walking experiments were utilized to demonstrate the performance of the proposed method, limitations and further development steps are discussed below.

- Experiments were performed only on indoor flat surfaces
  Proposed method was only tested for walking along flat surfaces. With the current implementation, special cases like walking along sloped surfaces and climbing staircases may not provide accurate location estimation because of deviation of actual velocity from the

velocity model that was employed.

- Our experiments did not include movements other than walking such as running or jumping. In order to accomodate these special movements, identification of the special movement from acceleration/gyroscope signal patterns is required. Then corrections from special velocity or movement models and other special corrections can be applied to the basic INS system. Research on activity classification algorithms can be utilized in movement identification. Further improvements in experiments need to include variety of indoor environments.

- Analysis was performed offline on a server rather than on the smartphone platform. Indoor localization application should ideally be included in the smart phone itself without the support of any external systems. This is required for security and privacy reasons as well as sparing the data usage of the user. Transmission of all sensor data in real time used a bandwidth of 0.85 Mbps (including both upload and download). This transmission can be avoided by implementing calculations in the mobile phone itself. Application development on resource constraint environments needs special attention on how the resources are handled in the program code itself. So, in search of the performance of proposed method, implementation on a server was carried out for pragmatic reasons such as faster development and easier troubleshooting. In moving the analysis to a smartphone, simple calculations with lower memory requirements are essential. In this thesis, simple methods were employed in implementation so that it can be easily deployed on to a resource constrained smart phone with an efficient implementation.

- Experiments were performed only for one common orientation of the phone at hip level. In first steps of evaluating the performance of proposed approach, analysis for one orientation is sufficient, since the the proposed method is independent of the orientation of the phone. Acceleration and angular velocity components along the walking direction, which were calculated by orientation of the phone, were used in this method. Hence extention of same equations to calculate Eular angles for other orientations of the phone can incorporate other orientations easily. This will include the scenario of smartphone being on trouser pocket too.

- With the use of FSM method, step detection accuracy was around 98% in these experiments. Identification of correct acceleration samples which belong to each step is important in this application. When dealing with more individuals, more reliable methods of threshold selection are required since general threshold values are not feasible with every individual. ROC curve approach suggested and tested by Diaz et al. is a good candidate for the selection and fine tuning of thresholds used for step detection [34].

- In the prototype system of this thesis, orientation was calculated using gravity component accessed by Android API. Tracking of orientation using Kalman filter state can be suggested as a further improvement. Instead of gravity sensor based calculation, gyroscope output can be used to keep track of the orientation after a initialization as used by many foot mounted sensor applications [38]. Then, orientation errors can also be related to positioning errors which allows orientation to be corrected with the application of velocity and heading errors using a advanced Kalman tranfer matrix.

- Magnetic sensor usage for correction of heading direction was not successful due to severe local distortions of magnetic field. Advanced magnetic calibration methods which has the capability to produce good results even with such local disturbances, can be utilized in corrections.

- Simple velocity models based on Sinusoidal, saw tooth and Gaussian were used in this thesis to model the actual velocity at hip level. More accurate actual velocity curves can be obtained by advanced velocity measurement systems such as video processing systems. When the velocity curve is more reliable, more accurate advanced velocity models can be generated using approaches like non linear regression which will result in improved accuracy.

- Kaman filter framework was used to apply the corrections in to basic INS system in the proposed method. Kalman filter was utilized instead of more advanced Particle filter because it requires too much computational resources. We have shown that with a simpler approach, we are still able to achieve better accuracy.

- Due to the variety of infrastructure, devices and deployment effort requirements and lack of uniform testing methods, comparison of different approaches is relatively difficult [27]. So, in this thesis, a SHS system which is the current best method in dead reckoning approach, was re-implemented for the comparison purposes. As a next step, other existing methods can also be re-implemented with similar indoor environment conditions.

With the results from this experiment, it is observed that dead reckoning systems employing low cost sensors cannot track users for a long period of time because of the exponentially accumulating drift from the actual location even with external corrections. So, dead reckoning can only be used to track only for a short time period using frequent initiations from reliable external location fixes. Fingerprinting systems, GPS fixes can be used for these initializations opportunistically. Indoor mapping guidance systems can use these dead reckoning systems to guide indoor passengers in an efficient way. This leads to a hybrid method implementations. These have already been explored with the use of maps and particle filters.

Finally, better combination of all these approaches should grow in to a navigation system indoors which will fit in to any type of indoors.

