User Displacement Estimation in Indoor Environments with Smartphone using Runge-Kutta Method

by

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Abstract

Estimating user position in indoor environments relative to the indoor space is a challenging problem. Especially when it must be obtained without infrastructure or any added costs to install the system. User displacement estimation in Indoor environments with smartphone using Runge-Kutta method presents efficient method using self-contained inertial sensors with no additional infrastructure to solve this problem. The accelerometer, the rotation sensor and the magnetometer sensor are three main sensors used in this method. The algorithm derives the user position with Runge-Kutta method using inertial data collected from the user smartphone while the user is in motion. The magnetometer data is used to self-correct the any existing noise in the user displacement. This method was experimented for various user motions like walking, wheelchair and driving. The results demonstrate that accumulated error rate and heading error rate were significantly reduced.

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I appreciate the process of learning and thankful to auburn university for creating such opportunities. I would like to show my gratitude to my committee chair Dr. Wei-Shinn Ku for giving me this opportunity and providing guidance throughout the research. I would like to thank my committee members Dr. Senthil Kumar and Dr. Cheryl Seals towards completion of this work. I would also like to thank my colleagues, friends and family for their support.

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Chapter 1: Introduction

Societies are changing towards urbanization and almost half of the world populations is living in and around urban areas. Be it University, Shopping Mall, Office Space and other relevant areas, people are spending time in indoor spaces more than ever. The number of tracking applications created are increasing day by day which uses the localization techniques in backend to answer the user queries. Navigation in indoor spaces is used to reach from one point to another. Currently, we only depend on signs, directions and human help to reach the destination point in Indoor environments. For Example, reaching a food station from a shopping store in a multi-storied shopping building can be challenging and demands a lot of our time. Outdoor navigation is supported by GPS, but its services are not extended to indoor spaces for various reasons like frequency, collisions, bandwidth and other associated reasons. When it comes to indoor localization which means identifying user location relative to the indoor space the user is in, the existing solutions like GPS, Cellular positioning are not applicable.

Various technologies like RFID [1]–[3][4][5], Wi-Fi [6] and ultrasound [7] were proposed for better indoor localization. Each technology has its own challenges while implementing the solution. Wi-Fi and RFID used Solutions are based on installed infrastructure. Solutions using Ultrasound need model training before they can be put into use. It is still an open question when it comes to reducing the complexity in helping the user to navigate indoor spaces.

Smartphones have become part of our lives. The number of smartphone users is growing tremendously year over year. As the technology is becoming increasingly intelligent, smartphones come with various sensors that aid many current researches in indoor localization. Utilizing this feature of the smartphones, sensor based pedestrian tracking models have been developed. PDR (Pedestrian Dead Reckoning) [8] is one such model that is based on smartphone sensors. In this PDR model, detecting number of steps and displacement is calculated. It uses estimated step length and heading to identify the user position. This type of model accumulates error in the step length estimation. As the model based out of steps, the approach will not be applicable to different moving patterns where step estimation cannot be derived like Wheelchair Navigation and Vehicle Navigation. In case of user motion with wheelchair the algorithm is not efficient to produce navigation results as step estimation is not applicable. Similarly, in case of driving or vehicle navigation also step estimation cannot be implemented it may not be the efficient. Solution for vehicles searching for a parking space in shopping mall and other public places would need an approach that is independent of step calculation. Other research focusses on integrating PDR with Wi-Fi localization [9][10] with Kalman and Particle filters. As this model also depends on PDR it carries over the same drawback of step detection for non-walking user motions along with Infrastructure installation.

Runge Kutta (RK) method is an iterative model and is widely used in temporal discretization for approximation-based solutions. The main aim was to minimize the displacement error and heading error in calculating the user position and improve the location accuracy. We will utilize the smartphone inertial sensors and collect data to calculate the displacement of the user with Runge-Kutta method. Runge-Kutta method estimates the user displacement and updates the system iteratively over time. Accelerometer records change in velocity of the user along the three axes in the device frame which can be transformed to navigation frame to calculate the displacement. To reduce the accumulation error in user position estimation and heading direction, magnetometer data is used to self-correct the error.

The remainder of the thesis is organized as follows. Chapter 2 reviews the related work in the field of Indoor localization to estimate user position. Chapter 3 shows the details of the system model. The estimation approach is mentioned in Chapter 4 and the experiment details are discussed in Chapter 5. Finally, conclusions and future directions are presented in Chapter 6.

Chapter 2: Related Work

Gradual increase in use of intelligent sensors in smartphones has made many of our jobs easy. In most of the cases it requires basic commands to proceed with the user wanted feature to popup and perform its functionality. When it comes to Navigation, Identifying the user location is very important to recommend user with various service options. When it is confined to indoor spaces it has become challenging. The outdoor navigation is efficiently done with GPS but do not satisfy the Indoor navigation environment for various reasons.

Existing Indoor localization approaches can be categorized as Wi-Fi based localization, RFID based, Ultrasound based and Pedestrian Dear Reckoning models. Other models primarily are combinations of any of these above-mentioned approaches. In case of Wi-Fi localization as mentioned in [11] is based on infrastructure and huge location datasets to identify the user position. After the installation of the required setup the experiment is based on the wireless signals and geometry between the installed access points (APs) in the given range. Methods such as pattern matching, nearest neighbor and trilateration can be used to find the user location.

The nearest neighbor method depends on the Access point range to identify the location. Usually, this method gives the range of user localization and often used to correct the localization obtained through other available methods. In other method named trilateration at least three access points needs to be installed in the indoor space. Each access point stands as a center for the range created by it and intersections of these ranges will be used to locate the user location. Pattern matching which uses huge datasets depends heavily on database collection. This database stores the object movement data relative to the indoor space. Maintaining the databases for various indoor spaces and their relative datasets is a burden in such kinds of methods. Prior collection of moving data, maintaining the data associated with each indoor space are some of the challenges in this method. [3] RFID technology-based systems mainly contains three major components RFID tag, Antenna and a Reader. The RFID tag when activated by RFID reader the encoded information is collected and stored in the database. The tag encoding associated to the location is used to derive the latest results for user location queries. As mentioned in [12] the model that feeds on RFID data uses particle filter method to infer the user location. Many models like indoor walking graph and anchor point model are developed to track the object throughout the indoor space.

In case of Pedestrian Dead Reckoning(PDR) method mentioned in [13][8] detects user steps by integrating the sensor data with WLAN location data to estimate the user position. These sensors provide multiple measurements based on movement, distance and direction. Also, by estimation of step length, the distance measure and user location can be calculated. [14][15] Integrating various methods can help us to take advantage of various features each method can offer. Integrated PDR and Wi-Fi is a popular approach among them. The location error created while running in PDR models can be corrected using Wi-Fi locations by utilizing the particle [16] or Kalman filters [17]–[21].

The proposed method is not dependent on any infrastructure or any prior training of the system. Fundamentally, it utilizes the inertial sensor data recorded in the user’s smartphone. It is different from PDR model which uses the inertial sensors data in the sense that no calculations of steps and fixed estimation of user step length are used. As the model is independent of such user step details it can be used in other various navigation patterns such as wheelchair or vehicle mode.

