Multi Sensor Data Fusion for Land Vehicle Navigation

Dissertation Submitted in partial fulfilment of the requirements for the award of degree of

Master of Engineering

in

Electronic and Instrumentation and Control

Submitted by

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CERTIFICATE

I hereby declare that the work which is being presented in the dissertation entitled, **"Multi Sensor Data Fusion for Land Vehicle Navigation"** in partial fulfillment of the requirement for the award of degree of Master of Engineering **Electronic Instrumentation and Control Engineering** at **Thapar University, Patiala**, is an authenticate record of my own work carried out under the supervision of **Dr. Smarajit Ghosh**, Professor, Electrical and Instrumentation Engineering Department, and **Mr. Vinod Karar**, Professor, Senior Principal Scientist, Department of Optical Devices and Systems CSIO, Chandigarh, and refers other researcher's work which are duly listed in the reference section. The matter presented in this dissertation has not been submitted in any other University/Institute for the award of degree.

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ACKNOWLEDGEMENTS

Any work employed consists of not only the experience but also the skills of a person and it also includes an organized body of people with their expertise and ideas put forward in completing the work.

I would like to express my deepest gratitude towards **Director and DOAA** Thapar University**,** Patiala, **Director** of CSIR-CSIO, Chandigarh for providing me with an opportunity to do my M.E thesis work in these premier research organizations.

I sincerely thank **Prof. Vinod Karar**, Senior Principal Scientist and Head, Optical Devices and Systems, CSIO for taking out his precious time and giving his valuable suggestions.

I am also highly grateful to **Dr. Smarajit Ghosh**, Department of Electrical and Instrumentation Engineering, Thapar University. His academic excellence and ineffable faith made me to work towards my goal.

I would also like to thank to our PG coordinator **Dr. Mandeep Singh**, Department of Electrical and Instrumentation Engineering, Thapar University.

I find it difficult to verbalize my deepest sense of indebtedness to my parents and friends for their boundless love and support, which has always been a source of inspiration.

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ABSTRACT

Navigation is a tool, which has gained popularity for land vehicles in recent years. However, achieving navigation with high accuracy is still a desire to be accomplished. In pursuit of achieving this goal in a low cost budget multi-sensor data fusion has been seen as a promising solution.

The Global Positioning System (GPS) and an Inertial Navigation System (INS) are two basic navigation systems. Due to their complementary characters in many aspects, a GPS/INS integrated navigation system has been a hot research topic in the recent decade. The estimation accuracy of a low-cost inertial navigation system (INS) is limited by the accuracy of the used sensors and the imperfect mathematical modelling of the error sources. By fusing the INS data with GPS data, the errors can be bounded and the accuracy increases considerably. For fusion of data and minimization of error a Kalman filter based approach has been developed in this work. The work puts forward a cost benefit solution for achieving accurate navigation through sensor fusion.

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LIST OF ABBREVIATIONS

AS	Anti-Spoofing
C/A	Coarse-Acquisition
CUPT	Coordinate Update
DGPS	Differential GPS
DoD	Department of Defence
DOP	Dilution Of Precision
DR	Dead Reckoning
ECEF	Earth-Centred-Earth-Fixed
EKF	Extended Kalman Filter
GPS	Global Positioning system
GNSS	Global Navigation Satellite System
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
ISA	Inertial Sensor Assembly
LAMBDA	Least Square Ambiguity Decorrelation Adjustment
LKF	Linearized Kalman Filter
MEMS	Micro Electrical-Mechanical System
PDOP	Position Dilution Of Precision
PRN	Pseudo-Random Noise
RMS	Root Mean Square

SA	Selected Availability
SHU	Small Heading Uncertainty
TEC	Total Electron Content
UTC	Universal Coordinate Time
WGS84	World Geodetic System 1984
WL	Widelane
HUD	Head Up Display

CHAPTER

1

INTRODUCTION

1.1 Introduction

This chapter gives a brief outline about the area of research being explored in this study. The chapter also gives a glimpse about the organization profile of the institute where the research work has been carried out.

1.2 Background

For exact position on the Earth of an object different types of Navigation Systems are used. In the case of outdoor applications, like for navigation or geodetic measurements, mainly Global Navigation Satellite Systems (GNSS) is used [18]. With the help of different types of equipment, it is very easy to determine the position of anyone on the Earth’s surface with accuracy of few centimetres. However, consumer grade receivers have accuracy in the order of 15-100 meters. Furthermore, it implies a line-of-sight connection to the satellites. But in the case of urban areas it gives very poor performance [17]. Apart from urban areas, its performance in normal areas also not up to the mark due to the high buildings, which block the signals. As well as in forests, the quality of the position estimates degrades or even leads to a signal blocking. Another drawback of this system is the slow update rate, it gives output usually once in a second. In applications such as driver training, car racing, driving exercises, and in performance measurements, more frequent position estimation is required for an accurate trajectory. In addition to that, to know the exact position, more information such as the velocity, position and attitude of the vehicle is desired.

Inertial measurement units (IMU) are a common complement to GPS, although it is technically more correct to state that GPS augments an inertial navigation system (INS). The advantage being that together the GPS and inertial sensors can provide a continuous navigation solution, where GPS alone cannot [21].

1.3 Global Positioning System

There are two main working global navigation satellite system (GNSS) systems now, i.e. GPS and GLONASS, plus another two under construction, i.e. Galileo and Compass. GPS is the most commonly used system. We could use GNSS also, but in this thesis only GPS is used.

The Global Positioning System (GPS) is a space-based GNSS, which provides reliable positioning as well as time information in all weather and at all times and anywhere on or near the Earth. U.S. Department of Defence was the first who invented GPS in 1973. It was represented by three segments: the space segment, the control segment and the user segment. The space segment consists of 24 satellites, with in minimum of 4 satellites are required for a stable GPS signal.

The most important advantage of GPS positioning is the limited positioning errors. Once signals from more than 4 satellites are received with suitable PDOP (Position Dilution of Precision), the quality of positioning results can be guaranteed, i.e. the errors are limited. Other important advantages are the light weight and cheap price. As a result, since the beginning GPS positioning is becoming more and more popular. Nowadays GPS is used almost everywhere, in cell phones, cars, laptops and so on.

However, GPS positioning has many inherent shortcomings. GPS is always suffered with signal outage problem. As earlier mentioned it is quite common that satellite signals are blocked in urban and mountainous areas. GPS signal is very poor in indoor and underground situations. The signal acquisition and tracking is difficult for high dynamic movements. The availability of satellite signals takes a vital role in these types of situations.

Moreover, the security system of GPS signals is also a big matter. We all know that the satellite signals are vulnerable to interference and spoofing. The security of wireless signal including satellite signal is always a vital problem for electronics engineers, especially when it is related with communication and military applications.

Another vital problem related with high dynamics applications is its low update frequency. The update frequency of GPS receivers is normally 1-10 Hz, which are 1-2 orders of magnitude lower than that of Inertial Navigation System (INS). For high speed sport cars and airplanes, this update frequency is too low to be acceptable, because they change their position very fast. With the help of fast development of CPU and the ongoing research, this problem wished to be overcome in the future.

In real applications, if there is only one GPS receiver or one antenna is used. Then there is no possibility to get the attitude information from GPS navigation. This is a great loss of sufficient information in many cases like airplane navigation.

1.4 Inertial Navigation Systems

INS will provide the estimates of the desired information about the position and velocity of land vehicle or air craft. Based on accelerometers and gyroscopes (gyros) values, and using Newton’s laws of motion, it is possible to determine the attitude, position, and velocity if the initial values are known. The most important one is that it does not rely on external information and does not radiate any energy when operating. Therefore, it is a kind of autonomous or self-contained navigation system, which is quite suitable for military applications.

The inertial sensors are classified as dead reckoning sensors since the current evaluation of the state is formed by the relative increment from the previous known state.

INS is mainly divided into two types: platform INS and strap down INS (SINS) [26]. Now SINS is becoming more and more dominated with the powerful computation ability of embedded MCU (Micro Controller Unit).

INS is very accurate over short periods with high update frequency. Usually the update frequency is at least 100 Hz. But the biggest problem of INS is the sensor errors, the mean value of which is not zero but keeps on increasing with time. We cannot completely eliminate this physical phenomenon, but the errors can be modelled and reduced thereafter. To get the precise result of the noise parameters, usually a long time testing and recording the error data are needed beforehand. This part is crucial to reduce the effects of different kind of error sources.

1.5 Motivation

Navigation deals with trajectory determination and guidance. Trajectory determination relates to the derivation of the state vector of an object at any given time. The state vector includes position, velocity, and attitude. On the other hand, guidance forces the moving object onto a predetermined route to reach a given destination. Because of low update rate of GPS positioning, the INS values can be used along with GPS positioning for determining the positioning solutions in high dynamic applications. Whenever the receiver gets a new GPS update, it is used to correlates with the data from INS and can correct the INS sensor errors in real time so that the errors of INS solutions can be reduced. This thesis is aiming at designing an accurate and robust GPS/IMU navigation system for Land Vehicle Navigation using multi sensor data fusion [10].

CHAPTER

2

LITERATURE REVIEW

2.1 Survey of Previous Research Work

This chapter describes a brief history of previous work done by various researchers and scientists that made efforts to in the direction of integration of inertial sensors and GPS data for accurate as well as cost-effective navigation.

Davidson *et al.* [17]. discussed integration of GPS and DR sensor (Dead Reckoning). In urban areas they augmented GPS data with DR sensors, through Extended Kalman Filter (EKF). When GPS signal was available then DR sensors were calibrated with it. If there was no GPS signal due to various reasons might be for multipath or for lost cost GPS accuracy, and then only calibrated GPS sensor would use to determine position of a land vehicle. DR sensor consists of gyroscope for directional measurements and 3D accelerometer for acceleration measurement. It also showed that practical applications of this GPS/DR integration, and also its efficiency in a high multipath environment and GPS signal outage areas.

Fakharian *et al*.[23] presented integration of GPS with Inertial Measurement Unit (IMU), for those areas where there was no GPS signal. Supplementary relative positioning was used for reference purpose. This integration process was carried out by Kalman filter. It could be done by two processes one was tightly coupled integration and another was loosely coupled integration. The main advantage of tightly couple integration was its working properly even in poor satellite coverage, but it was very complicated, and very difficult to implement. In tightly coupled integration a single Kalman filter was used, so that it took less time for measuring both GPS and INS sensor.

Abuhadrous *et al.* [9] discussed multi sensor data fusion method in software format, name RTMAPS. It also used GPS and INS sensor with an odometer for better values about the position of the ground vehicle. The speed of that vehicle could be determined by the wheel encoder. RTMAPS stands for real time multi sensor advanced prototyping software; it was used for the application of that proposed method in real time. Apart from GPS and INS, there were so many different types of sensors used like, encoder, odometer, steering sensor, video camera break sensor, etc. using this technique if we used Differential GPS was used, instead of GPS, then the error could be reduced up to 1m, and using odometer/INS integration. The system had an accumulative error of 15m maximum and that is after 10 minutes.

Kais *et al.* [16] developed multi-sensor data acquisition architecture for localization of a land vehicle. Special attention had been given to main parameters that could affect the accuracy of the localization system. It proposed a new function that was Advance Driving Assistance Systems (ADAS), using it we could fully performed driver assistance or even fully autonomous driving could store information about driver also. It used high accuracy GPS receiver, which could give errors in centimetre value. This method uses many types of sensors, like:

- Speed sensor Hall effect sensor mounted on the output of the gearbox.
- Steering angle absolute encoder mounted on the steering column.
- Micro Strain 3DM-GX1.
- Crossbow IMU VG400 three axis Inertial Measurement Unit, MEMS gyroscope.
- Crossbow IMU VG600 three axis Inertial Measurement Unit, FOG gyroscope.
- KVH E-Core 2100 single axis FOG gyroscope.
- Compass KVHC100.
- GPS Ashtech A12 C/A GPS receiver.
- GPS Trimble AG132, Position/Velocity filters ON.
- GPS Trimble AG132, Position/Velocity filters OFF.

Steux *et al.* [25] proposed a software framework called RTMAPS, (Real-Time Multi-Sensor Advance Prototyping Software). It also used various sensors, collected the values from those sensors and put them in RTMAPS, which could simulate the data in real time and also giving output in real time. In this paper the author showed mainly two applications of RTMAPS, one was obstacle detection system and another one was data-logger/data-reader used to build a background database.

