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Indoor Pedestrian Positioning and Tracking using INS and RF Sensor Fusion

Mohd Nazrin Muhammad

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in Electrical and Electronics Engineering, the University of Auckland, 2018.
ABSTRACT

In this digital era, electronic devices are developing into more sophisticated equipment to perceive the local and global information such as fitness and activity trackers as well as for navigational purposes. The spatial awareness is fast becoming the key element in improving human life and navigation solutions are growing in demands. While accurate outdoor navigation has been widely available through Global Positioning System (GPS), the GPS does not work in indoor environments due to weak received signal and multipath reflection. In this regard, a number of indoor positioning and tracking solutions have been proposed, e.g. inertial and radio frequency (RF) based navigation. Low-cost inertial sensors are economically attractive and miniature in size, thereby become a popular choice in indoor positioning solutions. However, such devices are prone to errors that result in a large position drift. For accurate RF based navigation, the techniques rely on expensive high-precision time hardware and complex deployment of the wireless transceivers.

This thesis describes the development of indoor pedestrian positioning and tracking using Inertial Navigation System (INS) and RF sensor fusion. The proposed system fuses the positioning and tracking information from INS and RF to produce better positioning and tracking accuracies. This research tackles the existing issues on low-cost INS, position and heading drifts, by proposing two novel techniques. First, we propose a better stance phase detector that directly improve the position drift. Secondly, we develop an efficient turn detector that is threshold-less, thus robust to different group of pedestrians and operating conditions. The proposed turn detector provides information of turns made by pedestrians that greatly assists in correcting the heading drift. The introduction of both techniques in the Kalman-based navigation framework produce a better positioning and tracking performance compared to the state of the art. The unconvinced performance of INS based navigation in the long run or challenging indoor arrangements, resulted from accumulated drift over time and insufficient dynamic range of the inertial sensors, are discussed in literature. This research proposes the fusion between INS and RF based navigation technology known as Device Free Location (DFL). The DFL provides absolute positioning that benefits in resetting the drifted positioning of INS. The DFL network uses low-cost IEEE 802.15.4 wireless transceivers and deploys in square-shape arrangement.
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<td>RMSE</td>
<td>Root Mean Square Error</td>
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<td>RPE</td>
<td>Return Position Error</td>
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<td>RSS</td>
<td>Received Signal Strength</td>
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<td>RTI</td>
<td>Radio Tomography Imaging</td>
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<td>RTT</td>
<td>Return-Trip Time</td>
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<td>SFS</td>
<td>Specific Force Sensor</td>
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<td>SL</td>
<td>Step Length</td>
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<td>SPINS</td>
<td>Strapdown Pedestrian Inertial Navigation System</td>
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<td>SRAM</td>
<td>Static Random Access Memory</td>
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<td>TDE</td>
<td>Travelled Distance Error</td>
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<td>TDoA</td>
<td>Time Difference of Arrival</td>
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<td>ToA</td>
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<td>Tof</td>
<td>Time of Flight</td>
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<td>ToT</td>
<td>Time of Transmission</td>
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<td>Un-filtered Heading</td>
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<td>Ultra-Wide Band</td>
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<td>Wireless Sensor Network</td>
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<td>Waist’s Yaw</td>
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<td>Waist’s Yaw Update</td>
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<tr>
<td>ZARU</td>
<td>Zero Angular Rate Update</td>
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<td>ZUPT</td>
<td>Zero Velocity Update</td>
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| Nature of contribution by PhD candidate | Design, conducting experiments, analyzing data, and writing the article. |
| Extent of contribution by PhD candidate (%) | 95 |

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1.1 Background

Indoor positioning system is fast becoming an attractive research field over the last decade as a result of progressive development in inertial and radio frequency positioning technologies. In addition, people spend almost 90% of their time indoors [1]–[3] and in cumulative, 70% at home and 20% at other indoor places, including, but not limited to, office, factory, and mall. These numbers highlight the significant potential of indoor positioning systems. Yet, until now, not a single system is able to provide robust and reliable indoor positioning and tracking solution.

Positioning by definition is to find the location of something or someone in relation to a specific reference area or region. Specifically, positioning is a process to estimate the location in two-dimensional (2D) or three-dimensional (3D) space, of a point of interest with respect to a coordinate system constructed based on known references [4]. Although the position itself is obviously a very important source of information, it must be related to a specific time to be even more useful. Thus, tracking is a process for estimating the current position of something or someone [5], as a function of time. Meanwhile, navigation is a tracking solution that uses position information to help users to move towards a desire destination.

Historically, positioning and tracking systems have played a significant role in fulfilling human needs in different areas. By positioning and tracking stars and natural landmarks, the ancient people planned for settlement, farming and travelling. As time passed, the positioning technology has evolved. Human-made innovations such as tall buildings that could be spotted from afar and lighthouses for maritime were built. With the advancement in science and engineering, nowadays, there are satellites orbiting around the earth enabling Global Positioning System (GPS) technology. With GPS, the receiver is able to infer its own location from the received signals coming from satellites. In ideal conditions, GPS can achieve a sufficient accuracy, within few meters. Since the past decade, GPS units became smaller and more affordable achieving its public acceptance.
Many of electronics devices such as mobile phones, tablets and car entertainment units, are equipped with GPS to provide navigation systems.

While GPS accomplishes the demand for outdoor positioning applications, it is not applicable to indoor scenarios. The interruptions of connection between receiver and the satellites in the buildings cause positioning systems from GPS to be severely degraded or completely fail [6]. This leads to great demands on developing alternative positioning system for indoor environments, notably that people spend more time indoors. At home, unusual mobility routine of the elderly or disabled or people with disease such as Alzheimer can be remotely tracked and monitored [7]–[9] thus allowing them to live more independent life. In other indoor places such as library and hospital, less time will be spent to find the correct bookshelves or wards, respectively [10], [11]. Although these places provide the floor plan and signs, those are passive and not as dynamics as indoor positioning system that is able to show near or at real-time direction indicators.

Worth to note that the hype in the media for indoor positioning is increasing every year with the publication of a number of articles to inform the people that the technology is already here and growing. In one of Forbes’ articles [12], the writer shared the impact of the technology including enhanced shopper engagement and experiences, easier for discovering and accessing information and services, and better wayfinding to indoor destinations. In the future outlook, summarizing from various research reports, [13] tipped that the indoor positioning market will be worth $ 41 billion by 2022, with about 200 start-ups already working on the technology since 2014.

The indoor positioning technology to extract position information can be categorized into two major categories [14], sensors-based systems and radio frequency-based system. The introduction of Micro-machined ElectroMechanical System (MEMS) sensors and devices, as well as wireless sensor networks (WSN), have fortified the indoor positioning’s acceptance and growth. The MEMS inertial sensors are rugged, low cost, small and lightweight to enable the development of embedded indoor positioning systems. The Inertial Measurement Unit (IMU) is an integrated MEMS inertial sensor package that combines multiple accelerometers and gyros to produce a 2- or 3-dimensional measurements of both specific force and angular rate, with respect to an inertial reference frame. The combination of IMU and computing engine such as processor to compute the position are collectively known as Inertial Navigation System (INS). INS integrates the inertial measurements to provide navigation solutions; the relative position and orientation of the device with respect to a known initial position. In the strapdown INS, the sensors are mounted rigidly onto human body, benefitting from the small size.

On the other hand, the omnipresence of Radio Frequency (RF) communication technology such as Bluetooth and Wi-Fi, has become a key factor in enabling a new indoor positioning technology. Backed by practical positioning techniques such as Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA) and Received Signal Strength (RSS), the wireless technology seems to be promising candidate for ultimate indoor positioning.
1.2 Motivation

The main motivation of this thesis comes from the fact that there is growing need for reliable yet cost effective indoor positioning system. A reliable system means minimum requirement for positioning accuracy is met at most of the time. At the same time, cost effective system ensures better adoption by users. Despite hundreds of different approaches in indoor positioning have been proposed in the literature, there is no single, widely accepted solution that has been acknowledged by the research and industry community. Among the challenges to pick the best, yet practical indoor positioning technology are high overhead cost to carefully deploy custom wireless hardware [15] and expensive, navigation-grade sensors to achieve required accuracy [16]. Furthermore, most of the proposed systems are evaluated in highly-controlled environments which could positively bias the performance of the systems [15]. In addition, the complexity of floor plans altogether with furniture arrangement is another obstacle on achieving a reliable and trusted positioning solution.

1.3 Objectives

The aim of this thesis is to explore and develop an indoor pedestrian positioning and tracking system using low-cost INS and RF sensors and their fusion. The main goal has been carried out through the following three research objectives:

a. To develop a new algorithm to reduce error accumulated in distance estimation when using low-cost INS.

b. To develop a new method to correct the heading drift using low-cost INS that is robust when used by different people and in different operating conditions.

c. To develop a sensor fusion technique that combines position information from INS and RF to achieve more accurate position information.

1.4 Contributions

The main contributions of this thesis are presented as follows:

- We propose a new algorithm based on subtractive clustering to suppress the error growth in estimating distance travelled due to imperfection of low-cost INS. The current implementations focus on magnitudes of IMU measurements to extract gait information for distance estimation purpose which are not robust enough when applied to different people. Unlike this, the proposed algorithm tracks the measurements pattern to obtain the gait information. As a result, the distance estimation is improved.

- We propose a novel approach to detect the pedestrian turns and subsequently correct the headings. The approach observes the pelvic rotation and gait to determine the
pedestrian turns. The proposed turn detector is a threshold-less method which is robust to any group of pedestrians and operating conditions, yet requires fewer pedestrian step than the state of the art. The obtained turn information effectively aids to correct the headings. As a result, the heading accuracy is improved.

- We propose a new sensor fusion between the INS and a RF positioning technology known as Device-Free Localization (DFL). The hybrid system avoids the need to carry additional computing devices to support the RF positioning. In contrast, the DFL positioning, which is based on IEEE 802.15.4, is based on ability of wireless sensor network to detect signal attenuations resulted from the presence of pedestrian within the deployment area. The loosely-coupled integration between INS and RF results in improvement of indoor positioning and tracking performance.

1.5 Thesis Outlines

The following chapters are included in this thesis:

- Chapter 2 reviews the current indoor positioning technologies including inertial-based positioning and RF-based positioning. A brief explanation of the position extraction techniques based on various positioning technologies is given. The state of the art presented in this chapter, gives a review of the most promising approaches in hybrid solutions that can be found in the literature. These hybrid solutions combine multiple positioning technologies with focus on foot-mounted inertial-based and RF-based positioning technologies.

- Chapter 3 describes a new algorithm to determine the specific gait of the pedestrian using subtractive clustering method. Different approaches have been studied in literature and summarized in this chapter. The working procedures of the proposed algorithm are presented. The validation through simulations is complemented by the experimental tests using real data. The results are compared with the other approaches.

- Chapter 4 describes a novel turn detector method constructed from the relationship between the pelvic rotation and gait of the pedestrian. A review of state of the art in heading correction and their limitations are presented in this chapter. An introduction to pelvic rotation is provided and its relationship with the gait of the pedestrian is studied with a series of observations. The relationship is proved to be a strong relationship and the algorithm to detect pedestrian's turn is developed based on the relationship. The turn detection algorithm is compared with the other approaches. The turn information is then applied to perform heading correction. The corrected heading is analysed and compared with the untreated heading.

- Chapter 5 describes the proposed pedestrian tracking framework based on foot-mounted inertial navigation system. The tracking is performed using the Kalman filter tracking framework with measurements obtained from the proposed gait
detection algorithm in Chapter 3 and the heading correction method in Chapter 4. The working procedures and parameters are presented and experiments are conducted. The results are compared with the other approaches in foot mounted navigation.

- Chapter 6 describes the DFL positioning technology and the fusion between INS and DFL as an integrated indoor positioning solution. The two critical components in the fusion, different sampling times between the positioning technologies and the integration scheme itself, are explained. The validation through simulations is complemented by the experimental tests using real data. The results from the fusion and individual positioning technologies are compared.

- Chapter 7 gives conclusions about the presented indoor pedestrian positioning and tracking using INS and RF sensor fusion and provides some directions for the future work.
In this section, the sensing technologies behind the existing indoor positioning and tracking systems are reviewed. At the end, a list of works that fused multiple technologies as a unified solution is presented and discussed. The gaps in fulfilling the design requirements are identified and discussed. At the end of this chapter, the system architecture for this research is proposed.

### 2.1 Indoor Positioning Technologies

Indoor positioning technologies are adopted to solve the problem of locating target of interest in closed and constrained environment. However, none of the existing indoor positioning technologies are considered de facto standard due to their uniqueness in various aspects such as accuracy and sophisticated hardware requirement. Though higher accuracy is desirable for an indoor positioning system, fulfilling the sophisticated hardware requirements remains a major obstacle that affects its popularity and adoption. Generally, higher accuracy comes with higher cost as the hardware involved gets increased either in quantity or quality.

A number of surveys have been conducted to categorize different indoor positioning technologies. For instance, a survey conducted by [17] categorized the indoor positioning technologies into four; lateration and angulation systems (e.g. ultra-wide band radio), proximity systems (e.g. Radio-Frequency Identification or RFID), radio fingerprint systems (e.g. database of received signal strength at various locations) and dead-reckoning systems (e.g. inertial sensors). In another classification, modern indoor positioning technologies are categorized into inertial-based and radio frequency signal based [18]. The next sub-sections will discuss these two categories of indoor positioning technologies.
2.2 Inertial-based Positioning

Inertial sensors are the types of transducers that exploit the Newton’s First Law, where inertia is a property that maintains a body state of motion unless disturbed by forces or torques [18]. One of them, the accelerometer, measures acceleration along the axis of motion and the other one is the gyroscope that measures the angular velocity around a fixed axis. A unit that integrates inertial sensors is known as Inertial Measurement Unit (IMU), a package that combined tri-axial accelerometers and tri-axial gyroscopes [19].

Inertial-based positioning technology is a type of dead-reckoning navigation technique. This technique measures the acceleration and double integrate it to estimate the distance travelled. This is added to the previous position in order to obtain the current position. The distance travelled is measured in body-aligned axes, thus a separate attitude solution is required to obtain the direction of travel with respect to the global coordinate frame. While inertial-based positioning does not rely on any surrounding infrastructure, it has a major weakness as errors accumulate over time and computed position in relation to its environment becomes less certain.

2.2.1 Accelerometers

The Newton’s second law states that the acceleration of an object as produced by a net force is directly proportional to the magnitude of the net force, and inversely proportional to the mass of the object \(a = f/m\). Accelerometer is also called as specific force sensor (SFS) measure the external force per unit mass [20], [21]. The output of an accelerometer is given by

\[
f = a - g
\]

where \(f\) is the specific force, \(a\) is the acceleration with respect to the inertial frame and \(g\) is the gravitational acceleration.

Recently Micro-machined ElectroMechanical System (MEMS) accelerometers have been gaining popularity as their performance improves. For mass market applications the use of MEMS accelerometers is attractive because they consume very little power, are small and affordable. However, most consumer grade MEMS accelerometers have inferior performance from navigation grade inertial sensors. Those accelerometers offer cost effective solutions for performing inertial measurements but with reduced specifications [22]. The technology behind their construction determines accelerometer’s performance. For instance, piezo-resistive accelerometers have small output sensitivity and measurement is easily swayed by temperature changes. Capacitive type accelerometers have higher sensitivity and less influence of temperature, but are prone to electromagnetic interference [23]. Another common type of accelerometer is based on piezoelectric that provide very stable and accurate measurement, although it is associated with a large undesired temperature sensitivity and small output sensitivity [23].
2.2.2 Gyroscopes

Gyroscopes are used to either measure an angle (displacement gyroscope) or to measure the angular rate of rotation about an axis (rate gyroscope). The former is used in stabiliser platforms and the latter is used in inertial systems for positioning. In the rest of the thesis, rate gyroscopes will simply be referred to as gyroscopes. The construction of gyroscopes is closely related to their measurement principles. Historically, the angular velocity measurement observed through the spinning wheel fabricated from mechanical gyroscopes. Later, Stagnac-effect and Coriolis-effect gyroscopes based on angular momentum conservation are invented. Laser ring and fiber optic gyroscopes are invented by utilizing the Stagnac-effect. Meanwhile, MEMS gyroscopes have been developed based on the Coriolis-effect. In inertial-based positioning, the gyroscopes are arranged orthogonally and used to keep track of the orientation of the body. The angles, computed by integrating the rate of rotation, are combined with measurements from the accelerometers to estimate the position over time given a known starting point.

2.2.3 Inertial Sensor Application Grades

Inertial sensors provide a wide range of accuracy, that has become useful to characterize them in terms of the application grade for which their accuracy is best suited. The more critical and strategic applications are, the higher performance grade of sensors is demanded. Accordingly, the higher grade comes with the higher price. Figure 2.1 shows the range of inertial sensors grades summarized from [24].

Consumer-grade MEMS inertial sensors are available in self-contained IMU units. Typical applications of these sensors are in smartphones, gaming controllers, smartwatches, and entertainment units. These are low-cost units and not accurate enough to be used for inertial navigation [26]. A navigation-friendly, built from the low-cost units, is available as commercial tracking devices. Commercial tracking devices are mostly calibrated, and some have on-board processing system to compute attitude and heading.
Table 2.1: The important error sources and their typical values for MEMS inertial sensors [26], [29], [30].

<table>
<thead>
<tr>
<th>Errors</th>
<th>Descriptions</th>
<th>Accelerometer</th>
<th>Gyroscope</th>
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<tr>
<td>Bias or zero offset error</td>
<td>Displacement from zero in the absence of any applied acceleration / rotation input</td>
<td>2400 µg</td>
<td>250 °/h</td>
</tr>
<tr>
<td>Scale error</td>
<td>Error in the ratio of output value to applied accelerations / rotation input</td>
<td>5 %</td>
<td>± 10 %</td>
</tr>
<tr>
<td>Cross-coupling error</td>
<td>Non-orthogonality of the sensor triad</td>
<td>1 %</td>
<td>6 %</td>
</tr>
<tr>
<td>Non-linearity</td>
<td>Output variation in which the output does not vary exactly linearly with the applied acceleration / rotation input</td>
<td>0.5 %</td>
<td>0.2 %</td>
</tr>
<tr>
<td>Temperature effects</td>
<td>Cause bias, scale and other errors to change with changes in temperature</td>
<td>0.8 mg/°C</td>
<td>10 °/h</td>
</tr>
<tr>
<td>Alignment error</td>
<td>The measurement axis is not perfectly aligned with the desired axis</td>
<td>± 1 mrad</td>
<td>± 1 mrad</td>
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information known as Attitude Heading and Reference Systems (AHRS). These upgraded devices price range is from $200 to $2000 [27], [28].

2.2.4 Limitation of Inertial Sensors

Accelerometers and gyroscopes are subject to errors and some of the important error sources are listed in Table 2.1 [18].

Low-cost MEMS inertial sensors exhibit high biases, scale factor variations, axis non-orthogonalities, drifts, and noise characteristics. Thus, it is difficult or even impossible to use only MEMS inertial sensors for navigation due to the accumulative type of possible errors. For instance, the MEMS gyroscopes have biases in the range of 100°/hr and above in which the errors build up over time and affect the precision of the measurements badly. However, the biases are negligible for higher grade sensors, i.e. tactical grade has 1°/hr bias. Specifically, the accelerometer and gyroscope biases introduce errors proportional to $t^2$ and $t^3$ in the position, respectively [23].

2.3 Strapdown Pedestrian Inertial Navigation System

Strapdown Pedestrian Inertial Navigation System (SPINS) is defined as one where an IMU is attached to the human body, being positioned in a fixed and known alignment with the body axes of the human body [18]. The IMU measurements are obtained in its own body frame with respect to an inertial frame. The computed orientation from the angular rate is used to transform accelerometer measurements from the body frame to the navigation frame. Next, after subtracting gravity, the transformed accelerometer measurements are integrated to obtain velocities. The velocities are integrated to obtain
displacement. The displacement is then added to the previous position solution to update the current position. This type of navigation is also known as Pedestrian Dead-Reckoning (PDR) system.

There are two popular body locations have been proposed to fix the IMU, e.g. foot-mounted and waist-mounted. Waist-mounted is relatively innovative approach which promote less obtrusive attachment. However, unlike the foot-mounted approach, the implementation is not referenced to absolute information to reset positioning error. Figure 2.2 shows the common placements of INS in foot-mounted navigation. As shown, in practice, foot is not literally being used to attach the INS, but rather a shoe.