The proposed method calculates the displacement [21]of the user position without the detection of steps. The inertial data is collected and calculates the displacement using mathematical techniques. The method does not implement estimating the user step length which is a big difference between PDR algorithms and the proposed algorithm. To avoid the noise, measurements recorded in acceleration data is transformed using the attitude of the phone. Runge-Kutta method is used to reduce the error in the process of calibration. To support heading movement of the user, magnetometer data is used.

Chapter 3: System Design

This chapter has all details regarding the system design of the proposed solution and how Runge Kutta method is used to estimate the position. The proposed model exists independently without depending on any infrastructure in the Indoor environment around user. All the components and their role towards the process are explained below.

3.1 System Description

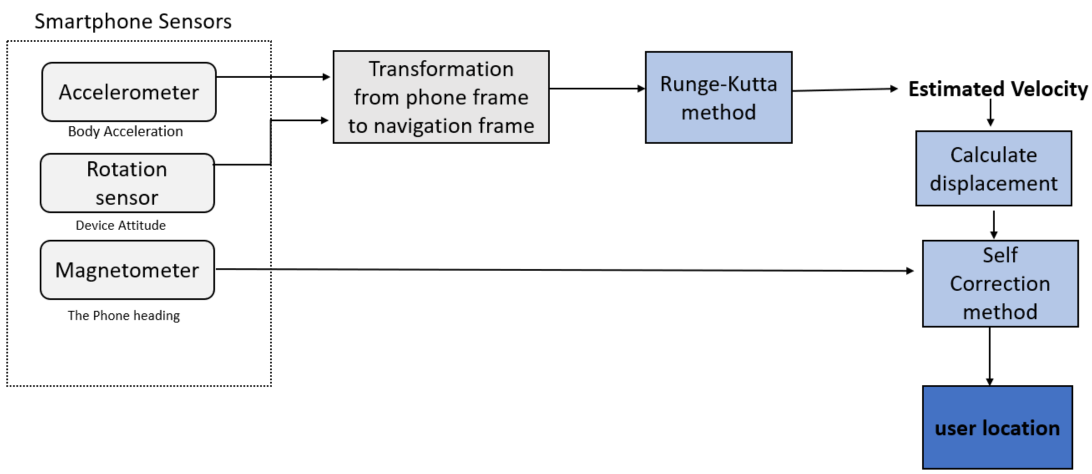

Figure 1: An overview of the system model

The proposed system is based on inertial sensors on smartphones. The main inertial sensors used in this work are accelerometer, device motion sensor and magnetometer. The Accelerometer sensor collects the user acceleration along three perpendicular axes x, y and z. The Device motion sensor records the rotation angles the pitch, roll and yaw. The Magnetometer sensor collects the data relative to the earth's magnetic north. These inertial sensors are embedded in almost all the smartphones that are available to users in recent times. The measurements are recorded usually in phone frame of reference and are transformed to the navigation frame of reference before they are further processed to derive the velocity. Runge-Kutta method is applied to this transformed data to measure the velocity of the user. Applying basic laws of motion, displacement is derived. The data set collected from the smartphones also consists of the data which provides phone heading which is fed into the system to self-correct the errors that might have occurred in the above calculation of user displacement. After performing one step of self-correction on the displacement, these observations are integrated to identify the location of the user from his initial position. The system is iteratively updated with the user location.

To perform this experiment, all the readings related to three inertial sensors were collected using a Smartphone (iPhone 7). Table 1 refers to all the notations that are used in this work.

Table 1: Symbols and Description

Symbols	**Description**
$l(t)$	The location at time t in the navigation frame
v_n^t	The Velocity at time t in the navigation frame
a_n^t	The Acceleration at time t in the navigation frame
a_p^t	The Acceleration at time t in the phone frame
t	Time
$C_{p,n}^t$	The Transformation matrix at time t
φ, θ, Ψ	The attitude of the phone
ΔT	Iteration period

α	Heading difference
$dis(k.\Delta T, \Delta T)$	Measured displacement between a time interval

3.2 Moving Patterns

Sensor enabled smartphones made possible to collect large sets of user motion data and identify various moving patterns. In the proposed method, the work focuses on walking pattern, wheelchair pattern and driving pattern. The below sections explain in detail how the data is collected and considered in the three types of moving patterns.

Walking Pattern:

The user carries phone while walking in indoor space. The location of the user and phone are considered same. The data from the inertial sensors is collected while the user is walking with the phone. The walking pattern of the user is also video captured to maintain the ground truth and validate. This type of moving patterns is generally applicable to larger section of people who navigates in indoor spaces.

Wheelchair Pattern:

The user carries phone and will navigate the indoor space using the wheelchair. The location of the wheelchair, user and phone are considered as same in this work. Like walking pattern, the wheelchair navigation is also video captured to maintain the ground truth. This section of moving pattern is applicable to group of users who uses walking aids like wheelchair to move from one place to another. The data is collected when the user is in motion in Indoor spaces using wheelchair.

Driving Pattern:

The user carries phone and will navigate the indoor space through a vehicle. The location of the vehicle, user and phone are considered as same in this work. Wheelchair and vehicle operate at two different types of motion which is why these are considered as separate groups. The data is collected when the vehicle is in motion and not while it is stationery. Like above patterns the vehicle motion is also captured visually to maintain the ground truth.

3.3 Reference Frames

There are two reference frames in the proposed model: the phone reference frame and Navigation frame. In this section relationship between two reference frames will be established

Phone Frame/ Body Frame:

Sensor enabled smartphone is the key component of the model where we observe the user motion through various sensors. These sensors collect the data according to phone reference frame or Body Frame (p-frame). The phone reference frame has x, y and z axis with origin defined at the center of the phone. These axes should be considered fixed to the device and can be also be referred as body frame coordinate axes. The x-axis is along the short length of the device pointing positive axis toward right and negative axis toward left. The y-axis is along the long length of the device pointing positive axis towards the “on” button and negative axis towards the “home” button. The Z-axis is pointing away from the face of the iPhone pointing positive away from the front screen and negative away from the back cover. The orientation of the axes follows the Right-Hand Rule. The acceleration measured in the body frame is denoted with a_p^t,

where a_p^t = $[a_{p,x}^t, a_{p,y}^t, a_{p,z}^t]^T$ acceleration along x, y, z axes at time t respectively. Figure 2 show the illustration of phone frame of reference.

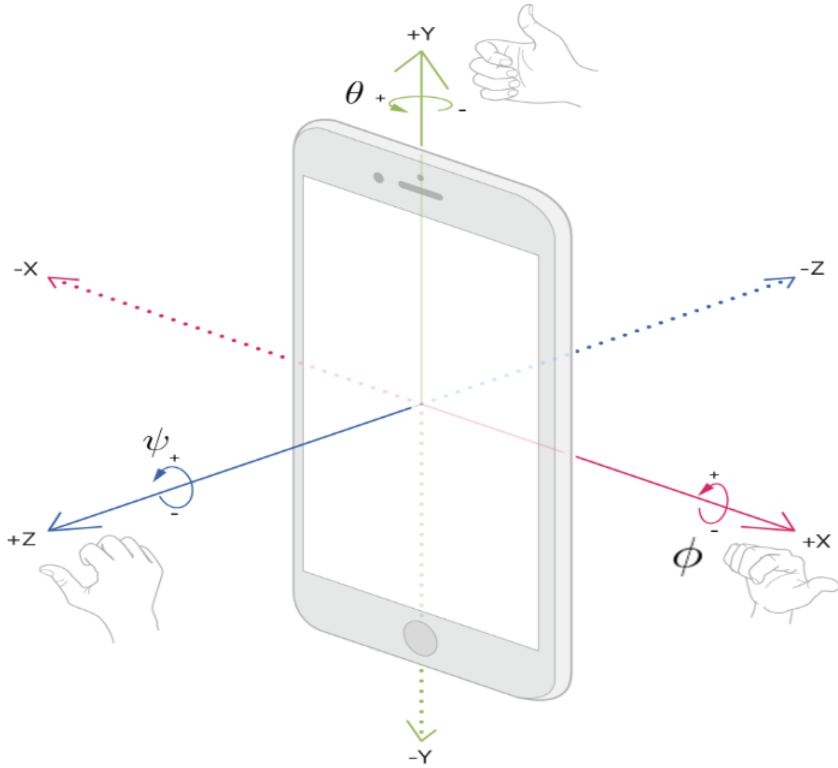

Figure 2: The Phone frame of reference

Navigation Frame/Earth Frame:

