4 Navigation in Urban Environments

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Abstract

This chapter provides an overview of technologies and methodologies for navigation in urban environments. It covers a range of technologies including wireless sensors, inertial and feature based that can be used either alone or within an integration. This chapter also discusses the brief principles of multi-sensor integration and outlines commonly used methodologies and approaches.

Keywords

Navigation, positioning, statistical estimation techniques, sensor fusion, Inertial Measurement Unit

4.1 Introduction

Navigation is defined as the process of planning an object's position or trajectory using geometry, radio signals, etc. Therefore, navigation as a process, may involve estimating the object's position on earth, and/or guiding it through the course so that the object reaches the target destination. The importance and relevance of navigation and associated technologies has grown manifold in the last few years, so much so that not only almost all of the modern day cars are equipped with navigation systems, even the cheapest mobile phones in the market now offer navigation technologies at minuscule costs. The availability of affordable hardware and associated navigation technologies has made it possible for an average consumer to benefit from these technologies. This has been made possible primarily by the advent of Global Navigation Satellite Systems (GNSS). Today, these navigation systems are being used for day-to-day activities such as finding driving directions or vehicle tracking, as well as in advanced and complex applications such as driverless cars and robotic platforms.

The early navigators relied on ground landmarks and/or celestial observations for locating themselves and finding their way at sea. Another technology that was commonly used in the early navigation was *dead reckoning* (DR). The DR technique estimates the current position relative to the previous known position by keeping track of the distance traveled (or velocity measurement) and direc-

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tion of movement. Inertial sensors, first conceived in the early 19th century were commonly used for DR. The earliest inertial sensors were mechanical in nature, but were later transformed to strapdown systems with advancements in microprocessor technology in the 20th century. As will be explained later, the position estimated using DR techniques diverges from the true position over time due to an accumulation of errors. It is due to the accumulation of errors that inertial sensors cannot provide a navigation solution on their own for an extended duration.

The development of radio technology paved the way for the development of terrestrial radio-navigation systems during the mid-20th century. LORAN (Long Range Navigation) and Omega were the first radio-navigation systems to be developed, with Omega being the first worldwide radio-navigation system to become operational in the 1970s. Although Omega was decommissioned in 1997, LORAN-C continued operations in the US until it was turned off in 2010. The Russian counterparts of LORAN and Omega called Chayka and Alpha RSDN-20, respectively, were also developed around the same time as the ones in the US. Although Chayka was operational at least until 2014, some reports suggest that RSDN-20 continues to be operational to this day.

The interest in terrestrial radio-navigation systems saw a sharp decline with the arrival of satellite radio-navigation in the early 2000s. Recently, there has been a renewed interest in terrestrial radio-navigation systems fueled primarily by the vulnerabilities of satellite radio-navigation (i.e. GNSS), leading to the development of e-LORAN (Enhanced LORAN). The US and South Korea have already initiated efforts to deploy e-LORAN to complement the GNSS.

The modern day navigation systems are primarily powered by satellite based radio-navigation, collectively called GNSS. GNSS based navigation uses radio signals that are transmitted by the GNSS satellites, and received by the receivers (installed on cars, mobile phones, etc.) on the earth's surface. Using the information from these radio signals and satellite orbits, a receiver can estimate its position (and therefore, the position of the platform on which it is installed) almost in real-time. The US-based Global Positioning System (GPS) was the first GNSS system worldwide. The first GPS satellite was launched in 1978 and the system became operational in 1995. Following the success of the GPS and to reduce reliance on the US based GPS, other countries followed suit and started developing their own navigation systems. As of today, the GNSS satellite constellation includes the Global Positioning System (GPS) satellites by the United States, the GLONASS (Global Navigation Satellite System) by Russia, Galileo by the European Union (EU), Beidou by China, and other regional systems such as the QZSS (Quasi-Zenith Satellite System) by Japan, and the most recent one being the IRNSS (Indian Regional Navigation Satellite System) by India. Combined together, there are a total of about 132 GNSS satellites in operation as of date which includes 31 GPS (as on February 20, 2020), 23 GLONASS, 22 Galileo, 44 Beidou, 4 QZSS and 8 IRNSS satellites. A typical modern day navigation system (including recent mobile phones) can make use of all or some of these constellations to provide ubiquitous navigation solutions anywhere on the earth.

While GNSS remains the default and the most common navigation technology being used today on almost all platforms including aerial, terrestrial and marine, it is prone to various vulnerabilities such as spoofing and jamming. Even when there is no threat of spoofing or jamming, GNSS requires a clear line of sight between the receiver and satellites, and therefore, fails in indoor and other occluded environments such as dense urban regions or under a tree canopy. Furthermore, the signals received by a GNSS receiver in an urban environment are often corrupted by multipath, leading to significant reduction in navigational accuracy. Consider an example shown in Figure 4.1 where two GNSS receivers R_1 and R_2 are installed. The receiver R_1 is in a relatively open environment, while R_2 is installed in a typical urban environment consisting of urban canyons. The signals from two of the satellites, S_1 and S_2, can reach R_1 directly, while the signals from the same satellites to R_2 are obstructed by buildings. Some of these signals may reach R_2 but after undergoing multiple reflections from various surfaces, they cause multipath errors. The GNSS signals cannot penetrate buildings and, hence, a user at R_2 may be rendered incapable of navigation using GNSS only. It is because of these major reasons that developing a robust navigation system remains one of the most important and challenging problems for urban mobility to this day.