Continual integration of the IMU measurements leads to exponentially growing errors in the final position. The smallest error in the initial conditions will eventually grow to be unacceptably large and the sensor errors will be integrated over time leading to very large position errors. In the effort to reduce the accumulating error, Foxlin [34] has proposed to mount the inertial sensors on the shoe to track pedestrians and introduced Zero-velocity UPdaTe (ZUPT). This technique uses stance phase as reference because it instinctively produces zero-velocity and update the navigation equations. He obtained a remarkable positioning performance by exploiting the stance phase.

There are large number of publications that proposed improvement to the ZUPT-aided foot-mounted navigation that trade-off between accuracy and cost. There are two active research areas that are of interest;

a. improving ZUPT technique in order to reduce position drift.

b. improving heading drift in order to achieve better tracking accuracy.

A number of publications address different methods in detecting ZUPT. Some are based on statistical methods such as in [32], [35]–[37] and others relied on external sensors such as pressure sensor [38], [39] and magnetometer [40]. The statistical methods relied on signal amplitudes, thus require extensive data collections to improve the robustness of the detection. Meanwhile, the external sensors mean additional cost will be incurred which is not preferable option to many researchers.

In tackling the heading drift, several publications suggested adding magnetometer to improve the tracking accuracy [41]–[44]. However, many researchers are unconvinced to use the magnetometer due to electromagnetic interference especially from electrical equipment or objects made from iron, thereby producing unreliable measurements [45],

![Figure 2.2. The common placements of INS in foot-mounted navigation. (Left) Inside the heel [31]. (Middle) At the side of the shoe [32]. (Right) On top of the shoe [33].](image)
Alternative to a magnetometer, which supposedly alleviate heading divergence during tracking, direction constraints have been introduced [47]–[49]. Direction constraints approach takes advantage that majority buildings have their corridors parallel to each other or they intersect at right angles.

However, the current techniques require several steps before acknowledged that the pedestrian made a heading change, thus subjected to mis-heading for short direction changes [50]. Another heading correction method is called Zero Angular Rate Update (ZARU) which applies constant heading as the heading update at stance phase, akin to ZUPT. However, ZARU itself has little influence in heading correction [51] since heading is not observable in conventional navigation solutions [52].

The process of producing navigation solutions, i.e. position, velocity and attitude, from a set of raw measurements measured by inertial sensors is known as INS mechanization [53]. An error model is used to describe the temporal behaviour of inertial sensor errors because of the uncertainties in the sensors, which cause the navigation parameters computed from INS mechanization to have errors [23]. To correct the navigation parameters, an estimation filter, e.g. Kalman filter (KF), can be used to estimate the inertial sensor errors over time based on the knowledge from the error model.

Figure 2.3 shows the typical Kalman filter framework for strapdown pedestrian inertial navigation - foot-mounted (SPINS-FM). Kalman filter is supplied with an initial set of estimates then operate recursively, updating its working estimates as a weighted average of their previous values and new values derived from the latest measurement data, accelerations and angular velocities [54]. The ZUPT functions as constraint to correct the INS and calibrate the sensor errors.

2.4 RF-based Positioning

Radio frequency (RF) based localization techniques become increasingly popular because they offers pervasive, less intrusive and even cost-effective solutions. The working princi-
ple of these systems when employed for the positioning purposes is based on converting the radio frequency signals into distance measurements using the appropriate signal propagation models. Consequently, the main element of the RF-based positioning is the deployment of many wireless location sensing devices that measure the location metrics. The location metrics may include the strength of the received signals, arrival direction of the signal, the time of arrival (ToF) and others. Figure 2.4 shows the divisions of radio frequency based on IEEE 802 Standards that are being used in indoor positioning systems and techniques to approximate the position.

The IEEE 802 Standard comprises a family of networking standards that cover the physical layer specifications of technologies from Ethernet to wireless. Wireless communication is a technology to transfer information between two or more points using radio frequency. Therefore, in many publications, RF positioning is commonly referred as wireless positioning.

The research in wireless indoor positioning is generally divided between the types of wireless technologies and the methods of estimation. The wireless technologies include Wi-Fi, Bluetooth, High-Rate Wireless Personal Area Networks (HR-PANs) such as Ultra-Wide Band (UWB), and Low-Rate Wireless Personal Area Networks (LR-WPANs) such as ZigBee. Among the factors in choosing the wireless technology are readily available infrastructure (e.g. Wi-Fi), easy to use and energy-saving (e.g. Bluetooth), and high accuracy (e.g. UWB). However, those technologies are subject to a few drawbacks. For instance, generic Wi-Fi platforms lack high precision hardware for time-of-flight measurements, thus making positioning inaccurate [55]. Meanwhile, Bluetooth has small coverage area and require a high density of them, in which incur more cost. Likewise, UWB platforms are expensive in comparison with other technologies [56].

On the other hand, substantial number of indoor positioning systems rather work on the methods of position estimation. As shown in Figure 2.4, there are three major

![Figure 2.4. IEEE 802 Standards of RF which have been used in indoor positioning techniques.](image-url)
approaches for position estimation: proximity, triangulation and scene analysis. Proximity detection estimates the position based on the proximity of the user to previously known positions. Furthermore, proximity detection does not provide location in form of coordinates but rather in form of sets of possible areas. The proximity to different locations can be used to intersect these sets and find the smaller regions of possible position of the user [57]. Thus, proximity detection provides fair position information. Such approach has been reported in [58]–[60].

Majority that work in triangulation approach use distance and angle measurements in order to estimate the position. Lateration is a technique that performs positioning by using the distance between the user and at least three known points [61]. The distance can be measured from time-of-flight (ToF) or received signal strength (RSS).

Two common derivatives from ToF are time of arrival (ToA) and return-trip time (RTT) and the techniques are proposed in [62]–[64]. In one-way ranging, the sender transmits a packet and records the time of transmission (ToT) $t_0$. The receiver receives the packet and records the time of arrival (ToA) $t_0a$. If the sender and receiver are time synchronized, the range between them can be estimated as $r = c \cdot (t_0a - t_0)$ where $c$ is the propagation speed of the signal. However, time of arrival method needs a tight synchronization of clocks of a transmitter and a receiver in a fraction of a nanosecond time resolution, which is costly to implement [65]. Furthermore, a timestamp should be labelled in the transmitting signal for the measuring unit to discern the distance that the signal has travelled. In contrast, the return-trip time method measures time between send ($t_0t$) and receive ($t_0a$) of a responded message, thus relies on the same on-board clock system. The range is estimated, including a processing time delay $t_{proc}$ of the receiver, as $r = c \cdot (t_0a - t_0 - t_{proc})/2$. Though time synchronization between the sender and receiver is not required, the processing delay at the receiver must be fixed and known precisely [66].

Time difference of arrival (TDoA) method captures the time difference when, 1) a sender transmits signals to multiple receivers (known positions) or 2) a receiver receives signals from multiple senders (known positions). The former needs accurate timing synchronization for all the receivers. The latter is similar to GPS concept but has issue with packets collision. This technique has been explored in [67]–[70].

To avoid dependency on strict time synchronization where performance can be easily tampered by slight time deviation, the received signal strength (RSS) that readily extracted from most wireless devices is a welcomed substitution. The RSS is a measure of the magnitude of the power of the signal (measure of dBm) that the receiver measures at its terminal. Using RSS, the distance can be estimated based on the attenuation introduced by the propagation of the signal from transmitter to receiver where the longer the distance, the lesser the signal strength value. Theoretically, the signal strength is inversely proportional to square of distance. The biggest advantage of RSS based system is the systems do not need any additional hardware to the existing wireless infrastructure as almost every radio receiver provides an information about strength of received signal. However, the major drawbacks of this method are multi-path reflections, non-line-of-sight (NLoS) conditions and shadowing effects which might lead to erroneous distance estimates [5], [71], [72]. The RSS based system is one of active research areas in indoor
positioning [73]–[76].

Angulation is a technique that makes use of angular measurements from at least three known points to the user [61]. This technique estimates the position of a target by measuring the angle of arrival (AoA) of signals arriving at the measuring node through the adoption of directional antennas or antenna arrays [77]–[80]. It exploits the fact that in a triangle, once the length of the two sides and two angles are known, the position of the third point is known as the intersection of the remaining sides of the triangle. It needs multiple measurements for acquiring precise position information as multipath propagation might drastically impact the accuracy of the final position estimate [81].

Next approach in indoor positioning is scene analysis which collects information or features from a scene and then estimates the position of an object by matching or comparing the collected information with the one in an existing database [82]. The most popular method in this approach is known as fingerprinting [83]–[85]. In fingerprinting, the radio metrics such as received signal strength in subdivided areas can be measured beforehand, stored in a database, and compared with current situation. In aiming for high accuracy, the database must be as complete as possible, with as much of variety of measurements as possible. The measurements include the received power, time of flight and angle of arrival. In small areas, the creation of the database can be done by dividing the entire area into small clusters. Then, in each cluster, measurement samples are obtained and stored in the database. In general, the smaller the cluster, the higher the accuracy. The process of collecting measurements is laborious, time-consuming and becomes unfeasible for positioning in large areas [5]. Furthermore, fingerprinting technique is very dependent on the surrounding, thereby for any physical changes in the area, the database must be recalibrated all over again.

The recent approach in indoor positioning is known as Device-Free Localization (DFL). This approach eliminates the need of equipping the target with any wireless device. When a pedestrian moves within the deployment area of a wireless network, it will shadow some wireless links unavoidably and cause variation of the RSS and Time of Flight (ToF) of the shadowed links [86]. The DFL approach can be classified into two; grid and geometry. Radio tomography imaging (RTI) is a grid technique that determine the position of pedestrian by imaging the attenuation detected in a wireless network [87]–[89]. The technique assumes that a person attenuates the RSS on link when they cross through the line between the transmitter and receiver. Acknowledging that RTI needs a reliable statistical model to describe the impact of attenuating, diffracting and scattering on the RSS measurements, another grid technique, Bayesian method is proposed [90]. In Bayesian method, a joint model based on the theory of diffraction to deal with average path loss and the fluctuations of the RSS measurements induced by the moving target is developed. However, the method suffers from computational complexity [91]. Alternatively, Geometric Filter (GF) treats the links shadowed by the target as line segments whose intersection points are considered as probable target locations [92]–[94]. A target location is estimated using weighted mean with weights derived from the shadowing experienced by the intersecting links and the distance of each intersection point to the prior location estimate.
2.5 Hybrid Indoor Positioning Technologies

Self-contained strapdown pedestrian inertial navigation system suffers from position and heading drifts, and both may dramatically decrease the accuracy of pedestrian positioning and tracking. On the other hand, radio frequency positioning suffers from multipath effect and non-line-of-sight (NLOS) conditions. Addressing the challenges in both positioning technologies, researchers have proposed the combination of them to improve the overall positioning and tracking performance. There are two common modes of integration; loosely coupled and tightly coupled.

In loosely coupled integration scheme, the positions and velocities from the RF positioning system based on the Kalman Filter (KF) are merged as updates of the INS estimates positional information, through another estimation filter such as KF [95]. One advantage of using this integration scheme is the smaller size of state vectors as compared to the state vector in the tightly coupled integration. However, the presence of two KFs introduce extra process noise which lead the integration filter biased towards predicted states more than the measurements [23]. On the other hand, the tightly coupled integration scheme uses one centralized KF to estimate the positions, velocities and attitudes information from the mechanization of the inertial system [23]. This scheme is mostly used for high-precision application but at the cost of bigger size of state vectors, thereby larger computational cost and memory requirements.

Alternatively, some works have applied Particle filter (PF) as the integration scheme. Particle filter gives an approximate solution to an exact model, rather than the optimal solution to an approximate model, which is the basis for the KF [23]. However, the large computation load of the particle filter makes it unsuitable for running on resource-constrained devices [96]. Table 2.2 shows three state-of-the-art hybrid positioning of strapdown pedestrian inertial navigation system-foot mounted (SPINS-FM).

<table>
<thead>
<tr>
<th>Publication (Year)</th>
<th>System architecture</th>
</tr>
</thead>
<tbody>
<tr>
<td>INS Model</td>
<td>Xsens MTx</td>
</tr>
<tr>
<td>INS Position drift correction</td>
<td>Adaptive step motion model</td>
</tr>
<tr>
<td>INS Heading drift correction</td>
<td>Adaptive step motion model</td>
</tr>
<tr>
<td>RF Radio technology</td>
<td>Wi-Fi, ZigBee</td>
</tr>
<tr>
<td>RF Positioning technique</td>
<td>RSS</td>
</tr>
<tr>
<td>RF Receiver platform</td>
<td>Laptop</td>
</tr>
<tr>
<td>Integration scheme</td>
<td>Particle filter</td>
</tr>
</tbody>
</table>

Table 2.2: The state-of-the-art hybrid indoor positioning of SPINS-FM.
From the Table 2.2, [97] and [98] have used commercial grade tracking INS, which are much pricier than stand-alone sensors. Oppositely, [99] has used a more affordable inertial sensors, but needed to use magnetometer to correct the heading. Statistical based ZUPT has been used by [98] and [99], which are thresholds dependent in achieving robustness. In RF positioning, all of them have used external RF receiver platforms; i.e. laptop, tablet and smartphone. Laptop and tablet have internal Wi-Fi modules to support the RF technology used. Meanwhile, UWB dongle was connected to smartphone via USB in [99]. As a result, the hybrid systems are not convenient as additional hardware need to be used besides the INS.

### 2.6 System Architecture

In this thesis, we propose an indoor pedestrian positioning and tracking using INS and RF sensor fusion that is robust to different people and operating conditions, besides improvement in term of practicality and accuracy. The proposed system uses stand-alone consumer-grade INS and mount on the foot to take advantage of ZUPT. We reduce the position drift using our proposed ZUPT detector algorithm that is robust to different people and operating conditions (Chapter 3). We develop turn detection and heading correction algorithms with additional gyroscope mounted on the waist to reduce heading drift, which is also robust to different people and operating conditions (Chapter 4). We use the ZUPT and corrected heading in Kalman-filter framework to estimate the position and track the pedestrian (Chapter 5).

We choose device-free localization (DFL) technology as the secondary positioning system. In contrast to the state-of-the-art, the proposed hybrid indoor positioning does not need the pedestrian to carry additional wireless receiver platform such as laptop or smartphone to support the DFL technology. We apply radio tomography imaging (RTI) technique where the deployed IEEE 802.15.4 wireless sensor network (WSN) detects attenuations in the received signal strength and present the attenuations in an image. Lastly, we implement loosely coupled mode of integration to fuse the INS and RF positioning system (Chapter 6). Overall, the proposed system architecture is more accurate in the real-world application.

### 2.7 Summary

In this chapter, inertial and radio frequency based indoor positioning technologies have been presented. The types and limitations of MEMS inertial sensors have been covered. It is then followed by an introduction to strapdown pedestrian inertial navigation system. Next, various radio frequency positioning technologies based on IEEE 802 family standard and positioning techniques have been discussed. Three state-of-the-art hybrid indoor positioning systems have been analysed and their limitations pointed out. Finally, the proposed new system architecture is outlined.
3.1 Foot-Mounted Inertial Navigation System

In Chapter 2, the inertial navigation technology has been introduced. The small form factor and affordable price make inertial navigation system (INS) attractive for wearable navigation systems. One of the earliest wearable navigation technologies is the foot-mounted navigation. In the foot-mounted navigation, an INS is attached to the foot, either on top of the shoe or slotted into the shoe’s heel. In some cases, INS is attached to both feet. One particular reason of having the INS attached to the foot is to exploit a known velocity reference called as Zero-velocity UPdaTe (ZUPT). In this work, a new method is proposed to detect the ZUPT. The performance of the method is compared with the other approaches. At the end of this chapter, the high accuracy of ZUPT detection (99.5 % detection accuracy recorded in experiments) is accounted in improving the linear tracking.

3.1.1 Zero-Velocity Update

During a walk, the gait of a pedestrian changes from swing to stance phases, and stance to swing phases, alternately. The trajectory of the walk ideally can be estimated by performing double integration on the forward acceleration. The swing phase shall produce displacement of the walk and the stance phase shall produce zero displacement. Nonetheless, in real-life scenario the inertial data is contaminated with multi-source of errors that cause enormous and accumulated position drift. To minimize the position drift, [34] suggested to update the position estimation by comparing the velocity of the foot when it is completely on the ground. Intuitively, the velocity is zero when the foot is completely on the ground, thus any non-zero velocity measured by the accelerometer should be updated to zero. Backed by the theory, the term zero-velocity update (ZUPT) is coined by the author.
3.1.2 Stance Phase Detection Methods

The prerequisite for using the ZUPT to update the velocity measurement is the detection of stance phase. There are two ways of implementing the detection method; statistical method and external trigger. The statistical method to compute the signal amplitude is the most commonly used to detect the stance phase. The data from accelerometer or gyroscope or sometimes both are statistically processed to determine the stance phase. Table 3.1 shows some of the statistical methods to detect the stance phase together with reference to the publications.

On the other hand, the stance phase can be detected by external trigger such as pressure sensor and magnetic disturbance. Pressure sensor that uses strain gauge will measure the resistance whenever the pedestrian forces the body weight to the ground in stance phase. The difference in resistance indicates the change in gait phase, thus enables stance phase to be detected [103]. Another method in external trigger is to put a permanent magnet to the side of a foot [40]. The magnetometer from INS attached to other foot will experience a maximum magnetic disturbance cause by the permanent magnet when the feet are at mid-stance. The disturbance is at lowest when one of the foot is at initial contact to the ground, just before the stance phase. By thresholding, the stance phase can be successfully determined.

3.1.3 Limitations

The performance of ZUPT, and consequently the positioning, highly relies on the accuracy of stance phase detection. However, the major concern in applying the stance detection methods is the robustness of the detection. The thresholds used in those methods will significantly affect the performance of detection [104] and might require different values for different users or conditions as most of the thresholds are usually pre-defined empirically.

Different users have unique gait whereas some walk faster or slower than others in their normal walk. However, most of the stance detection methods directly use sensor measurements such as acceleration in the Method 1 to Method 5 in Table 3.1 before thresholding to determine the stance. Accordingly, a number of samples of different users are collected to fine-tune the threshold in order to accommodate variety of gait of the users. Still, the detection performance is positively biased towards that group of users.

In this thesis, a solution on stance phase detection is proposed based on the pattern of sensor measurements. Unlike the statistical method that perform the detection computation from the measurements, in which they are highly influence by the gait of the user, the proposed detection method analytically detects the pattern of stance phase, in which revealing zero flat acceleration. In the proposed method, a cluster of zero acceleration is determined as a potential stance phase. The clustering process is based on subtractive clustering method, detailed in the next sub-section.
Table 3.1: Stance phase detectors.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Method 1</strong></td>
<td>Thresholding normalized acceleration [100]</td>
<td>$\text{norm}<em>{\text{acc}} = \sqrt{a_1^2 + a_2^2 + a_3^2}$ &lt;br&gt;$\text{zupt} = {i \mid \text{norm}</em>{\text{acc}} _i &lt; 0.8}$&lt;br&gt;where $a_i$ is the acceleration in the corresponding axis and $i$ is the data index.</td>
</tr>
<tr>
<td><strong>Method 2</strong></td>
<td>Thresholding and filtering normalized acceleration [101]</td>
<td>$\text{norm}<em>{\text{acc}} = \sqrt{a_1^2 + a_2^2 + a_3^2}$ &lt;br&gt;$\text{filtered}</em>{\text{acc}} = \text{LPF} \left(\text{abs}(\text{HPF}(\text{norm}<em>{\text{acc}}))\right)$&lt;br&gt;* HPF: high pass filter, * LPF: low pass filter&lt;br&gt;$\text{zupt} = {i \mid \text{filtered}</em>{\text{acc}} _i &lt; 0.05}$&lt;br&gt;where $a_i$ is the acceleration in the corresponding axis and $i$ is the data index.</td>
</tr>
<tr>
<td><strong>Method 3</strong></td>
<td>GLRT - Generalized likelihood ratio test [102]</td>
<td>$T(z_n^a, z_n^w) = \frac{1}{W} \sum_{k=n}^{n+W-1} \frac{1}{\sigma^2_a} \left| y_k^a - 8 \frac{y_n^a}{|y_n^a|}\right|^2 + \frac{1}{\sigma^2_a} |y_n^w|^2$&lt;br&gt;$\text{zupt} = {i \mid T_n &lt; 0.3e5}$&lt;br&gt;where $y_k^a, y_n^w, \sigma$ are the acceleration, angular rate, variance.</td>
</tr>
<tr>
<td><strong>Method 4</strong></td>
<td>MV - Accelerometer measurements variance [102]</td>
<td>$T(z_n^a, z_n^w) = \frac{1}{\sigma^2_a W} \sum_{k=n}^{n+W-1} \left| y_k^a - \bar{y}_n^a\right|^2$&lt;br&gt;$\text{zupt} = {i \mid T_n &lt; 0.3e5}$&lt;br&gt;where $y_k^a, \sigma$ are the acceleration and variance.</td>
</tr>
<tr>
<td><strong>Method 5</strong></td>
<td>MAG - Accelerometer measurements magnitude [102]</td>
<td>$T(z_n^a, z_n^w) = \frac{1}{\sigma^2_a W} \sum_{k=n}^{n+W-1} (|y_k^a| - g)^2$&lt;br&gt;$\text{zupt} = {i \mid T_n &lt; 0.3e5}$&lt;br&gt;where $y_k^a, \sigma$ are the acceleration and variance.</td>
</tr>
<tr>
<td><strong>Method 6</strong></td>
<td>ARE - Angular rate measurement energy [102]</td>
<td>$T(z_n^a, z_n^w) = \frac{1}{\sigma^2_a W} \sum_{k=n}^{n+W-1} |y_k^w|^2$&lt;br&gt;$\text{zupt} = {i \mid T_n &lt; 0.3e5}$&lt;br&gt;where $y_k^w, \sigma$ are the angular rate and variance.</td>
</tr>
</tbody>
</table>
3.1.4 Subtractive Clustering

In most of clustering algorithms, the users need to pre-define the number of cluster centres and their initial locations. However, the quality of the solution is significantly affected by the choice of those initial parameters [105]. Correspondingly, a method called mountain clustering has been developed to estimate the number and initial location of the cluster centres [106]. This method divides the data space into grids and computes a potential value for each grid point based on its distances to the actual data points. High potential value reflects a grid point with many data points nearby. The grid point with the highest potential value is chosen as the first cluster centre.

