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Méthodes Coopératives de Localisation de Véhicules
Cooperative Methods for Vehicle Localization

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À ma femme et mes parents

RÉSUMÉ

L’intelligence embarquée dans les applications véhiculaires devient un grand intérêt depuis les deux dernières décennies. L’estimation de position a été l'une des parties les plus cruciales concernant les systèmes de transport intelligents (STI). La localisation précise et fiable en temps réel des véhicules est devenue particulièrement importante pour l'industrie automobile. Les améliorations technologiques significatives en matières de capteurs, de communication et de calcul embarqué au cours des dernières années ont ouvert de nouveaux champs d'applications, tels que les systèmes de sécurité active ou les ADAS, et a aussi apporté la possibilité d'échanger des informations entre les véhicules. Une localisation plus précise et fiable serait un bénéfice pour ces applications. Avec l'émergence récente des capacités de communication sans fil multi-véhicules, les architectures coopératives sont devenues une alternative intéressante pour résoudre le problème de localisation. L'objectif principal de la localisation coopérative est d'exploiter différentes sources d'information provenant de différents véhicules dans une zone de courte portée, afin d'améliorer l'efficacité du système de positionnement, tout en gardant le coût à un niveau raisonnable.

Dans cette thèse, nous nous efforçons de proposer des méthodes nouvelles et efficaces pour améliorer les performances de localisation du véhicule en utilisant des approches coopératives. Afin d'atteindre cet objectif, trois nouvelles méthodes de localisation coopérative du véhicule ont été proposées et la performance de ces méthodes a été analysée.

Notre première méthode coopérative est une méthode de correspondance cartographique coopérative (CMM, Cooperative Map Matching) qui vise à estimer et à compenser la composante d'erreur commune du positionnement GPS en utilisant une approche coopérative et en exploitant les capacités de communication des véhicules. Ensuite, nous proposons le concept de station de base Dynamique DGPS (DDGPS) et l'utilisons pour générer des corrections de pseudo-distance GPS et les diffuser aux autres véhicules. Enfin, nous présentons une méthode coopérative pour améliorer le positionnement GPS en utilisant à la fois les positions GPS des véhicules et les distances inter-véhiculaires mesurées. Ceci est une méthode de positionnement coopératif décentralisé basé sur une approche bayésienne.

La description détaillée des équations et les résultats de simulation de chaque algorithme sont décrits dans les chapitres désignés. En plus de cela, la sensibilité des méthodes aux différents paramètres est également étudiée et discutée. Enfin, les résultats de simulations concernant la méthode CMM ont pu être validés à l'aide de données expérimentales enregistrées par des véhicules d'essai. La simulation et les résultats expérimentaux montrent que l'utilisation des approches coopératives peut augmenter de manière significative la performance des méthodes de positionnement tout en gardant le coût à un montant raisonnable.

Mots clés: Localisation du véhicule coopérative, GPS, Systèmes de transport intelligents, VANET, CMM, DDGPS.

Abstract

Embedded intelligence in vehicular applications is becoming of great interest since the last two decades. Position estimation has been one of the most crucial pieces of information for Intelligent Transportation Systems (ITS). Real time, accurate and reliable localization of vehicles has become particularly important for the automotive industry. The significant growth of sensing, communication and computing capabilities over the recent years has opened new fields of applications, such as ADAS (Advanced driver assistance systems) and active safety systems, and has brought the ability of exchanging information between vehicles. Most of these applications can benefit from more accurate and reliable localization. With the recent emergence of multi-vehicular wireless communication capabilities, cooperative architectures have become an attractive alternative to solving the localization problem. The main goal of cooperative localization is to exploit different sources of information coming from different vehicles within a short range area, in order to enhance positioning system efficiency, while keeping the cost to a reasonable level.

In this Thesis, we aim to propose new and effective methods to improve vehicle localization performance by using cooperative approaches. In order to reach this goal, three new methods for cooperative vehicle localization have been proposed and the performance of these methods has been analyzed.

Our first proposed cooperative method is a Cooperative Map Matching (CMM) method which aims to estimate and compensate the common error component of the GPS positioning by using cooperative approach and exploiting the communication capability of the vehicles. Then we propose the concept of Dynamic base station DGPS (DDGPS) and use it to generate GPS pseudorange corrections and broadcast them for other vehicles. Finally we introduce a cooperative method for improving the GPS positioning by incorporating the GPS measured position of the vehicles and inter-vehicle distances. This method is a decentralized cooperative positioning method based on Bayesian approach.

The detailed derivation of the equations and the simulation results of each algorithm are described in the designated chapters. In addition to it, the sensitivity of the methods to different parameters is also studied and discussed. Finally in order to validate the results of the simulations, experimental validation of the CMM method based on the experimental data captured by the test vehicles is performed and studied. The simulation and experimental results show that using cooperative approaches can significantly increase the performance of the positioning methods while keeping the cost to a reasonable amount.

Key words: Cooperative vehicle localization, GPS, Intelligent transportation systems, VANET, CMM, DDGPS.

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LIST OF ACRONYMS

Acronyms	Definition
CA	Constant Acceleration
CV	Constant Velocity
CT	Constant Turn
CMM	Cooperative Map Matching
DDGPS	Dynamic base station DGPS
DGPS	Differential Global Positioning System
DOD	U.S. Department of Defense
DOT	U.S. Department of Transportation
EKF	Extended Kalman Filter
GNSS	Global Navigation Satellite System
GLONASS	Russian Global Navigation Satellite System
IMU	Inertial Measurement Unit

INS	Inertial Navigation System
SLAM	Simultaneous Localization And Mapping
UKF	Unscented Kalman Filter
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VANET	Vehicular ad hoc network

LIST OF SYMBOLS

Symbol	Definition
$\hat{B}_{GPS}$	GPS bias vector
$D_j^{(i)}$	Distance between the j^{th} satellite to i^{th} GPS receiver
$D_0^{(ij)}$	True distance between V_i and V_j
$\hat{D}^{(ij)}$	Estimated distance between V_i and V_j
$\hat{P}$	Covariance of the estimation
V_N	N^{th} Vehicle
$\tilde{X}^{(i)}$	Measured position of the vehicle i^{th}
$\hat{X}^{(i)}$	Estimated position of the vehicle i^{th}
$X_0^{(i)}$	True Position of vehicle i^{th}
ρ	Pseudorange measurement
ς	Common GPS pseudorange error component
η	Non-common GPS pseudorange error component
δt	GPS receiver clock offset from the GPS time

Chapter 1 Introduction

1.1 Introduction to Intelligent Vehicles

Today with the improvement of technologies, their application in human life increases day by day and a vast effort is made for solving problems in everyday life using these new technologies.

Sensor technology is also growing and improving rapidly. These new achievements provide us with more accurate, smaller and cheaper sensors and make it possible to use lots of different sensors in an application with low cost.

One of the most important applications which we profit from in our everyday life is automotive industry. Applying new technologies in automotive industry can bring a huge profit to this industry and improve the quality of transportation either in personal applications or other business purposes.

Today, there are hundreds of different sensors which are used in vehicles. These sensors are used in different parts of vehicles. Sensors in automobile applications can be divided in five categories [90]:

1. Engine control sensors
2. Vehicle control sensors
3. Safety systems sensors
4. Navigation system sensors
5. Surrounding comfort sensors

On the other hand, as the number and variety of sensors which are used in vehicles increases, it is essential to find ways to better analyze and extract useful data from these sensors (Figure 1-1). Therefor using signal processing methods and data fusion algorithms is inevitable.

There are many different kinds of data fusion algorithms. Some of these methods have been used for many years and proved their efficiency like Kalman filters family and others are based on newly introduced methods. One of the most famous methods of these newly introduced methods is particle filters. We will discuss more details about different data fusion methods in the next chapter.

Among the applications of sensors in automotive industry, safety in particular has been a major concern since it is directly related to passenger's health. There are two kinds of safety systems:

- Active safety systems, which tries to prevent accidents.
- Passive safety systems, which tries to reduce damages.

One of the well-known examples of passive systems is airbag, which becomes activated by a sudden deceleration of speed. Some highly reliable accelerometers are used in order to drive the system and detect collision.

Active systems, on the other hand, are more complicated systems and much attention has been given to them in the recent years. Some of the topics in vehicle safety are anti-collision sensors,

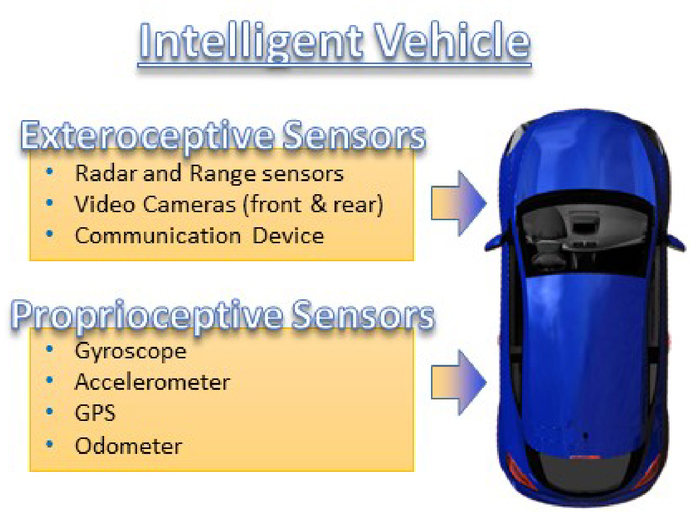

Figure 1-1. A typical Intelligent vehicle equipped with different sensors.

ice on the road sensors, road roughness sensors, assisted driving systems, lane change alarm system, vehicle localization on the road, obstacle recognition, etc. In the next chapter we will have a short review on some of these methods.

1.1 Vehicle localization

One of the most important information which is essential for many intelligent vehicle systems is vehicle localization. For example an anti-collision system which tries to avoid collision between vehicles needs to know at least relative position of vehicles. For another example in a lane change alarm system which is trying to warn driver whenever vehicle is going to change lanes, it is necessary for the system to know the absolute position of the vehicle with an acceptable accuracy and a precise map of the road. Hence it is very important to estimate the position of the vehicle as precise as possible.

There are many kinds of sensors which can be used for positioning and localization purposes like radars, lidars, cameras, GPS receivers, range sensors, etc. Some of these sensors are more powerful and accurate. Some of them like GPS receivers can help us to find absolut position of vehicle while others may help us to find relative position like range sensors.

There are two major concepts that should be taken into consideration when we are talking about positioning systems:

- Accuracy
- Reliability

Accuracy means that the estimated position is to what extent near to the actual position of the vehicle. The needed accuracy in a particular system differs between applications.

Reliability can be referred to as the availability of estimation. It means that in what portion of time the position estimation can be performed and the result is trustable.

In addition to these two characteristics, it is essential to keep in mind that if we are going to propose a vehicle positioning system in automotive industry, we should take the cost of the system into the account too. In other words, in order to introduce a new system with the possibility of being commercialized, the cost of the system should be considered.

As we mentioned before, some sensors and systems could be very useful in accurate and reliable positioning like radars, lidars and DGPS receivers, but they have some drawbacks. One of the problems is that they are rather expensive. Also in the case of DGPS signals may not be available everywhere. So it is important to find new less expensive ways with the accuracy and reliability comparable to existing methods. Therefore one solution could be to find effective combination of cheap sensors along with using the sensors which are already available in many vehicles. Then applying more efficient data fusion methods in order to achieve a vehicle positioning system with desired accuracy, reliability and with lower cost.

One of the methods that has attracted lots of attention in the recent years is cooperative localization (see Figure 1-2). With the inclusion of different kinds of sensors and communication devices in the vehicles a question is raised that how we can use different sources of information in a cluster of vehicles using the ability of communication between them in order to enhance positioning system efficiency. In other words, considering a network of connected vehicles equipped with range sensors, GPS receivers and other proprioceptive and exteroceptive sensors, the question is how to define a proper combination of sensors, find effective data fusion algorithms and use information coming from different sources and vehicles in order to better estimate the position of the vehicles in a cooperative framework. The most interesting point about cooperative localization is that we can increase the performance of the positioning system without adding high cost sensors and only by using a cooperative approach. Another advantage of cooperative localization is that if a vehicle has a high cost high accuracy sensor, other vehicles can benefit from this sensor too and improve their positioning. Also from a different point of view, assuming that we want to design a group of vehicle which can localize themselves with a given accuracy, then by using a cooperative localization method we don’t need to put all the expensive accurate instruments on every vehicle and we can distribute them between the group members and they share their information with each other.

Therefore in this project we are trying to find efficient combination of different sensors in vehicles along with using inter-vehicle communication abilities to enhance the positioning system accuracy and reliability. In other words, considering a network of connected vehicles equipped with range sensors, GPS receivers and other proprioceptive and exteroceptive sensors, our goal is to define a proper combination of sensors, find effective data fusion algorithms and use information coming from different sources and vehicles in order to better estimate the position of the vehicles and reduce the positioning uncertainty in a cooperative framework.

To reach this purpose we need to use a proper data fusion method or a combination of different data fusion methods to fuse different sources of data together and reduce uncertainty by using the characteristics of each source of information. The basic idea behind this is that by using information which comes from different sources while each of them has their own uncertainty, we have redundancy in information and if we can fuse these data together we could be able to reduce uncertainty of positioning and achieve more accurate positioning estimation and more reliability, while we have kept the cost to a reasonable amount.

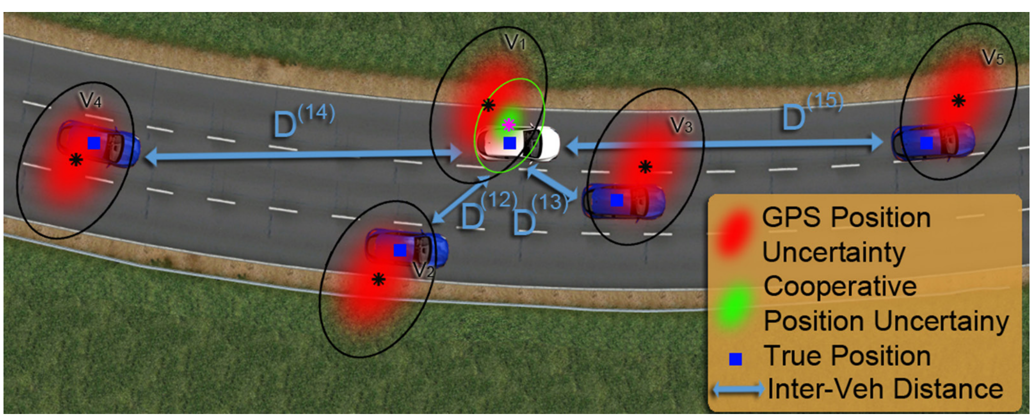

Figure 1-2. A typical scenario of collaborative localization.

1.2 Research project objectives

1.2.1 Principal objectives

As discussed in previous section, accurate and reliable vehicle localization is a key component of numerous automotive and Intelligent Transportation System (ITS) applications, including active vehicle safety systems, real time estimation of traffic conditions, and high occupancy tolling. Various safety critical vehicle applications in particular, such as collision avoidance or mitigation, lane change management or emergency braking assistance systems, rely principally on the accurate knowledge of vehicles' positioning within given vicinity. With the recent emergence of multi-vehicular wireless communication capabilities, cooperative architectures have become an attractive alternative to solving the localization problem [19, 83, 97].

The main goal of cooperative localization is to exploit different sources of information coming from different vehicles within a short range area, in order to enhance positioning system efficiency, while keeping the computing cost at a reasonable level. Vehicles share their location and environment information to others in order to increase their own global perception.

In this Project, we aim to improve the vehicle positioning by using cooperative approaches. This means to improve vehicle position estimates by using the additional information measured from different sources and sensors of the target vehicle and information recieved from the other vehicles in a cluster of vehicles. These vehicles should be able to share their information by means of a vehicular ad-hoc telecommunication network (VANET).

1.2.2 Intermediate objectives

To reach the principal objective of this study, it is necessary to fulfill certain intermediate objectives:

1. Study Single vehicle localization methods. This can be divided as follow:
    - To study and implementing different kinds of Kalman filters (EKF, UKF) with different models like CA, CV, CT.

- To study other localization methods such as particle based, Markov localization, probabilistic methods.
- To study Methods for improving the vehicle localization such as Map matching.
- To study available methods which can improve the positioning performance of GPS systems such as DDGPS.

2. Study cooperative localization algorithms developed for Vehicular networks and in outdoor applications. Also research on the possible ways to relate acquired information of the different vehicles to each other, such as inter-vehicle distances.

3. To propose new methods for cooperative localization by exploiting the communication capability of the vehicles for exchanging sensor information and environment perception.

This can be made by either:

- Designing proper filters to fuse information sources from different vehicles.
- Finding effective ways to combine each vehicle perception of the environment with other vehicles perception of the environments (vehicles, obstacles, road constraints) and achieve a more accurate perception.

Also there are some problems that we should overcome such as:

- Considering the interdependency of the measurements which can lead to convergence to a non-accurate estimation.
- The effect of time delay which can occur during communication.

4. Uncertainty analysis of the proposed method, either by using mathematical analysis or by experimental or statistical analysis.

1.3 Contribution, originality of this study

Considering the importance and limitations of the cooperative positioning the contributions of this study are:

- Development and implementation of a new cooperative map matching method which exploits the communication capability of the vehicles to share the road constraints related to each vehicle and provide for all the vehicles the possibility to perform a better positioning by having more accurate map matching.

- Development and implementation of the new concept of dynamic base station DGPS which is an extension to the DGPS. This method is a distributed cooperative method which can significantly improve the performance of the GPS based positioning methods. Unlike the DGPS, this method doesn't need to have a static base stations and each vehicles acts as a receiver and a base station at the same time.
- Development and implementation of a new decentralized Bayesian approach for cooperative localization based on fusion of GPS and VANET based inter-vehicle distance. This method uses the GPS measured position of the vehicles and by fusing this information with the relative distance of the vehicles using a Bayesian approach it can achieve a better position estimation.

The originality of this study can be summarized in these major aspects:

- Our cooperative map matching method unlike the other cooperative map matching methods [121], doesn't need to have the relative distance between vehicles and more importantly it takes into account the effect of the non-common pseudorange error between different GPS receivers participating in the cooperative map matching process. In addition to this our method considers the possibility of observing different sets of satellite by different vehicles and propose a solution for it.
- The effect of non-common pseudorange error is an important issue which has been considered in the cooperative map matching. Without considering this error, the true vehicles position may fall outside the expected area and leads to an over converged position estimation.
- The Dynamic base station DGPS is an extension of the DGPS method by using mobile reference stations instead of fixed one. This method brings an interesting possibility for improving positioning performance in distributed systems.
- The Bayesian approach developed in this study is an interesting way to improve the quality of the positioning. Unlike other Bayesian approaches [13, 52] which basically have been developed for indoor robotic applications, our method is developed for outdoor usage and automotive applications. This method should be seen as a pre-filtering

of GPS positioning measurement using inter-vehicle distances and other vehicles' GPS measurements, prior the tracking algorithms such as the Extended Kalman Filter (EKF). Therefore this method has the advantage to be incorporated with any existing ego localization algorithm which uses GPS.

1.4 Hypothesis

The Hypothesis and assumptions made in developing each algorithm is detailed and described in the introduction of their respective chapters. However in order to have a general overview of the assumptions made in this thesis, here we briefly review these assumptions.

1.4.1 Hypothesis for CMM and DDGPS algorithms

These methods are described in Chapter 5 . The assumptions made in this chapter are as follow:

1. First it is assumed that we have several vehicles with communicating capabilities by means of a communication device. For this purposes the IEEE 802.11p can be considered as a suitable standard. This standard is an inter-vehicular communication technology designed for both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications.
2. Each vehicle is equipped with a GPS receiver and it can use this GPS receiver to measure its position and respective covariance matrix. Also the GPS receiver must have the capability to provide us with the raw GPS pseudorange measurements.
3. Each vehicle is equipped with a digital map of the road with known accuracy.

1.4.2 Hypothesis for the Bayesian Cooperative Vehicle Localization method

This method is described in Chapter 6 . The assumptions made in this chapter is as follow:

1. We assume that each vehicle is able to measure its position and respective covariance matrix using its embedded GPS receiver independently.

2. We consider also that each vehicle is able to estimate its distance to other vehicles, using a VANET based method and independent from their GPS signals.
3. Finally, it is assumed that the vehicles share their information by means of a VANET.

1.5 Thesis plan

The thesis is structured in 8 chapters.

The purpose of the present chapter is to introduce the motivations, objectives, originalities and contributions of this study. In this chapter the general overview of research project and the problem to be faced is described.

