# 1

# Introduction

## 1.1 Navigation

Navigation is the process of planning, recording, and controlling the movement of a craft or vehicle from one place to another [1]. It is an ancient subject but also a complex science, and a variety of methods have been developed for different circumstances, such as land navigation, marine navigation, aeronautic navigation, and space navigation.

One of the most straightforward methods is to use landmarks. Generally speaking, a landmark can be anything with known coordinates in a reference frame. For example, any position on the surface of the Earth can be described by its latitude and longitude, defined by the Earth's equator and Greenwich meridian. The landmarks can be hills and rivers in the wilderness, or streets and buildings in urban areas, or lighthouses and even celestial bodies when navigating on the sea. Other modern options, such as radar stations, satellites, and cellular towers, can all be utilized as landmarks. The position of the navigator can be extracted by measuring the distance to, and/or the orientation with respect to the landmarks. For example, celestial navigation is a well-established technique for navigation on the sea. In this technique, "sights," or angular distance is measured between a celestial body, such as the Sun, the Moon, or the Polaris, and the horizon. The measurement, combined with the knowledge of the motion of the Earth, and time of measurement, is able to define both the latitude and longitude of the navigator [2]. In the case of satellite navigation, a satellite constellation composed of many satellites with synchronized clocks and known positions, and continuously transmitting radio signal is needed. The receiver can measure the distance between itself and the satellites by comparing the time difference between the signal that is transmitted by the satellite and received by the receiver. A minimum of four satellites must be in view of the receiver for it to compute the time and its location [3]. Navigation methods of this type, which utilize the observation of



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landmarks with known positions to directly determine a position, are called the position fixing. In the position fixing type of navigation, navigation accuracy is dependent only on the accuracy of the measurement and the "map" (knowledge of the landmarks). Therefore, navigation accuracy remains at a constant level as navigation time increases, as long as observations of the landmarks are available.

The idea of position fixing is straightforward, but the disadvantage is also obvious. Observation of landmarks may not always be available and is susceptible to interference and jamming. For example, no celestial measurement is available in foggy or cloudy weather; radio signals suffer from diffraction, refraction, and Non-Line-Of-Sight (NLOS) transmission; satellite signals may also be jammed or spoofed. Besides, a known "map" is required, which makes this type of navigation infeasible in the completely unknown environment.

An alternative navigation type is called dead reckoning. The phrase "dead reckoning" probably dated from the seventeenth century, when the sailors calculated their location on the sea based on the velocity and its orientation. Nowadays, dead reckoning refers to the process where the current state (position, velocity, and orientation) of the system is calculated based on the knowledge of its initial state and measurement of speed and heading [4]. Velocity is decomposed into three orthogonal directions based on heading and then multiplied by the elapsed time to obtain the position change. Then, the current position is calculated by summing up the position change and the initial position. A major advantage of dead reckoning over position fixing is that it does not require the observations of the landmarks. Thus, the system is less susceptible to environmental interruptions. On the other hand, dead reckoning is subject to cumulative errors. For example, in automotive navigation, the odometer calculates the traveled distance by counting the number of rotations of a wheel. However, slipping of the wheel or a flat tire will result in a difference between the assumed and actual travel distance, and the error will accumulate but cannot be measured or compensated, if no additional information is provided. As a result, navigation error will be accumulated as navigation time increases.

Inertial navigation is a widely used dead reckoning method, where inertial sensors (accelerometers and gyroscopes) are implemented to achieve navigation purpose in the inertial frame. The major advantage of inertial navigation is that it is based on the Newton's laws of motion and imposes no extra assumptions on the system. As a result, inertial navigation is impervious to interference and jamming, and its application is universal in almost all navigation scenarios [5].