The principle of this method is to reduced potential value of grid points that close to the cluster centre, thereby acknowledged the selected cluster centre represents that particular region of data space. The next cluster centre is accepted at the grid point with the highest remaining potential value. These process of acquiring new cluster centre and reducing the potential of adjacent grid points repeats until the potential of all grid points falls below a threshold. The problem with this method is the computation grows exponentially with finer grids in order to accurately locate the exact cluster centres.

Subtractive clustering has been developed by [107] as an extension to the mountain clustering. In this method, each data point is treated as a potential cluster centre instead of using grid points. The computation for this technique is now proportional to the problem size instead of the problem dimension [105]. It eliminates the need to specify the grid resolution, in which trade-offs between accuracy and computational complexity must be considered.

In this work, stance phases are required to be identified before correcting the position drift. The stance phases comprise data samples that represent zero velocity, i.e. zero acceleration, as the foot is completely on the ground. As a stance phase lasts for a few milliseconds, a cluster of zero acceleration is formed. Naturally, the zero acceleration forms due to two reasons. First, there is no foot motion detected such as in stationary or in stance phase. Secondly, there are zero-crossing samples that results from the change in magnitude of the acceleration signal from positive to negative direction or vice versa.

3.2 ZUPT Detector Algorithm

Subtractive clustering method has been used to detect the stance phases based on the signal pattern in the vertical acceleration signal, $a^z$. The vertical acceleration is chosen because, visually after plotting the measurements, the stance phases are recognizable by clusters of zero acceleration. In the first step, the gravity influence in the vertical acceleration was removed by using a simple complementary filter as follows:

$$ gravity^z_k = alpha \ast gravity^z_{k-1} + (1 - alpha) \ast a^z_k \quad (3.1) $$

$$ \bar{a}^z_k = a^z_k - gravity^z_k \quad (3.2) $$
CHAPTER 3. ZERO-VELOCITY UPDATE DETECTOR

where initial value of gravity (\(g_z^0\)) set as \(-9.8\, \text{m/s}^2\) and the filter constant, alpha, defined as 0.8 [108]. The \(\bar{a}_k^z\) represents the gravity compensated acceleration and \(k\) is the index of the data. Next, the gravity compensated acceleration was filtered to select data that were close to zero, i.e. samples with magnitude between \(\pm 0.8\, \text{m/s}^2\). The indices of the filtered samples formed a sorted, 1-dimensional vector \(\bar{x}\), which represent samples that were bounded by the limits.

\[
\bar{x} = \left\{ k_1, k_2, \ldots, k_m \mid -0.8 < \bar{a}_k^z < 0.8 \right\} \tag{3.3}
\]

where \(k\) can be a value from 1 to the total number of samples, \(m\). The dataset \(\bar{x}\) was then normalized as in (3.4) so that all data were bounded by a range of values of [0, 1]. The \(\min(x)\) represented by \(x_1\), i.e. \(k_1\), and \(\max(x)\) represented by \(x_m\), i.e. \(k_m\). The subscript \(i\) denotes the index of vector \(x\).

\[
\hat{x}_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{3.4}
\]

Each data point of \(x\) was considered as a potential cluster centre and the potential was computed as

\[
P_i = \sum_{j=1}^{n} e^{-\frac{\|\hat{x}_i - \hat{x}_j\|^2}{(ra/2)^2}} \tag{3.5}
\]

where \(r_a\) is a positive constant that defines the neighbourhood radius. The data points outside this radius have little influence on the potential. The first cluster centre, \(\hat{x}_1^*\), was determined by the highest cumulative potential value \(P_1^*\). Afterwards, the potential of each data point was revised against the first cluster centre as follows:

\[
P_i = P_i - P_1^* e^{-\frac{\|\hat{x}_i - \hat{x}_1^*\|^2}{(rb/2)^2}} \tag{3.6}
\]

where \(r_b\) is a positive constant and defined as \(r_b = 2r_a\) to avoid closely spaced cluster centres. The process of acquiring the new cluster centre were repeated until the remaining potential of all data points in the group was below some fraction of the potential of the first cluster centre \(P_1^*\). The general revised potential formula is given as:

\[
P_i = P_i - P_c^* e^{-\frac{\|\hat{x}_i - \hat{x}_c^*\|^2}{(rc/2)^2}} \tag{3.7}
\]

where \(\hat{x}_c^*\) is the location of the \(c^{th}\) cluster centre and \(P_c^*\) is its potential value. It is suggested in [109] to use \(P_c^* < 0.15P_1^*\) as stopping criterion to halt the process of searching the cluster centre. However, from our analysis, \(0.3P_1^*\), would produce a solid result in detecting the stance phase. A lower threshold would cause the algorithm to
detect the zero-crossings as well. Afterwards, a row vector, \( \vec{c} \), that comprises of all cluster centres would be formed as follows:

\[
\vec{c} = \{ \hat{x}_1^*, \hat{x}_2^*, \ldots, \hat{x}_g^* \}
\]

where \( g \) is the number of detected cluster centres. The computed cluster centres might belong to the stance phases or zero-crossings. The clusters that belong to stance phases are wider (more samples in sequence) than those that belong to zero-crossings. The wider clusters have higher probability to have cluster centres compared to zero-crossings due to the dense neighbourhood.

The last step was to form a ZUPT vector by using the information of cluster centres. A ZUPT vector comprises of 1's and 0's that denotes stance phase and swing phase, respectively. The ZUPT vector has \( m \) elements, which is the number of samples. The value 1's in ZUPT vector were assigned to data points which were part of clusters represented by cluster centres. Therefore, all clusters were identified and defined by a column vector, \( \vec{h}_v \), as follows:

\[
\vec{h}_v = \{ \{ k_1; k_{1+n} \}, \{ k_{1+n+1}; k_{1+n+1+p} \}, \ldots, \{ k_f; k_m \} \}
\]

where \( k_{*a} \) is the index at the beginning of a cluster, \( k_{*b} \) is the index at the end of the cluster and \( f \) is the number of clusters. If a computed cluster centre was located at any point between \( k_{*a} \) and \( k_{*b} \), then the all elements of \( t_z \) in (3.12) will be positive.

\[
t_z = J\vec{h}_v - c_w J \begin{bmatrix} 1 \\ 1 \end{bmatrix}
\]

\[
J = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}
\]

where \( v = 1 \) to \( f \), \( w = 1 \) to \( g \) and \( z = 1 \) to \( f \times g \). Matrix \( J \) corrects the polarity of the elements \( h_v \) and \( c_w \). A new dataset of \( t \) will establish the binary state transition for ZUPT. All values between \( k_{*a} \) and \( k_{*b} \) of cluster \( h_v \) that satisfy \( t_z > 0 \), will be set as 1, or 0 otherwise.

\[
ZUPT = \begin{cases} 
1 & t_z > 0 \\
0 & t_z < 0 
\end{cases}
\]
CHAPTER 3. ZERO-VELOCITY UPDATE DETECTOR

**Figure 3.1.** Illustration of clusters in dataset x (smaller dots represent data points and two larger dots represent cluster centres).

Table 3.2: IMU specifications.

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Accelerometer</th>
<th>Angular Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>ADXL345</td>
<td>ITG3200</td>
</tr>
<tr>
<td>Range</td>
<td>± 2g</td>
<td>± 2000°/s</td>
</tr>
<tr>
<td>Sampling rate</td>
<td>50 Hz</td>
<td>50 Hz</td>
</tr>
</tbody>
</table>

Figure 3.1 on page 23 shows illustration of data points with two detected cluster centres, \( h_{v-1} \) and \( h_{v+1} \), thereby two stance phases. The cluster of data points in the middle (\( h_v \)) that is not represented by a cluster centre is acknowledged as not a stance phase, i.e. zero-crossings.

The algorithm is summarized in a flowchart as shown in Figure 3.2.

### 3.3 Experiments

#### 3.3.1 Setup

Virtenio Preon32 inertial measurement unit (IMU) with digital tri-axial accelerometers and tri-axial gyroscopes were used in this research for data acquisition. The sensors details are given in the Table 3.2. The sensors were strapped on top of right shoe in which the position and coordinate system is shown in Figure 3.3 on page 25.

Besides IMU, the device is embedded with ARM-based microcontroller, IEEE 802.15.4 radio transceiver and 8 Mb flash memory. The data were recorded to the flash memory during operation and processed offline after uploading to a PC. The pedestrian is 173 cm in height and about 87 kg in weight. Table 3.3 lists the score of experiments that had been done in-house where the number of actual steps and duration of experiments had been recorded. The data recorded were labelled as dataset A.
FIGURE 3.2. The flowchart of using subtractive clustering as ZUPT detector.
3.3.2 Public Datasets

There are three types of dataset that have been evaluated using seven ZUPT extraction techniques. The dataset A was collected in-house. The dataset B and C were downloaded from x-io Technologies Limited (http://www.x-io.co.uk/gait-tracking-with-x-imu) and OpenShoe (http://www.openshoe.org/?page_id=362) websites. Both resources are released under the Creative Commons Attribution License. The datasets were retrieved along with the MATLAB implementation for pedestrian tracking, but no changes were made to the original MATLAB code. The summary of the datasets is given in Table 3.4.

![Sensors position and the coordinate system.](image)

**Figure 3.3.** Sensors position and the coordinate system.

<table>
<thead>
<tr>
<th>#</th>
<th>Descriptions</th>
<th>Number of stance phases</th>
<th>Duration (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>Normal walk trial 1</td>
<td>30</td>
<td>47</td>
</tr>
<tr>
<td>A2</td>
<td>Normal walk trial 2</td>
<td>30</td>
<td>48</td>
</tr>
<tr>
<td>A3</td>
<td>Slow walk trial 1</td>
<td>30</td>
<td>66</td>
</tr>
<tr>
<td>A4</td>
<td>Slow walk trial 2</td>
<td>30</td>
<td>67</td>
</tr>
<tr>
<td>A5</td>
<td>Fast walk trial 1</td>
<td>30</td>
<td>38</td>
</tr>
<tr>
<td>A6</td>
<td>Fast walk trial 2</td>
<td>30</td>
<td>37</td>
</tr>
<tr>
<td>A7</td>
<td>Stairs (walking up) trial 1</td>
<td>23</td>
<td>37</td>
</tr>
<tr>
<td>A8</td>
<td>Stairs (walking up) trial 2</td>
<td>23</td>
<td>38</td>
</tr>
<tr>
<td>A9</td>
<td>Stairs (walking down)</td>
<td>47</td>
<td>67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>#</th>
<th>Descriptions as given by sources</th>
<th>Number of stance phases</th>
<th>Duration (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>Straight line (x-io)</td>
<td>12</td>
<td>39</td>
</tr>
<tr>
<td>B2</td>
<td>Stairs &amp; corridor (x-io)</td>
<td>34</td>
<td>59</td>
</tr>
<tr>
<td>B3</td>
<td>Spiral stairs (x-io)</td>
<td>32</td>
<td>52</td>
</tr>
<tr>
<td>C1</td>
<td>Walk (OpenShoe)</td>
<td>42</td>
<td>49</td>
</tr>
</tbody>
</table>
3.3.3 Results and Discussion

The aim of this experiment is to count the number of stance phases detected from the dataset. Therefore, the standing phases at the beginning and at the end of the dataset have been excluded. A successful detection means the method correctly identifies the stance phase, whereas a failed detection means either the method does not detect the stance phase, detect at the wrong place or there are multiple detections within the same stance phase.

Three metrics are used to evaluate the performance of each method. First is the precision (P) of the techniques which is the percentage of the actual ZUPT correctly classified. Table 3.5 shows the computed precision of Method 1 (M1) to Method 7 (M7). M7 is the proposed method.

\[
P = \frac{\text{number of correct stance phase computed}}{\text{actual number of stance phase}} \times 100\% \quad (3.15)
\]

Second is the sensitivity (S) of the technique which is the proportion of positive cases (i.e. correctly detected real ZUPT) that were correctly identified. A 100% means all the detected ZUPT are indeed the real ones. Lower percentage represents higher false positive generated by the detection algorithm. Table 3.6 shows the computed sensitivity of Method 1 (M1) to Method 7 (M7).   

\[
S = \frac{\text{number of correct stance phase computed}}{\text{total number of stance phase computed}} \times 100\% \quad (3.16)
\]
Lastly, a metric that summarizes both precision and sensitivity by taking their harmonic mean, F1 score [110], is computed as in (3.17). The average values from precision and sensitivity over 13 experiments are used in the computation.

\[
F_1 \text{ score} = 2 \times \frac{\text{precision} \times \text{sensitivity}}{\text{precision} + \text{sensitivity}}
\]  

(3.17)

F1 score, which is based on Van Rijsbergen’s effectiveness measure [111], penalizes a technique that has imbalance in performance between precision and sensitivity. In Figure 3.4, M1 scores the worst even though it performed well in precision as shown in Table 3.5. Table 3.6 however, shows M1 recorded the highest mean of false detections. The false detections are primarily attributed to detecting the zero crossings.

M2, which is the improved version of M1 managed to score better. It recorded about 83 and 86 percent in average for precision and sensitivity respectively. The combination of low and high pass filters manages to ignore the zero crossings. However, upon scrutiny, M2 failed badly in detecting ZUPT in experiment A5. The selected threshold is well below the limit of the sensor data, thus no stance phase is detected. This lowers the overall precision and F1 score. Not surprisingly, it excelled in extracting ZUPT of dataset which come from the same source (B1, B2 and B3). Still, multiple ZUPT detections at the same phase causes sensitivity to drop for B2 and B3 as shown in Table 3.6. It is noteworthy that in position estimation procedures, where double integration would be performed, different ZUPT detections within the same phase will result in unwanted displacement at the gaps when they are supposed to be stationary.

Methods M3 and M6 score almost 95 percent in F1-measure with M3 leads the latter. The high performance of both detectors confirms the findings in their original literature [102] which stated that they outperformed the other two methods, M4 and M5. The inclusion of angular rate in the algorithms of M3 and M6 proves to be key factor of achieving such performance. Interestingly, as mentioned in the original literature, angular rate can provide reliable ZUPT detection on levelled ground but might fail to whenever walk up or down. This also has been proven in this work where more false detections are recorded.
detections are retrieved by those methods for experiments A7 to A9 and B2 to B3 where the subject travelled through stairs. A number of false detections are reflected in lower sensitivity values in comparison to other experiments.

M4 and M5 recorded about 58 percent in performance. They slump in sensitivity due to the high number of false detections. This relates to the failure of the algorithms to differentiate between the actual ZUPT and other parts of the signal that are close to zero acceleration.

Lastly, M7, which is the proposed method in this chapter performed almost flawlessly in all experiments. Besides striking 100 percent sensitivity, which means there is no false detection, the method only failed to detect a total of four stance phases in experiments B3 and C1. The failures happened because of special case where the computed cluster centres do not lie in any cluster of data points.

3.4 Tracking Performance

In the beginning of this chapter, the use of ZUPT to reduce position drift has been explained. Since the accuracy of ZUPT detection highly influences the effectiveness in reducing position drift, a ZUPT detector based on subtractive clustering has been proposed. The proposed ZUPT detector has been proved to outweigh other detection methods. In this research, the result from the proposed detector, ZUPT vector, have been proved to:

i. improve linear tracking performance,

ii. support real-time tracking.

Off-the-shelf INSs have different specifications and many of the standalone systems include an embedded microcontroller and external memory. However, the embedded platforms are generally resource-constrained in order to achieve small footprint and low energy consumption. The resource-constrained embedded platform has brought researchers in unfavourable situation as high-performance positioning algorithms, such as particle filter, typically require powerful computing machines.

3.4.1 Linear Tracking

The results from subtractive clustering produce an important piece of information to compute the distance travelled by a pedestrian. The established ZUPT can be used to segregate the forward acceleration into motion and non-motion states. Knowing that a motion state is the period where the foot swings forward to make up a step, the state will be integrated twice to obtain the displacement of the foot. In this case, whenever the ZUPT equals zero (motion state) and the displacement is calculated by integrating the corresponding forward acceleration. The formula to perform numerical integration are given as follows:
where $d$ is the cumulated distance, $a^x$ is the forward acceleration, $t$ is the sampling time, $q$ is the previous discrete sampling and $q + 1$ is the current discrete sampling. The forward acceleration samples are filtered in the first place to remove the gravitational force.

To limit the computed current distance into a reasonably expected value, in case if there is unexpectedly high magnitude of noise in the acceleration data, a threshold of 1.0 meter is applied which refers to the longest possible distance a long stride can make. A study by Peruzzi et al. [112] reported a range of stride lengths, for three different walking speeds (slow = 1.122 m, comfortable = 1.300 m and fast = 1.324 m) from data collected out of 20 participants. Nonetheless, those values will over-estimate the travelled distance when used in the proposed system. Threshold values of 0.9 m, 1.0 m and 1.1 m produced better results for slow, normal and fast walks, respectively, as they have been tested in conducted experiments.

Figure 3.5 shows an overview of the linear pedestrian tracking system. However, it is a challenge to implement the above-mentioned algorithm in the real-time without powerful computing machine such as a laptop or a high-end smartphone. Still, we managed to get them work on the limited-resource embedded INS as discuss in the following section.

3.4.2 Realization of Real-Time Operation

In this research, the real-time linear tracking is achieved using embedded INS, which updates the positioning results in less than a second. For a record, Anacleto et al. [113] have attempted to develop a localization system with below 2 seconds delay between position updates. The resource-constrained device requires an agile tracking algorithm to produce fast and accurate tracking results. Specifically, there are three resources of concern when dealing with constrained embedded platforms, namely processor (speed), memory capacity and power consumption.

In our study, without any optimization, the computation time of a laboratory embedded INS to perform the subtractive clustering to determine ZUPT for a sample size of 40 with
a sampling frequency of 50 Hz is about 6 seconds. The device is powered by ARM-Cortex M3 with maximum clock frequency of 72 MHz in active mode, 256 kB flash memory, 64 kB static random access memory (SRAM) and tri-axial IMU [114]. In order to tackle the limited resources implementation, we have refined the whole tracking algorithm by substituting processes that can be done in parallel into pipelined operations and the use of lookup table for the time-consuming computation of the exponent calculation.

As we have foreseen to use two embedded INS in this research to achieve an integrated indoor positioning system, the whole operation was split into two parts. The first device which is also known as foot node (FN) has been used to collect all the sensor data. As shown in Figure 3.6, our system used interrupt service routine (ISR) to collect the sensor data; forward acceleration \( (a_x) \) and vertical acceleration \( (a_z) \). The sampling frequency was set at 50 Hz thereby the ISR would be triggered every 20 ms. At each sampling time, the sensor data were pipelined to perform the Equation (3.1) and (3.2) that took up to 1.8 ms to complete, for both acceleration samples.