In the second chapter we have a short review on several different sensors and systems which are being used in vehicles and specifically the ones which are used in positioning purposes. In the third chapter, we briefly study the most common data fusion methods in vehicle localization. In the fourth chapter, we have a review on existing methods of vehicle localization and specifically cooperative vehicle localization methods.

The fifth chapter concentrates on the two proposed cooperative methods which can estimate and compensate the common position error component of the GPS positioning. In this chapter we first introduce the different sources of error on the GPS positioning and then separate them in two categories, common and non-common error components. Then we describe our proposed CMM (Cooperative Map Matching) method which aims to estimate and compensate the common error component of the GPS positioning by using cooperative approach and exploiting the communication capability of the vehicles. Then after that we propose the concept of DDGPS (Dynamic base station DGPS) and use it to generate GPS pseudorange corrections and broadcast them for other vehicles.

In chapter sixth, we introduce a cooperative method for improving the GPS positioning by incorporating the GPS measured position of the vehicles and inter-vehicle distances. This method is a decentralized cooperative positioning method based on Bayesian approach. The detailed derivation of the equations and the simulation results are described in this chapter. In addition to it, the sensitivity of the method to different parameters is also studied and discussed.

Chapter seventh includes the experimental validation of the cooperative map matching method described in chapter fifth based on the experimental data captured by the test vehicles.

The final chapter concludes the final overview of this research project. Finally, the perspectives of this research project that can be proposed to continue this study in future works are illustrated.

Chapter 2 Sensors for Localization and Navigation

In this chapter we have a quick review on different kinds of sensors used in localization and navigation. In order to help users obtain the position of vehicle and provide proper manoeuvre instructions, vehicle position must be determined precisely. Hence, accurate and reliable positioning is an essential part of any good localization and navigation system.

Between the positioning technologies three are most commonly used: stand-alone, satellite based, and terrestrial radio based. Dead reckoning is a typical stand-alone technology. A common example for satellite-based technology is to equip a vehicle with a global positioning system (GPS) receiver. Dead reckoning and GPS technologies together, have been used widely in vehicle industry. It is necessary to remember that, no single sensor is adequate to estimate position and location information to the accuracy often required by a location and navigation system. A common solution and in most of the cases the only way of obtaining the required levels of reliability and accuracy is to fuse information from a number of different sensors. Therefore, a positioning module typically integrates multiple sensors, which compensate for one another to meet overall system requirements. Therefore, in order to have an efficient positioning module we should study a variety of sensors (Figure 2-1), fusion methods, and algorithms [146].

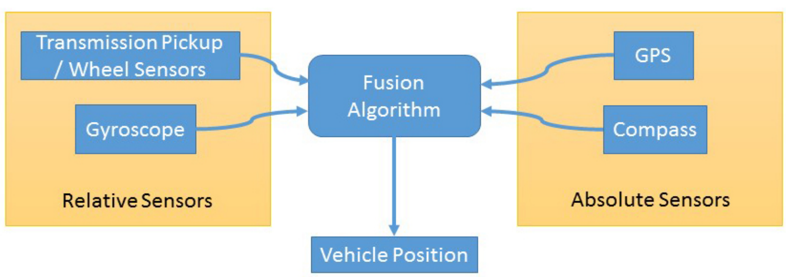

Figure 2-1. A generic positioning module.

As seen in Figure 2-1, the positioning module is based on a variety of different positioning sensors. More details about some automotive sensor developments and automotive sensor technologies can be found in [58, 59, 90, 112]. A detailed discussion of sensor technologies, sensor principles, and sensor interface circuits can be found in [33, 113]. In-depth coverage of sensor integration and fusion can be found in [76].

Positioning sensors can be separated in two categories:

- Relative Positioning Sensors
- Absolute Positioning Sensors

In the following, we briefly discuss these two categories of sensors.

2.1 Relative positioning sensors

Relative sensors are sensors that can measure the variations of a quantity such as distance, position, or heading based on an initial condition or previous measurement. These sensors cannot determine absolute values, without knowing an initial reference.

Some of the relative positioning sensors are:

Transmission pickups, which are sensors used to measure the angular position of the transmission shaft. The most common technologies for transmission pickup sensors are variable reluctance, the Hall-effect, magneto resistance, and optically based technologies, which are used to convert the mechanical motion into electronic signals. The sensor's output are pulse counts which are proportional to the movement of the vehicle. We can convert the output of the sensor into distance using the number of pulse counts and the relative conversion scale factor.

Differential odometer, which is a technique used to estimate traveled distance and heading direction change by integrating the outputs from two odometers, one for a pair of front or rear wheels. An odometer is a relative sensor that measures distance traveled with respect to an initial position [146].

Gyroscopes, rate-sensing gyroscopes measure angular rate, and rate-integrating gyroscopes measure attitude. At the present time, most location and navigation systems use gyroscopes to measure the angular rate [146].

A steering encoder measures the angle of the steering wheel. It measures the angle of the front wheels relative to the forward direction of the vehicle. Knowing the wheel speed, the steering angle can be used to calculate the heading rate of the vehicle.

An accelerometer measures the acceleration of the vehicle to which it is attached. In other words, an accelerometer produces an output proportional to the specific force exerted on the instrument, projected onto the coordinate frame mechanized by the accelerometer [30]. Also a gyroscope can provide the information about an object's orientation and rotation (rate-gyro), by measuring the angular velocity of the object relative to the inertial frame of reference. Therefore, by using the inertial sensors, i.e., accelerometers and gyroscopes, we can estimate the position and the velocity of a vehicle.

2.2 Absolute positioning sensors

Absolute positioning sensors are a kind of sensor that can provide information on the position of the vehicle with respect to the reference coordinate system. Therefore absolute position sensors are very important in solving location and navigation problems. The most commonly used absolute positioning sensors are the magnetic compass and GPS.

A magnetic compass measures the Earth's magnetic field. A compass is able to measure the orientation of an object (such as a vehicle) to which it is attached. The orientation is measured with respect to magnetic north [146].

Due to the importance of the GNSS (Global Navigation Satellite Systems) in localization methods, we briefly study these systems in the next section.

2.2.1 Global Navigation Satellite Systems

Currently, there are two GNSSs available, the Russian GLONASS and the American GPS [134]. Also Galileo is under construction as the European satellite navigation system. These Systems have some similarities and also the GPS and Galileo are intended to be directly compatible while GLONASS needs a receiver with a different structure. The orbit plans of the systems' satellite constellations is different and this provides a good coverage across various regions [123, 134]. In this section we have a quick review on the GPS.

The GPS is a satellite-based radio navigation system. It provides a practical and affordable means of determining position, velocity, and time around the globe. GPS was designed and paid for by the U.S. Department of Defense (DOD). Civilian access is guaranteed through an agreement between the DOD and the Department of Transportation (DOT) [146].

GPS includes three main parts: the space segment (satellites), the user segment (receivers) and the control segment (management and control). In location and navigation systems only the first two parts are concerned. More details and descriptions of each of these main parts, as well as various theoretical and practical aspects of GPS can be found in [51, 71, 99].

In order to determine the user position and the time offset between the receiver and GPS time, it is necessary for the user to be able to observe at least four satellites simultaneously [60].

The GPS constellation consists of 24 satellites arranged in six orbital planes with 4 satellites per orbital plane. This satellite constellation is designed to provide a 24-hour global user navigation and time determination capability [60]. The characteristics of GPS are summarized in Table 2-1 [22, 146].

Position measurement is based on the principle of time of arrival (TOA) ranging. In order to obtain the satellite-to-receiver distance, the time interval taken for a signal transmitted from a satellite to reach a receiver is multiplied by the speed of the signal. Multiple signals received by a receiver from multiple satellites at known locations are used to determine its location. Because of clock offset between satellite and receiver, propagation delays, and other errors, it is impossible to measure the actual range, so a pseudorange is measured. The clock offset is the constant difference in the clock of the satellite and receiver.

Table 2-1. GPS characteristics.

Item	Characteristics
Satellites	24 satellites broadcast signals autonomously
Orbits	Six planes, at 55-degree inclination, each orbital plane includes four satellites at 20,231-km altitude, with a 12-hr period
Carrier frequencies	L1: 1575.42 MHz L2: 1227.60 MHz
Digital Signals	C/A code (coarse acquisition code): 1.023 MHz P code (precise code): 10.23 MHz Navigation message: 50 bps
Position accuracy	SP: 100m horizontal (2dRMS) and 140m vertical (95%) PPS: 21m horizontal (2dRMS) and 29m vertical (95%)
Velocity accuracy	SPS: 0.5-2 m/s observed PPS: 0.2 m/s
Time accuracy	SPS: 340 ms (95%) PPS: 200 ms (95%)

In addition to position of the receiver, as the receiver clock used to measure the signal propagation times is not synchronized to GPS time, the clock offset between receiver time and GPS time must be determined. Therefore, at least 4 satellites are needed to determine receiver position. By design, all of the satellite clocks are synchronized using very precise atomic clocks. As atomic clocks are expensive it is economically impractical for receivers to use atomic clocks, so instead, inexpensive crystal oscillators are used. These clocks are not precise and they have a time offset (clock bias) with GPS clocks. The receiver clock bias is the time offset of the receiver, and it is the same for each satellite. Thus both the receiver position and clock offset can be derived from the following equations:

$$\rho_1 = \sqrt{(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2} + dt.c$$

$$\rho_2 = \sqrt{(x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2} + dt.c \qquad \text{2-1}$$

$$\rho_3 = \sqrt{(x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2} + dt.c$$

$$\rho_4 = \sqrt{(x - x_4)^2 + (y - y_4)^2 + (z - z_4)^2} + dt.c$$

where (x_i, y_i, z_i) are the known satellite positions, ρ_i are measured pseudoranges and *dt* is the unknown receiver clock offset from GPS time. In the above equations, several error terms have been left out for simplicity. For instance, the range errors due to ionospheric delay and tropospheric delay can both be estimated using atmospheric models. However, receiver noise, multi path propagation error, satellite orbit errors, and SA effects remain [146].

Errors in range estimates can be divided in two categories, depending on their spatial correlation, as common and non-common mode errors [31, 40]. *Common mode* errors are the errors which are highly correlated between GNSS receivers in a local area (50–200 km) and are due to ionospheric radio signal propagation delays, satellite clock error, ephemeris errors, and tropospheric radio signal propagation delays. The other error category is *Non-common mode* errors. These are the errors which depend on the precise location and technical construction of the GNSS receiver and are due to multipath radio signal propagation and receiver noise. Table 2-2 shows a typical standard deviation of these errors in the rang estimates of a single-frequency GPS receiver, working in standard precision service mode [31].

2.2.1.1 Augmentation Systems

Since common mode errors are highly correlated between GNSS receivers in a local area, it is possible to compensate these errors by having a stationary GNSS receiver at a known location

Table 2-2. Standard deviation of errors in the range measurements in a single-frequency GPS receiver [31].

Error Source	Standard deviation (m)
Common mode	
Ionospheric	7.0
Clock and ephemeris	3.6
Tropospheric	0.7
Non-common mode	
Multi-path	0.1-3.0
Receiver noise	0.1-0.7
Total (UERE)	**7.9-8.5**
CEP with a horizontal dilution of precision, HDOP=1.2	**6.6-7.1**

which can estimate the common mode errors and transmit the correction information to rover GNSS receivers. This technology is called differential GNSS (DGNSS).

As the distance between the reference station and the rover unit increases, the correlation of the common mode error decreases and therefore the system performance will decreases [70]. In order to solve this problem a network of reference stations over the intended coverage area is used. These stations observe the errors and send them to the central processing station. Then at the central processing station a map of the ionospheric delay, together with ephemeris and satellite clock corrections, is calculated. The correction map is then transmitted to the receivers, which can use this map to calculate correction data for their specific location [30], [105].

Here we have to note that, even if the GNSS receivers' positioning accuracy is enhanced by various augmentation systems, still there are some problems that restrict the usage of the GNSS receivers. The problems of poor satellite constellations, satellite signal blockages, and signal multipath propagation in urban environments still remain. For example in the areas such as tunnels a reliable GNSS receiver navigation solutions is not available. This problem can be reduced by using pseudolites which some ground-based stations are acting as additional satellites. However, this also has its own drawbacks such as it only solves the coverage problem locally, it requires an additional infrastructure, and the GNSS receiver must be designed to handle the additional pseudolite signals.

Chapter 3 Data Fusion Methods

In this chapter we are going to have an overview on some of the most common data fusion methods. Some of these methods have been used for more than 30 years like nonlinear filtering [46]. Some other methods have been in the focus of interest in the recent years. First we will take a look at the nonlinear filters and in particular Kalman filters.

3.1 Nonlinear filtering

In nonlinear filtering the problem is to estimate sequentially the state of a dynamic system having a series of noisy measurements. In a dynamic system we can model the evolution of the system using difference equations and using the noisy measurements. These methods use state space approach. A state vector is a vector which has all the relevant information needed to describe the system. As an example in a tracking system a state vector could have information about position, velocity, acceleration and other kinematic characteristics of the target.

In many problems, it is desired for the system to be able to calculate an estimation of the state whenever a measurement is received. A good solution for this is using recursive filters. A recursive filter doesn't need to store all the received data, it processes data sequentially. These kinds of filters usually consist of two steps: prediction and update.

Prediction step is the step in which we can predict the state vector by using a model which describes the evolution of the system.

Update step is the step in which system uses new measurements to modify the prediction.

Hence, two models are needed for a nonlinear filter, one model describing the evolution of the state and other one describes the relation between measurements and state vector. These two models should be available in a probabilistic form. A Bayesian approach, then, is a suitable choice for formulation of these models. Using this approach, in the prediction step, the filter tries to construct the posterior probability density function based on all the available information and the system model. It usually translates, deforms, and broadens the state pdf due to the presence of unknown disturbance. In the update step, filter uses the new information from new measurements to modify the prediction pdf (typically tighten) using Bayes theorem.

3.1.1 The problem and its conceptual solution

Let x_k be the target state vector where k is the time index. The target state changes according to the model of system:

$$x_k = f_{k-1}\left(x_{k-1}, v_{k-1}\right) \tag{3-1}$$

Where f_{k-1} is a function of previous state x_{k-1} and v_{k-1} is the process noise sequence. This noise stands for the model errors and disturbances in the target motion model. In order for the filter to be able to estimate x_k from observations it needs to have the measurement equation which relates the measurements to the state vector:

$$z_k = h_k\left(x_k, w_k\right) \tag{3-2}$$

Where h_k is a function of target state and w_k is the measurement noise sequence. In these equations v_{k-1} and w_k are mutually independent and white. We assume to know the probability density functions of v_{k-1} and w_k and the initial state pdf $p(x_0)$.

We need to find $p\left(x_k | Z_k\right)$ where Z_k are all available measurements up to time k. suppose that we have the pdf of $p\left(x_{k-1} | Z_{k-1}\right)$. Form Chapman-Kolmogorov equation and using system model we will have:

$$p(x_k \mid Z_{k-1}) = \int p(x_k \mid x_{k-1})\, p(x_{k-1} \mid Z_{k-1})\, dx_{k-1} \tag{3-3}$$

Where $p\left(x_{k-1}|Z_{k-1}\right)$ is defined by knowing the system model and statics of the process noise v_{k-1}.

In the time step of k, when we have the measurement z_k, the update stage is calculated from the following equation:

$$p\left(x_k|Z_k\right)=p\left(x_k|z_k,Z_{k-1}\right)=\frac{p\left(z_k|x_k,Z_{k-1}\right)p\left(x_k|Z_{k-1}\right)}{p\left(z_k|Z_{k-1}\right)}=\frac{p\left(z_k|x_k\right)p\left(x_k|Z_{k-1}\right)}{p\left(z_k|Z_{k-1}\right)} \qquad 3\text{-}4$$

Where

$$p\left(z_k|Z_{k-1}\right)=\int p\left(z_k|x_k\right)p\left(x_k|Z_{k-1}\right)dx_k \qquad 3\text{-}5$$

In which $p\left(z_k|x_k\right)$ is calculated using the measurement model and statics of the measurement noise w_k. The update step modifies the prior density and gives the posterior density of the current state.

Knowing the posterior density functions gives us the ability to calculate the optimal estimate with respect to a specific criterion. For example a minimal mean square error can be calculated as:

$$\hat{x}_{k|k}^{MMSE}\triangleq E\left\{x_k|Z_k\right\}=\int x_k\,p\left(x_k|Z_k\right)dx_k \qquad 3\text{-}6$$

And a MAP estimator calculates the maximum a posterior as:

$$\hat{x}_{k|k}^{MAP}\triangleq argmax_{x_k}\,p\left(x_k|Z_k\right) \qquad 3\text{-}7$$

And in a similar way an estimate of the covariance can be calculated from this posterior density function.

In order to implement the conceptual solution we need to store the whole pdf (possibly non-Gaussian) which is not possible in all cases and in general case it needs an infinite dimension vector [3].

3.2 Kalman Filter

Kalman filter is a special case of recursive Bayesian filtering in which it assumes that the posterior probability density function is Gaussian so it can completely be described by its mean and variance and the system model and measurement equations are linear. Assuming that v_{k-1} and w_k are Gaussian densities with known parameters and f_{k-1} and h_k are linear, we can say that if $p\left(x_{k-1}|Z_{k-1}\right)$ is Gaussian, $p\left(x_k|Z_k\right)$ is Gaussian too.

Therefore the prediction and update equation for state vector of dimension n_x and measurement vector of size n_z can be written as:

$$x_k = F_{k-1}x_{k-1} + v_{k-1} \qquad \text{3-8}$$

$$z_k = H_k x_k + w_k \qquad \text{3-9}$$

Where F_{k-1} is of dimension $(n_x \times n_x)$ and H_k is of dimension $(n_z \times n_x)$ and v_{k-1} and w_k are zero mean white Gaussian noises with covariance Q_{k-1} and R_k and these noises are mutually independent. Noise covariance matrixes and F_{k-1} and H_k can be time variant.

The Kalman equations are as follow:

$$\hat{x}_{k|k-1} = F_{k-1}\hat{x}_{k-1|k-1} \qquad \text{3-10}$$

$$P_{k|k-1} = Q_{k-1} + F_{k-1}P_{k-1|k-1}F_{k-1}^T \qquad \text{3-11}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(z_k - H_k \hat{x}_{k|k-1} \right) \qquad 3\text{-}12$$

$$S_k = H_k P_{k|k-1} H_k^T + R_k \qquad 3\text{-}13$$

$$P_{k|k} = P_{k|k-1} - K_k S_k K_k^T \qquad 3\text{-}14$$

And the Kalman Gain is defined as:

$$K_k = P_{k|k-1} H_k^T S_k^{-1} \qquad 3\text{-}15$$

Using these equations we can recursively estimate the optimal solution while the assumptions hold. These equations recursively estimate the mean and covariance of the posterior pdf, $p\left(x_k|Z_k\right)$ [3]. This estimation is the optimal solution of the problem if the following assumptions hold:

- v_{k-1} and w_k have Gaussian densities with known parameters.
- f_{k-1} and h_k are linear functions.

In this case we can say that no filter can perform better than Kalman filter for the linear Gaussian problem.

3.3 Extended Kalman Filter

In many real cases because of the nonlinearity and non-Gaussian nature of systems it is not possible to use Kalman filter. In these cases we must use suboptimal filters. Extended Kalman Filter (EKF) is an example of the suboptimal filter using analytical approximations. The main difference of this method is that it linearizes the measurement and state dynamic models.

Therefore the prediction and update equation for state vector of dimension n_x and measurement vector of size n_z can be written as:

$$x_k = f_{k-1}\left(x_{k-1}\right) + v_{k-1}. \tag{3-16}$$

$$z_k = h_k\left(x_k\right) + w_k \tag{3-17}$$

As in the Kalman filters v_{k-1} and w_k are zero mean white Gaussian noises with covariance Q_{k-1} and R_k and they are mutually independent. In this equation f_{k-1} and h_k are nonlinear functions and EKF approximate these functions with the first term of Taylor series expansion. The mean and covariance of the posterior probability density function is estimated as:

$$\hat{x}_{k|k-1} = f_{k-1}\left(\hat{x}_{k-1|k-1}\right) \tag{3-18}$$

$$P_{k|k-1} = Q_{k-1} + \hat{F}_{k-1} P_{k-1|k-1} \hat{F}_{k-1}^T \tag{3-19}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(z_k - h_k\left(\hat{x}_{k|k-1}\right)\right) \tag{3-20}$$

$$P_{k|k} = P_{k|k-1} - K_k S_k K_k^T \tag{3-21}$$

Where

$$S_k = \hat{H}_k P_{k|k-1} \hat{H}_k^T + R_k \tag{3-22}$$

$$K_k = P_{k|k-1} \hat{H}_k^T S_k^{-1} \tag{3-23}$$

$\hat{H}_k$ and $\hat{F}_{k-1}$ are the linearization of h_k. and f_{k-1} around $\hat{x}_{k-1|k-1}$ and $\hat{x}_{k|k-1}$ respectively.

$$\hat{F}_{k-1} = \left[\nabla_{x_{k-1}} f_{k-1}^T \left(x_{k-1}\right)\right]^T |_{x_{k-1}=\hat{x}_{k-1|k-1}} \qquad 3\text{-}24$$

$$\hat{H}_k = \left[\nabla_{x_k} h_k^T \left(x_k\right)\right]^T |_{x_k=\hat{x}_{k|k-1}} \qquad 3\text{-}25$$

Where

$$\nabla_{x_k} = \left[\frac{\partial}{\partial x_k\left[1\right]} \cdots \frac{\partial}{\partial x_k\left[n_x\right]}\right]^T \qquad 3\text{-}26$$

And $x_k\left[i\right]$ is the i^{th} component of x_k.