## 1.2 Inertial Navigation

The operation of inertial navigation relies on the measurements of accelerations and angular rates, which can be achieved by accelerometers and gyroscopes, respectively. In a typical Inertial Measurement Unit (IMU), there are three accelerometers and three gyroscopes mounted orthogonal to each other to measure the acceleration and angular rate components along three perpendicular directions. To keep track of the orientation of the system with respect to the inertial frame, three gyroscopes are needed. Gyroscopes measure the angular rates along three orthogonal directions. Angular rates are then integrated, and the orientation of the system is derived from these measurements. The readout of the accelerometers is called the specific force, which is composed of two parts: the gravity vector and the acceleration vector. According to the Equivalence Principle in the General Theory of Relativity, the inertial force and the gravitational force are equivalent and cannot be separated by the accelerometers. Therefore, the orientation information obtained by the gyroscopes is needed to estimate the gravity vector. With the orientation information, we can subtract the gravity vector from the specific force to obtain the acceleration vector, and revolve the acceleration vector from the system frame to the inertial frame before performing integration. Given the accelerations of the system, the change of position can be calculated by performing two consecutive integrations of the acceleration with respect to time.

The earliest concept of inertial sensor was proposed by Bohnenberger in the early nineteenth century [6]. Then in 1856, the famous Foucault pendulum experiment was demonstrated as the first rate-integrating gyroscope [7], whose output is proportional to the change of angle, instead of the angular rate as in the case of most commercial gyroscopes. However, the first implementation of an inertial navigation system did not occur until the 1930s on V2 rockets and the wide application of inertial navigation started in the late 1960s [8]. In the early implementation of inertial navigation, inertial sensors are fixed on a stabilized platform supported by a gimbal set with rotary joints allowing rotation in three dimensions (Figure 1.1).

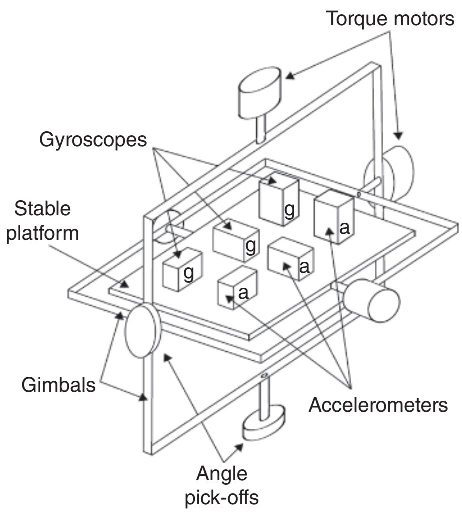


**Figure 1.1** A schematic of gimbal system. Source: Woodman [5].

The gyroscope readouts are fed back to torque motors that rotates the gimbals so that any external rotational motion could be canceled out and the orientation of the platform does not change. This implementation is still in common use where very accurate navigation data is required and the weight and volume of the system are not of great concern, such as in submarines. However, the gimbal systems are large and expensive due to their complex mechanical and electrical infrastructure. In the late 1970s, strapdown system was made possible, where inertial sensors are rigidly fixed, or "strapped down" to the system. In this architecture, the mechanical complexity of the platform is greatly reduced at the cost of substantial increase in the computational complexity in the navigation algorithm and a higher dynamic range for gyroscopes. However, recent development of microprocessor capabilities and suitable sensors allowed such design to become reality. The smaller size, lighter weight, and better reliability of the system further broaden the applications of the inertial navigation. Comparison of the schematics of algorithmic implementations in gimbal system and strapdown system is shown in Figure 1.2.

Inertial navigation, as a dead reckoning approach to navigation, also suffers from error accumulations. In the inertial navigation algorithm, not only accelerations and angular rates are integrated but all the measurement noises are also integrated and accumulated. As a result, unlike the position fixing type of navigation, the navigation accuracy deteriorates as navigation time increases. Noise sources include fabrication imperfections of individual inertial sensors, assembly errors of the entire IMU, electronic noises, environment-related errors (temperature, shock, vibration, etc.), and numerical errors. Thus, inertial navigation imposes challenging demands on the system, in terms of the level of errors,