To mitigate some of the limitations of GNSS, it is often integrated with complementary technologies and/or sensors, some of which include inertial sensors, vision sensors such as cameras, and even LiDAR (Light Detection and Ranging), to name a few. Modern day inertial sensors include a triaxial gyroscope, triaxial accelerometer, triaxial magnetometer, and other optional temperature and pressure sensors. The DR principle may be used to derive the navigation solution using inertial sensors, that provide the accelerations and rotation rates around the body axis. The vision sensors including cameras and LiDAR can provide information about the location of landmarks, which can then be used to estimate one's position and provide the navigation solution. The expectation from such an integration is that the complementary sensor/technology will provide the navigation solution in the partial (or extended) absence of the GNSS. At the heart of this integration of one or more sensors with the GNSS, lies an estimation framework that fuses the observations from multiple sensors including the GNSS, to yield a navigation solution. This estimation framework may utilize knowledge about the characteristics of the observations from each sensor, platform behavior, and the operating environment to yield the navigation solution. Kalman Filter (KF) (and its variants) have been the popular choice of the estimation framework since they were first proposed in the 1960s. The KF became popular after its application in trajectory estimation for the Apollo program and was ultimately incorporated

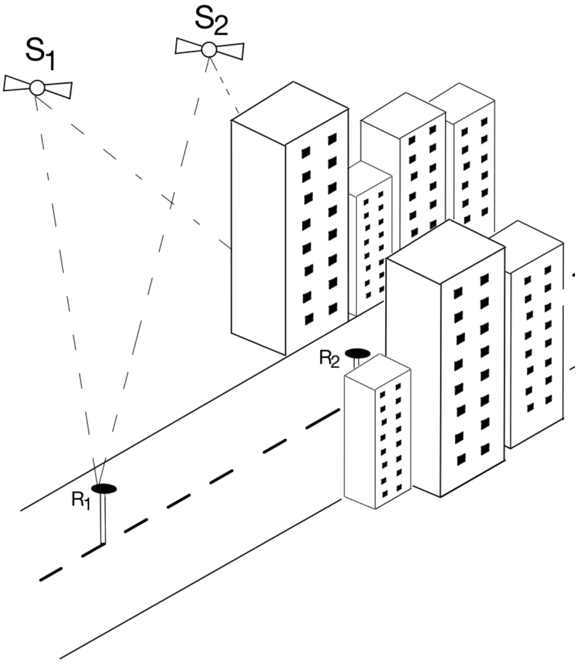

Figure 4.1: GNSS navigation in urban environments.

in the Apollo navigation computer. Even today, different variants of KF are being used in many commercial navigation systems. To overcome the assumptions of KFs (discussed in the later part of this chapter), many new filters and estimation frameworks have been proposed. While it is not possible to cover all estimation frameworks within this chapter, the overall philosophy and broad concepts of these frameworks are discussed. This chapter will also touch upon some recent and upcoming trends and navigation technologies (in Section 4.4) and discuss how these technologies are expected to help mitigate some of the major challenges of the navigation community. A summary of this chapter and conclusions are given in Section 4.5.

4.2 Navigation Technologies: An Overview and Comparison

Modern day navigation technologies can be classified into three broad categories. The first class of navigation technology makes use of proprioceptive sensor observations to perform navigation. Some examples of such types of sensors include odometers, accelerometers, gyroscopes, compass, magnetometers, barometers and more. Such systems rely on internal observations such as turning rate (gyroscope), velocity/acceleration (accelerometers), magnetic variation (compass/magnetometer), pressure variation (barometer), wheel rotation (odometer) etc. to perform navigation. Essentially, this form of navigation comes under the purview of DR. The second class of technology uses specially designed radio signals for navigation. This includes satellite based navigation (i.e. GNSS), terrestrial radio-navigation such as LORAN and modern terrestrial system Locata, and even signals that were not originally intended for navigation, including Wi-Fi, 3G/4G telecommunication signals, and even the upcoming 5G signals. The third class of navigation technology relies on observing and detecting distinct features in the operating environment (such as lines, edges, or corners) from multiple locations of the observer and then using these 'observations' to assist the user in navigation. These three classes of navigation technologies are discussed in the following sections and a qualitative comparison of the same is presented.

4.2.1 Proprioceptive Sensor Observations

Proprioceptive sensors, by definition, record observations that are 'internal' to a system. A navigation system that relies on proprioceptive sensors is oblivious to the external features or environment around it and uses only the internal observations for navigation. These internal observations may include acceleration, turn-rate, wheel rotation rate etc. The observations are sent to an estimation framework that derives the navigation solution. Some of the commonly used sensors include accelerometers, gyroscopes, and odometers. An accelerometer measures the acceleration of a body, a gyroscope measures the rate of rotation, while an odometer measures the distance traveled by a wheeled vehicle. An integration of appropriate combination of these sensors, combined with a suitable estimation framework can yield the navigation solution of a moving vehicle, with respect to a local origin, from where the vehicle started moving. At each instant of time, k, the vehicle estimates the distance vector from the instant $k-1$ to k using the sensor observations. The resulting position at any instant, k, can be computed from the position at $k-1$ and the displacement vector. This is demonstrated in Figure 4.2, where the red line denotes the estimated displacement vector.