The second frame of reference which is called Navigation frame or Earth frame (n-frame) whose origin is defined at the fixed point in the indoor space map as shown in Figure 4. The x-axis is from east (positive) to west (negative) and y-axis is from north (positive) to south (negative). The z-axis is defined always as perpendicular to the horizontal plane. The orientation is earths frame of reference also follows the Right-Hand Rule. The position of the user is determined in earths frame of reference. The acceleration in Navigation frame is denoted as a_n^t at time t. Acceleration in navigation frame is defined as

$$a_n^t \;=\; [a_{n,x}^t, a_{n,y}^t,\; a_{n,z}^t - g]\mathrm{T} \qquad (1)$$

‘g’ is defined as gravitation force which depends on the coordinates of the location. ‘g’ is considered constant due to low variance in indoor space coordinates. Indoor space horizontal plane is, user moving space which is parallel to earths horizontal frame. Acceleration due to gravity is acted up on the perpendicular axes to horizontal plane which is z-axis. In the proposed model $a_{n,x}^{t}$, $a_{n,y}^{t}$, $a_{n,z}^{t} - g$ are used to represent the acceleration measured with mobile device on x, y, z axes on the navigation frame. Also, in assumption that there is no difference in the location of the mobile device and user in the navigation frame.

In the following section user position is estimated, where the position estimation is defined as x, y, z coordinates in the navigation frame derived from the user motion observations at time t. The Equation 2 represents the estimated position represented with location coordinates.

$$l(t) = [X_{n,t}, Y_{n,t}, Z_{n,t}]^T \tag{2}$$

Where l(t) represents the estimated position in the navigation frame and $X_{n,t}, Y_{n,t}, Z_{n,t}$ are the position coordinates in navigation frame respectively. Figure 3 shows the illustration for the navigation frame of reference

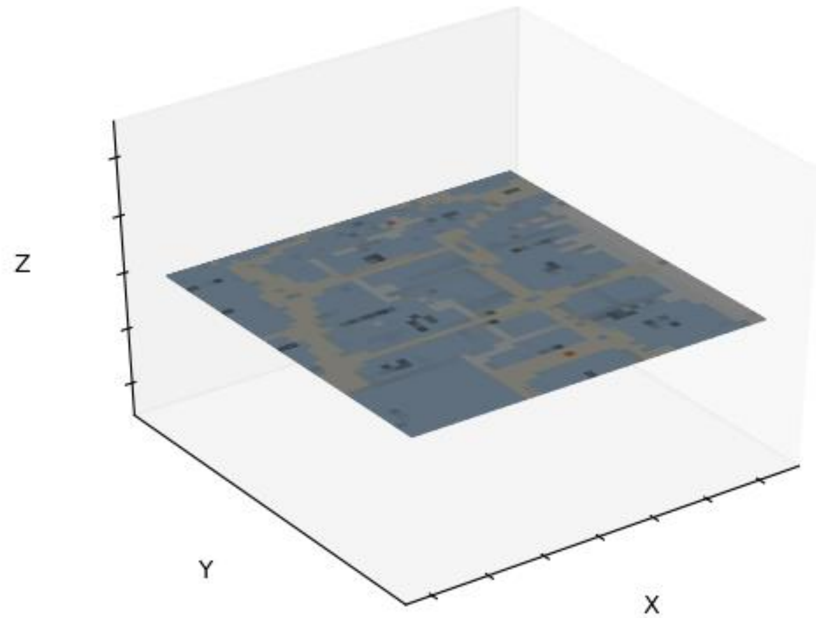

Figure 3: The Navigation Frame of Reference

Reference frame Transformation

As mentioned in above sections the data points were collected using mobile device that are embedded with inertial sensors. These data points are by default collected in phone reference frame (p-frame). In order to estimate the position in the navigation frame (n-frame) the measurements that are observed in body frame needs to be transformed into navigation from to estimate the position. Transformation is a process where coordinates in one frame of reference are transformed to target frame of reference using the angle of rotation respective to the target frame of reference. Angle of rotation or phone attitude is nothing, but the orientation of phone measured in Euler angles. In this method rotation angles along x, y, z is used as φ, θ, Ψ. If the body frame and navigation frame align with each other these angles are equal to zero as there is no rotation observed. While the device changes its orientation the corresponding angles also change accordingly. The phone frame observation can be transformed into navigation frame using Equation 3.

$$\begin{bmatrix} \dot{v}_{n,x}^{t} \\ \dot{v}_{n,y}^{t} \\ \dot{v}_{n,z}^{t} \end{bmatrix} = C_{p,n}^{t} \begin{bmatrix} \dot{v}_{p,x}^{t} \\ \dot{v}_{p,y}^{t} \\ \dot{v}_{p,z}^{t} \end{bmatrix} \tag{3}$$

Where $\dot{v}_{n,x}^{t}, \dot{v}_{n,y}^{t}, \dot{v}_{n,z}^{t}$ are acceleration along x, y, z axes in navigation frame transformed from $\dot{v}_{p,x}^{t}, \dot{v}_{p,y}^{t}, \dot{v}_{p,z}^{t}$ acceleration in phone frame. $C_{p,n}^{t}$ is the Euler angle rotation matrix to perform the rotation of coordinates to navigation frame. $C_{p,n}^{t}$ is defined in Equation (4)

$$C_{p,n}^{t} = \begin{pmatrix} \cos\theta\cos\varphi & \sin\emptyset\sin\theta\sin\varphi - \cos\emptyset\sin\varphi & \sin\emptyset\sin\varphi + \cos\emptyset\sin\theta\cos\emptyset \\ \cos\theta\sin\varphi & \cos\emptyset\cos\varphi + \sin\emptyset\sin\theta\sin\varphi & \cos\emptyset\sin\theta\sin\varphi - \sin\emptyset\cos\varphi \\ -\sin\theta & \sin\emptyset\cos\theta & \cos\emptyset\cos\theta \end{pmatrix} \tag{4}$$

Rotation matrix $C_{p,n}^{t}$ is updated periodically to align with the motion of the user. We update the position of user periodically at $\Delta\mathrm{T}$ and rotation matrix at $\frac{\Delta\mathrm{T}}{2}$.

Chapter 4: Approach

In this chapter the position estimation using inertial sensors data with Runge-Kutta method will be explained. The estimated position is corrected for any further noise using magnetometer data.

