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# Inter-Vehicle Position Estimation For NLOS Condition In The Persistence Of GPS Outages

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# INTER-VEHICLE POSITION ESTIMATION FOR NLOS CONDITION IN THE PERSISTENCE OF GPS OUTAGES

by

Meharoon Shaik

B.Tech, Jawaharlal Nehru Technological University, India, 2003

A thesis

presented to Ryerson University

in partial fulfillment of the

requirements for the degree of

Master of Applied Science

in the Program of

Electrical and Computer Engineering

Toronto, Ontario, Canada, 2009

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# Abstract

## INTER-VEHICLE POSITION ESTIMATION FOR NLOS CONDITION IN THE PERSISTENCE OF GPS OUTAGES

Meharoon Shaik

MASc. Electrical and Computer Engineering, Ryerson University, 2009.

The main focus of thesis work addresses one of the functional key points of Cooperative Collision Warning application which is an accurate estimation of the range data of neighboring vehicles during persistent GPS outages under both line-of-sight (LOS) and non-line-of-sight (NLOS) situations. Cooperative Collision Warning, based on vehicle-to-vehicle radio communications and GPS systems, is one promising active safety application that has attracted considerable research interest. One of the severe estimation error is due to NLOS that can be mitigated by applying biased Kalman filter on range measurements. For our algorithm these inter-vehicle distances are measured from using one of the radio-based ranging techniques. Main objective is to establish an accurate map of positions for neighboring vehicles in the persistence of GPS outages. GPS outages can be possible in multipath environments where NLOS component is introduced to the true range measurements. These position estimates mainly depend on two factors: (i) Preprocessed inter-vehicle distances (range data is processed from biased Kalman filter); (ii) Road constraints (the vehicle uncertainty is more in the direction of road than the uncertainty in the direction opposite to the road); This thesis suggests smoothing and mitigating the NLOS for radio-based ranging measurements under multipath conditions. In order to find accurate positions of neighboring vehicles an extended Kalman filter is implemented along with road constraints. Unbiased Kalman filter, biased Kalman filter and extended Kalman filter performances are experimentally verified using Matlab simulation tool with random number of vehicles at unknown random distinct positions in some physical region along a section of road for vehicular environment.

## Acknowledgment

My time at Ryerson University has been influenced and guided by a number of people to whom I am deeply indebted. Their help, friendship, and support during my graduate studies helped make this thesis come to light.

I would like to thank the members of my thesis committee, Dr. Alagan Anpalagan and Dr. Xiaoping Zhang and Chair Dr. Truman Yang for their invaluable suggestions. I feel very fortunate to have had the opportunities to receive their support.

In particular, my supervisor, Dr. Lian Zhao, my co-supervisor, Dr. Olivia Das, and my advisor, Dr. Zaiyi Liao have had the greatest impact on my academic development during my time at graduate school. They have been a tremendous mentors, collaborators, and friends, providing me with invaluable insights about academic research, and continue help and support through my M.A.Sci. study. I feel exceedingly privileged to have had their guidance and I owe them a great many heartfelt thanks. My sincere gratitude to my supervisor, Dr. Lian Zhao, for her great support, encouragement, guidance throughout on this thesis, especially for her patience. This work would not have been possible without her broad knowledge and deep insight into the research. It has truly been a great privilege to be her student.

I would like to gratefully acknowledge Ministry of Transportation of Ontario (MOT), Natural Sciences and Engineering Research Council of Canada (NSERC), the program research graduate scholarship and graduate teaching assistantship from Ryerson University for the financial sponsorship of this research.

My deepest gratitude and appreciation are reserved for my beloved spouse, Nayab Rasool, my loving parents Moulali and Mastanbi, my dearest brothers Basha and Gouse and my loving niece, Sara. Without their constant love, support and encouragement, I would not have gone so far as to produce this thesis.

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# Chapter 1

## Introduction

This chapter provides an overview of the thesis. This chapter begins with an introduction on inter-vehicle communication in Section 1.1. Section 1.2 deals with the motivation behind thesis work. Section 1.3 describes the existing technology in position estimation for vehicular communications. Limitations due to current technology is listed in Section 1.4. In Section 1.5 problem is formulated. Out of these challenges, the objective and scope of the thesis are established and narrowed down in Section 1.6. Section 1.7 summarizes the contributions and provides outlines of this thesis.

### 1.1 Introduction

As a component of the Intelligent Transport Systems (ITS) and one of the concrete applications of mobile *ad hoc* networks, inter-vehicle communication (IVC) has attracted research attention from both the academia and industry. The term ITS refers to efforts to add information and communication technology to transport infrastructure and vehicles in an effort to manage factors that typically are at odds with each other, such as vehicles, roads, and people. Main goal of ITS is to improve safety, reduce traffic flow, congestion, provide alternate routes to travelers, enhance productivity and save lives, time, money and fuel usage.

One of the earliest studies on IVC was started by JSK (Association of Electronic Technol-

ogy for Automobile Traffic and Driving) of Japan in the early 1980s [1]. Later, well-known research results on platoon scenario has been demonstrated by California PATH [2] and Chauffeur of EU [3]. The cooperative driving systems of Japan in the late 1990s and 2000 (*e.g.*, DEMO 2000 [2] exhibit adaptive cruise control application of the IVC. Traditional solutions to this issue involve mainly the automatic control systems for individual vehicles [4], but the IVC can help to make the coordination more efficient. The newly initiated European Project CarTALK 2000 [5] tries to cover problems related to safe and comfortable driving based on IVC. It focuses on the design, test and evaluation of co-operative driver assistance systems by taking into account both IVC and road-to-vehicle communication [6]. CarTALK 2000 also co-operates with other projects like German FleetNet [7] for the development of IVC.

### 1.1.1 Types of Vehicular Communications

Two types of wireless communications are currently being proposed to help enable new vehicle control applications. These two types are distinguished based on the terminals for wireless signals. The first type comprises communication between vehicles and road side base units, while the second type comprises communications between vehicles. **Vehicle-to-infrastructure (V2I)** communications allow devices mounted on the side of the road to upload data from passing vehicles or download data to these vehicles. The messages uploaded from vehicles can for instance be used to estimate travel time between known points, thereby converting each passing vehicle into a probe vehicle. At the other side, the information reaching vehicles may provide travelers with local maps and business directions, inform travelers of construction zones and congested traffic conditions ahead, and propose alternative routes.

In contrast, **vehicle-to-vehicle (V2V)** communications provide direct information between neighboring vehicles. This allows direct data sharing between vehicles. V2V communications are being more versatile and cost efficient than applications requiring road side equipment. V2V helps to improve traffic flow and vehicle stability, efficiency of infrastructure

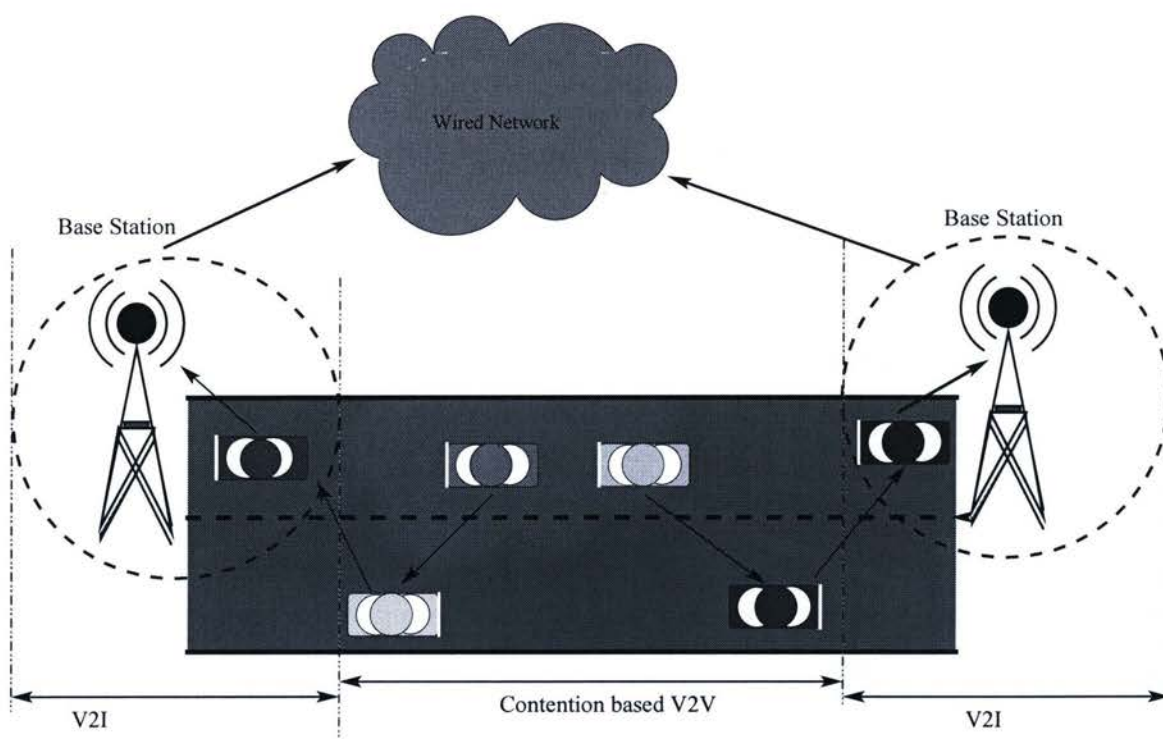


Figure 1.1: Model for V2V and V2I communication



utilization and reduce air pollution. Fig.1.1 illustrates these two types of communication.

### 1.1.2 Applications of Vehicular Communication System

The applications of inter vehicular communication system includes,

- **Data Dissemination:** The manner in which pertinent information is disseminated throughout the vehicular environment is an important aspect of ITS and is critical to the successful operation of cooperative applications. Efficient and timely propagation of information among all vehicles is essential and highly dependant on the performance capabilities of the core communication platform and is more clearly described in [8] to provide “always on” connectivity for vehicles traveling at high speeds to help prevent accidents.
- **Cooperative Collision Warning (CCW):** This is an important class of safety applications that target the prevention of the vehicular collisions using V2V communications. The ultimate goal of the CCW is to realize the concept of “360 degrees driver situation awareness” [9], whereby vehicles alert drivers of impending threats without expensive equipment. The main application of the CCW is to identify the abnormal vehicles in the emergency situation. Disseminate actively emergency warning messages which include the geographical location, speed, acceleration and moving direction of that abnormal vehicles to all the neighboring vehicles. The CCW applications also include the forward collision warning, lane change assistance and an electronic emergency brake light.
- **Cooperative Sentient Vehicle:** ITS utilizes inter vehicle cooperation without human assistance to provide autonomous vehicle navigation from a given source to a pre-determined destination. The resultant sentient vehicles are context-aware autonomous cars that form cooperative “flotillas of peers using mobile *ad hoc* network environments (MANETs)”. Each vehicle needs to build a real-time perception of its surrounding environment within some bounded error to make informed decisions regarding its next

move. The cooperation between vehicles is critical to avoid collisions, to follow a leading vehicle and to travel safely. The vehicles must obey external traffic signals and give way to pedestrians who cross the road by sensing their presence. The key research challenges include communication model, routing protocol, context-awareness, end-to-end Quality-of-Service (QoS) and fail-safety [10] for cooperative sentient vehicles.

- **Platooning:** This is the technique of coupling two or more vehicles together electronically to form a group. Platoon is defined as a group of vehicles heading in the same direction. The benefit of this technique is that the total headway for vehicles going in the same direction can be reduced, and the capacity of the road would consequently be increased [3], [11].
- **Adaptive Cruise Control:** Here vehicles are equipped with a V2V communication system which allows a vehicle to automatically adjust its speed to that of a vehicle ahead in order to improve the comfort of the driving task and avoids emergency accidents [12]. The range of information is extended to other vehicles than the vehicle just in front, yielding preview information that can be used for automated anticipatory braking or acceleration actions. It is meant that the follower vehicles can react sooner on, for example a braking action of a vehicle further in front, even before its direct predecessor starts to brake. This has as effect that the follower vehicle does not have to brake as severely compared to the case without communication. In this way, so called shock wave effects can be reduced, which has a positive effect on the traffic flow.
- **Automated Highway Systems (AHS):** The concept of AHS is based on the belief that an appropriate integration of sensing, communication and control technologies placed on the vehicle and on the highway can significantly decrease the average longitudinal spacing between vehicles and hence lead to a large improvement in capacity and safety without requiring a significant amount of additional right-of-way which improves the efficiency of automatic control systems for individual vehicles through V2V communication [13], [14].



### 1.1.3 DSRC Wireless Technology

The rapid evaluation of wireless data communication technologies witnessed, recently, creates an ample opportunity to utilize Dedicated Short Range Communications (DSRC) [15] for vehicular applications. DSRC is a proposed variant of IEEE 802.11a and the 802.11 MAC. It is targeted to operate over a 75MHz licensed spectrum in the 5.85 and 5.925GHz band allocated by the Federal Communications Commission (FCC) in 1999 for the support of low-latency vehicular for operation within high-speed vehicular environments [16]. Commercial applications are also allowed to operate in this spectrum, as long as they do not interfere with its primary purpose. DSRC related research is currently undergoing joint development by government and industry partners for adoption as the de-facto standard for communications-based vehicular safety and non-safety applications. In general, the DSRC physical layer is adapted from the IEEE 802.11a standard using orthogonal frequency division modulation, and the DSRC medium access control layer is adapted, in part, from the original IEEE 802.11 and IEEE 802.11e QoS [17] standards.

Table 1.1: Wireless Communications Alternatives

Application Category	DSRC	WiFi	WiMAX
V2V communications based applications	B	-	-
R2V active safety	B	-	-
Highway information(secure payment transaction)	A	A	-
Electronic payments(location-based warning control)	A	A	A
Active High way information	A	A	A
Driver information (location-based or tracking services)	A	A	A
Fleet management	A	A	A

Table 1.1 lists categories of applications that are currently being considered and the various communication standards that enable these applications [18]. In Table 1.1: 'A' refers alternative communications available and 'B' stands for best suitable communication technology. Different applications have different choice of selecting an appropriate communication

standard to avoid large communication delays and frequent communication failures. For V2V and V2I communications, DSRC is currently viewed as the best choice due to a long communication range (1000m), 27Mbps data transfer rate, and low likelihood of interferences. Long-range communications is possible through WiMAX to provide general information to the drivers. For shorter communications WiFi or DSRC standards are suitable (*e.g.*, non-safety applications).

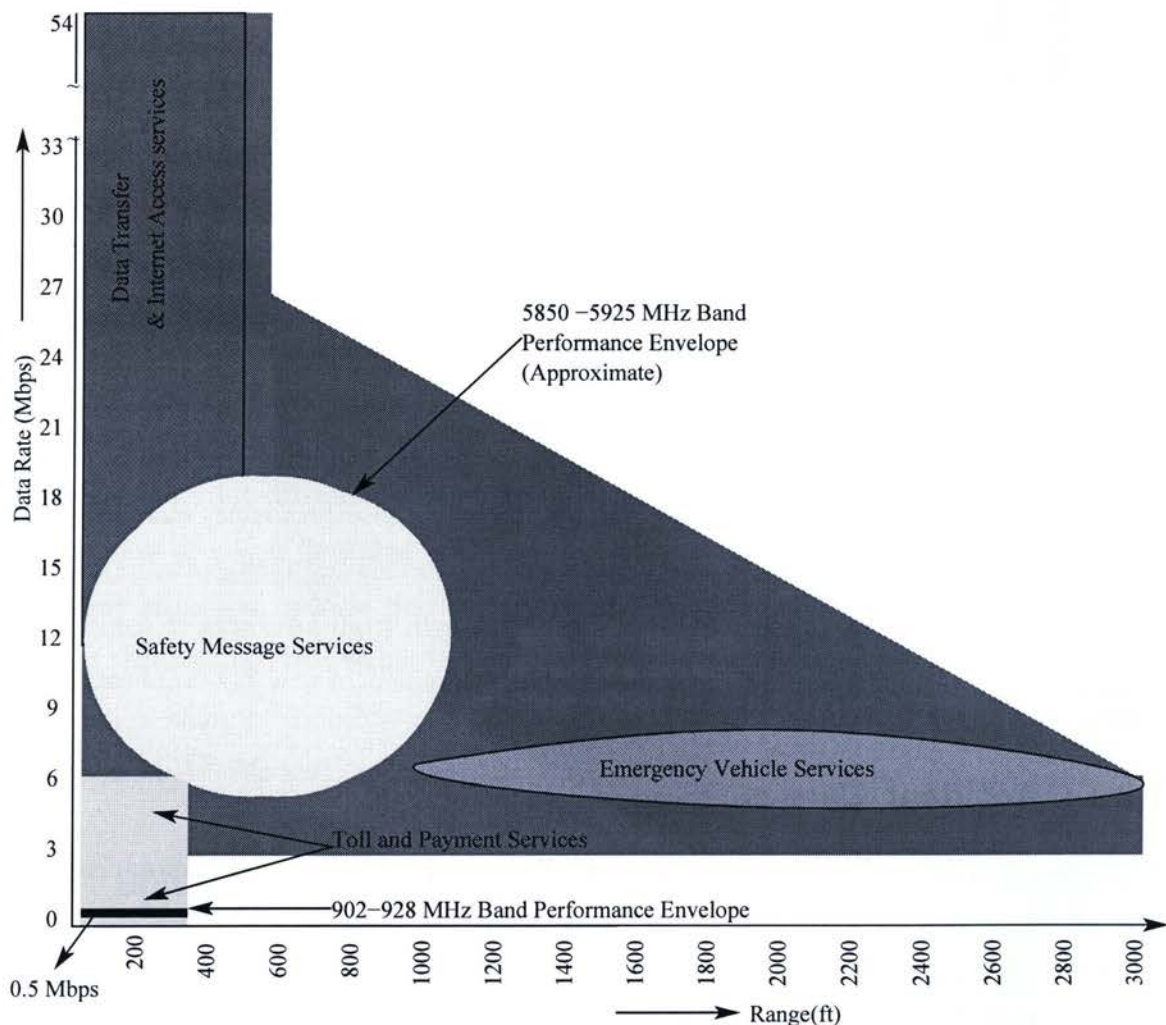


Figure 1.2: Data rate versus range of DSRC

As shown in Fig.1.2, the performance envelope of the 5.9GHz band is designed to cover a



wide variety of applications not supported by the older 915 MHz standard. The new standard specifically extends the effective communication range from 30m to 1000m, when appropriate transmit power is used. This range allows long-range ITS applications. Data rates are further increased from 0.5 Mbps to a range of 6 to 27 Mbps. This increase enables the development of data-intensive real-time ITS applications in addition to providing opportunities for high-speed in-vehicle Internet services [16].