It is obvious from the demonstration in Figure 4.2 that the 'quality' of the estimated trajectory or vehicle position is dependent on the sampling rate of the sensors, as well as, the maneuvers undertaken by the vehicle. Using a sensor with a relatively low sampling rate on a highly maneuverable vehicle would lead to an inaccurate representation of the trajectory undertaken by the vehicle. An Inertial Measurement Unit (IMU) is one of the most commonly used sensors that integrates triaxial accelerometers and triaxial gyroscopes in a single unit. While an IMU yields only the raw sensor observations, AHRS (Attitude Heading Reference System) includes a filter, in addition to an IMU, that processes the raw observations to yield the platform position, orientation, or velocity. While in the early days inertial sensors were quite large and mechanical in nature, modern

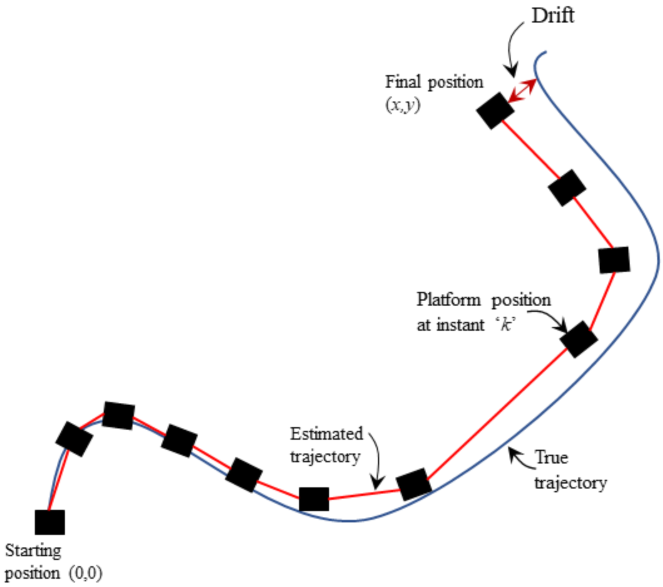

Figure 4.2: Navigation using proprioceptive sensors.

day sensors can be of the size of a few microns, such as the ones used in modern day smartphones and hand-held devices. In terms of cost and performance, modern day inertial sensors can range from costing a few dollars that may drift by hundreds of meters in a few minutes, to costing over a million dollars that drift less than 1–2 km in one day.

Given the initial vehicle position, accelerations and vehicle turn rate (in three directions), the displacement vector, and the final vehicle position can be estimated using Newtonian kinematic equations. This principle of navigation is commonly referred to as DR and was the earliest form of navigation adopted by sailors. Although the principle is relatively simple in theory, it suffers from various practical limitations. The major limitation is the corruption of sensor observations with errors, which get accumulated over time as they get integrated through the kinematic equations, causing the estimated vehicle position to drift from its 'true' position. It is primarily because of this reason that DR cannot be used for an extended period, and is often combined with complementary sensors that can help contain the drifts caused by the errors in inertial sensors.

4.2.2 Using External Signals

The use of external signals for navigation dates back to the early 20th century when radio technology was just being adopted across the world. The early 'external signals' based navigation systems made use of terrestrial signals, such as LORAN and Omega. While very few terrestrial navigation systems remain operational today, satellite based radio navigation has become quite popular recently. As shown in Figure 4.3, a satellite based navigation system comprises three major components: the Control segment, the Space segment, and the User segment.

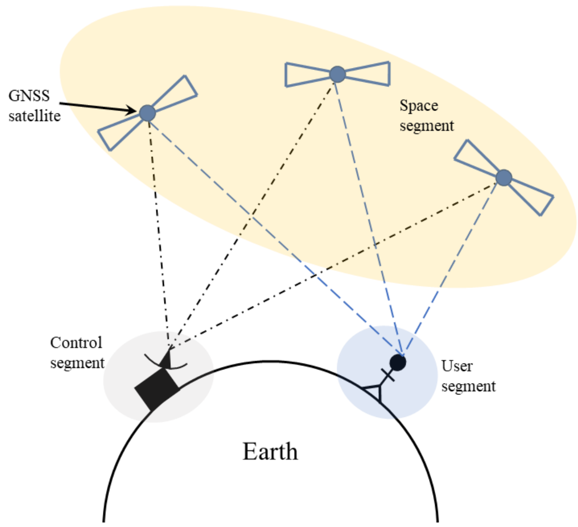

Figure 4.3: Three broad segments of GNSS.