4.1. Estimation of displacement using Runge-Kutta method

In the previous section the acceleration is transformed from the phone frame to the navigation frame using transformation equation. For estimating the position, the acceleration data points which are collected through smartphone sensors are transformed into navigation frame. These transformed acceleration points will now be used to calculate the displacement and estimate the position using Runge -Kutta Integration method.

Displacement is defined as change in position of an object from its initial position. In the proposed method the initial position of the user is considered to be x_0 and the final position of the user is x_f which is taken as the approximate solution. The final position will be obtained by integrating the data points using the Runge-Kutta method. The observations recorded from inertial sensors are processed using temporal discretization to estimate the final position of the user. The position of the user varies as a function of time which is integrated at a regular time step ΔT to update the displacement of position over a given time. Each position is calculated by using its previous estimated position and its current displacement over time ΔT. Considering that estimated previous position be $l(k.\Delta T)$ at time $t = (k.\Delta T)$. The new position at $l(k+1.\Delta T)$ can be obtained from its previous position added to the displacement from $l(k+1.\Delta T)$ to $(k.\Delta T)$. This can be expressed in equation as

Final position = initial position + displacement over time interval

$$l\big((k+1).\Delta T\big) = l(k.\Delta T) + dis(k.\Delta T, \Delta T) \tag{5}$$

$$dis(k.\Delta T, \Delta T) = v_n^{k.\Delta\mathrm{T}}.\Delta T \tag{6}$$

$$v_n^{k.\Delta\mathrm{T}}.\Delta\mathrm{T} = \int_{k.\Delta\mathrm{T}}^{k+1.\Delta\mathrm{T}} a_{nf}^{t}\, d(t) \tag{7}$$

Displacement is found by using the mathematical Equation (6) where $v_n^{k.\Delta\mathrm{T}}$ is velocity at time (k. ΔT) times the time interval when the ΔT is small enough. The velocity at $k.\Delta T$ is derived from integrating the acceleration at the initial position. As we can see in Figure 5 the acceleration is very sensitive to time which can lead to more errors if we try to use Euler's method to integrate over time. The proposed model implements Runge-Kutta method of integration to avoid the error created during integration. Runge-Kutta comes in various form and Runge-Kutta 4th order is revised and proposed to better fit the model of integration using inertial data. Runge Kutta 4th order uses four variables to find the integrated value. In this method as the time interval (ΔT) is smaller, according to integration principles the velocity remains linear.

Where,

$$\begin{pmatrix} l \\ \dot{v_n} \end{pmatrix} = \begin{pmatrix} v_n \\ a_n \end{pmatrix} \tag{8}$$

$$v_n^{k+1.\Delta T} = v_n^{(k).\Delta T} + \frac{\Delta T}{6}\,.(K_1 + 2K_2 + 2K_3 + K_4) \tag{9}$$

$$K_1 = a_n^{(k).\Delta T} \tag{10}$$

$$K_2 = \frac{2(v_n^{\left(k+\frac{1}{2}\right).\Delta T} - v_n^{(k).\Delta T})}{\Delta T} \tag{11}$$

$$K_3 = a_n^{\left(k+\frac{1}{2}\right).\Delta T} \tag{12}$$

$$K_4 = a_n^{k+1.\Delta T}.\Delta T \tag{13}$$

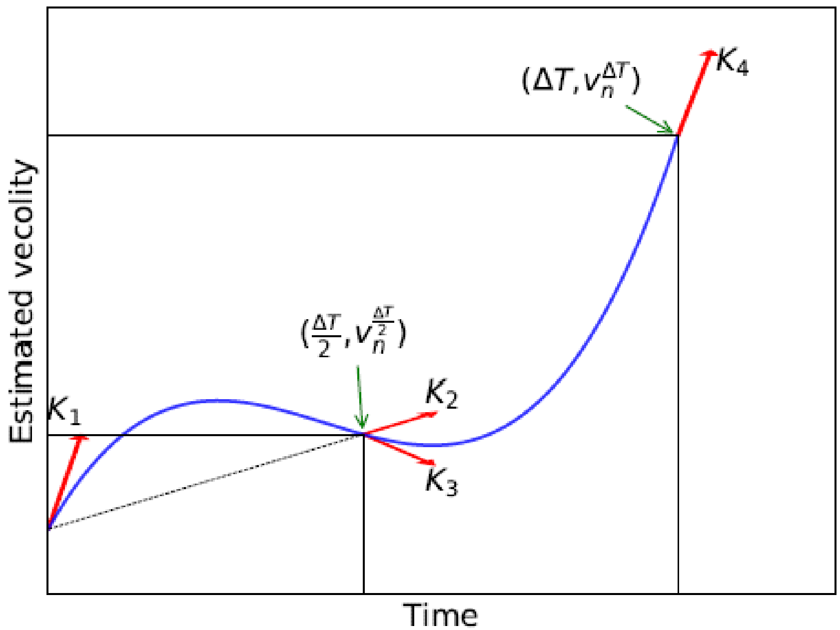

Figure 4: The Slope in Runge-Kutta Method

In the above equation previous velocity ($v_n^{(k).\Delta T}$) and weighted average of the four variables are calculated to derive the velocity at time t ($v_n^{k+1.\Delta T}$). Initial acceleration is taken as K1 at time t, Slope of the points between k ΔT and (k+1/2) ΔT is taken as K2, Acceleration of the body at k+1/2 is taken as K3 and final acceleration is taken as K4. The acceleration at (k+1/2) is obtained as the cycle to transform the phone metrics to navigation metrics which is iteratively performed at $\Delta T/2$T Initial Velocity is taken as v0 and velocity at midpoint is also taken as 0. As the velocity at the midpoint of the time interval is also used to calculate the variable K2 in Runge-Kutta integration method, the velocity is iteratively updated at time interval t/2. Weighted average is obtained by assigning weights to all four variables giving more importance to variables at the midpoint of the time interval. The derived velocity in Equation 9 is calculated and updated iteratively over the time interval. As defined in Equation 6 the displacement of the body is calculated by using the updated velocity in Equation 9 on a given time interval. After obtaining the user velocity at time t, the user displacement for the current time interval is calculated. This user displacement is added to its previous position to derive the final position of the user from the initial point. This will be the user position at time t calculated with runge-kutta method. Self-correction method is introduced in next section to reduce any noise error created during estimation of displacement. The Magnetometer sensor is used to implement the self-correction method.