Brown *et al.* [12] discussed the performance of the integrated MEMS GPS/inertial navigation system. It used very low cost accelerometer and gyroscopes. Data was provided showing the position, velocity, and attitude accuracy when operating with GPS aiding and also for periods, where GPS dropouts occurred and alternative navigation update sources were used to bound the MEMS inertial navigation error growth. It could be used in unmanned ground vehicle (UGVs) or unmanned air vehicle (UAVs). Here they used different software for MEMS integration named INTERNAV. INTERNAV combined the values get from inertial sensor, raw data of accelerometers and gyroscope with Kalman filter.

Garcia-Moreno *et al.* [25] showed working of LIDAR 64E and a differential GPS together. This was mainly used in urban areas. LIDAR 64E was used to construction of urban areas from the data it supplied. In this case, a georeferencing system was created by using GPS sensor rigidly with mapping sensor. Using terrestrial laser scanners, a 3D-modelling, and documentation, restoration and reconstruction of object could be created.

Wang *et al*. [10] proposed a new method of integrating IPS with GPS, which was able to provide an accurate and high update rate position estimate with GPS, NAV 200, and optical encoder for the supplementary relative positioning system. NAV200 was basically a 360 degree laser scanner; it needed at least 3 reflectors which pre-located in an area where the value of GPS signal was not reliable. Some other techniques like Kalman filtering or extrapolation were used to integrated low updating data for real-time feedback control purposes. IPS was to provide clear and smooth positioning with great accuracy, where there are some obstacles obstructing the GPS signals.

Pradalier *et al.* [6] proposed a new method- simultaneous localization and mapping (SLAM). It was a kind of architecture; it used a common way of localization, when the robot faces different kinds of problems while moving, modelling error and execution error. This kind of architecture mainly consists of three steps:

- Feature extraction
- Feature identification and landmark identification.
- Computation the robot poses thanks to the identified landmarks.

The main objective of this paper was to show that both robust matching and robust SLAM could be obtained.

Zhou *et al.* [22] designed multi-sensors system for realizing autonomous mobility of outdoor robot. The number of sensors used in this process were GPS, two laser range finders, encode, electronics compass and camera were used to obtain the feeling information for outdoor autonomous mobile robot. The reason behind of using so many numbers of sensors were because the surrounding environment of robot was very complex and also because of uncertainty of or its own state it was very difficult to obtain information from only one sensor. So they needed a variety of sensors to provide all kind of sensory information and for better position estimation. This circuit was very complex due to several numbers of sensors, and also there might be some problem occurred during data acquisition. The CCD camera was used to capture or record the motion of the robot.

Yu *et al.* [20] integrated GPS and INS sensors through extended Kaman filter for position estimation. This paper presented three types of integration technique, loose, tight, and ultra-tight integration. Loosely coupled integration technique was easiest among all integration technique. In this technique INS and GPS worked separately, it was very easy to implement, but the main disadvantage of this type of integration was that it was not reliable. If the vehicle moved fast or there were some changes in the environment, it affects the integration technique, so to overcome this type of problem, tightly coupled integration could be used. In ultra tight integration, they use extended Kalman filter instead of Kalman filter, due to the non-linear relationship between states and Kalman filter.

Yonghao *et al.* [26] describe a micro SINS/GPS Integrated Navigation System based on MEMS sensors. Test results showed the performance of the integrated MEMS SINS/GPS. Data was provided showing the position, velocity, and attitude accuracy. This paper was mainly implementing the IMU/GPS integration through Kalman filter in MATLAB. For reducing the error of MEMS IMU, it was the very common method to be used.

Hoseini *et al.* [28] discussed different methods of multi sensor single target data fusion in Kalman filter. In order to tracking target through Kalman filter, four types of methods were used. In this paper the author discussed about all four methods and tried to find that which one was better. These four methods were –

- Group Sensor Method
- The Sequential-Sensor Method
- The Inverse Covariance Method
- The Track-to-track Fusion Method

Godha *et al.* [14] described the whole integration process of GPS and INS. They discussed about previous applications of GPS/INS integration, and their limitations.

Wegmann *et al.* [7] presented real time mapping, of ortho-images immediately after the plane landing. To achieve exact position information from the sensor, they conducted a series of tests for good accuracy. First integration result might show some error in y-parallaxes. Therefore they needed further calibration of sensors and data processing for reducing the problem.

Piras *et al.* [19] demonstrated use of GPS/INS sensors for indoor positioning. It has been proved that this process could be used for GIS application.

Walter *et al.* [5] discussed how to correct the noisy, biased accelerometer signal at 200Hz using a Kalman filter with an inertial reference system; also using corrupted GPS signal at 5Hz. Using MATLAB, the Kalman filter algorithm could be implemented over 30 seconds for sinusoidal acceleration with an initial velocity of 100meters/second approximately. That system resulted velocity error less than 0.06m/s and position error 0.5-1.0 meter approximately. That filter simultaneously checked the accelerometer noise and bias, corrected it and provided an accurate position for the vehicle.

Singhal *et al*. [24] developed applications of Kalman filter for a system model based on constant acceleration and examined its performance for various cases. Optimally predicting acceleration for different applications along with velocity and position, their method could also be used.

Angrisano *et al.* [18] described the integration method of GNSS and INS at which mainly investigated and concerned about the position estimation of a land vehicle in urban areas using GNSS and low-cost INS sensors. They also showed that real-time positioning could be obtain using pseudo-range observable in single point mode without using extra infrastructure with an accuracy of about 10 meters.

Schultz *et al*. [13] proposed integration process of GPS and INS through Kalman filter, and described the functions of different type of GPS. Advantages and disadvantages of them, and why using GPS and INS integration was more useful than using GPS alone.

2.2 Gap of Work

Navigation system is mainly used in commercial military purpose. Uses of GPS navigation for civilians are very limited. There are very few practical instruments for civilians which can be use for vehicle navigation and those instruments are very costly too.

2.3 Objective of Work

1) To minimize the cost, so that it can use by everyone.

2) Estimate position of a road vehicle with maximum accuracy when there is no GPS signal or very low signal.

2.4 Organization of Thesis Work

The thesis is organized into six chapters:

- Chapter 1 – Present the Introduction
- Chapter 2 – Present the Literature Survey
- Chapter 3 –Present the Theory
- Chapter 4 – Present the Methodology
- Chapter 5– Present the Results & Discussions
- Chapter 6 – Present the Conclusion

CHAPTER

3

THEORY

This chapter gives details about the inertial navigation systems also; it discusses fundamentals important in understanding integration of sensors for navigation.

3.1 Inertial Navigation

In this chapter we will discuss about the principles of inertial navigation system. At first we describe about the basics of modelling motion in land vehicle. Second an introduction to inertial sensors is given and then discuss about some useful information like position, velocity, what we get from inertial navigation system as output. Finally we will discuss the drawbacks of inertial navigation systems and try to understand why inertial navigation system is better to use with other navigation system than using it alone.

Basically, inertial sensors have two main implementations one is the gimballed arrangement, and another is the strap-down arrangement. In gimballed type of arrangement, the sensors are mounted on a gimballed mechanized platform, which is always remain aligned with the navigation frame. In the case of strap-down arrangement, it is directly mounted to the vehicle. This, however, requires a higher dynamic range and bandwidth, with a higher computational load also. The advantages of strap-down arrangements are less costly, the smaller size, low power consumption, with decreased weight. Therefore, strap-down arrangements are preferred for low-cost applications.

The acceleration is measured by an accelerometer. These sensors used to measure the acceleration due to local gravity as well as acceleration due to an external force. If we know the attitude of the accelerometers then we can easily mathematically remove the local gravity component.

In order to determine the attitude, an angular velocity sensor, i.e. a gyroscope can be employed. Mathematically integrating these values allows us to determine the rotation of the platform and therefore the change in its attitude.

3.1.1 Coordinate Frames

In an inertial navigation system, several information sources usually come from different coordinate systems. Therefore, it is necessary to transform the measured quantities into a common coordinate frame in order to process all the data. Coordinate frames are basically of three types [13];

a) Local systems,
b) Earth centred systems,
c) Vehicle-centred systems.

Accelerations are measured in their inertial frame of reference, resolved in their instrumental frame and transformed into the platform frame (vehicle centred).The same applies to the angular rates from the gyros. For the data fusion with other systems, e.g. GPS, the coordinates are transformed into the navigation frame (e.g. Earth centred). Different co-ordinate frames are:

i. Earth-Centred Earth-Fixed Frame (ECEF, e-frame): As the name indicates, this type of frame has its origin at the center of mass of the Earth and rotates with it. The x-axis points to the reference meridian, the z-axis is parallel to the mean spin axis of the Earth, and the y-axis completes the right-handed orthogonal frame.

ii. Local Geodetic Frame (t-frame): This type of frame is also called as north-east-down or NED system. Because its x-axis pointing towards geodetic north, the y axis completes the right-handed orthogonal frame on the geodetic reference frame, and the z axis pointing towards the origin of the e-frame. It has a coordinate system at its origin coinciding with that of the instrumental frame.

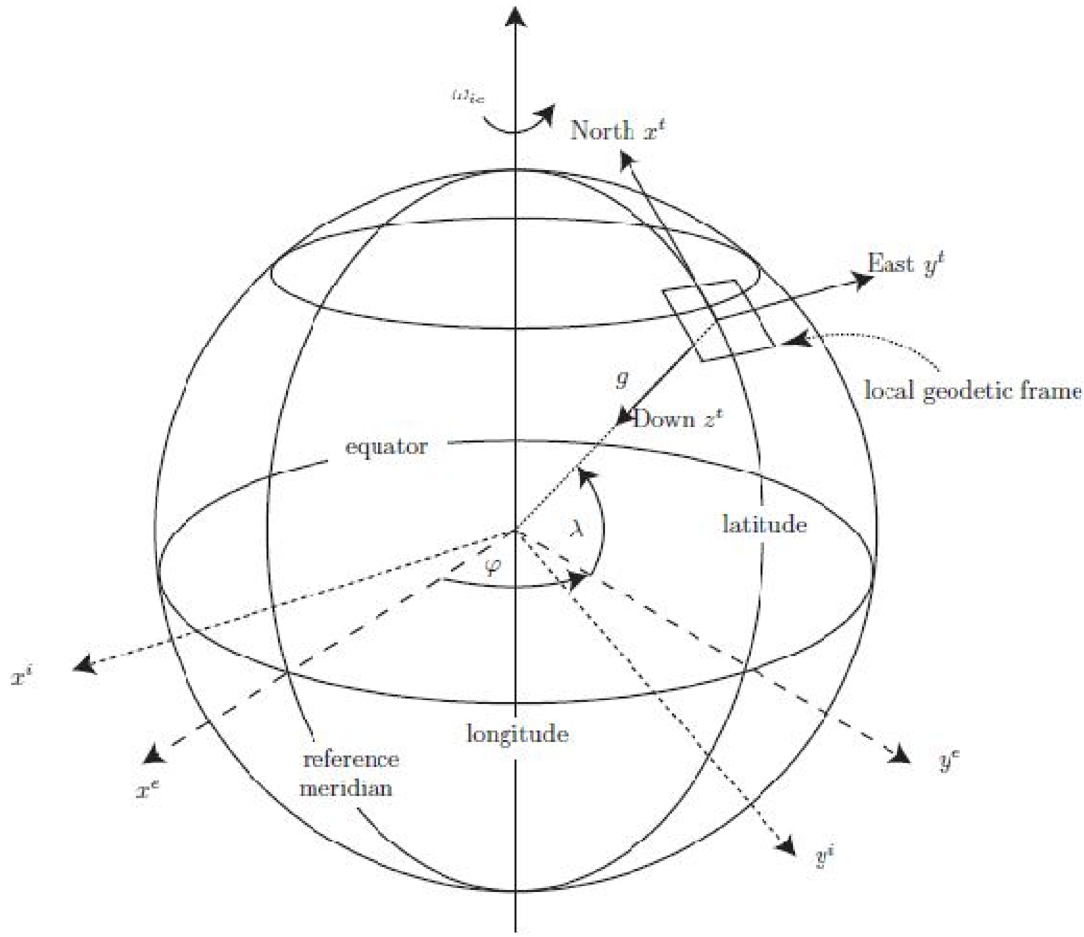

Figure 3.1Relations between Different Co-ordinate Frames

iii. Inertial Frame (i-frame): This type of coordinate frame works on the principle of Newton's laws of motion. It is not accelerating type coordinate system. It could be chosen arbitrary but it is convenient to let it allows its origin to coincide with the one of the e-frame.

iv. Body Frame (b-frame): This coordinate system has its origin at the centre of gravity of the vehicle. As we seen in figure 3.1 its x-axis goes with the forward direction, the y-axis completes the right-handed orthogonal system, and the z-axis down through the bottom of the vehicle. In case the instrumentation platform is not aligned with the body frame, an additional transformation has to be done.