## 1.2 Motivation

Recently, vehicular active safety applications have attracted considerable research interest in ITS, due to the potential of saving tens of thousands of lives and hundreds of billions of dollars per year in the US alone. In 2002, these accidents accounted for \$230 billion in damaged property, 2,914,000 nonfatal injuries, and 42,850 deaths. Every year, 6 million traffic accidents occur in the United States [19]. In addition, increasing urban congestion in the 85 largest cities in the nation is now estimated to account for \$63 billion in lost productivity time and wasted fuel consumption [20]. In response to these problems, increasing efforts are being directed to improve the safety and efficiency of existing transportation networks. In recent years, these tasks have received significant help from advances in computer and communication technologies and the subsequent development of new ITS applications.

### 1.2.1 Accident Causes

A quarterly review prepared by the Japanese ITS committee [21] shows that approximately 75% of traffic accidents are caused by driver behavior immediately before the accident. Fatalities have been on a downward trend since 1990, but accidents and casualties have continued to rise. Fig.1.3 shows a breakdown of the fatality causes and fatality rate in traffic accidents, the most common cause is late recognition around 47% of accidents, errors in judgement causing 16% of accidents and errors in operation another 12%, due to speeding, drinking and driving, etc. another 25%.

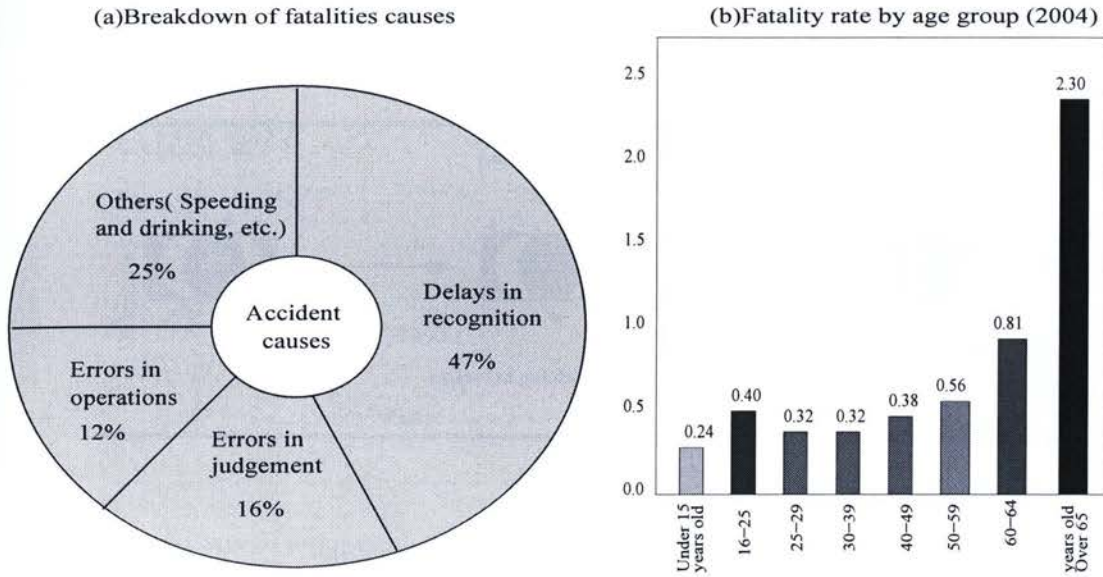


Figure 1.3: Breakdown of fatalities causes and fatality rate in traffic accidents by age group

In addition, looking at traffic fatality rates by age group from, the fatalities rate is markedly higher for drivers of age group 65 and older as shown in Fig 1.3.(b). This is not only because of vision declining with age, but also because of slower decision time. In an emergency situation, vehicle drivers rely on the brake lights of the vehicles immediately ahead of them to decide whether or not to apply their own braking system in order to avoid a collision or chain of collisions in a platoon. The typical time for a driver to stop a vehicle safely is around 0.75s to 1.5s [22].

## 1.2.2 Solution to Avoid Accidents

In order to reduce the driver mistakes in traffic accidents, it is therefore necessary to provide prior knowledge about error recognition, alarm and driving assistance functions during the vehicles operation. The intelligent cooperative collision warning system is an important class of safety applications that target the prevention of vehicular collisions and provide real-time alerts about hazards and accidents. The cooperative collision warning systems use

Speed= 32m/s(72mph)  
 Deceleration=4m/s/s  
 Driver reaction time=1.5s

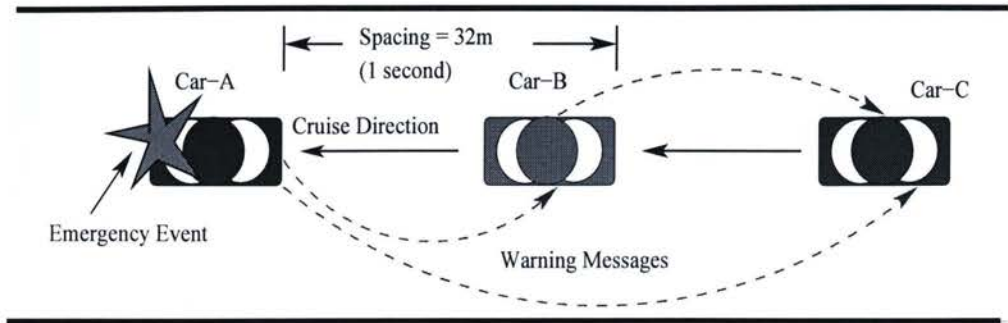


Figure 1.4: Model for chain car collisions.

V2V and V2I communications for wireless vehicular networks to improve the level of safety, efficiency, and information availability by the periodic broadcast of short messages bearing status information (*i.e.*, accurate estimations of location, velocity and control settings).

In general, when an emergency event occurs, there are usually a group of vehicles affected by the abnormal situation. Fig.1.4 shows a model for the chain collisions in a platoon. All cars are cruising at a steady state speed of 72mph (32m/s), and an inter car separation of 1 second (32m). If car-A has met an accident or become an abnormal due to the mechanical failure or by loosing its control over speed, immediately warning messages from Car-A has to be disseminated to all other following neighboring vehicles(*i.e.*, Car-B and Car-C) in order to avoid the chain collisions in the platoon.

If drivers react only on visual information as shown in Fig.1.5(a), all three cars in the platoon end up in chain collision. For the same platoon, the effects with the cooperative collision avoidance with wireless communication is illustrated in Fig.1.5(b). In this case, upon meeting the emergency event Car-A starts sending wireless warning messages to all cars behind it. Upon reception of warning messages, the driver reacts by decelerating even if the brake light in the car ahead is not lit to avoid collision. Similar platoon scenarios can also be considered and in general, using vehicle communication to send safety messages has



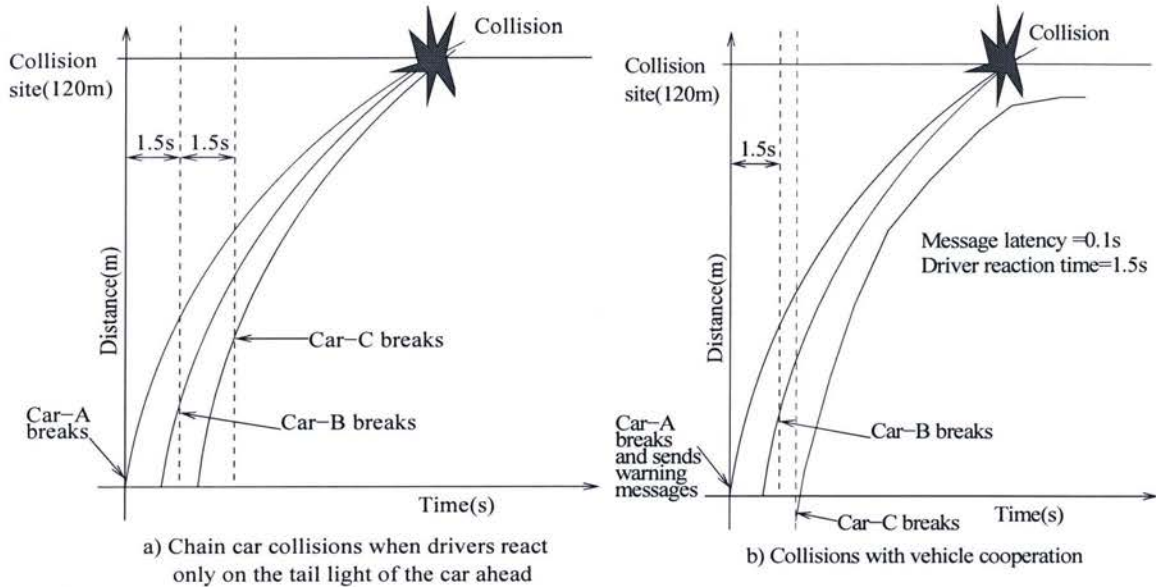


Figure 1.5: Without and with vehicle communication collisions

been shown significantly reduce the probability of collision with a platoon [11], [3].

Fig.1.6 illustrates the importance of disseminating warning messages. A car is stalled on the road around a blind corner. By the time the driver of the following car sees the abnormal vehicle, it may be too late to react in order to avoid collision. If a driver receive forewarned messages containing position information prior to the emergency event occurs, he or she can take appropriate action in time to avoid collision. Both of these scenarios exemplify the importance of disseminating position information. In addition, these examples highlight the idea that when vehicles are equipped with dedicated short range communication devices, drivers can gain an expanded awareness of their surrounding, which enables them more time to react to the potential road hazards.

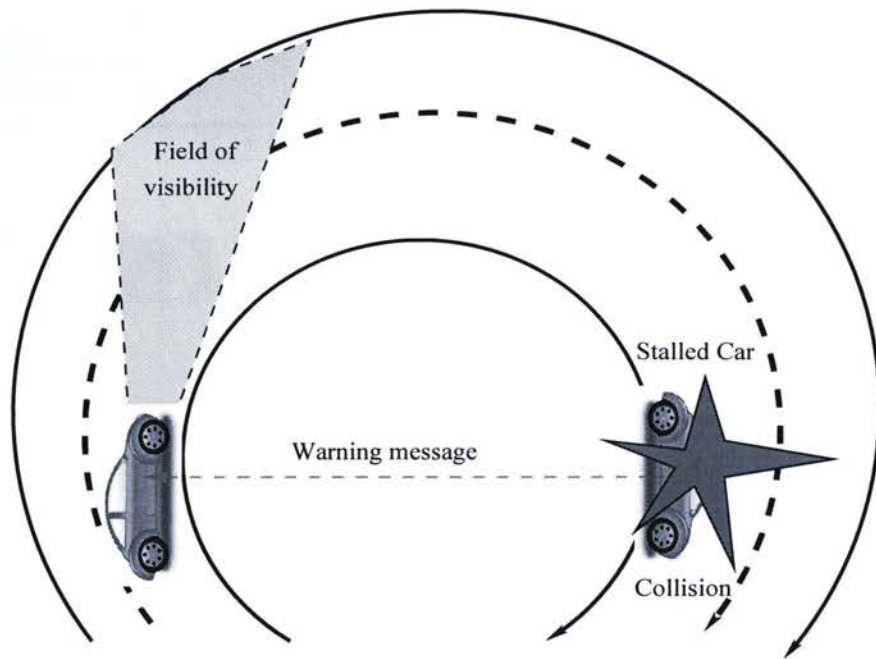


Figure 1.6: Collision at blind corners.

## 1.3 Current Technology

### 1.3.1 GPS

Currently, the widely used positioning techniques are global positioning systems (GPS). GPS uses 24 satellites which orbit the earth. At any time, at least four satellites are “visible” (i.e. a signal can be received from the satellite) from any point on the earth. Each satellite transmits a unique signal that can be used by a ground receiver. A receiver triangulates the signals received from 4 or more satellites to accurately determine the position of the receiver on the earth’s surface. This system has been used in vehicle navigation systems as well as dedicated hand held devices for some time, and now it is making its way into the Mobile Internet. The GPS system was originally developed and deployed by the United States for military purposes. Because of this, the signal which is currently transmitted by earth satellite is intentionally degraded via a process called Selective Availability (SA) to

prevent opposing forces from using the signal for military purposes. SA produces random positional errors which “drift slowly about within 100m radius circle centered on the true GPS receiver location” [23]. Later US government removed SA mask in May 2000. This means that GPS now can achieve around 5m-40m accuracy provided there is a clear view of the sky. Chip makers have now reached an increasing level of integration of GPS chips, and there are now very power efficient, low cost one-chip solutions available.

### 1.3.2 Assisted GPS

Relative GPS is one of the approach to improve the accuracy in position estimation [24]. Since SA is the systematic error, the error experienced by two receivers is the same. Thus, when the positions of two GPS receivers are examined, the calculated position of each receiver can vary from the true position by as much as 100m, but since each receiver’s position varies by the same amount and has the same direction, the relative position between the receivers can be determined quite accurately. In fact, sub-meter relative positions and centimeter-per-second relative velocities can be calculated [25]. Network Assisted GPS uses fixed GPS receivers that are placed at regular intervals of every 200km to 400km in order to fetch data that can complement the readings of the terminal. The assistance data makes it possible for the receiver to make timing measurements from the satellites without having to decode the actual messages. This assistance greatly reduces the time needed for a GPS receiver to calculate the location. Without the assistance information the Time-to-First-Fix (TTFF) could be in the range of 20-45 seconds. With assistance data the TTFF could be in the range of 1-8 seconds. The assistance data is broadcast around once each 1 hour. Existence of assistance data makes very little impact on the network. Assisted GPS [26] and differential GPS [27] can achieve an average accuracy of 3m to 10m in open flat areas. However, in reality, satellite signals are often disturbed or blocked when the vehicles are traveling through tunnels, under bridges and sky scrapers. Vehicles can also experience sustained GPS outages due to high solar activity, terrestrial interference and multipath fading.



### 1.3.3 Dead-reckoning System

In persistent GPS outages, vehicles can use dead reckoning systems to obtain position information [28], [25]. The dead reckoning systems can accurately determine its GPS coordinates with a permissible error of less than 10m for approximately 30s outages if the vehicle is traveling at a speed of 60km/h [29]. This invention extends GPS coverage in an automotive environment without requiring direct interfaces to the vehicle's sensors in a unique and cost effective way. Since it removes all the required vehicle interfaces (except power), it produces a virtually portable navigation system with no installation requirements beyond that of the GPS receiver itself. It also removes the necessary "customization" of the navigation system to each particular vehicle. Fundamentally, the position of a vehicle is obtained by GPS receiver data augmented with a low cost gyro whereby the gyro accurately tracks the heading changes of the vehicle (in the absence of sufficient GPS information), and the GPS receiver includes an innovative algorithm for deriving speed information from Doppler measurements from just one or two GPS satellites. However, dead reckoning systems are prone to errors.

## 1.4 Limitation of Current Technology and Research Objective

Line-of-sight (LOS) between the object to multiple satellites is not always possible, therefore, GPS alone cannot be applied for vehicular safety applications in order to achieve higher accuracy in position estimates to avoid traffic accidents. The addition of radio-based ranging techniques in the absence of GPS signals can be applied as a promising technique [29]. Radio ranging techniques have a number of attractive properties. Received signal strength (RSS) is the least expensive to implement in the CCW systems. All that required is a wireless card to have access to the physical layer to interpret the RSS. Also, radio-based ranging techniques allow us to take full set of distance constraints between vehicles, therefore creating the potential to improve upon accuracy of GPS. RSS and time-of-arrival (TOA) ranging

technologies are most suitable for vehicular communications. Regardless of the radio-ranging estimation techniques used, the distance measurements are inherently noisy due to a number of factors, including the limitations of measurement device, multipath fading, shadow fading, and non-line-of-sight (NLOS) errors. In addition, vehicle mobility complicates the situation. Therefore, accurate positioning of vehicles cannot solely depend on inter-vehicle distance measurements using one of the aforementioned techniques. In Fig1.7, satellite signals are blocked due to high buildings by introducing NLOS in the measurements. As a result, vehicle deviates from its true position.