The following figures shows some of the user acceleration graphs along the navigation frame x-axis and y-axis

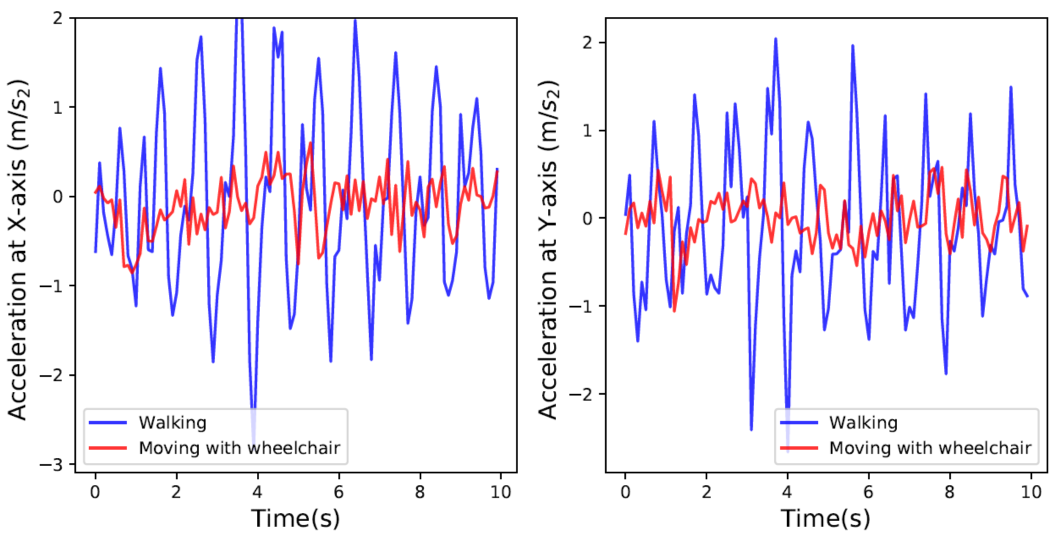

Figure 5: The Acceleration measurements for various user motions

4.2. Self-correction

This section will illustrate how magnetometer data is used to self-correct the displacement calculated in the previous section. In previous sections user acceleration over a time period is used to calculate the displacement and updated iteratively to track the user motion. To better maintain the accuracy of the user motion direction, magnetometer data is introduced to correct the direction estimated through acceleration and reduce any noise created in the above step. Magnetometer is also inertial sensor which records the device orientation ranging from 0 degrees to 360 degrees. The 0 degrees indicate the heading of the device is parallel to earth's magnetic north. Magnetometer data is collected at the beginning and ending of the cycle to update the user motion direction. The orientation of the device is represented as α. Let α(k) be the orientation at the beginning of the cycle ΔT and α(k+1) be the orientation at the ending of the cycle. It is assumed that change in user motion is a linear change. Figure 6 shows an example where the α is measured during the phone orientation.

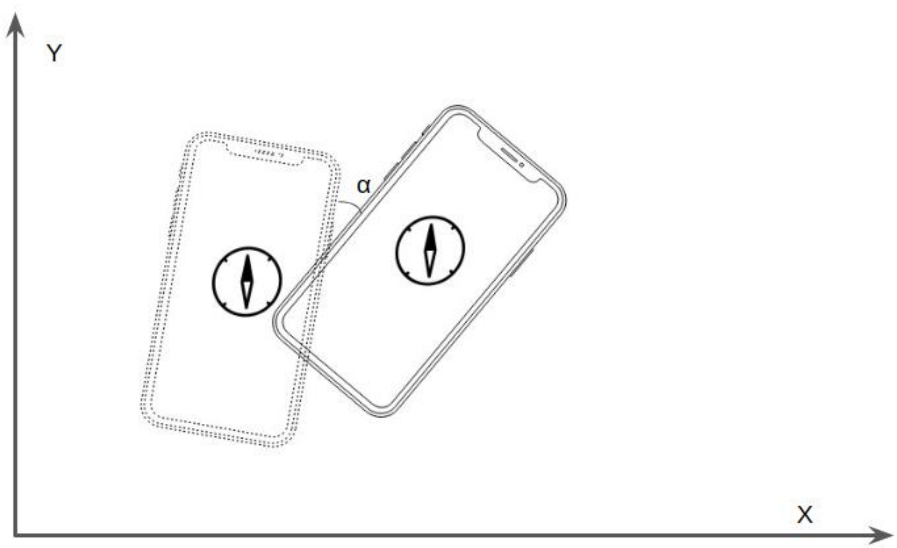

Figure 6: The Phone Orientation

Once the orientation is measured for a cycle, the displacement $(dis(k.\Delta T, \Delta T))$ measured is projected into the horizontal plane. The heading difference is defined in Equation 14.

$$\alpha = \alpha_{k+1} - \alpha_k \tag{14}$$

The estimated displacement $(d_x, d_y, d_z)^T$ is projected into the horizontal plane and their corresponding projected vector will be (d_x, d_y). Figure 7 shows the self-correction illustration.

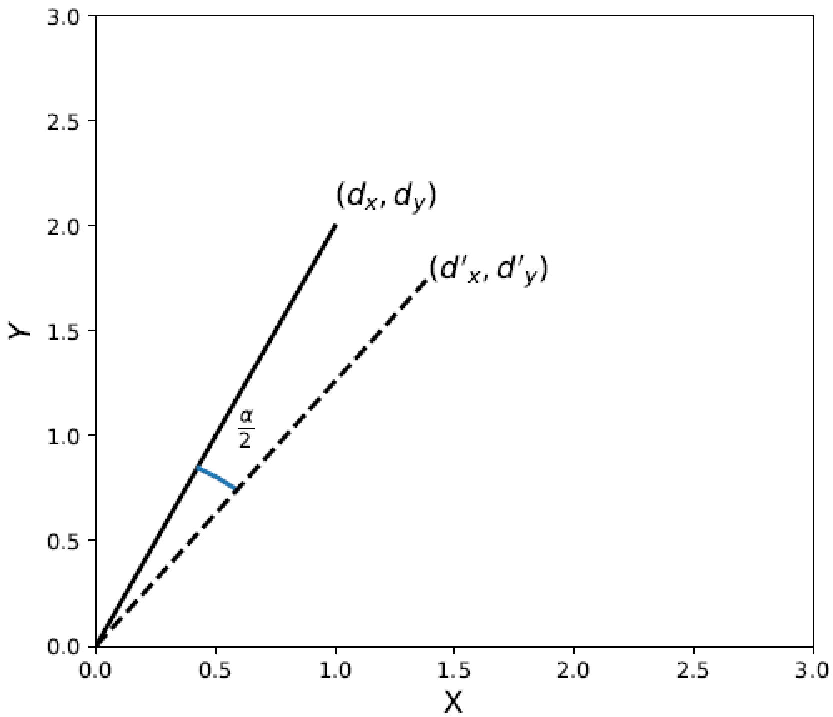

Figure 7: Self-correction

The average heading difference is calculated for a given time interval ΔT as $\frac{\alpha_{k+1} - \alpha_k}{2}$. The estimated displacement is rotated to with angle of average heading difference on the projected plane to correct any displacement errors caused in previous step. Equation 15 and Equation 16 represents the corrected displacement using the magnetometer sensor data.

$$d'_x = \sqrt{d_x^2 + d_y^2} \,.\cos\,(arctan\frac{d_y}{d_x} - \frac{\alpha}{2}) \qquad (15)$$

$$d'_y = \sqrt{d_x^2 + d_y^2} \,.\sin\,(arctan\frac{d_y}{d_x} - \frac{\alpha}{2}) \qquad (16)$$

Equation 17 represents the final displacement after incorporating the self-correction method to the estimation. The self-correction steps are repeated while the user is in motion and updated periodically along with user position.

$$l(k+1.\Delta T) = l(k.\Delta T) + \left(d_x', d_y', d_z\right)^T \qquad (17)$$

Chapter 5: Experiment

This chapter shows the details of the experiment conducted on various user movements like walking, driving and wheelchair. The results were compared against the existing methods to measure the performance.