3.4 Particle Filters

Particle filters (PFs) are categorized as suboptimal filters. They are also known as sequential Monte Carlo (SMC) estimation technics which are based on point mass representation of probability densities. These points are called particles. In this section we describe the basic concepts of the SMC estimations [3].

3.4.1 Monte Carlo Integration

Monte Carlo Integration is the basis of all the SMC methods. Consider that we want to calculate the following equation by a numerical approach:

$$I = \int g(x)dx \qquad 3\text{-}27$$

Where $x \in R^{n_x}$. Monte Carlo (MC) methods (Davis & Rabinowitz, 1984) are based on factorizing $g(x)$ as $g(x) = f(x).\pi(x)$ while $\pi(x)$ satisfying the probability density conditions $\pi(x) \geq 0$ and $\int \pi(x)dx = 1$. These methods assume that if we draw $N >> 1$ samples $\{x^i; i = 1,..., N\}$ distributed according to $\pi(x)$ then the MC estimate of integral:

$$I = \int f(x).\pi(x)dx \qquad 3\text{-}28$$

is the sample mean:

$$I_N = \frac{1}{N}\sum_{i=1}^{N} f(x^i) \qquad 3\text{-}29$$

3.4.2 Importance Sampling

It is Ideal to generate samples directly from $\pi(x)$ and estimate I. However there are only special cases that using $\pi(x)$ is possible and in the general case this is not possible. In the general case sampling from a density $q(x)$ which is similar to $\pi(x)$ and then using a corrected weighting of the sample set makes the MC estimation possible. This pdf $q(x)$ is called the importance or proposal density function. $\pi(x)$ and $q(x)$ are similar if they have the following condition:

$$\pi(x) > 0 \Rightarrow q(x) > 0 \text{ for all } x \in R^{n_x} \qquad 3\text{-}30$$

which means that $\pi(x)$ and $q(x)$ have the same support. This is a necessary condition for the importance sampling theory to hold. If it is valid, any integral of the form 3-28 can be expressed as:

$$I = \int f(x).\pi(x)dx = \int f(x).\frac{\pi(x)}{q(x)}q(x)dx \qquad 3\text{-}31$$

A Monte Carlo estimate of I is then calculated by:

$$I_N = \frac{1}{N}\sum_{i=1}^{N} f(x^i)\tilde{w}(x^i) \qquad 3\text{-}32$$

Where $\{x^i; i = 1,...,N\}$ are independent samples distributed according to $q(x)$ with $N >> 1$ and

$$\tilde{w}(x^i) = \frac{\pi(x^i)}{q(x^i)} \qquad 3\text{-}33$$

are the weight importance. When we don’t know the normalizing factor of the $\pi(x)$, normalization of the importance weight is needed as follow:

$$I_N = \frac{\frac{1}{N}\sum_{i=1}^{N} f(x^i)\tilde{w}(x^i)}{\frac{1}{N}\sum_{j=1}^{N} \tilde{w}(x^j)} = \sum_{i=1}^{N} f(x^i)w(x^i) \qquad 3\text{-}34$$

Where $w(x^i)$ is the normalized importance weights:

$$w(x^i) = \frac{\tilde{w}(x^i)}{\sum_{j=1}^{N} \tilde{w}(x^j)} \qquad 3\text{-}35$$

We have to note that when apply this method in the Bayesian framework, $\pi(x)$ is the posterior density [3].

3.4.3 Sequential Importance Sampling

Sequential importance sampling (SIS) algorithm is a Monte Carlo method. Most of the other MC filters have the same basis as SIS. SIS is referred in [3] as "a technique for implementing a recursive Bayesian filter by Monte Carlo simulations". The main idea of the MC filters is to estimate the posterior density function using a set of random samples with their associated weights.

Let $X_k = \{x_j; j = 1,...,k\}$ be the sequence of all target states from the beginning up to time k. $p(X_k \mid Z_k)$ is the joint posterior density at time k. We define $\{X_k^i, w_k^i\}_{i=1}^N$ as a random measurement which can characterize $p(X_k \mid Z_k)$, where $\{X_k^i, i = 1...N\}$ is a set of support points and $\{w_k^i, i = 1...N\}$ are their respective weights while $\sum_i w_k^i = 1$. Therefore, we can approximate the posterior density as follow:

$$p(X_k \mid Z_k) \approx \sum_{i=1}^{N} w_k^i \delta(X_k - X_k^i) \qquad 3\text{-}36$$

w_k^i is calculated using the importance sampling principles as follow:

$$w_k^i \propto \frac{p(X_k^i \mid Z_k)}{q(X_k^i \mid Z_k)} \qquad \text{3-37}$$

We can expand $q(X_k \mid Z_k)$ at time k using the existing samples $X_{k-1}^i \sim q(X_{k-1} \mid Z_{k-1})$ with the new state $x_k^i \sim q(x_k \mid X_{k-1}, Z_k)$ as:

$$q(X_k \mid Z_k) \triangleq q(x_k \mid X_{k-1}, Z_k) q(X_{k-1} \mid Z_{k-1}) \qquad \text{3-38}$$

Now we need to derive the weight update equation, we have:

$$\begin{aligned}
p(X_k \mid Z_k) &= \frac{p(z_k \mid X_k, Z_{k-1}) p(X_k \mid Z_{k-1})}{p(z_k \mid Z_{k-1})} \\
&= \frac{p(z_k \mid X_k, Z_{k-1}) p(x_k \mid X_{k-1}, Z_{k-1}) p(X_{k-1} \mid Z_{k-1})}{p(z_k \mid Z_{k-1})} \\
&= \frac{p(z_k \mid x_k) p(x_k \mid x_{k-1})}{p(z_k \mid Z_{k-1})} p(X_{k-1} \mid Z_{k-1}) \\
&\propto p(z_k \mid x_k) p(x_k \mid x_{k-1}) p(X_{k-1} \mid Z_{k-1})
\end{aligned} \qquad \text{3-39}$$

By substituting 3-38 and 3-39 in 3-36 we have:

$$w_k^i \propto \frac{p(z_k \mid x_k^i)p(x_k^i \mid x_{k-1}^i)p(X_{k-1}^i \mid Z_{k-1})}{p(x_k^i \mid X_{k-1}^i, Z_k)q(X_{k-1}^i \mid Z_{k-1})} = w_{k-1}^i \frac{p(z_k \mid x_k^i)p(x_k^i \mid x_{k-1}^i)}{q(x_k^i \mid X_{k-1}^i, Z_k)} \qquad \text{3-40}$$

Furthermore, in many cases we can assume that $q(x_k \mid X_{k-1}, Z_k) = q(x_k \mid x_{k-1}, z_k)$, which means that the importance density is only dependent on the previous state x_{k-1} and last observation z_k. Then the weight becomes

$$w_k^i \propto w_{k-1}^i \frac{p(z_k \mid x_k^i)p(x_k^i \mid x_{k-1}^i)}{q(x_k^i \mid x_{k-1}^i, z_k)} \qquad \text{3-41}$$

Finally we can approximate the posterior density as:

$$p(x_k \mid Z_k) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i) \qquad \text{3-42}$$

It is possible to proof that if $N \to \infty$ the approximation 3-42 approaches to the true value of $p(x_k \mid Z_k)$. To summarize, the SIS filtering is a recursive filtering that in each iteration when a measurement is received it propagates the support points X and updates their importance weights.

The only remaining point is how to choose the importance density function which is one of the most critical steps in the design of particle filters. In [24] it has been proposed to that the optimal choice for importance density function can be derived by minimizing the variance of the importance weights. This optimal function is as follow:

$$q(x_k \mid x_{k-1}^i, z_k)_{opt} = p(x_k \mid x_{k-1}^i, z_k) = \frac{p(z_k \mid x_k, x_{k-1}^i)\, p(x_k \mid x_{k-1}^i)}{p(z_k \mid x_{k-1}^i)} \qquad 3\text{-}43$$

And the weights are:

$$w_k^i \propto w_{k-1}^i p(z_k \mid x_{k-1}^i) \qquad 3\text{-}44$$

However there are only few specific cases that the using the optimal function is possible. One example is when x_k is a member of a finite set such as a jump-Markov linear system for tracking maneuvering targets [25]. The second example is the models for which $p(x_k \mid x_{k-1}^i, z_k)$ is Gaussian.

In most of the cases we must use suboptimal choices. The most popular method is the transitional prior where:

$$q(x_k \mid x_{k-1}^i, z_k) = p(x_k \mid x_{k-1}^i) \qquad 3\text{-}45$$

Let the state dynamics of the system and measurement equation be expressed by the following equation:

$$x_k = f_{k-1}(x_{k-1}) + v_{k-1} \qquad 3\text{-}46$$

$$z_k = h_k(x_k) + w_{k-1} \qquad 3\text{-}47$$

Where v_{k-1} and w_{k-1} is a zero mean white Gaussian sequence with the variance Q_{k-1} and R_{k-1} respectively. Then transitional prior becomes:

$$q(x_k \mid x_{k-1}^i, z_k) = p(x_k \mid x_{k-1}^i) = N(x_k; f_{k-1}(x_{k-1}), Q_{k-1}) \quad 3\text{-}48$$

Then the weight update equations are:

$$w_k^i \propto w_{k-1}^i p(z_k \mid x_k^i) \quad 3\text{-}49$$

3.4.4 Degeneracy Problem

One of the problems with SIS is the degeneracy problem. As it has been shown in [24] the variance of importance weights will increase over time. This means that after a while, most of the particles will have negligible normalized weights. Degeneracy decreases the efficiency and accuracy of the SIS based filters because a large computational effort is done to updating particles whose contribution to the approximation of $p(x_k \mid z_k)$ is negligible. Effective sample size can be used as a measurement of the degeneracy:

$$\widehat{N}_{eff} = \frac{1}{\sum_{i=1}^{N} (w_k^i)^2} \quad 3\text{-}50$$

where N is the number of particles and w_k^i is the normalized weight. As $\widehat{N}_{eff}$ becomes smaller the probability of the degeneracy increases.

3.4.5 Resampling

Resampling is a step which is added to SIS to solve the degeneracy problem. When $\widehat{N}_{eff}$ falls below a specific threshold, resampling will be required. Resampling removes the samples with low importance weights and adds samples with higher importance weights. It maps the random measure $\{x_k^i, w_k^i\}$ to a new random measure $\{x_k^{i*}, 1/N\}$ where all the particles have a uniform weight. The new sample set $\{x_k^{i*}\}_{i=1}^{N}$ is generated by resampling N times from $p(x_k \mid Z_k)$ (with replacement) in the way that $p(x_k^{i*} = x_k^j) = w_k^j$ where $p(x_k \mid Z_k)$ is:

$$p(x_k \mid Z_k) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i) \qquad \text{3-51}$$

By using this method, the probability of choosing new samples from the previous samples who had higher weights is more than choosing from previous samples with lower weights. Figure 3-1 shows a graphical representation for different steps of the SIS with resampling (with N=7 Samples).This example uses the transitional density as the importance function.

First 7 particles randomly have been selected with a uniform weight which approximates the prediction density $p(x_k \mid Z_{k-1})$. At the second step we use the received measurement to compute the importance weight for each samples using 3-49. This results to $\{x_k^i, w_k^i\}$ which is an approximation of the $p(x_k \mid Z_k)$. If resampling is needed important particles will be selected according to their weights and form $\{x_k^{i*}, 1/N\}$. The final step is the prediction that results in $\{x_{k+1}^i, 1/N\}$ which approximates $p(x_{k+1} | Z_k)$ and will be used for next iteration.

3.4.6 Particle filter limitations

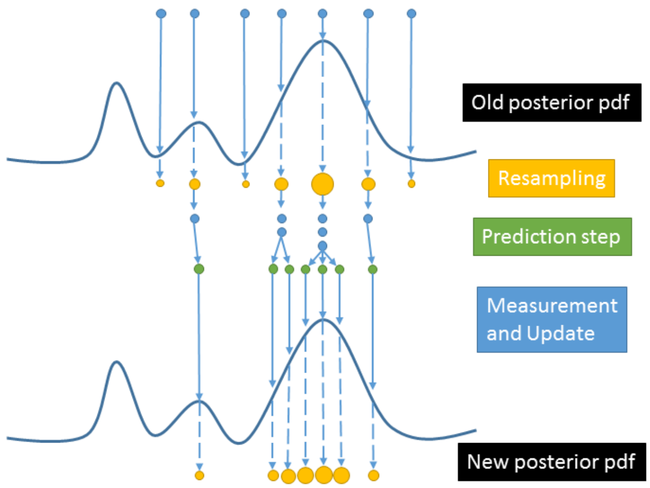

Figure 3-1. Typical steps of SIS.

Some of the most important limitations of particle filters are as following:

- *Computationally expensive*: Particle filters are computationally expensive and they need lots of computational requirements therefore as a general rule, in practice particle filters should only use if Kalman filters can't provide satisfactory results or they are difficult to implement [3].

- *Degeneracy problem*: This mean that after a while, most of the particles will have negligible normalized weights. Degeneracy decreases the efficiency and accuracy of the particle filters because a large computational effort is done to updating particles whose contribution to the approximation of $p(x_k | z_k)$ is negligible [3].

- *Sample impoverishment*: This problem is caused after resampling. In resampling the particles with higher weights are more likely to be selected and this causes the situation that after a while all the samples collapse in a single point. Therefore the samples diversity decreases and complete true density can't be estimated. This problem is more important in the cases that the state dynamics noise is very small [3].
- *Dimensions:* They are not suitable for problems with high dimension spaces because they tend to grow exponentially with dimensions of space [133].

Chapter 4 State of the Art

This chapter draws a picture over the different studies on the related topics of vehicle localization and cooperative vehicle localization. These topics will cover from the basic concepts to more complicated systems and cooperative localization technics. First a review on some of the interesting recent works on single vehicle localization methods is given, followed by a description of Map Matching methods. Finally a review on the subject of cooperative localization is given in the last section. During this chapter our goal is to mention the most interesting articles from the primary articles on this topic up to the latest ones.

4.1 Single Vehicle localization

Localization with high accuracy can bring many benefits to different navigation applications. However, because of multipath and satellites visibility achieving this accuracy is more challenging in urban areas. Therefore positioning technologies based on stand-alone GPS receivers are vulnerable and, thus, have to be supported by additional information sources.

When we are talking about the performance of a navigation system, it is important to mention that accuracy is not the only thing that matters. There are four performance measurements that characterize the system [30, 49, 94].

1) ***Accuracy***: the amount of conformity between the measured and estimated information (position, velocity, etc.) and the actual values.

2) ***Integrity***: a measure of the consistency of the estimated information. It depends on the probability of undetected failures in the given accuracy of the system.

3) ***Availability***: provides a measure of the coverage area in terms of percentage.

4) ***Continuity of service***: provides the probability of the system working continuously without any unintended interruption happening during a working period.

Generally, most of the in-car navigation systems use map matching in order to find their position [55, 56, 91, 92]. Finding an estimation of the position using Map matching is based on comparing the trajectory and position information from the GPS receivers with the roads in the digital map.

However in urban environments, the presence of high buildings (also big trees) may partly block satellite signals and reduce the number of visible satellites, therefore reducing the accuracy of the position estimates or even worse, the number of detected satellites may become less than four and this makes the position estimation impossible [9, 38, 57, 78].

Another problem in urban areas is multipath propagation of the radio signal due to reflection in surrounding objects. This may lead to decreased position accuracy and thereby reducing the integrity of the navigation solution [78]. Therefore, to overcome these problems, advanced navigation systems use complementary navigation methods, relying upon information from sensors such as accelerometers, gyroscopes, and odometers.

Adding more sensors to the GNSS receiver provides a navigation system with higher accuracy and better integrity and providing a more continuous navigation solution and also increases the update rate of the system along with the extra information about the acceleration, roll, and pitch, depending on which types of sensors are used.

4.1.1 Positioning using Dead- Reckoning

Velocity encoders, accelerometers, and gyroscopes all provide information on the position and attitude of the vehicle and their respective velocity. All the measurements of these sensors only contain information on the relative movement of the vehicle and therefore the translation of these sensor measurements into position and attitude estimates is of an integrative nature, requiring the knowledge of the initial state of the vehicle. As a consequence, measurement errors will accumulate with time and the traveled distance. Moreover, the provided measurements by the vehicle-mounted sensor are represented in the vehicle coordinate system. Therefore, in order to use the sensor measurements to estimate a position, velocity, and attitude, they must be transformed into a coordinate system where they are more easily interpreted.

Dead Reckoning is the process of transforming the measurements from the vehicle-mounted sensor into an estimate of the vehicles position and attitude. In the case that the sensors are only inertial sensors, it is also called inertial navigation.

In [124] the major properties of the Dead Reckoning systems are described as follow:

1) They are not dependent on any external source of information and therefore they cannot be disturbed or blocked.

2) They have high update rates.

3) Their error is cumulative as a function of time or traveled distance due to the integrative nature of the systems.

On the other side, the GNSS and other radio-based navigation systems have bounded errors on the estimated position and velocity, but at a relatively low update rate, and also their measurements depend on information from an external source that may be blocked or disturbed. The complementary characteristics of the DR and GNSS systems make their integration favorable and can result in navigation systems with higher update rates, accuracy, integrity and continuity of service.

In the remaining paragraphs of this section we will describe the basics of some interesting works that have been done in this topic.

In [73], they use 3D maps of urban environment and propose a technique for high-accuracy localization of moving vehicles. This technique is based on integrating GPS, IMU, wheel odometer, and LIDAR data acquired by an instrumented vehicle, to generate maps of environments. Considering that urban environments are dynamic, they reduce the map to features which are with high probability static and by using this method they can separate dynamic aspects of the world (like vehicles) from static aspects of it (like the road surface). Having the map of the environment, they use LIDAR sensor measurements to find the position of the vehicle relative to this map.

They use a particle filter to localize the vehicle in real-time. This particle filter uses range data collected by LIDAR sensor and analyzes them to extract ground plane underneath the vehicle. After that they correlate this information with the map of the environment and find the position of the vehicle. Particles are projected trough time with respect to the velocity of the vehicle which is measured by using wheel odometer, an IMU and a GPS system. This system can find the position of the vehicle with relative accuracy of around 10 cm.

They extended their work in [72] and proposed an extension to the previous approach which resulted in a substantial improvement over previous work in vehicle localization. This new method provides higher precision, the ability to learn and improve maps over time, and increased robustness to environment changes and dynamic obstacles. The major change in this approach is that they used a probabilistic grid instead of spatial grid of fixed infrared remittance values. By using this idea each cell can be expressed with a Gaussian distribution over remittance values. In addition to that, they used an offline SLAM[1] to align multiple passes from same places and build an increasingly robust understanding of surrounding environment and then use it for more precise localization.

In [5], a localization method for road vehicles using a push-broom 2D laser scanner and a prior 3D map of the environment has been proposed. They placed their laser downward, to acquire a continual ground strike. They use this method to build a small 3D map of laser data and match that within the 3D map of environment using statistical methods. They show that their method has a better performance than a high caliber DGPS/IMU system over a 26 km of driven path in their test site and also has lower cost.

In [11] author presents a low cost vehicle localization system, using measurements from one gyroscope, two wheel speed sensors and a GPS, to estimate the heading, velocity and position

[1] Simultaneous Localization And Mapping

of a vehicle. Instead of using popular filtering models like Kalman filters, they proposed a simple easy-to-tune nonlinear observer for vehicle localization systems which reduces some sensor measurement imperfections. This filter is based on the theory of "symmetry-preserving observers" in [10]. They also used nonholonomic constraints to improve vehicle localization.