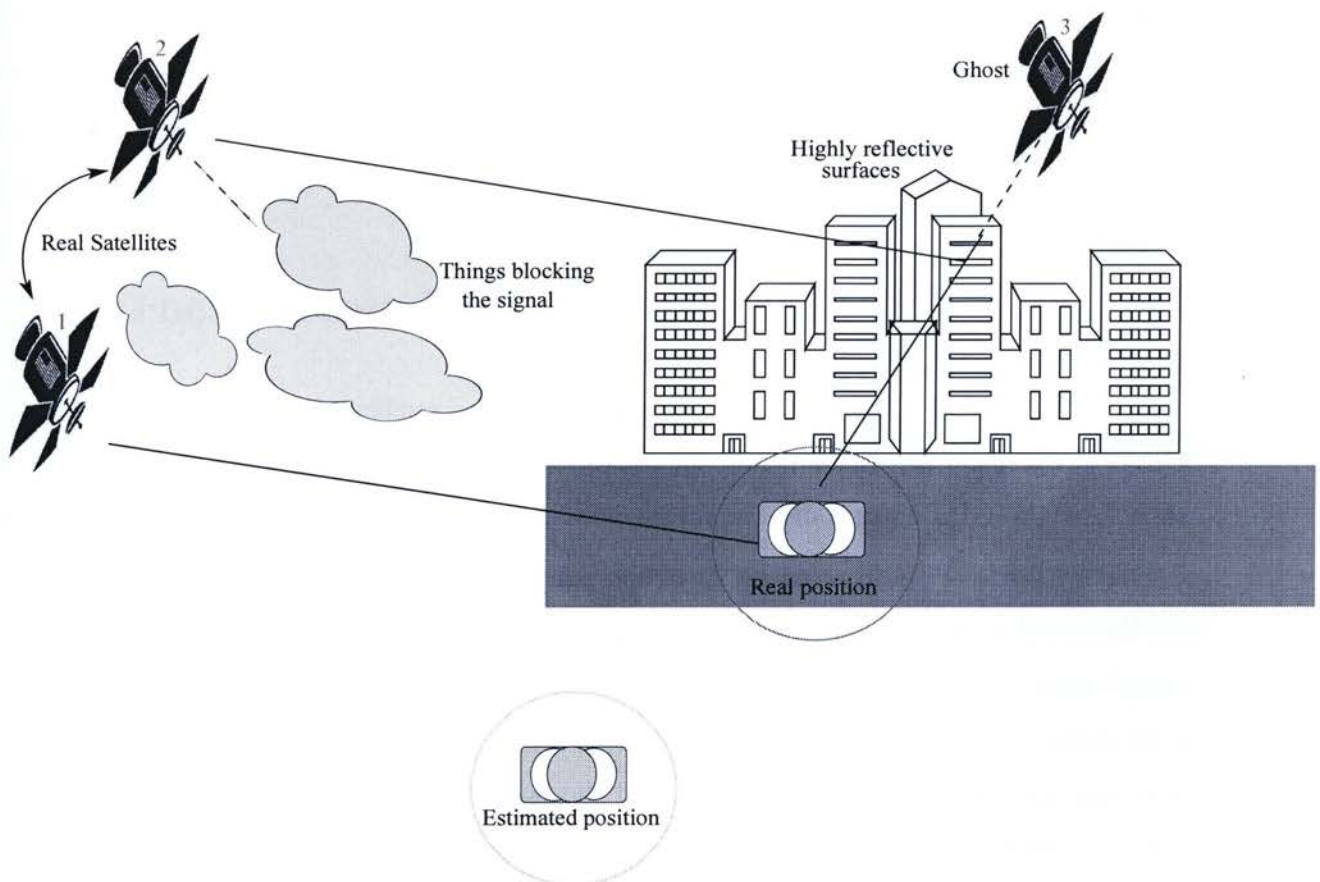


Figure 1.7: Importance of position estimation

In summary, the main purpose of this thesis is to show that the accuracy and reliability



of position estimates provided by existing GPS can be improved by making use of inter-vehicle distance measurements taken from a radio-based ranging technique. One of the severe estimation error is due to NLOS. NLOS can be mitigated by applying biased Kalman Filter on the range measurements. For our algorithm these inter-vehicle distances are measured from using one of the radio-based ranging techniques. Our algorithm includes ‘N’ number of vehicles at unknown random distinct positions in some physical region along a section of road. Our objective is to establish an accurate map of positions for neighboring vehicles in the persistence of GPS outages. GPS outages can be possible in multipath environments where NLOS component is introduced to the true range measurements. These position estimates mainly depend on two factors: (i) preprocessed inter-vehicle distances (range data is processed from biased Kalman filter); (ii) road constraints (from the fact that the vehicle uncertainty is more in the direction of road than the uncertainty in the direction opposite to the road).

## 1.5 Thesis Objectives

Given the problem description from the previous section, the objective of this research is to show how the GPS can produce accurate position coordinates with the addition of radio-based ranging techniques.

We implement the biased Kalman filter for vehicular networks where vehicle mobility complicates the case. Among vehicles, noisy measurements can be misinterpreted as an observed motion and the effects of fading become prevalent for a road topology. Vehicles on the road are not uniformly distributed and the positions of the vehicles are not fixed. We consider the problem of NLOS identification and mitigation for vehicular communications in the absence of GPS signals to smooth the range data between randomly selected vehicles. A simple hypothesis test, based on standard deviation of the measured noise, is applied to distinguish between LOS and NLOS range measurements. If measurements contain NLOS error, then NLOS must be mitigated before position estimation takes place for accurate

results. NLOS error correction is possible by applying the biased Kalman filter instead of the unbiased Kalman filter where it can mitigate unexpected high erroneous NLOS data. IEEE 802.15.3a Ultra Wideband (UWB) model parameters are applied to model LOS and NLOS environments between vehicles for short-range communications [30].

These preprocessed range data is applied to the Extended Kalman Filter (EKF) along with road constraints to measure accurate position of vehicles. Cooperatively sharing range data among neighboring vehicles on a road can significantly improve position estimates even under multipath (NLOS) conditions. Simulation results show that the biased Kalman filter can easily track and effectively smooth the positively biased NLOS noise in the measured range data to mitigate NLOS errors and maintain high accuracy in the estimated range data. Position estimates can be improved with the implementation of road constraints along with smoothed inter-vehicle range data.

## 1.6 Thesis Contributions and Outline

### 1.6.1 Thesis Contributions

The main contributions of this thesis are described below:

- **Inter-vehicle range smoothing for various noise levels:** The main novel contribution of this thesis is the algorithms applied to mitigate NLOS in the range measurements in the persistence of GPS outages which are directly applicable to vehicular networks. The novelty of the work is based on the received signal strength. If the signal arrives stronger the measurement error decreases by improving accuracy in the estimated range data (refer Chapter 3 and Chapter 4).
- **Non-linear filter for position estimation:** Thesis is further extended to find the accuracy in position estimates by applying non-linear filter. This non-linear filter makes use of inter-vehicle distance measurements, created using radio-based ranging

techniques, to allow a vehicle to drive an accurate and reliable position estimates under LOS and NLOS situations (refer Chapter 3).

- **Road Constraints :** We focussed on the effect of road constraints, because, the vehicle uncertainty is more in the direction of road than the vehicle uncertainty in the direction orthogonal to the road (refer Chapter 3). We apply road constraints along with smoothed inter-vehicle range data to estimate position of a vehicle in order to achieve accuracy in estimates.
- **Error Models :** Studied the effects of Additive white Gaussian noise distributions on the performance of our algorithms. Applied a compatible NLOS model for inter-vehicle communications for the short-range safety applications for MATLAB simulations (refer Chapter 4).

### 1.6.2 Thesis Outline

This thesis is organized as following:

- Chapter 2 covers background information on position estimation techniques. This background involves a discussion of accurate position estimation and NLOS mitigation methods applied to smooth inter-vehicle range measurements for vehicular CCW safety applications. This chapter also provides a basic tutorial on radio ranging techniques and common statistical models used to identify or characterize the techniques.
- Chapter 3 presents an analysis on the inter-vehicle distance and position estimation algorithms. The study includes inter-vehicle distance measurement model, NLOS model and non-linear position estimation algorithms. This Chapter analyses the unbiased Kalman filter and biased Kalman filter to smooth range data. Nonlinear least square method and Extended Kalman filter are discussed to find vehicle accurate position estimates.



- Chapter 4 provides the simulation discussion of each algorithm applied. Here performance metrics are listed, as well as provided insights into the run-time complexity of each of the algorithms. This Chapter provides complete discussion on algorithms with simulation results and compared the accuracy of applied algorithms with the previously proposed ones. Also, the study includes the performance of our algorithms in all different operating and environmental conditions.
- Chapter 5 concludes our work and summarizes the future directions of the work.



# Chapter 2

## Background

The objective of this chapter is to provide some related work on the problem we are trying to solve and discuss some previous works related to ours.

### 2.1 Related Work

Radio based ranging techniques have a number of attractive advantages. For example, radio based ranging techniques allow us to take advantage of the full set of distance constraints between vehicles, therefore creating the potential to improve upon the accuracy of position estimates. The idea of using a radio based ranging technique to provide range estimation, so that node estimation can be performed is not new. Recently, this problem has been tackled by researchers for stationary sensor networks [31]. Instead of summarizing and analyzing each of the previously proposed algorithms in detail, in this section, we will mainly focus on providing an overview of the techniques and methods that are closely related to our work.

Ranging and positioning accuracy could be limited by the presence of multipath fading, non-line-of-sight (NLOS) conditions, and extra propagation delay, due to the presence of obstacles. Thus, the accuracy of the estimated position depends on the accuracy of the range measurements. In a dense urban environment there may not always be a direct path between the vehicles. Due to reflection and diffraction, the range measurements tend to

be positively biased, which is known as NLOS error. This problem has been recognized by many researchers as a “killer issue” for accurate ranging and positioning [32]. Therefore, the NLOS problem must be taken into consideration. The NLOS error dominates the standard measurement noise, and tends to be the main cause of the error in the range estimation. The position estimation error linearly increases with the distance error [33].

There are many positioning approaches established for wireless nodes when LOS exists between the transmitter (Tx) and the receiver (Rx). A method of positioning neighboring vehicles is proposed along with the triangulation to determine the relative position coordinates of vehicles in [29]. The inter-vehicle distance measurements made using the one of radio-based ranging technique. Here the position estimation may become very inaccurate since the distance measurements are noisy.

Authors in [34] proposed a TDOA error minimizing localization method to estimate the location of group of blind nodes in LOS and NLOS propagations for fixed reference node positions. This is more appropriate for cellular mobile networks where the base stations are at fixed locations but not suitable for the inter-vehicle communication where the vehicles are moving randomly.

To improve the accuracy of the ranging and positioning of the vehicles, NLOS mitigation techniques must be applied. A polynomial fitting was applied to all available measured range data to mitigate NLOS effects [32]. A method is proposed to correct and detect NLOS error. Authors also showed that it is possible to detect a NLOS environment by using the standard deviation of the measurement noise and history of the range measurements. This is not accurate due to the time delay in total data gathering. A different approach is presented in [35], which shows that if the NLOS measurements are unrecognizable, it is still possible to correct the position estimation errors, if the number of range measurements is greater than the minimum required. This algorithm is referred as Residual Weighting Algorithm(RWA).

Two categories of NLOS mitigation techniques have emerged to render the localization without errors. First is residual weighting [35] and the second is called the LOS identification methodology [32], [36]. The former is to minimize the effect of NLOS, the latter focusses



on the identification of NLOS and discards them from positioning. Even though the LOS signal is present, it may not be the dominant path in the multipath environment. It has been shown that the performance of the positioning scheme is a function of signal-to-noise ratio (SNR) of the received signal [37]. The greater the SNR of the received signal, the smaller the positioning error. Therefore, it would be advantageous to be able to perform localization under the multipath environment with as few reference devices as possible while maintaining a good performance bound by using the paths of the received signal that have a maximum SNR even though they may not be the LOS path.

A modified Kalman filter algorithm is presented in [38] to estimate NLOS bias for UMTS mobile positioning. The estimation of range bias in the proposed algorithm improves the performance of location tracking in NLOS environments. NLOS mitigation with biased Kalman filter for range estimation in Ultra wideband (UWB) systems for wireless sensor networks was proposed in [39], where the mobility of users had not been considered.

In [40], the author described a distributed, linear-time algorithm for localizing sensor network nodes in the presence of range measurement noise and demonstrates the algorithm on a physical network. They also introduced the probabilistic notion of robust quadrilaterals as a way to avoid flip ambiguities that otherwise corrupt localization computations. They formulated the localization problem as a two-dimensional graph realization problem, given a planar graph with approximately known edge lengths, recover the Euclidean position of each vertex up to a global rotation and translation. This formulation is applicable to the localization of sensor networks in which each node can estimate the distance to each of its neighbors, but no absolute position reference such as GPS or fixed anchor nodes is available. Robust quads algorithm supports noisy distance measurements, and is designed specifically to be robust under such conditions. It is fully distributed, requiring no beacons or anchors. It positions each node correctly with high probability, or completely mislocate. Thus, rather than produce a network with an incorrect layout, any nodes with ambiguous locations are not used as building blocks for further positioning. Cluster-based localization supports dynamic node insertion and mobility.



In [41], GPS free positioning algorithm has been proposed in which each node uses the distances between the nodes to build a relative coordinate system. Range between the nodes can be obtained by using TOA method. As GPS is not used to know their geographic positions, relative positions of the nodes can be calculated with respect to the network topology. One most limitation to this algorithm is a large number of messages to be exchanged between nodes by increasing algorithm complexity. As a result, this algorithm is not suitable for vehicular networks where vehicle mobility changes frequently.

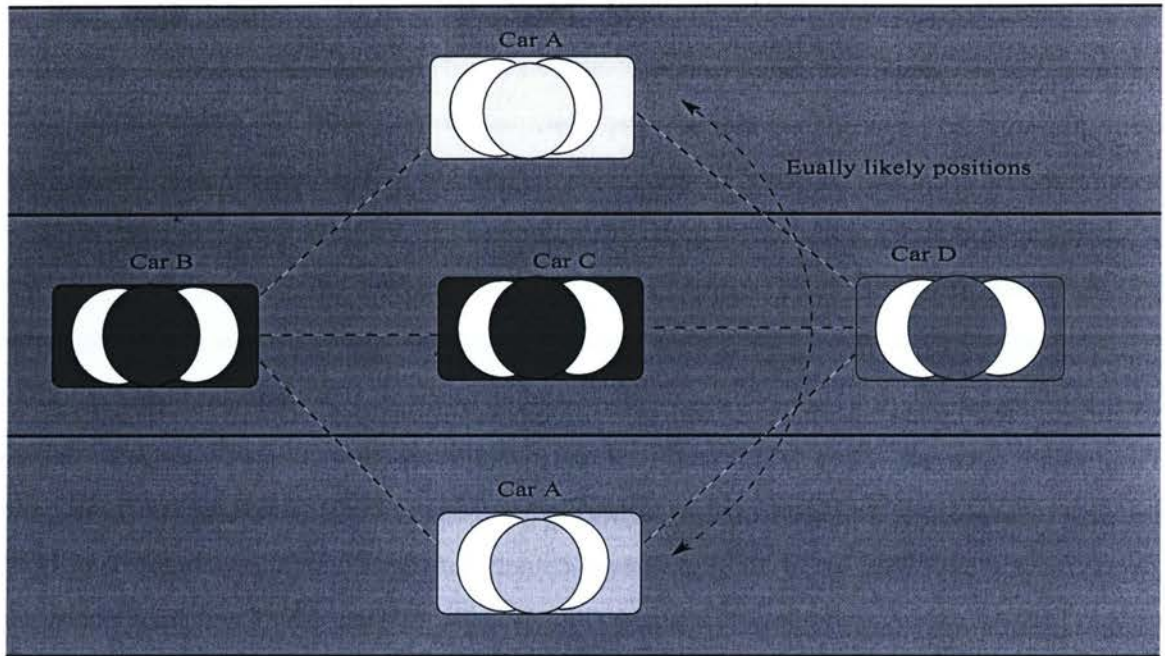


Figure 2.1: Ambiguity in vehicle positioning

In [42], an improved version of [41] was derived to tackle above problems, their algorithm improves scalability and convergence times of nodes.

The authors proposed fixed radio beacons distributed over given geographical regions, as well as those that rely on known fixed positions coordinates of some nodes in the ad-hoc network [43], [44]. However, due to highly dynamic nature of the cooperative collision warning application, these relative positioning techniques cannot be used for vehicular environments.

In [29], authors created a method of localizing neighboring vehicles based on radio-range measurements. They proposed a novel system solution for achieving accurate estimation of relative positions of all neighboring vehicles based on real-time exchange of their GPS coordinates during persistent GPS outages. Their algorithm involves integration of three techniques. a) Clustering technique, which establishes master/slave associations to exchange information between vehicles. b) Ranging technique, which stores inter-vehicle distance information between vehicle pairs, share and update this distance information for every time step. c) Positioning technique, which uses inter-vehicle distance tables based on their priority, applies triangulation method to establish individual position coordinates. The main limitation for this work is to maintaining master/slave relations for highly uncertain vehicular environments. Here, maintaining the relation between the vehicles becomes difficult and complexity increases with large number of vehicles. Also, it is difficult to ignore noise in distance measurements due to multipath condition. Another main draw back of the algorithm is to have two equally likely positions for a single vehicle with triangulation method as shown in Fig.2.1. Therefore, vehicles may have two possible same set of distance constraints.

In [45], a novel cooperative-vehicle position estimation algorithm was proposed. This algorithm proves that the reliable and accurate position estimates can be achieved by adding extra information to the above mention algorithms. Their algorithm includes signal-strength-based inter-vehicle distance measurements, GPS initial positions, vehicle kinematics and road maps to estimate the relative positions of vehicles in a cluster. The main limitation to this algorithm is noisy inter-vehicle distance measurements in multipath environments.

Our proposed algorithm can work effectively under multipath conditions (*i.e.* in the persistence of GPS outages). Algorithm allows inter-vehicle range data to smoothing and preprocessing under NLOS conditions. For real-time vehicular environments, an accurate and reliable position estimate is possible with the proposed algorithm.



## 2.2 Types of Radio Ranging Techniques

One of the fundamental steps for positioning is accurate ranging, *i.e.*, an action of estimating the distance between the transmitter and the receiver. There are several main causations following for the positioning error of transportation system: the sender end error; the space propagation error caused by wireless link delay; the receiver end error. In addition, there are NLOS influence, the noise interference, the synchronism among the reference nodes and the error from solving equations *etc.* to reduce the accuracy of the estimation.