The Space segment comprises a satellite constellation which transmits radio signals to the users on the ground. The control segment is responsible for proper operation of the space segment and includes a network of monitor and control stations. These stations maintain the satellite orbits, track satellites, upload navigational data and maintain the satellite status. The user segment consists of the GNSS receivers that make use of the information received from the satellites to estimate their navigation solution. A vehicle/platform on Earth uses specially designed signals transmitted by four or more satellites, to compute its navigation solution using multilateration. In general, GNSS signals consist of a carrier, a ranging code, and navigation data. Accordingly, a user can either use the carrier phase or pseudorange observations to estimate the user's position. The navigation data provides the satellite ephemeris, clock bias parameters, satellite health status, and other information that is used in position estimation.

The first step in position estimation using GNSS is to derive the satellite position in an earth fixed coordinate system using the satellite ephemeris information. This is followed by a pseudorange or carrier phase model that makes use of either the pseudorange or the carrier phase (derived from either the ranging code or the carrier signal) and satellite position to estimate the user position. The quality of the GNSS solution is dependent on the receiver's antenna, choice of signals used (code based vs. carrier phase observations) and processing methodology adopted. In general, low-cost GNSS receivers can achieve accuracy in the order of ~ 5 m, while high end GNSS receivers that use multiple frequencies and different corrections can achieve accuracies of the order of a few centimeters. Although the GNSS has become ubiquitous and navigation using this technology has become quite easy, it suffers from two major limitations. Firstly, GNSS is prone to spoofing and jamming and many instances have been reported across the world where the GNSS was intentionally or unintentionally jammed or spoofed. This limitation poses a risk to the user, in the sense that the user may be intentionally denied access to the GNSS by jamming the GNSS signals, or the user may be 'mis-directed' by spoofing the signals. The second limitation of this system is that GNSS signals require a direct line of sight between the satellite and receiver antennas. This condition cannot always be fulfilled due to obstruction caused by trees or buildings in urban environments. This limitation is so severe that it is becoming increasingly difficult to use GNSS in urban environments, due to the expansion of urban canyons, tunnels, underground/covered spaces (e.g. parking). Hence, GNSS alone may not be capable of meeting the navigational requirements of a majority of the users in a modern day environment. GNSS is therefore integrated with other complementary sensors or technologies, and the commonly used sensors for this purpose are inertial sensors.

GNSS is more suitable for long-term solutions, while inertial sensors can provide short-term solutions. An integration of these two technologies helps to overcome the limitations of each of them. For example, a vehicle passing through a tunnel may be denied GNSS due to unavailability of direct line of sight, whereas inertial sensors can provide a short-term navigation solution. When the vehicle emerges from the tunnel, GNSS signals can be re-acquired and the navigation solution can be maintained. For navigation in indoor and other GNSS-denied environments, various other types of signals are also being used these days, including but not limited to Wi-Fi, cellular signals, AM/FM signals, Ultra-Wide Band (UWB), and more. Signals such as Wi-Fi, cellular and AM/FM, collectively referred to as Signals of Opportunity (SoOP), were not originally intended for navigational purposes, but are now being applied in navigation. The common disadvantage of using SoOP is the low precision of the navigation solution (typically $\sim$50–100 m) offered by them that limits their usability in demanding navigational applications.

UWB technology is gaining prominence as an alternative or complement to the GNSS for navigation in partially GNSS denied or indoor environments. UWB is a radio technology designed for short range and high bandwidth applications and operates in the 3.1 to 10.6 GHz frequency range. Use of UWB for localization or navigation requires a master and a slave combination. The master UWB node may be installed at a known location and the slave UWB node is carried by the vehicle/user. This master-slave UWB combination can be used to estimate the range between these nodes, using either Time of Arrival (ToA) or Return Trip

Time (RTT) observations. ToA methods measure the time of arrival at the slave node, while RTT methods measure the total time taken for the pulse to travel from the master to the slave and back to the master. Unlike RTT methods, ToA based methods require the master and receiver clocks to be perfectly synchronized and, therefore, RTT based methods are a popular choice for range estimation. As demonstrated in Figure 4.4, the user position (equipped with slave node) can be estimated once the range from the slave to three or more master nodes is known. Typical UWB sensors can cost $\sim$50–100 USD and offer an accuracy range of $\sim$2 cm, therefore, allow the user position to be estimated with an accuracy of of better than $\sim$ 10 cm.

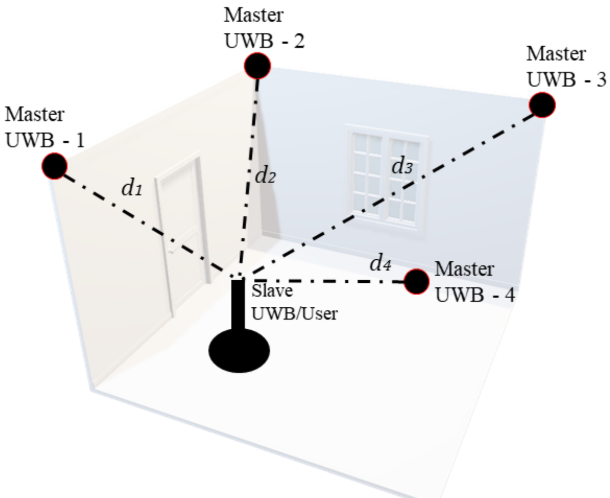

Figure 4.4: Navigation in GNSS-denied environment using UWB.