3.1.2 Motion of a land vehicle

In most of the cases, navigation system is used to detect the position of an object. The general motion of a land vehicle is typically calculated by the values that are given by accelerometer and gyroscope.

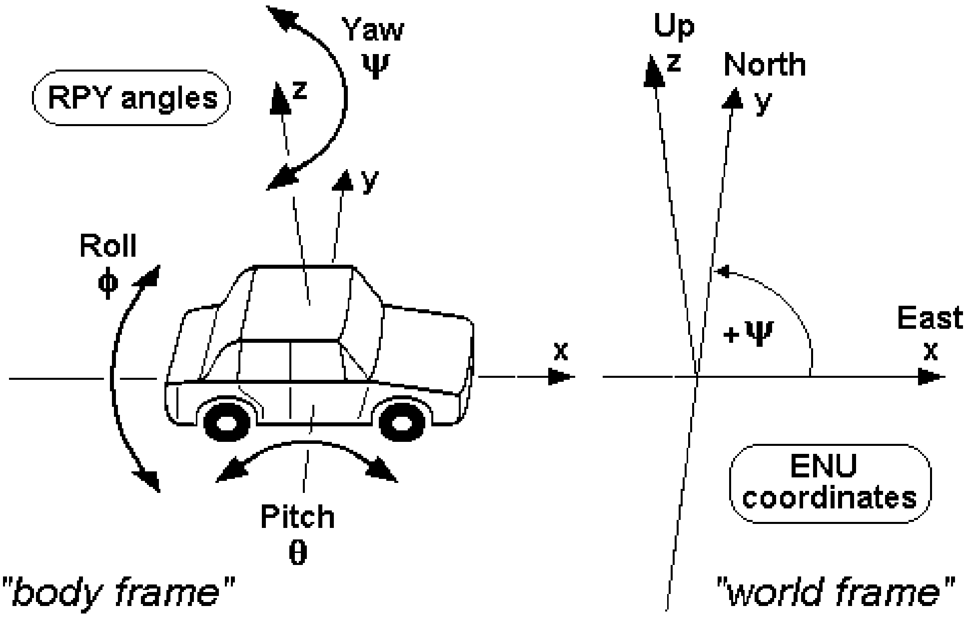

Figure 3.2 Land Vehicle Navigation Co-ordinate Frame

3.1.3 Accelerometer

An accelerometer is generally a proof mass that is kept away from a case by a pair of springs. The mass proof will be in a specific calibrated position in zero accelerometer called the equilibrium position. In Figure 3.2 we can see the sensitive axis by accelerometer through an arrow. Any kind of acceleration will take place through the proof mass to be displaced along the axis. It works on the principle of Newton's 2nd law. The movement of mass proof is proportional to the force of acceleration, that's why when we measure displacement from the equilibrium position will give the acceleration along the axis.

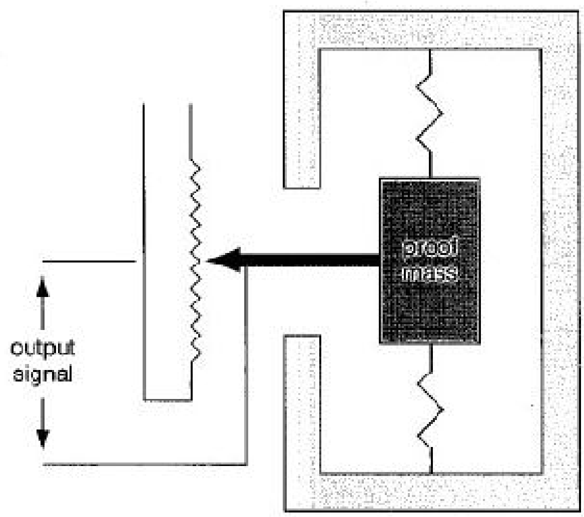

Figure 3.3 Accelerometer

An accelerometer shown in Figure 3.3 is generally used for measure the acceleration of a moving vehicle or an air craft or a gravitational acceleration. When an accelerometer placed in a gravitational field the proof mass will be displayed in positive of the sensitive axis that shows on the below figure. But this is also true that when we are measuring acceleration of a vehicle in a positive direction the output of vehicle acceleration as well as gravitation acceleration is goes in positive sign.

3.1.3.1 Acceleration and force

Here in this column we will discuss about the g-force. It is mainly used to measure of acceleration, not force. When acceleration is in vector quantity, g-force accelerations are expressed as a scalar. It's mainly operated on the principle of Newton's 3rd law, which says that law of reciprocal actions and the direction of forces are pointing to upward and downward with the positive g-forces and negative g-forces respectively. The output from an accelerometer measures by vehicle acceleration minus gravitational acceleration, it's known as specific force. It's represented by this formula:

$$a = f - g$$

where, 'a' is the acceleration of that vehicle, 'f' is the acceleration that is given by non-gravitational forces and 'g' is the acceleration due to gravity.

So many types of accelerometers are there, the first accelerometer have been invented, is known as the Atwood machine and it was invented by the English physicist George Atwood (1746-1807) in 1783. There are mainly two types of accelerometer. One is "open loop" accelerometer and the other is "closed loop" accelerometer. The main difference between these two types of accelerometer is in the way they measure the specific force. Open loop accelerometer measures the displacement of the mass proof from the equilibrium position while when the force is applied to keep the mass in its equilibrium position then it's acted as a closed loop accelerometer.

Now a day's accelerometers are used in so many types of applications in scientific and engineering systems. Accelerometers are can be made by embedded system or by micro electro-mechanical system (MEMS) [14]. MEMS accelerometer is used because it has lot of advantages like it is very small is dimension and weight, it's just one mm in dimension and less than one gram in weight. These types of accelerometers are mainly used in airbags system or in low cost navigation systems, so the manufacturers are needed to be very cheap to make this type of sensors. But expensive accelerometers are also there, and those accelerometers are used for high performance purposes like in INS. It is given the output in [radian/s^2] unit for specific force and in [degree/hr] for velocity increment due to specific force.

3.1.4 Gyroscope

Gyroscope is used to measure or maintain the angular velocity or rotation of a vehicle. It was first invented in 1852 by the French physicist Leon Foucault (1819-1868) and it works on the principle of conservation of angular momentum. Primarily, gyroscopes are purely mechanical and worked with a rotor (spinning mass), which is used for the spin of one axis as shown in Figure 3.4.

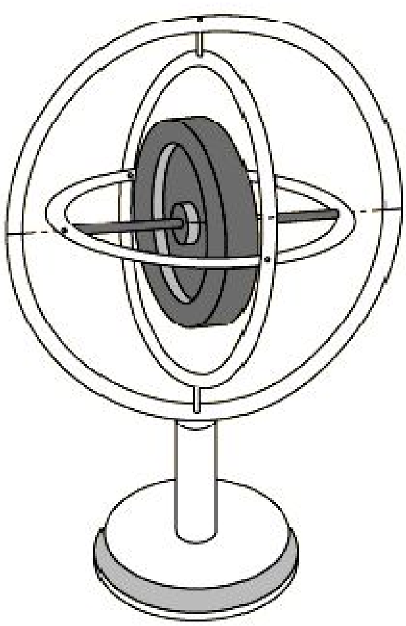

Figure 3.4 Mechanical Gyroscope

As shown in Figure 3.4 we see that that there is a rotor mounted in two gimbals that are suspended on the base. For these two gimbals it given the gyroscope 3 degrees of freedom to the rotor and makes it possible to keep its orientation while the base is rotated in any direction. An error will always occur because of the friction between the moving parts. Just like accelerometer gyroscope will also work on an inertial frame and output given by the gyroscope is in degrees/hour or in rad/s unit for angular velocity and in degrees or radian for angular rotation.

Three types of gyroscopes available are [27]:

1) MEMS gyroscope
2) FOG gyroscope
3) Laser gyroscope

3.1.4.1 MEMS Gyroscope

The main advantage of MEMS gyroscope is that it is comparatively less expensive than any other mode of gyroscopes. MEMS gyroscopes are working on the principle of Coriolis Effect to measure the angular rate as shown in Figure 3.5.

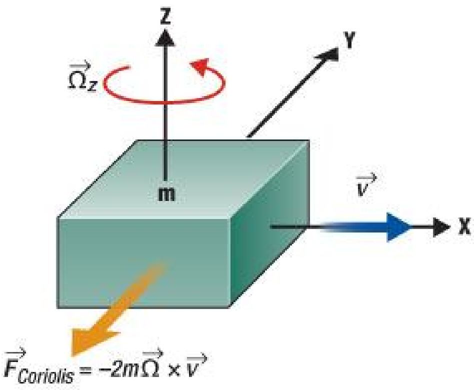

Figure 3.5 MEMS Gyroscope

From Figure 3.5 we can easily say that when a mass (m) is moving in direction $\vec{v}$ and angular rotation velocity $\vec{\Omega}$ is applied, then the mass will experience a force in the direction of the Coriolis force. From the capacitive sensing structure we know the resulting physical displacement which is caused by Coriolis force. Most of the available MEMS gyroscopes use a tuning fork configuration as shown in Figure 3.6.

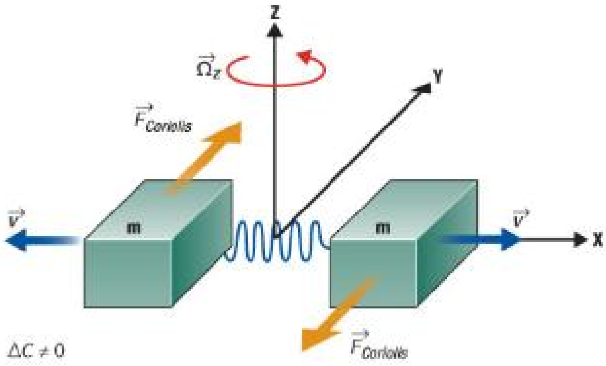

Figure 3.6 Tuning Fork Configuration of MEMS Gyroscope

3.1.4.2 FOG Gyroscope

This type of gyroscope is very recent in gyroscope families, and it is uses an external laser and two beams going opposite directions in long spools or several kilometres of fibre optic cable, with the two beams compared after their travel through the spools of fibre. The basic mechanism of fog gyroscope is dependent upon the monochromatic laser light travelling in opposite paths. It also depends upon sagnac effect. FOG gyroscope is an abbreviation of fibre optic gyroscope.

3.1.4.3 Laser Gyroscope

Just like FOG gyroscope ring laser gyroscope also splits laser light into two beams in opposite directions by a narrow tunnel in a closed optical path.

3.2 Global Positioning System

Currently the Russian Global Orbit Navigation Satellite System (GLONASS) and Global Positioning System (GPS) from the U.S. Department of Defence are two widely used Global Navigation Satellite Systems (GNSS).

With the GPS, the restricted Standard Positioning Service (SPS) only can be used by the civilian users. U.S. military and other authorized users are only projecting The Precise Positioning Service (PPS).

Around the Earth at least 24 satellites are equally spread on six orbits. With a 55° angle with respect to the equator the six orbital planes are inclined. About 20200 km above the Earth's surface the orbits are situated.

3-Dimensional position estimation and the accurate Coordinated Universal Time UTC are chiefly provided by the GPS. To estimate a 3-d position, the signals of at least 4 satellites are need to be received by the receiver.

In turn to compute the location of the receiver, the place of the satellites must be known. With the GPS almanacs which are transmitted by the satellites can roughly calculates these coordinates. The ephemeris data also transmitted in the satellite message, to get a more accurate satellite message.