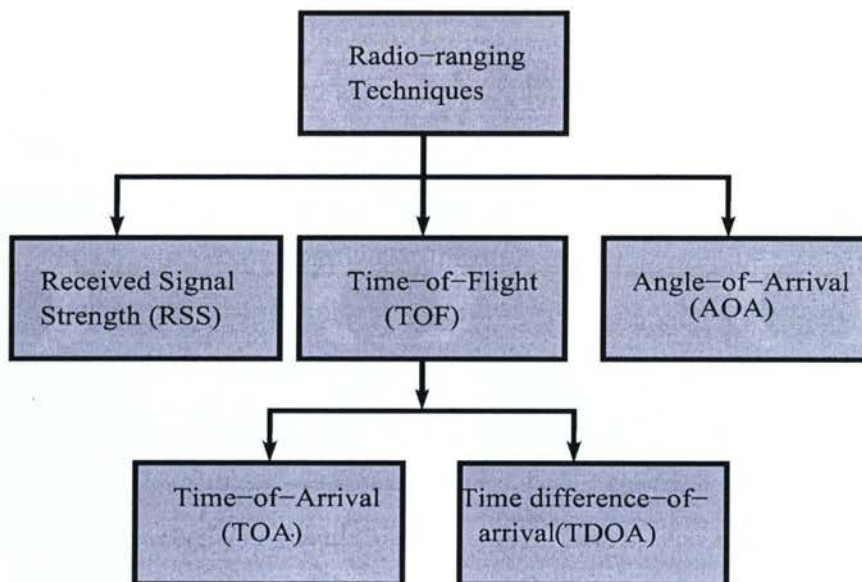


Figure 2.2: Radio-ranging Techniques

There are four common radio-based ranging techniques applied for position estimation [46]. These techniques are illustrated in Fig.2.2, Received Signal Strength (RSS), Time Of Arrival (TOA), Time Difference Of Arrival (TDOA) and Angle Of Arrival (AOA) [47].

## 2.3 Received Signal Strength (RSS)

### 2.3.1 Introduction

Distance is measured based on the attenuation introduced by the propagation of the signal from Tx to Rx [48]. Among the above techniques, RSS is the least expensive to implement in the cooperative collision warning systems in the vehicular communications as it uses known mathematical channel path loss models, therefore, special hardware is not required [49]. Distance can be extracted by using free-space large scale path loss models between the vehicles for inter-vehicular LOS distances of less than 100m. The primary source of error for RSS-based position systems is multipath fading and shadowing. Variations in the signal strength may be as great as 30-40dB over distances in the order of a half wave length. Signal strength averaging can help, but low-mobility vehicles may not be able to average out the effects of multipath fading, and there will still be variability due to shadow fading such as the attenuation of a signal due to obstructions (furniture, walls, trees, buildings, and more).

RSS is defined as the voltage measured by a receiver's received signal strength indicator (RSSI) circuit. RSS is equivalently known as measured power (*i.e.*, the squared magnitude of the signal (*e.g.*, RF, acoustic, UWB, or other signals) strength). In free space, signal power decays proportional to  $d^{-2}$ , where  $d$  is the distance between the transmitter and receiver. For real-world environment, the mean received power for an obstructed channel decays proportional to  $d^{-n_p}$ , where  $n_p$  is the path-loss exponent ( $n_p$  varies between 2 to 4 depending on the environment).

RSS-based range estimates have variance proportional to their actual range. RSS is most widely used in high-density sensor networks. Vehicle mobility and unpredictable variations in the channel behavior can occasionally lead to large errors in distance evaluation. Thus, the RSS technique alone is not accurate method, and its adoption is confined to the applications that require coarse ranging.



## 2.4 Time Based Ranging Techniques

TOA and TDOA are the time-based ranging techniques. Distance can be extracted from the time of arrival of the signals or time difference of arrival of the signals. These require high-resolution timing measurements, accurate real-time clock synchronization among nodes and LOS propagation conditions. TDOA has been a favorite for land-based positioning systems and TOA has been for space-based positioning systems [51]. Although both of them rely on essentially the same measurements (TOA pseudo ranges and TDOA pseudo ranges can be converted to each other without ambiguity) and are proven to be equivalent [52], questions remain on their performance in practical situations where imperfect weights are used to calculate position solutions. A number of these techniques have been proposed in the literature [53], [54] for various ranging applications. However, all of them work in a controlled environment and require high-resolution timing measurements, accurate real-time clock synchronization among nodes and line-of-sight propagation conditions. Operability of these techniques is severely impaired in the presence of multipath interference and positioning becoming difficult if the circles or hyperbolas do not intersect in a single point due to timing measurement errors. In such cases, position can be accurately measured using linear least squares method [55].

### 2.4.1 Time of Arrival (TOA)

For time-of-arrival (TOA) method, the time of transmission, plus a propagation-induced time delay between transmitter(Tx) and receiver (Rx) is measured. Distance information is extracted from the propagation delay between Tx and Rx. This time delay can be used to find the distance between nodes since the distance is equal to the time delay multiplied by light velocity. This method works well with high resolution time measurements where there is a LOS between targets. However, this method is susceptible to both multipath and additive white Gaussian noise. This technique can be classified into TOA one-way-ranging (TOA-OWR) and TOA two-way-ranging(TOA-TWR). The former requires perfect synchronization

between transmitter and receiver, while the later does not require synchronization between Tx and Rx. In TOA-TWR method, one sensor transmits a signal to the second sensor which immediately replies with its own signal. At the first sensor, the measured delay between its transmission and its reception of the reply is twice the propagation delay plus a reply delay internal to the second sensor. This internal delay is either known, or measured and sent to the first sensor to be subtracted. Fig.2.3 shows these two classes of ranging. A unique two-way reciprocal time of arrival based ranging technique was proposed in [56]. This technique provides high ranging accuracy of less than 3m even under multipath conditions. According to this technique, vehicles do not need to maintain clock synchronization among the transmitter-receiver vehicle pairs.

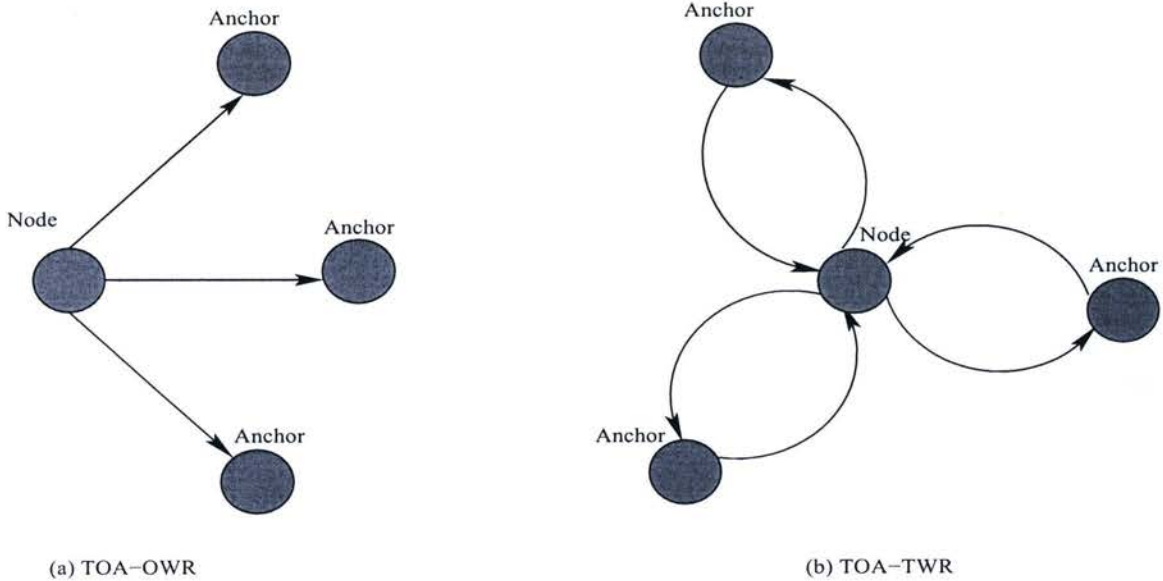


Figure 2.3: Two classes of TOA ranging techniques

The milestone of the TOA techniques is the receivers ability to accurately estimate the arrival time of the line-of-sight signal. This estimation is hampered both by additive white Gaussian noise and multipath signals.

Cramer-Rao bound(CRB) provides a lower bound on the variance of the TOA measurements in multipath-free channel. For a given bandwidth ( $B_W$ ) and SNR, time delay estimate

can only achieve a certain accuracy, given as

$$\text{var}(TOA) \geq \frac{1}{8\Pi^2 B_W T_s f_c^2 SNR} \quad (2.1)$$

where  $T_s$  is the signal duration in seconds and  $f_c$  is the center frequency. Equation 2.1 provides intuition about how the signal parameters like duration, bandwidth, and power affect on TOA estimates. This CRB on TOA variance is complementary to the bound that will be presented for location variance because the location variance requires TOA variance as an input.

## 2.4.2 Time Difference of Arrival (TDOA)

The difference between TOA's in several RXs is used to reconstruct a TX's position. This requires highly precise synchronization between RXs, but not precise synchronization between Tx and Rx's. However, ranging and positioning accuracy can be limited by the presence of multipath, NLOS conditions and extra propagation delay due to the presence of the obstacles (*e.g.*, heavy trucks, under the sky scrapers etc.). TDOA is suitable for V2I communications. The hyperbola is a set of points at a constant range difference from two foci. Each pair gives an hyperbola where unknown user lies. Position of unknown user is the intersection of all hyperbolas. This method is more accurate with higher bandwidth and greater transmit power. In LOS environments, TDOA systems can achieve greater accuracy than RSS systems. TDOA is best suitable for longer distances.

## 2.5 Angle of Arrival (AOA)

In AOA, the angles of the signals received from other vehicles are applied to extract range. This technique gives errors in the position estimation if the separation between vehicles is large, due to the severe interference between multipath components and the angle measurements. As the distance between nodes increases, the performance degrades, particularly in scenarios where line of sight is not possible, since the antenna array may lock onto a mul-



tipath component which would corrupt the angle measurements and introduce significant positioning errors. The AoA technique measures the angles between a given node and a number of reference nodes to estimate the location, this is done by means of antenna arrays, which increases the system cost [57].

The RSS based ranging technique and two-way reciprocal time of arrival based ranging technique can be applied in vehicular communications for LOS distances of 100m.





## Chapter 3

# Proposed Range and Position Estimation Algorithms

In the previous chapters, we provided the motivation for our work, and reviewed the relevant previously proposed positioning algorithms. In this chapter, we introduce a system model followed by NLOS model. A complete flow chart of the thesis work is presented in Section 3.3. Two algorithms that work well to mitigate NLOS from inter-vehicle range measurements are presented and compared. We also introduce two positioning algorithms to find the position of vehicles along with road constraints. First is nonlinear least square method of finding position in Section 3.5.1. Second positioning technique will be discussed in Section 3.5.2 (*i.e.*, extended Kalman filter).

### 3.1 Inter-vehicle distance measurement model

Vehicle range estimation problem can be formulated as follows. In the model, we consider a random number of vehicles at unknown random distinct locations at time  $t_i$ . The range measurement between vehicles is random and can be modeled as:

$$r(t_i) = d_T(t_i) + d_{NLOS}(t_i) + d_{AWGN}(t_i) \quad (3.1)$$

where  $r(t_i)$  is the total measured range at sampling time  $t_i$ ;  $d_T(t_i)$  is the true range;  $d_{NLOS}(t_i)$  is the range due to multipath, reflection and diffraction;  $d_{AWGN}(t_i)$  is the measurement noise, and modeled as additive white Gaussian random variable with zero mean and variance  $\sigma_v^2$ . In the LOS scenario only Gaussian measurement noise will be present and distance error due to NLOS equals to zero. Measurement noise can vary depending on the signal strength. The true distance between vehicles can be determined from the initial positions noted by the GPS and is determined as following:

$$d_T(t_i) = \sqrt{[x_N(t_i) - x_v]^2 + [y_N(t_i) - y_v]^2} \quad (3.2)$$

where  $(x_N(t_i), y_N(t_i))$  are the  $N^{th}$  vehicle coordinates at time  $t_i$  and  $(x_v, y_v)$  are the coordinates of the  $v^{th}$  vehicle, which is a randomly selected vehicle from among all neighboring vehicles.

## 3.2 NLOS model

In general, exponential, uniform, or delta random distributions are applied to model NLOS error in wireless communications. To model excess distance added due to the NLOS component, we used IEEE 802.15.3a UWB model parameters [30]. These parameters are compatible to model LOS and NLOS noise components in vehicular environments for short-range communications between vehicles [63]. Saleh - Valenzuela (S-V) model was a good fit to define LOS and NLOS scenarios in the vehicular communications. According to S-V model as shown in Fig.3.1, the multipaths arrive in the form of clusters rather than in a continuous form [59]. For a dense multipath environment, the estimation of the arrival time of the first ray of the first path ( $T_0$ ) can be directly related to the range data. Therefore, NLOS component can be modeled as an exponential distribution as follows [30]:

$$p(T_0) = \Lambda \exp[-\Lambda(T_0)] \quad (3.3)$$

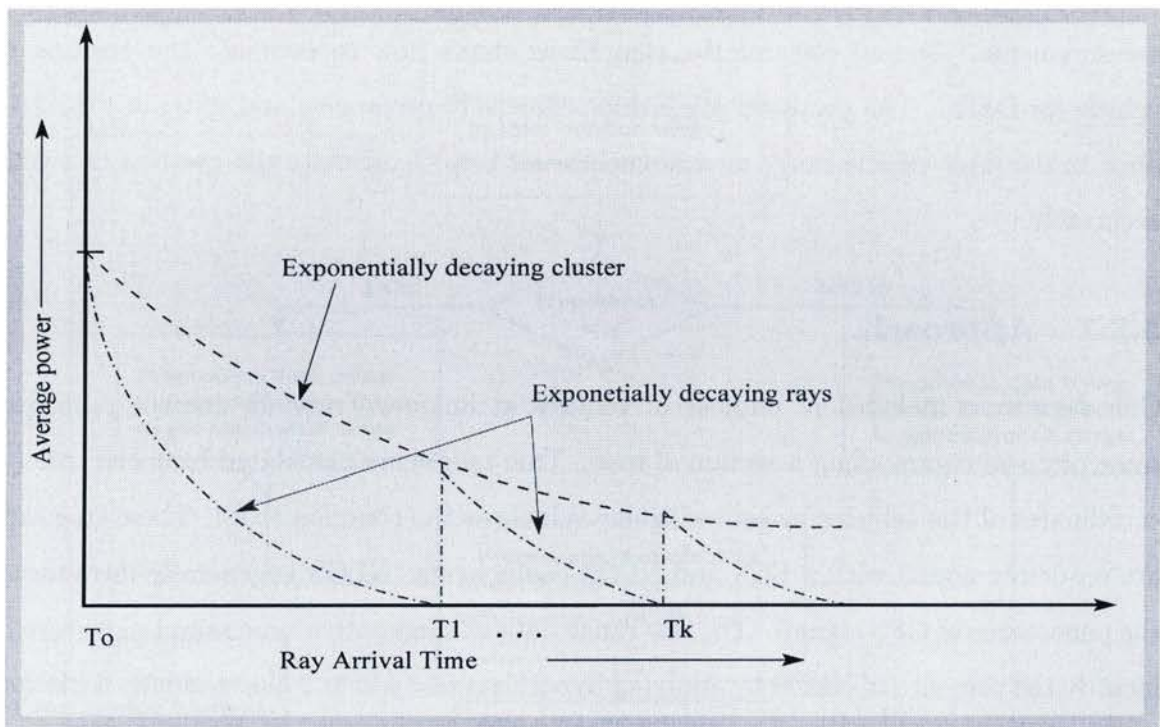


Figure 3.1: Schematic representation of NLOS model



where  $\Lambda$  is the cluster arrival rate,  $T_0 \times c$  gives an extra range added due to NLOS where  $c$  is the light velocity.

### 3.3 Flow Chart of Thesis Work

Fig.3.2 shows the complete structure of the thesis work. In this work we present two different classes of algorithms. First class of the algorithms solves the NLOS problem in the range measurements. Second class of the algorithms shows how to estimate the position of a vehicle for DSRC. The proposed algorithms effectively preprocess and mitigates the NLOS error in the inter-vehicle range measurements and help to estimate the position of a vehicle accurately.