In [63] a position estimation algorithm based on an interacting multiple model (IMM) has been developed. This filter uses two different models to reduce errors caused by using only one model for vehicle movement. They used a kinematic vehicle model for low speed and low slip driving conditions based on the bicycle model and a dynamic vehicle model for more high speed and high slip situations and they used EKF for both models. They showed that their algorithm achieves better results in most of the cases.

In [41] authors used IMM filters with different models of Constant Velocity (CV), Constant Turn (CT), Constant Acceleration (CA), Constant Stop (CS) and Constant Rear (CR) In order to better describe dynamic behavior of vehicles. The main idea of this work is to combine proprioceptive information using IMM. They showed that by using the Interactive Multi Model approach, the position of the vehicle can be estimated more accurately.

[140] introduces a positioning method based on the GPS receiver and a stereo vision camera. They use stereo vision to estimate the vehicle motion by feature detection, matching, and triangulation from every image pair. Then use a RTK-GPS receiver to correct position and direction estimated from stereo vision. They showed that this method works better than stereo vision alone, and can correct GPS signal failures caused by multipath and other noises.

In [111], the authors use an Extended Kalman filter to fuse data from a GPS receiver and a machine vision system to find a better estimation of the vehicle's position. They apply MHT (Mutliple Hypothesis Tracking) to use multiple data association hypotheses to find the road on which the vehicle is driving and identify detected objects. They also use map matching in order to reduce the errors of GPS and dead- reckoning system. They showed that using EKF to fuse GPS and machine vision and map matching along with using MHT can reduce the multipath effect in urban areas and increase the probability of finding the correct hypothesis.

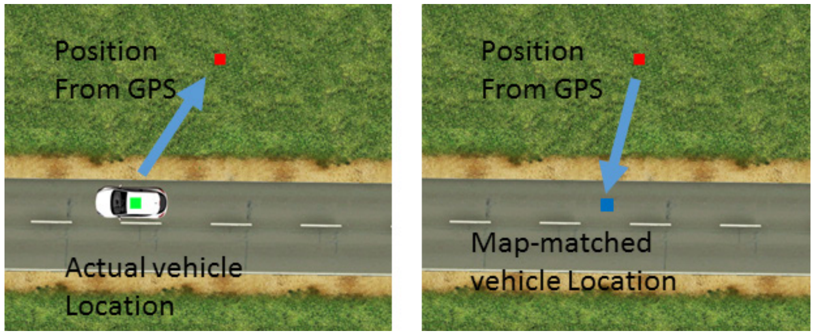

Figure 4-1. Map Matching.

4.2 Map Matching

As described before vehicle navigation system is the result of integration of various positioning sensors such as GPS, odometer and INS. However even with a robust sensor calibration and most complicated sensor fusion methods error in positioning accuracy is sometimes unavoidable. Map matching is a method which is widely used in vehicular satellite based navigation systems. Conventionally, it has been used to estimate the vehicle position on a digital road map, using GPS and motion sensors data as input to the map matching algorithm. However, the improvement of digital maps quality in recent years has brought the possibility for those to be seen as observations in the positon estimation problem. This means that the result of map matching can be compared to the navigation solution and used to calibrate the system's sensors in order to provide a higher robustness, accuracy and availability [28, 29, 42, 75, 123, 128].

The first generation of the digital maps were produced from paper maps and their accuracy were no better than 14 meters. In the current generation of the digital maps aerial photos and accurate DGPS is used in order produce more accurate digital maps (typically less than 1 meter). In addition to these, there is another type of digital maps which are used in intelligent vehicle applications. These maps may include additional information such as design speed of the curves, grade of slopes, road signs, speed limits and etc. which can help intelligent vehicles in performing their driving tasks.

4.2.1 Map Matching Methods

Map matching usually involves three steps. In the first step the candidate the algorithm has to select a set of candidate arcs or segments from the map. In the second step, the algorithm evaluates the likelihood of each candidate based on the geometrical information, topological information and the correlation of the vehicles trajectory to the candidate shape in the map. The last step is to find the location of the vehicle on the road segment [108].

In [145] different methods of map matching is introduced. Most of the existing map matching methods is based on these theories with some enhancements [39, 107, 109, 141].

Generally map matching approaches can be categorized in three groups: geometric, topological and advanced.

In *geometric* map matching, the matching algorithm only uses the geometric information of the map by using the shape of the road segments. These methods doesn't consider the connection between the segments. The geometric map matching can further categorize in to point-to-point [6, 7, 34], point-to-curve [7, 141] and curve-to-curve matching [141]. Some enhancements to the geometric map matching methods have been given in [12, 102, 126, 132].

In *topological* map matching in addition to geometric information, topological information is also used. The topological information determines the connectivity of the road segments. These methods also use additional information such as historical matching information, vehicle speed and candidate road connections.[39, 103, 107, 138, 142]. The topological map matching methods have better performance than geometric methods.

The *advanced* map matching methods have been developed to provide better map matching performance in complex areas such as dense urban areas. In these areas the road network is complex and GPS data may suffer from lots of errors like multipath and signal outage. These errors cause difficulties in selecting the candidate road segments even for topological methods. Most of the advanced methods are used in correct road segment selection. Some of these algorithms are based on Extended Kalman Filter (EKF) [48, 64, 66, 130, 136], Bayesian interference [106, 125], belief theory [29, 85, 143], fuzzy logic [65, 127, 129, 144, 145] and artificial neural networks [20, 127].

To conclude the map matching algorithms, we can say that the advanced methods have better performance than two other algorithms since they use more constraints. However they need more input data and more computation time in return.

4.3 Cooperative Vehicle Localization

With the recent emergence of multi-vehicular wireless communication capabilities, cooperative architectures have become an attractive alternative to solving the localization problem [18, 83, 97]. Cooperative positioning (CP) was originally developed for use across wireless sensor networks. Nowadays, with the inclusion of Dedicated Short Range Communications (DSRC) infrastructure in vehicles, CP techniques can now be used for vehicle localization across vehicular networks. These techniques usually aim to fuse GPS information and sensors information of one vehicle with the information that come from other vehicles and also additional sensed information such as inter-vehicle distances to achieve a better positioning for vehicles within a neighbourhood. A vehicular ad hoc network (VANET) can be seen as a wireless, mobile ad hoc network and thus any localization scheme devised for ad hoc networks can be adopted and applied to VANETs [27].

By considering cooperative localization in a more general case, [37] suggest that a typical cooperative localization algorithm should tackle the following tasks:

- Find and identify nearby vehicles in a given range;
- Distinguish cluster topology and decide vehicle membership;
- Determine absolute position estimates (local data fusion) of each member in the cluster;
- Measure inter-vehicular distances, heading (relative positions) of member vehicles (by DSRC, Radar, Lidar, etc.);

- Compute confidence interval on estimates: measures the accuracy/uncertainty of the local absolute/relative position estimates;
- Decide which local estimates and uncertainty data is relevant for broadcasting to vehicle members;
- Fuse all the received broadcasted data to local data fusion systems in order to perform global fusion and improve localization of individual vehicle members (developing a data fusion algorithm)

As a result, we can conclude that cooperative localization system is the result of a tight coupling of the ranging technique, localization algorithm and communication protocol.

Cooperative localization can be divided in two major categories:

- Centralized techniques.
- Distributed localization algorithms.

Distributed localization algorithms are more common techniques in VANET localization (due to their ad hoc nature); however, a centralized, or hierarchical (i.e. combination of centralized and distributed) algorithm that supports vehicle to infrastructure communication has its own attractiveness for higher accuracy and greater availability [14].

[37] also describes that the decentralized data fusion architectures for automotive applications have several advantages such as:

- To remove bottleneck and risk factors associated with centralized systems;
- To decrease processing and communication burdens by distributing this among several vehicles in the cluster;
- Each vehicle fuse data which comes from its own information source and from the information generated and broadcasted by surrounding vehicles;
- No vehicle needs to form a global data fusion of the total information at once;
- A Global solution can also be achieved if the decentralized fusion is in a broadcast mode and all vehicles can communicate their data with all others;

- This system is more scalable due to the decreasing of processing power and bandwidth;
- Flexibility and robustness of the system when one node (vehicle) fails;
- Modularity, since each vehicle does not require total knowledge about all the nodes in the network and the whole network topology.

We can say that, a localization algorithm is a computational algorithm based on some given measurement sets and their associated uncertainty that addresses:

- Problem formulation,
- Robustness,
- Estimation accuracy,
- Coordination
- Computational complexity.

Another important concept that we should mention according to [8] is that, VANETs have frequent fragmentation, rapid topological development over time and short link life (e.g. even less than a second when vehicles are travelling in opposite directions).Therefore, any localization algorithm must take these factors into consideration since increasing the communication rate can overwhelm the network and exhaust its channel capacity.

According to [27], a Cooperative Positioning algorithm for VANETs must have the following characteristics:

- Real time and fast;
- Adaptive with respect to the traffic conditions, the node density and topological development;
- Robust to inter-node connection failure ;
- Flexible enough to handle the communication constraints.

The most popular network localization techniques are Monte Carlo localization [16], Convex Optimization [23], Iterative Multilateration [131], and Multidimensional Scaling (MDS) [15].

Parker and Valaee [96, 98] proposed a distributed positioning algorithm for VANETs which uses inter-vehicle distance estimates to localize the vehicle among its neighbours. These inter-vehicle distances are measured using a radio-based ranging technology. In [96] they presented an iterative algorithm based on LMSE. In other words, considering that inter-vehicle distance estimates contain noise, their algorithm reduces the residual of the Euclidean distance between the vehicle and their measured distances. This algorithm has two steps: initialization and refinement. In the initialization stage an initial estimate of all vehicle positions is made through exchanging GPS information. Then in the refinement stage, each vehicle uses all the other nodes' information to refine its position estimate and make a more accurate estimate. In [98] they used an extended KF to incorporate kinematic information and road map constraint into the position estimation. They showed that the KF algorithm outperforms the non-linear least squares estimation technique. Another similar approach is introduced in [27] which has better performance than that of [98] with some changes in the Map matching algorithm.

Another distributed approach for cooperative positioning based on a centralized extended Kalman filter is introduced in [118]. In this approach the state of the group of robots is viewed as a single system. The localization is obtained by fusion of the proprioceptive and exteroceptive measurements which are collected and exchanged by different robots of the group.

The results show that the uncertainty of the estimated pose (position and orientation) is reduced for each individual member of the group. This reduction is gained by the exchange of the relative positioning information (relative position and orientation) among the group. A similar approach is presented by [77]. They implemented their method with a heterogeneous group of mobile robots in an outdoor environment. [79] extended the approach introduced by [118] by considering the observation of the relative bearing. These approaches are based on sensor information exchange. In these approaches each member of the group shares its observations with the other members of the group and the cooperative localization is obtained by updating the global state of the group with the collected observations. The large quantity of the transmitted information is one of the disadvantages of these methods. This quantity can be even larger when the group members are heterogeneous. In this case, the vehicles have to send also the error model of the sensors in addition to the sensors measurements [62].

Another idea is to exchange the updated global state. Although this approach can reduce the quantity of transmitted information, it can cause the over-convergence problem. This means that by fusing the interdependent states it can quickly converge to an inaccurate value. [52] considered the problem of over-convergence in their work. They assume that every robot of the team can estimate the position probability distribution of every other robot, relative to itself and broadcast this information to the team as a whole. For example an over convergence may happen when the robot *i* observes the robot *j*, the robot *j* can update its position distribution using the observation of the robot *i*. After that the position distribution of the robot *j* depends on the position distribution of the robot *i*. Therefore, robot *i* cannot use the position distribution of the robot j to update its position distribution. This is because of the interdependency between position probability distribution of the two robots.

In order to solve this problem, they proposed to maintain a *dependency tree* to update the history of distributions dependency. However this approach has some limitations since the *dependency tree* assumes that distributions are only dependent on the last distribution that was used to update them, and therefore they are independent on all other distributions which is not a good assumption and it is restrictive as circular updates can still occur.

In [62] a method for cooperative localization of a heterogeneous group of vehicles is introduced. This method has three steps. In the first step each member of the group estimates its own position and also estimates the position of the other vehicles that it has seen before using an Extended Kalman Filter. This stage is called Group state estimation. In the next step which is the Group State Update, the estimated state is updated using its sensors measurements and measured relative position of the other vehicles. In the last step, which is called collective localization a group state fusion is performed by each vehicle. Each vehicle fuses its Group state by using the Group states that receives from other vehicles and shares its updated Group state with its neighbors. This fusion is also based on Extended Kalman Filter. They also proposed to use the

Mahalanobis distance between position estimations and observations to identify the detected vehicles.

[32] applied the method introduced in [117] to the cooperative mapping and localization problem. This method builds an augmented covariance matrix composed of the covariance and cross-covariance matrices relating all the robots in the group and also the landmarks observed by each robot. He also extended the work of [21, 89] that characterize the performance of the single vehicle CML (collaborative multi robot localization) algorithm, to the cooperative localization and proofed that by using his proposed method we have the following theorem:

> *In the collaborative CML case, in the limit, as the number of observations increases, the lower bound on the covariance matrix of any vehicle or any single feature equals to the inverse of the sum of the initial collaborating vehicle covariance inverses at the time of the observation of the first feature or observation of a collaborating vehicle.*

Which states that multiple vehicles performing CML together can attain a lower absolute error than the single vehicle initial covariance which bounds the single vehicle CML case according to [117].

Although most of the previous mentioned methods are based on Kalman filters, some other approaches also exist for cooperative localization such as *Markov localization* [13], *Bayesian approaches* [52] and *Maximum likelihood methods* [53].

[13] introduced a statistical algorithm for collaborative mobile robot localization. Their approach uses a sample-based version of *Markov localization*. Robots localize themselves in the environment and whenever they meet each other probabilistic methods are employed to synchronize each robot's belief. This causes the robots to localize themselves faster, maintain higher accuracy, and high-cost sensors are distributed across multiple robot platforms. Despite this, they confess that the probabilistic method that they use has the possibility to lead to over convergence as their proposed formula is only true when the prior position distribution of the robots are independent of each other which means that the robots can exchange the information

only if it is the first time that they meet each other and they never have met the same third robot. In order to partially solve this problem they put the following rule that: each robot has a counter that, once a robot has been sighted, blocks the ability to see the same robot again until the detecting robot has traveled a pre-specified distance (2.5 m in their experiments). In their approach when a robot doesn't see another robot it performs the Markov localization and whenever it sees another robots updates its belief using other robot belief to reduce the uncertainty. They implemented and tested their technic using two mobile robots equipped with cameras and laser range-finders for detecting other robots. The results, obtained with the real robots and in series of simulation runs, illustrate severe improvements in localization speed and accuracy.

Chapter 5 Avant-Propos

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Titre français: Une nouvelle approche pour un meilleur positionnement des véhicules en utilisant une correspondance cartographique coopérative et une station de base dynamique DGPS.

Résumé français :

Dans cet article, une nouvelle approche pour améliorer le positionnement des véhicules est présentée. Ce procédé est basé sur la coopération des véhicules, en communiquant les informations sur leur environnement proche et leur position. Cette méthode comprend deux étapes. Dans la première, nous introduisons la méthode de correspondance cartographique coopérative qui utilise les communications V2V dans un VANET afin d'échanger les informations GPS entre les véhicules. Grâce à une carte routière précise, les véhicules peuvent appliquer les contraintes de la route des autres véhicules dans leur propre processus correspondance cartographique dans le but d'acquérir une amélioration significative de leur positionnement. Après nous proposons le concept d'une station de base dynamique DGPS (DDGPS) qui est utilisée par les véhicules dans la deuxième étape pour générer et diffuser les corrections de pseudo-distance GPS qui peuvent être utilisés par les véhicules nouvellement

arrivés pour améliorer leur positionnement. Le DDGPS est une méthode collaborative décentralisée qui vise à améliorer le positionnement GPS par estimation et de compensation de l'erreur commune dans les mesures de pseudo-distance. Cela peut être considéré comme une extension de DGPS où les stations de base ne sont pas nécessairement statiques avec une position exacte connue. Dans la méthode DDGPS, les corrections de pseudo distance sont estimées, sur la base de la croyance du récepteur sur son positionnement et de son incertitude, puis diffusés à d'autres récepteurs GPS. La performance de l'algorithme proposé a été vérifiée avec des simulations dans plusieurs scénarios réalistes.

Chapter 5 A Novel approach for Improved Vehicular Positioning using Cooperative Map Matching and Dynamic base station DGPS concept

5.1 Abstract

In this paper a novel approach for improving Vehicular positioning is presented. This method is based on the cooperation of the vehicles by communicating their measured information about their position and neighbor environment. This method consists of two steps. In the first step we introduce our cooperative map matching method. This map matching method uses the V2V communication in a VANET to exchange GPS information between vehicles. Having a precise road map, vehicles can apply the road constraints of other vehicles in their own map matching process and acquire a significant improvement in their positioning. After that we have proposed the concept of a dynamic base station DGPS (DDGPS) which is used by vehicles in the second step to generate and broadcast the GPS pseudorange corrections which can be used by newly arrived vehicles to improve their positioning. The DDGPS is a decentralized cooperative method which aims to improve the GPS positioning by estimating and compensating the common error in GPS pseudorange measurements. It can be seen as an extension of DGPS where the base stations are not necessarily static with an exact known position. In the DDGPS method, the pseudorange corrections are estimated, based on the receiver's belief on its positioning and its uncertainty, and then broadcasted to other GPS receivers. The performance of the proposed algorithm has been verified with simulations in several realistic scenarios.

5.2 Introduction

Navigation systems constitute an essential component of intelligent vehicles and are being used in a great variety of active or informative ADAS applications. GNSS based navigation systems allow to easily obtain information on the absolute position of the vehicle and their use are widely spread in ITS applications [68]. However, low cost GPS receiver-based navigation systems used in automotive applications suffer from low accuracy and frequent signal outages.   Typically, the GPS nominal accuracy is about 15m, which is usually not sufficient for active safety and ADAS applications such as lane level positioning. One of the most common ways to improve accuracy for ego-localization is to use other embedded sources of information and to combine them with GNSS data. Those other sources can be dead reckoning sensors, such as INS and odometer, or video cameras [2, 135]. This approach typically use data fusion algorithms, like Kalman filters or particle filters [45] to combine the information of those different sensors in order to obtain a better position estimate than the one obtained by the GPS receiver alone or by each of the individual sensor.

A classical approach to enhance the GPS positioning accuracy is to use a differential method exploiting a fixed known position as a ground based reference, hence the name differential GPS (DGPS) [60]. In DGPS, the ground based reference station with an exactly known position, broadcasts its GPS receiver information, which allows to calculate and correct the errors of the measured pseudoranges obtained by other non-fixed GPS receivers in the vicinity. The method exploits the fact that GPS receivers, which are close to each other, are affected by the various sources of errors in a similar way. This assumption can be done because of the use of the same set of satellites in order to assess ego-localization. To apply this approach in the real world and with static road side stations it requires to deploy a large number of reference stations in order to be able to enhance the GPS position in a given region. This approach is therefore very expensive in terms of infrastructure. In addition DGPS to operate properly always requires a communication link between the reference stations and the mobile GPS receivers. These two constraints make the DGPS approach difficult to implement and also very expensive to use for general vehicle positioning in automotive applications.

Map matching is a method which is widely used in vehicular satellite based navigation systems. Conventionally, it has been used to estimate the vehicle position on a digital road map, using GPS and motion sensors data as input to the map matching algorithm. However, the improvement of digital maps quality in recent years has brought the possibility for those to be seen as observations in the positon estimation problem. This means that the result of map matching can be compared to the navigation solution and used to calibrate the system's sensors in order to provide a higher robustness, accuracy and availability [123]. The basic assumption behind the map matching is that the vehicles are usually drive on the roads. If the GPS estimated position falls off the road, by using the past trajectory of the vehicle and the measured GPS position along with a precise road map, we can better estimate the true position of the vehicle [101, 122].

However, with the recent emergence of wireless communication capabilities and VANETS, cooperative positioning is becoming an attractive alternative for improving positioning performance [37, 47, 62, 115, 116]. The main goal of cooperative positioning is to exploit different sources of information coming from not only an ego-vehicle but different vehicles within a short range area, in order to enhance positioning system efficiency and have a better perception of the surrounding environment while keeping the computing and infrastructure costs at a reasonable level.