The data is transmitted simultaneously by each GPS satellite on the two frequencies L1 (1575.42MHz) and L2 (1227.60MHz). The data (50 bit/s) spread with binary codes (CDMA) and is BPSK modulated. The later are accustomed to differentiate between the satellites. On L1, the signal is widen with a Precision or p-code and a Coarse/Acquisition or C/A-code. The signal on L2 is only widen with the p-code. While the C/A-code is publicly available (SPS), the p-code is further encrypted for a regulated access and is only known by authorized users (PPS). The fundamental frequency of p-code is 10.23MHZ and it is repeated after every 267 days, where the C/A-code has a transmission frequency of 1/10 of the fundamental GPS frequency. It also consists of 1023 samples and is repeated in every 1ms.

3.2.1 GPS signal and system structure

GPS system was first developed by United States Department of Defence (DOD) in the year of late 1960's, the name of this GPS is NAVSTAR GPS (Navigation system with timing and ranging- Global Positioning System), and it is approved in 1973 [11]. In the year of 1978 the first prototype satellite was launched, and it's fully start working in July 1995.

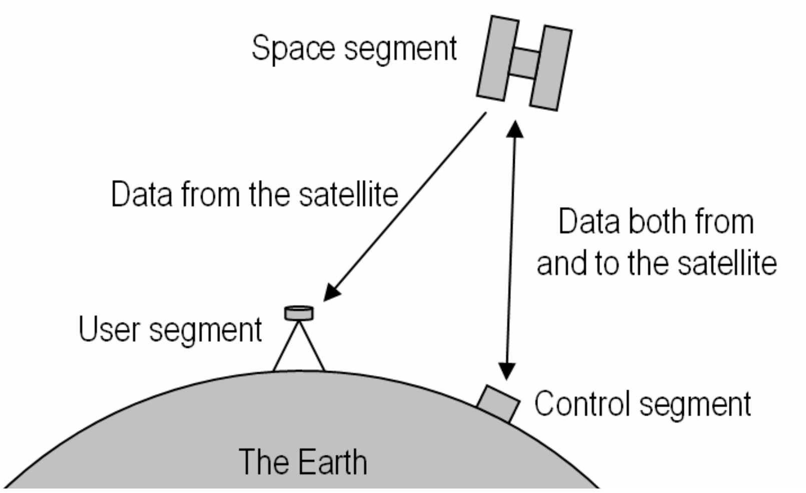

Figure 3.7Segments of the GPS System

It was mainly developed for metre-level positioning accuracies, though after that it has going through different developments since the beginning. Now we are using centimetre positioning. Its mainly using for determining the range from a known signal transmitted in between a satellite and a user, by measuring the transmitting time between this two. While measuring the transmit time we have careful about the précising of synchronized clock because the transmit time is measured as precise time marking.

3.2.1.1 Space Segment

The space segment having 24 satellites out of which minimum 21 must be activated, plus a number of active spares in mostly every circular orbits, whose radius is 20,200 km approximately above the earth. These satellites are placed in six planes with an angle of 55 degree relative to the equatorial plane with a circulation time of 11 hours and 58 minutes. Time onboard on a satellite is control by some high precision clocks made by caesium and rubidium. Since the 5th of January 1980 the GPS system used it own timing system, which is characterized by the continuous timescale and the number of seconds from the beginning of that present week. Due to the earth rotation, Sometimes UTC time adds an extra second or leap second, and GPS-time which is own time system of GPS, is doesn't the difference between the two time systems, from July 2006 and its value is 14 seconds [10].

3.2.1.2 Control Segment

The control segment consists of several types of ground elements (six monitor stations, three ground antennas, and one master control station) that will help to operate the whole GPS system. The monitor stations detect the satellites and send the data back from the satellites to the master control station. Then the master control station analysis the data which was getting from satellites, then corrected and updated the information to the satellites by the ground antennas [10].

3.2.1.3 User Segment

These are most important, dynamic and the largest segment of GPS and it consists of several hundred or sometimes several thousands of different receiver-processor models and antennas. All of them are capable of measure the signal and decoding that receiving signal from the satellites, in order to give the information about your current vehicle position to the user. Selling of that private GPS is heavily increased from last couple of years and the area of its applications will also increased dramatically during the last decade. The applications of GPS become a bigger part of daily live, like GPS receivers in cell phones, car navigation systems, military applications, hand held navigation systems, etc.

3.2.1.4 Signal Structure

Each satellite continuously sending a signal on a two different carrier frequencies (K1 = 1575.42 MHz and K2 = 1227.60 MHz). These two signals are modulated through two Pseudo-Random Noise (PRN) codes is the coarse-acquisition code (C/A-code) only modulated on K1. The frequency of K1 is 1.023 MHz and after each millisecond it repeated.

3.2.1.5 Pseudo Code Measurement

The very first value we got from the PRN codes is the entire code that is generated in the receiver and after that it compared with the measured code also. When these two codes match or correlated we get the best transmit time of the signal, and from the pseudo range. This range is measured by the distance the receiver and satellite, including the clock bias between this two. If we remove clock bias between this then it's just the range instead. Here is the equation from which we can measure the pseudo range by code. [11] Lachapelle 2005).

$$p = \rho + c.dt - c.dT + d_{orb} - d_{ion} + d_{trop} + d_{noise} \tag{3.1}$$

where p significant the calculated pseudorange from code measurements, c is for light of speed, in vacuum, dT is the error of receiver clock, d_{orb}, d_{ion}, d_{trop} represent satellite orbital error, ionospheric error, and tropospheric error respectively, and d_{noise} is for error due to noise.

3.2.1.6 Carrier Phase Measurement

We can derive the second set of measurements from the phase of the incoming carrier frequencies. The method is similar to the method previously mentioned, just a copy of that signal is created by the receiver and compared to the measured. The ambiguity need to be known. For this reason several methods have been developed. A new ambiguity has been determined after each period. Here is an equation, from which we can express the range by barrier phase measurements as:

$$\Phi = \rho - \lambda N + c.dt - c.dT + d_{orb} - d_{ion} + d_{trop} + d_{noise} \qquad (3.2)$$

where λ is the carrier phase wavelength, N represents the ambiguity, using these we can calculate Φ, and this denotes the measured range from phase measurement.

3.2.1.7 Doppler measurement

Doppler shift is defined by the rate of change of the carrier phase measurement. We can express the Doppler measurement by an equation when the rate of change is scaled by the carrier phase wavelength. This is typically K1 [11].

$$\overset{*}{p} = \overset{*}{\rho} + c.d\overset{*}{t} - c.d\overset{*}{T} + \overset{*}{d}_{orb} - \overset{*}{d}_{ion} + \overset{*}{d}_{trop} + \overset{*}{d}_{noise} \qquad (3.3)$$

$\overset{*}{\rho}$ Is for true range rate between receiver and satellite, c is already discussed, it's for light speed in vacuum, $d\overset{*}{t}$ satellite clock error drift, $d\overset{*}{T}$ represents receiver clock error drift, $\overset{*}{d}_{orb}$, $\overset{*}{d}_{ion}$, $\overset{*}{d}_{trop}$ represent satellite clock error drift, ionospheric clock error drift, and tropospheric clock error drift respectively. It should be noticed that the ambiguity term is omitted after time derivation calculus.

3.3 Sources of Error

There are always some errors include in the output of sensors. So the values that are given by accelerometer and gyroscope are subject to errors. There are several types' errors, which are discussed here.

3.3.1 Bias

Bias is the output that does not has any correlation with the input. It could be asymmetric in nature for both of negative and positive inputs and also has an instability that is given by random variation when the output in compared over a specified sampled intervals. Bias is generally measured in [m/s2 of mg] for accelerometer and for gyroscopes it gives value in [deg/hr or rad/s].

3.3.2 Scale Factor

Scale factor is the ratio of change in the measured output upon intended input. Just like bias error scale factor also can be asymmetric in nature for negative and positive inputs. Sometimes the term scale factor and sensitivity is mixed up by the manufactories, but sensitivity and scale factor are not same, the difference between sensitivity and scale factor. Sensitivity is related to the secondary input whereas the scale factor is related to the intended primary input.

Through calibration we can easily measure both drift and scale factor. The calibration method is mainly used to measure accurately three-axial turn tables, angle rate, and six-position static test. The above mentioned equipments are used to determine the bias and scale factor by comparing with known parameters like the earth gravity or well known angles to measure the output.

3.3.3 Repeatability

Repeatability is the closeness of repeated measure values in the same condition by the same input variable and for accelerometer it is expressed in m/s2 or mg and for gyroscopes it gives the values in deg/hr or rad/s.

3.3.4 Resolution

Resolution is the also another vital term that should be monitored in inertial navigation sensors. It is the minimum value, which is greater than noise level that gives an output above a certain level and just like repeatability the unit of accelerometer and gyroscope are expressed in m/s^2 or mg and deg/hr or rad/s respectively.

3.3.5 Stability

When the sensor giving you same type of output with a constant input then this ability if that sensor is called stability. It is also expressed as same as repeatability and resolution and measured over a single run.

3.3.6 Noise

Noise is a random type error, which occurs in output it can only be removed by stochastic models. Sometimes it modelled as a 1st order Gauss Markov process. The term random walk is used to describe a stochastic process in evaluating accelerometer and gyroscopes with zero mean and standard deviation, which grows as the square root of time. Angle random walk process is one of the most popular random walk process, that describes the error built up with time for gyroscopes due to white noise in angular rate. It is generally gives output in deg/h. For both accelerometers and gyroscopes the parameters for the stochastic models is measured by long time collection of static data.

CHAPTER

4

METHODOLOGY

This chapter describes implementation methodology adopted for developing an adaptive intensity control.

4.1 Integration methods

The basic things, which is used in all methods in INS and GPS, is that the INS is used for the reference purpose, and GPS is used for the updating the server. The measurement frequency of INS is many times higher than GPS measurement frequency, INS measurement frequency normally around 1-10 Hz for GPS where GPS measurement frequency is only 100-400Hz [12]. The state vector parameters can determine in higher frequency only, but it can update only in low frequency. The main difference between them is in data flow. Further some methods provide feedback information to improve its performance while others don't. Here we will discuss three types of integration technique, loose integration, tight integration and ultra tight integration [4].

4.1.1 Loose Integration

This is the simplest and very common type of integration method. Generally in this method two different Kalman filters are operated individually, one for

GPS measurement and other for INS measurement. But here it is built a three input Kalman filter. Using this we can reduce the step of integration process. Here the basic in the loose integration method is described in the following steps:

1) Processing of the raw GPS measurements through Kalman filter in order to obtain the velocity and position from GPS.

2) Processing of the raw INS measurements through Kalman filter in order to obtain the values of accelerometers and gyroscope and then determine the position and velocity from them [14].

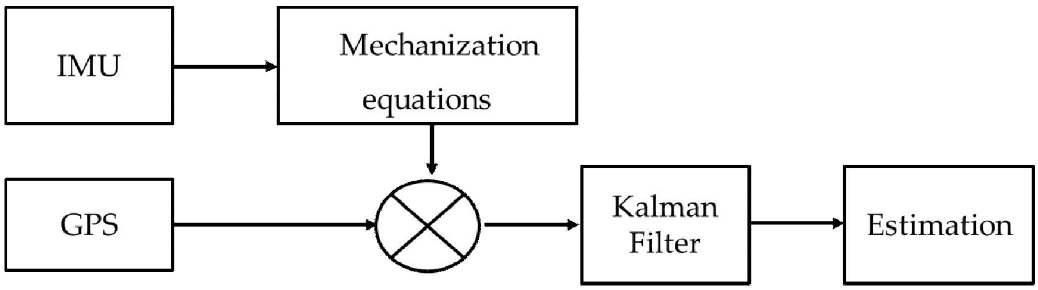

Figure 4.1 Loose Integration

The main advantage of using loose coupled integration technique shown in Figure 4.1 is that it's very simple by its architecture and also robustness. If anyone of them stopped working, still we are able to determine the position through the other. Apart from that there also some other advantages are there. Loose integration can take short time period and its processing time of the algorithm due to generally smaller state vectors [6]. The disadvantage is mainly that it given poor GPS result when GPS signal is very low. It happens only when it receives signals less than four satellites. This drawback can be removed by using tight integration method and this is one of the main reasons why tight integration is better than loose integration. It mainly uses in urban areas. We can use two different Kalman filter for loose integration method. This procedure is explained is also referred to decentralized integration method [14].