5.1. Experimental Setting

The experimental is performed primarily on three basic moving patterns namely walking, wheelchair and driving. The Experiment is conducted in a real indoor space at Auburn administrative complex which includes four spaces connected by doors with size measured as 30.2 m * 23.5 m as shown in Figure 8. A 100 meters parking space was used to experiment the driving pattern as shown in Figure 9. All the experiments were conducted with apple iPhone 7 collecting the inertial sensors data for each of the moving patterns while conducting the experiment. The device was held in the hand position for collecting data while the user is in walking motion and mounted to chair or car while the user is in wheelchair or driving activity respectively. The inertial data is collected at 10 Hz frequency with time interval (ΔT) as 0.2 to perform the calculations. All the experiments were conducted on windows server equipped with intel processor and 16 GB memory. The moving patterns are recorded with camera which are further processed to establish the ground truth. The proposed algorithms are implemented in python.

Figure 8: The Indoor Space Layout

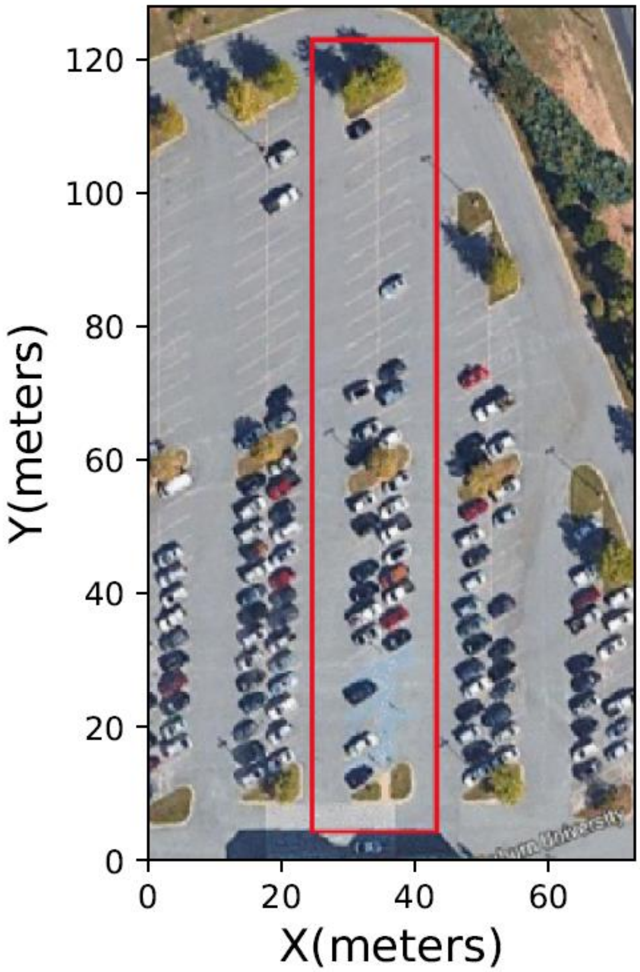

Figure 9: The Navigation Track for Driving

The experiment is evaluated considering the user movement in horizontal plane and the location estimation is done for XY plane and subtracting the gravitational force along Z-axis. The gravitational force g is defined with value 9.80665 m/s^2. The Experiment is repeated four times for each moving pattern.

5.2 Performance Metrics

After estimating the displacement using the Runge-Kutta method, the model is evaluated against the two main metrics and compared with the existing strapdown INS system. The error of accumulated displacement and the heading error are the two main metrics that were considered to evaluate the proposed model. The following sections explains more details about the metrics

5.2.1 The error of accumulated displacement

The error of accumulated displacement is defined as difference between the estimated position that is calculated by the proposed model and ground truth which is established through processing experiment video that is captured while the experiment is performed. The estimated model periodically updates the position at regular intervals of time t in the navigation frame. Consider at time t, the model returns the displacement of the user position by calculating the difference between original position and position estimated at time t as |l(t) -l(0)| where l(0) is taken as original position and l(t) as estimated position at time t. If the actual position represented as l(t), then accumulated error for a given query is absolute difference between |l(t)-l (0) | and $|\widehat{l(t)} - l(0)|$. This error of accumulated displacement is calculated iteratively for each time interval. The process is repeated for different types of moving pattern. The calculated error for various moving patterns is reported.

5.2.2 The Heading Error

The accumulated heading error is defined as difference between the estimated heading that is calculated by the proposed model and ground truth which is established through processing video recording that is capture while the experiment performed. The estimated model periodically updates the heading estimation at regular intervals of time t in the navigation frame. The user heading h_n^t at time t is determined by velocity vector which is defined as in Equation 18

$$h_n^t = atan2(v_{n,x}^t, v_{n,y}^t) \tag{18}$$

Where $v_{n,x}^{t}$ and $v_{n,y}^{t}$ are velocities measured along horizontal XY plane respectively. If the actual heading is represented as $h^{(t)}$, then accumulated heading error for a given query is absolute difference between $|\hat{h}_n^t - h_n^t|$. The heading error is calculated iteratively for each time interval of 1 second and reported average heading error for each user moving pattern walking, wheelchair and driving.

5.2.3 Strapdown INS

The proposed model is compared against strapdown INS [21] which is also based on inertial sensor data. Strapdown INS uses gyroscope and accelerometer sensor to implement the navigation system. The model uses gyroscope data for orientation and acceleration data is used to calculate the displacement using Kalman filter technique. This model was implemented to compare against the proposed model. The data collected for the experimental settings also contains gyroscope data which enables to implement and compare this model against the proposed inertial navigation system using Runge -Kutta method. Comparison of these two models is performed for all the three moving patterns.

5.3 Performance Analysis

The error of accumulated displacement measured in Inertial navigation system (INS-R) is compared with strapdown INS which is plotted down in Figure 10

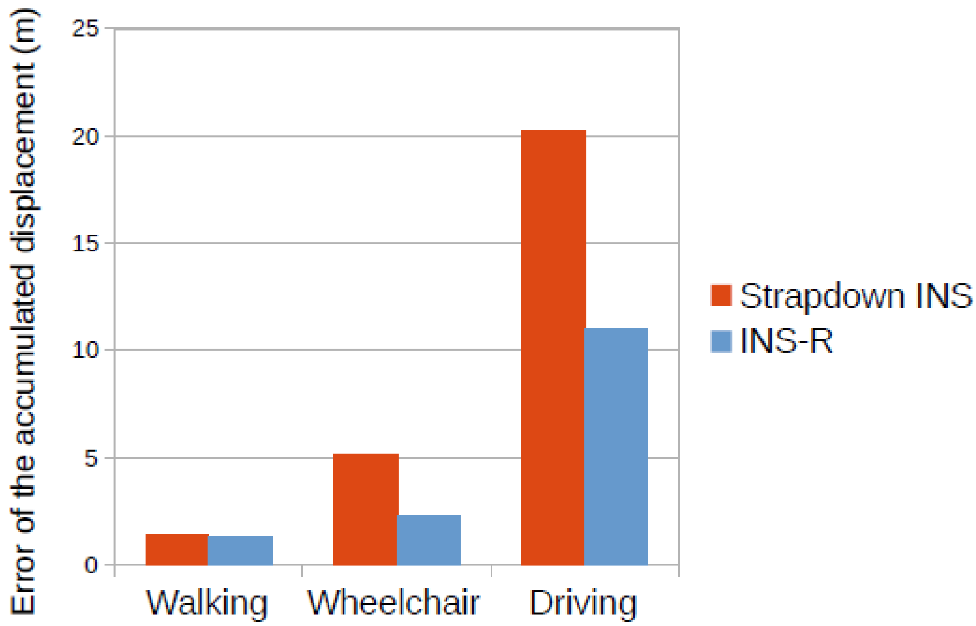

Figure 10: The Comparison of the accumulated displacement error across various moving patterns