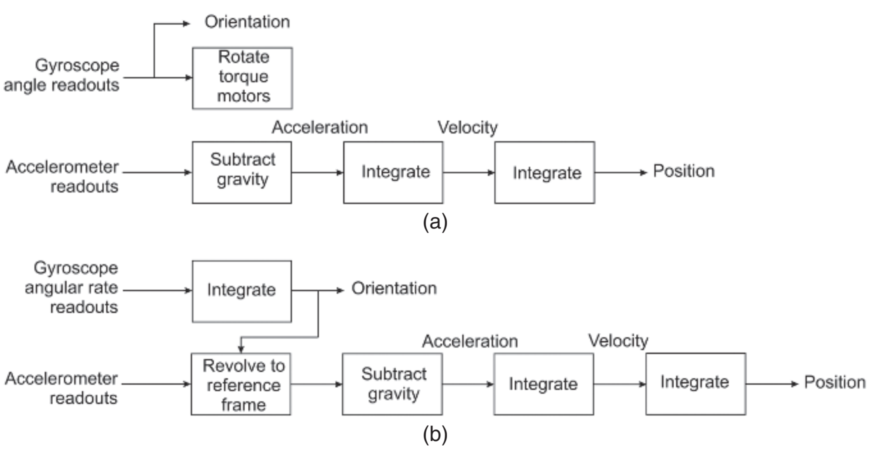


**Figure 1.2** Comparison of (a) gimbal inertial navigation algorithm and (b) strapdown inertial navigation algorithm.

to achieve long-term navigation. This partially explains why inertial navigation systems were developed around 100 years later than the development of inertial sensors. It has been shown that without an error-suppressing algorithm, the position error accumulates without bound and approximately proportional to time cubed. For example, for navigation grade IMUs, which cost a few hundred thousand dollars per axis, the navigation error will reach about one nautical mile after an hour of navigation, or equivalently less than 0.01 m of navigation error within a minute of navigation. However, for consumer grade IMUs, which cost a few dollars, the navigation error will exceed a meter of error within a few seconds of navigation [9]. Therefore, aiding techniques are necessary to limit the navigation error propagation in inertial navigation, especially in the case of pedestrian inertial navigation, where the cost and size of the system are limited.

## 1.3 Pedestrian Inertial Navigation

Pedestrian navigation has been of great interest in recent years for path finding, personal security, health monitoring, and localizers for first responder systems. Due to the complicated environment in which a person may need to navigate, self-contained navigation techniques are fundamental for pedestrian navigation. An example of the self-contained navigation technique is inertial-only navigation of pedestrians, which became recently a popular topic. Most pedestrian navigation systems rely on inertial sensors and inertial navigation techniques in their core, just as any other navigation applications. However, the pedestrian navigation poses much stricter requirements on the size and weight of inertial instruments, or IMUs, due to the limitation of human carrying capacity, and the inertial-only pedestrian application was technologically not feasible until recently.

Thanks to the development of Micro-Electro-Mechanical Systems (MEMS) technology in the past 20 years, MEMS-based IMUs have become smaller in size and more accurate in performances, and as a result, pedestrian inertial navigation has been made possible [10]. MEMS-based IMUs with a size on the order of millimeters have become widely available on the market, and they can be installed in portable devices that can be easily carried around, such as mobile phones, smart watches, or devices that are small enough to be carried in a pocket. Figure 1.3 compares the IMU that was developed for the Apollo missions 50 years ago and a current commercial MEMS-based IMU. This is an illustration of technological advances in size, and it should be acknowledged that performances of the two systems are still not the same. Note that a gimbal inertial navigation was implemented for the Apollo mission, instead of the more commonly used strapdown inertial navigation systems in these days. The IMU for the Apollo missions had a volume of 1100 $in^3$ (or $1.8 \times 10^7$ $mm^3$) and a weight of 42.5 lb [11], whereas the volume of

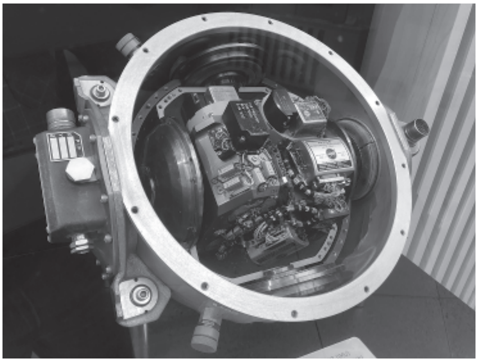



**Figure 1.3** A comparison of (a) an IMU developed for the Apollo missions in 1960s. Source: https://en.wikipedia.org/wiki/Inertial_measurement_unit and (b) a current commercial MEMS-based IMU. Source: https://www.bosch-sensortec.com/products/smart-sensors/bhi160b/.