4.1.2. Tight Integration

The tight integration method also uses single Kalman filter. Unlike loose integration method, it will not use two different Kalman filters for two different sensors. There are basic steps of tight integration method is described as follows:

1. Getting the raw data from INS sensors and through the mechanization equations it uses to determine the position and velocity.
2. Same as like INS, using GPS sensor also for getting the information about position and velocity, from step 1 to predict pseudo-range and Doppler measurement.
3. Use predicted pseudo-range and Doppler measurements from step 2 as input to an INS/GPS Kalman filter. Here Kalman filter takes the difference between the pseudo-range and Doppler in order to determine the error of the position and velocity plus misalignment error.
4. Using the error estimates from Step 3, we update the position and velocity from Step 1 in order to get a full state vector.

The main advantage of using tight integration method is that it is working properly even when the signal strength is not so good and gives proper output. It can happen because INS can be still updating. So this process is mainly used in urban areas, where this process is use in the absence of strong GPS signal.

The tight integration is comparatively complex process than loose integration, due to state vector increases in size which is its disadvantage.

The tight integration method is shown in Figure 4.2 below.

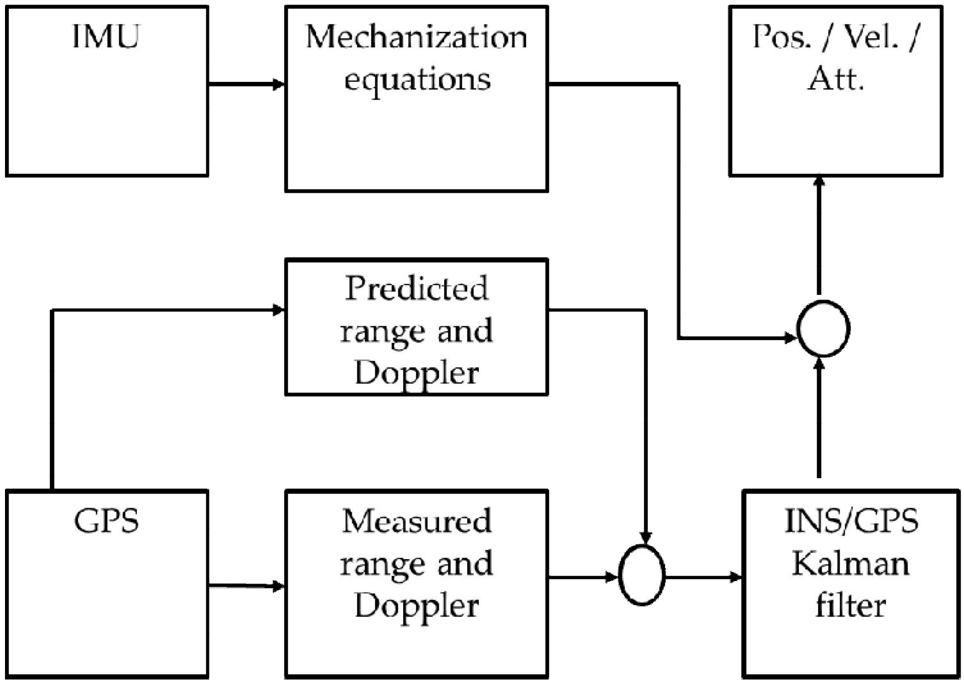

Figure 4.2 Tight Integration

4.2 Estimation Techniques

Estimation is quietly the procedure of obtaining unknown parameters from a set of observations. Depending on the amount of the observations we can use different type of estimation techniques. One of the most common methods is least square method. If we know the systems dynamic over time then we can easily obtained better estimate of the parameters [11]. Figure 4.3 shows the estimation block diagram.

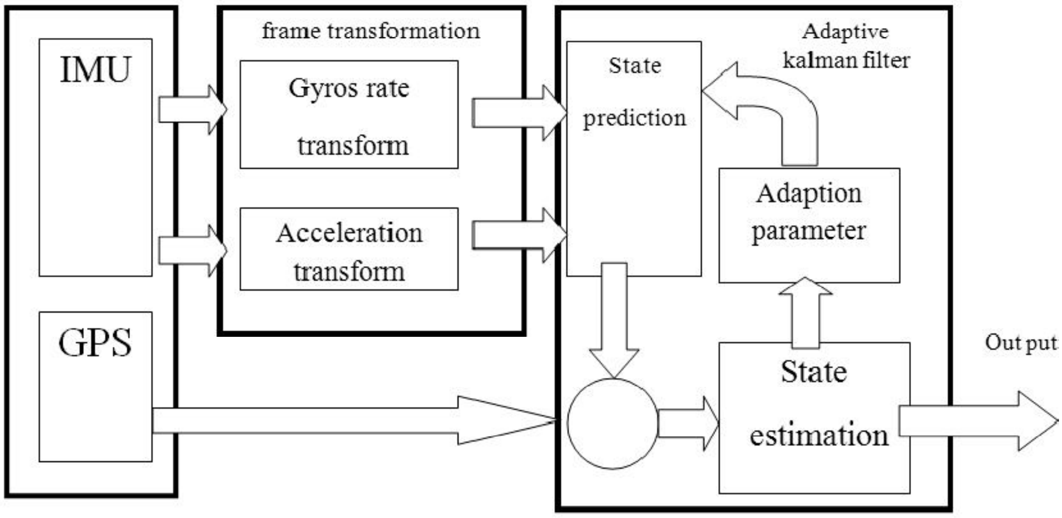

Figure 4.3Estimation Block Diagram

4.2.1 Estimation of Dynamic Systems

Kalman filter is one of the most common and very useful methods, for sensor integration. It consist of 7 steps, the main reason of using this technique is, because it changes its value with changing time, and updated and corrected your position. As most of the navigation system behaves like non linear system. In Kalman filter all subscripts indicate a certain time epoch.

$$\overset{*}{X} = F_t X_t + G_t w_t \tag{4.1}$$

In order to compute optical estimates of the state vector, X_t while using knowledge of the behaviours of the systems dynamic a Kalman filter is used. It is recursive algorithm that uses a series of prediction and measurement update step with a minimum variance [11].

According to the principle of Kalman filter the process can be modelled as

$$X_{t+1} = \phi_{t,t+1} X_t + W_t \tag{4.2}$$

where $\Phi_{t,t+1}$ is the transition matrix of a given system, from time period t to t+1.

The transition matrix can under the assumption is that by using exponential function we can express the time interval between epoch t and t+1.

$$\Phi_{t,t+1} = e^{F_t \Delta t} = I + F_t \Delta t + \frac{(\mathrm{F}_t\, \Delta\, \mathrm{t})^2}{2!} + \frac{(\mathrm{F}_t\, \Delta\, \mathrm{t})^3}{3!} + \ldots \qquad (4.3)$$

Where Δt is the time interval between two consecutive time epoch, t and t+1, and I represents as identity matrix. The higher orders terms may be neglected.

To relate the observation to the unknown parameters we need to know the measurement model. For time t, the measurement model will be written as:

$$Z_t = H_t X_t + \eta_t \qquad (4.4)$$

Where X_t is already defined, H_t is a design matrix, Z_t is the observation matrix, and η_t is the measurement noise for covariance matrix, R_t.

At zero means white noise sequences with zero correlation, we assume that the measurement noise η_t and process driving noise, H_t, an updated estimate of the state vector and its covariance can be found as:

$$\hat{X}_t^{+} = \hat{X}_t^{-} + K_t v_t \qquad (4.5)$$

$$P_t^{+} = (\mathrm{I} - \mathrm{K}_t \mathrm{H}_t)\,\mathrm{P}_t^{-} \qquad (4.6)$$

Where the signs "+" and "-" indicates the state of measurement update after and before respectively, P_t represents the covariance, v_t is for innovation sequence, and K_t denotes the Kalman gain.

$$K_t = P_t^{-} H_t^{T} (\mathrm{H}_t \mathrm{P}_t^{-} \mathrm{H}_t^{T} + R_t)^{-1} \qquad (4.7)$$

The innovation sequence v_t is actually the difference between actual and predicted observation, where actual observation denoted as z_t, and $\hat{z}_t$ is given as predicted observation

$$\mathrm{v}_t = \mathrm{z}_t - \hat{\mathrm{z}}_t = \mathrm{z}_t - \mathrm{H}_t \hat{X}_t^- \tag{4.8}$$

This is the new part in the system which introduced new information in to the system. If values of actual measurement and predicted measurements are same, then the value of innovation sequence is zero, so it means that no new information is introduced in the system. So the values of $\hat{X}_t^-$ and $\hat{X}_t^+$ will also be same, the updated and predicted state vector. Clearly if some difference creates between actual and predicted values, then it added some new information to the system. Just like measurements contains measurement noise. It is not mentioned that weather the new information will fully accepted by the system or not, this thing we know from Kalman gain matrix, it works like a weighting factor with a minimum error variance. The measurement will be very reliable is the value of Kalman gain matrix is greater than noise covariance R_t. But if the value of R_t is small then Kalman will also be small.

$$K_t = \mathrm{P}_t^- \mathrm{H}_t^T (\mathrm{H}_t \mathrm{P}_t^- H_t^T + \mathrm{R}_t)^{-1} \tag{4.9}$$

Predicted state and its covariance forward in time can be expressed by these two equations

$$\hat{X}_{t+1}^- = \Phi_{t,T+1}^T \hat{X}_t^+ \tag{4.10}$$

$$P_{t+1}^- = \Phi_{t,t+1} P_t^+ \Phi_{t,t+1}^T + Q_t \tag{4.11}$$

Where we already know that $\Phi_{t,t+1}$ denotes the transition matrix as the previous equation, and Q_t is process noise, which can be determined by

$$Q_t = \int_{t}^{t+1} \Phi_{c,t,t+1} G(\mathrm{t})\, \mathrm{Q}_c(\mathrm{t})\, \mathrm{G}^T(\mathrm{t}) \Phi^T_{c,t,t+1} dt \qquad (4.12)$$

Where $\Phi_{c,t,t+1}$ is denotes the value of continuous-time transition matrix between time t and t+1. Is given the value of continuous-time spectral density matrix of W_t and G(t) is defined previously.

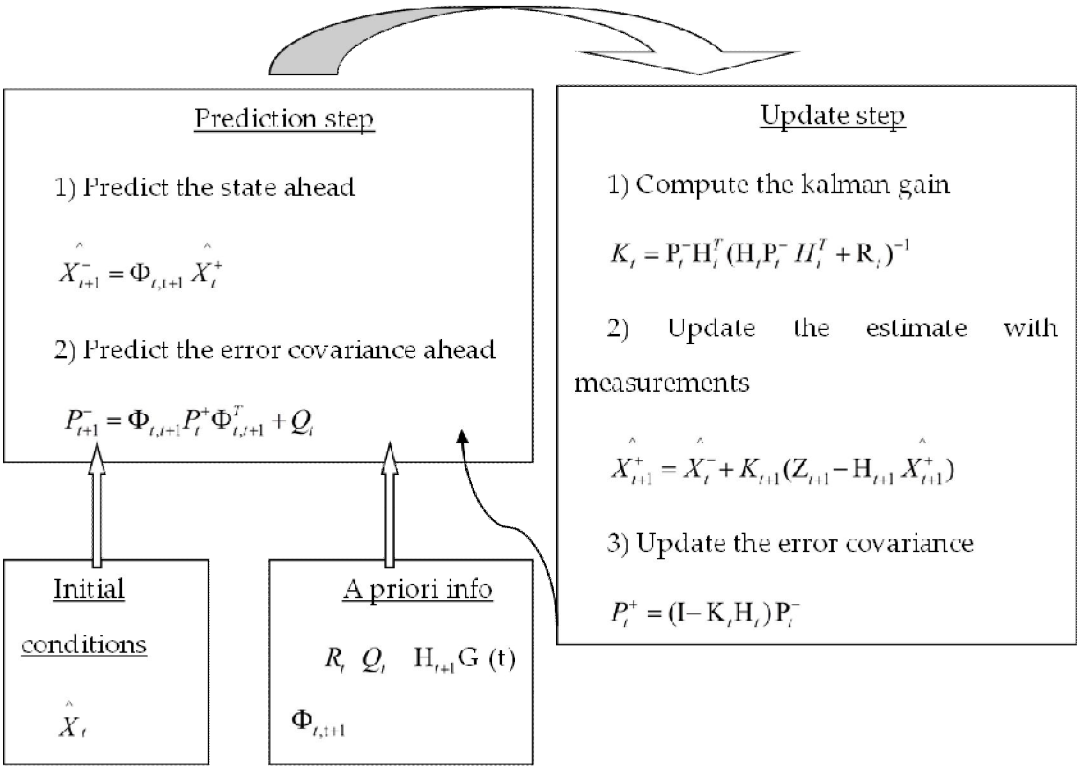

Figure 4.4 Algorithm for Estimation-Prediction using Kalman Filter

Figure 4.4 describes the whole operational process of Kalman filter. It consists of process model, and the measurement model, this works exclusively for linear systems only

4.2.2 Estimation of Non-Linear Systems

In this section we will discuss about a non-linear process and measurement model. It can be given as

$$\dot{X} = f(\mathrm{X}_t, \mathrm{t}) + G_t w_t \qquad (4.13)$$

$$Z_t = h(\mathrm{X}_{t,}\mathrm{t}) + \eta_t \qquad (4.14)$$

Where, h and f represents the non-linear functions of the process model and relation between observation and the state. For linearzing these two above equations a nominal state vector, $\overset{*}{X}_t$ is represented as:

$$X_t = \overset{*}{X}_t + \delta X_t \qquad (4.15)$$

Where δX_t is represents the value of perturbation from the nominal state. Let the value of δX_t is very small, then a first order Taylor series will be perform about the nominal state.

$$\delta X_t = \Phi_{t,\mathrm{t}+1} \delta X_t + w_t \qquad (4.16)$$

$$\delta Z_t = H_t \delta X_t + \eta_t \qquad (4.17)$$

Where δZ_t represents the value of difference between actual measurements over predicted measurements, and δX_t is the linear model of error state vectors.