#### 3.3.1 Approach

Our algorithms includes  $N$  number of vehicles at unknown random distinct positions in some physical region along a section of road. True ranges are calculated from the true (x,y) coordinates of the vehicles by centering one vehicle as the common to all. These true ranges are randomly added with a LOS and NLOS components. NLOS is generally introduced in the persistence of GPS signals. The raw range data at consecutive time samples are tested to identify the presence of NLOS by applying hypothesis test which is the standard deviation of NLOS measurements is much larger than that of LOS measurements. In the LOS scenario, unbiased Kalman filter output converges to the true range and position estimation gives quite accurate results. However, the unbiased Kalman filter cannot track the sudden changes in the variance due to positively biased NLOS, thus, it can cause severe position error. Our proposed biased Kalman filter can effectively preprocess the inter-vehicle range data for both LOS and NLOS and also effectively track and smooth the measurement noise variations due to signal strength fluctuations when vehicle mobility is high. These processed range data is applied to extended Kalman filter to estimate the position of a vehicle. Further, we consider the road constraints to improve the accuracy of the position estimates. Our algorithm

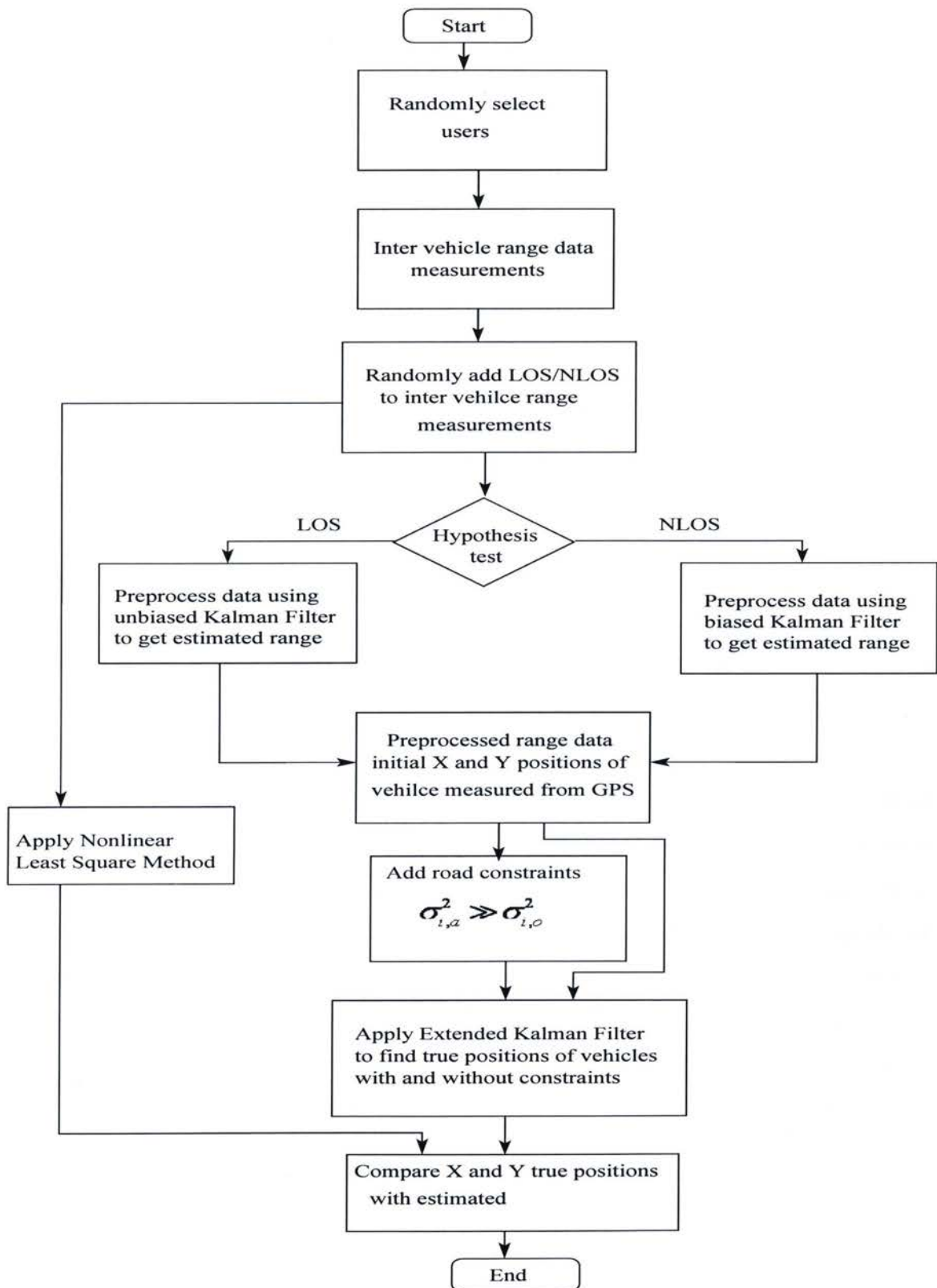


Figure 3.2: Flow chart of position estimation algorithm

performance is compared with the traditional Nonlinear Least Square method of finding positioning algorithm. Algorithms are developed to smooth range data and to estimate the position of a vehicle with and without NLOS. Unbiased Kalman filter and biased Kalman filter are applied to mitigate NLOS component to smooth range measurements. Results are compared with true results.

### 3.4 Algorithms applied to smooth range data

In this Section, we give a detail analysis of the unbiased Kalman filter and the biased Kalman filter algorithms [58]. These algorithms are developed to smooth range data and to mitigate the NLOS component from the inter-vehicle range measurements. A hypothesis test is also explained to identify which range measurements have NLOS component.

#### 3.4.1 Unbiased Kalman Filter (UKF)

In order to smooth the inter-vehicle measured range data, it is preferred to define a dynamic system with a state vector. The state of the system can be estimated for every time step to track the behavior of the system and to compare it with the true state by reducing the variance between the estimated and the true range. This means that the estimated state from the previous time step and the current measurements are needed to compute the estimate for the current state. The Kalman filter is one of the estimation algorithm which satisfies the above criteria and allows a recursive set of operations by processing data from the inter-vehicle distance estimates and incorporates this into a motion model with the addition of additive white Gaussian noise (AWGN) distribution to the measurement model. The model which we have used for distance estimation is defined as in [60]:

$$\mathbf{X}_{k+1} = \mathbf{A}\mathbf{X}_k + \mathbf{B}\mathbf{W}_k \quad (3.4)$$

where  $\mathbf{X}_k$  is the input state vector with the size of  $2 \times 1$  and defined as:



$$\mathbf{X}_k = [d_N(k) \quad \dot{d}_N(k)]^T \quad (3.5)$$

where  $d_N(k)$  is the true range;  $\dot{d}_N(k)$  is the first derivative of true range, which is the speed of the vehicle at time  $k\Delta t$ , with a sampling interval of  $\Delta t$ . For our model we chose  $\Delta t = 1s$ . The matrix  $\mathbf{A}$  in Eqn.3.29 relates the state at the current state  $k$  to the state at the future step  $k + 1$  with the size  $(2 \times 2)$ . The matrix  $\mathbf{B}$  with a size  $(2 \times 1)$  relates the control input and defined as:

$$\mathbf{A} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0 \\ \Delta t \end{bmatrix}$$

and  $\mathbf{W}_k$  is the process noise vector describing the mobility variations. We assumed that  $\mathbf{W}_k$  is an independent and additive white Gaussian random vector, with the following scalar covariance matrix:

$$Q = E\{\mathbf{W}_k \mathbf{W}_k^T\} = \sigma_w^2 \quad (3.6)$$

The measurement process is the output scalar and it can be written as:

$$\mathbf{Z}_k = \mathbf{H}\mathbf{X}_k + \mathbf{V}_k \quad (3.7)$$

where  $\mathbf{H} = \begin{bmatrix} 1 & 0 \end{bmatrix}$  is the observation model with the size of  $(1 \times 2)$  which maps the true state space into the observed space and describes the relationships between the state  $\mathbf{X}_k$  and the measurement  $\mathbf{Z}_k$ ,  $\mathbf{V}_k$  is the observation noise, which is a zero mean Gaussian random vector with covariance matrix  $R$  which is scalar and describes the noise characteristics of the measurements, with the following covariance matrix:

$$R = E\{\mathbf{V}_k \mathbf{V}_k^T\} = \sigma_v^2 \quad (3.8)$$

However, considering the noises of inter-vehicle distances are continuous, independent and white Gaussian ones with unchanged distributions,  $Q$  and  $R$  are assumed to be constant in this thesis.



Define  $\hat{\mathbf{X}}_{k|k-1}$  to be a priori state estimation at step  $k$  given knowledge of the process prior to step  $k - 1$ , and  $\hat{\mathbf{X}}_{k|k}$  to be a posteriori state estimation at step  $k$  given measurement  $\mathbf{Z}_k$ . Thus the covariances of the priori and posteriori estimates are  $\mathbf{P}_{k|k-1}$  and  $\mathbf{P}_{k|k}$  respectively.

The Kalman filter can be viewed as the following set of recursive relationships:

$$\hat{\mathbf{X}}_{k|k-1} = \mathbf{A}\hat{\mathbf{X}}_{k-1|k-1} \quad (3.9)$$

$$\mathbf{P}_{k|k-1} = \mathbf{A}\mathbf{P}_{k-1|k-1}\mathbf{A}^T + \mathbf{B}\mathbf{Q}\mathbf{B}^T \quad (3.10)$$

$$\tilde{\mathbf{Z}}_k = \mathbf{Z}_k - \mathbf{H}\hat{\mathbf{X}}_{k|k-1} \quad (3.11)$$

$$\mathbf{S}_k = \mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^T + \mathbf{R} \quad (3.12)$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}^T\mathbf{S}_k^{-1} \quad (3.13)$$

$$\hat{\mathbf{X}}_{k|k} = \hat{\mathbf{X}}_{k|k-1} + \mathbf{K}_k\tilde{\mathbf{Z}}_k \quad (3.14)$$

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k\mathbf{H})\mathbf{P}_{k|k-1} \quad (3.15)$$

$\tilde{\mathbf{Z}}_k$  is denoted with the difference  $(\mathbf{Z}_k - \mathbf{H}\hat{\mathbf{X}}_{k|k-1})$  in the Eqn. (3.11) and named as the measurement innovation matrix, or the residual. It reflects the discrepancy between the predicted measurement  $\mathbf{H}\hat{\mathbf{X}}_{k|k-1}$  and the actual measurement  $\mathbf{Z}_k$ .  $\mathbf{K}_k$  is the Kalman gain from the Eqn. (3.13) that minimizes the posteriori error covariance,  $\mathbf{S}_k$  is the innovation covariance,  $(\cdot)^T$  denotes matrix transpose and  $(\cdot)^{-1}$  denotes matrix inverse.

The Eqn. (3.14) computes a posteriori state estimate  $\hat{\mathbf{X}}_{k|k}$  as a linear combination of a priori estimate  $\hat{\mathbf{X}}_{k|k-1}$  and a weighted difference between an actual measurement  $\tilde{\mathbf{Z}}_k$  and a measurement prediction  $\mathbf{H}\hat{\mathbf{X}}_{k|k-1}$ .

The Kalman filter iterative process can be summarized in two distinct phases: predict and update. Equations (3.9) and (3.10) show the predict phase. Here, predict state uses the state estimate from the previous time step to produce an estimate of the state at the current time step. In the update phase from equations (3.11) to (3.15), measurement information at the current time step is used to refine this prediction to arrive at a more accurate state estimate, again for the current time step. The time update equations can also be thought

of as *predictor* equations, while the measurement update equations can be thought of as *corrector* equations. Indeed the final estimation algorithm resembles that of a *predictor-corrector* algorithm for solving numerical problems as shown in Fig.3.3

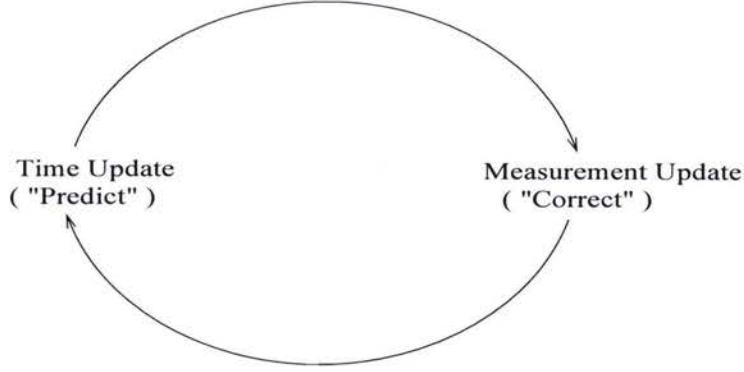


Figure 3.3: The ongoing Kalman Filter cycle. The time update projects the current state estimate ahead in time. The measurement update adjusts the projected estimate by an actual measurement at that time.

### 3.4.2 Hypothesis Test

For LOS situations, the UKF procedure, described from equations (3.9) to (3.15), can be applied and the filter output converges to the true range and gives accurate range results. When LOS transmission exists between a pair of transmitter and receiver, the signal arrival time may be correctly obtained if the signal to noise ratio (SNR) is high and the multipaths from the propagation channel are resolved properly. However, the UKF cannot track the sudden changes due to the NLOS component in the measured range data. The biased version of the Kalman filter can be applied for both LOS and NLOS scenarios. In order to identify the change in channel situation between LOS and NLOS, the hypothesis test is applied as following:

$$H0 : \hat{\sigma}_v < \beta\sigma_v \text{ LOS} , \quad H1 : \hat{\sigma}_v \geq \beta\sigma_v \text{ NLOS} \quad (3.16)$$

where  $\beta > 1$  is used to reduce the probability of a false alarm which is chosen experimentally [39];  $\sigma_v$  is the standard deviation of measurement noise in the LOS environment; and  $\hat{\sigma}_v$  is the standard deviation of the estimated range data and is calculated over a block of  $L$  measured ranges as following:

$$\hat{\sigma}_v = \sqrt{\frac{1}{L} \sum_{i=1}^L [r(t_i) - \hat{d}_T(t_i)]^2} \quad (3.17)$$

### 3.4.3 Biased Kalman Filter (BKF)

NLOS error is considered the major error source in wireless vehicular position estimation. In most cases, the errors caused by NLOS effects cannot be ignored in the vehicular position systems where higher accuracy is demanded. UKF cannot follow an unexpectedly high erroneous data such as an NLOS error. When an NLOS situation is detected the dependence of the estimation on the measurements should be decreased. This is called biasing. This can be done by increasing the measurement error covariance matrix.

In order to mitigate the NLOS range error, the BKF is employed. The BKF is proposed to process the range measurement according to the feedback identification result from the previous processed data. Before computing the Kalman gain in Eqn. (3.13), the measurement noise covariance  $\sigma_v^2$  or the range prediction covariance  $\mathbf{P}_{k|k-1}$  is adjusted by the following rules.

The positive bias error can be canceled by implementing the following two rules:

1. Update priori error covariance matrix as follows when the  $\mathbf{Z}_k - \mathbf{H}\mathbf{X}_{k-1} < 0$  condition is true:

$$\hat{\mathbf{P}}_{k|k-1} = \mathbf{P}_{k|k-1} + \frac{(\mathbf{Z}_k - \mathbf{H}\mathbf{X}_{k|k-1})^2}{\gamma} \quad (3.18)$$

where  $\gamma$  is the experimentally chosen scaling factor [39].

2. Increase the diagonal elements of the measurement noise covariance matrix as follows:

$$\hat{\sigma}_x^2(k) = \sigma_v^2 \quad (3.19)$$



The inclusion of Eqn. (3.18) is essential in compensating the range prediction covariance  $\hat{\mathbf{P}}_{k|k-1}$ . The biased term avoids inaccurate estimation of the range rate  $\dot{d}_N(k)$  from the NLOS mitigation.

The UKF can be modified to the BKF, by implementing the above two rules before calculating the Kalman gain, to decrease the dependence on the measurements as a biasing technique. Simulation results will show that the performance of the BKF can be improved significantly over the UKF in the NLOS condition.

## 3.5 Position Estimation Algorithms

We presented two distinct classes of positioning algorithms. The first position estimator class is a deterministic approach of finding the position of a vehicle *i.e.*, Nonlinear Least Square method. Here the positioning process is repeated each time step and attempts to minimize the mean square error in the relative position estimate. For this class of estimator, we have formulated the position estimation problem, such that it can be solved using a Nonlinear Least Squares Optimization as shown in Section 3.5.1.

Therefore, we have extended previous works so that positioning process includes the additional information available to vehicles (*e.g.*, vehicle road constraints). Second class of position estimator is the stochastic approach. Here we will extend upon the previous algorithm so that each position estimate is a random variable with some probability density function (*i.e.*, a level of uncertainty will be associated with each position estimate) while taking into account vehicle velocity and road boundaries, it can be solved by Extended Kalman Filter. The extended Kalman filter allows the seamless integration of velocity information and produces a set of position estimates that are minimized in the mean square sense.

### 3.5.1 Nonlinear Least Squares Approach

The Nonlinear Least Squares method is the more traditional to solve the positioning problem. However, traditional approaches are generally applied to the positioning problem where the



nodes are stationary. One of the limitation to this approach is that method provides only a single position estimate. Consider a set of  $N$  vehicles within a cluster. For each pair of vehicles  $(i, j)$  a distance measurement is made,  $\hat{d}_{i,j}$  where  $(i, j) \in \{1, 2, \dots, N\}$ . These distance measurements contain noise; therefore, it is the goal of the algorithm to mitigate the noise in these range estimates and formulate an relative estimate of the position of a vehicle. Making use of the Pythagorean relationship in Fig 3.4, let the cost function be:

$$f_{i,j} = \hat{d}_{i,j} - \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (3.20)$$

where  $\hat{d}_{i,j}$  is the inter-vehicle distance estimate between vehicle  $i$  and  $j$ ;  $(x_i, y_i)$  and  $(x_j, y_j)$  are the position of vehicle  $i$  and  $j$ , respectively; and  $f_{i,j}$  is the element of an  $N \times N$  matrix, (where  $N$  is the number of vehicles on the road region), which has the form:

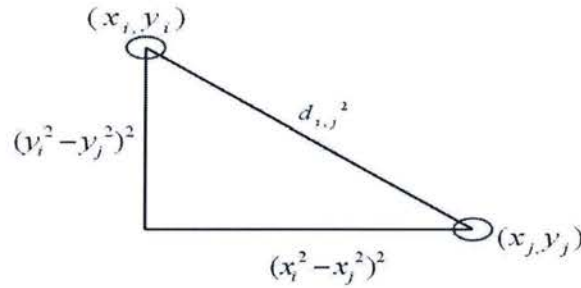


Figure 3.4: Illustrating the Pythagorean theorem relationship.

$$\begin{pmatrix} 0 & f_{1,2} & f_{1,3} & \dots & f_{1,N} \\ f_{2,1} & 0 & f_{2,3} & \dots & f_{2,N} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ f_{N-1,1} & f_{N-1,2} & f_{N-1,3} & 0 & f_{N-1,N} \\ f_{N,1} & f_{N,2} & f_{N,3} & \dots & 0 \end{pmatrix}$$

If we let  $w_{i,j}$  be a weighting function based on the relative distance between vehicle  $i$  and  $j$ , then we can formulate the optimization problem as follows:

$$\hat{\mathbf{X}} = \underset{A}{\operatorname{argmin}} \sum_{i=1}^N \sum_{j=1}^N w_{i,j} f_{i,j}^2 \quad (3.21)$$

where  $\mathbf{X} = [x_1, x_2, \dots, x_N, y_1, y_2, \dots, y_N]$

Therefore, in Eqn.(3.21) our objective is to minimize the mean square error in the inter-vehicle distance estimates.