the shown MEMS-bases IMU is 8.55 $mm^3$ and the weight is on the order of tens of milligrams. Six orders of magnitude of reduction in both volume and weight has been demonstrated over the past 50 years, though to achieve the matching performance is still an on-going area of research. Such a great technical advancement in the miniaturization of IMUs started enabling the pedestrian inertial navigation. Along with the size reduction, the performance of inertial sensors is continuously improving. The use of miniaturized sensors in these new applications inspired the development of new algorithms and new approaches for solving the challenges of navigation. These approaches are discussed next.

### 1.3.1 Approaches

There are two general approaches in the pedestrian inertial navigation. One is the strapdown inertial navigation as introduced in Section 1.2, where IMU readouts are integrated into position and orientation. This approach is universally applicable, but the integral step makes the algorithm computationally expensive and the navigation error accumulates as time cubed due to the gyroscope bias. In order to limit the error propagation, the most commonly used method is to apply the Zero-Velocity Updates (ZUPTs) when the velocity of the foot is close to zero (the foot is stationary on the ground) [12]. The stationary state can be used to limit the long-term velocity and angular rate drift, thus greatly reduce the navigation error. In this implementation, IMU is fixed on the foot to perform the navigation and to detect the stance phase at the same time. Whenever the stance phase is detected, the zero-velocity information of the foot is fed into the Extended

Kalman Filter (EKF) as a pseudo-measurement to compensate for IMU biases, thus reducing the navigation error growth in the system. In this architecture, not only the navigation errors but also IMU errors can be estimated by the EKF. The limitation of this approach is that the IMU needs to be mounted on the foot.

In order to avoid the integral step in the pedestrian inertial navigation and also relax the requirement of IMU mounting position, a Step-and-Heading System (SHS) is an alternative. It is composed of three main parts: step detection, step length estimation, and step heading angle estimation [13]. Unlike the first approach, this approach can only be applied in the pedestrian inertial navigation. In this approach, the step length of each stride is first estimated based on some features of motion obtained from the IMU readouts. Methods based on biomechanical models and statistical regression methods are popular for the estimation. Some commonly used features include the gait frequency, magnitude of angular rate, vertical acceleration, and variance of angular rate. Then, the heading angle is estimated by the gyroscope readout, which is typically mounted at the head. This step can also be aided by magnetometers to improve the accuracy. In this way, the total displacement can be estimated combining the traveled distance and the heading angle. However, two major challenges exist for this approach. First, the gazing direction needs to be aligned with the traveling direction, implying that the subject needs to look at the traveling direction all the time, which is not practical. Second, the step length estimation remains difficult. The average value of the estimated step length may be accurate when median value generally less than 2%, but the estimate precision is generally low, with the Root Mean Square Error (RMSE) about 5% [14]. With a wide adaption of hand-held and fitness devices, this is currently an active area of research.

### 1.3.2 IMU Mounting Positions

In pedestrian inertial navigation, depending on the approaches to be taken and the application restrictions, the IMU can be mounted on different parts of body to take advantage of different motion patterns, such as head, pelvis, foot, wrist, thigh, and foot. Pelvis, or lower back, was the first explored IMU mounting position in the literature, because these parts of the body experience almost no change of orientation during walking, which greatly simplifies the modeling process for both strapdown inertial navigation and SHS [15]. In subsequent studies, thigh and shank were explored, such that IMU can directly measure the motion of the leg, which is directly related to the step length by the biomechanical models [16, 17]. More recently, in order to integrate pedestrian inertial navigation with smart phones and wearable devices, such as smart watches and smart glasses, pocket, wrist (or hand hold), and head are becoming the IMU mounting positions of interest [18–20]. The foot-mounted IMU has also been demonstrated for SHS, but this placement of sensors is mostly used in the ZUPT-aided pedestrian inertial navigation, instead of SHS.