The second device was a body node (BN) that has been used to perform the detection of ZUPT and to compute the travelled distance. In future, in a practical scenario of a wearable system, the body node would act as a network gateway to relay useful information from a person to a wireless sensor network (WSN) as part of location-aware services. This was a deliberate plan to free up more resources in the foot node for future development.

Once the 40 samples of sensor data were collected after 800 ms, the FN would transfer the data to BN. The transmission of data from FN to BN would take an average of 100 ms including byte conversions (wireless network packets) and buffering. The computation of zero-velocity update and distance took 335 ms and 25 ms, respectively. Those values were the maximum time measured to process 40 samples. However, as revealed later, the maximum times were different in case of a stationary state and a motion state. The time required to obtain the estimated travelled distance was less than 460 ms per window size of 40 samples. There was an idle period of 340 ms before the next iteration starts.

Figure 3.7 indicates the position update interval for subsequent windows. Except the first window where a delay of 800 ms was required to collect the first window of samples, the position updates for every 800 ms, after 1.26 s the system started.
CHAPTER 3. ZERO-VELOCITY UPDATE DETECTOR

FIGURE 3.7. Position update interval.

The efficient time required for the computation of ZUPT using subtractive clustering is credited to the use of lookup tables. A normal exponential operation in subtractive clustering takes up a few seconds to complete and it is not acceptable for real-time operation. By making up all possible computations that use exponential operation in Equation (3.5) and (3.7), two lookup tables were pre-loaded into the device memory to speed up the computation time.

The time taken to compute the exponential operations for a set of samples using look-up tables equals $0.19n^2$ where $n$ is the window size. For instance, the average time to compute the exponential operations in Equation (3.5) for 40 samples is about 267 ms. It is close to the expected value which is 304 ms ($40 \times 40 \times 0.19$). It is 21-fold faster than the original performance estimated at $4n^2$. The lookup tables are prepared by tabulating all possible values for exponential terms in (3.5) and (3.7). The terms can be rearranged as follows:

\[
\exp(5) = e^{-\frac{\|x_i - x_j\|^2}{(ra)^2}}
\]

\[
\exp(5) = e^{c_a \left( \frac{x_i-x_j}{max-min} \right)^2}
\]

\[
\exp(7) = e^{c_b \left( \frac{x_i-x_j}{max-min} \right)^2}
\]

where $c_a = 4$ (because $r_a = 1$) and $c_b = 8$ (since $r_b = 2r_a$). The $x_i - x_j$ and $max - min$ are varied between 0 to 39 and 1 to 39, respectively (window size = 40). The results are tabulated into corresponding lookup tables, $\exp(5)$ and $\exp(7)$. During the execution, the results of exponential terms for (3.5) and (3.7) are retrieved by referring to the values of $x_i$, $x_j$ and $max - min$.

3.4.3 Offline Simulations

Another challenge to run the above-mentioned algorithms in the real-time is to ensure the quality of results comparable to the original offline model. To ensure no compromise in the performance, the execution of the algorithms had been simulated using a laptop. There were two results that were expected: the detection of ZUPT and the estimation of travelled distance using Equation (3.18). The procedure started with logging the accelerations in X- and Z-axes during a walk. A person of 1.78 m in height, walked normally with an average
speed about 4 km/h for a distance of 20 m, straight line. The data was then downloaded and processed in the MATLAB.

In Figure 3.8, it is shown that all the stance phases have been correctly detected using the subtractive clustering algorithm. The solid line is the acceleration in Z-axis and the dotted line is the detected ZUPT. Based on the zero-velocity updates, the acceleration in X-axis was integrated twice to obtain the distance. Figure 3.9 depicts the displacement result from the integration where the final position is calculated as 20.25 m. The offline simulation produces an error of 1.25 %.

Another similar experiment with a different person (1.74 m height) yields an error of 1.20 % in the offline simulation. In short, there are two observations from the simulations. First, the high accuracy of estimated distance reflects the hardware was setup correctly. Secondly, the algorithms work as expected where all stance phases are detected and errors in estimating distance are acceptable.
3.4.4 Experiment Setup

The experimental setup comprised three units of embedded INS [114] with similar specifications described in sub-section 3.3.1. Since the purpose of the experiment was to measure the travelled distance based on subtractive clustering and double integration, only accelerometers were enabled. An overlap of 4 samples (10% of 40 samples per window size) was introduced. Therefore, except for the first window, for the rest of windows there were only 36 new samples to be collected and then concatenated with the four samples from the previous window.

The placement of foot and body nodes is shown in Figure 3.10. The nodes communicate to each other wirelessly by using the IEEE 802.15.4 standard. The computed travelled distance from the body node was then streamed to a laptop connected through the third device (receiver node) for logging and visualization purposes.

3.4.5 Results and Discussion

In the conducted experiments, nine participants (6 males and 3 females) had been asked to walk normally for a 49.6 m straight-line path. The chosen distance was very relevant for indoor buildings which comprise mostly of short distance corridors. The participants walked at their own speed and style to show that the proposed system is invariant to people’s gaits. They were required to walk the course twice in each direction. Table 3.7 presents the error of the distance computed by the embedded platform against actual distance. The error was computed by using the following formula:

\[
\text{error} (\%) = \left( \frac{\text{abs}(d_1 - 49.6m) + \text{abs}(d_2 - 49.6m)}{49.6m + 49.6m} \right) \times 100% \tag{3.23}
\]

where \( d_1 \) and \( d_2 \) were the computed distances in meters for the first and second walk respectively. The 49.6 m is the ground truth. The average error was recorded as 3.1%. The majority of the errors were due to misdetection of the stance phase by the ZUPT detector.
The undetected stance phase causes the respected non-ZUPT cluster to have a wider width as two non-ZUPT clusters are combined. Consequently, the estimated travelled distance was longer than the actual distance after performing the double integration. Errors of more than 5% have two misdetections and those within 2–5% indicate one misdetection. Besides misdetection, slight noise in the X-axis acceleration contributes to the errors.

Table 3.8 shows the timing characteristics of the main processes of the designed system. There are two different phases have been considered, stationary (i.e. stance phase) and in motion (i.e. swing phase). The interval cycle reflects the expected positional update in milliseconds which is about 720 ms, the time to collect all the samples ((40-4) x 20 ms). The time includes the transmission and reception of data between the foot and body nodes. The minimum values that are below that 720 ms shows little discrepancy in the timer interrupt thread which sometimes triggered at 19 ms instead of 20 ms per sample.

The second row represents the time taken to complete the Equation (3.1 – 3.2) for the 40 samples. It is about the same for stationary and motion phases. Distinctively, the third row denotes differences in time for both phases. The stationary phase took a longer time to complete because the number of samples to be processed in Equation (3-13) equals to the window size, 40. This is a result of Equation (3.3) where all the acceleration samples
at stationary phase are within the tolerance. Meanwhile, in motion phase, fewer samples
would be processed that indicates only a few samples are within the tolerance and thereby
process faster.

Similarly, the fourth row shows the time to perform double integration is longer in
the swing phase. This results from execution of Equation (3.18) on the non-zero ZUPT
clusters, \( \vec{h}_{n_z} \), that existed in the motion phase.

3.5 Summary

The importance, techniques and limitations of existing ZUPT detectors have been thor-
oughly explained. The working principles and advantages of subtractive clustering have
been discussed. Accordingly, a new ZUPT algorithm based on subtractive clustering
has been proposed. The proposed ZUPT algorithm has been compared with other ZUPT
detectors using three datasets, which two are from public repositories. The results show
the proposed ZUPT detector outweighs the other methods.

The efficiency of proposed ZUPT detector in producing better linear tracking perfor-
ance as well as possibility to perform in real-time processing have been verified. A
linear tracking model has been validated from offline simulation and tested on resource-
constrained hardware. The distance error and timing characteristics from the test have
been presented which indicate good linear tracking accuracy with position update less
than a second.
4.1 Introduction

The fast adoption of inertial navigation sensor (INS) into many products comes with a wide range of performance grades of INS. Consumer grade INSs are on the low-end of both performance and cost, and as such are suitable for applications such as video game controllers and smartphones. Applications such as navigation systems demand industrial-grade performance and they are much more expensive. The key factor to superior performance is their better gyro bias stability, which indicates how stable the bias of a gyro is over a certain specified period. The lower the bias stability the lower the errors will be when integrating the gyro output to estimate the heading angles.

On the other side, consumer-grade INSs have greater bias stability and generally are not suitable for navigation purposes. The poor orientation estimated from gyros contains drift that results in errors in the navigation in two ways \cite{115}. First, orientations (pitch, roll and yaw) are used to separate accelerations from gravitational acceleration. The poor estimates of orientations cause the accelerations estimation to be erroneous and upon double integration result in errors in the magnitude of movement. Second, the tracking will go in the wrong direction due to inaccurate orientation estimation. The high bias stability could be related to several causes such as manufacturing defects and angular random walk.

Still, consumer-grade INSs offer low-cost and small platform navigation solutions, such as the foot-mounted INS \cite{116}. It has been demonstrated that position drift can be minimized in foot-mounted INS by applying Zero-velocity Update (ZUPT). The detected stance phase instinctively produces zero velocity that can be used as reference to reset the position drift. To the contrary, the heading drift has not been well solved as the heading error is unobservable in the Kalman-based navigation framework \cite{47}. Some have resorted to use geomagnetic information from magnetometer \cite{117} but the information is susceptible to magnetic disturbance under certain operational conditions.

To minimize the negative effects of heading drift in indoor navigation, researchers
have proposed to use corridor’s directions as constraints. For instance, the authors in [118] stressed that most of indoor corridors are in the 4 major directions (called as dominant directions), either parallel or orthogonal to each other and to the peripheral walls of the building. They have developed Heuristic Drift Elimination (HDE) algorithm that corrects the computed heading to match with the closest dominant direction. The algorithm is based on a feedback control system and works well for short stretch of walking in non-dominant directions. However, a longer walk (30 – 60s) in non-dominant directions will cause the algorithm to overcorrect the headings and leads to wrong positions. To resolve the problem, an adaptive gain function is introduced where one or more attenuators are multiplied with the gain in every iteration. The attenuators would suspend the HDE algorithm from correcting the heading if walks along non-dominant directions are detected.

Still, the heading drift is present in a prolonged walk in the non-dominant directions, as reported by [119]. The authors showed the position error from HDE by using circular path as an example. Besides, HDE also fails to determine the correct position when the pedestrian walks in a straight line, which is not aligned with the dominant directions. To solve these problems, the authors proposed an improved HDE method (iHDE). The iHDE still uses dominant directions to correct the heading but also incorporates movement analysis and confidence estimator to estimate the heading error as well as the confidence level of that estimation. Their tracking results, particularly for circular paths, indicate better performance than the HDE. Nonetheless, our in-house experiments used to replicate the method indicate that the given thresholds (i.e. step size attenuator’s threshold) are not robust. In many occasions, walking along circular paths is detected as straight walk.

Moreover, researchers in [120] claimed that the iHDE performance suffers when the pedestrian is not walking along the dominant directions for a long time. They proposed an Advanced HDE (AHDE) that will classify the motion of a pedestrian into 3 types; non-straight motion, straight motion and straight motion along the dominant directions. The AHDE algorithm is based on linear regression that fits a straight line to a 6-position data. A residual function $D$, sum of squares of the perpendicular offsets, is computed and used to determine the first two types of motions. If the value of $D$ is higher than the pre-determined threshold, $T_hD$, the motion is considered as non-straight or otherwise, straight. If the motion is straight, and the difference with respect to the dominant direction is smaller than another pre-determined threshold, $T_h$, then the motion is a straight motion along the dominant directions. However, since 6 pedestrian’s steps are required to start the process, the algorithm lags in classifying the motion. The lag that causes the short stretches of non-dominant directions will not be detected.

Besides, the choice of inertial sensors greatly influences the performance of pedestrian tracking. High-end consumer-grade INS have better specifications and cost hundreds of dollars. Some of them such as the one from XSens Inc. used by [119], are equipped with attitude heading reference system (AHRS) which have performance almost on par with the high-grade INS. The low-cost inertial sensors, on the other hand, experience more drifts and noises that affect the tracking performance.
In this chapter, a new method is proposed for accurate turn detection that is robust for different people and operating conditions using low-cost INS. The new method is based on the relationship between pelvic rotation and ZUPT, and this method is called Pelvic Rotation-ZUPT Turn Detection (PZTD). The proposed method is able to determine the direction of the turn, made by the pedestrian, with fewer number of pedestrian steps and the accuracy outperforms the state of the art.

The information from PZTD is then used to correct the heading angles derived from the waist’s gyro using the proposed filtering method. The proposed filtering method can differentiate a straight walk that is along the dominant or non-dominant directions. The new filtering produces more accurate heading angles compared to the un-filtered version. In tracking, accurate heading angles will produce a better navigation performance.

4.2 Pelvic Rotation and ZUPT

4.2.1 Background

The authors in [121] proposed that pelvic rotation reduces the vertical movements of the body’s centre of mass (COM), thus save energy. It is based on premise that the COM displacements are costly in terms of used energy. However, other studies suggested the contribution of pelvis rotations to reducing the vertical displacement is either negligibly or far less than previously thought [122], [123].

A study in [124] on pelvic kinematics in gait discovered that the mean of maximum pelvic rotation from thirty participants is up to six degrees. Other studies, [125], [126] indicated that the maximum pelvic rotations in normal walks with speed between 3 – 4km/h are around 6 and 10 degrees, respectively.

Usually, the pelvic rotation is measured using vision systems that locate the markers attached to the waist [124], [127]. In recent approaches, inertial sensors have been used to estimate the pelvis kinematics as an alternative to the vision systems [128], [129]. An inertial sensor has been placed at the sacrum as opposed to the markers and the results show that the devices are reliable alternative.

In [127], it is noted that the rotation angle is periodic when a person is walking fast in a straight line. Another conclusion drawn is the trajectory of the waist joint is like the sinusoidal signal. In [130], it is reported that during turning, the pelvis and torso orientations should follow the direction of the turn. From these, we can conclude that pelvis rotation angle is sinusoidal when walking in a straight line, but the angle follows the direction of turn when turning.

4.2.2 Walking Trials

Trials were done with an INS node attached to the right side of the waist of a healthy pedestrian to measure the yaw angle (pelvic rotation). Another INS node is attached to the right foot to compute the ZUPT. The setup and technique to compute the ZUPT are described in [131]. The pedestrian has been asked to walk along a corridor that consists of straight path and sharp corners. The computed pelvic rotation and ZUPT are plotted
together as shown in Figure 4.1. The plot indicates a complete gait cycle from the right foot during a straight walk. The dashed curve represents the pelvic rotation as measured by the INS and the solid curve represents the ZUPT. As observed, the polarity of the pelvic rotation angle changes from positive to negative in the stance phase and vice-versa in the swing phase.

The angular velocity recorded for the straight walk is plotted together with the ZUPT signal as shown in Figure 4.2. In the straight walk, the angular velocities spread oppositely in the stance and swing phases. The results of integral of the angular velocity that produce the angles of pelvic rotation are shown on the left column.

When the pedestrian turned to the left, the angular velocities spread consistently in the positive side during the left turn (Figure 4.3, t = 29s to 31s). On the other hand, when the pedestrian turns to the right, the angular velocities stay in the negative side during the right turn (Figure 4.4, t = 34.2s and 36.1s). Another key component to establish the relationship is the ZUPT. Our developed technique to detect the ZUPT is based on subtractive clustering algorithm [132]. The algorithm clusters all stationary vertical accelerations measured from the foot-mounted INS as stance periods. This technique has been compared with others ZUPT algorithms and achieves an outstanding accuracy.

The characteristics of the detected stance and swing phases have been analysed and the distributions of average time of swing and stance phases are depicted in the Figure 4.5. The data is collected from 9 healthy pedestrians who walked 20 steps in a straight path. The average time of stance phases and swing phases of all pedestrians are recorded based on the computed ZUPT. Meanwhile, 3 steps are recorded at every right or left (90° directional change) turn. Study presented in [133] reported that 3 steps are sufficient to execute direction change. Herewith, the average time is computed from the 3 steps that comprise of 3 swing and 3 stance phases.
Figure 4.2. The pelvic rotation (top) and angular velocity (bottom) against ZUPT during straight walk.
Figure 4.3. The pelvic rotation (top) and angular velocity (bottom) against ZUPT during left turn.
CHAPTER 4. PELVIC ROTATION-ZUPT TURN DETECTOR

Figure 4.4. The pelvic rotation (top) and angular velocity (bottom) against ZUPT during right turn.
4.3 Relationship Analysis

4.3.1 Pearson’s Chi-Square

To determine whether there is a significant association between the pelvic rotation and ZUPT, the data gathered from the 9 pedestrians was analysed. An association test called Pearson’s chi-square (or simply the chi-square) is used to test whether the two variables were independent of each other [134], [135]. The test will determine which of the following hypotheses holds true:

Null hypothesis: The walking direction and polarity of the sum of angular velocity are independent.
Alternative hypothesis: The walking direction and polarity of the sum of angular velocity are dependent.

If the null hypothesis is accepted from the test result, then there is no concrete relationship between the pelvic rotation and walking direction. On the other hand, if the null hypothesis is rejected, then the relationship is established. The significant level or cut off value to test whether to accept or reject the null hypothesis is set as 0.05, widely used in most chi-square test literature [134], [136]. The significant level is the probability of failing to accept the null hypothesis when it is indeed true (Type I error).

Table 4.1 summarizes the polarity comparison for a straight path. Two consecutive gait phases, swing phase to stance phase or vice versa, is called as a cycle. Therefore, for 20 steps walking in a straight path, there will be 39 cycles. For every cycle, the polarity of summation of the angular velocities for each of gait phases was determined. Polarities for consecutive gait phases were categorized as having same polarities (both positive or both negative) or different polarities (positive and negative) and the occurrence of each case was counted. Technically, the occurrence can be formulated using the XNOR logic as follows:
Table 4.1: Analysis of pelvic rotation’s angular velocities for straight path.

<table>
<thead>
<tr>
<th># Cycles</th>
<th>Stance (rad/s)</th>
<th>Swing (rad/s)</th>
<th>Polarity comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sum</td>
<td>Mean</td>
<td>Sum</td>
</tr>
<tr>
<td>P1</td>
<td>39</td>
<td>-13.6</td>
<td>24.4</td>
</tr>
<tr>
<td>P2</td>
<td>39</td>
<td>-106.5</td>
<td>99.2</td>
</tr>
<tr>
<td>P3</td>
<td>39</td>
<td>-116.4</td>
<td>118.4</td>
</tr>
<tr>
<td>P4</td>
<td>39</td>
<td>-81.2</td>
<td>87.8</td>
</tr>
<tr>
<td>P5</td>
<td>39</td>
<td>-77.2</td>
<td>66.2</td>
</tr>
<tr>
<td>P6</td>
<td>39</td>
<td>-1.99</td>
<td>28.6</td>
</tr>
<tr>
<td>P7</td>
<td>39</td>
<td>-151.0</td>
<td>159.6</td>
</tr>
<tr>
<td>P8</td>
<td>39</td>
<td>-54.5</td>
<td>38.1</td>
</tr>
<tr>
<td>P9</td>
<td>39</td>
<td>-63.9</td>
<td>51.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th># Cycles</th>
<th>Stance (rad/s)</th>
<th>Swing (rad/s)</th>
<th>Polarity comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sum</td>
<td>Mean</td>
<td>Sum</td>
</tr>
<tr>
<td>P1</td>
<td>3</td>
<td>15.7</td>
<td>21.4</td>
</tr>
<tr>
<td>P2</td>
<td>3</td>
<td>5.5</td>
<td>24.3</td>
</tr>
<tr>
<td>P3</td>
<td>3</td>
<td>34.0</td>
<td>32.0</td>
</tr>
<tr>
<td>P4</td>
<td>3</td>
<td>21.9</td>
<td>25.5</td>
</tr>
<tr>
<td>P5</td>
<td>3</td>
<td>14.4</td>
<td>16.5</td>
</tr>
<tr>
<td>P6</td>
<td>3</td>
<td>4.9</td>
<td>17.6</td>
</tr>
<tr>
<td>P7</td>
<td>3</td>
<td>-1.6</td>
<td>33.5</td>
</tr>
<tr>
<td>P8</td>
<td>3</td>
<td>23.4</td>
<td>20.5</td>
</tr>
<tr>
<td>P9</td>
<td>3</td>
<td>9.6</td>
<td>14.2</td>
</tr>
</tbody>
</table>

Table 4.2: Analysis of pelvic rotation’s angular velocities for left turn.

\[
\text{state} = \frac{\text{sum}_{p1}}{\text{abs} (\text{sum}_{p1})} \times \frac{\text{sum}_{p2}}{\text{abs} (\text{sum}_{p2})} + \frac{\text{sum}_{p1}}{\text{abs} (\text{sum}_{p1})} \times \frac{\text{sum}_{p2}}{\text{abs} (\text{sum}_{p2})} \tag{4.1}
\]

where state produces -1 (different) or 1 (same), \( \text{sum}_{p1} \) is the sum of angular velocities in the first gait phase and \( \text{sum}_{p2} \) is the sum of angular velocities in the second phase. The table also shows the sums and means of the angular velocities. The average accuracy of getting the different polarities is about 81% with two pedestrians score sub 70-percent. The means of pelvic rotation angles in stance and swing phases are close to each other for each of the pedestrian thereby confirm the first findings that the rotation angle is periodic when walking in a straight path.