In general, the design of the weighting function,  $w_{i,j}$  is a non-trivial task. It must take into account the relative uncertainty in the inter-vehicle distance estimates. If a model for the noise measurements available, then we can tailor the weights to the variance of the model. For example, if the measurement noise is Gaussian distributed with standard deviation linearly increasing with the true distance (*i.e.*,  $\sigma = k * \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$  where  $k$  is a constant) then one could select a weighting function:  $w_{i,j} = \frac{1}{(k*d_{i,j}^2)}$ . However, if a reliable model for the errors is not available, then an independent adaptive weighting scheme can be used, such as the one presented in [61].

The optimization problem formulated in Eqn.(3.21) can be viewed as attempting to minimize the mean position error in the final position estimate. In general, there is no closed form solution for Eqn.(3.21), unless some nodes within a cluster have fixed known position (*e.g.*, road side base units). However, for the purpose of this work, we assume that all the vehicles are mobile units. Thus there is no closed form solution of Eqn.(3.21) for our problem and numerical search methods are required. Classic estimation theory provides the gradient steepest descent method [62].

Consider, a vehicle moving with constant velocity over some time interval  $\Delta t$  where  $\Delta t$  denotes the update rate of our filter. This position evolves from one time period to the next according to the following motion model:

$$\mathbf{X}_{k+1} = \mathbf{X}_k + \Delta t \mathbf{v}_k + \Delta t \mathbf{W}_k \quad (3.22)$$

where

$$\mathbf{X}_k = [x_{1,k}, \dots, x_{N,k}, y_{1,k}, \dots, y_{N,k}]^T \quad (3.23)$$

$$\mathbf{v}_k = [v_{x1,k}, \dots, v_{xN,k}, v_{y1,k}, \dots, v_{yN,k}]^T \quad (3.24)$$

where  $N$  is the number of vehicles in the region at the  $k$ th time instant;  $(x_{i,k}, y_{i,k})$  is the position of the  $i$ th vehicle at the end of  $k$ th interval.  $\Delta t$  is the sampling interval;  $v_{xi,k}$  and  $v_{yi,k}$  are the velocity of the vehicle  $i$  in the  $x$  and  $y$  directions at time  $k$  respectively; superscript  $T$  denotes transpose; and  $\mathbf{W}_k$  is the process noise describing the mobility variations. We assume that  $\mathbf{W}_k$  is a zero mean Gaussian random variable, with the following covariance:

$$\mathbf{Q}_k = E[\mathbf{W}_k \mathbf{W}_k^T] = \text{diag}(\sigma_{x1}^2, \sigma_{x2}^2, \dots, \sigma_{xn}^2, \sigma_{y1}^2, \sigma_{y2}^2, \dots, \sigma_{yn}^2) \quad (3.25)$$

where  $\text{diag}(\cdot)$  denotes a matrix with values on the matrix diagonal equal to the argument of this function.

Therefore the original optimization problem Eqn.(3.21) can be reformulated as:

$$\hat{\mathbf{X}}_k = \underset{A}{\text{argmin}} \sum_{i=1}^n \sum_{j=1}^N w_{i,j} f_{i,j}^2$$

$$\mathbf{X}_{k+1} = \mathbf{X}_k + \Delta t \mathbf{v}_k + \Delta t \mathbf{W}_k \quad (3.26)$$

$$-\mathbf{d} \leq \mathbf{W}_k \leq \mathbf{d}$$

where  $w_{i,j}$  is the weighting function for the  $i$ th,  $j$ th term at time  $k$ ;  $\mathbf{W}_k$  is a noise vector;  $\mathbf{d}$  is vector of deterministic values that act as constraints on  $\mathbf{W}_{k-1}$ ;  $\hat{\mathbf{X}}_k$  is a vector of the estimated  $x, y$  coordinates of the vehicle's positions and

$$f_{i,j}(k) = \hat{d}_{i,j}(k) - \sqrt{(x_{i,k} - x_{j,k})^2 + (y_{i,k} - y_{j,k})^2} \quad (3.27)$$

where  $\hat{d}_{i,j}(k)$  is the distance measurement between vehicle  $i$  and  $j$  at time step  $k$

There are multiple entries to solve Eqn.(3.26), one is to use recursive least squares(RLS) algorithm, which is an adaptive version of the Gauss-Newton search algorithm [62]. When we implemented this algorithm we calculated the gradient of Eqn.(3.26) analytically, since calculating the partial derivatives with respect to the  $x_{i,k}$  term is:



$$\frac{\partial w_{i,j}(k) f_{i,j}^2(k)}{\partial x_{i,k}} = 2w_{i,j}(k) \frac{(1 - \sqrt{(x_{i,k} - x_{j,k})^2}) + (y_{i,k} - y_{j,k})^2}{\sqrt{(x_{i,k} - x_{j,k})^2 + (y_{i,k} - y_{j,k})^2}} (x_{i,k} - x_{j,k}) \quad (3.28)$$

and the other partial derivatives are calculated similarly.

### 3.5.2 Extended Kalman Filter (EKF)

The Kalman Filter is a tool that can estimate the variables of a wide range of processes. Kalman Filter estimates the state of a linear system. The standard Kalman Filter is an effective tool for estimation, however, it is limited to linear systems. Most real world systems are nonlinear, in which case Kalman Filters do not directly apply. If a nonlinear system can be linearized we can use kalman filter to estimate the states. To linearize a nonlinear system we apply a Taylor series expansion. However, in actual applications, the process to be estimated are usually nonlinear. Due to nonlinearities in our process model, an extended Kalman filter (EKF) [60] is defined from Kalman filter to solve the problem.

By means of the Taylor series, the nonlinear relationships around the current time step can be linearized by using the partial derivatives of the process and measurement functions. To realize linearization of a nonlinear process some parts of the Kalman filter must be modified.

Usually vehicles are the moving objects. The Extended Kalman filter nonlinear stochastic difference motion model can be described as follows:

$$\mathbf{X}_{k+1} = f(\mathbf{X}_k, \mathbf{v}_k) + \mathbf{W}_k \quad (3.29)$$

where  $\mathbf{X}_k = [x_{1,k}, x_{2,k} \dots x_{N,k}, y_{1,k}, y_{2,k} \dots y_{N,k}]^T$

$$\mathbf{v}_k = [v_{x1,k}, \dots, v_{xN,k}, v_{y1,k}, \dots, v_{yN,k}]^T$$

where  $N$  is the number of vehicles in the cluster at the  $k^{th}$  snapshot; the nonlinear function  $f$  can be used to compute the predicted state from the previous estimate and includes a driving function  $\mathbf{v}_k$ ;  $(.)^T$  denotes the matrix transposition;  $v_{xN,k}$  and  $v_{yN,k}$  are the velocities of vehicle  $n$  in the  $X$  and  $Y$  directions at time  $k$ , respectively;  $\mathbf{X}_{k+1}$  is the position of the



vehicle at time  $k$ ; and  $\mathbf{W}_k$  is the process noise describing the mobility variations. We assume that  $\mathbf{W}_k$  is a zero-mean Gaussian random variable, with the following covariance:

$$\mathbf{Q}_k = E[\mathbf{W}_k \mathbf{W}_k^T] = \text{diag}(\sigma_{x1}^2, \sigma_{x2}^2, \dots, \sigma_{xn}^2, \sigma_{y1}^2, \sigma_{y2}^2, \dots, \sigma_{yn}^2) \quad (3.30)$$

where  $\text{diag}(\cdot)$  denotes a diagonal matrix.

Eqn.(3.30) structure shows how the error covariance is traditionally defined for a motion model when the uncertainty in each direction is equiprobable; however, for a vehicular environment this is not the case. In general, vehicle motion is constrained to the roads. Therefore it is not convenient for us to define variance in terms of  $X$  and  $Y$  directions.

- **Enforced Road Constraints:**

Considering that the vehicles usually move along the direction of lanes on the road, the uncertainty in the direction orthogonal to the road is lesser than the uncertainty in the direction of lanes on the road.

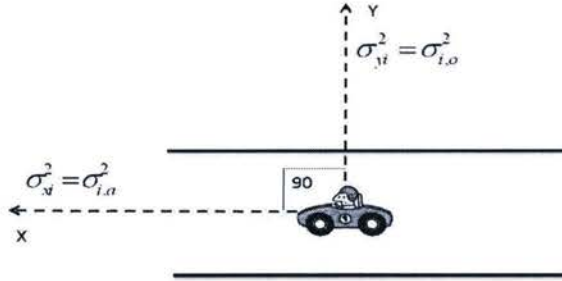


Figure 3.5: Road constraints

Let us define the variance for the vehicle in the direction of road  $i$  to be  $\sigma_{i,a}^2$  and the variance in the direction orthogonal to the road is  $\sigma_{i,o}^2$ . Due to higher uncertainty of the motion along the road,  $\sigma_{i,a}^2 \gg \sigma_{i,o}^2$ . Thus for a road that runs in a direction that is  $\theta$  radians from the  $Y$ -axis, the following transformation must be applied:

$$\begin{bmatrix} \sigma_{xi}^2 & 0 \\ 0 & \sigma_{yi}^2 \end{bmatrix} = \begin{bmatrix} -\cos\theta & \sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \sigma_{i,o}^2 & 0 \\ 0 & \sigma_{i,a}^2 \end{bmatrix} \begin{bmatrix} -\cos\theta & \sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \quad (3.31)$$

This can also be written as:

$$\sigma_{xi}^2 = \sigma_{i,o}^2 \cos^2\theta + \sigma_{i,a}^2 \sin^2\theta \quad (3.32)$$

$$\sigma_{yi}^2 = \sigma_{i,a}^2 \cos^2\theta + \sigma_{i,o}^2 \sin^2\theta \quad (3.33)$$

Eqn.(3.32)and Eqn.(3.33) allow  $\mathbf{Q}_k$  to bias in the direction of the road.

Fig. 3.5 shows the variances in the X and Y directions if the vehicle is making an angle of  $90^\circ$  with the road.

The observations of the inter-vehicle measurements are expressed as:

$$\mathbf{Z}_k = h(\mathbf{X}_k) + \mathbf{V}_k \quad (3.34)$$

where  $h(\mathbf{X}_k)$  is a nonlinear equation describing the measurements at time k; the function  $h$  can be used to compute the predicted measurement from the predicted state and shows the relationship between the state vector  $\mathbf{X}_k$  and the measurement vector  $\mathbf{Z}_k$ ; and  $\mathbf{V}_k$  is the zero-mean Gaussian random vector with the covariance matrix  $\mathbf{R}_k$  describing the noise characteristics of the measurement.

The general form of Kalman filter requires that the measurement equation be in a linear form, therefore if we linearize the Eqn.(3.34) and Eqn.(3.29) using a first order Taylor series expansion around the current position estimates. State transition and observation matrices are defined to be the following Jacobian matrices:

$$\hat{\mathbf{H}}_k = \frac{\partial h}{\partial \mathbf{X}} \big|_{\hat{\mathbf{x}}_{k|k-1}} \quad (3.35)$$

$$\hat{\mathbf{A}}_k = \frac{\partial f}{\partial \mathbf{X}} \big|_{(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{v}_k)} \quad (3.36)$$

$\hat{\mathbf{H}}_k$  can be referred to as the observation Jacobian matrix and  $\hat{\mathbf{A}}_k$  can be referred as state transition Jacobian matrix.

One iteration of the EKF consists the following consecutive steps:

1. Consider the last filtered state estimate  $\hat{\mathbf{X}}_{k|k}$ ,
2. Linearize the system dynamics,  $\mathbf{X}_{k+1} = f(\mathbf{X}_k, \mathbf{v}_k) + \mathbf{W}_k$  around  $\hat{\mathbf{X}}_{k|k}$ ,
3. apply the prediction step of the Kalman filter to linearized system dynamics just obtained, yielding  $\hat{\mathbf{X}}_{k|k-1}$  and  $\mathbf{P}_{k|k-1}$ ,
4. Linearize the observation dynamics,  $\mathbf{Y}_k = \mathbf{h}(\mathbf{X}_k + \mathbf{V}_k)$  around  $\hat{\mathbf{X}}_{k|k-1}$
5. Apply the filtering or update cycle of the Kalman filter to the linearized observation dynamics, yielding  $\hat{\mathbf{X}}_{k|k}$  and  $\mathbf{P}_{k|k}$ .

The extended Kalman filter algorithm can be viewed as the following set of recursive relationships:

**Predict Cycle:**

$$\hat{\mathbf{X}}_{k|k-1} = f(\hat{\mathbf{X}}_{k-1|k-1}, \mathbf{v}_k) \quad (3.37)$$

$$\mathbf{P}_{k|k-1} = \mathbf{A}_k \mathbf{P}_{k-1|k-1} \mathbf{A}_k^T + \mathbf{Q}_k \quad (3.38)$$

**Filtered Cycle:**

$$\hat{\mathbf{Z}}_k = \mathbf{Y}_k - h(\hat{\mathbf{X}}_{k|k-1}) \quad (3.39)$$

$$\mathbf{S}_k = \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R}_k \quad (3.40)$$

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T \mathbf{S}_k^{-1} \quad (3.41)$$

$$\hat{\mathbf{X}}_{k|k} = \hat{\mathbf{X}}_{k|k-1} + \mathbf{K}_k \hat{\mathbf{Z}}_k \quad (3.42)$$

$$\mathbf{P}_{k|k} = [\mathbf{I} - \mathbf{K}_k \mathbf{H}_k] \mathbf{P}_{k|k-1} \quad (3.43)$$

Here, EKF is not an optimal filter, but rather it is implemented based on a set of approximations. Thus the matrices  $\mathbf{P}_{k|k}$  and  $\mathbf{P}_{k|k-1}$  do not represent the true covariance of the state estimates.

The matrices  $A_k$  and  $H_k$  depend on previous state estimates and therefore on measurements, and the filter gain  $K_k$  and  $P_{k|k}$  and  $P_{k|k-1}$  cannot be compute off-line as occurs in the Kalman filter.

Contrary to the Kalman filter, the EKF may diverge, if the consequent linearizations are not good approximation of the linear model in the associated uncertainty domain.





# Chapter 4

## Simulation Results and Discussion

### 4.1 Traffic Model

In order to test the performance of the algorithms applied, we considered a road topology of a length of 4km and a width of 30m with six lanes, each with a width of 5m. There are 3 east-bound and 3 west-bound lanes with vehicles entering from both directions. Vehicles are randomly selected with a minimum threshold distance of 30m between them, which was the minimum requirement in order to avoid collisions in an emergency situation. Vehicle speed limit was set to 30m/s. For simulations we tracked a single vehicle's ability to determine the range estimation with all other vehicles. We assumed each vehicle had 6 neighboring vehicles with 6 inter-vehicle range measurements at any given time as depicted in Fig.4.1. For simulations  $\beta$  is fixed to 1.1.

### 4.2 NLOS Model

UWB channel model parameters have been used to model the NLOS error for simulations [30] with a mean of  $1/\Lambda$  and a variance of  $(1/\Lambda^2)$ . The NLOS error is modeled by equation (3.3) with  $\Lambda = 0.0667ns^{-1}$ . The measurement noise  $\mathbf{V}_k$  is assumed to be AWGN with zero mean and variance  $0.25m^2$ . It is also assumed that 1000 data samples are measured with a

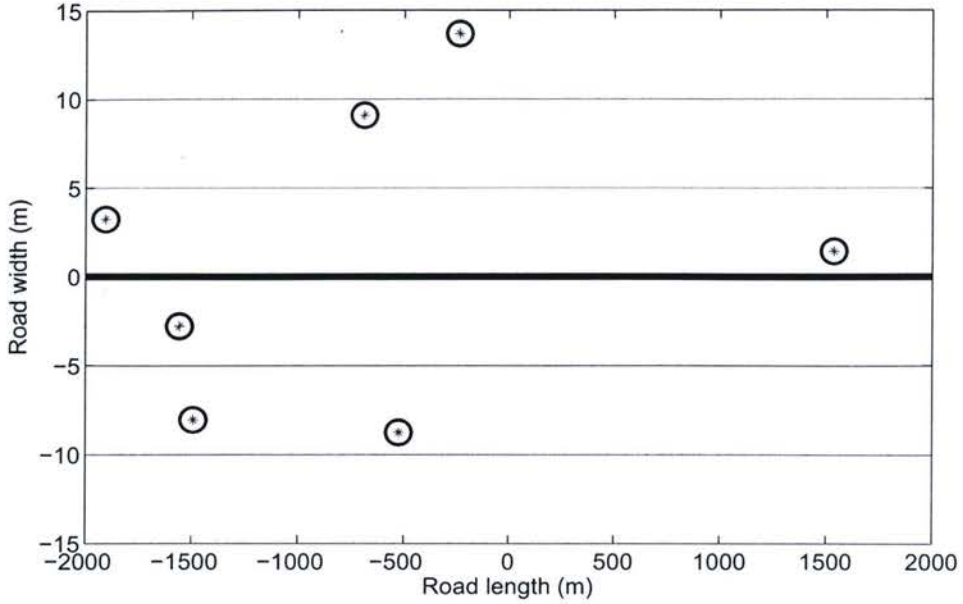


Figure 4.1: Road topology for vehicles

sampling period of 2ms. The true range is calculated by applying the performance metric  $|x_i + jy_i - x_j - jy_j|$  with initial positions of the vehicles recorded by GPS.

For simulations, LOS and NLOS have been applied randomly to the range measurements and a hypothesis test is used to determine which range measurements have LOS and NLOS. Basically, the true range with the addition of AWGN is known as the LOS condition.