Head-mounted IMUs are usually used for heading angle estimation, since it experiences lowest amount of shock and almost no change of orientation. Besides, it is usually convenient to mount the IMU on the helmet for first responders and military applications [21]. However, the low amplitude of angular rate and acceleration during walk makes it hard for step length detection. In addition, the gazing direction may not be aligned with walking direction during navigation. Pelvis-mounted IMUs have the ability of estimating the step length for both legs with one single device, compared to the IMUs mounted on the legs. It is also more convenient to align the IMU to the walking direction compared to the head-mounted IMUs. Pocket-mounted IMUs and hand-held IMUs are mostly developed for pedestrian inertial navigation for use with smart phones. In this approach, the IMU is not fixed to a certain part of the body, and its orientation may change over the navigation applications due to different hand poses and different ways to store the smart phone in the pocket. It makes the SHS algorithm more complicated than other IMU mounting positions. Foot-mounted IMUs will experience the highest amount of shock and vibration due to the heel shocks during walking [22]. As a result, a more stringent requirement on the IMU performance will be necessary, such as high shock survivability, high bandwidth and sampling rate, low g-sensitivity, and low vibration-induced noise [23]. However, with foot-mounted IMUs, a close-to-stationary state of the foot during the stance phases will greatly reduce the navigation errors in the ZUPT-aided pedestrian inertial navigation.

### 1.3.3 Summary

Between the SHS and the ZUPT-aided strapdown inertial navigation, the latter is the more widely used approach for precision pedestrian inertial navigation. The main reasons are:

- ZUPT-aided strapdown inertial navigation has demonstrated a better navigation accuracy compared to the SHS. For example, in a navigation with the total walking distance of 20 km, position estimation error on the order of 10 m was demonstrated, corresponding to a navigation error less than 0.1% of the total distance [24]. The navigation error for SHS, however, is typically about 1% to 2% of the total walking distance.
- ZUPT-aided strapdown inertial navigation is more universal compared to SHS, with only one assumption that the velocity of the foot is zero during the stance phase. As a result, it can be applied to many pedestrian scenarios, such as walking, running, jumping, and even crawling. In the case of SHS, it has to classify

different motion patterns, if the system has been trained with such patterns, and correspondingly fit the data to different models.
- SHS is user-specified and needs to be calibrated or trained according to different subjects, while ZUPT-aided strapdown inertial navigation in principle does not need any special calibration for different users.
- Even though IMU will experience high level of shock and vibration when mounted on the foot in the ZUPT-aided strapdown inertial navigation, the developed MEMS technologies are able to reduce the disadvantageous effects. For example, it has been demonstrated that IMU with gyroscope maximum measuring range of $800^\circ\ s^{-1}$ and bandwidth of 250 Hz would be able to capture most features of the motion without causing large errors [25].

In this book, we will mainly focus on the ZUPT-aided strapdown inertial navigation.

## 1.4 Aiding Techniques for Inertial Navigation

Many aiding techniques have been developed to fuse with inertial navigation to improve the navigation accuracy. They can be roughly categorized into self-contained aiding and aiding that relies on external signals (non-self-contained aiding). We start with non-self-contained aiding.

### 1.4.1 Non-self-contained Aiding Techniques

According to the property of the external signals, non-self-contained aiding techniques can be divided into two categories. In the case where the external signals are naturally existent, such as the Earth's magnetic field and the atmospheric pressure, no extra infrastructure is needed, but the signals may be subject to disturbance since their sources are not controlled. However, in the other case where man-made signals are used, implementation of infrastructures is needed with the benefit that the signals are engineered to facilitate the navigation process.

#### 1.4.1.1 Aiding Techniques Based on Natural Signals

Magnetometry and barometry are two commonly applied techniques that are used to improve the navigation accuracy. Magnetometry is one of the most ancient aiding techniques developed for navigation applications, where measurement of the Earth's magnetic field can provide information about the orientation of the system. Nowadays, not just the orientation, but also the location of the system can be obtained by measuring the anomalies of the Earth's magnetic field in the navigation of low-earth-orbiting spacecraft (altitude less than 1000 km), where the position of the spacecraft can be estimated with resolution on the order of 1 km. Barometry estimates the altitude of the system by measuring the atmospheric air pressure. It has been shown that low altitudes above sea level, the atmospheric pressure decreases approximately linearly as the altitude increases with a rate of about 12 Pa/m. A pressure measurement resolution of 1 Pa, or an altitude measurement accuracy of less than 0.1 m, can be achieved with the currently available commercial micro barometers [26].