Linearized Kalman filter is that where the linearization is done about the nominal state vector. If this linearization is done in the last computed solution X_{t-1} then it's called an Extended Kalman filter (EKF).

4.2.3 Reliability Testing

Reliability is the ability to identify and reject errors that errors occur which we see in the previous measurements section, and a test for detecting such a kind is needed to obtain the optimal path. The testing of that reliability can be determined by the difference the actual and predicted observation. But there are some limitations of measurement model, if the errors come from the GPS, or from multipath or poor satellite geometry, then this type of errors can't be detected, and they are different from the measurement noise.

Any type of measurement outlier will cause the innovation sequence, otherwise normally distribution and zero mean is occur, and this is determined by the testing of innovation sequence, and it is given as

$$v_t \sim N(0, \sigma_{v,t}) \qquad (4.18)$$

Where, the innovation variance at time t is defined by $\sigma_{v,t}$. $\sigma_{v,t}$ is determined as:

$$\sigma_{v,t} = H_t P_t^- H_t^T + R_t \qquad (4.19)$$

Here in this above equation all the variables are already defined in the previous sections, the normally distribution is given as:

$$v_t \sim N(\mathrm{M}_t \nabla_{t,\sigma_{v,t}}) \qquad (4.20)$$

For two hypotheses a global chi-square test is performed. These two hypotheses are bias free and biased. If the reader wants to know more about reliability testing, it's in [13].

4.3 Measurement Instruments

The IMU and GPS that was used for this experiment for collecting data were "6 Degrees of Freedom IMU Digital Combo Board - ITG3200/ADXL345" and "GPS shield with GPS-A6B". Both the IMU and GPS are connected with laptop through Arduino UNO.

Table 4.1 Specifications of IMU unit

Specification	Accelerometers	Gyroscope
Bias:	-150 to +150	1 deg/hr
Sensitivity:	232 to 286	2000 deg/s
Noise:	<1.0	0.38
Scale Factor:	3.5 to 4.3	14.375

Table 4.2 Specifications of GPS Sensor

Parameter	Specification
Frequency	1575.42MHz
Sensitivity	Acquisition-148 dBm, Tracking-165 dBm
Position accuracy	3.0 m
Protocol	NMEA
Baud Rate	4800 to 115200 bps
Working Temperature:	-40 *C to +85* C

CHAPTER

5

RESULTS AND DISCUSSIONS

This chapter describe the results that have been obtained from this study.

5.1 Experimental Set-Up

The experimental set up comprised of: Arduino UNO board, GPS Shield, INS Shield, a laptop for data logging and a moving vehicle shown in Figure 5.1.

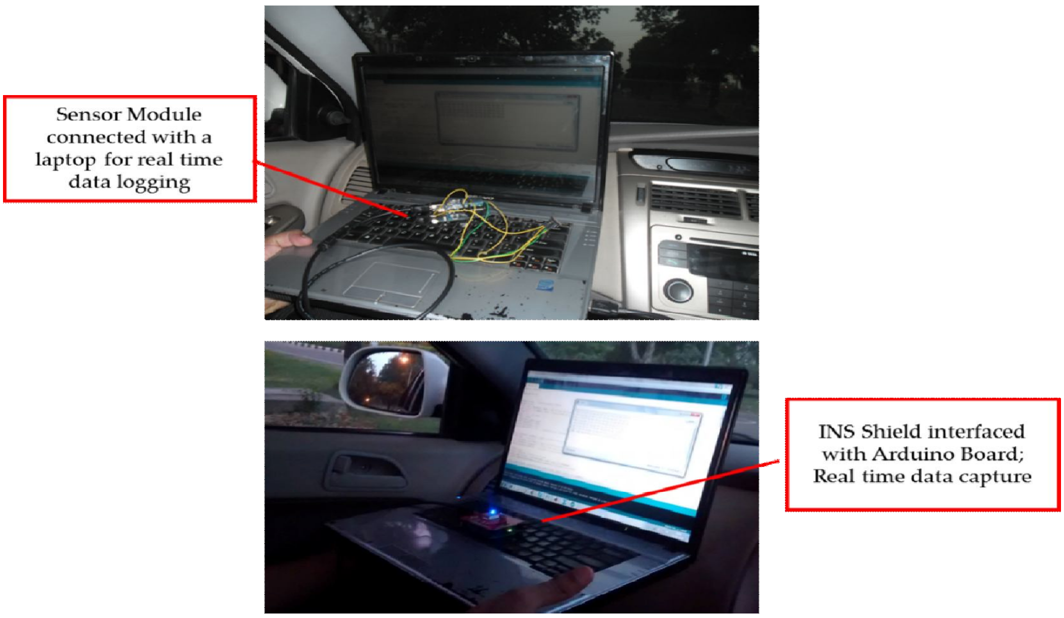

Figure 5.1 Experimental Set-Up

5.2 Reference Trajectory

In order to evaluate the values of the IMU measurement, the magnitude of the corrected INS derived position, velocity applied from GPS update shown in below figure. It gives a clear idea about the position and velocity correction of INS data after each update.

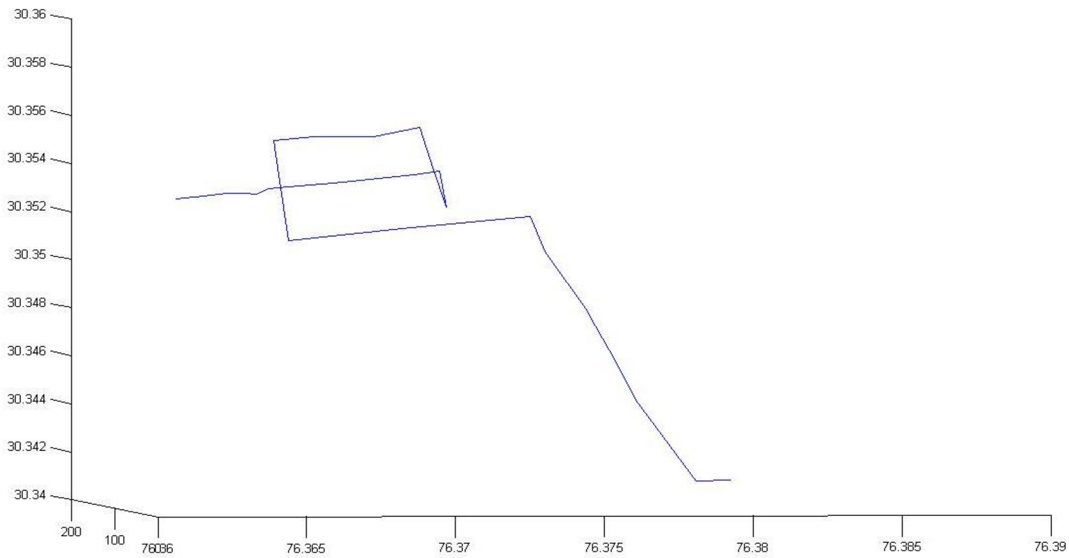

Figure 5.2 Reference Trajectory

As the 3D RMS (root means square) correction, it gives centimetre level correction in position, so it is expected that the for reference trajectory it is accurate couple of centimetre in 3D position at all time.

5.3 Simulated GPS Data Outage

While performing that experiment of integrated INS and GPS, here 4 different data outage (gaps) were simulated. The gaps were created for examine the performance the INS filter clearly, the duration of each gap were up to 40 seconds.

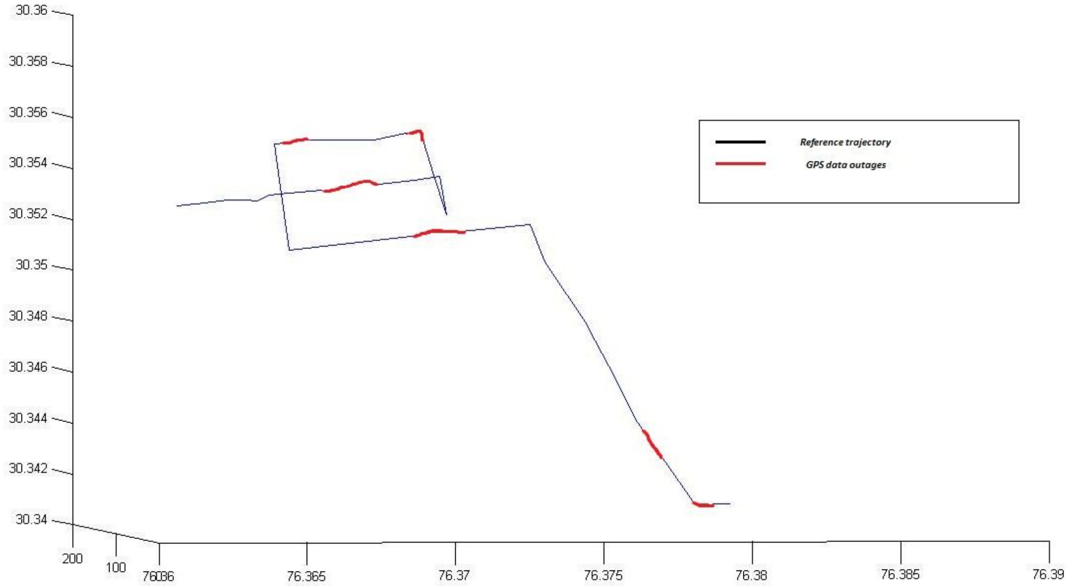

Figure 5.3 Thirty Seconds Gap Reference Frame

Here in the above figure it described the full 30 seconds gap. Here the different baseline length is taken from master location, so that it can be seen clearly.

Two different levels of data gaps were used instead of using only simulation gaps without any GPS coverage. Here the gaps created in order to simulate the data in a tunnel like fully data outage and partially outage conditions, where no GPS signals were available in kind of form. Here we intentionally cut off the GPS shield connection in order to create such conditions. A standalone GPS solution was therefore impossible. For these kinds of situations tight integration will be very helpful.

5.4 Position Accuracy

The position or you can say its displacement accuracy of the integrated GPS and INS solution were calculated as the RMS error between of the reference trajectory provided by GPS and the position during the data outage. The RMS error was calculated during the unavailability of GPS signal in order to reduce the effect of large error in a single gaps and obviously get a better estimate for an average accuracy. We consider that in reference trajectory the position error is in centimetre error, so for integrated solution we expected that error will be reduced, this is the main reason for the RMS error. Hence for the centimetre level integrated solution RMS error will be a good choice for estimated solution.

The Figure 5.4 shows the difference between the priori (predicted) value in BLUE line, and posteriori (updated) value are shown by GREEN line. Priori is nothing but the estimate of position from previous values obtained from GPS and posteriori value is calculated from present position. It is obvious that posteriori values give better estimation than priori values.