In this paper we aim to propose a new cooperative map matching method (CMM), which is based on exchanging the GPS raw measurements between the vehicles and a precise road map. Unlike the other cooperative map matching method presented in [121], our method doesn't need to have the relative distance between vehicles and more importantly it takes into account the effect of the non-common pseudorange error between different receivers participating in the cooperative map matching process. The effect of non-common pseudorange error is an important issue which has to be considered. Without considering this error, the true vehicles position may fall outside the expected area and leads to an over converged position estimation. In addition to this we introduce the new concept of Dynamic base station DGPS (DDGPS). This method is another cooperative method which can be used to further improve the result of CMM and introduces an interesting approach for cooperative positioning. This method is able to improve GPS vehicle position estimates by exploiting position information from other vehicles or mobile objects (pedestrian, bicycle etc.). The basic idea is to extend the DGPS method by using mobile reference stations instead of fixed one, thus generating pseudo-range corrections by nearby vehicles and broadcasting them to be used by nearby vehicles. This idea brings challenges as the mobile reference stations do not have a precisely known position, and therefore, the pseudo-range corrections generated by them also suffer from significant uncertainties. By incorporating these two methods together significant improvements over GPS positioning is achieved. The performance of the proposed algorithm is tested based on Monte Carlo simulations and the data used in these simulations were provided by Pro-SiVIC software from Civitec and GPSoft Satellite Navigation toolbox for MATLAB.

The paper is organized as follow. In the next section we briefly describe different error components of the GPS pseudorange measurements. Then, in section III we describe our proposed map matching method. In section IV, our Dynamic base station DGPS is presented followed by a description of our simulation setup, scenarios and results in section V. Finally, a conclusion and some perspectives on potential future works are presented in section VI.

5.3 Pseudorange Measurement Errors

The GPS positioning accuracy depends on the quality of the pseudorange measurement between satellites and the GPS receivers and the error level on these measurements. The GPS pseudorange measurements errors can be divided in two parts, the common error and non-common error. The common error component is the part being highly correlated between the receivers, which are close to each other. These errors consists of satellite clock error, ephemeris error, ionospheric delay and tropospheric delay. The non-common error component is the part which varies from receiver to receiver and consists mainly of receiver noise and multipath error [60]. The pseudorange can therefore be expressed as,

$$\rho_j^{(i)} = D_j^{(i)} + c\delta t^{(i)} + \varsigma_j^{(i)} + \eta^{(i)} \qquad 5\text{-}1$$

where $\rho_j^{(i)}$ is the measured pseudo-range from j^{th} satellite to i^{th} receiver, $D_j^{(i)}$ is the true distance between them, $\delta t^{(i)}$ is the receiver clock offset from the GPS time, c is the speed of electromagnetic wave, while $\varsigma_j^{(i)}$ and $\eta^{(i)}$ are common error and non-common error components respectively.

The similarity of the common error components in pseudorange measurement from each satellite to vehicles, leads to the same bias in GPS position computed by each vehicle in a vicinity [60]. This characteristic of the pseudorange noise is used in this paper by our cooperative map matching method to improve the positioning performance by compensating the effect of pseudoranges common error component on the positioning and after that in our DDGPS method to generate pseudorange corrections in order to broadcast them to be used by other vehicles.

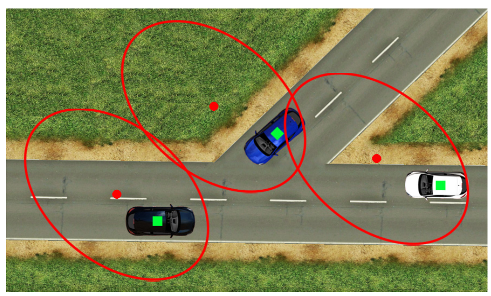


Figure 5-1. A typical vehicles configuration

5.4 Cooperative Map Matching

5.4.1 Method description

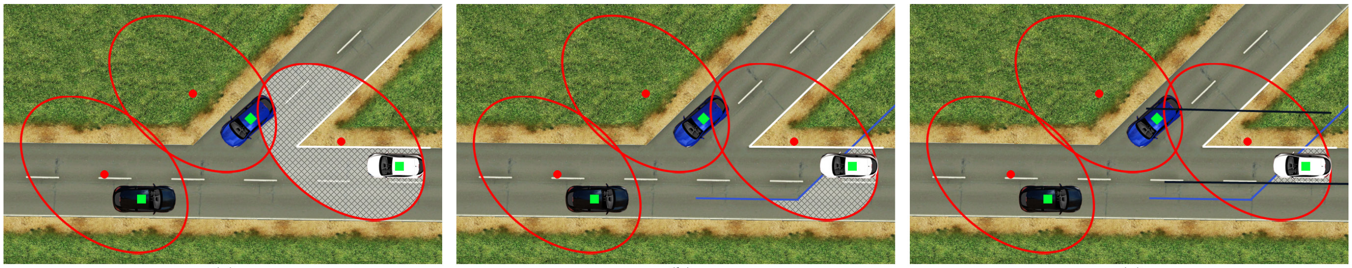
Vehicular Cooperative map matching (CMM) is a map matching method in which vehicles exchange their sensor information and position estimations in order to allow other vehicles to better match their position to a precise lane level road map. Unlike the conventional map matching methods, each vehicle with the CMM can use the information it receives from other vehicles to incorporate other vehicles road map constraints and combine it with its own constraints in order to achieve a better map matching result. This method is based on the fact that the vehicles which are in a close vicinity generally can observe the same set of satellites and almost suffer from the same amount of pseudorange measurement errors. Therefore the resulting GPS positioning solutions will face the same error (bias). Therefore it is possible to apply the other vehicles road constraints to each selected vehicle. The CMM aims to estimate this bias by using the received GPS information from other vehicles and using a lane level road map.

Figure 5-1 demonstrates a typical configuration of the vehicles with their true positions (green), their GPS computed positions (red) with their uncertainty ellipses (red). At the beginning, in order to simplify the description of the CMM method, we assume that all the vehicles observe the same set of satellites. We also assume that the amount of non-common error component is negligible. Later in this paper we will discuss the more general case in which different neighbor vehicles can observe different satellites and how to consider the effect of the non-common error on the pseudorange measurements. With these assumptions, all of the pseudorange measurements from each vehicle to a specific satellite has almost the same amount of error. Each vehicle measures its pseudoranges to the visible satellites and broadcast them to other vehicles. Now let’s say the white vehicle in Figure 5-1 wants to perform the CMM method. We refer to this vehicle as the target vehicle in the rest of this paper. Figure 5-3 demonstrates different steps of our map matching method. The target vehicle uses the measured pseudoranges to resolve its GPS position and compute its position covariance. Assuming that the vehicles can only drive on the road, InFigure 5-3.a the target vehicle applies its own road constraints (white lines) to its measured GPS position. The remained possible positions for the target vehicle after applying its own road constraints is shown by the white hatch. After that, the target vehicle uses the received pseudoranges from the blue vehicle and compute the GPS position and corresponding position covariance of the blue vehicle. Having these information, the target vehicle can apply the road constraints of the blue vehicle (blue lines) to its own positioning (see Figure 5-3.b). In a similar way the target vehicle uses the road constraints of the black vehicle and as a result the uncertainty of the target vehicle position reduces as it is shown in Figure 5-3.c, and so on.

We used a particle filter to implement our method as follow. First, the target vehicle initiates 1000 particles according to its prior position estimation, which is in this case the GPS measured position. The next step is to update the weights of the particles with respect to the road constraints. With the given assumption of negligible non-common error, we can first set the weights of the particles falling out of the constraints to zero and then normalize the remaining particle weights in each iteration of the filter. We apply the road constraints of each communicating vehicle transformed for the target vehicle to the initiated particles. Figure 5-2 summarizes the particle filter steps and Figure 5-4 illustrates an example of the particle filter implementation. Finally, the result of the particle filter is approximated by a Gaussian distribution to calculate the mean and the covariance matrix of the position estimation. This calculated mean and covariance matrix are referred as $\hat{X}^{(i)} = [\hat{x}^{(i)}, \hat{y}^{(i)}, \hat{z}^{(i)}]$ and $\hat{P}_{X^{(i)}}$ respectively, where i is the index of the target vehicle. Having the measured GPS position of the vehicle $\tilde{X}^{(i)} = [\tilde{x}^{(i)}, \tilde{y}^{(i)}, \tilde{z}^{(i)}]$, and its CMM position estimate $\hat{X}^{(i)}$, the GPS bias vector then can be approximated as:

```
Initiate M particles according to the GPS
positioning pdf of the target vehicle, Px(k),
k=1…M.
For l = number of communicating vehicles
     For itt = Number of iterations for particle
filter
          For k=1:M
if Px(k) is outside of the road constraints of l^th
vehicle transformed for the target vehicle,
then:  Wx(k) = 0;
          End
          Normalize Wx(k);
          Resampling Px(k);
     End
End
```

Figure 5-2. CMM algorithm implementation using a particle filter.



(a) (b) (c)

Figure 5-3. Applying vehicles road constraint to the target vehicle (white).

$$\hat{B}_{GPS} \sim N(\tilde{X}^{(i)} - \hat{X}^{(i)}, \hat{P}_{X^{(i)}}) \qquad 5\text{-}2$$

It is important to mention that the map constraints of other vehicles are applicable to the target vehicle only if the position of all vehicles are resolved using the same set of satellites. In the general case in order to make sure that this condition holds, the target vehicle has to verify the received pseudoranges and compute the position of all the vehicles using the same set of satellites (same constellation). With this condition we can be sure that the bias of the GPS positioning for all of the vehicles in a close vicinity are the same and we can apply the CMM method as described above.

5.4.2 Effect of non-common noise

Another important issue that we have to consider is the effect of the non-common pseudorange error, $\eta^{(i)}$, on the GPS positioning and CMM. As mentioned before, without considering the non-common pseudorange errors in our CMM algorithm we may over converge to a non-true position. Therefore modeling this component of the noise in order to considering its effect and avoiding over convergence is vital.

Since the non-common error components are uncorrelated from receiver to receiver and it can change very rapidly [60], we consider a zero mean Gaussian distribution to model this error,

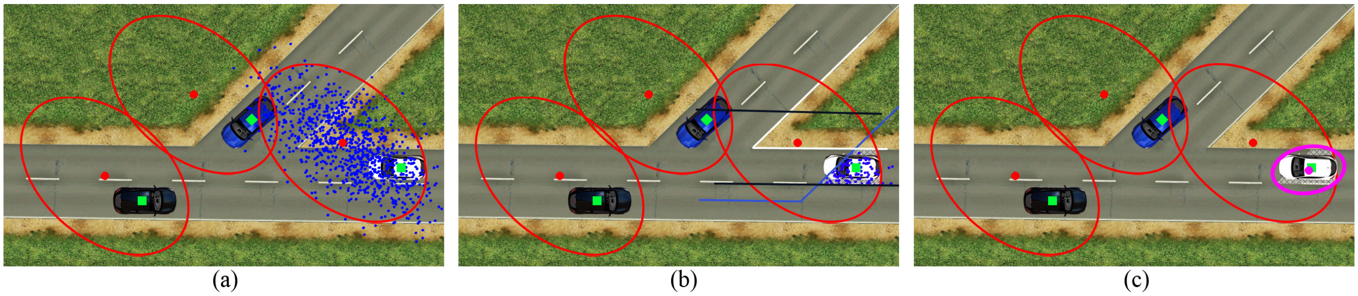


Figure 5-4. Particle filter used for CMM

$$\eta^{(i)} \sim N(0, \sigma_\eta^2) \qquad 5\text{-}3$$

where σ_η is the standard deviation of the non-common pseudorange error. The non-common pseudorange errors lead to a position error which is independent from vehicle to vehicle and for each vehicle the effect of this error on the positioning covariance can be calculated as:

$$P_\eta^{(i)} = ((H^{(i)})^T H^{(i)})^{-1} \sigma_\eta^2 \qquad 5\text{-}4$$

where $H^{(i)}$ is the $n \times 4$ matrix

$$H^{(i)} = \begin{bmatrix} a_{x1} & a_{y1} & a_{z1} & 1 \\ a_{x2} & a_{y2} & a_{z2} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ a_{xn} & a_{yn} & a_{zn} & 1 \end{bmatrix} \qquad 5\text{-}5$$

and $a_j = (a_{xj}, a_{yj}, a_{zj})$ is the unit vector pointing from the GPS position of i^{th} vehicle to the j^{th} satellite [60].

Since this error is independent from one vehicle to another vehicle, the target vehicle can't apply the road constraint of the other vehicles directly as it does for its own constraints. In order to overcome this problem, instead of using the road constraint as a zero-one mask (Figure 5-5.a), we use a weighted road map where the on road points keep their previous weights, and the off road points are weighted with respect to their distance from the road edge (Figure 5-5.b). The new weight for the i^{th} particle which is off the road is assigned with the following equation,

$$w_i' = W(d_w, 0, \sigma_w^2) = w_i \times e^{-\frac{d_w^2}{2\sigma_w^2}} \tag{5-6}$$

where d_w is the distance between the i^{th} particle and the road edge, w_i is the previous weight of the particle and the σ_w^2 depends on the non-common error variance as the norm of the diagonal elements of $P_\eta^{(i)}$,

$$\sigma_w^2 = \left\| diag(P_\eta^{(i)}) \right\| \tag{5-7}$$

Figure 5-5.b demonstrates the difference between the zero-one road mask and the probabilistic road mask.

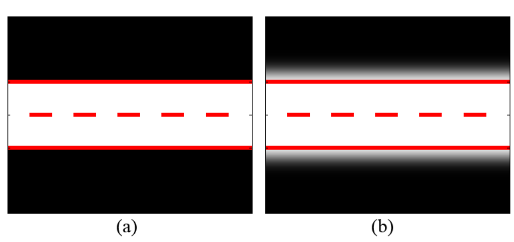


Figure 5-5. Zero-one road mask (a) and the probabilistic road mask (b).

5.5 Dynamic base station DGPS

In the previous section we described the CMM method. Now by using this method a cluster of vehicles which can communicate with each other can calculate the position bias for their cluster. Now the question is that how can we share the estimated bias to the vehicles which were not participating in the CMM. In order to do this we introduce the concept of Dynamic base station DGPS [114] and adapt this method to be used with the CMM method.

As mentioned before, Dynamic base station DGPS method is an extension to the DGPS introduced in [114] and aims to improve the positioning performance by using mobile reference stations instead of fixed ones. This means that each communicating vehicle which has an estimation of its position can generate pseudorange corrections and exchange them with nearby vehicles.

In DDGPS we aim to estimate and compensate the common component of the pseudorange error by incorporating the ego-localization information of vehicles (here the map matching positioning results) and their communication capability. Each vehicle generates a set of pseudorange corrections for its visible satellites based on the received pseudorange corrections from other vehicles and its own positioning belief.

In addition to this, vehicles can broadcast the generated pseudorange corrections and other vehicles can use them to correct their pseudorange measurements and obtain a better positioning. The pseudorange corrections produced by DDGPS also have a reliability parameter which express the variance of the estimated GPS pseudorange corrections. Vehicles can use this parameter to properly combine different DDGPS corrections that they receive from different vehicles and thus estimate a better pseudorange correction data.

5.5.1 Calculation of Pseudorange correction

By using CMM, the target vehicle acquires its estimated position $\hat{X}^{(i)} = [\hat{x}^{(i)}, \hat{y}^{(i)}, \hat{z}^{(i)}]$ and the position uncertainty given by the covariance matrix $\hat{P}_{X^{(i)}}$, where *i* is the vehicle's id. Given that the position of the j^{th} satellite is $[x_j, y_j, z_j]$, the computed geometric distance from the i^{th} vehicle's estimated position $\hat{X}^{(i)}$ to the j^{th} satellite is

$$\hat{D}_j^{(i)} = \sqrt{(x_j - \hat{x}^{(i)})^2 + (y_j - \hat{y}^{(i)})^2 + (z_j - \hat{z}^{(i)})^2} \quad 5\text{-}8$$

Then the i^{th} vehicle makes a pseudorange measurement $\rho_j^{(i)}$ to the j^{th} satellite. This pseudorange contains the distance to the satellite j^{th} and the pseudorange measurement errors.

$$\rho_j^{(i)} = D_j^{(i)} + c\delta t^{(i)} + \varepsilon_j^{(i)} \quad 5\text{-}9$$

Where

$$\varepsilon_j^{(i)} = \varsigma_j^{(i)} + \eta^{(i)} \quad 5\text{-}10$$

In order to form the differential corrections, the i^{th} vehicle makes a difference between the computed geometric distance and the measured pseudorange.

$$\Delta\rho_j^{(i)} = \hat{D}_j^{(i)} - \rho_j^{(i)} = -\delta D_j^{(i)} - c\delta t^{(i)} - \varepsilon_j^{(i)} \quad 5\text{-}11$$

where

$$\delta D_j^{(i)} = D_j^{(i)} - \hat{D}_j^{(i)} \qquad 5\text{-}12$$

is the residual satellite to vehicle distance. This correction then is broadcasted to other vehicles. The receiver vehicles then add this correction to their measured pseudorange from the same satellite to compensate the pseudorange common error:

$$\begin{aligned} &\rho_{j,cor}^{(r)} = \rho_j^{(r)} + \Delta\rho_j^{(i)} = \\ &D_j^{(r)} + c\delta t^{(r)} + \varepsilon_j^{(r)} - (\delta D_j^{(i)} + c\delta t^{(i)} + \varepsilon_j^{(i)}) \end{aligned} \qquad 5\text{-}13$$

As we discussed earlier, a significant part of the pseudorange error components are common between different receivers, which are close to each other and can therefore be compensated using this method. The only parts that remain to be addressed are multipath, receiver noise and the residual satellite to vehicle distance. By simplifying (5-13), we have,

$$\rho_{j,cor}^{(r)} = \rho_j^{(r)} + \Delta\rho_j^{(i)} = D_j^{(r)} + c\delta t^{(ri)} + \varepsilon_j^{(ri)} - \delta D_j^{(i)} \qquad 5\text{-}14$$

where $\varepsilon_j^{(ri)}$ is the residual pseudorange error and $\delta t^{(ri)}$ is the difference between the time offsets of the transmitter vehicle (*i*) and the receiver vehicle (*r*). The most important component in (5-14) which dominates the corrections error is $\delta D_j^{(i)}$. This parameter tells us that, the better we can estimate the position of the transmitter vehicle, the less is $\delta D_j^{(i)}$ and the more accurate the correction data can be generated for broadcasting. On the other hand, there may be other vehicles who generate a pseudorange correction and can broadcast it for others. In order to provide an estimation of the produced pseudorange correction accuracy and to give the receiver vehicle the possibility to fuse the received correction from different sources, we define the variance of

$\delta D_j^{(i)}$ based on the vehicle's estimated position and its covariance matrix, $\hat{P}_{X^{(i)}}$, having the satellites' calculated position.

$$\left(\sigma_j^{(i)}\right)^2 = H_{\hat{X}^{(i)}} \hat{P}_{X^{(i)}} H_{\hat{X}^{(i)}}^T \qquad \text{5-15}$$

Where

$$H_{\hat{X}^{(i)}} = [\frac{x_j - \hat{x}^{(i)}}{\hat{D}_j^{(i)}}, \frac{y_j - \hat{y}^{(i)}}{\hat{D}_j^{(i)}}, \frac{z_j - \hat{z}^{(i)}}{\hat{D}_j^{(i)}}] \qquad \text{5-16}$$

is the cosine direction of the unit vector pointing from the estimated user position to the j^{th} satellite. $\sigma_j^{(i)}$ is used as a parameter to describe the confidence level of the generated pseudorange corrections.

5.5.2 Broadcasting the corrections

Each vehicle uses equation (5-11) to generate the pseudorange corrections for its visible satellites and uses equation (5-15) to calculate their respective variances.

Before going further in to the details of the method, another important issue in distributed systems that we should take in to the consideration is the data dependency problem which may lead to over-convergence. Each vehicle may receive several sets of corrections from different vehicles. In order to have a better estimation of the corrections these received corrections must be combined and fused together. The over-convergence usually occurs when we fuse the information which are not independent from each other without considering their dependency.

In order to avoid this problem, vehicles add an id list to each of their generated pseudorange corrections. This id list is used to identify the dependencies of the pseudorange correction to the different vehicles. At the beginning, this list is empty and each vehicle after generating the pseudorange corrections adds its id to the id list of that pseudorange correction. Let's call this set of corrections, their variances and their id lists generated by vehicle i^{th}, $C^{(i)}$. This correction set will be broadcasted for other vehicles. Now assume that the r^{th} vehicle receives the correction $C^{(i)}$. First it checks its visible satellites and verifies if the correction for those satellites are available in the received set of corrections and applies those when available. Therefore, it uses these corrected pseudoranges in its own positioning algorithm and estimates its position. Now consider the time when the r^{th} vehicle wants to generate corrections for broadcasting. The sequence of operations is as follow:

1. It uses (5-11) and (5-15) to generate the pseudorange corrections and their variances for its visible satellites.

2. Then it forms the correction set $C^{(r)}$ and adds its own id to the generated corrections id list.

3. Also if these corrections were available in the received correction that used to generate new one the id list of those correction will be added to the new correction id list.