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Appendix A

Prototype System Architecture

In order to analyze the feasibility of the proposed method with the accuracy results, a prototype system was built using several hardware and software systems. Sensor data of a smart phone carried by a walking user was captured online and stored. Then this data was used offline in analysis algorithms. The prototype system consists of four main nodes named Mobile Node, Velocity Measurement Node, Server Node and Analysis Node and the architecture of the overall system is depicted in figure A.1.

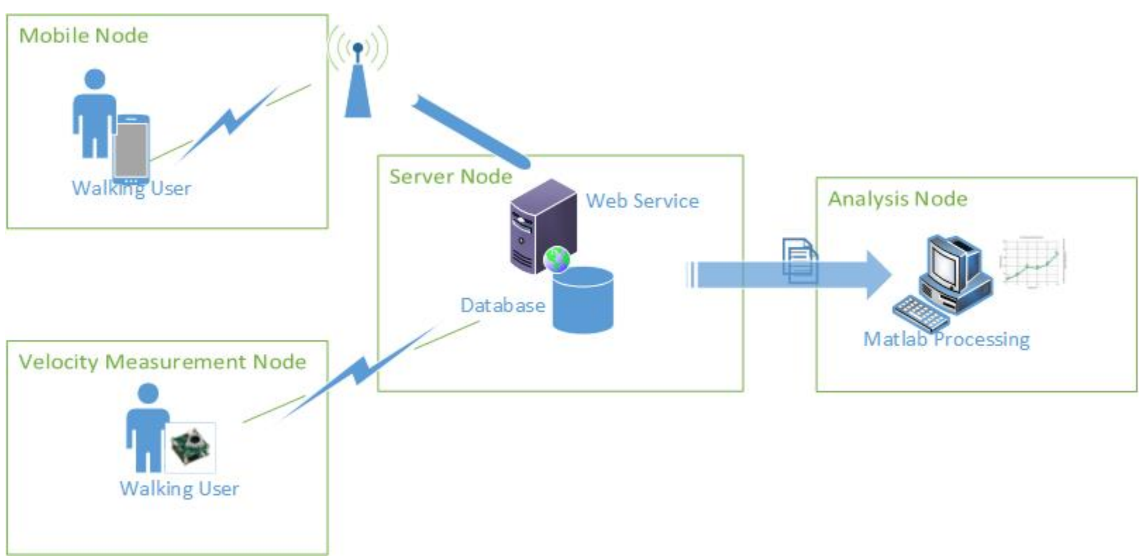

Figure A.1: Architecture of the prototype system used for experiments.

The main data capturing component is the Mobile Node which is the smart phone with necessary sensors, mounted on the hip of the walking user. Once started, mobile node captures the readings from the selected sensors and transmits them to the server node in realtime. The Velocity measurement node which consists of actual walking dynamics measurement unit, also transfers the data to the Server node. Data from velocity measurement node is used in development of actual velocity models and data from mobile unit is used in the actual positioning system operation. So, in this experiment, mobile node and the velocity measurement node does not necesasarily need to read and transmit at the same time. Server node accepts the data, stores them in the database and makes them available for further use. Analysis node extracts the data from the server node for the main analysis, interprets the results and sends them back again to the server node for storing and advaced user oriented display options.

A.1 Mobile Node

Android (an open source mobile operating system) based smart phone manufactured by Samsung was selected as the mobile node in this experiment. Android allows easy integration of external applications and resource access though available API. Smart phone details are summarized in table A.1.

Model	Samsung Galaxy S3 Mini I8190N	LG Nexus 5
Platform	Android v4.1	Android v5.0
Resources	1GHz dual-core CPU, 1GB RAM	2.3GHz Quad-core CPU, 2GB RAM

Table A.1: Details of the smartphones used in experiments

Phone was placed in a case connected to hip level belt vertically. This positioning is not a highly restricted mounting and is a common way of holding the phone. However, in these experiments, phone was placed facing walking direction, so that the Roll angle approximated to zero.

A custom Android application was made for the phone to run in this experiment which performs the following tasks and the application interface is shown in the figure A.2.

- Sensor access

  Following sensors were used in this experiment. Sensor readings are relative to phone

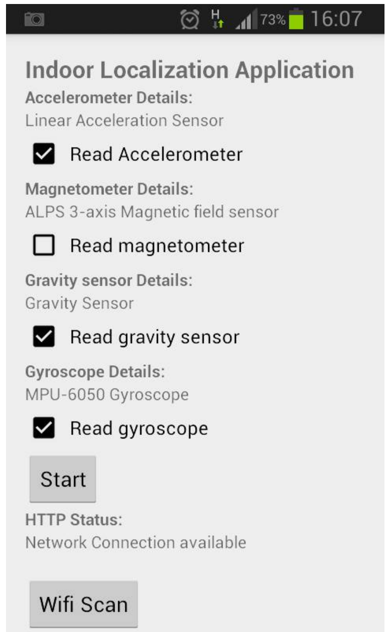

Figure A.2: Interface of custom Android application developed for smartphone.

body which are based on the reference axis system depicted in figure A.3 and each reading consists the timestamp.