Table 4.2 and Table 4.3 summarize the counts of polarity comparison for the pedestrians when they turned to the left and right, respectively. The numbers of cycles are set as 3. In-house analysis indicates that 3 cycles have the best accuracy. The average accuracies of getting the same polarity are 96% and 93% for left turn and right turn, respectively.

In the Table 4.2, the mean for the swing phase is larger than the mean for the stance phase, which is due the fact that the right foot makes a longer step when the person turns to the left as compared with the left foot. This causes the pelvis to rotate more in the swing phase. Similarly, in the Table 4.3, the mean for the stance phase is larger than the mean for the swing phase because the left foot makes a longer step when the person
Table 4.3: Analysis of pelvic rotation’s angular velocities for right turn.

<table>
<thead>
<tr>
<th># Cycles</th>
<th>Stance (rad/s)</th>
<th>Swing (rad/s)</th>
<th>Polarity comparison</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#</td>
<td>Sum</td>
<td>Mean</td>
<td>Sum</td>
</tr>
<tr>
<td>P1</td>
<td>3</td>
<td>-18.5</td>
<td>-9.3</td>
<td>-14.9</td>
</tr>
<tr>
<td>P2</td>
<td>3</td>
<td>-23.1</td>
<td>-11.5</td>
<td>-10.9</td>
</tr>
<tr>
<td>P3</td>
<td>3</td>
<td>-26.1</td>
<td>-13.0</td>
<td>-16.4</td>
</tr>
<tr>
<td>P4</td>
<td>3</td>
<td>-22.4</td>
<td>-11.2</td>
<td>-12.0</td>
</tr>
<tr>
<td>P5</td>
<td>3</td>
<td>-19.3</td>
<td>-9.6</td>
<td>-9.6</td>
</tr>
<tr>
<td>P6</td>
<td>3</td>
<td>-14.0</td>
<td>-7.0</td>
<td>-11.8</td>
</tr>
<tr>
<td>P7</td>
<td>3</td>
<td>-22.8</td>
<td>-11.4</td>
<td>-15.5</td>
</tr>
<tr>
<td>P8</td>
<td>3</td>
<td>-18.9</td>
<td>-9.5</td>
<td>-13.9</td>
</tr>
<tr>
<td>P9</td>
<td>3</td>
<td>-23.4</td>
<td>-11.7</td>
<td>-13.3</td>
</tr>
</tbody>
</table>

27 | -20.9 | -10.5 | -13.1 | -6.6 | 25 | 2 | 0.93 |

Table 4.4: Joint frequency distribution between polarity comparison and walking direction.

<table>
<thead>
<tr>
<th>Walking Direction</th>
<th>Polarity comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Same</td>
</tr>
<tr>
<td>Straight</td>
<td>68</td>
</tr>
<tr>
<td>Left Turn</td>
<td>26</td>
</tr>
<tr>
<td>Right Turn</td>
<td>25</td>
</tr>
</tbody>
</table>

turns to the right as compared to the right foot. Thus, the right pelvic rotation is smaller during the swing phase.

By identifying the relationship between the pelvic rotation and walking directions based on the underlying hypotheses, Table 4.4 has been prepared. The number of counts for the same and different polarities were cross-tabulated against the walking directions. The four assumptions to apply chi-square analysis as described in [136] are met: 1) sample is not biased, 2) independent observations where sampling of one observation does not affect the choice of the second observation, 3) no categories overlap and include all observations and 4) large expected frequency.

The first step in computing the chi-square is to compute the expected frequency for each cell in the Table 4.4 by using the following equation:

$$E_{ij} = \frac{T_i \times T_j}{N} \quad (4.2)$$

where $E_{ij}$ is the expected frequency for cell in the $ith$ row and the $jth$ column, $T_i$ is the total number of counts in the $ith$ row, $T_j$ is the total number of counts in the $jth$ column and $N$ is the total number of counts in the table.

The next step is to calculate the chi-square using the following equation:

$$\chi^2_{ij} = \frac{O_{ij} - E_{ij}}{E_{ij}} \quad (4.3)$$

where $\chi^2_{ij}$, $E_{ij}$ and $O_{ij}$ are the chi-square, expected frequency and observed frequency for the cell in the $ith$ row and the $jth$ column, respectively. The calculated expected frequency and chi-square for each cell are shown in Table 4.5. In the 4th assumption, the
cell expected requirements of the chi-square could be verified by checking the expected frequency in each cell. To meet the requirement, 80% (0.8 × 6 cells = 5 cells) of the cells must have expected value of 5 or more. This table meets the requirement that all the cells have expected frequency of more than 5.

The sum of the calculated chi-square is 127.2 and the number of degrees of freedom is 2. The P-value is obtained from executing MATLAB function chi2cdf by inputting the sum of chi-square and degree of freedom. The result shows the P-value is smaller than 0.00001. As the P-value of the chi-square table is less than 0.05, the null hypothesis is rejected and the alternate hypothesis is accepted. Lastly, the strength of the relationship between polarity and walking direction is measured using Cramer’s V formula:

\[ V = \sqrt{\frac{x^2}{N \times \min(r-1, c-1)}} \]  

(4.4)

where \( r \) is the total number of rows, \( c \) is the total number of columns and \( N \) is total number of counts. The calculation gives Cramer’s \( V \) equals to 0.56 which should be viewed as a large effect by following the guidelines shown in Table 4.6.

The large effect implies that the polarity comparison is a significant factor in determining in which direction a pedestrian walked, i.e. there is strong relationship between the pelvic rotation and ZUPT that can be used to classify the walking direction.

### 4.4 Algorithms

#### 4.4.1 Turn Detector Algorithm

The classification of walking directions is based on the naïve Bayes method using the information of joint frequency distribution as shown in Table 4.4. However, the single attribute referred so far, polarity comparison, is insufficient to classify the left or right
Table 4.7: The Distribution of Counts in Different Attributes to Represent Varying Walking Direction.

<table>
<thead>
<tr>
<th>Walking Direction</th>
<th>Polarity comparison</th>
<th>Polarity dominant</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Same</td>
<td>Different</td>
</tr>
<tr>
<td>Straight</td>
<td>10</td>
<td>53</td>
</tr>
<tr>
<td>Left Turn</td>
<td>26</td>
<td>1</td>
</tr>
<tr>
<td>Right Turn</td>
<td>25</td>
<td>2</td>
</tr>
</tbody>
</table>

turn. Therefore, another attribute, polarity dominant is introduced. The polarity dominant classifies a cycle as positive if the sum of angular velocities in the cycle is positive and as a negative if the sum is negative.

The total counts for each attribute from all the pedestrians are presented in the Table 4.7. The values presented are the total counts from all the pedestrians for each of the attributes. Note that the total count for straight walk has been changed from 351 (39 cycles x 9 pedestrians) to 63 (7 cycles x 9 pedestrians). The reason is the previous total counts caused bias to the detection algorithm, which inclines to misclassify turns as straights.

The turn detector algorithm needs to classify the 3 cycles into one out of the 3 classes: $c_j = \text{straight, left, right}$. The input will be based on 2 attributes: $a_1 = \text{same, different}$ and $a_2 = \text{positive, negative}$. The parameters of the attributes are determined as follows:

$$a_1 = \begin{cases} \text{same} & \text{counts of same} > \text{counts of different} \\ \text{different} & \text{otherwise} \end{cases} \quad (4.5)$$

$$a_2 = \begin{cases} \text{positive} & \text{counts of positive} > \text{counts of negative} \\ \text{negative} & \text{otherwise} \end{cases} \quad (4.6)$$

The general notation of the posterior probability of naïve Bayes can be written as:

$$P(c_j|a_1,a_2) = \frac{P(a_1|c_j) \cdot P(a_2|c_j) \cdot P(c_j)}{P(a_1) \cdot P(a_2)} \quad (4.7)$$

The objective function in the naïve Bayes classifier is to maximize the posterior probability

$$\text{predicted class} = \arg \max P(c_j|a_1,a_2) \quad (4.8)$$

In Equation (4.8), the predicted class will be obtained by calculating all the possible posterior probability and set the one with the highest probability as the class for the 3 cycles. The pseudocode of the turn detector algorithm is shown as follows:

Pseudocode of PZTD Algorithm

1. initialize PZTD variables
2. for i from 2 to length of ZUPT
CHAPTER 4. PELVIC ROTATION-ZUPT TURN DETECTOR

3. if diff(ZUPT_i, ZUPT_{i-1}) equals 1
4. \( \text{sum}_{sw} \) equals sum of \( gyr_{sw} \)
5. elseif diff(ZUPT_i, ZUPT_{i-1}) equals -1
6. \( \text{sum}_{st} \) equals sum of \( gyr_{st} \)
7. end if
8. if \( \text{sum}_{sw} \) AND \( \text{sum}_{st} \) are non-Zero
9. state=\text{XNOR}(\text{sum}_{sw}, \text{sum}_{st})
10. if state=1 then count_{same} + 1
11. else count_{diff} + 1
12. end if
13. if (\text{sum}_{st} + \text{sum}_{sw}) > 0 then count_{pos} + 1
14. else count_{neg} + 1
15. end if
16. \text{vec}_{state} \) increments with value of state
17. end if
18. if size(\text{vec}_{state}) equals 3
19. \( a_1 \) equals to same or different (Equation (4.5))
20. \( a_2 \) equals to positive or negative (Equation (4.6))
21. \( PZTD_i = \max(p(\text{straight}, \text{left}, \text{right} \mid a_1, a_2)) \)
22. decrement \text{vec}_{state} by removing 1st index
23. end if
24. end for

where \( \text{vec}, \text{count}_{same}, \text{count}_{diff}, \text{count}_{pos} \) and \( \text{count}_{neg} \) represent vector, counts of same, different, positive and negative, respectively. The subscripts \( sw \) and \( st \) represent swing and stance, respectively. Meanwhile, \( \max(p(\text{straight},\text{left},\text{right} \mid a_1,a_2)) \) is a short form for the operation stated in Equation (4.8). The predicted class will depend on the maximum probability between specific classes and attributes.

The probabilities for all classes such as \( p(\text{straight} \mid \text{same}, \text{positive}) \), \( p(\text{right} \mid \text{same}, \text{positive}) \) and \( p(\text{left} \mid \text{same}, \text{positive}) \) will be computed. The result will be set to either 0 (if straight has the maximum probability), 1 (if left turn has the maximum probability) or -1 (if right turn has the maximum probability). The result is stored in the PZTD vector.
4.4.2 Heading Correction

The yaw angle from the waist can be used to update the heading of the pedestrian. It is the result of the integral of the angular velocity of the gyroscope attached to the waist. Usually, the obtained yaw angle from the waist is contaminated with noise and drift, due to body vibration, and sensor’s casing movement, due to loosen attachment, in addition to the sensor misalignment.

However, by utilizing the PZTD, the yaw angle can be filtered to the extent sufficient to provide accurate heading information. The filtering is done in two stages. In the first stage, the angular velocity of the waist was integrated if the PZTD is non-zero (true) discretely. The yaw angle or also denoted as heading angle at time \( k \) was computed as follows:

\[
\text{heading}_k = \begin{cases} 
\text{heading}_{k-1} + \int \omega_{\text{waist}} \, dt, & \text{PZTD} (k) \neq 0 \\
\text{heading}_{k-1}, & \text{otherwise}
\end{cases}
\] (4.9)

In stage 2, the heading angle was subtracted with bias which had been computed using Equation (4.11). Round is a MATLAB function that will round a value towards the nearest integer. Noteworthy, the Equation (4.11) was used only when the PZTD vector at time \( k \) equals zero. Bias has an initial value of zero.

\[
\text{filteredheading}_k = \text{heading}_k - \text{bias}_{k-1} 
\] (4.10)

\[
\text{bias}_k = \text{filteredheading}_k - \text{round} \left( \frac{\text{filteredheading}_k - \text{bias}_{k-1}}{\pi/2} \right) \cdot \pi/2 
\] (4.11)

By applying Equation (4.11), the drift in the heading angle as the result of accumulation of bias over time was removed. Since no turn should be detected when PZTD equals zero (walking straight), the bias at the time can be measured and compensated. Thus, the bias will not be accumulated and has very small drift due to un-filtered noise.

As depicted in the Figure 4.6, the un-filtered angles (original) stay between -220º to -265º when \( t = 58s \) to 97s, a period of walking straight, though the angles are supposed to be -180º. The deviation from the actual angle is due to the inherited drift. The figure also shows the turns detected by PZTD algorithm.

The quality of the filtering processes is enhanced by suspending the bias correction if a straight walk along non-dominant direction is detected. The last motion type, walking along non-dominant directions, can be determined by using the computed heading from Stage 1. At first, let a circle be divided into 16 sectors that comprises of both dominant and non-dominant directions as shown in Figure 4.7.

If the walk is straight and belongs to the even numbered sectors, then it is a walk along the dominant directions (DD), and a straight walk in the odd numbered sectors will be determined as a walk along non-dominant directions (NDD). The classification is formulated using the general formulas as follows:
FIGURE 4.6. Waist’s yaw angles in three representations (no filtering or original, stage 1 filtering and stage 2 filtering.

![Diagram of waist's yaw angles](image)

FIGURE 4.7. The even numbered sectors represent the dominant directions and the odd numbered sector represent the non-dominant directions.

\[
w = \text{rem} \left( \text{round} \left( \frac{\text{heading}_k}{22.5} \right), 2 \right)
\]  \hspace{1cm} (4.12)

\[
\text{class of straight walk} = \left\{ \begin{array}{ll}
\text{DD} & , w = 0 \\
\text{NDD} & , \text{otherwise}
\end{array} \right.
\]  \hspace{1cm} (4.13)

where \( \text{rem} \) is a MATLAB function that return the remainder after the division (in this case it is 2). Therefore, the Equation (4.10) is revised as follows:

\[
\text{filteredheading}_k = \left\{ \begin{array}{ll}
\text{heading}_k - \text{bias}_{k-1} & , \text{DD} \\
\text{heading}_k & , \text{NDD}
\end{array} \right.
\]  \hspace{1cm} (4.14)

In an experiment, a pedestrian walked in a straight path along a dominant direction before entering an angled path, 22° off the straight path. The headings, before and after the filtering processes, are shown in Figure 4.8. The filtering successfully identifies the walk along the angled path (t=13s to 18.5s) and suspends the bias correction until the
pedestrian walked in the dominant direction again. Other experiments indicate that identification of non-dominant directions work for angles bigger than 20°. However, it partially works for angles between 10° to 20° and fails for angles smaller than 10°. The reason is the proposed turn detection method is not able to differentiate between pelvic rotation of a person, which can be around 10° for a normal walk [126], and the actual turn to change the course of walk.

4.5 Experiments

In the first experiment, the proposed turn detection algorithm is compared with the state-of-the-art methods. The second experiment compares the headings, before and after filtering processes are applied.

4.5.1 Comparison of Turn Detection Methods

The turn detection methods are applied to three walking tests as shown in Figure ???. The first test requires the pedestrian to walk along a curved path and back to the initial point. The second test is like the first, but the pedestrian had to round the circular path for three times. This test simulates a situation where the pedestrian walked for more than 30s along non-dominant directions. Lastly, the pedestrian had to walk along an angled path. In all tests, the pedestrian would walk in the dominant directions from the starting point.

The methods to determine the straight and non-straight paths in iHDE and AHDE are compared. For non-straight paths, PZTD represents them by indicating the directions where the pedestrian turns to. The comparison between INS devices, Preon and XSens MTw Awinda, has been established as well. Preon, manufactured by Virtenio GmbH [114], uses ADXL345 accelerometers and ITG-3200 gyroscopes. A node of Preon and a node of XSens are paired side by side, and two pairs have been used simultaneously in the experiments; first mounted on the foot and then attached to the right side of the waist.
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Figure 4.9. (a) Line segments and circular path, (b) line segments and circular path that repeated 3 times and (c) line segments with angled path. The dot represents the starting and ending (except (c)) points.

Table 4.8: Comparison of accuracy between detection methods as well as INS devices.

<table>
<thead>
<tr>
<th>Methods</th>
<th>True Positive</th>
<th>False Positive</th>
<th>True Negative</th>
<th>False Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>iHDE (Preon)</td>
<td>67%</td>
<td>33%</td>
<td>77%</td>
<td>23%</td>
</tr>
<tr>
<td>AHDE (Preon)</td>
<td>50%</td>
<td>50%</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>PZTD (Preon)</td>
<td>93%</td>
<td>7%</td>
<td>94%</td>
<td>6%</td>
</tr>
<tr>
<td>PZTD (Xsens)</td>
<td>95%</td>
<td>5%</td>
<td>95%</td>
<td>5%</td>
</tr>
</tbody>
</table>

From the datasheet, the pricier XSens MTw has a better bias stability than Preon; 10°/hr for the gyros. Meanwhile, from the Allan variance plots, Preon’s gyros has an average (RMS) bias stability of 24°/hr.

From Figure 4.10, it is obvious that the detection of non-straight walk when using iHDE and AHDE lags the ground truths. The reason is those methods require 5 to 6 pedestrian’s steps to determine the type of the walk. The detection algorithms are severely affected when the change of walking directions happened in a short distance. For instance, AHDE is not able to detect the walk along the angled path as shown in Figure 4.10.

Meanwhile, the PZTD algorithm requires only 3 cycles of gait (2 stance phases and 1 swing phase, or 2 swing phases and 1 stance phase) to detect the change of walking direction immediately. The proposed method also successfully detects the walk along the non-dominant directions, marked by the circles (Figure 4.10). The performance of all the methods from the tests is summarized in Table 4.8. The PZTD performs better than other methods and scores above 90% of correct predictions. The detection performance between Preon and XSens is comparable and indicates that the proposed method works well for low-cost INS.

4.5.2 Performance of Filtering Method

In the first test, a healthy male pedestrian walked normally in an anti-clockwise manner, following a rectangular shape (5.5m x 2.8m) for 20 times. The waist’s yaw angle that represents the heading angle was computed using two methods and compared. First, the trapezoid method was used to calculate heading angle from the angular velocity denoted as UH (un-filtered heading). In the second method, PZTD and heading correction were
applied to acquire the filtered heading angle denoted as FH. Both methods were compared with the ground truth where the direction error is restricted by map matching.

Table 4.9 lists the estimated heading error of UH and FH over 20 iterations of walking in rectangular shape. The PZTD successfully detects all the turns in each of the iterations. The UH recorded a linear mean error growth, about 11º per iteration, which causes an accumulated mean error about 222º after 20 iterations. As expected, FH performs better by achieving 2.2º in average of the mean error. The bias compensation in the filtering process proves to minimize the drift in the heading angles. Thereby, zero minimum errors are attainable in all the iterations. Still, errors existed because bias compensation is not active when PZTD equals other than zero. The highest maximum error for FH is 9.0% that of UH.

Another round of tests by the same pedestrian but in clockwise direction indicates
similar error performance. The mean error grows linearly at 13° per iteration for UH. Meanwhile, FH achieves 1.6° in average of the mean errors. Again, the highest maximum error for FH is 9.2% that of UH. Also, PZTD detects all the turns successfully.

In the next tests, other two healthy male pedestrians had been asked to walk in two tracks. In the first track, the first pedestrian would make a 180° turn at the end of the corridor and walked back to the initial position. Meanwhile, for the second track, another pedestrian had to turn around at the end of the long corridor and had to pass through two access doors on the way back. The tracks are labelled with checkpoints as shown in Figure 4.11. The actual distances are 150.3m and 111.4m for Track 1 and Track 2, respectively. The results are tabulated in Table 4.10 and Table 4.11 for track 1 and track 2 respectively. Again, the PZTD detects all the turns without any failure in both tracks. The mean errors for UH are gradually increased on both tracks. Meanwhile, FH scores 2.0° and 1.0° in average of mean errors for track 1 and track 2, respectively.