### 4.3 Performance Metrics

There are four metrics we use for evaluating the effectiveness of the positioning algorithms. The first metric we used is the root mean square error (RMSE) in the inter-vehicle range measurements. RMSE was applied to determine the range error, which is very sensitive to the distance measurements:

$$\epsilon_{range} = \sqrt{\frac{1}{N} \sum_{i=1}^N [\hat{d}_T(i) - d_T(i)]^2} \quad (4.1)$$

where  $d_T(i)$  is the true range of the  $i^{th}$  vehicle and  $\hat{d}_T(i)$  is the estimated range of the  $i^{th}$  vehicle;  $N$  is the number of vehicles at the current time;

Similarly we used RMSE in the final position estimates. The metric can be thought of as the average distance of the final position estimate from the actual position. We have defined RMSE in the final position estimate as:

$$\epsilon_{final} = \sqrt{\frac{1}{N} \sum_{i=1}^N \{[x_{final.est.}(i) - x_{true}(i)]^2 + [y_{final.est.}(i) - y_{true}(i)]^2\}} \quad (4.2)$$

where  $(x_{truei}, y_{truei})$  represents the true position of the  $i$ th vehicle;  $(x_{final.est.i}, y_{final.est.i})$  is the position estimate for the  $i$ th vehicle after running the positioning algorithm.

The third metric we use to find the deviation in the X-direction from the actual. We defined RMSE in X-direction alone is as following:

$$\epsilon_{X-direction} = \sqrt{\frac{1}{N} \sum_{i=1}^N [x_{final.est.}(i) - x_{true}(i)]^2} \quad (4.3)$$

The fourth metric we used to find the deviation in the Y-direction from the actual. We defined RMSE in Y-direction alone is as following:

$$\epsilon_{Y-direction} = \sqrt{\frac{1}{N} \sum_{i=1}^N [y_{final.est.}(i) - y_{true}(i)]^2} \quad (4.4)$$

## 4.4 Simulation Results

### 4.4.1 Unbiased Kalman Filter Output

In Fig.4.2, the propagation situation changes from LOS to NLOS at each time instant of 1s. Simulation results show that the UKF can preprocess the range data with a RMSE of 0.05m



for only the LOS scenario; for the NLOS scenario, the RMSE could be too high. Therefore, NLOS needs to be filtered out for acceptable measurements.

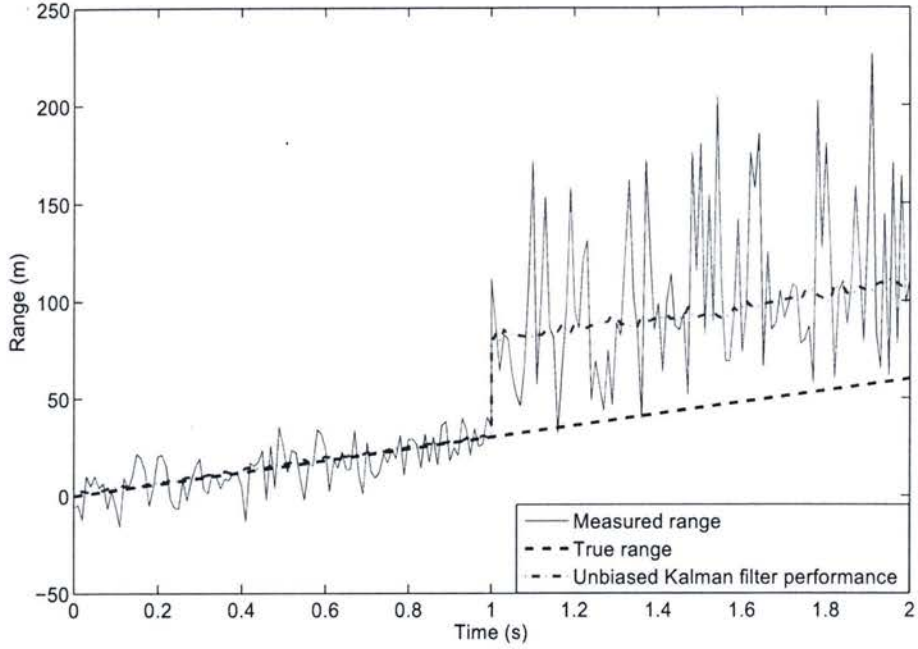


Figure 4.2: Unbiased Kalman filter output for LOS and NLOS.

Fig.4.3 shows a zoomed version of Fig.4.2 from the start to 0.6s. It shows that by using the UKF, the estimation is almost overlapped with the true range. However, the UKF cannot eliminate the positively biased NLOS data added for the time period of 1s to 2s.

#### 4.4.2 Biased Kalman Filter Output

Fig.4.4 shows the biased versus unbiased smoothed range data for the propagation situation changes from LOS to NLOS at time instant of 1s. The inter-vehicle range data smoothed by the UKF cannot track the sudden changes due to NLOS from time instant of 1s to 2s. However, the NLOS error from the range measurements is mitigated by using the BKF with a RMSE value of less than 0.7m.

Fig.4.5 shows the BKF smoothed output for a mixed LOS condition from 0s to 1s, the

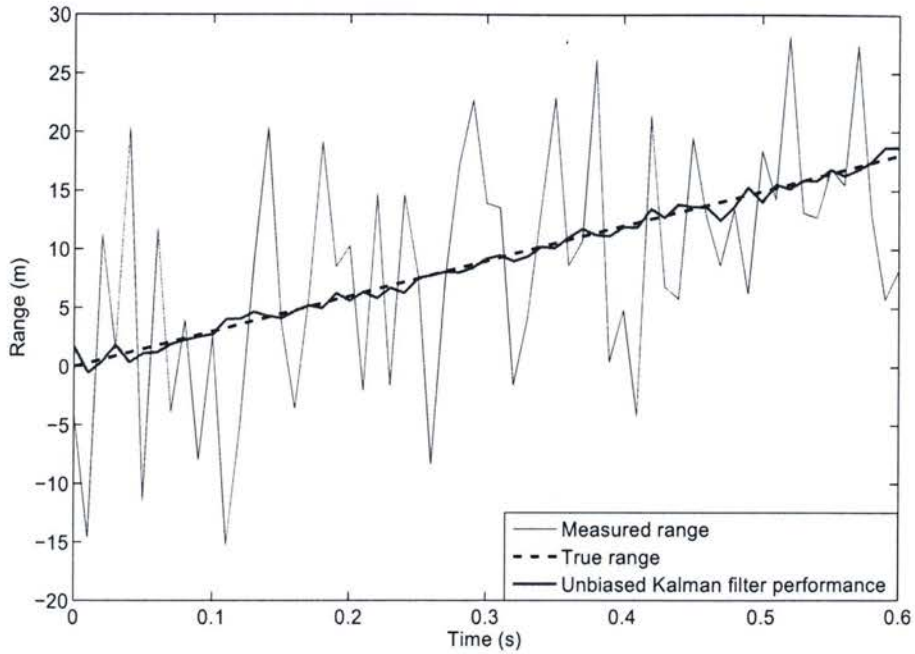


Figure 4.3: Unbiased Kalman filter output for LOS in  $[0, 0.6]$ s.

NLOS condition from 1s to 2s, and again the LOS condition from 2s to 3s. The BKF can effectively mitigate the NLOS error even when the vehicle travels with an abrupt change between the LOS and NLOS conditions.

## 4.5 Effect of Different Noise Levels on Measurement Range

If we assume that the two Gaussian random variables with the standard deviations of 1m and 10m respectively describing the noise characteristics of the distance measurements, then we obtain the results as shown in Fig.4.6. The curve with higher peaks is the BKF performance to smooth the inter-vehicle range data over a time period of 100s. Also, for reference we have included the average performance of the BKF (*i.e* the horizontal line with RMSE of approximately 1.5m). The bottom curve with lower peaks shows the BKF performance

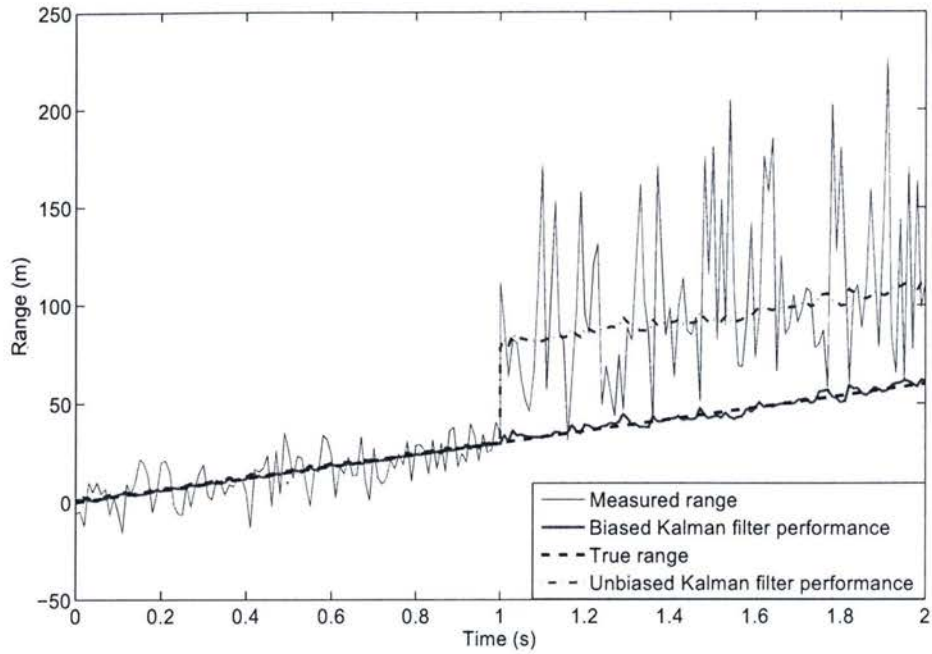


Figure 4.4: Biased vs unbiased Kalman filter smoothed range data.

for the measurement noise of 1m. The dashed horizontal line shows the average RMSE of approximately 0.5m. Overall, the BKF can effectively smooth range data for various noise levels of strength.

## 4.6 RMSE variation with different noise levels for inter-vehicle range measurements

Fig.4.7 and Fig.4.8 show the variation of the RMSE with respect to the number of range measurements for two different levels of the measurement AWGN standard deviation (*i.e.*, 1m and 10m respectively at  $\beta = 1.1$  and  $\beta = 1.6$  respectively). A moving linear average fit of the data points is overlaid on each plot. Each data point on the plots represents a single run of the simulation for the inter-vehicle range measurements. The ability of the BKF performance goes down as the number of inter-vehicle range measurements increases.

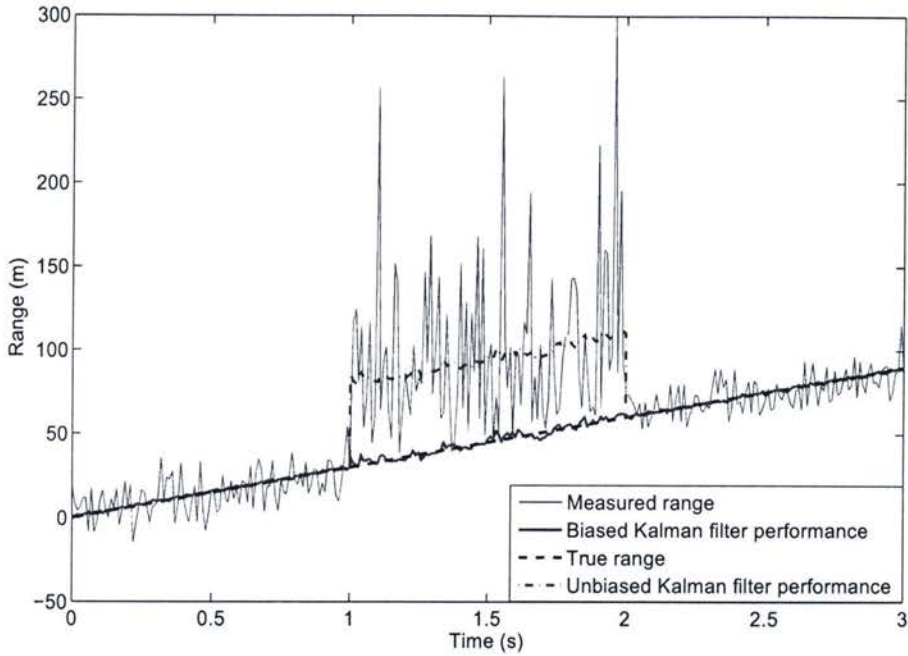


Figure 4.5: Estimated range data with an abrupt change between LOS and NLOS.

Interestingly, the algorithm is most effective with the AWGN standard deviation of 1m at  $\beta = 1.1$ . With higher measurement noise (*i.e.*, AWGN) in the inter-vehicle range data, the algorithm is still effective, but the RMSE could be higher.

The results of RMSE in the measurement range are summarized in Table 4.1 by selecting different standard deviation values for the AWGN. Since the Gaussian noise is the measurement noise, if the signal arrives stronger, we can assume the measurement noise to be lower. For different values of AWGN standard deviation, the measurement range of less than 400m and less than 1000m on average is listed. It shows the maximum RMSE in the measured range after smoothing with the biased Kalman filter. The proposed algorithm can achieve an accuracy of less than 0.7m in the inter-vehicle range data when the measured range is less than 1000m and the AWGN standard deviation is less than 0.1m. A maximum inter-vehicle distance of 1000m, based on the dedicated short-range communication (DSRC) standards listed in [19], is compatible for vehicular safety applications.



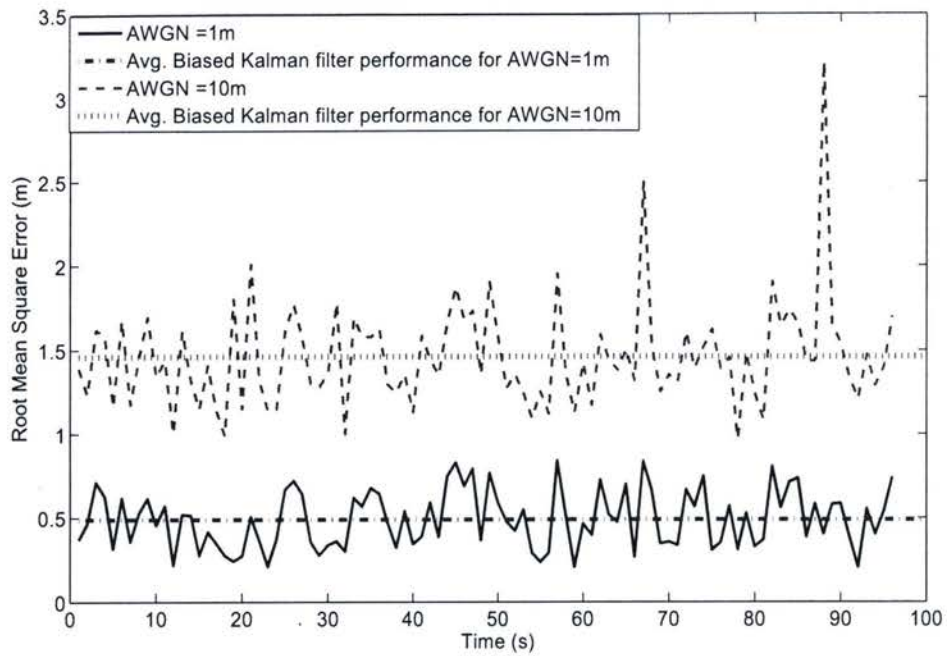


Figure 4.6: Biased Kalman filter performance on different AWGN variance.

Table 4.1: RMSE for different AWGN measurement noise

AWGN Standard deviation (m)	Measurement range ( $<400\text{m}$ )	Measurement range ( $<1000\text{m}$ )
10m	$< 1.0\text{m}$	$< 1.5\text{m}$
5m	$< 0.8\text{m}$	$< 1.3\text{m}$
1m	$< 0.6\text{m}$	$< 1.1\text{m}$
0.1m	$< 0.3\text{m}$	$< 0.7\text{m}$

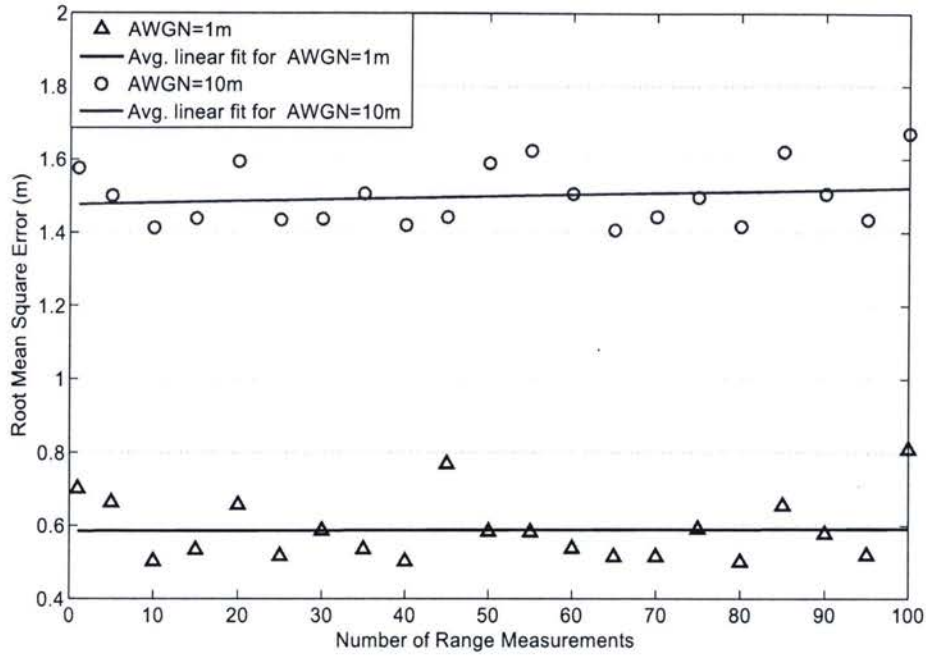


Figure 4.7: RMSE vs. number of inter-vehicle range measurements for  $\beta = 1.1$ .