As it can be seen the proposed model performs better than the strapdown INS in estimating the user position in various moving patterns. In case of walking, the proposed method can reduce the accumulated error of displacement by 9.4% (0.14m) compared to strapdown INS. In case of user movement with wheelchair, the proposed method can reduce the accumulated error of displacement by 54.8% (2.8m) compared to strapdown INS. Similarly, when compared with user movement in driving pattern, the proposed method can reduce the accumulated error of displacement by 45.8% (9.24m) compared to strapdown INS. The proposed approach was performing better because the model was not using gyroscope data to transform the acceleration unlike the other approach. The gyroscope data contains noise which needs to be taken care before it is further processed to estimate the position. This has significant effect while the user in driving or wheelchair moving pattern.

As seen in Figure 10, the driving pattern records the higher error in accumulated displacement due to the significant noise recorded in the measurements of gyroscope used in transformation from navigation frame to phone frame. As the measurements are integrated to derive the final position, the error also propagates to the result. Since, the average velocity for driving pattern is comparatively higher than other two moving patterns, which also played a role in increase in error caused in this moving pattern.

The Heading error measured in Inertial navigation system (INS-R) is compared with strapdown INS which is plotted down in Figure 11

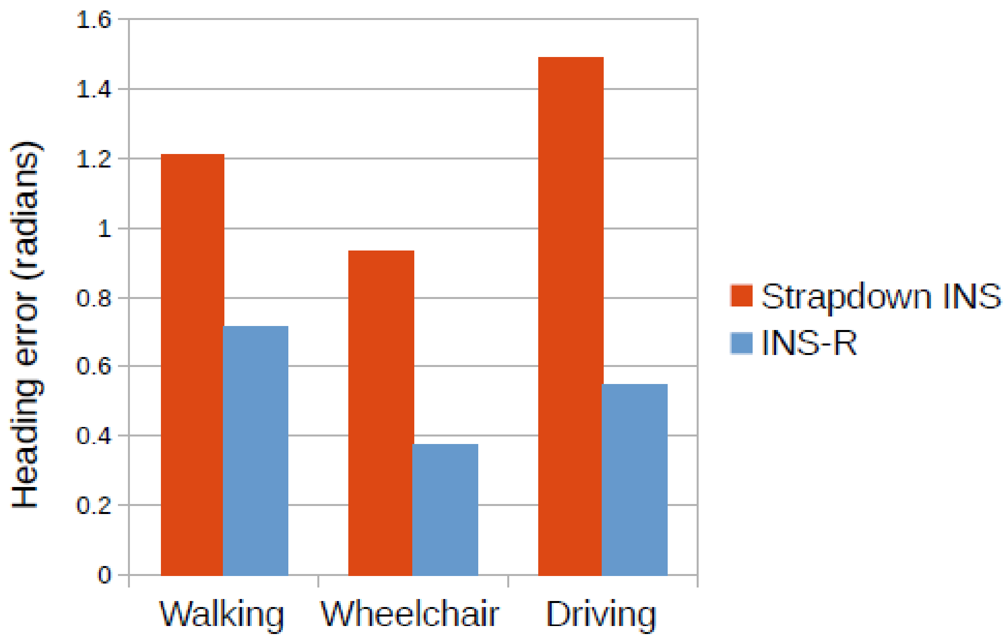

Figure 11: The heading error comparison across moving patterns

Like the error of accumulated displacement, the proposed model performs better than the strapdown INS in various moving patterns. In case of walking, the proposed method can reduce the heading error by 42.05% (0.508 radians) compared to strapdown INS. In case of user movement with wheelchair, the proposed method can reduce the heading error by 57.9% (0.5564) compared to strapdown INS. Similarly, when compared with user movement in driving pattern, the proposed method can reduce the heading error by 63.1% (0.94radians) compared to strapdown INS.

We have seen how INS-R and strapdown INS performed when compared on error of accumulated displacement and heading error. Extending the comparison over time, the below two graphs illustrate the error pattern over time. Figure 12 depicts the error of accumulated displacement and Figure 13 depicts the heading error. The INS-R method has lower trends over time for both the metrics.

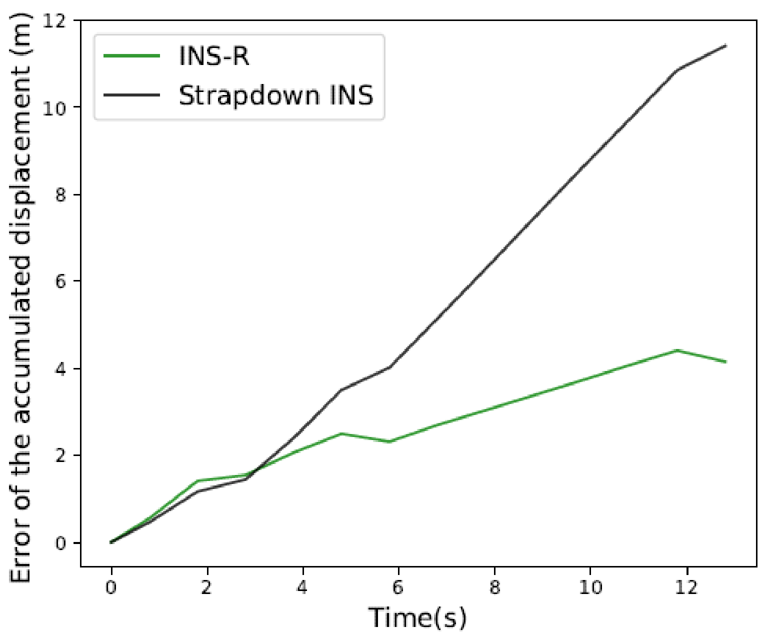

Figure 12: The error of accumulated displacement trends over time

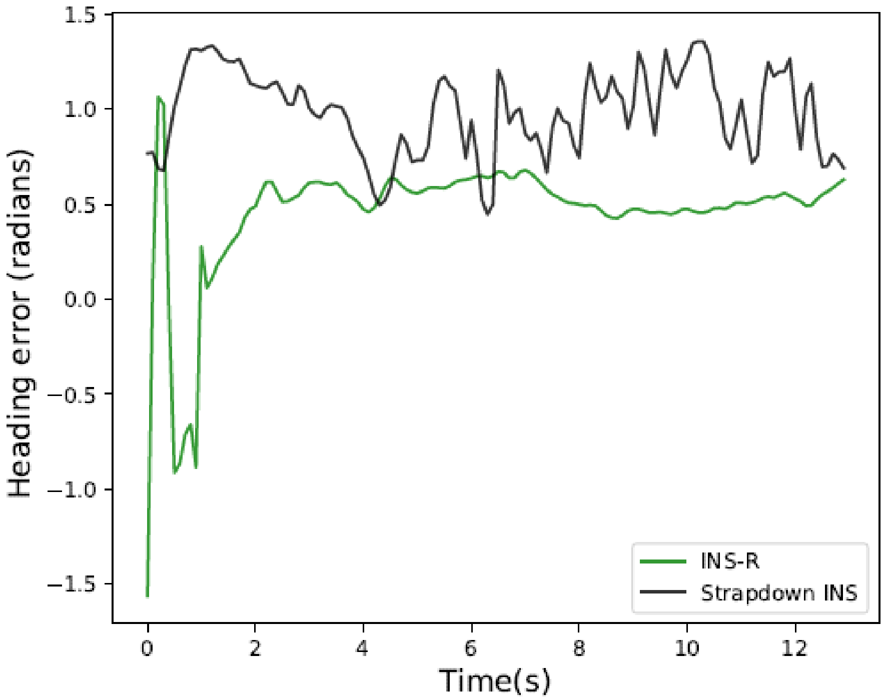

Figure 13: The heading error trends over time

As demonstrated above, the proposed approach INS-R can estimate the position with reduced error of accumulated displacement.