A UWB system requires all master UWBs to possess unique identifiers that identify it. The accuracy of the user is also dependent on the geometry of the network formed by these sensors, and hence, care must be taken to design 'optimal' networks that yield the best possible accuracy to the user. The use of UWBs has been successfully demonstrated in indoor environments, even in indoor/underground parking spaces where GNSS is absent. There have been efforts to integrate UWBs with GNSS to allow a seamless transition to a user when transiting from indoor to outdoor environments. Although UWB technology has proven to yield sufficiently high accuracies, it is limited by the short range of the sensors, investment and efforts required in setting up a sufficiently large infrastructure and poor penetration of UWB devices in the mass consumer market. Furthermore, the presence of a large number of master and/or slave nodes within the same environment is shown to cause network congestion, which causes significant drops in the communication range and hence severely affects the user's navigation. Despite these limitations, UWB technology can be used in limited indoor environments such as underground/indoor parking spaces, or the other specific areas where stringent navigational accuracy requirements are required to be met in the absence of GNSS.

4.2.3 Using Environmental Features

A unique characteristic of the urban environments is the presence of distinct artificial features, using which a user can locate himself/herself. This principle of navigation using environmental features is quite similar to the navigation process that humans and other animals use on a day-to-day basis. It is, then obvious, that a navigation system that relies on environmental features needs at least one sensor that can capture information about the surrounding environment, extract *useful* features, and sequentially track those features to locate itself as it is navigating through a feature rich environment (for example, urban cities). Such a sensor could be a camera that can capture highly detailed semantic information or a LiDAR sensor that can record detailed geometric information. Figure 4.5 demonstrates an example of navigating using environmental features.

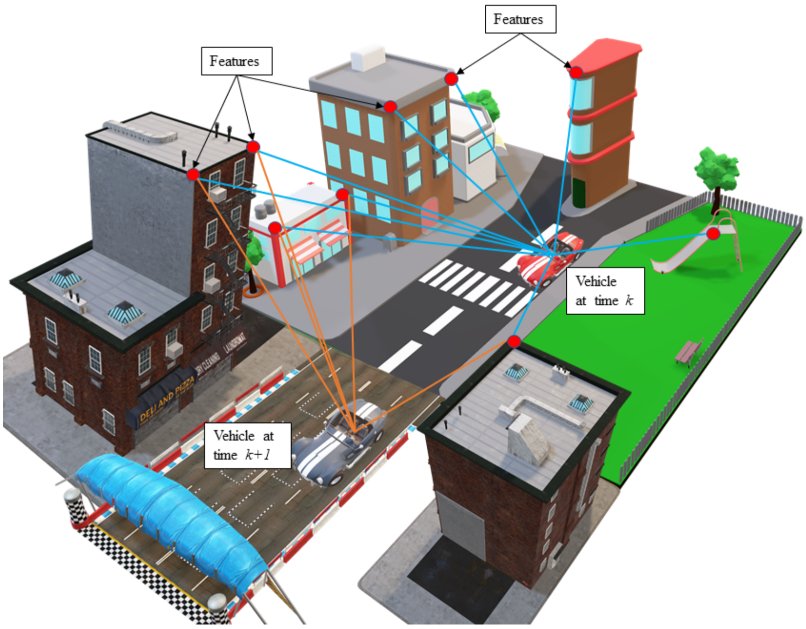

Figure 4.5: Urban navigation using environmental features.

Different types of distinct features are available in a typical urban environment, such as the ones demonstrated in figure 4.5. Some of the features that may be useful in navigation are marked in red. A vehicle senses the surrounding environment, extracts useful features, and tracks these features as it moves along. Given an initial starting point, the location of these features is first estimated in a user defined coordinate system. As the vehicle moves to the next location, these features are tracked and used to estimate the new vehicle position. Additionally, new features that may be visible to the vehicle from the new position are also added to the estimation process. This process continues, and the location of the features and vehicle position may be estimated simultaneously. To ensure that the features are georeferenced, and the vehicle position is estimated in a global coordinate system (such as the World Geodetic System 1984), the initial vehicle position and orientation must be initialized with respect to this system. This approach of navigation using environmental features comes under the purview of simultaneous localization and mapping (SLAM) or odometry, depending on whether a map of the environment is simultaneously constructed or not. SLAM approaches attempt to construct a map of the environment, while simultaneously estimating the vehicle position. On the other hand, odometry using cameras (called Visual Odometry) or camera and inertial sensors (called Visual Inertial Odometry (VIO)), or even LiDAR odometry, focuses only on estimating the vehicle trajectory and does not consider simultaneously mapping the environment. Map matching is another technique that has been quite popular for localization in indoor/outdoor environments. Map matching methods require the user to have access to a precise map of the environment in advance. The user derived position is 'matched' to one of the features on the map, thereby assisting the user in improving its own position on the map.