## 4.7 Sensitivity to Noisy Range Measurements Study

For the following simulation results we assume that a Gaussian random variable with the standard deviation of 10m describes the noise characteristics of inter-vehicle distance measurements and the road length is of 200m. To see how well our EKF based algorithm performs in relation to the bound, we will first consider there is no smoothed range data to estimate final position. Further, we apply BKF to mitigate noise from the range data. These smoothed range is then applied to the EKF to estimate position. Finally, we compare the performance of EKF applied on smoothed range data along with road constraints.

If we apply noisy inter-vehicle range measurements without smoothing to the EKF, then we get the estimated position as shown in Fig.4.9. Here true X-position deviates from estimated position with an error of approximately 5m to 10m (shown by using green arrow). As well as true Y-position deviates with an error of 2m to 3m.

Fig 4.10 shows the EKF performance on position estimates with the application of

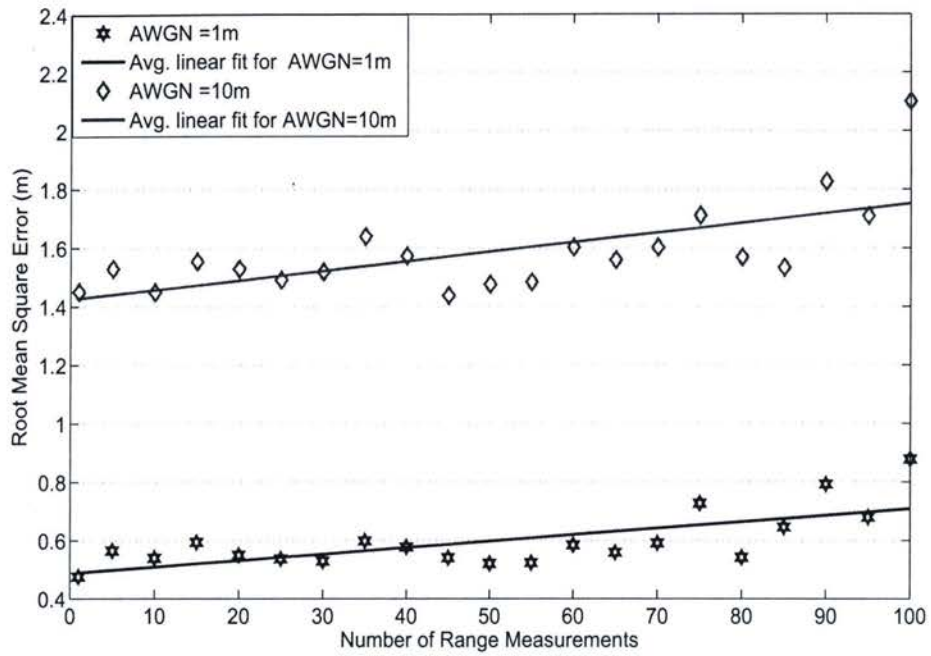


Figure 4.8: RMSE vs. number of inter-vehicle range measurements for  $\beta = 1.6$ .

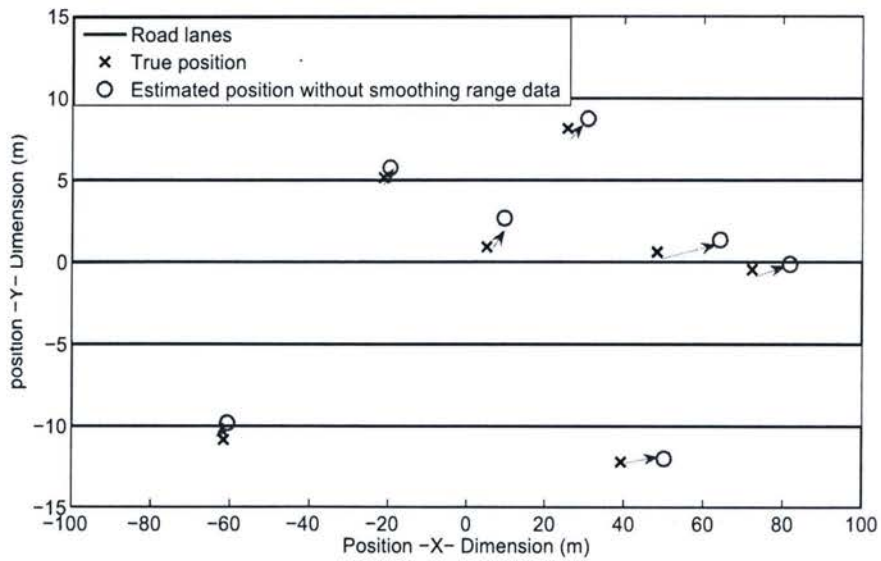


Figure 4.9: Position error with the application of measured range.

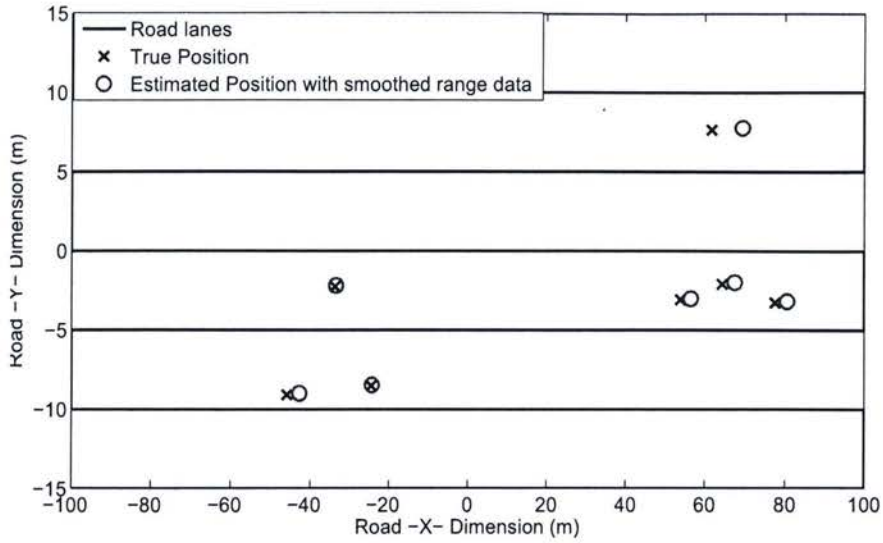


Figure 4.10: EKF performance on estimated position with the application of smoothed range data.

smoothed range data. Inter-vehicle distance measurements are smoothed by using BKF before applying to the EKF to mitigate noisy component in the range measurements. If we closely observe Fig.4.10, still there is approximately 2m to 3m error exists in the X-direction. This error is due to the high uncertainty in the X-direction compared to Y-direction.

In Fig.4.11 we measure X-axis in the same position 100 times with EKF. Fig. 4.11 shows the deviation between true and the estimated position in X direction.

As shown in Fig.4.12, we measured the Y-axis in the same position 100 times to check the performance of the EKF. The difference between true and estimated position in Y-direction is shown in Fig.4.12.

Fig.4.13 show the EKF algorithm with the application of road constraints. Simulation result show the deviation in X and Y direction can be reduced to approximately around <1m with the application of road bounds by choosing appropriate variances in X and Y directions.



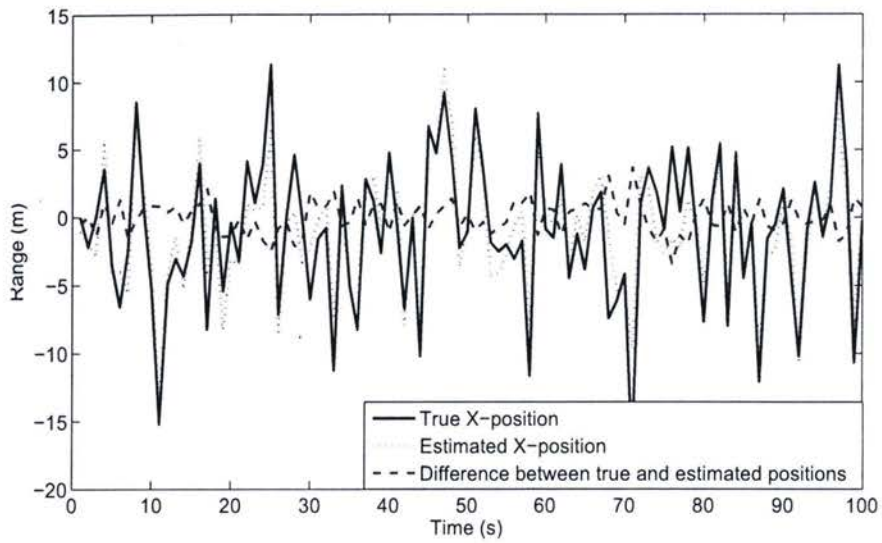


Figure 4.11: Position error in X-direction.

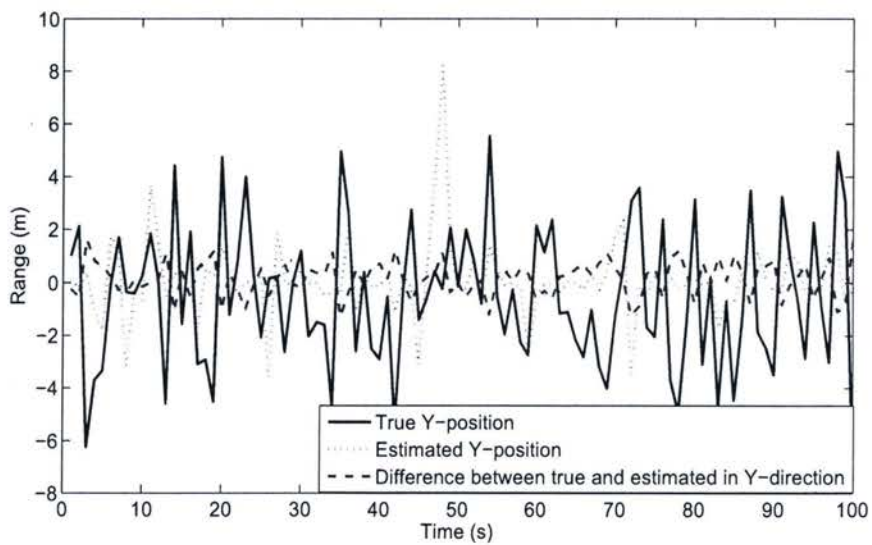


Figure 4.12: Position error in Y-direction.

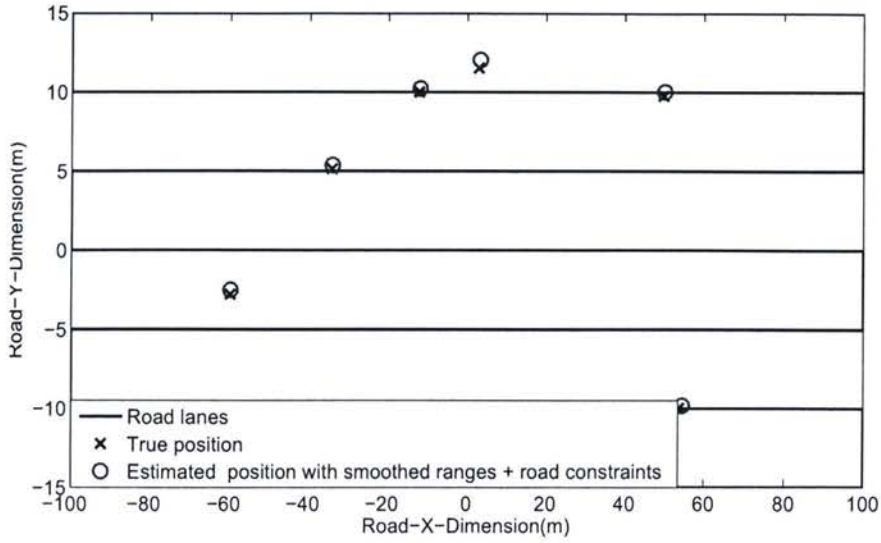


Figure 4.13: EKF performance with road constraints.

## 4.8 RMSE performance on position estimates

If we assume that a Gaussian random variable with standard deviation of 10m describes the noise characteristics of inter-vehicle distance measurements, then we get the results shown in Fig.4.14. The constant line with an error of approximately 5.45m is the Nonlinear Least Square approach implementation. The curve with square peaks is our EKF performance before applying the preprocessed range data. Also, we have included the average performance of the EKF, after applying EKF with noisy range measurements, results show the error of approximately 3m. We further compared the EKF performance with and without the application of road constraints. The curve with circles shows our algorithm performance with the application of only smoothed range data to estimate position. The average RMSE error is also shown in the Fig.4.14, which is approximately equal to 2m. Over all error varies between 2m to 3m. The bottom curve with stars shows reduced error compared to upper curve after applying the EKF approach along with smoothed range data in addition to road constraints. An average RMSE presented after the application of our algorithm is  $<1\text{m}$ .

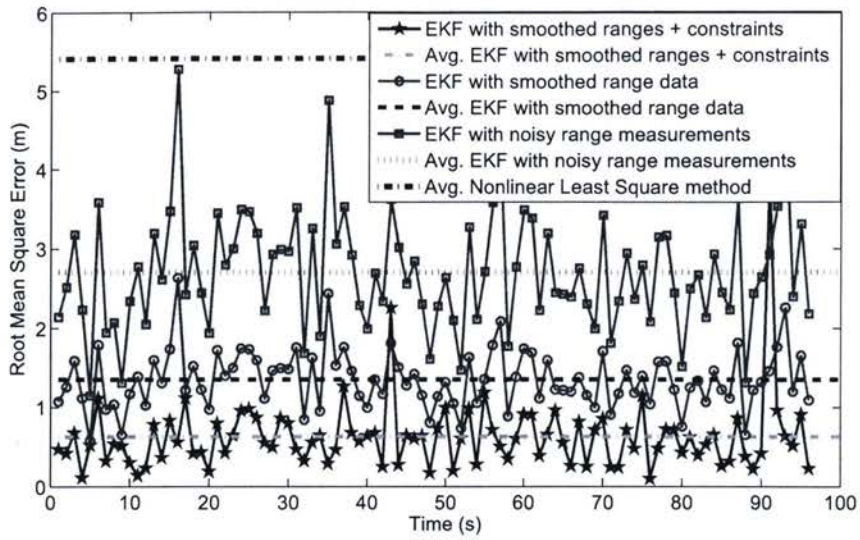


Figure 4.14: RMSE comparison

Overall there is much variation in the RMSE levels of the Nonlinear Least Square approach versus applied EKF algorithm with the addition of road constraints along with smoothed inter-vehicle range data.

## Chapter 5

# Conclusions and Future Directions of Work

### 5.1 Conclusion

In this thesis range and position estimation algorithms for typical GPS outages in the presence of NLOS error are presented. The BKF to mitigate the positive bias introduced by the NLOS component in the inter-vehicle range measurements is applied. These preprocessed range data is applied to the EKF to estimate position of the vehicle. The uncertainty in the direction of road is more than uncertainty in the opposite direction of road. These road constraints are applied to the EKF to get an accurate results. Simulation results show that the proposed algorithm for NLOS identification and mitigation with the BKF promises to achieve higher accuracy for vehicle positioning and tracking systems under different received signal noise levels. Position estimation is accurate with the application of smoothed range data along with road constraints.



## 5.2 Future Directions

We are confident this area of research will be an active broadening field. We just focussed on small part of positioning system which produces accurate and reliable estimates in the GPS outages. There are many more real time issues that need to be addressed. Some of them has been listed below:

- In our work, we ignored malicious hosts that are trying to corrupt position accuracy. The role of security is one of the main concern. The idea of tolerating attacks and also eliminating them, by exploiting redundancies at various levels within wireless networks is an open issue for positioning systems.
- This work could be extended upon examining how road side units (*e.g.* access points with fixed known position) could be incorporated into our algorithm. By making use of these road side equipments it may be possible to create a more accurate global map, instead of merely creating a position map.
- We considered flat surface for vehicles, still work needs to be done when vehicle is moving on terrain regions.
- In the future it may be possible to extend the localization algorithm for higher accuracy localization with the method of visual pattern matching between navigation information and visual cues on the road.

Vehicular Ad-hoc Networks characterized by extremely high mobility and rapidly changing topology. However, this mobility is constrained in motion due to the existence of roadways and can therefore be cleverly exploited for message propagation with low latency in message delivery.

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# Appendix A

## Abbreviation List

ITS	Intelligent transportation System
IVC	Inter-vehicle Communication
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
CCW	Cooperative Collision Warning
MANETs	Mobile <i>Ad hoc</i> Network Environments
QoS	Quality of Service
AHS	Automated Highway Systems
DSRC	Dedicated Short-range Communication
FCC	Federal Communications Commision
GPS	Global Positioning Systems
SA	Selective Availability
TTFF	Time-to-First-Fix
LOS	Line-of-sight
NLOS	Non-line-of-sight
RWA	Residual Weighing Algorithm
SNR	Signal to Noise Ratio

UWB	Ultra Wideband
S-V	Saleh - Valenzuela
RSS	Received Signal Strength
TOA	Time Of Arrival
TDOA	Time Difference Of Arrival
AOA	Angle Of Arrival
RSSI	Received Signal Strength Indicator
Tx	Transmitter
Rx	Receiver
TOA-OWR	TOA One-way-ranging
TOA-TWR	TOA Two-way-ranging
CRB	Cramer-Rao Bound
BW	Bandwidth
AWGN	Additive White Gaussian Noise
RMSE	Root Mean Square Error
UKF	Unbiased Kalman Filter
BKF	Biased Kalman Filter
EKF	Extended Kalman Filter
dBm	Milli Decibels