- Linear Acceleration Sensor
  This sensor provides the 3-dimentional vector for acceleration along each axis without the gravity.
- Gravity Sensor
  The 3-dimentional vector with the acceleration due to gravity.
- Gyroscope Sensor
  The 3-dimentional vector with the rotational velocity of the phone around each axis.
- Magnetometer Sensor
  The 3-dimentional vector with magnetic field intensity in each direction of the phone.

• Reading frequency
  Different sensor types have different rates at which the readings can be accessed based on hardware capabilities. API allows the use of two reading rate types called Normal

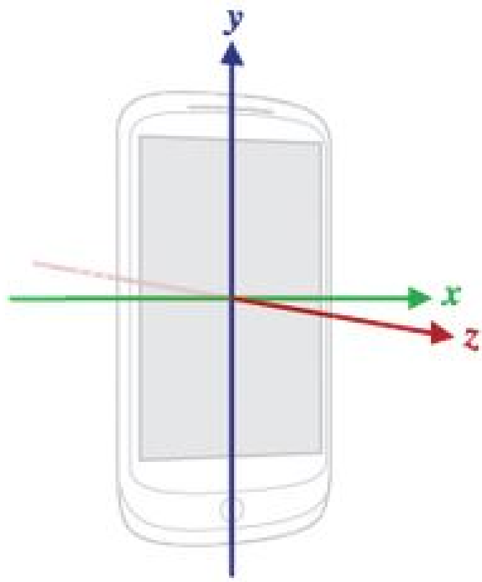

Figure A.3: Cartesian reference system on smartphone (local) frame.

Delay and Fastest. For the sensor types used in this experiment, normal delay frequency was 20 samples per second (20 Hz) and fastest was 100 Hz. Rate of 100 samples per second was used throughout the experiments in this thesis.

- Data Transmission

  Sensor reading data is transmitted to server node using the data connectivity of the phone (Wifi or cellular data). Standard client-server communication in REST (Representational State Transfer) architecture on HTTP protocol was used in this process. Measurements were transmitted in batches after been formatted in JSON data format. JSON format was chosen because of the integration efficiency with the chosen webservice in server node providing easy reading, handling and storing capabilities.

In a walking experiment, application waits for 10 seconds after pressing the start button to start reading and transmitting sensor data. This allows the user to press start and place the phone accordingly.

Actual time, actual number of steps and actual walking length were also recorded along with the sensor data for each walking experiment.

A.2 Velocity Measurement Node

As a supporting waveform for the actual velocty model derivation which is used for corrections, hip level velocity was measured by a system commonly used in robot indoor localization applications. Robot indoor localization system by "Hagisonic" called "StarGazer Indoor Positioning System" was used in these experiments [40]. This system is shown in figure A.4.

Figure A.4: Hagisonic StarGazer system

System details from the manufacturer are summarized in table A.2.

Model	HSG-A-03
Measurement Time	10 times/sec
Repetitive precision	2 cm
Hardware interface	UART
Communication protocol	User protocol based on ASCII code

Table A.2: Details of Stargazer indoor positioning system

System consists of an infrared projector, an infrared camera and a processing unit connected by an UART interface. Location is estimated using passive labels placed on the ceiling. An example of a label is shown in figure A.5

Basic operation is summarized below and is depicted in figure A.6.