Navigation systems that make use of environmental features have found applications in mapping and/or navigating indoor environments and exploration missions. A key advantage of such approaches is that they do not require any prior infrastructure setup, except sensors on the vehicle platform. However, such an approach is successful only if there are sufficiently *distinct* features available in an environment. For example, SLAM or VIO may not work successfully in long hallways, that may be devoid of any distinct features. Similar to DR approaches, this method also suffers from drift due to accumulation of errors in the sensor observations. Hence, various techniques are deployed to constrain these drifts, which includes loop closures followed by an optimization (e.g. bundle adjustment) and/or inclusion of absolute positioning systems such as GNSS. Unlike the earlier navigation technologies, systems using features for navigation can be computationally expensive, due to the computational complexity involved in feature detection, feature tracking and optimization.

4.2.4 Qualitative Comparative Analysis

The last few years have witnessed a proliferation of different sensors that are being used in navigation technologies. This is primarily due to the increasing demand for navigation solutions and the increasing role of navigation (and mapping) technologies in possibly all sectors and aspects of life including but not limited to transportation, construction, mining, and exploration, urban management, disaster management, etc. As of today, a significantly large number of people are using one or other navigation technologies. While most everyday users are satisfied with low-cost GNSS sensors (that may be installed in smartphones), various advanced applications require the use of complementary sensors to develop robust solutions. It is therefore, important for a user to understand the limitations of each of these technologies, and possibly, have an understanding of the performance offered by these technologies before they are integrated into a system.

To assess and compare the strengths and weaknesses of each of the navigation approaches, five different parameters have been chosen: accuracy, coverage, stability of the navigation solution, dependence on infrastructure, and computational complexity. Accuracy here refers to the closeness of the estimated solution to the 'true' value, while coverage refers to the area over which the navigation solution can be estimated. Stability of the solution refers to the ability of the navigation technology to maintain the estimated solution over a period of time. Dependence on infrastructure attempts to qualitatively assess the investment required for making the solution work and the computation complexity attempts to compare the computational infrastructure needed for achieving the desired solution. A broad comparison of various navigation technologies in terms of coverage and accuracy is presented in Figure 4.6.

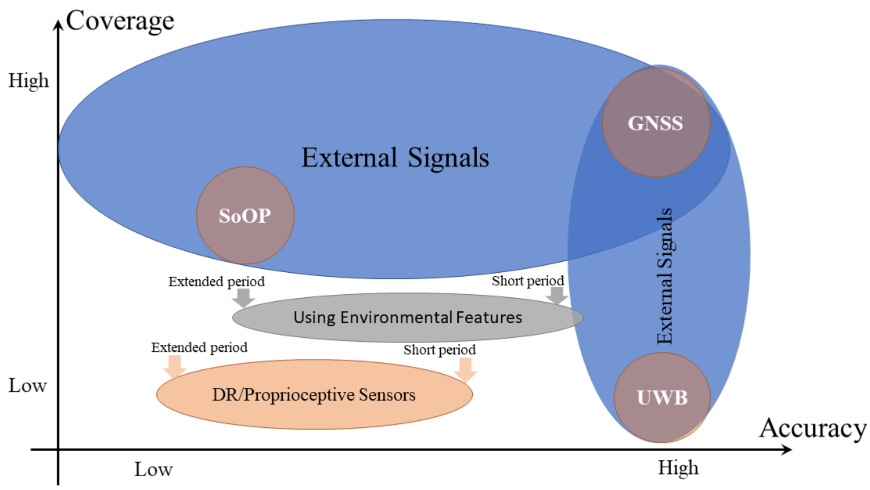

Figure 4.6: Accuracy versus coverage: Comparison of navigation solutions.

The technologies that make use of external signals for navigation cover the broadest spectrum on the coverage-accuracy plot. GNSS is capable of providing global coverage to the extent that it can be used ubiquitously, while also providing high navigational accuracies. This makes them a good candidate for use in a wide variety of applications. On the other hand, UWB technology can provide high localization accuracy comparable with the GNSS but is limited to local areas only. Other signals such as 4G/5G, AM/FM etc. that fall under the broad category of SoOP provide a broader coverage as compared to UWB, but have significantly poorer accuracy. Terrestrial signals, such as LORAN, provide higher coverage and better accuracy compared to the SoOP, but also require higher investment in terms of infrastructure and maintenance. In contrast, technologies based on proprioceptive sensors and use of environmental features provide lower coverage, and accuracies ranging from low to high, depending on the optimization techniques used and time period over which the solution is used. Over an extended period of usage, the accuracy of both feature based and proprioceptive sensor based technologies tends to degrade due to accumulation of errors, causing the solution to drift.

As can be seen in Figure 4.7, a significant investment is needed in terms of infrastructure development and maintenance to be able to use external signals (such as GNSS or UWB) for navigation. In contrast, proprioceptive sensor based solutions require the least amount of infrastructure, but they also offer poor solution stability over extended periods of time. Extraction and tracking of useful features from the surrounding environment can be quite computationally expensive and therefore, a significant investment in terms of computational resources is needed for feature based navigation. Another implication of the higher computational complexity is that the navigation solution may not be available to a user in real-time, which may be a critical requirement in certain applications. Although each of the navigation solutions have their own advantages and limitations, many of the limitations, at least in terms of accuracy, coverage and solution stability can be overcome by a suitable integration of complementary technologies at cost of increased complexity and higher financial investment.