Table 4.9: Comparative analysis of heading estimation error.

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Elapse (s)</th>
<th>Step Number</th>
<th>Turn Detected</th>
<th>Mean Error (degrees)</th>
<th>Max. Error (Degrees)</th>
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Table 4.10: Heading estimation error of track 1.

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CHAPTER 4. PELVIC ROTATION-ZUPT TURN DETECTOR

Figure 4.11. (a) The path for the first track. (b) The path for the second track. The triangles represent the access door where pedestrians need to swipe access card to enter and press button to exit. The paths are labelled with checkpoints (from a to i).

Table 4.11: Heading estimation error of track 2.

<table>
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<th>Steps</th>
<th>Turn Detected</th>
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Besides manufacturing defect and random walk error, the mean error can be contributed by the body movement during the walk such as shakes due to heel strikes the ground. The sliding friction between sensor’s casing and body also could create noise to the angular velocity. These are the probable reasons for the differences in mean errors for UH. Interestingly, despite those problems, the mean errors for FH are very low compared to UH.

The second track was designed to challenge the algorithm as the pedestrians needed to turn the body to swipe the access card which could be detected as making a turn. Even though the turns of the body are detected when swiping the access card, the displacement of the body is virtually zero as the pedestrian was in the stance phase (checkpoints e and g). A similar situation is discussed in [137] where the access reader was used to reset a position to their handheld tracking system.

4.6 Summary

The techniques and limitations of existing heading correction methods have been explained. The behaviour of pelvic rotation during walks has been studied. A theory of relationship between pelvic rotation and ZUPT in determining turn detection made by pedestrian has been presented based on observations of walking trials. Accordingly, the relationship has been analysed and verified. As a result, a turn detection algorithm has been proposed. Aiding by turn information, a heading correction technique has been proposed. These turn detection and heading correction techniques have been tested and validated in a set of experiments, which include circular and angled paths. The results show better detection performance for the proposed turn detector compares to other approaches. Also, better heading estimations are obtained through the proposed heading correction technique.
5.1 Introduction

In the inertial-based foot-mounted navigation, inertial sensors provide measurements to track the positions and attitudes of a pedestrian relative to the known starting parameters: position, attitude and velocity. In Section 2.3, the principles of strapdown pedestrian inertial navigation system for foot-mounted (SPINS-FM) has been discussed. The section has listed two aspects in SPINS-FM which have gained much interest to produce better positioning and tracking performance: improving ZUPT accuracy and heading correction.

In this chapter, the proposed ZUPT detector and heading correction techniques from Chapter 3 and Chapter 4, respectively, will be incorporated into the Extended Kalman filter (EKF) based navigation framework [138]. The accurate proposed ZUPT detector helps to produce better positioning. Meanwhile, the turn detector algorithm provides an affordable tracking solution that is a strong replacement to the ones which use expensive commercial-grade INS. The section first defines various reference frames and describes the properties pertaining to them. This is important as the inputs to the navigation framework, accelerations and angular velocity, are resolved in the body frame of the IMU. To acquire the navigation states, these measurements must be transformed into the navigation frame of interest.

5.2 Coordinate Frames

The goal of a navigation system is to describe the position, velocity and attitude of the body frame in respect to the navigation frame. There are different Cartesian coordinate frames that can be used to describe the measurements of inertial sensors and their mechanization. For instance, the accelerometers and gyroscopes measure the acceleration and angular velocity between the inertial- and body-frame. A basic navigation system consists of at least four frames; earth-, navigation-, body- and inertial-frame.
5.2.1 Earth-Centred Earth-Fixed Frame (e-frame)

The Earth-Centred Earth-Fixed (ECEF) coordinate system rotates with the earth around its spin axis. A such, a fixed point on the earth surface has a fixed set of coordinates. In this coordinate system, the origin is located at the centre of the earth, the Z-axis points north pole, the X-axis intersects the sphere of the earth at 0 latitude and 0 longitude, and the Y-axis is orthogonal to the Z- and X-axes with the right-hand rule [139].

5.2.2 Local North-East-Down Frame (n-frame)

The local North-East-Down (NED) coordinate system is also known as a navigation or ground coordinate system. It is a coordinate frame fixed to the earth’s surface. The origin is arbitrary fixed to a point on the earth’s surface, the D-axis is pointing at the centre of the earth, N-axis is pointing ellipsoid north and E-axis is pointing ellipsoid east [139]. NED corresponds to XYZ when compared to Cartesian suffix.

5.2.3 Body Frame (b-frame)

The body coordinate system is associated with the platform where the sensors are mounted. Its origin coincides with the navigation frame’s origin, the X-axis points forwards which represents the typical direction of travel, the Z-axis points downwards which is the direction of gravity and the Y-axis is orthogonal to the Z- and X-axes with the right-hand rule.

5.2.4 Inertial Frame (i-frame)

It has origin at the centre of the earth and axes which are fixed and non-rotating with respect to fixed stars [140]. It is commonly known as Earth-Centred Inertial (ECI) frame, where earth-centred means that the frame’s origin is at the earth’s centre of mass.

5.2.5 Simplification to n-frame

Figure 5.1 illustrates the ECEF, NED, ECI and body frames which have been discussed previously. In this research, the consumer-grade inertial sensors used are not accurate enough to measure the earth’s rotation [141]. As a result, the earth can be simplified to have fixed position and attitude in space. The curvature of the earth becomes much less than the bias and noise characteristics of the sensors. Thus, the curvature of the earth can be neglected. The reference frames, i.e. earth, NED and inertial, can therefore be reduced to one frame, navigation frame. Throughout this thesis, there will be two Cartesian frames, namely the body frame and the navigation frame.
5.3 Kalman Filter Framework

5.3.1 Initialization

There are two essential elements before executing the framework; initialization and alignment of the system. Initialization is a process of obtaining the initial position and velocity of the system. In general, the position and velocity need to be initialized from absolute measurements such as GPS. Since there is no external measurement available, a manual initialization is performed using known information such as zero velocity in stationary state.

Alignment is a process of obtaining the initial attitude parameters of the system. There are two ways to obtain the initial attitude; horizontal and heading alignments. When IMU is stationary, the only specific force sensed by the accelerometers is the gravity. Therefore, the raw measurements in body frame, $a^b$, can be compared with the known gravity vector as follows:

$$ a = C_0 \begin{pmatrix} 0 \\ 0 \\ g \end{pmatrix} = \begin{pmatrix} \sin \theta \\ -\sin \varphi \cos \theta \\ -\cos \varphi \cos \theta \end{pmatrix} g $$

(5.1)

where $a$, $g$ and $C_0$ are accelerations in body frame, gravity acceleration and rotation between body and navigation frames, respectively. The initial roll, $\varphi$, and pitch, $\theta$, can be solved as follows:

$$ \begin{pmatrix} \varphi \\ \theta \end{pmatrix} = \begin{pmatrix} \text{atan}2(-a_y, -a_z) \\ \text{atan}2(a_x, \sqrt{a_y^2 + a_z^2}) \end{pmatrix} $$

(5.2)

For heading alignment, the underlying principle is that while stationary, the only rotation sensed by the gyroscopes is the earth rotation, which rotates about the Z-axis direction of the ECEF frame. However, the used gyroscopes are not sensitive enough to measure
the earth rotation rate. Therefore, manual alignment is set by comparing the building orientation with respect to the navigation frame.

### 5.3.2 Inertial Navigation System

In the foot-mounted navigation, the obtained acceleration data must be transformed from the body axes into the navigation axes. The transformation is realized through the angular information. Thus, the two inertial data recorded, accelerations and angular velocities, determine the displacement and direction of a walking pedestrian from a known position with respect to the navigation axes.

In the basic inertial navigation system (INS), the accelerations are transformed into the navigation frame before gravity is subtracted from the vertical component of acceleration as follows:

\[ a_{\text{nav}}^k = C_k \cdot a_k^b - \begin{bmatrix} 0 & 0 & g \end{bmatrix}^T \]

(5.3)

where \( a_{\text{nav}}^k \), \( a_k^b \), \( g \) and \( C_k \) are accelerations in navigation frame, bias compensated accelerations in body frame, gravity acceleration and rotation between body and navigation frames, at time \( k \), respectively. The rotation between body and navigation frames are obtained from the bias compensated angular velocities. The bias compensated accelerations and angular velocities \((\omega_k^b)\) are obtained as follows:

\[ a_k^b = a_k^m - b_a \]

(5.4)

\[ \omega_k^b = \omega_k^m - b_\omega \]

(5.5)

where \( a_k^m \) is the measured acceleration and \((\omega_k^m)\) is the measured angular velocities at time \( k \). The \( b_a \) and \( b_\omega \) are the known static biases of the accelerometer and gyroscope, respectively.

Then, the velocities, \( v_k^- \), are obtained by integrating the accelerations over the sampling time, \( t \), prior to the EKF correction at time \( k \):

\[ v_k^- = v_{k-1} + \int_0^{\Delta t} a_{\text{nav}}^k \]

(5.6)

Next, the predicted positions in the navigation frame, \( p_k^- \), are calculated by integrating the velocities:

\[ p_k^- = p_{k-1} + \int_0^{\Delta t} v_k^- \]

(5.7)

In dealing with noisy sensors measurements, the error-state Kalman filter has been adapted to perform the correction and produce better estimate of the position and attitude information.
5.3.3 Extended Kalman Filter

The pedestrian tracking algorithm that we use is based on the framework proposed by Foxlin [34] and later refined by Jiménez et al. [142]. The EKF has 15-element error state vector: 
\[ x = [\delta At, \delta \omega^b, \delta P, \delta V, \delta a^b] \]
where \( \delta \omega^b \) is the estimated bias of gyroscopes, \( \delta a^b \) is the estimated bias of accelerometers, \( \delta At \) is the attitude error, \( \delta P \) is the position error and \( \delta V \) is the velocity error.

There are two stages in Kalman filter: 1) prediction stage which computes the priori estimates of the current state and error covariance; 2) measurement update stage which incorporates a new measurement into the priori estimates to obtain improved posteriori estimates.

5.3.3.1 Prediction Stage

\[ \hat{x}_k^- = F_k \cdot \hat{x}_{k-1} + w_k \] (5.8)

where \( \hat{x}_k^- \) is the predicted error state, \( \hat{x}_{k-1} \) is the previous filtered error state, \( w_k \) is the process noise with covariance matrix \( Q = E(w_k w_k^T) \) and \( F_k \) is the 15×15 state transition matrix:

\[
F_k = \begin{bmatrix}
I & \Delta t \cdot C_k^- & 0 & 0 & 0 \\
0 & I & 0 & 0 & 0 \\
0 & 0 & I & \Delta t \cdot I & 0 \\
\Delta t \cdot S_k & 0 & 0 & I & \Delta t \cdot C_k^- \\
0 & 0 & 0 & 0 & I 
\end{bmatrix}
\] (5.9)

The I and 0 elements represent 3×3 identity matrix and 3×3 empty matrix, respectively. The skew-symmetric cross-product operator matrix \( S_k \) is formed from the accelerations in the navigation frame as follows:

\[
S_k = \begin{bmatrix}
0 & -a^z_k & a^y_k \\
-a^z_k & 0 & -a^x_k \\
a^y_k & a^x_k & 0 
\end{bmatrix}
\] (5.10)

Meanwhile, \( C_k^- \) is the rotation matrix that transforms from the body to the navigation frame:

\[
C_k^- = C_{k-1} \cdot (2 \cdot I + \Omega_k \cdot \Delta t) \cdot (2 \cdot I - \Omega_k \cdot \Delta t)^{-1}
\] (5.11)

where \( \Omega_k \) is the skew-symmetric matrix for angular rates used to define the small angular increments in orientation [142] as follows:

\[
\Omega_k = \begin{bmatrix}
0 & -\omega^Z_k & \omega^Y_k \\
\omega^Z_k & 0 & -\omega^X_k \\
-\omega^Y_k & \omega^X_k & 0 
\end{bmatrix}
\] (5.12)
The filter propagates the error covariance matrix, \( P_k^- \), as follows:

\[
P_k^- = F_k \cdot P_{k-1} \cdot F_k^T + Q
\]  

(5.13)

### 5.3.3.2 Measurement Update

The first task during the measurement update is to compute the Kalman gain, \( K_k \), as follows:

\[
K_k = P_k^- \cdot H^T \cdot \left( H \cdot P_k^- \cdot H^T + R \right)^{-1}
\]  

(5.14)

where \( R \) is the covariance matrix of the measurement noise and \( H \) is the measurement matrix. The formation of \( R \) and \( H \) matrices will be discussed in the following sub-sections.

The filtered error state, \( \hat{x}_k^- \), is calculated after a measurement at time \( k \) is available as follows

\[
\hat{x}_k^- = \hat{x}_k^- + K_k \cdot (z_k - H \cdot \hat{x}_k^-)
\]  

(5.15)

where \( z_k \) is the actual error measurement. There are four error measurements that would be measured:

i) Zero Velocity Update (ZUPT) ZUPT resets the drift in the accelerometers when the foot is stationary. The error measurement for ZUPT is calculated as follows:

\[
m_k = \partial V el_k = V el_k - [0,0,0]
\]  

(5.16)

where \( V el_k \) is the estimated velocity at time \( k \) and zero vector indicates the velocities are expected to be zero while the foot is stationary. The ZUPT were computed based on subtractive clustering method as presented in the Chapter 3 and [132].

ii) Zero Angular Update (ZARU) ZARU considers the fact that the heading is unchanging if the pedestrian is static. Based on this constraint, any non-zero angular rate measured is considered as error that will cause bias.

\[
\partial \omega_b^k = \omega_b^k - [0,0,0]
\]  

(5.17)

Equation (5.17) indicates \( \omega_b^k \) is the gyroscope’s bias at time \( k \) and zero vector indicates the angular rates are expected to be zero while the foot is still.
iii) Position Update (SL+WY) The displacement over a step, also known as a step length (SL), and filtered waist’s yaw angle (WY) from the waist can be used to determine the track of a pedestrian using the following formulas:

\[
\begin{align*}
\mathbf{z}_{k}^{\text{pos,x}} &= \mathbf{z}_{k-1}^{\text{pos,x}} + \cos(WY_{k}) \cdot SL_{kS} \\
\mathbf{z}_{k}^{\text{pos,y}} &= \mathbf{z}_{k-1}^{\text{pos,y}} + \sin(WY_{k}) \cdot SL_{kS} \\
SL_{kS} &= \sqrt{\left[\left(\mathbf{Pos}_{kS}^{x} - \mathbf{Pos}_{kS-1}^{x}\right) + \left(\mathbf{Pos}_{kS}^{y} - \mathbf{Pos}_{kS-1}^{y}\right)\right]^2}
\end{align*}
\]  

(5.18)  
(5.19)  
(5.20)

where \( \mathbf{z}_{k}^{\text{pos,x}} \) and \( \mathbf{z}_{k}^{\text{pos,y}} \) denote measurements of position in X-axis and Y-axis at the current sample \( k \), respectively; \( k_{S} \) is the sample of last detected step. The error measurement for position update is as follows:

\[
m_{k} = \delta\mathbf{Pos}_{k} = \left[\mathbf{Pos}_{k}^{x}, \mathbf{Pos}_{k}^{y}\right] - \left[\mathbf{z}_{k}^{\text{pos,x}}, \mathbf{z}_{k}^{\text{pos,y}}\right]
\]

(5.21)

where \( \mathbf{Pos}_{k}^{*} \) is the estimated velocity at time \( k \) and \( \mathbf{z}_{k}^{\text{pos}} \) is the measurements of the position as described previously.

iv) Waist’s Yaw Update (WYU) The vector PZTD and filtered waist’s yaw were obtained by following the algorithms detailed in [50]. The filtered waist’s yaw provides useful measurement against the estimated yaw angle from the EKF. The error measurement for WYU is calculated as follows:

\[
m_{k} = \delta\Psi_{k} = \Psi_{k} - \Psi_{k,w}
\]

(5.22)

where \( \Psi_{k} \) is the estimated yaw angle and \( \Psi_{k,w} \) is the filtered waist’s yaw at time \( k \), respectively.

Finally, the measurement matrix, \( \mathbf{H} \), that includes all the components, is formulated as below:

\[
\mathbf{H} = \begin{bmatrix}
001 & 0_{1\times3} & 0_{1\times3} & 0_{1\times3} & 0_{1\times3} \\
0_{3\times3} & I_{3\times3} & 0_{3\times3} & 0_{3\times3} & 0_{3\times3} \\
0_{2\times3} & 0_{2\times3} & I_{2\times2} & 0_{2\times3} & 0_{2\times3} \\
0_{3\times3} & 0_{3\times3} & 0_{3\times3} & I_{3\times3} & 0_{3\times3}
\end{bmatrix}
\]

(5.23)

and the error measurement vector will be:

\[
\mathbf{z}_{k} = \left[\delta\Psi_{k}, \delta\omega_{k}^{b}, \delta\mathbf{Pos}_{k}, \delta\mathbf{Vel}_{k}\right]
\]

(5.24)
Next is to obtain a posteriori error covariance estimate as follows:

\[ P_k = (I - K_k \cdot H) \cdot P_k^- \quad (5.25) \]

The last step is the Kalman error estimates from \( \hat{x}_k \) are passed to the INS to correct the position \( (p_k) \), velocity \( (v_k) \) and attitude estimate \( (C_k) \), as follows:

\[ p_k = p_k^- - \partial p_k \quad (5.26) \]
\[ v_k = v_k^- - \partial v_k \quad (5.27) \]
\[ c_k = C_k^- \cdot (2 \cdot I + \Delta \Omega_k \cdot \Delta t) \cdot (2 \cdot I - \Delta \Omega_k \cdot \Delta t)^{-1} \quad (5.28) \]

where \( \Delta \Omega_k \) is the skew-symmetric matrix for small angles:

\[ \Delta \Omega_k = \begin{bmatrix}
0 & -\partial \omega^x_k & \partial \omega^y_k \\
\partial \omega^y_k & 0 & -\partial \omega^z_k \\
-\partial \omega^z_k & \partial \omega^x_k & 0
\end{bmatrix} \quad (5.29) \]

As shown in Figure 5.2, there are four measurement updates applied to the EKF, namely Zero Velocity Update (ZUPT), Zero Angular Update (ZARU), position update (SL+WY) and Waist’s Yaw Update (WYU).
5.3.4 Filter Tuning

The proposed EKF framework had to be fine-tuned to ensure a stable operation. The values of matrices $Q_k$, $R_k$ and $P_k$ were selected to obtain the optimal performance based on the sensors used. The process noise covariance matrix, $Q_k$, is initialized for $k=1$ as a diagonal 12x12 matrix with these in-diagonal elements: accelerometer’s variance = $0.1m/s^2 \times I_{1 \times 3}$, gyro’s variance = $0.0349rad/s \times I_{1 \times 3}$, accelerometer’s driving noise = $1 \times 10^{-5}m/s^2 \times I_{1 \times 3}$ and gyro’s driving noise = $1 \times 10^{-5}rad/s \times I_{1 \times 3}$.

The measurement noise matrix, $R_k$, is a diagonal 9x9 matrix with these in-diagonal elements: ZUPT = $0.01m/s \times I_{1 \times 3}$, ZARU = $0.5rad/s \times I_{1 \times 3}$, position = $0.1m \times I_{1 \times 2}$ and yaw = $0.1rad$.

The state estimation covariance matrix, $P_k$, is a diagonal 15x15 matrix with these in-diagonal elements: position = $1 \times 10^{-3}m \times I_{1 \times 3}$, velocity = $1 \times 10^{-3}m/s \times I_{1 \times 3}$, attitude = $1 \times 10^{-3}rad \times I_{1 \times 3}$, acceleration’s bias = $1 \times 10^{-3}m/s^2 \times I_{1 \times 3}$ and gyro’s bias = $1 \times 10^{-3}rad/s \times I_{1 \times 3}$.

5.4 Experiments

5.4.1 Setup

Each pedestrian is equipped with Preon INS nodes [114] with ADXL345 accelerometers and ITG-3200 gyros. The sampling frequency is 50Hz. From the Allan variance plots, Preon’s gyros have an average (RMS) bias stability of $24^\circ/hr$. The experiment required each pedestrian to attach Preon INS nodes as shown in Figure 5.3.