4. The final step is to add the corrections available in $C^{(i)}$ which were not regenerated by the r^{th} vehicle (because those satellites were not visible for the r^{th} vehicle), to the $C^{(r)}$ without adding the id of the r^{th} vehicle to their id list.

Now if a given vehicle receives several independent pseudorange corrections for one satellite (j), which is the case when the id lists don't have an overlap, it uses a weighted mean to fuse the received corrections. The id list for the new pseudorange correction is the union of the received corrections.

$$\Delta\bar{\rho}_j = \frac{\sum_{i=1}^{N} \omega^{(i)} \Delta\rho_j^{(i)}}{\sum_{i=1}^{N} \omega^{(i)}}, \omega^{(i)} = \left(\frac{1}{\sigma_j^{(i)}}\right)^2 \qquad \text{5-17}$$

the variance of the weighted mean being,

$$\left(\bar{\sigma}_j\right)^2 = \frac{1}{\sum_{i=1}^{N}\left(\sigma_j^{(i)}\right)^{-2}} \qquad 5\text{-}18$$

and where N is the number of received pseudorange corrections for the j^{th} satellite. However as we discussed earlier if the received pseudorange corrections are not independent, using the weighted mean causes over convergence. Therefore the vehicle selects first the pseudorange correction which has the smallest $\sigma_j^{(i)}$ from the dependent corrections and then calculated the weighted mean using (5-17) and (5-18) for the independent pseudorange corrections. After this, steps 1 to 4 are performed to correct the pseudoranges and generate the new correction for the r^{th} vehicle.

5.6 Simulation Results

In this section the simulation setup for assessing the performance of the proposed method is described and the results are presented. The vehicles trajectory and sensors data were generated with Pro-SiVIC software from Civitec and the GPS data were generated by the GPSoft Satellite Navigation toolbox for MATLAB. The results presented here are the average of Monte Carlo simulation for 100 runs of the algorithm.

Figure 5-6 shows the road map. The simulation consists of three sets of vehicles driving on the road. Each set consists of 5 vehicles. Each vehicle has its own trajectory and speed profile

Figure 5-6. Road map.

therefore the relative position and speed of the vehicles changes over time in order to simulate realistic situations. In the first scenario our goal was to assess the performance of the cooperative map matching method. The communication range for the vehicles is considered to be 100 m.

The average position error of the vehicles after using CMM with respect to the number of vehicles available in the communication range and cooperating in CMM algorithm is illustrated in Figure 5-7. As we expected from the CMM, sharing the other vehicle's map constraints and applying more map constraints to the vehicles can improve the positioning accuracy. Table 5-1 also shows the position errors for the GPS measured position, single vehicle map matching and

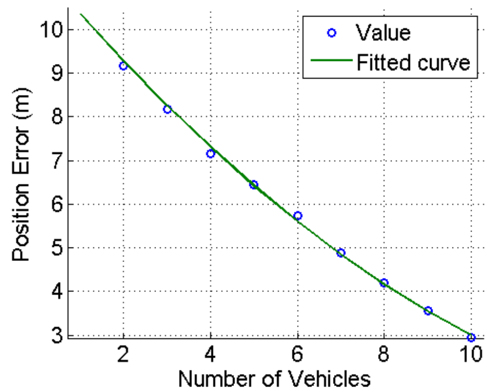


Figure 5-7. Average position error of the vehicles by using CMM with respect to the number of vehicles participating in CMM.

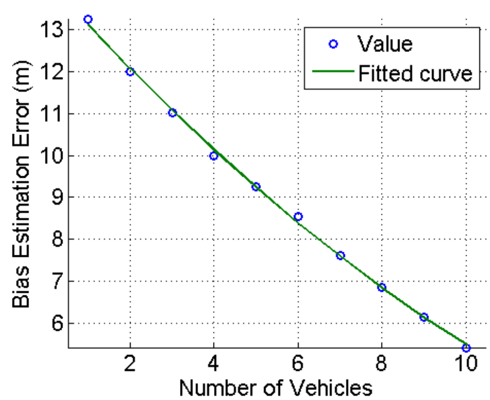


Figure 5-8. GPS bias estimation error by using CMM with respect to the number of vehicles participating in CMM.

CMM with various number of cooperative vehicles. By comparing these results we can interpret that while the single vehicle map matching considerably improves the GPS positioning accuracy, using the CMM method can improve the performance of the single vehicle map matching and give a more accurate position estimation.

Figure 5-8 shows the average bias estimation residual error with respect to the number of cooperative vehicles and Figure 5-9 Shows the average standard deviation of the CMM position estimation. We can interpret from these figures that similar to the position error, the bias estimation error also decreases by increasing the number of cooperative vehicles. In addition to this the amplitude of the position standard deviation reduces and the estimated position resolves with less uncertainty. This also leads to less ambiguity in the map matching especially when the vehicle position is close to a road intersection.

In the second scenario we designed the simulation in a way that we can test the performance of the whole system which means using the CMM to estimate the common error component of the positioning and using DDGPS to share this estimation with other vehicles. In this scenario a target vehicle in each set of vehicles performs the CMM. We refer to these three vehicles as $V^{(1)}$, $V^{(2)}$, $V^{(3)}$. Then in the next step these three vehicles generate and broadcast their pseudorange corrections according to the DDGPS algorithm. In addition to these three sets of vehicles we have another vehicle, $V^{(r)}$, which haven't participated in the CMM algorithm with any other vehicle and only receives the DDGPS corrections.

The vehicle $V^{(r)}$ receives the broadcasted pseudorange corrections, applies these corrections to its measurements, and then estimates its corrected GPS position. Table 5-2 presents the average pseudorange measurement errors for the satellites which were visible for vehicle $V^{(1)}$ along with the average pseudorange corrections generated by the proposed algorithm and their average standard deviations for the case that $V^{(1)}$ performs the CMM with 4 other vehicles. However it is important to remember that the accuracy of these pseudorange corrections and their standard deviations depend largely on the accuracy and positioning uncertainty of the CMM estimated position of $V^{(1)}$.

Table 5-3 provides the pseudorange errors, which is the difference between the true satellite-receiver distance and the measured pseudorange, for $V^{(r)}$ along with the residual errors after applying the corrections received from $V^{(1)}$ and the positioning error before and after applying the corrections. This table shows that by applying the pseudorange corrections, a large amount of the error on the measured pseudorange can be compensated and therefore, a more accurate positioning can be achieved. Table 5-4 compares the accuracy and uncertainty of the pseudorange corrections with respect to the number of sources which have generated the

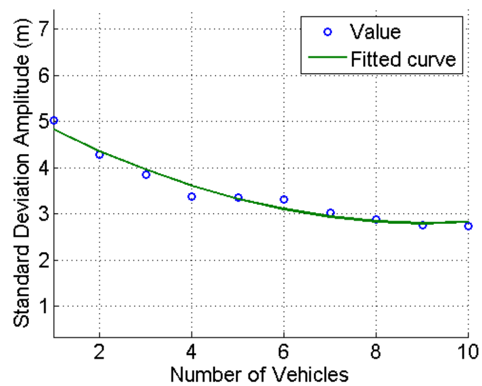


Figure 5-9. Standard deviation of the CMM estimated position with respect to the number of vehicles participating in CMM.

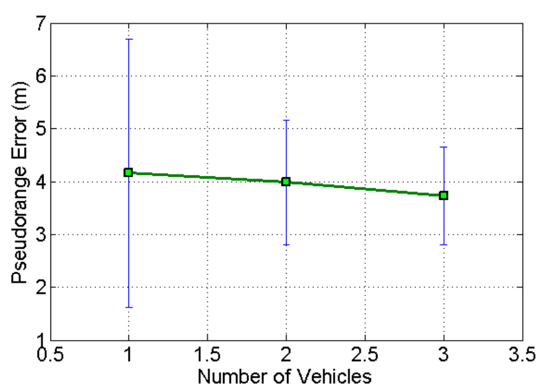


Figure 5-10. Average pseudorange error and their standard deviation vs. the number of received corrections by $V^{(r)}$.

correction data. This table provides the corrections generated by every possible combination of the sources and the results of their data fusion.

Figure 5-10 illustrates the average pseudorange error and their standard deviation with respect to the number of received corrections by $V^{(r)}$. This shows that receiving more sets of corrections from different sources and fusing them improves the overall pseudorange correction estimation accuracy. As we mentioned before the accuracy and uncertainty of the generated corrections depends on the positioning performance of the vehicle which produced the corrections. However by receiving more correction data from various sources and fusing them, on average we can exceed the performance of each individual correction.

Table 5-1. Comparison of the residual position error, residual bias error and the position std. between the GPS, single vehicle map matching and the CMM with various number of cooperative vehicles.

	GPS	**Single Vehicle MM**	**CMM – Number of Cooperative Vehicles**								
			2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Residual Position Error	15.48	10.47	9.17	8.18	7.16	6.44	5.73	4.88	4.19	3.55	2.93
Residual Bias Error	N/A	13.23	11.99	11.00	9.99	9.25	8.53	7.61	6.85	6.14	5.41
Std. of the position error	14.06	5.02	4.27	3.84	3.36	3.35	3.30	3.02	2.88	2.76	2.74

Table 5-2. True pseudorange errors of $V^{(1)}$, its generated corrections and their standard deviation for its visible satellites

Sat id.	PR error	Correction	Residual PR error	Correction Std	id list
4	12.95	16.38	-3.43	4.38	V1
7	17.82	16.10	1.72	2.41	V1
8	16.41	21.03	-4.62	5.08	V1
10	15.15	16.00	-0.85	2.52	V1
19	19.21	22.85	-3.64	4.52	V1
22	9.92	12.42	-2.49	3.24	V1

Table 5-3. True pseudorange errors of $V^{(r)}$, its residual pseudorange error and the position error before and after applying corrections

Sat id.	PR error	PR error after Correction	GPS Error Before	GPS Error After
4	12.95	-3.43	15.48	6.31
7	17.82	1.72		
8	16.41	-4.62		
10	15.15	-0.85		
19	19.21	-3.64		
22	9.92	-2.49		

Table 5-4. Performance analysis of the generated pseudorange corrections with respect to the number of sources which have generated the correction data.

Cluster	PR Error	PR Error after Correction	Correction Std.	GPS Error Before	GPS Error After
1	15.24	3.75	2.61	15.48	7.18
2	15.24	5.06	2.47	15.48	6.43
3	15.24	3.66	2.53	15.48	6.40
1,2	15.24	4.06	1.18	15.48	7.82
2,3	15.24	3.90	1.16	15.48	5.18
1,3	15.24	3.36	1.22	15.48	6.73
1,2,3	15.24	3.72	0.92	15.48	7.37

5.7 Conclusion & future work

GPS receiver is an important component of automotive navigation systems as it provides an estimate of the absolute position of the vehicle. Commercial GPS is subject to several sources of noise and offers insufficient accuracy for most ADAS and ITS applications. The major sources of noise in the pseudorange detection process are highly correlated between the receivers which are close to each other.

In this paper we have proposed a new cooperative map matching method which is based on applying the road constraint of the neighbor vehicles to the target vehicle in order to reduce the uncertainty of the positioning and improving its accuracy. Unlike other cooperative map matching method this method only relies on exchanging the GPS measurements of different vehicles and having a precise digital road map. In addition to this the effect of non-common pseudorange error which can lead to over converging to a wrong position in the cooperative map matching has been considered and circumvented in our approach. In addition to this we have used the concept of decentralized Dynamic base DGPS method (DDGPS) which takes advantage of the communication capability of the vehicles in order to generate and exchange the pseudorange corrections in a VANET.

Unlike the DGPS, our method does not require a network of static base stations with precisely known positions to generate pseudorange corrections. These corrections are generated by each vehicle from their map matching position estimate. Since the position of the vehicles are not known exactly, a parameter describing the confidence level of each pseudorange correction is introduced, which is calculated based on the uncertainty of the ego position estimate. The results indicates that by using the cooperative approach, the map matching task significantly improves and a better positioning can be performed. Also by taking benefit of DDGPS approach the vehicles can share their generated GPS corrections and by fusing these corrections together a better positioning with higher accuracy and less uncertainty can be achieved.

For future work, we intend to study the interdependency of the pseudorange corrections generated by vehicles. We also consider that the fusion method for merging the received corrections can also be improved. In addition to this a method for considering the life time of the corrections must be used to help the vehicles detect the expired corrections and not to broadcast them to other vehicles. Also a vehicle selection procedure can be useful in the case of having a large number of communicating vehicles in order to have a good performance for the map matching algorithm while keeping the computation time at a reasonable level.

5.8 Acknowledgment

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Chapter 6 Avant-Propos

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Titre français: Une nouvelle approche décentralisée bayésienne pour la localisation coopérative des véhicules basée sur la fusion du GPS et de la distance inter-véhiculaire grâce aux VANETs.

Résumé français :

L'intelligence embarquée dans les applications de véhicules a pris de l'ampleur depuis les deux dernières décennies. La croissance significative des capacités de détection, de communication et de calcul au cours des dernières années a ouvert de nouveaux champs d'applications, tels que les systèmes de sécurité active et ADAS, et a apporté la possibilité d'échanger des informations entre les véhicules. Dans cet article, une nouvelle méthode pour améliorer le positionnement du véhicule est proposée. Il s'agit d'une méthode décentralisée basée sur le partage des données GPS et des mesures de distance inter-véhiculaires dans un groupe de véhicules. Une approche bayésienne est utilisée pour fusionner les données GPS et les distances inter-véhiculaires. Afin

d'étudier la performance de cette nouvelle approche sur la localisation du véhicule, un filtre de Kalman a été utilisé pour intégrer la dynamique du véhicule. L'effet de cette méthode sur la réduction de l'incertitude de la localisation, les questions sur-convergence et l'identification des véhicules sont également discutés dans le présent document.

Chapter 6 A New Decentralized Bayesian Approach for Cooperative Vehicle Localization based on fusion of GPS and VANET based Inter-vehicle Distance

6.1 Abstract

Embedded intelligence in vehicular applications is becoming of great interest since the last two decades. The significant growth of sensing, communication and computing capabilities over the recent years has opened new fields of applications, such as ADAS and active safety systems, and has brought the ability of exchanging information between vehicles. In this paper, a new method for improving vehicle positioning is proposed. This method is a decentralized method based on sharing GPS data and inter-vehicular distance measurements within a cluster of vehicles. A Bayesian approach is used to fuse the GPS data and inter-vehicular distances. In order to investigate the performance of this new approach on vehicle localization, a Kalman filter has been employed to incorporate the dynamics of the vehicle. The effect of this method on the reduction of the localization uncertainty, over-convergence issues and identification of the vehicles are also discussed in this paper.

6.2 Introduction

Accurate and reliable vehicle localization is a key component of numerous automotive and Intelligent Transportation System (ITS) applications, including active vehicle safety systems, real time estimation of traffic conditions, and high occupancy tolling. Various safety critical vehicle applications in particular, such as collision avoidance or mitigation, lane change management or emergency braking assistance systems, rely principally on the accurate and reliable knowledge of vehicles' positioning within given vicinity.

Distributed algorithms as proposed in [88] and [100] have underlined a recent and important interest for the collaborative localization. Since the number and type of sensors used in vehicular applications increases, it is essential to find ways to better analyze and extract useful data from these sensors and share them between vehicles when it is relevant.

Sensors which are used in localization can be divided in two categories: proprioceptive and exteroceptive sensors. Proprioceptive sensors are those which can provide information about the vehicle dynamic states like position, velocity and acceleration (GPS, accelerometer, gyroscope etc.). Exteroceptive sensors provide information about the states of the environment (video camera, lidar, etc.). GPS is one of the most common positioning devices being used in vehicle localization as it provides absolute position of the vehicles, whereas dead reckoning sensors such as odometers or INS (Inertial Navigation Systems) provide relative information only. GPS signals are however subject to different sources of noise, and degradation as well as being subject to temporary signal loss in cluttered environment. Many of the intelligent vehicles systems like safety systems can benefit from more accurate and reliable positioning [69]. Data fusion technique is one of the common ways to improve the position estimate by exploiting the information coming from multiple sensors [44, 45, 135].

In the recent years, vehicular ad hoc network (VANET) applications has become of great interest. With the recent emergence of multi-vehicular wireless communication capabilities, cooperative architectures have become an attractive alternative for solving the localization problem [18, 26, 35, 36, 84, 93, 104, 114, 115]. The main goal of cooperative localization is to exploit different sources of information coming from different vehicles within a short range area, in order to enhance positioning system efficiency while keeping the computing cost at a reasonable level. In other words, vehicles share their location and environment information to others in order to increase their own global perception. Some of the most prominent approaches for cooperating localization are based on Kalman filtering [4, 61, 119], Bayesian methods [52], Markovian modeling [13] and maximum likelihood methods [53] and Split covariance intersection filter [74, 139].

In addition to the information exchanging, VANET has brought the capability for communicating vehicles to use their wireless communication devices to measure the distance between each other. There are basically two methods of measuring distance between communicating devices. The first method is the Time-of-Flight (TOF) which is based on the time that it takes for a signal to travel from one node to another node, where the nodes are vehicles in a VANET. The second method is the Radio Signal Strength (RSS) which is based on the attenuation of the signal strength while traveling from the transmitter node to the receiver node [50]. Using the communication devices to measure distance between vehicles has several advantages and disadvantages over the other range measurement devices like radar and lidar. One of the advantages is that the vehicle identification problem and the data association between the received information and range measurements is easier to solve. Another advantage of these method is that its detection performance in the crowded areas is better since it can still be used while an object or another vehicle blocked the line of sight between two vehicles but it doesn't block the line of sight between antennas. However the disadvantages of these methods over radar and lidar is that in their general form they cannot provide the relative bearing between the vehicles and they can only provide the distance. In addition to this, lidars usually can provide more accurate measurements. Although not all of the RF range measurement methods can provide the acceptable accuracy needed for our method, there are several more accurate RF based methods such as [120] and [54, 67] which can provide the needed accuracy to be used in our method. In [120] a low cost accurate radio ranging technic is proposed and field trials has been conducted in different environments to characterize the ranging error.

In this article, we aim to improve the GPS vehicle position estimates by using available VANET based inter-vehicle distance measurements in a cluster of vehicles. The reason that we decided to use VANET based inter-vehicle distance measurements is that in addition to the mentioned advantages, using this method of distance measurements reduces the cost of the system as it doesn't need a new range sensor to be used and vehicles can use their existing communication device to measure the distance.

Our proposed cooperative vehicle localization method is a decentralized Bayesian approach which allows a vehicle to incorporate its GPS position estimate with other vehicles' GPS data and inter-vehicle distance measurements. Unlike [13, 52], which basically have been developed for indoor robotic applications, our method is developed for outdoor usage and automotive applications. Also this method is taking the advantage of using GPS which is available in outdoor usages. Our method should be seen as a pre-filtering of GPS positioning measurement using inter-vehicle distances and other vehicles' GPS measurements, prior the tracking algorithms such as the Extended Kalman Filter (EKF). Therefore this method has the advantage to be incorporated with any existing ego localization algorithm which uses GPS (see Figure 6-1).

Furthermore, the data dependency problem, which is a common issue in probabilistic approaches [13, 52, 53] and which leads to over convergence, has been circumvented in our approach. Another advantage of this method is the ability to use the true probability distribution model of distance measurement sensors instead of using their Gaussian approximation which is usually being done in Kalman based methods. In addition to the performance analysis of the method, the Sensitivity of the proposed method to the vehicle to vehicle distance measurement accuracy, communication latency and communication failure is also studied. The results presented in this article are based on Monte Carlo simulations and the data used in these simulations were provided by Pro-SiVIC software from Civitec and GPSoft Satellite Navigation toolbox for MATLAB.

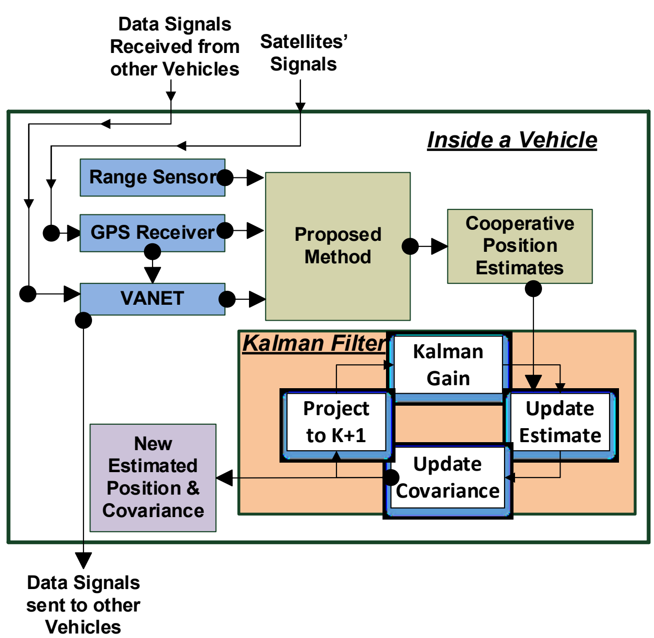

Figure 6-1. Schematic of the system, the input data (blue), the proposed method (green), the Kalman filter (orange) and the new Position Estimation.