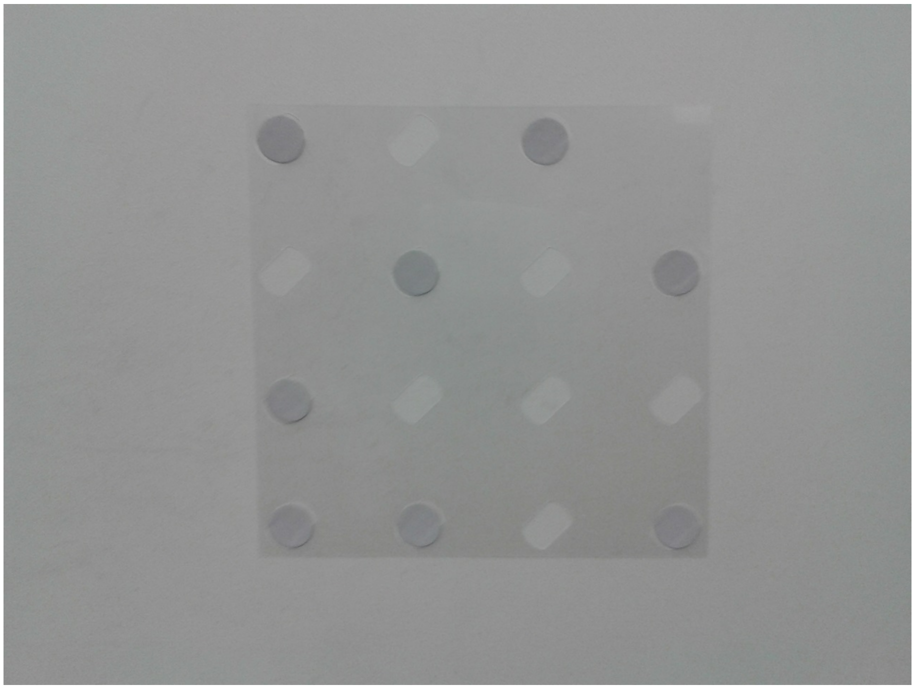

Figure A.5: A label used with Stargazer system

- IR projector projects IR towards the passive label
- IR camera aquires the reflected IR and it is converted in to a image
- Digital image processing on aquired image calculates the position and direction
- Output the calculated location periodically via UART (Universal Asynchronous Receiver Transmitter) interface using proprietary protocol based on ASCII.

System operates in two modes named 1) Alone and 2) Map mode. In alone mode, only one label is processed and the estimated location is relative to the single label and coverage is limited. Map mode estimates the distance in a cordinate system based on one selected label across multiple labels covering an area of interest. Map mode requires the proper placing of labels without any dead zones and a prior survey thougth them so that labels are learnt and stored in device memory. Once the mapping process is completed, system outputs the location accurately with a frequency of 10Hz through the UART interface. In the operation of the device, serial communication allowed through UART interface enables the reading of data as well as sending commands to the device.

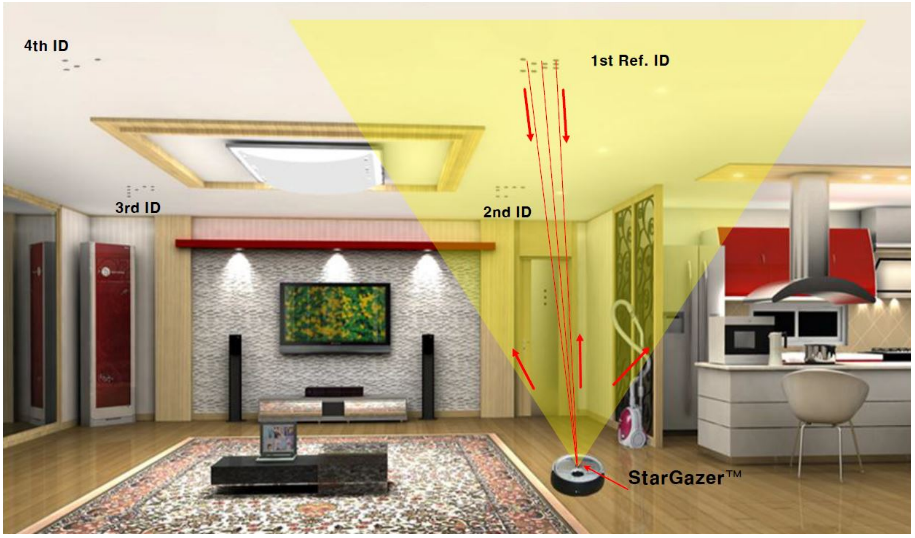

Figure A.6: Demonstration of Stargazer operation in MapMode. From product manual [40]

4x4 labels (shown in figure A.5) in map mode were used in this experiment. In order to make it flexibe and fit on to this experiment setup, two major modifications were required.

- Power Supply requirement

  System required 5V supply for the processing board and 12V supply for the infrared camera and emmitter operation with an average current of 5mA and 90mA respectively. This power supply was implemented by a 12V battery with a 7.0 Ah capacity providing 5V voltage using a voltage regulator.

- UART connectivity to server

  UART interface available in the device communicates with a baudrate of 115200 bits/second. Since a wireless connection to the server is more preferable in this setting, serial coommunication was achieved using Zigbee protocol. Serial communication capability in transparent mode configuration of two Xbee radio devices were utilized. One radio module was configured as a leaf node and connected to the stargazer device while the other radio was connected to the server after configured as a cordinator.