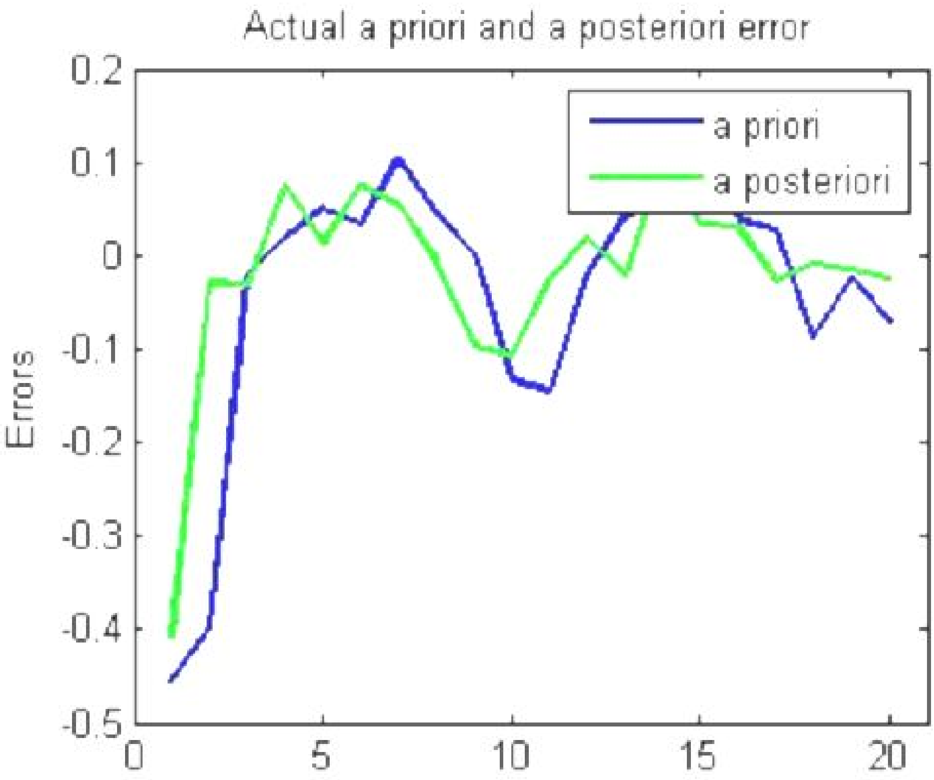

Figure 5.4 Positional Error between Priori and Posterior Values.

From the Figure 5.4 we can easily differentiate between the positional errors between priori and posterior value. This figure only shows the difference between predicted and updated value.

In Figure 5.4 shows the difference between exact, priori and posterior values. If we reduce the values of noise covariance's than the value gives by Kalman filter in priori and posterior position will be more accurate with the respect to exact position. The exact position is shown by RED line, priori position from Kalman filter is shown by BLUE line and posterior position is shown by GREEN line. If we reduce the noise covariance, then it gives more accurate position, which is shown in Figure 5.5

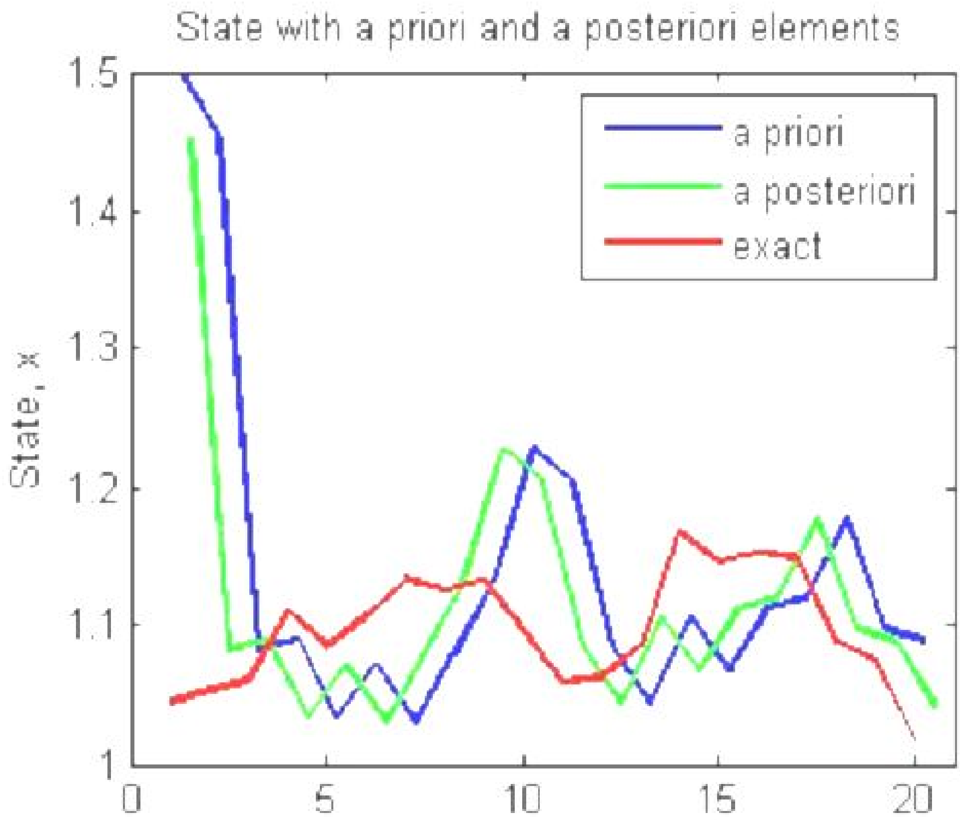

Figure 5.5 Difference Exact, Priori and Posterior Values

Figure 5.6 shows that when we reduce the noise covariance's, the difference between exact positions, is also reduced with priori and posterior positions.

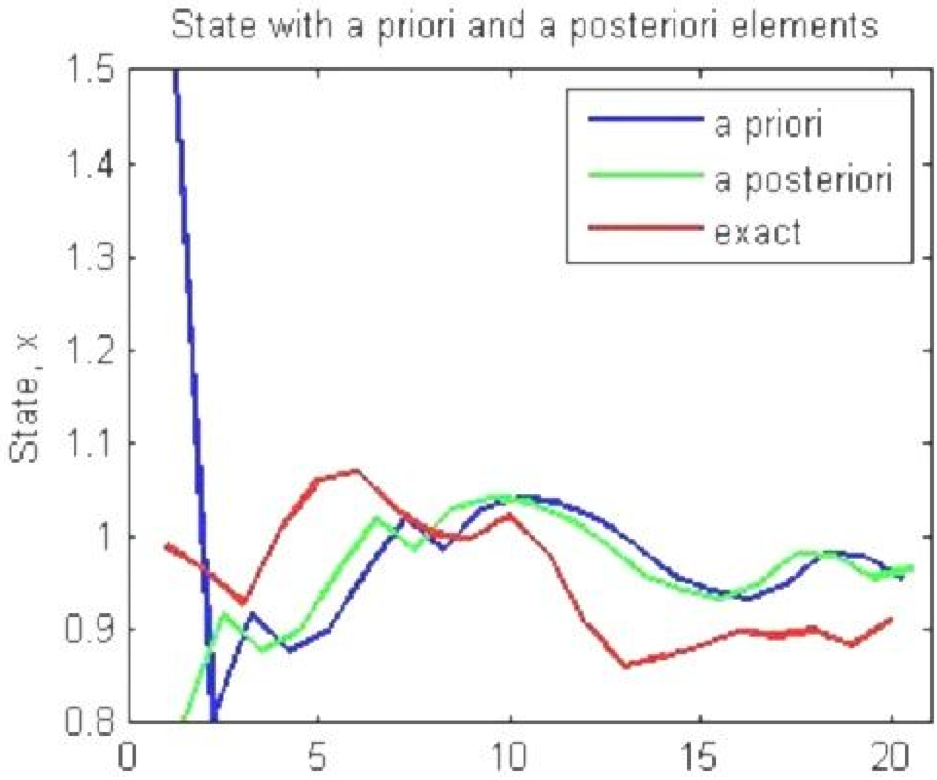

Figure 5.6 Exact, Priori and Posterior Values with Reduced Noise

Apart from position, Kalman filter also has some other important parameters which affect the output of Kalman filter, the parameters are Kalman gain and covariance calculation.

Figure 5.6 shows the covariance difference between priori and posterior state. This Figure 5.6 clearly shows that the posterior covariance value gives a better result than priori covariance values. Covariance is nothing but the noise of that process model, for priori state we assumed a fixed covariance. But as time increases it check predicted value to the estimated value and updated it. So as time goes on it decreases the covariance. As we seen in Figure 5.7 covariance will decreases with the increase of time.

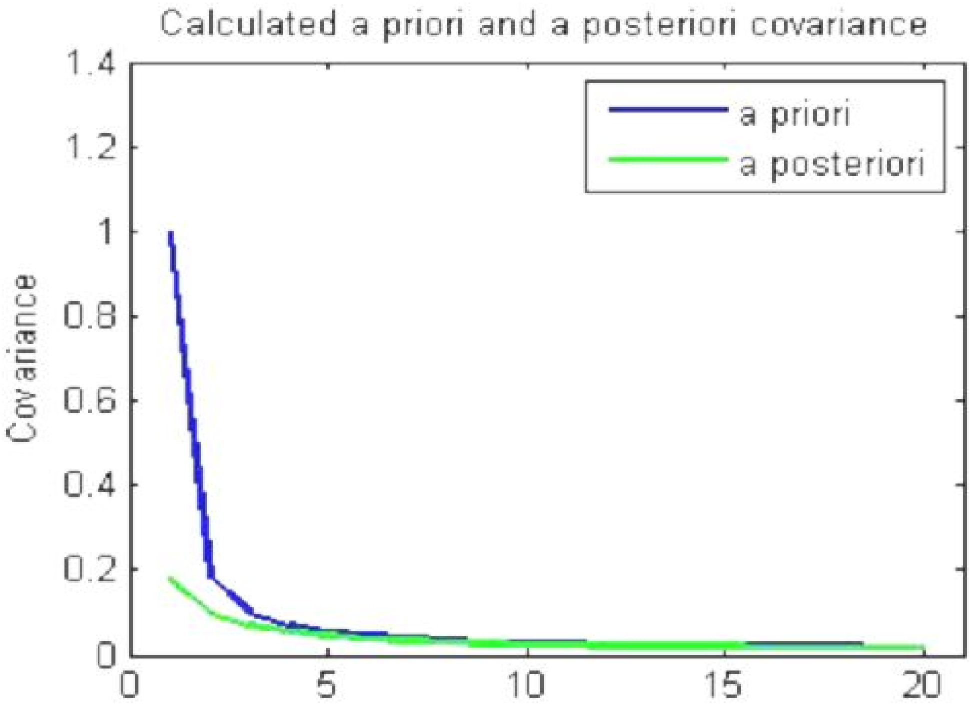

Figure 5.7 Covariance of Priori and Posterior Values

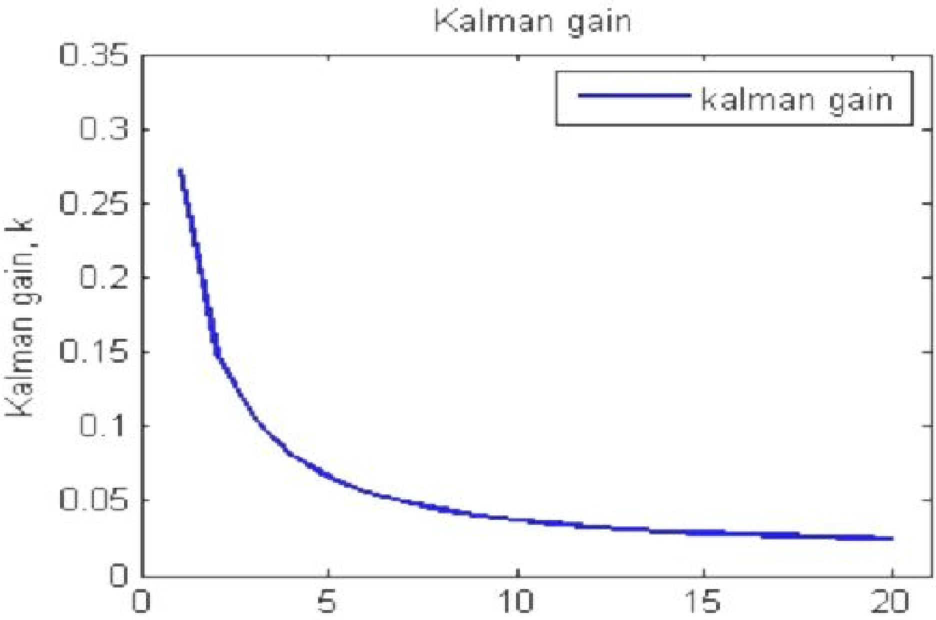

Figure 5.8Calculated Kalman Gain

Figure 5.8 shows the change of Kalman gain with respect to time. Kalman gain is used to indicate how much we trust on our innovation. It represents by

$$K_k = P_{k/k-1} H^T S_k^{-1}$$

In which S denotes the innovation covariance. What it does is that it tries to predict how much we should trust the measurement based on the priori error covariance matrix $P_{k/k-1}$ and the measurement covariance matrix R.