Chapter 6: Conclusion

This work discussed the indoor navigation method based on inertial data to better estimate the user position relative to the indoor location. The model is built using Runge-kutta method. Inertial data from accelerometer, device rotation sensor and magnetometer were collected in phone frame and transformed to navigation frame throughout the method to better assist the user in real frame of reference. The user displacement is derived by using the accelerometer data and runge-kutta method. Magnetometer data is introduced to correct the displacement iteratively. The INS-R method performed efficiently for three kinds of user moving patterns namely walking, wheelchair and driving motion when compared against strapdown INS. The method efficiently reduced the error of accumulated displacement, heading error giving rise to more accuracy level to estimate the position.

In future, the work can be extended by introducing deep learning methods and with installing more relevant infrastructure. Integrating multiple various methods can further reduce the error and improve the position accuracy. Wi-Fi can be introduced to improve the location accuracy by integrating the with the location data from other sensor devices. Also, this work can be extended for other kinds of moving patterns as well.

References

[1] A. Bekkali, H. Sanson, and M. Matsumoto, “RFID indoor positioning based on probabilistic RFID map and Kalman Filtering,” *3rd IEEE Int. Conf. Wirel. Mob. Comput. Netw. Commun. WiMob 2007*, no. WiMob, pp. 1–3, 2007.

[2] G. Y. Jin, X. Y. Lu, and M. S. Park, “An indoor localization mechanism using active RFID tag,” *Proc. - IEEE Int. Conf. Sens. Networks, Ubiquitous, Trust. Comput.*, vol. 2006 II, pp. 40–43, 2006.

[3] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. P. Landmarc, “indoor location sensing using active RFID,” *Wirel. Networks, 10, Novemb.*, pp. 701–710, 2004.

[4] P. Davidson and R. Piché, “A Survey of Selected Indoor Positioning Methods for Smartphones,” *IEEE Commun. Surv. Tutorials*, vol. 19, no. 2, pp. 1347–1370, 2017.

[5] J. Zhang, Y. Lyu, J. Patton, S. C. G. Periaswamy, and T. Roppel, “BFVP: A Probabilistic UHF RFID Tag Localization Algorithm Using Bayesian Filter and a Variable Power RFID Model,” *IEEE Trans. Ind. Electron.*, vol. 65, no. 10, pp. 8250–8259, 2018.

[6] S. Boonsriwai and A. Apavatjrut, “Indoor WIFI localization on mobile devices,” *2013 10th Int. Conf. Electr. Eng. Comput. Telecommun. Inf. Technol. ECTI-CON 2013*, pp. 1–5, 2013.

[7] S. P. Tarzia, P. A. Dinda, R. P. Dick, and G. Memik, “Demo: Indoor localization without infrastructure using the acoustic background spectrum,” *MobiSys’11 - Compil. Proc. 9th Int. Conf. Mob. Syst. Appl. Serv. Co-located Work.*, p. 385, 2011.

[8] A. Serra, D. Carboni, and V. Marotto, “Indoor pedestrian navigation system using a modern smartphone,” *ACM Int. Conf. Proceeding Ser.*, pp. 397–398, 2010.

[9] F. Evennou and F. Marx, “Advanced integration of WiFi and inertial navigation systems for indoor mobile positioning,” *EURASIP J. Appl. Signal Processing*, vol. 2006, pp. 1–11, 2006.

[10] N. Zhu, H. Zhao, W. Feng, and Z. Wang, “A novel particle filter approach for indoor positioning by fusing WiFi and inertial sensors,” *Chinese J. Aeronaut.*, vol. 28, no. 6, pp. 1725–1734, 2015.

[11] K. G. S. D. Kotz; and B. Noble, “Proceedings of the 3rd international conference on Mobile systems, applications, and services,” in *MobiSys ’05 Proceedings of the 3rd international conference on Mobile systems, applications, and services*.

[12] J. Yu, W. S. Ku, M. Te Sun, and H. Lu, “An RFID and particle filter-based indoor spatial

query evaluation system," *ACM Int. Conf. Proceeding Ser.*, pp. 263–274, 2013.

[13] P. D. Groves, "Navigation using inertial sensors," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 30, no. 2, pp. 42–69, 2015.

[14] M. Alzantot and M. Youssef, "CrowdInside," p. 99, 2012.

[15] M. Alzantot and M. Youssef, "UPTIME: Ubiquitous pedestrian tracking using mobile phones," *IEEE Wirel. Commun. Netw. Conf. WCNC*, pp. 3204–3209, 2012.

[16] H. Wang, H. Lenz, A. Szabo, J. Bamberger, and U. D. Hanebeck, "WLAN-based pedestrian tracking using particle filters and low-cost MEMS sensors," *4th Work. Positioning, Navig. Commun. 2007, WPNC'07 - Work. Proc.*, vol. 2007, pp. 1–7, 2007.

[17] G. Chen, X. Meng, Y. Wang, Y. Zhang, P. Tian, and H. Yang, "Integrated WiFi/PDR/smartphone using an unscented Kalman filter algorithm for 3D indoor localization," *Sensors (Switzerland)*, vol. 15, no. 9, pp. 24595–24614, 2015.

[18] X. Li, J. Wang, C. Liu, L. Zhang, and Z. Li, "IntegratedWiFi/PDR/Smartphone Using an Adaptive System Noise Extended Kalman Filter Algorithm for Indoor Localization," *ISPRS Int. J. Geo-Information*, vol. 5, no. 2, 2016.

[19] A. Correa, E. Munoz Diaz, D. Bousdar Ahmed, A. Morell, and J. Lopez Vicario, "Advanced Pedestrian Positioning System to Smartphones and Smartwatches," *Sensors (Basel).*, vol. 16, no. 11, pp. 1–18, 2016.

[20] J. Wang, A. Hu, X. Li, and Y. Wang, "An improved PDR/magnetometer/floor map integration algorithm for ubiquitous positioning using the adaptive unscented Kalman filter," *ISPRS Int. J. Geo-Information*, vol. 4, no. 4, pp. 2638–2659, 2015.

[21] C. Fischer, P. T. Sukumar, and M. Hazas, "Tutorial: Implementing a pedestrian tracker using inertial sensors," *IEEE Pervasive Comput.*, vol. 12, no. 2, pp. 17–27, 2013.