Another way of implementing estimations of absolute position is through computer vision, where images of the environment are captured to extract information. One of the most popular implementations is called the Simultaneous Localization and Mapping (SLAM), where the localization and mapping of the environment is conducted simultaneously. As a result, no pre-acquired database of the environment is needed. The sensors used for this application do not necessarily have to be cameras, LIght Detection And Ranging (LIDAR) and ultrasonic ranging can also be used. In either case, the system extracts some information about the environment as an aiding technique to improve the navigation accuracy.

#### 1.4.1.2 Aiding Techniques Based on Artificial Signals

Radio-based navigation is another popular technique in this category. It was first developed in the early twentieth century and its application was widely developed in the World War II. More recently, it was considered as a reliable backup of the global positioning system (GPS) in the United States, and could reach a navigation accuracy of better than 50 m. One of the most common aiding techniques in this category is Global Navigation Satellite System (GNSS), where a satellite constellation is implemented in the space as “landmarks,” transmitting radio waves for navigation purposes. The navigation accuracy of GNSS for civilian use is currently about 5 m along the horizontal direction, and about 7.5 m along the vertical direction. Long-term evolution (LTE) signals have also been proposed and demonstrated to be used for navigation purposes. The principle of LTE-based navigation is similar to GNSS, except that the landmarks are the LTE signal towers instead of satellites. The greatest advantage of LTE over GNSS is its low cost, since no special signal towers has to be established and maintained. Currently, a horizontal navigation accuracy of better than 10 m has been reported.

In the case of short-range navigation aiding techniques, Ultra-Wide Band (UWB) radio, WiFi, Bluetooth, and Radio-Frequency Identification (RFID) have all been explored. They are typically used in indoor navigation due to their short signal propagation range. Unlike radio-based navigation, in which the radio frequency is fixed, UWB radio occupies a large bandwidth (>500 MHz), thus increasing capability of data transmission, range estimation accuracy, and material penetration. WiFi and Bluetooth devices are popular in smartphones, and therefore utilizing them as aiding techniques in indoor navigation does not require any additional infrastructures. RFID has also been proposed due to its low cost for implementation. More recently, 5G and millimeter-wave communication infrastructure have been explored as a potential source of signals for navigation [27]. For all these aiding techniques, there are two kinds of methods to perform localization: Received Signal Strength (RSS) and fingerprinting. RSS-based localization algorithm takes advantage of the fact that the strength of the received signal drops as the distance between the source and the receiver increases. Therefore, the strength of the received signal can be used as an indicator of ranging information. Fingerprinting localization algorithm is based on comparing the measured RSS values with a reference map of RSS. Table 1.1 summarizes the non-self-contained aiding techniques with artificial signals.

### 1.4.2 Self-contained Aiding Techniques

Another category of aiding techniques is self-contained aiding. Instead of fusing external signals into the system, self-contained aiding takes advantage of the system's patterns of motion to compensate for navigation errors. Therefore, self-contained aiding techniques vary for different navigation applications due to different dynamics of motions.

For example, in ground vehicle navigation, the wheels can be assumed to be rolling without slipping. Thus, IMU can be mounted on the wheel of the vehicle to take advantage of the rotational motion of the wheel. In this architecture, the velocity of the vehicle can be measured by multiplying the rotation rate of the wheel by the circumference of the tire [28]. In addition, carouseling motion of the IMU provides the system more observability of the IMU errors, especially the error of yaw gyroscope, which is typically nonobservable in most navigation scenarios [29]. Besides, low frequency noise and drift can also be reduced by algorithms taking advantage of the motion of the IMU [30].

Another approach is to take advantage of biomechanical model of human gait instead of just the motion of the foot during walking. This approach typically requires multiple IMUs fixed on different parts of human body and relate the recorded motions of different parts through some known relationships derived from the biomechanical model. In this approach, a more accurate description of the human gait is available, through for example, human activity classification and human gait reconstruction. Recognition of gait pattern can help to reduce the navigation error obtained from a single IMU.