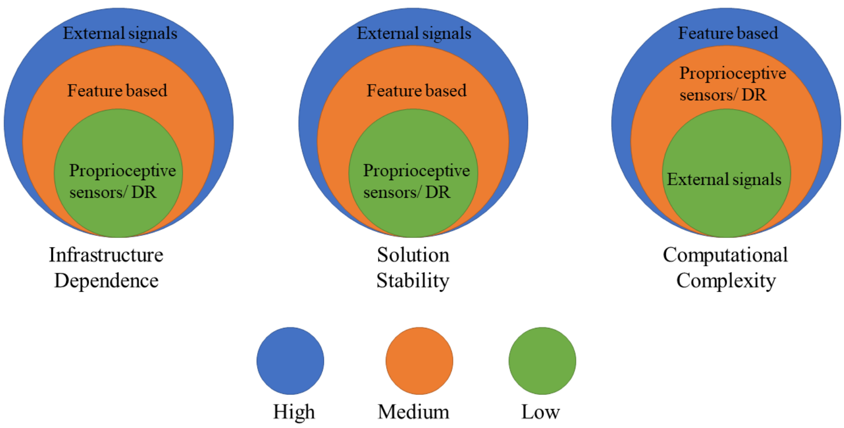

Figure 4.7: Qualitative comparison of navigation systems.

4.3 Sensor Fusion for Navigation

At the heart of a navigation system is a navigation processor (e.g. a filter) that takes the raw observations from one or more sensors as input and provides an estimate of the vehicle state, including position and velocity. Over the years that many different types of processing filters and architectures have been proposed, each with their own advantages and limitations. The Kalman Filter, originally proposed in the 1960s, has enjoyed quite a significant amount of popularity and remains one of the popular choices for estimation even today. The KF employs a predictor-corrector architecture to sequentially process the sensor observations and generate the state estimates of a moving platform (e.g., car, pedestrian). The predictor component of the KF generally uses a kinematic motion model to predict the state vector, given an initial state estimate and inertial sensor observations. This motion model should represent the platform characteristics and maneuvering capabilities. The predicted state estimate is then passed to the corrector component of the KF that makes use of the predicted state, sensor observations (e.g., GNSS, LiDAR, camera), and a measurement model to update the predicted state and generate the corrected state estimate, along with the sensor biases. The employed measurement model represents the relationship between the platform state that needs to be estimated, and the sensor observations. The sensor biases, thus estimated, are generally fed back to the KF to correct the sensor observations, and the whole process repeats itself. A simplified graphical representation of this method is represented in Figure 4.8.

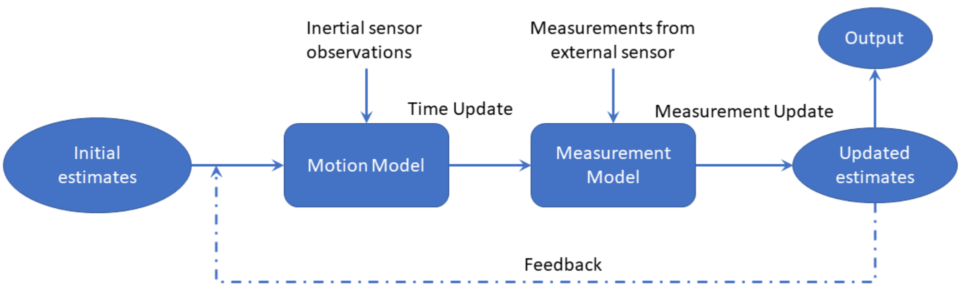

Figure 4.8: A generic predictor-corrector framework employed in navigation processors.

The traditional KF made various simplifying assumptions such as linear motion and measurement models, uncorrelated measurement and process noise, Gaussian nature of the noise etc. Therefore, various filters have been developed over the years, that employ a similar predictor-corrector framework but attempt to overcome the limitations of the conventional KF. Extended Kalman Filter (EKF) can be suitably employed when the non-linearity in motion and/or measurement models is not very high. Unscented Kalman Filter (UKF) performs better than EKF and KF in case of highly non-linear motion and/or measurement models, while assuming the noise to be Gaussian in nature. Particle filters are one of the most generic forms of KF that do not make any assumption about noise distribution and do not assume the models to be linear. There are multiple other variants of each of these filters that tackle other assumptions such as colored noise or correlated errors. The architecture of the employed filter is dependent on the types of sensors integrated in a multi-sensor platform, and therefore, multiple variants of these filters exist. For example, EKF is generally suitable for a GNSS/IMU integration, while SLAM or odometry based filters are needed for integration of camera and/or LiDAR sensors. These days graph based methods (e.g., Belief Propagation) are gaining popularity for vehicle navigation and/or tracking applications. Nevertheless, the basic architecture of a multi-sensor platform for navigation is depicted in Figure 4.9.