The focus of this article is to describe the derivation of the Bayesian cooperative vehicle localization method and demonstrate its performance by integrating this algorithm with a Kalman filter to incorporate the dynamic properties of the vehicle.

6.3 Proposed Method

The proposed method aims to improve GPS vehicle positioning using additional inter-vehicle distances and vehicle-to-vehicle (V2V) communication capabilities in a cluster of vehicles. We assume that each vehicle is able to estimate its position and respective covariance matrix using its embedded GPS receiver independently. We consider also that each vehicle is able to estimate its distance to other vehicles, using a VANET based method and independent from their GPS signals [80], we refer to these method as Range Sensor in the rest of this article. Finally, it is assumed that the vehicles share their information by means of a VANET.

With their GPS receivers, the vehicles can calculate the pseudo ranges between them and the visible satellites. These pseudo ranges has a standard deviation which is referred as σ_{UERE} [60]. With the following notation:

$$V_N = \text{N}^{\text{th}} \text{ Vehicle} \tag{6-1}$$

$$X_0^{(N)} = \text{True Position of} V_N \tag{6-2}$$

$$\hat{X}^{(N)} = \text{Estimated position of } V_N \tag{6-3}$$

$$D_0^{(ij)} = \text{True distance between } V_i \text{ and } V_j \tag{6-4}$$

$$\hat{D}^{(ij)} = \text{Estimated distance between } V_i \text{ and } V_j \qquad \text{6-5}$$

where $X_0^{(N)}$ and $\hat{X}^{(N)}$ are two dimensional vectors providing the (unknown) true position and estimated position of V_N respectively, the distance between two vehicles for the no-noise case is simply given by:

$$D_0^{(ij)} = \left\| X_0^{(i)} - X_0^{(j)} \right\| \qquad \text{6-6}$$

where $D_0^{(ij)}$ is the distance between $X_0^{(i)}$ and $X_0^{(j)}$. As said before, we assume that $\hat{D}^{(ij)}$ is measured independently from $\hat{X}^{(i)}$ and $\hat{X}^{(j)}$ and that we have a zero mean additive noise on the GPS estimated positions:

$$X^{(N)} \sim N(X_0^{(N)}, R_{X^{(N)}}) = f_{X^{(N)}}(x^{(N)}) \qquad \text{6-7}$$

where $R_{X^{(N)}}$ is the covariance matrix of the position and $f_{X^{(N)}}$ is the probability density function of $X^{(N)}$. Also, we assume that the inter-vehicular distances have a zero mean additive noise:

$$D^{(ij)} \sim N(D_0^{(ij)}, \sigma^2_{D^{(ij)}}) = f_{D^{(ij)}}(d^{(ij)}) \qquad \text{6-8}$$

where $D_0^{(ij)}$ is the true distance between V_i and V_j, $\sigma^2_{D^{(ij)}}$ is the distance variance corresponding to the accuracy of the sensors. Here it is important to mention that these assumptions (6-7,6-8) is only made to simplify the problem; our method is not restricted to them. This method can work with any other probability distribution model which can better describe the properties of the range measurement method. Now it is desired to estimate $X^{(i)}$ from the observations. Let us define:

$$Y^{(ij)} = \left\{ X^{(j)}, D^{(ij)} \right\} \tag{6-9}$$

where $Y^{(ij)}$ is the observation of $X^{(j)}$ and $D^{(ij)}$ by V_i. Therefore $X_Y^{(ij)}$ estimates the position $X^{(i)}$ from $Y^{(ij)}$.

$$X_Y^{(ij)} = X^{(j)} - \begin{bmatrix} D^{(ij)} \cos(\theta) \\ D^{(ij)} \sin(\theta) \end{bmatrix}, i \neq j \tag{6-10}$$

where θ is the bearing of the inter-vehicle distance measurement. Since we assumed that our distance measurement device is only able to provide us with the inter-vehicle distance and not the bearings the value of θ is unknown. Therefore the solution space for $X_Y^{(ij)}$ is a circle around $X^{(j)}$ with the radius of $D^{(ij)}$.

6.3.1 The 2 vehicles case

Let us first consider a simple 2-vehicle scenario. From a probabilistic point of view, we have:

$$f_{X^{(i)}|X_Y^{(ij)}}(x^{(i)} \mid x_Y^{(ij)}) = \frac{f_{X_Y^{(ij)}|X^{(i)}}(x_Y^{(ij)} \mid x^{(i)}).f_{X^{(i)}}(x^{(i)})}{f_{X_Y^{(ij)}}(x_Y^{(ij)})} \tag{6-11}$$

Eq. (6-11) is an application of the Bayes theorem, where the left member is the posterior probability to observe $x^{(i)}$ given $x_Y^{(ij)}$ and $f_{X_Y^{(ij)}|X^{(i)}}(x_Y^{(ij)} \mid x^{(i)})$ is the likelihood of the observations. Using our model (6-10) we find:

$$F_{X_Y^{(ij)}}(x_Y^{(ij)}) = \int_{-\infty}^{+\infty} \int_{-\infty}^{x^{(j)} - x_Y^{(ij)}} f_{X^{(j)} D^{(ij)}}(x^{(j)}, d^{(ij)}) dd^{(ij)} dx^{(j)} \tag{6-12}$$

Differentiating with respect to $x_Y^{(ij)}$ we obtain:

$$f_{X_Y^{(ij)}}(x_Y^{(ij)}) = \int_{-\infty}^{+\infty} f_{X^{(j)} D^{(ij)}}(x^{(j)}, x^{(j)} - x_Y^{(ij)}) dx^{(j)} \tag{6-13}$$

Since $X^{(j)}$ and $D^{(ij)}$ are independent, we have:

$$f_{X_Y^{(ij)}}(x_Y^{(ij)}) = \int_{-\infty}^{+\infty} f_{X^{(j)}}(x^{(j)}) f_{D^{(ij)}}(x^{(j)} - x_Y^{(ij)}) dx^{(j)} \tag{6-14}$$

Similarly we can obtain:

$$f_{X_Y^{(ij)} | X^{(i)}}(x_Y^{(ij)} \mid x^{(i)}) = \int_{-\infty}^{+\infty} f_{X^{(j)}}(x^{(j)} \mid x^{(i)}).f_{D^{(ij)}}(x^{(j)} - x_Y^{(ij)} \mid x^{(i)}) dx^{(j)} \tag{6-15}$$

$X^{(j)}$ is independent of $X^{(i)}$ and the second term in the integral (6-15) is the probability that V_i and V_j observe each other at the given distance $\left\| x^{(j)} - x^{(i)} \right\|$, Which becomes like a doughnut whose center is $x^{(i)}$ (see Figure 6-2). Therefore (6-15) becomes:

$$f_{X_Y^{(ij)} | X^{(i)}}(x_Y^{(ij)} \mid x^{(i)}) = \int_{-\infty}^{+\infty} f_{X^{(j)}}(x^{(j)}).f_{D^{(ij)}}(x^{(j)} - x^{(i)}) dx^{(j)} \tag{6-16}$$

Also we have:

$$f_{X_Y^{(ij)}}(x_Y^{(ij)}) = \int_{-\infty}^{+\infty} f_{X^{(i)}}(x^{(i)}).f_{X_Y^{(ij)}|X^{(i)}}(x_Y^{(ij)} \mid x^{(i)})dx^{(i)} = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f_{X^{(i)}}(x^{(i)}).f_{X^{(j)}}(x^{(j)}).f_{D^{(ij)}}(x^{(j)} - x^{(i)})dx^{(j)}dx^{(i)} \quad \text{6-17}$$

As we don't know the true position of the vehicles neither the distance between them, we use instead, the PDFs of the estimates coming from the GPS receivers and range sensors:

$$f_{X^{(i)}}^{GPS}(x^{(i)}) = N(\hat{X}_{GPS}^{(i)}, \hat{R}_{GPS}^{(i)}) \quad \text{6-18}$$

where, $\hat{X}_{GPS}^{(i)}$ is the position estimate obtained from the GPS receiver of V_i and $\hat{R}_{GPS}^{(i)}$ is its estimated covariance.

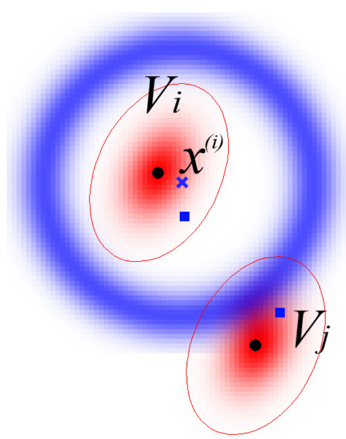

Figure 6-2. Real positions (squares), estimated GPS positions (dots), their PDF and uncertainty ellipses (red) and inter-vehicle PDFs centered at $x^{(i)}$ (blue) for $\sigma_{UERE} = 6.5(m)$ and $\sigma_{RS} = 4.5(m)$.

$$f_{D^{(ij)}}^{RS}(d^{(ij)}) = N(\hat{D}_{RS}^{(ij)}, \sigma_{RS}^2) \tag{6-19}$$

where, $\hat{D}_{RS}^{(ij)}$ is the distance estimate between V_i and V_j given by the range sensor (*RS*) and σ_{RS}^2 is the variance of distance measurements using range sensor.

Our prior PDF for $X^{(i)}$ is therefore the one of its GPS estimate:

$$f_{X^{(i)}}(x^{(i)}) = f_{X^{(i)}}^{GPS}(x^{(i)}) \tag{6-20}$$

In a similar way for the inter-vehicular distances, we use the PDF of our range sensor measurement:

$$f_{D^{(ij)}}(d^{(ij)}) = f_{D^{(ij)}}^{RS}(d^{(ij)}) \tag{6-21}$$

As an example, Figure 6-2 shows the real positions, estimated GPS positions for V_i and V_j along with their PDF in red and the inter-vehicle distance PDF centered at $x^{(i)}$. The uncertainty ellipses have been drawn using a 3 sigma deviation from the center. Substituting (6-20) and (6-21) in (6-16) and (6-17) we have:

$$f_{X_Y^{(ij)}|X^{(i)}}(x_Y^{(ij)} \mid x^{(i)}) = \int_{-\infty}^{+\infty} f_{X^{(j)}}^{GPS}(x^{(j)}).f_{D^{(ij)}}^{RS}(x^{(j)} - x^{(i)})dx^{(j)} \tag{6-22}$$

And,

$$f_{X_Y^{(ij)}}(x_Y^{(ij)}) = \int_{-\infty}^{+\infty} f_{X^{(i)}}^{GPS}(x^{(i)}).f_{X_Y^{(ij)}|X^{(i)}}(x_Y^{(ij)} \mid x^{(i)})dx^{(i)} =$$
$$\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f_{X^{(i)}}^{GPS}(x^{(i)}).f_{X^{(j)}}^{GPS}(x^{(j)}).f_{D^{(ij)}}^{RS}(x^{(j)} - x^{(i)})dx^{(j)}dx^{(i)} \quad \text{6-23}$$

Therefore by substituting (6-22) and (6-23) in (6-11) we obtain the following posterior PDF for V_i:

$$f_{X^{(i)}|X_Y^{(ij)}}(x^{(i)} \mid x_Y^{(ij)}) = \frac{f_{X^{(i)}}^{GPS}(x^{(i)}).\int_{-\infty}^{+\infty} f_{X^{(j)}}^{GPS}(x^{(j)}).f_{D^{(ij)}}^{RS}(x^{(j)} - x^{(i)})dx^{(j)}}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f_{X^{(i)}}^{GPS}(x^{(i)}).f_{X^{(j)}}^{GPS}(x^{(j)}).f_{D^{(ij)}}^{RS}(x^{(j)} - x^{(i)})dx^{(j)}dx^{(i)}} \quad \text{6-24}$$

The corresponding MAP estimator is given by:

$$\hat{X}^{(i)} = argmax_{x^{(i)}} f_{X^{(i)}|X_Y^{(ij)}}\left(x^{(i)}|x_Y^{(ij)}\right) \quad \text{6-25}$$

where $\hat{X}^{(i)}$ is the new estimated position for V_i. Figure 6-3 shows this posterior PDF for i =1 and j =2, obtained from (6-24). As one can foresee, such a Bayesian approach allows one vehicle to exploit the information contained in the other vehicles' GPS position and in the range sensor measurements to improve its own position estimate and more importantly reduce its uncertainty.

6.3.2 The N vehicles case

Now, let us consider the case of *N+1* vehicles present in a cluster. We assume that each vehicle has its own GPS position estimate and that all the inter-vehicle distances can be measured. We also assume that all range sensors and GPS receivers are the same, within the vehicle cluster, leading to identical prior distributions. Again this is only to simplify the equations but in practice, for each GPS receivers and range sensors, we can use their own prior distribution. We then have:

$$f_{X^{(i)}|X_Y^{(i1)},\dots,X_Y^{(iN)}}(x^{(i)} \mid x_Y^{(i1)},\dots,x_Y^{(iN)}) = \frac{f_{X_Y^{(i1)},\dots,X_Y^{(iN)}|X^{(i)}}(x_Y^{(i1)},\dots,x_Y^{(iN)} \mid x^{(i)}).f_{X^{(i)}}(x^{(i)})}{\int_{-\infty}^{+\infty} f_{X_Y^{(i1)},\dots,X_Y^{(iN)}|X^{(i)}}(x_Y^{(i1)},\dots,x_Y^{(iN)} \mid x^{(i)}).f_{X^{(i)}}(x^{(i)})dx^{(i)}} \tag{6-26}$$

Considering that $X_Y^{(i1)},\dots,X_Y^{(iN)}$ are independent from each other, equation (6-26) becomes:

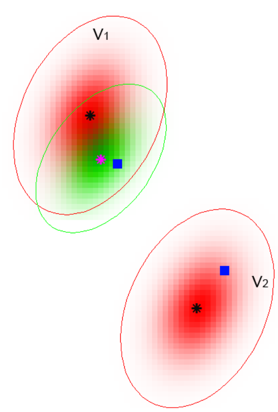

Figure 6-3. Posterior probability of V_1 and its uncertainty ellipse (green), new estimated position (star on green area), real position (squares), estimated GPS position (star on red area), their PDF and uncertainty ellipses (red) for $\sigma_{UERE} = 6.5(m)$ and $\sigma_{RS} = 3.5(m)$.

$$f_{X^{(i)}|X_Y^{(i1)},\ldots,X_Y^{(iN)}}(x^{(i)} \mid x_Y^{(i1)},\ldots,x_Y^{(iN)}) = \frac{f_{X^{(i)}}(x^{(i)}).\prod_{\substack{j=1\\ j\neq i}}^{N} f_{X_Y^{(ij)}|X^{(i)}}(x_Y^{(ij)} \mid x^{(i)})}{\int_{-\infty}^{+\infty} f_{X^{(i)}}(x^{(i)}).\prod_{\substack{j=1\\ j\neq i}}^{N} f_{X_Y^{(ij)}|X^{(i)}}(x_Y^{(ij)} \mid x^{(i)})dx^{(i)}} \qquad 6\text{-}27$$

By substitution of (6-22) in (6-27) we have:

$$f_{X^{(i)}|X_Y^{(i1)},\ldots,X_Y^{(iN)}}(x^{(i)} \mid x_Y^{(i1)},\ldots,x_Y^{(iN)}) = \frac{f_{X^{(i)}}^{GPS}(x^{(i)}) \times \prod_{\substack{j=1\\ j\neq i}}^{N} \int_{-\infty}^{+\infty} f_{X^{(j)}}^{GPS}(x^{(j)}).f_{D^{(ij)}}^{RS}(x^{(j)} - x^{(i)})dx^{(j)}}{U} \qquad 6\text{-}28$$

where U is a normalization factor that can be computed by substituting (6-22) into(6-27):

$$U = \int_{-\infty}^{+\infty} f_{X^{(i)}}^{GPS}(x^{(i)}) \times \prod_{\substack{j=1\\ j\neq i}}^{N} \int_{-\infty}^{+\infty} f_{X^{(j)}}^{GPS}(x^{(j)}).f_{D^{(ij)}}^{RS}(x^{(i)} - x^{(j)})dx^{(j)}dx^{(i)} \qquad 6\text{-}29$$

Finally, the MAP estimator for the position of vehicle V_i given the N other vehicles, is given by:

$$\hat{X}^{(i)} = argmax_{x^{(i)}} f_{X^{(i)}|X_Y^{(i1)},\ldots,X_Y^{(iN)}}(x^{(i)} \mid x_Y^{(i1)},\ldots,x_Y^{(iN)}) \qquad 6\text{-}30$$

Since there is no analytical solution for equation (6-30), a particle filter has been applied in order to solve this equation. A sample set of 1000 particles has been selected for each $X^{(j)}, (j = 1 \ldots N)$

according to its PDF $f_{X^{(j)}}^{GPS}(x^{(j)})$. The results shown here have been obtained with 5 filter's iterations.

Figure 6-4 shows the posterior probability (6-28) for V_1 in a cluster of 5 vehicles. The new position estimation for V_1 is calculated using (6-30) and is shown as a star in the central green area. As we can see from Figure 6-4 the new estimated position is much closer to the real position of V_1 and the uncertainty has been reduced as the green area illustrated in Figure 6-4 is smaller in size than the red area. Since the most computationally complex part of this algorithm is solving (6-30) with a particle filter, therefore the order of this algorithm is $O(N \cdot N_p^2)$, where N is the number of vehicles in the cluster and N_p is the number of particles. With proper choose of N_p and N each iteration of the algorithm can run in real-time and the result can be sent for further use in the tracking algorithms.

One should note that depending on the method chosen for estimating the inter-vehicular distances, different methods for identifying neighbor vehicles and associating the measured distances with the received information from VANET can be applied. Although in the case of VANET based distance measurement methods there is no need to use any special method because vehicles can be identified and data can be associated using their communication device's MAC address, However in the case of Radar and Lidar, different approaches can be utilized like the one used in [61] which is based on the Mahalanobis distance between position estimations. Details on association and identification methods is outside the scope of this article as we will focus only on the fusion method for cooperative localization.

One important point that must be mentioned here with our Bayesian approach is the *over-convergence* issue. This usually occurs when the fused information coming from different vehicles are not independent of each other. For each time step of our method, only the GPS and inter-vehicle distance measurements of the vehicles present in the cluster are used in the calculation of the posterior PDF. These measurements are independent from each other (in the probabilistic sense) and supposedly non-Markovian, i.e. non-related to the previous measurements and position probability distribution of the other vehicles. Therefore, our proposed method shall not lead to over-convergence. This method should be seen as a pre-filter, which reduces the measurement noise and provides more accurate measurements for further calculations.