Data bits received from the device are coded in ASCII and packets are formed using a format described in the manuafacturer's manual. So, a custom program was written in Java to implement that specific protocol and enable following operations.

- Read data from the system
- Write user input commands to the system
- Store positioning data received from the system in database. (Data was stored in the same database which is used for sensor data by web service)

A.3 Server Node

Other three nodes are connected to the server node using different communication protocols as below.

- Mobile Node: HTTP protocol based client server communication
- Velocity Measurement Node: Zigbee serial communication
- Analysis Node: TCP/IP communication enabled by MongoDB Java driver

Web service can be considered as the main component in the server node. In practice, software bundles are used for web service implementations so that they are well integrated to each other making it easy to develop the application. LAMP (Linux Apache MySql Php) and MEAN (MongoDB Express AngularJS NodeJS) are two major open source software bundles in use currently. MEAN stack, being the newest and most flexible bundle available, was used to implement the web service in server node. Web API interface was built in NodeJS language with Express framework and database was created using MongoDB which is an no-sql, document based system. Webservice followed the standard RESTful architecture by providing standard operations as below over HTTP protocol.

- GET : Output data for calculations or display purposes. e.g. get the current position to display in the browser
- POST : Receives data into the database. e.g. Insertion of sensor readings in JSON format with a data label for each sensor type.
- DELETE : Deletes selected measurement reading collection. e.g. delete the old position data

- UPDATE : This operation was not implemented since no modifications were needed for the data itself.

Server node was running the web service on port 8080 which allowed using “http://< server address>/api” for above operations.
Mongo database, which was accessible through the default port 27070, was used for standard database actions. Store and select actions on data were performed using NodeJS mongoose package (in web service) and Java Mongo driver (in Stargazer data and Analysis node connection).

A.4 Analysis Node

After the online data collection process, main analysis and algorithms were implemented in matlab. Aquired data was made available to matlab by using files created through intermediate Java application accessing the MongoDB through MongoDB java driver.
Calculated data was analyzed using plots and tools available in Matlab and location data were passed back to Mongo database to be used in other visualization (eg. In a web page) through webservice in server node.

Appendix B

Kalman Filter

Bayesian Filters are used in many applications to estimate the "State of a dynamic system probabilistically. In Bayesian filter, state of a system is represented by a probability distribution function called "Belief" and is defined in equation B.1 [41]. x_t and z_t are system state vector and measurement vector on system at time t respectively.

$$Bel(x_t) = p(x_t|z_1, ..., z_t) \tag{B.1}$$

Current belief of the state depends on measurements of system up to the current time. Normally in applications, systems are modeled using Markov process in which it is assumed that, current state depends only on the previous state. When Markov assumption is made, Bayesian state estimation can be simplified by current state being an update on previous state.
Different approaches have been proposed to implement the Bayesian filter and Kalman Filter is the most popular implementation used in many applications.
Kalman filter further assumes,

- Probability distribution or the belief of the system state is always Gaussian distributed
- Relationship between current and previous state is linear i.e. system evolves linearly.

In Kalman filter with above assumptions, next system state x_{t+1} is predicted by equation B.2 using current state x_t. F is defined as the "State transition matrix" which defines the linear relationship and Q is the noise variance of the state.

$$x_{t+1} = F * x_t + Q \tag{B.2}$$

Any measurement on the system can be related to the current state using the measurement matrix H using equation B.3 where y_t is the measurement with error variance denoted by R.

$$y_t = H * x_t + R \tag{B.3}$$

Estimate of the next state $\hat{x}$ is defined using equation B.4 where G is "Kalman Gain" and α is the "Innovation" which is defined in equation B.5.

$$\hat{x_{t+1}} = F * \hat{x}_t + G_t * \alpha_t \tag{B.4}$$

$$\alpha_t = y_t - H * \hat{x}_t \tag{B.5}$$

Value of Kalman gain which minimizes the variance of the estimate state (Error covariance matrix denoted by K) is solved by differentiation and the result is shown in equation B.6.

$$G = K_t * H' * (H * K_t * H' + R)^{-1} \tag{B.6}$$

Corresponding minimum value of error correlation is denoted in equation B.7.

$$K_{t+1} = K_t - G * H * K_t \tag{B.7}$$

Kalman filter employs two stages in above steps as prediction and update. Prediction estimates the next state according to transition matrix and update phase updates the estimate using the measurement for optimum solution. This process is repeated to track the state of the dynamic system continuously. Process is described with examples by Hargrave [42].

Curriculum Vitae

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