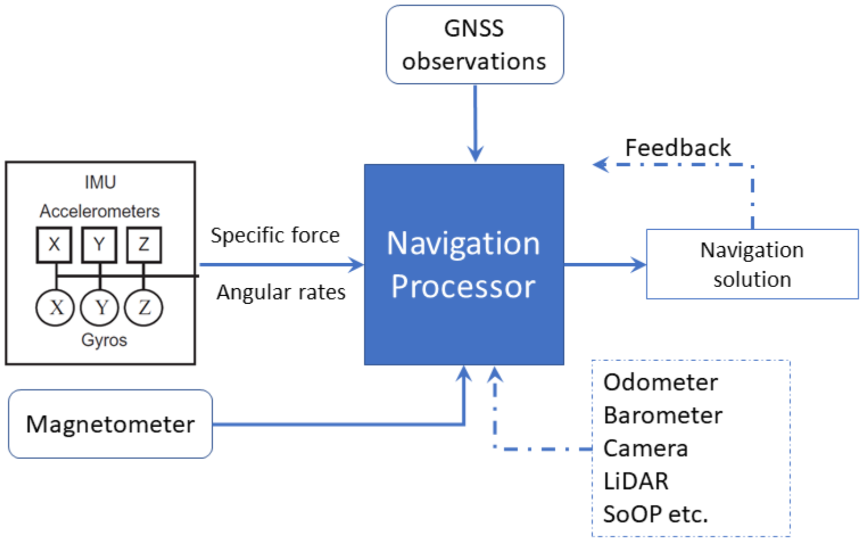

Figure 4.9: Generic multi-sensor fusion architecture for navigation.

An important area of research in developing such multi-sensor platforms is developing a robust navigation processor that is capable of handling sensor observations from multiple sensors such as GNSS, IMU, Odometer, Camera, or LiDAR. The complexity of the processor is dependent on the chosen set of sensors, the environment where the platform is expected to operate, deliverables of the processor (trajectory and/or map, etc.) and other application requirements such as expected accuracy, real-time versus post-processed solution, etc. Therefore, designing a robust navigation processor is a non-trivial and complex process that requires an ingenious combination of science and art.

4.4 Upcoming Trends in Localization and Navigation

The growing realization of the benefits of the navigation technologies has allowed them to be used in a wide variety of applications, to the extent that many modern day consumer electronics and some daily use items are now equipped with one or the other navigation technology. For example, GNSS has become synonymous with smartphones and smartwatches, and cars are now equipped with GNSS sensors. A whole new industry based on location based services has sprung up that is providing new solutions. This chapter identifies three broad upcoming trends in the area of localization of navigation. Firstly, there has been a rise in the types of signals that can now be used for navigation. For example, the newest 5G signals can provide a much better localization solution compared to their predecessors. Smartphones can now receive and process carrier phase observations, making them much more powerful and precise. The newer Wi-Fi standards are being designed to provide improved range estimates between the router and the Wi-Fi device (e.g., smartphone) using RTT methods, to enable improved navigation of these devices in indoor environments. Technologies such as UWB, Zigbee, or Dedicated Short Range Communication (DSRC) are gaining popularity for their navigational assistance capabilities. Secondly, there has been a tremendous development in designing better, robust and efficient navigation processors capable of integrating various complementary sensors. Deep learning architectures are now being investigated for their potential in providing navigation estimates and have shown significant promise. Efficient graphical SLAM approaches have been in the works for quite some time and are becoming mature. Thirdly, due to the proliferation of users relying on navigation technologies and availability of a wealth of signals, there is an increasing emphasis on developing *cooperative* solutions wherein, different users assist the neighboring users in localization and navigation. Since, some of the users may be better placed in terms of navigational capabilities, they may assist their neighbors (e.g., other cars in the vicinity of a car) who may not be so fortunate or capable (in terms of available navigational accuracy) by sharing their own information and some knowledge about their neighbors. This also opens up the doors for cooperation among different types of platforms, for example, Unmanned Aerial Vehicles (UAVs) assisting ground vehicles in navigating complex terrain.

4.5 Summary and Conclusions

Navigation has evolved from the days of relying on landmarks/celestial observations or DR to using multiple ubiquitous signals and integrated multi-sensor systems utilizing a wide variety of sensors. This chapter provided a brief overview of the navigation technologies currently available and being used across the world, and discussed the challenges and limitations of each of these technologies. Further, the chapter briefly explained the broad principles involved in integration of complementary sensors to develop robust navigation systems. While existing technologies are quite capable of providing navigation solutions in complex urban environments, challenges still exist, primarily in developing efficient navigation processors that can make the best possible use of complementary sensors. Therefore, developing novel filters and estimation frameworks has been an important research area for quite some time and will continue to be so in the near future. The sensors will improve over time, and more signals may become available in the future, but these signals and sensors can be best utilized only when efficient and robust navigation processors are available.

4.6 Further Reading

While this chapter has provided a broad overview of a field, I provide also a suggested reading list for those who want to go deeper and explore in more detail (Abbas et al., 2019; Atia and Waslander, 2019; Chang et al., 2019; Chao et al., 2020; Feng et al., 2020; Gabela et al., 2019; Gao et al., 2016; Goel et al., 2017; Guo et al., 2019; Hashemi and Karimi, 2014; Li et al., 2019; Maaref and Kassas, 2020; Masiero et al., 2020; Mohamed et al., 2019; Retscher et al., 2020; Williams, 1992; Zafari et al., 2019).

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