The system initiated after a command sent from PC was received by both nodes, wirelessly. The command was used to start the operation of data collection for both nodes and comprised of PC’s timestamp ($t_{PC}$) and duration to run the data collection. Once the command received, the timestamp of each node was recorded in their internal memories and labelled as $t_{0,IMU1}$ and $t_{0,IMU2}$. The time delays due to signal propagation are defined as:

$$t_{d,IMU1} = t_{0,IMU1} - t_{PC}$$

$$t_{d,IMU2} = t_{0,IMU2} - t_{PC}$$

Then, the timer interrupt was enabled in each of the nodes. The timer interrupt was called every 20ms, i.e. 50Hz sampling time, and 6 inertial measurements (3 accelerations and 3 angular velocities) as well as the timestamp (labelled $t_{1,IMU1}$) were recorded at each call. The processing times from receiving the command and enabling the interrupt are defined as:

$$t_{p,IMU1} = t_{1,IMU1} - t_{0,IMU1} - 20ms$$
Figure 5.3. The configuration of the inertial sensor nodes.

\[ t_{p,IMU2} = t_{1,IMU2} - t_{0,IMU2} - 20\text{ms} \]  (5.33)

After the 50th interrupt calls, the recorded data as well as \( t_{0,IMU1}, t_{d,IMU1} \) and \( t_{p,IMU1} \) were copied to a buffer which were then transmitted wirelessly to the PC. The operation stopped when the duration time lapsed. Similar processes were run in node two, the waist-mounted. The delay and processing times are important to synchronize the data from both nodes which is realized as follows:

\[ t_{i,IMU1} = t_{i,IMU1} - t_{0,IMU1} - t_{d,IMU1} - t_{p,IMU1} \]  (5.34)

\[ t_{i,IMU2} = t_{i,IMU2} - t_{0,IMU2} - t_{d,IMU2} - t_{p,IMU2} \]  (5.35)

where \( i \) is the data index.

In this experiment, nine healthy pedestrians had been asked to walk in the normal speed and style that they are used to. The tracks consist of corridors and corners where the pedestrians had to turn to the left and right. However, in the first track, three pedestrians would make a 180° turn at the end of the corridor and walk back to the initial position.

Meanwhile, for the second track, another three pedestrians had to turn around at the end of the long corridor and had to pass through two access doors on the way back. Lastly, the third track is a reverse track from the first track and used by the last three pedestrians. The layouts of the tracks are shown in the Figure 5.4. The actual distances are 150.3m for Track 1 and Track 3, and 111.4m for Track 2.
CHAPTER 5. POSITIONING AND TRACKING FRAMEWORK

5.4.2 Results and Discussion

The tracking results using the proposed turn detector with the tracking framework as shown in Figure 5.2 for the nine pedestrians are analysed and compared with three other existing methods. The methods neither use an electronic compass such as a magnetometer nor use any building map for position update. The first method to compare is a combination between EKF, ZUPT and ZARU (called as ZARU-based method or ZARU). The implementation of ZARU-based tracking is similar to the one described in Section III (b) as well as in [142].

Meanwhile, the second method is the state of the art in heading correction, namely improved Heuristic Drift Elimination (iHDE). The iHDE implementation is based on a method applied in [48]. The last method to compare is Advanced Heuristic Drift Elimination (AHDE) [120], which is the improvised version of iHDE. It is important to note that iHDE and AHDE required the dominant directions of the building beforehand to perform the heading correction.

In Figure 5.5, the walk of the first pedestrian on Track 1 is tracked using the four methods: ZARU, iHDE, AHDE and the proposed EKF framework. Obviously, ZARU-based tracking deviates from the original course as no update from any heading measurement is applied. The ZARU-based tracking results in other tracks are shown in the Figure 5.6 and Figure 5.7.

On the other hand, the iHDE-based tracking performs better than the ZARU-based tracking because of heading correction applied. However, the tracking results between the tracks are not consistent and indicate that the method is not robust for different people and tracks. Track 3 has a number of short turns at one end of the building (right end of
the Figure 5.6) and the method lagged in performing the heading corrections. Similar observation can be seen on AHDE-based tracking which perform poorly in Track 3. Both methods require 5 to 6 pedestrian’s steps to determine the type of walk before heading corrections could be performed.

Lastly, the proposed tracking method produces better mean tracking performance than the other methods. The tracking results closely resemble the actual trajectory and the Return Position Error (RPE) is convincing and acceptable. The travelled distance errors (TDE) in percentage of the actual distances are well under 5%. Table 5.1 lists the average of RPEs and TDEs of the pedestrians for the three tracking methods over the three tracks.

In average, the tracking performance table shows that the tracking framework with the proposed heading correction outperforms the other methods. The results also indicate that the proposed tracking solution is robust to the change of the pedestrians and the tracks. The mean RPEs for the three tracks is 2.3% and the mean TDEs is 2.9%. Although the TDEs for iHDE are lower in Track 1 and Track 2, but as aforementioned the method suffered from consecutive short turns in Track 3. Noticeably, AHDE is not far better than iHDE and even worse in Track 1. Worthy to note, it is found out that few stance phases have gone undetected, which indirectly causes the displacement due to undesired drift.

The experiments also indicate that consumer-grade inertial sensor may influence the performance of the tracking methods. The influence can be seen from the tracking performance of the simplest method, ZARU, which suffer from the heading drift. The heading corrections implemented in iHDE and AHDE are insufficient to produce reliable results. However, the proposed tracking method with PZTD manages to overcome the
heading drift and produce convincing tracking results.

Besides, the proposed tracking framework does not use magnetometer which is commonly integrated in the current pedestrian tracking systems [133], [143] which is susceptible to magnetic disturbance under certain operational conditions. Also, the proposed tracking framework is a map-free tracking system which have been applied in [144], [145]. Therefore, the proposed method works well in the case the building map is not available for various reasons and easily adapts to frequent layout changes.

5.5 Summary

A several types of coordinate frames have been discussed and the navigation frame of interest has been introduced. The procedures in implementing Extended Kalman filter-based navigation framework have been explained. This include the integration of proposed ZUPT and heading correction techniques into the measurement update of the framework. The performance of the navigation framework has been tested and validated in a set of experiments with comparison against the state of the art in heading correction methods. The results show the proposed tracking framework with the proposed ZUPT detector and heading correction technique outperforms the other methods.
6.1 Introduction

The strapdown pedestrian inertial navigation system for foot-mounted (SPINS-FM) using consumer-grade inertial sensors offers a miniature footprint, low-cost and low-power operation that fit nicely to the requirements of wearable devices. In Chapter 5, the proposed inertial positioning and tracking system based on Kalman filter framework has shown potential in the real-life activities. The system has been integrated with a better ZUPT detector and aided with heading from the waist which has been filtered through PZTD algorithm.

However, SPINS-FM alone suffers from the deterioration and absence of absolute positioning over time. Complex activities and random movements of the pedestrian could produce erroneous positioning information. For instance, pedestrian may sit in an office chair with fidgeting legs that might be interpreted as displacement or un-registered manoeuvring movement to avoid obstacles by emergency responders, which may include crawling and ducking.

To overcome this issue, researchers have proposed to fuse the positioning information from INS with absolute position acquired from external sources such as radio frequency (RF). Some of popular hybrid systems comprise of INS and Wi-Fi [146], INS and Bluetooth [147] as well as INS and ultra-wide band (UWB). Unsurprisingly, the research is more inclined for smartphone applications because the readily available inertial sensors and supporting multi-RF technologies, i.e. Wi-Fi and Bluetooth. On the other hand, the hybrid indoor positioning of SPINS-FM is still lacking attention. To the best of our knowledge, there are only three published articles which integrate SPINS-FM with radio frequency positioning technology. These works have been detailed in Section 2.5 [93]-[95].

Among the major drawbacks of the researches are the use of costly commercial-grade inertial sensors and the need to carry additional electronic devices such as smartphone to support the RF positioning. In this research, a hybrid SPINS-FM is proposed by adapting Device-Free Location (DFL) method while maintaining the use of consumer-grade inertial...
FIGURE 6.1. Position is updated with absolute information at DFL checkpoint.

sensors. We believe that this is the first work that fuses SPINS-FM with DFL as a unified positioning solution.

The innovation in RF-based positioning technology has introduced DFL method to provide absolute position information while the user is not required to wear the transmitter on the body anymore. In this chapter we propose the integration of SPINS-FM with DFL where the DFL works as a checkpoint to reset the (absolute) position information. A similar concept but with different approach for positioning has been researched in [137] where access card readers are used to provide absolute position information inside a building. In this research, the positions of access card readers were pre-determined. When a pedestrian swiped his or her access card to the reader, the position calculated from INS was reset to the position of that access card reader.

Figure 6.1 shows the concept of continuous position monitoring where the position from INS is being monitored in a specified interval. The position from INS with drift will be updated with absolute position at a DFL checkpoint. The absolute position can be computed locally at the checkpoint. The remote monitoring will integrate the position updates received from INS and DFL.

In a similar approach to the access card reader, this work envisions the DFL checkpoint as a positioning corrector. The DFL checkpoints can be set up in strategic locations such as corridors, complex paths or offices. Moreover, the checkpoints can be easily removed or transferred to other locations depending on the demand. In contrast, the installation of access card readers is normally fixed close to doorways, for granting access to authorize personnel.

In other areas where DFL checkpoints are not available, the position information will be extracted from the SPINS-FM alone. The presence of DFL checkpoints will assist the positioning from SPINS-FM to produce a better tracking performance. Therefore, in this thesis, the integration between SPINS-FM and DFL positioning technologies is referred as assisted SPINS-FM. However, the work focuses on the integration when a pedestrian is already in the DFL checkpoint or deployed area. There are two critical components of the integrations that will be discussed in this chapter; 1) the multi-rate measurements and 2) the integration framework.

The integration between SPINS-FM and DFL involves different sampling times
and the situation is known as multi-rate measurements. A solution to the multi-rate measurements is required to produce stable positioning results. Next is to determine the integration technique and the tuning parameters in order to achieve a better tracking performance.

The following section introduces a technique in DFL positioning technology and its working principle. Later, the two critical components of integrations will be explained. Afterwards, the performance of the components was analysed in simulations as well as in practical experiment.

### 6.2 Radio Tomography Imaging

One of the technique to extract position information from DFL is known as Radio Tomographic Imaging (RTI) [87]. RTI exploits the shadowing losses on links between many pairs of transceiver nodes in a wireless network to image the attenuation caused by objects within the network area. Shadowing-based RTI assumes that a person or object attenuates the RSS on a link when they cross through the line between the transmitter and receiver, thus will be able to estimate where the person is located. Attenuation-based RTI means the change in RSS measurement $y$ depends on the difference between the current and average RSS measured during system calibration. During calibration, no targets are present inside the measurement area.

Figure 6.2 (left) depicts an area surrounded by 16 wireless nodes. In RTI, two nodes will communicate to each other at a time, and each node will communicate to all other nodes in sequence. For instance, in the beginning, node 1 will communicate with node 2. Once the communication has been completed, the node 1 will proceed to communicate with node 3 and the process continues until the last node, node 16. Then, node 2 takes the role to initiate the communication with others. One rule in RTI is no overlap of communication between the nodes. Thus, instead communicate to node 1, node 2 starts its communication with node 3 and ends with node 16. Once the node 15 communicates with node 16, the first cycle of node communication is ended. The next cycle will start with node 1 once again.

Therefore, the total number of unique two-way links is $M = (K^2 - K)/2$. $K$ is the total number of nodes in the network and a link is a pair of nodes. In this case, $K$ is 16 and subsequently, $M$ equals 120 links. During the communication between the nodes, the received signal strength (RSS), $y_i(t)$, of a particular link $i$ at time $t$ is recorded. Therefore, for a complete cycle of node communications, there will be 120 measurements of RSS recorded from all the unique links.

Figure 6.2 (right) represents the equivalent radio tomography imaging grid from an RTI network that contains 16 wireless nodes. The region is discretized with a grid of 10x10 voxels. A voxel is a unit of graphic information that defines a point in three-dimensional space. The voxel index is represented by $j$, which starts from lower left corner ($j = 1$) to the upper right corner ($j = 100$). The link that experience signal attenuation due to the pedestrian is illustrated in the figure by the dashed line.
CHAPTER 6. HYBRID INDOOR POSITIONING AND TRACKING

Figure 6.2. The network geometry with an illustration of a single RTI link shadowed by a pedestrian. (Left) The arrangement of wireless nodes that constitutes an RTI network and a pedestrian. (Right) The equivalent radio tomography imaging grid. The darkened voxels represent the image areas that have a non-zero weighting for this particular link and the irregular shape represents the pedestrian.

A weight model is required to describe the linear effect of the attenuation field on the path loss for the link [87]. In [148], the authors proposed to use an ellipsoid with foci at each node location for determining the weighting for each link in the network. In the Figure 6.2 (right), the ellipsoid is shown by the solid line. If a particular voxel falls outside the ellipsoid, the weighting for that voxel is set to zero. On the other hand, if a particular voxel is within the ellipsoid, its weight is set to be inversely proportional to the square root of the link distance. The non-zero weighting is illustrated in the figure by the darkened voxels. The signal strength $y_i(t)$ of link $i$ is described as

$$y_i(t) = P_i - L_i - S_i(t) - F_i(t) - v_i(t)$$  \hspace{1cm} (6.1)

where $P_i$ is the transmitted power in dBm, $S_i(t)$ is the shadowing loss in decibels due to objects that attenuate the signal, $F_i(t)$ is the fading loss in decibels and $L_i$ is the static losses in decibels due to distance, antenna patterns, device inconsistencies, etc. $v_i(t)$ represents noise and interference.

In the case where one of the time instants is when the deployment area is vacant (e.g. $S_i(0) = 0$), the change in RSS measurements between two time instants is assumed to be dominated by the target’s shadowing effect on the link. The change in RSS $\delta y_i(t)$ is

$$\Delta y_i(t) = y_i(t) - y_i(0) \approx S_i(t) + n_i(t)$$  \hspace{1cm} (6.2)

where the noise $n_i$ is the grouping of fading and measurement noise as follows:

$$n_i(t) = F_i(t) - F_i(0) + v_i(t) - v_i(0)$$  \hspace{1cm} (6.3)
and all static losses can be removed over time. If a link is shadowed, then the target is likely to be located along the link line. With multiple shadowed links, the intersection points of the link lines are likely locations of the target.

The shadowing loss can be approximated as the sum of the attenuation that occurs in each voxel. The weight model is applied to indicate different contribution of each voxel to the attenuation of a link. The shadowing loss for a single link is described as

$$S_i(t) = \sum_{j=1}^{N} W_{ij} x_j(t)$$ (6.4)

where $$x_j(t)$$ is the attenuation in voxel $$j$$ at time $$t$$, and $$w_{ij}$$ is the weighting of voxel $$j$$ for link $$i$$. Thus, the $$\delta y_i(t)$$ can be re-written as

$$\Delta y_i(t) = \sum_{j=1}^{N} w_{ij} x_j + n_i$$ (6.5)

Mathematically, the weighting can be described as

$$w_{ij} = \frac{1}{\sqrt{d_i}} \begin{cases} 1, & \text{if } d_{ij1} + d_{ij2} < d_i + \rho \\ 0, & \text{otherwise} \end{cases}$$ (6.6)

where $$d_{ij1}$$ and $$d_{ij2}$$ are the distances from the center of voxel $$j$$ to the two nodes of link $$i$$, $$d_i$$ is the distance between two nodes of link $$i$$ and $$\rho$$ is a tunable parameter defining the width of the ellipse. Consequently, the larger the width $$\rho$$ of the ellipse, the larger the area that the link will cover, thus the more voxels that will be selected. This also means the detail of where attenuation occurs may be reduced. Authors in [149] suggested to set $$\rho$$ to 0.02m.

When all links in the network are considered simultaneously, the system of RSS measurements can be described in matrix form as

$$y = Wx + n$$ (6.7)

where $$y = [y_i, \ldots, y_k]^T$$ is a $$K \times 1$$ vector that represents the change of the RSS measurements vector, $$x = [x_i, \ldots, x_k]^T$$ is a $$N \times 1$$ vector to be estimated, and $$W$$ is the weighting matrix of the dimension $$K$$, with each column corresponding to a single voxel, and each row describing the weighting of each voxel for that particular link. The $$K \times 1$$ vector $$n$$ represents noise terms.

When estimating an image from measurement data, it is common to search for a solution that is optimal in the least-squared error:

$$x_{LS} = \underset{x}{\arg \min} \| y - Wx \|^2_2$$ (6.8)

In other word, the least-square solution minimizes the noise energy required to fit the
measured data to the model. The least-square solution can be obtained by setting the gradient of Equation (6.8) equals to zero, resulting in

\[ x_{LS} = \left(W^TW\right)^{-1} W^T y \]  

(6.9)

which is only valid if \( W \) is full rank which is not the case in an RTI system because typically, the number of links is significantly smaller than the number of voxels [150]. In general, to achieve a better position accuracy, a higher image resolution is preferred such as 40x40 voxels or higher. To overcome the ill-posed inverse problem of RTI, an energy term is added to the least-square formulation in Tikhonov regularization, resulting in the objective function

\[ f(x) = \frac{1}{2}\|y - Wx\|^2_2 + \alpha \|Qx\|^2_2 \]  

(6.10)

where \( Q \) is the Tikhonov matrix that enforces a solution with certain desired properties, and \( \alpha \) is the regularization parameter [87]. Taking the derivative of Equation (6.10) with respect to \( x \) and setting the result to zero, the following Tikhonov solution is obtained:

\[ \hat{x} = \left(W^TW + \alpha \left(D_x^TD_x + D_y^TD_y\right)\right)^{-1} W^T y \]  

(6.11)

where \( D_x \) is the difference operator for the horizontal direction and \( D_y \) is the difference operator for the vertical direction. \( \alpha \) is a smoothing parameter that can be set to 0.3 for weak smoothing or 30 for strong smoothing [150]. Meanwhile, \( \hat{x} \) is a single column vector with size of 1 \( \times \) number of voxels. By reshaping the vector into the pre-defined grid (i.e. 10 \( \times \) 10), an image can be generated. The location of the pedestrian from the image can be obtained by retrieving the indices of row and column that represented the minimum value of \( \hat{x} \).

So far, the working principle of RTI has been presented. However, the RTI itself does not provide the location coordinates of moving pedestrian. The common way to track a pedestrian is by using a Kalman filter. The Kalman filter takes into account the current and previous measurements to generate a more accurate position estimate than a single instantaneous measurement can. Furthermore, constraints can be implemented in the Kalman filter to prevent illogical position transitions as pedestrian moves through space at a limited speed.

In this work, the Kalman filter is used in the implementation of RTI. The state to be estimated is made up of the physical position of the pedestrian being tracked. The state matrix \([pos_X; pos_Y]\) represent position with respect to X- and Y-axis. The state transition, \( A \), is 1, no control input and process noise, \( v_m \), is 0.6m. The measurement matrix, \( H \), is set as \([1; 1]\) with measurement noise, \( v_n \), of 1m. The Kalman filter algorithm for tracking movements in an RTI system can be described as follows:

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1. Initialize $c = (0,0)$ and $P = I_2$, where $c$ is predicted position, $P$ is covariance and $I_2$ is the $2 \times 2$ identity matrix.

2. Set $\tilde{P} = P + v_n^2 I_2$

3. Set $K = \tilde{P} H^T (H \tilde{P} H^T + v_n^2 I_2)^{-1}$

4. Take measurement $z$ equal to the coordinates from Equation (6.11).

5. Set $\hat{c} = c + K (z - Hc)$ where $\hat{c}$ is the estimated position

6. Set $P = (I_2 - KH) \tilde{P} (I_2 - KH)^T$.

7. Go to step 2 and repeat.

### 6.3 Multi-Rate Measurements

The sensor fusion is based on loosely coupled integration between SPINS-FM and DFL. In this integration scheme, the positions obtained separately from SPINS-FM and DFL are merged. However, the position updates from both positioning technologies occur at different sampling frequencies. Specifically, the inertial sensors are sampled several times faster than DFL and update its estimated position more frequently. Therefore, a mechanism to substitute the unavailable low frequency measurement (e.g. DFL) is needed to obtain stable and accurate position estimate. Examples of asynchronous sensor measurements are in mobile robot applications that use odometry and vision [151], and outdoor navigations that use INS and Global Positioning System (GPS) [152], [153].

The triaxial accelerometers and gyroscopes measure linear acceleration and angular velocity of the pedestrian at a frequency rate of 50Hz. Meanwhile, the wireless sensor network (WSN) for the device-free localization completes a positioning routine at a frequency rate of 2.5Hz. The difference in sampling time causes multi-rate issues when estimating the pedestrian’s position.