5.5 Velocity Accuracy

Velocity accuracy is calculated with velocity of vehicle in X axis and Y axis with respect to time. We get the values from IMU for acceleration in X, Y and Z axis. So we integrate those values and convert it into velocity and again integrate it to get the displacement of that vehicle. For this purpose we are using function "atan2", this function converts the vector form of acceleration (X, Y, Z) in scalar form and also integrate it. Then we convert those values in degree. For the case of land vehicle we can neglect that value of Z axis, because in a land vehicle move only in X and Y plane.

Figure 5.8 shows the velocity of vehicle in X-axis with respect to time, to show the change of velocity and angular rotation with respect to time. Similarly, Figure 5.9 shows the velocity and angular rotation change with respect to time in Y axis.

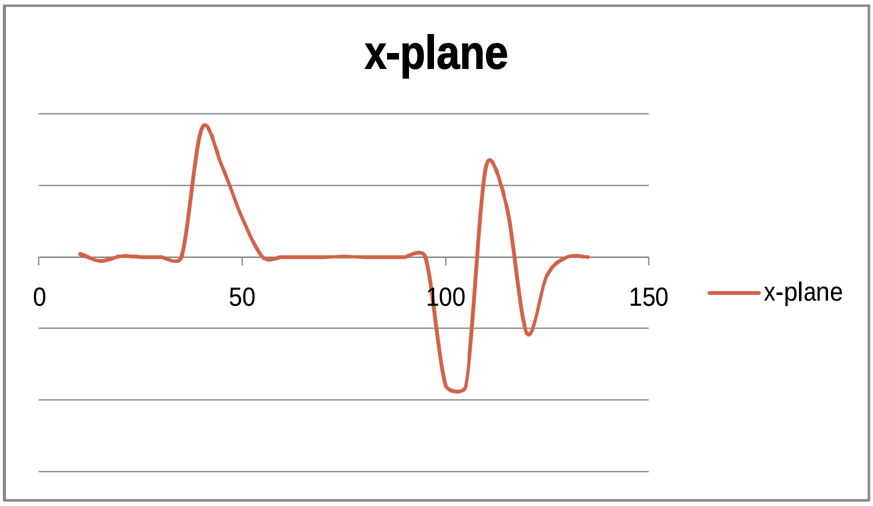

Figure 5.9 Calculated Velocity in X-axis with Time

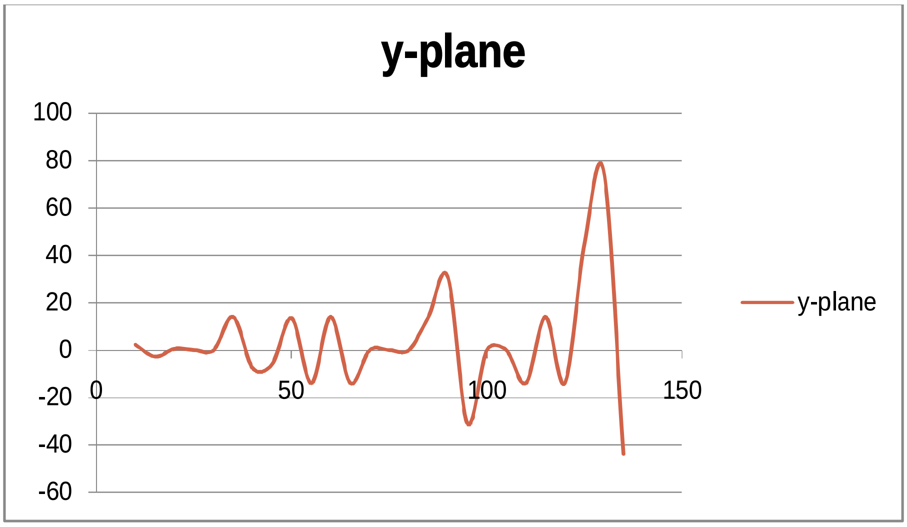

Figure 5.10 Calculated Velocity in Y-axis with Time

5.6 Time to Fix Ambiguity after Outage

The previous part of the data analysis discussed about the performance during either partial gaps or complete gaps. Another important thing is the ability to recover after the gaps and determine correctly fixed ambiguities. This is important in order to get accurate position updates from the GPS as it provides the necessary accuracy to the integrated INS and GPS solution.

5.7 Accelerometer and Gyroscope Bias

The final part of this data analysis part is to discuss about accelerometer and gyroscope bias. The biases were calculated for each epoch and were another sign for the performance of the integrated system. Table 5.1 shows the gyroscope bias as an average at different epochs for all five gaps. This is due to the relatively small gap period of only 30 seconds. Instead there is a larger difference between the bias at the beginning and the end of the dynamic model. The charges in the bias for the Z-gyroscope, is up to 0.5 deg/hr for the entire dynamic period (about 30mins). It should be remembered that the specifications for the IMUs gyroscope bias were 1 deg/hr. For most of epochs will the average bias therefore be under the specification level.

Table 5.1 Average Gyroscope Bias with and without Complete Gap

Average Gyroscope Bias [deg/hr]	Without gap		With complete gap			
	End of alignment	End of dynamic mode	Before gap	20 sec. in gap	40 sec. in gap	End of dynamic mode
X-gyroscope	0.114	0.245	0.320	0.320	0.314	0.255
Y-gyroscope	1.173	0.854	1.112	1.118	1.118	0.901
Z-gyroscope	0.065	0.598	0.532	0.549	0.546	0.590

Similar average biases for the accelerometers can be calculated at different epochs as shown in Table 5.2. It can be seen that large changes in bias occur over long time and not within the 30 seconds gaps. Again the specifications for the IMUs accelerometer bias were 1000µg and during no epoch this level was crossed.

Table 5.2 Average Accelerometer Bias with and without Complete Gap

Average accelerometer bias	Without gap		With complete gap			
	End of alignment	End of dynamic mode	Before gap	20 sec. in gap	40 sec. in gap	End of dynamic mode
X-accel.	347	593	565	565	565	593
Y-accel.	436	657	697	697	697	658
Z-accel.	796	705	759	759	759	705

5.8 Experimental Results

5.8.1 Accelerometer Output

The sample data of accelerometer values is shown in Table 5.3. Accelerometer gives output in 3-axis X, Y, and Z. It gives values in scalar from. In this table time represents in secs and accelerometer values represents in radian/ sec^{2} . Accelerometer gives values in every 0.5 secs.

Table 5.3 Changes of Accelerometer Values in X,Y,Z Axis with Time

Time	accX	accY	accZ
1	-0.96	8.16	4

1	-0.84	6.55	4
2	-1.03	6.07	8.45
2	-1.11	6.21	4
3	-0.65	4	4
3	-1.84	-0.08	4
4	1.68	-0.19	7.97
4	-1.76	-0.15	6.43
5	-1.46	-0.38	4.32
5	-1.41	7.43	4.8
6	0.23	5.32	7.97
6	1.34	3.83	9.01
7	1.18	6.13	7.79
7	1.04	5.25	7.49
8	0.79	4.30	6.51
8	3.39	4.58	9.12
9	0.25	3.42	9.35
9	-0.82	2.23	9.85
10	1.80	3.06	6.36
10	1.56	2.24	10.18

5.8.2 Gyroscope Output

The sample data of gyroscope values is listed in Table 5.4. Gyroscope gives output in 3-axis, X, Y, and Z. It gives values in scalar from. In this table time represents in sec and gyroscopes give its output in degree/hr. Gyroscope gives values in every 0.5s.

Table 5.4 Changes of Gyroscope Values in X, Y, Z Axis with Time

Time	gyroX	gyroY	gyroZ
1	0.02	-0.06	0.00
1	-0.53	1.65	-0.90
2	-0.07	-1.04	-0.22
2	-0.45	-0.34	-0.44
3	0.60	-0.15	-0.19
3	-0.38	-0.38	0.12
4	0.37	0.10	0.09
4	0.29	-0.23	-0.01
5	0.46	-0.09	-0.25
5	0.56	0.64	0.52
6	0.17	0.21	0.24
6	-0.18	-0.20	-0.52
7	-0.26	-0.18	0.02
7	0.50	0.12	0.99

8	0.07	-1.22	-1.47
8	0.04	0.14	0.21
9	0.06	-0.04	-0.09
9	0.12	0.07	0.02
10	-0.06	-0.09	0.08
10	0.05	-0.08	-0.02

5.8.3 GPS Output

This sample data gives the values of latitude and longitude with respect to time shown in table 5.5. This data was collected from GPS sensor in real time. GPS receiver updates the value after every 2s.

Table 5.5 Changes of Latitude and Longitude with Time

Time	**Latitude**	**Longitude**
1	30.35397	76.36741
3	30.35399	76.36745
5	30.35402	76.36748
7	30.35403	76.36801
9	30.35405	76.36845
11	30.35408	76.368561
13	30.35410	76.368660
15	30.35411	76.368704

17	30.35412	76.368813
19	30.35413	76.368257
21	30.35414	76.368753
23	30.35415	76.369056
25	30.35416	76.369175
27	30.35417	76.369287
29	30.35409	76.36977
31	30.35399	76.370041
33	30.35396	76.370044
35	30.35389	76.370050
37	30.35384	76.370059
39	30.35383	76.370063

5.8.4 Output of Kalman Filter in Kalman-X and Kalman-Y form

The output of the designed Kalman filter in form of KalmanX and KalmanY is shown in table 5.6. Here KalmanX means the values of Kalman filter in X axis and KalmanY means values of Kalman filter in Y axis. It shows the predicted movement of the vehicle in X and Y direction. Primarily when the vehicle is in stable position it shows its position is 180 in X plane and 180 in Y plane. It considers its stable state value as 180 at initial. After that when the vehicle starts moving with every changes of vehicle position, it’s also changes its present value with respect to previous values. The deflection of KalmanX and KalmanY axis shows it movement in X axis and Y axis. The Kalman filter output is updated after every 1 sec.

Table 5.6 Changes of KalmanX and KalmanY with Time

Time	KalmanX	KalmanY
1	181.22	170.94
2	180	174.83
3	180	180
4	180.16	180
5	179.22	172.02
6	180.85	180.8
7	180	165.96
8	180	173.71
9	179.92	90.29
10	180	179.98
11	180.41	178.83
12	180	90.11
13	180	173.66
14	180	165.98
15	180.56	179.84
16	179.97	180.17
17	180	165.96

18	180	173.66
19	179.97	180.17
20	179.91	179.91

CHAPTER

6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

It can be concluded that multi-sensor fusion for land vehicle navigation has been demonstrated. Integration of GPS and INS sensor was done for predicting the trajectory of a land vehicle using an estimation-prediction model. Experimental results demonstrate integration of INS and GPS together through Kalman filter estimation technique.

The main objectives of the data analysis was to access the integrated systems performance hereby determine the position and velocity accuracy during data outages under different conditions. The gaps showed that using GPS with INS can provide sub meter level position accuracy when GPS signal is not available.

6.2 Future Scope of the Work

In this dissertation, focus was to achieve multisensory fusion for land vehicle navigation. Thus, a Kalman filter based integration algorithm was developed. This work reports a linear estimation model for problem at hand. However, handling non-linear systems is a challenging task. Future scope of the work includes modelling of nonlinear systems using better estimation techniques like: extended Kalman Filter, Particle filter etc. to further reduce estimation error and enhance predictability of nonlinear systems as well.

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