Machine Learning (ML) has also been applied to pedestrian inertial navigation. ML has mostly been explored in the field of Human Activity Recognition (HAR) [31], stride length estimation [32], and stance phase detection [33]. However, few studies used the ML approach to directly solve the pedestrian navigation problem. Commonly used techniques include Decision Trees (DT) [34], Artificial Neural

**Table 1.1** Summary of non-self-contained aiding techniques.

| Aiding technique | Applicable area | Positioning accuracy (m) | Notes |
|---|---|---|---|
| GPS | Above earth surface | 5 | Large signal coverage area<br>Unavailable below the Earth's surface and in complex urban areas<br>Susceptible to jamming and spoofing |
| LTE/5G | Mostly in urban areas | 10 | No extra infrastructure needed<br>Rely on cellular signal coverage |
| Radar | In the air | 50 | Cheap and robust to different weathers<br>Very large effective range<br>Signal can penetrate insulators but will be obstructed by conductive material |
| UWB | Mostly indoor | 0.01 | Very accurate distance measurement in a short range<br>Simple hardware with low power consumption<br>Susceptible to interference |
| Lidar | In the air | 0.1 | Accurate position and velocity measurement<br>Affected by the weather, such as strong sunlight, cloud, and rain |
| WiFi | Indoor | 1 | A priori knowledge of WiFi router is needed<br>Algorithm is needed to compensate for signal strength fluctuations |
| Bluetooth | Indoor | 0.5 | Moderate measurement accuracy with very low power hardware<br>Short range of measurement (<10 m) |
| RFID | Indoor | 2 | Easy deployment<br>Very short range of measurement |

Network (ANN) [35], Convolutional Neural Network (CNN) [36], Support Vector Machine (SVM) [37], and Long Short-Term Memory (LSTM) [38].

Sensor fusion method can be used in a self-contained way, where multiple self-contained sensors are used in a single system, and their readouts are fused in the system to obtain a navigation result. For example, self-contained ranging technique is one possibility. In this technique, the transmitter sends out a signal (can be ultrasonic wave or electromagnetic wave) which is received by the receiver. This technique can be categorized as self-contained if both the transmitter and the receiver are within the system whose state is to be estimated. For example, in the foot-to-foot ranging, the transmitter and receiver are placed on two feet of a person to keep track of the distance between them [24]. In the cooperative localization, ranging technique is applied to measure the distance between multiple agents as a network to improve the overall navigation accuracy of each of the agent [39].

## 1.5 Outline of the Book

The topic of this book is about the pedestrian inertial navigation and related self-contained aiding techniques. In Chapter 2, we first introduce the technological basis of inertial navigation – inertial sensors, and IMUs. Their basic principles of operation, technology background, and state-of-the-art are included. Next, in Chapter 3, basic implementation and algorithm of strapdown inertial navigation are presented as a basis of the following analysis. Then, we demonstrate how the navigation errors are accumulated in the navigation process in Chapter 4, with a purpose of pointing out the importance of aiding in the pedestrian inertial navigation. Chapter 5 introduces one of the most commonly used aiding technique in pedestrian inertial navigation: ZUPT aiding algorithm. It is followed by an analysis on navigation error propagation in the ZUPT-aided pedestrian inertial navigation in Chapter 6, relating the navigation error to the IMU errors. Chapter 7 presents some of the limitations of the ZUPT-aided pedestrian inertial navigation, and methods have been proposed and demonstrated to be able to reduce the majority part of the errors caused by the ZUPTs. Chapter 8 discusses efforts in improving the adaptivity of the pedestrian inertial navigation algorithm. Approaches including ML and Multiple-Model (MM) methods are introduced. Chapter 9 discusses other popular self-contained aiding techniques, such as magnetometry, barometry, computer vision, and ranging techniques. Different ranging types, mechanisms, and implementations are covered in this chapter. Finally, in Chapter 10, the book concludes with a technological perspective on self-contained pedestrian inertial navigation with an outlook for development of the Ultimate Navigation Chip (uNavChip).

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