One technique to solve the multi-rate issue is by interpolating the unavailable low frequency measurements based on previous low frequency measurements and the latest high frequency measurement. The interpolation is made with a Bezier curve [154]. Bezier curve is widely used to model smooth curves. In this case, a set of control points consist of the latest high frequency measurement and previous low frequency sampling measurements is used to generate high frequency substitute.

Suppose that $u$ represents the low frequency measurement (DFL) and $v$ represents the high frequency measurement (INS). The high frequency substitute of $u$ denoted as $\tilde{u}$ and $\tilde{u}(k)$ at the $k - th$ time step of the high frequency measurement $v$ is

$$\tilde{u}(k) = \sum_{i=0}^{N} w(i, t_v(k), t_u(j)) u(j - i) \quad (6.12)$$

where $N$ is total number of the lowest frequency measurements stored, $t_v$ is the sampling time of high frequency and $t_u$ is the sampling time of low frequency. The $j$ and $k$ are the time step of $u$ and $v$, respectively. The vector $u$ is set as follows:
\[ \mathbf{u} = [\hat{z}(k), u_1, u_2, \ldots, u_{N-1}] \]  
\tag{6.13} 

where \( \hat{z}(k) \) is observation matrix from the high frequency measurement \( v \). The weight \( w(i) \) for a Bezier curve at absolute time of \( i-th \) time step is

\[ w(i, t_v(k), t_u(j)) = \frac{N!}{i!(N-i)!} w_1^{N-i} w_2^i \]  
\tag{6.14} 

\[ w_1(i, t_v(k), t_u(j)) = \frac{t_v(k) - t_u(j - N)}{T_N} \]  
\tag{6.15} 

\[ w_2(i, t_v(k), t_u(j)) = -\frac{t_v(k) - t_u(j)}{T_N} \]  
\tag{6.16} 

where \( T_N = t_u(j) - t_u(j - N) \).

### 6.4 Integration Framework

A Kalman filter provides a framework to fuse the multi-rate position information from INS and DFL. The model of the Kalman filter is given as follows:

\[ \hat{y}_{k}^- = A_k \cdot \hat{y}_{k-1} \]  
\tag{6.17} 

where \( \hat{y}_{k}^- \) is the priori position estimate and the state vector is defined as:

\[ \hat{y} = \begin{bmatrix} \text{posX} \\ \text{velX} \\ \text{posY} \\ \text{velY} \end{bmatrix} \]  
\tag{6.18} 

where \( \text{pos}^* \) and \( \text{vel}^* \) represent position and velocity, respectively. \( A_k \) is the state transition matrix and defined as follows:

\[ A_k = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \]  
\tag{6.19} 

There is no control vector as there is no external input to the system. The outputs of the system can be given as follows:

\[ z_{i,k} = C_i y_k + \eta_{i,k}, \quad i = 1, 2 \]  
\tag{6.20} 

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FIGURE 6.3. The proposed assisted SPINS-FM framework.

where $z_{1,k} = [x_{INS}^T, y_{INS}^T]$ is the measurement collected by the inertial sensors with sampling period $T_v$, $z_{2,k} = [x_{DFL}^T, y_{DFL}^T]^T$ is the measurement collected by the DFL technique with sampling period $T_u$, $\eta_i$ is the measurement noise and $C_i$ is a constant matrix of $[1 \ 0 \ 0 \ 0; \ 0 \ 1 \ 0 \ 0]$. $k-th$ time step refers to the absolute time when sampling a specific measurement.

Figure 6.3 shows the proposed assisted SPINS-FM framework. In the framework, the positioning results from IMU and DFL are merged using the Kalman filter. This type of integration is known as loosely-coupled integration scheme. One advantage of using this integration scheme is the smaller size of state vectors compared to the size of state vectors in tightly-coupled integration. This means lower computational cost and memory requirement.

6.5 Offline Simulations

As discussed earlier in the Section 6.1, the proposed assisted SPINS-FM framework has two critical components that require assessments before performing the practical evaluations. The components are the high frequency substitute technique and the Kalman filter integration. The aims of the assessments are to confirm that the high substitute technique is correctly applied and to evaluate the performance of Kalman filter in integrating the INS and DFL position data.

Therefore, offline simulations were designed to perform the assessments. Artificial position data of INS and DFL were generated for two different paths. The position data of INS was sampled at 50 Hz and drifted from the ground truth. Meanwhile, the position data of DFL was sampled at 2.5 Hz and generally close to the ground truth.

The filtered position data, resulted from the proposed assisted SPINS-FM framework, were compared to the ground truths. There are two types of filtered position data; first
Figure 6.4. The INS, DFL and filtered position data for Path 1. High frequency substitute technique was not applied.

is high frequency substitute technique, which was not applied, and the second is high frequency substitute technique, which was applied. The applied high frequency substitute technique based on Bezier curve is as presented in [154]. The N for Equation (6.11) is set to 20, the ratio of sampling rate of INS and DFL. The Kalman filter integration was tuned to trust DFL more than INS.

Path 1 has a close to straight ground truth with total displacement is about 224m. Figure 6.4 shows the position data of INS and DFL for Path 1. The ground truth is shown as a solid line. Besides, the filter integration absent the high frequency substitute technique. As seen in the figure, the filtered position data which are represented by hollow circle markers, grouped close to the DFL position data and disjointed between the groups. Figure 6.5 is the zoomed-in version of Figure 6.4. The figure indicates clearly the filtered position data in comparison with INS’s and DFL’s. The filtered position data in high frequencies aligned closely to each of DFL data. This phenomenon resulted from the sample and hold technique and the Kalman filter was biased towards the DFL.
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Figure 6.5. The zoomed-in position data for Path 1 (without high frequency substitutions).

Meanwhile, a different outcome is demonstrated when high frequency substitute technique was applied as shown in Figure 6.6. In the beginning, the technique stored the low frequency DFL data into the vector u as described in Equation (6.12). Thus, no data substitution was available during this period. Once the vector u is filled, the high frequency substitutions were generated and produced more stable as well as smooth tracking. The generated high frequency substitutions can be observed closely in Figure 6.7. This also confirm the technique was applied correctly.

Worth to note, as seen in the figure, the high frequency substitutions were moved towards INS position data after a while, in-between two DFL data. This can be explained by looking on Equation (6.12) again. In the equation, the observation from high frequency measurements was set as one of the control points of the Bezier curve, thereby forced the generated substitutions moved towards the INS data. In this way, the direction of the substitutions is controlled along the second source of position data, instead of arbitrary directions.

The next path, Path 2, has a sharp turn to navigate and has a total displacement of 151m. The tracking simulation without high frequency substitutions is shown in Figure 6.8. Similarly, the filtered position data are disjointed and aligned closely to every DFL data. This can be observed closely in Figure 6.9. Furthermore, the position data of INS and DFL are compacted around the corner. Thus, the filtered position data are condensed to the particular DFL data, unlike Figure 6.5.

Interestingly, when applying high frequency substitute technique for Path 2, the directions of substitutions are a bit curvy after the corner (Figure 6.10). In the straight path, the control points of Bezier curve influenced the substitutions to be in straight and smooth trajectory. However, after the corner, the Bezier curve was curved along the control points before and after the corner. At the same time, the end control point is the observation of high frequency measurement, thus directed the curve towards the INS data. The curvy effect is clearly seen in Figure 6.11. However, once the vector u started
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**FIGURE 6.6.** The INS, DFL and filtered position data for Path 1. High frequency substitute technique was applied.

**FIGURE 6.7.** The zoomed-in position data of Path 1 (with high frequency substitutions).
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**Figure 6.8.** The INS, DFL and filtered position data for Path 2. High frequency substitute technique was not applied.

**Figure 6.9.** The zoomed-in position data of Path 2 (without high frequency substitutions).
to be filled with DFL position data that were located after the corner, the Bezier curve straightened.

The simulations were done with the Kalman filter integration biased towards DFL. The measurement noise covariances were assigned as 0.7m and 0.03m for INS and DFL, respectively. The values were selected after fine-tuning the filter by considering the drift of INS that becomes larger over time than the position error of DFL in a constraint
Table 6.1: The RMSE of different types of filtered position data for offline simulation.

<table>
<thead>
<tr>
<th>Types of filtered position data</th>
<th>Path 1</th>
<th>Path 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without high frequency substitutions</td>
<td>48.1m</td>
<td>30.3m</td>
</tr>
<tr>
<td>With high frequency substitutions</td>
<td>18.8m</td>
<td>12.8m</td>
</tr>
</tbody>
</table>

area. The process noise was modelled as 5m. The root-mean-square-errors (RSME) are calculated for different types of filtered position data for each path. The calculation of RSME is described as follows:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N}(pos_{est} - pos_{truth})^2}{N}}
\]  

(6.21)

where \(N\) is the number of samples, \(pos_{est}\) is the estimated position and \(pos_{truth}\) is ground truth position. The calculated RMSE are presented in Table 6.1. The table indicates the RMSE for filtered position data with high frequency substitutions are lower than the ones without high frequency substitutions.

The ratios of RMSE against total displacement of filtered position data with high frequency substitutions are 8.0% and 8.5% for Path 1 and Path 2, respectively. In contrast, the ratios of RSME against total displacement of the filtered position data without high frequency substitutions are 21.4% and 20.0% for Path 1 and Path 2, respectively. The results show that the tracking is more efficient with the present of high frequency substitutions.

The next section will explain the practical experiment of the assisted SPINS-FM framework.

### 6.6 Experiments

#### 6.6.1 Setup

A wireless network containing 16 nodes was deployed where each node was placed 1.2m apart. The nodes covered a perimeter of 4.8m x 4.8m, surrounding a total area of 23.04 square meters. The network was deployed on a cemented floor, inside a building. Each node was placed on a tripod at 1.0m off the ground.

Markers were measured and placed in 4 locations within the area so that the pedestrian’s locations were known. A photograph of the experiment is shown in Figure 6.12. The network comprises Preon32 wireless nodes manufactured by Virtenio GmbH. Each node operates in the 2.4Ghz frequency band and uses the IEEE 802.15.4 standard for communication.

Each node was assigned an ID number and programmed with a specified order of transmission. In the beginning, the first node transmitted a packet of a 16-element vector that represents the received signal strength (RSS), while the rest of the nodes received
Figure 6.12. Photograph of the deployed RTI network.

Figure 6.13. The attachment of inertial sensor on the pedestrian’s foot.

and examined the sender’s ID and corresponding RSS. Each node then updated the RSS value in its own RSS vector. At first, the RSS in the first element that represents the first node was updated. If the receiving node’s ID is the next of the sender’s ID, then it transmitted its latest RSS vector and the other listen.

Additional node acted as a base station was connected to a laptop and listened to all transmitted messages. Each time it received a packet of the message, a program running on the laptop saved the link RSS measurement vector to a file. A complete cycle for all the nodes to transmit and receive took about 400ms, which corresponds to the cycle frequency of 2.5Hz. At the same time, the pedestrian was equipped with ADXL345 accelerometers and ITG-3200 gyros as shown in Figure 6.13. The sampling frequency was 50Hz. The pedestrian was asked to walk diagonally as shown in Figure 6.14.
6.6.2 Results and Discussion

The data were collected and saved in the PC. The computations to extract position from INS and DFL were done offline. The first result, the DFL tracking based on RTI technique was obtained as shown in Figure 6.15. The dotted line represents the original DFL tracking which was disturbed with multi-path problem. Using a simple Kalman filter, a constraint in displacement between previous and current DFL position data had been applied. As a result, the filtered DFL position data, represented by the solid line, are smoother.

The INS position data was calculated from the SPINS-FM framework. Then, based on the proposed assisted SPINS-FM framework, the filtered position data were computed in two ways; with and without high frequency substitutions. In Figure 6.16, the INS tracking drifts from the ground truth and the DFL tracking is close to the ground truth. The figure indicates the filtered position data condenses close to the DFL's when high frequency substitute technique was not applied and creates disjointed tracking.

On the other hand, when high frequency substitute technique was applied, a more stable and smooth tracking was produced. As seen in Figure 6.17, high frequency substitutions laid close to the ground truth and almost equally spaced during motion.

Table 6.2 summarizes the RMSE of the different types of position data for the practical experiment. As expected the RMSE for filtered position data with high frequency substitutions is lower than the other types. The total displacement for the experiment is 3.4m. The ratio of RMSE against the total displacement are 9.3% for filtered position data with high frequency substitutions and 30.8% for the another.
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FIGURE 6.15. The original and filtered DFL tracking.

FIGURE 6.16. The INS, DFL and filtered position data. High frequency substitute technique was not applied.
CHAPTER 6. HYBRID INDOOR POSITIONING AND TRACKING

Figure 6.17. The INS, DFL and filtered position data. High frequency substitute technique was applied.

<table>
<thead>
<tr>
<th>Types position data</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>INS</td>
<td>0.89m</td>
</tr>
<tr>
<td>DFL</td>
<td>0.49m</td>
</tr>
<tr>
<td>Filtered without high frequency substitution</td>
<td>1.03m</td>
</tr>
<tr>
<td>Filtered with high frequency substitution</td>
<td>0.31m</td>
</tr>
</tbody>
</table>

6.7 Summary

The issues of stand-alone SPINS-FM have been discussed. The importance of hybrid indoor positioning and the current problems with the state-of-the-art methods have been explained. An integration of SPINS-FM and DFL has been proposed and the challenge in multi-rate has been addressed with the solution. The offline simulations have been successfully ran and the results indicate the high substitute technique is correctly applied. The integration scheme using the Kalman filter is worked as expected. The concept of the assisted SPINS-FM has been tested on field and the results have been validated. The results show the RMSE is the lowest for the filtered position data with high frequency substitutions as compared to separate tracking techniques, INS and DFL, and the tracking without the high frequency substitutions.
The main aim of the research presented in the thesis is to develop an indoor pedestrian positioning and tracking system using INS and RF sensor fusion. The system uses primarily two sensing technologies for the positioning purposes, consumer-grade INS and standard RF transceivers. The advantages and disadvantages of both technologies have been described and discussed in the Chapter 2. Additionally, the chapter has listed two important criteria to ensure high accuracy of inertial based positioning, reducing position and heading drifts. Mitigating these two issues are among the key factors addressed in this thesis.

Accordingly, the first objective was to develop a new algorithm to reduce error accumulated in distance estimation when using low-cost INS. The solution to the objective has been presented in Chapter 3 in which a new enhanced zero-velocity update (ZUPT) has been proposed and proved to reduce the position error. The performance of the developed ZUPT detector using subtractive clustering algorithm outweighs the other ZUPT detection techniques, even at different walking speeds. The proposed ZUPT detector scores 99.5 percent F1 score, a performance metric based on Van Rijssbergen’s effectiveness measure. The performance of linear tracking that uses the proposed ZUPT detector has recorded an average of 3.1 percent error for 49.6 m walk. The results validate the success in meeting the first objective.

The second objective states to develop a new method to correct the heading drift using low-cost INS that is robust (invariant) to different people and operating conditions. The proposal of turn detector and heading correction has been presented in Chapter 4. The developed turn detector technique is based on the relationship between pelvic rotation and ZUPT and thereafter known as Pelvic rotation-ZUPT Turn Detector or (PZTD). This technique is a threshold-less method and robust to variations to different people and operating conditions. The technique also need less steps, in this case two steps, to perform the detection in comparison to state-of-the-art methods. In the experiments with three challenging paths used, two circular paths and an angled path, the proposed turn detection technique outperforms the state-of-the-art methods. The PZTD is then
applied to correct the heading derived from waist’s angular velocity to the extent sufficient
to provide accurate heading information. In a series of other experiments, the filtered
headings (FH) have recorded 1.7 degree of average of mean error as compared to 58.9
degree of un-filtered headings (UH). The results from the experiments affirm the second
objective has been achieved.

The last objective is to develop a sensor fusion technique that combines position
information from INS and RF. In the first stage, the estimated position is obtained from
the Strapdown Pedestrian Inertial Navigation System with Foot-Mounted (SPINS-FM)
sensors. The development of SPINS-FM which is based on Kalman filter navigation
framework has been elaborated in Chapter 5. The SPINS-FM has incorporated the
proposed ZUPT detector and the filtered headings from PZTD discrimination process. The
proposed SPINS-FM has outperformed the other tracking methods which apply different
heading correction technique. It has recorded 2.26 percent of Return Position Error (RPE)
and 2.91 percent of Travelled Distance Error (TDE).

The Chapter 6 has described the development of RF positioning based on Device-Free
Localization (DFL) method to estimate the position and its integration with SPINS-
FM. This is the second stage in the sensor fusion development whereas the proposed
hybrid indoor positioning technique offers practical implementation whilst maintaining
the use of consumer-grade inertial sensors as compared to the state-of-the-art methods
which also used high-grade inertial sensors. The issue of different sampling times for
both technologies has been addressed and a solution has proposed by interpolating the
un-available measurements from the low-frequency DFL using Bezier curve technique.
Offline simulations have been conducted to prove the interpolating technique has been
correctly applied and the Kalman filter for the integration has been tested. In the practical
experiment, the proposed assisted SPINS-FM has recorded RMSE of 0.31m and the ratio
of RMSE against the total distance travelled is 9.3

7.1 Achievements and Contributions

The different topics in the research are detailed throughout the thesis. Some of these
points have been published in a journal and conference proceedings. The following list
highlights the major contributions of this thesis:

Chapter 3: We have developed a robust and accurate ZUPT detector which is based on
subtractive clustering algorithm. The technique clusters zero acceleration in vertical axis
as potential stance phase and declare each cluster that has a computed cluster centre as
the detected stance phase. The ZUPT vector is formed from the information of detected
stance phases. The experiments indicate the ZUPT detector has better detection accuracy
even at different walking speeds. The accurate detection of ZUPT has proved to help in
reducing position error in linear tracking.

Chapter 4: We have developed a threshold-less turn detection in which essential to
correct the heading. The turn detection technique or PZTD exploits the unique arrange-
ments of pelvic rotation and ZUPT to classify whether a pedestrian walked straight,
turned to the left or turned to the right. The classification is executed based on Naïve
Bayes algorithm. The PZTD is then applied to filter the noise-contaminated heading derived from the waist’s angular velocity to produce an accurate heading information. The experiments indicate the PZTD technique has a better detection accuracy and the filtered heading has much lower error.

Chapter 5: We have established a strapdown pedestrian inertial navigation system for foot-mounted (SPINS-FM) based on Kalman filter navigation framework which has incorporated the proposed ZUPT and the filtered heading from the PZTD discrimination process. The experiments indicate the SPINS-FM has a better tracking performance.

Chapter 6: We have developed a hybrid indoor positioning from SPINS-FM and DFL. The proposed hybrid system is based on loosely coupled integration scheme using Kalman filter. The integration It works without require the pedestrian to carry additional electronic devices whilst use consumer-grade inertial sensors. A multi-rate measurement technique has been proposed to interpolate the lower frequency measurements. The experiments prove that assisted SPINS-FM has a better tracking performance as compared to INS or DFL only.

7.2 Future Work

The work described in this thesis has proposed a set of methods which have been developed to enhance the performance of indoor pedestrian positioning and tracking using INS and RF sensor fusion in a way that these systems can provide reliable position data for wider range of indoor applications. The following recommendations are made here to continue the research and perhaps make further advancements in the field:

- The proposed ZUPT detector shows promising results. The approach has been tested in varying walking speeds. Further investigations are however required to test and validate the accuracy of detection in special occasions such as back-stepping, walking up and down stairs, running and tip-toeing. These are possible, yet challenging activities and the success in achieving accurate ZUPT detection will bring the confidence of the proposed ZUPT detector into a higher level.

- The existing waist-mounted IMU, which was previously used to extract the pelvic rotation, can be used to detect steps and collaborate with the ZUPT in producing a unified step detection. In addition, positions can be estimated using the waist’s IMU and add an extra perspective in the navigation.

- The SPINS-FM may be tested in more challenging indoor environments such as cluttered rooms and with extended period of testing time. The longest time for the previous experiments took roughly about two minutes to complete. Accordingly, a rejection model for unnecessary movements such as fidgeting legs may introduce to the SPINS-FM framework. This will prevent spurious trajectory from being registered as part of the navigation.

- A recent development in DFL technology has introduced an alternative to RTI method, known as Geometric Filter (GF) technique. The GF technique is claimed
to use less computational power and has lower memory requirements which is attractive for resource-constrained platform. Moreover, the average execution time is much shorter than the RTI method. This technique may be used and compared to the RTI method and then fused with INS-based technique.
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