6.4 Algorithm Framework

In order to incorporate these new denoised measurements into a motion model to estimate the trajectory of the target vehicle and estimate the position of the vehicles (a Kalman filter in this study), as the calculated PDF by (6-28) doesn't necessarily have a Gaussian distribution, we first find the best Gaussian distribution approximation and use this estimation in the update stage of the Kalman filter. The implemented motion model is as follow:

$$A_k = FA_{k-1} + v_{k-1} \tag{6-31}$$

where $A_k = [x_k, \dot{x}_k, \ddot{x}_k, y_k, \dot{y}_k, \ddot{y}_k]^T$ is the state vector at time k and $x_k, \dot{x}_k, \ddot{x}_k$ are respectively the position, velocity and acceleration of the vehicle at time k in the x direction and $y_k, \dot{y}_k, \ddot{y}_k$ are

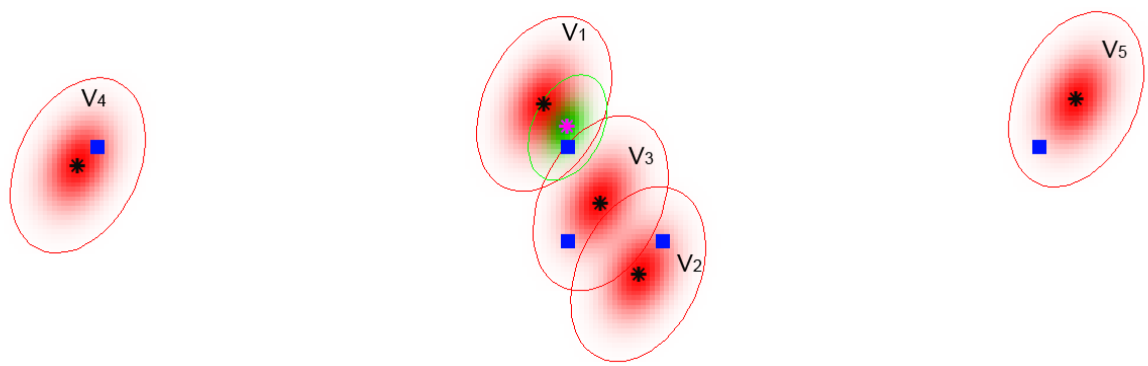

Figure 6-4. Posterior PDF of V_1 in a cluster of 5 vehicles (green), real position (squares), new estimated position for V_1 (star on green area) for $\sigma_{UERE} = 6.5(m)$ and $\sigma_{RS} = 1.5(m)$.

respectively the position, velocity and acceleration of the vehicle at time k in the y direction. F is the state transition matrix based on the constant acceleration model and v_{k-1} is the innovation process noise which describes the uncertainty in the state model. We assume that v_{k-1} is a zero-mean Gaussian variable with the covariance matrix:

$$Q_{k-1} \triangleq E\{v_{k-1}v_{k-1}^T\} = diag(\sigma_x^2, \sigma_{\dot{x}}^2, \sigma_{\ddot{x}}^2, \sigma_y^2, \sigma_{\dot{y}}^2, \sigma_{\ddot{y}}^2) \quad \text{6-32}$$

where *diag* means a diagonal matrix.

The observation model of the position is expressed as:

$$Z_k = HA_k + w_k \quad \text{6-33}$$

where H is the observation matrix and w_k is a zero mean Gaussian random vector which describes the noise of the measurements and with a covariance matrix R_k. Also Z_k is the measurement vector and in our scenario as our only measurement is the position of the vehicles, then Z_k only consists of the measured position of the target vehicle at time k. If the position measurements are from the GPS receiver then $Z_k = \hat{X}_{GPS}^{(i)}$ and if the measurements are from (6-30) then $Z_k = \hat{X}^{(i)}$ where i is the index of the target vehicle.

Our algorithm is summarized as follow (see Figure 6-1):

Step 1: Each vehicle measures its own position using its GPS receiver and transmit the position with its covariance matrix to all other vehicles in the cluster. It also measures its inter-vehicular distances with the other vehicles in the cluster.

Step 2: Each vehicle fuses its own GPS position with the measured inter-vehicular distances and also the received GPS information of the other vehicles, using (6-30) and obtains new position measurement.

Step 3: Each vehicle incorporates the result of Step 2 into its own motion model using a Kalman filter.

Step 4: Step 1 to 3 are repeated through time.

In the next section we will describe our simulation scenario and we will discuss the performance of this method from different aspects.

6.5 Simulation Results

In order to test the performance of the proposed method, we considered a cluster of 5 vehicles, each one equipped with a GPS receiver, communication device and a VANET based range measurement method to measure the distances between itself and other vehicles in the cluster. These vehicles are moving along a road and their relative positions are changing continuously. A typical vehicle formation is shown in Figure 6-5. We used the Pro-SiVIC software from Civitec to produce the vehicle data trajectories and the GPSoft Satellite Navigation toolbox for MATLAB to generate the GPS data for each vehicle. In order to generate inter-vehicular distances we used the real distance between vehicles and added a zero mean Gaussian noise.

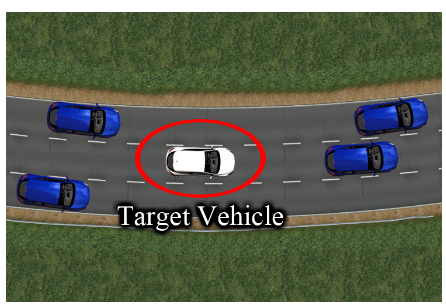

Figure 6-5. A typical formation of the vehicles

The simulation was done 100 times and the values presented here are the mean values over all the simulations.

The data synchronization of the various sensors between vehicles can be done using the GPS time. Each vehicle prepares the required data that must be transferred to other vehicles and attaches its GPS time to them and then broadcasts them for other vehicles. The target vehicle receives these broadcasted data and extract the sensor data and their timestamp. Then it can compare this timestamp to its own GPS time and do the data synchronization. The IEEE 802.11p is a good example for the vehicle–to-vehicle communication standard. This standard is an inter-vehicular communication technology designed for both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. In [17] the performance of IEEE 802.11p has been studied using field trials and a model for accurately simulating its performance has been proposed.

In order to investigate the performance of the proposed method, we applied the same Kalman filter for the target vehicle once with the GPS position estimation of it $Z_k = \hat{X}^{(i)}_{GPS}$, and once with the estimated data from our proposed method $Z_k = \hat{X}^{(i)}$,as the measurements in the update stage of the Kalman filter proposed in section III. The target vehicle is shown in the Figure 6-5. Figure 6-6 shows the real trajectory and also the Kalman filter estimated trajectories for GPS data and the proposed method for a typical run of the simulation. The road used in this simulation is a simulation of a test road in Satory, France and the data are provided by the Pro-SiVIC

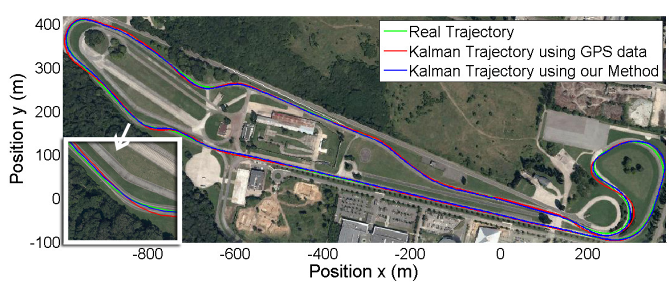

Figure 6-6. Real trajectory (Green), Estimated Kalman trajectory using only GPS of the target vehicle (Red), Estimated Kalman trajectory using the proposed method (Blue)

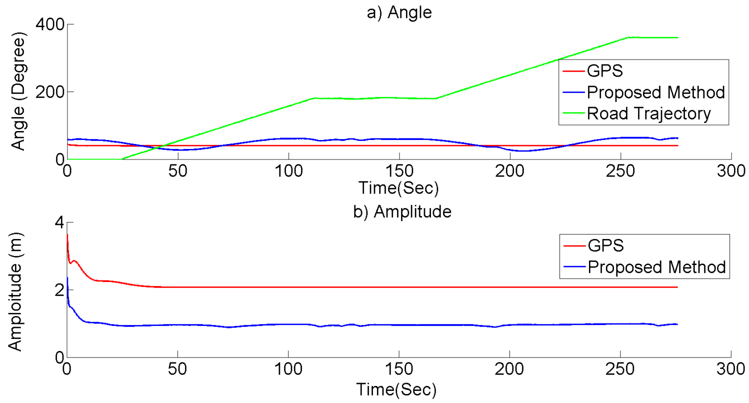

Figure 6-7. a) The angle of variances, $\tan^{-1}(\sigma_{yy}^2 / \sigma_{xx}^2)$ and the road trajectory angle. b) Comparison of variance amplitude, $\sqrt{(\sigma_{xx}^2)^2 + (\sigma_{yy}^2)^2}$ from the GPS and with the proposed method.

software. In Figure 6-6 the vehicles trajectories are mapped to the real road image to provide better understanding of the vehicles' trajectories.

Figure 6-8 compares the position error of the Kalman with the proposed method and the position error of the Kalman with GPS estimates. As we can see in this figure, using the proposed method decreases the position error and gives more accurate position estimations. Table 6-1 compares the average position error of these methods. In addition to the position error we can further

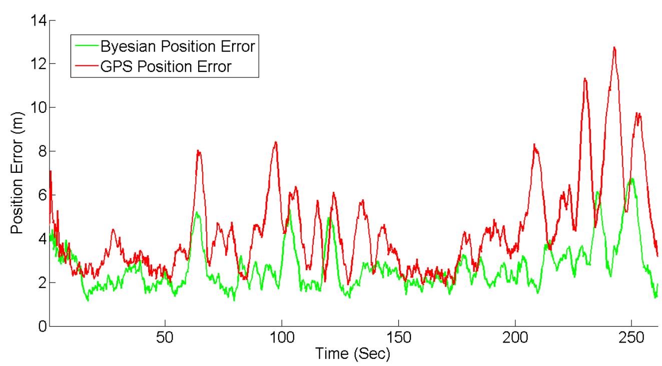

Figure 6-8. Position error of the Kalman with the proposed method (green) comparing to the Kalman with the GPS (red).

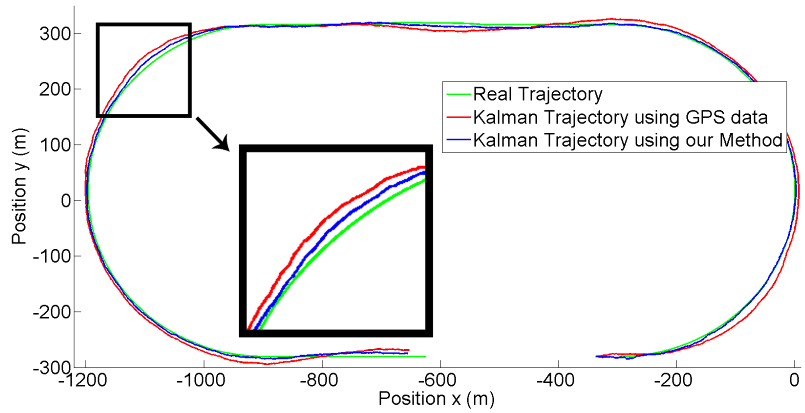

Figure 6-9. Real trajectory (Green), Estimated Kalman trajectory using only GPS of the target vehicle (Red), Estimated Kalman trajectory using the proposed method (Blue) used for position variance analysis.

investigate the performance of our method by comparing the variances of the positioning, $\boldsymbol{\sigma}_{xx}^{2}$ and $\boldsymbol{\sigma}_{yy}^{2}$. The average variances of the position estimates using our method and GPS before and after using Kalman filter has been compared in Table 6-1. This table shows that our method can significantly reduce the position uncertainty. In order to better investigate the dependency of the position variance reduction to the cluster configuration, a simpler trajectory (Figure 6-9) is used to produce data presented in in Figure 6-7. Figure 6-7.b shows the amplitude of the variances for the target vehicle, $\sqrt{(\boldsymbol{\sigma}_{xx}^{2})^{2}+(\boldsymbol{\sigma}_{yy}^{2})^{2}}$, in each time step and Figure 6-7.a shows the angle of these variances, $\tan^{-1}(\boldsymbol{\sigma}_{yy}^{2}/\boldsymbol{\sigma}_{xx}^{2})$. Figure 6-7.b shows a significant decrease of uncertainty by using our proposed method. As it is shown, the uncertainty, using the proposed method and by using the Kalman filter is always less than the uncertainty using only the GPS of the target vehicle and the same Kalman filter. Another interesting point that Figure 6-7.a shows is that the amount of variance reduction achieved, depends on the configuration of the cluster and is directional. Considering Figure 6-7.a at the beginning, the cluster is moving on the road and is spread in the X direction, the angle shows that the ratio of $(\boldsymbol{\sigma}_{yy}^{2}/\boldsymbol{\sigma}_{xx}^{2})$ is increased using our method which means that the amount of variance reduction was more in the X direction. As the

Table 6-1. Average Position Error and Variances of the target vehicle over time using different methods

Method	Variances (m^2)		Error (m)
	σ^2_{xx}	σ^2_{yy}	
GPS	37.73	22.73	6.75
Proposed method	4.94	5.50	4.16
Kalman with GPS	19.17	12.12	4.58
Kalman with Proposed method	2.95	3.23	3.30

cluster moves and changes its direction according to the road, the ratio decreases and from around 45(sec), the cluster is spread in the Y direction and angle shows that the amount of variance reduction is more in the Y direction in comparison with the variances before using our algorithm. In Figure 6-7.a the road trajectory angle is also given (green line) and by comparing it with the angle curve of the proposed method similarity in the variations is noticeable.

In order to estimate the computation time of the algorithm for the real time implementation, a fast C++ code was implemented. As the calculation time of the exponential function is relatively high we used a lookup table to increase the speed of the algorithm. Our experiments shows that each iteration of the algorithm having 5 vehicles in the cluster with 1000 particles around each vehicle takes approximately 20ms. By increasing the number of algorithm iterations to 5 the

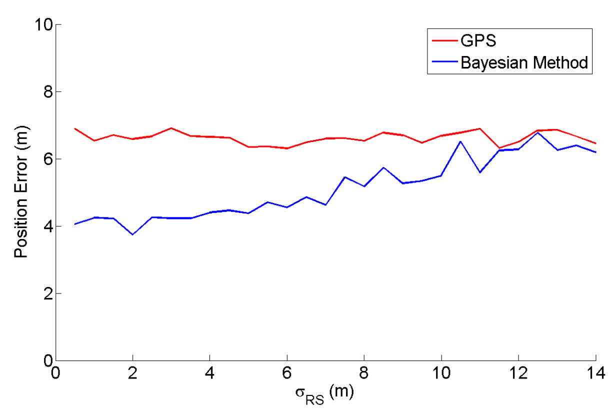

Figure 6-10. Effect of σ_{RS} on the position error for 5 vehicles using GPS positions (red) and proposed algorithm (blue)

computation time increases to 100ms. In order to speed up the algorithm it is possible to reduce the number of particles from 1000 to 500 which decreases the calculation time of each iteration for each vehicle in the cluster to 1ms which is an acceptable computation time for localization algorithms while it doesn't make a noticeable difference in the positioning accuracy. However a better implementation and optimization of the C++ code can still improve the speed of the algorithm.

6.5.1 Sensitivity Analysis

Another way to assess the performance of the algorithm is to analyze the sensitivity of the algorithm to different parameters. In this section we aim to analyze the sensitivity of the described algorithm to the accuracy of the inter-vehicle distance measurement described by σ_{RS}, the number of the vehicles in the cluster N, communication latency and communication failure.

The range sensor standard deviation, σ_{RS}, depends on the device or method which has been used to measure the inter-vehicle distance and its quality. For example laser based sensors such as lidar are typically more accurate than radar or VANET based methods. On the other hand the quality of the sensors always has a straight relation to the price of the sensors and most of the times we need to do a tradeoff between the quality and cost. Therefore it is important to investigate the sensitivity of the method to the accuracy of the range sensor, σ_{RS}. Figure 6-10 shows the average position error of the target vehicle against variations in the range sensor's std, σ_{RS}. As we can see in this figure, although the proposed method reduces the position error of the vehicles and gives a better position estimation, the amount of this improvement depends on the accuracy of the range sensor. We can deduce from the figure that by having a more accurate range sensor (less variance), we can achieve a more accurate cooperative position estimate. Also we can expect, by incre6-asing σ_{RS}, the position error increases and the estimated position will eventually approach the GPS initial estimations.

Moreover, the effect of range sensor's std, σ_{RS}, on the estimated posterior position variance can be seen in Figure 6-12. As this figure shows the uncertainty of the posterior positioning is

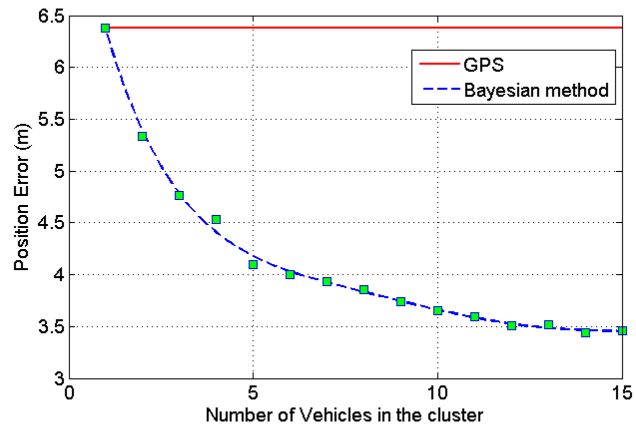

Figure 6-11. Position Error for V_1 with respect to number of vehicles in the cluster

increasing as σ_{RS} increases. Also we can deduce from (6-28) that by increasing σ_{RS}, eventually the $f_{D^{(ij)}}^{RS}$ becomes close to a uniform distribution and the posterior position PDF will become the same as the prior distribution. Therefore we can say that by increasing σ_{RS} the uncertainty of the Bayesian positioning increases and eventually it will approach the prior positioning uncertainty which is the GPS uncertainty.

In In order to investigate the effect of the number of vehicles on the position error of our MAP estimate, we applied the proposed method to V_1 and calculated the position error, using

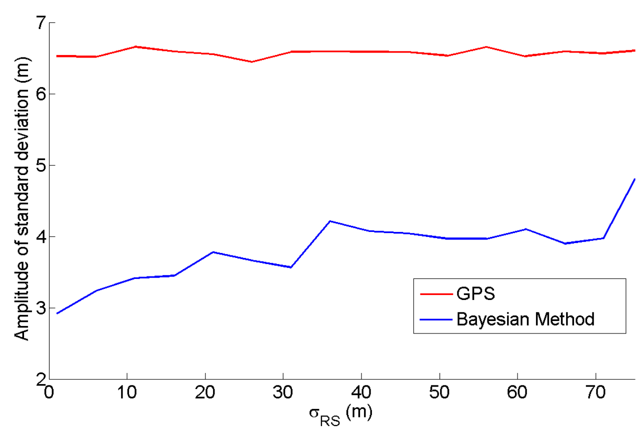

Figure 6-12. Effect of σ_{RS} on the positioning posterior standard deviation.

Table 6-2. Average variances of V_1 with respect to the number of vehicles in the cluster before and after using proposed method(m^2)

Variances	Number of Vehicles			
	2	*3*	*4*	*5*
σ_{xx}^2 Before	39.83	39.83	39.83	39.83
σ_{xx}^2 After	12.25	6.79	4.95	4.55
σ_{yy}^2 Before	35.99	35.99	35.99	35.99
σ_{yy}^2 After	10.42	6.45	4.17	4.23

different combinations of other vehicles. Fig. 12 shows the evolution of the position error with respect to the number of vehicles in the cluster. Clearly, as the number of vehicles in the cluster increases, the corresponding position error of the MAP estimate, decreases. The comparison of the variances before and after using the proposed method and their variations with respect to the number of vehicles in the cluster is shown in Table. II. This table describes that, the posterior position variances decrease as the number of vehicles increase which means, we can achieve more accuracy and less uncertainty by incorporating more vehicles in our fusion algorithm.

The effect of communication latency on the positioning error is presented in Figure 6-13. This figure shows that by increasing the communication latency the positioning error increases. This is because the target vehicle receives the other vehicles' information with a delay and during this time the vehicles have moved. Therefore the measured inter-vehicular distances belong to the new positions of them while their GPS positions belongs to slightly different position. The amount of this difference depends on the speed of the vehicles. In our simulations the average speed of the vehicles was 45km/h.

Figure 6-14 shows the position error of the proposed method during a communication failure. The position error of the Kalman with the proposed method (green) and the position error of the Kalman with GPS estimates (red) is shown in the figure. The communication failure happens during 79s to 124s after beginning of the simulation. During this period the target vehicle can't communicate with other vehicles therefore it only uses its own GPS measurements. It is obvious that after a while the estimated position by the proposed method will reach the Kalman with

GPS estimation. Then after 124s, when the communication restarts the target vehicle can use the information of other vehicles and a better position estimation is achievable. The position estimations during the communication failure is shown with blue color in the figure.

Finally it is important to mention that considering the error characteristics of the GPS measurements and the possibility of observing different sets of satellites by different vehicles, this method reduces more the non-common error component of the GPS positioning which is caused by the multipath and receiver noise. Therefore we can expect better performance from

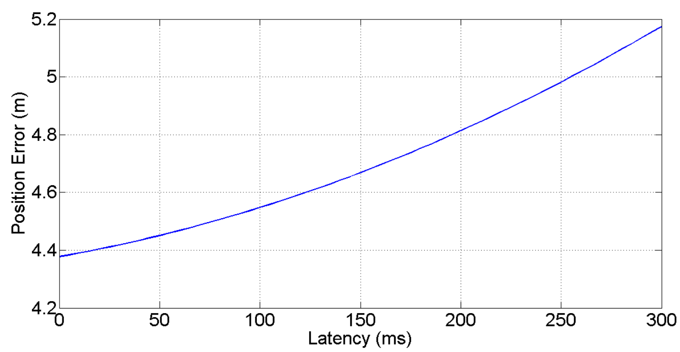

Figure 6-13. Position error of the proposed method with respect to the communication latency.

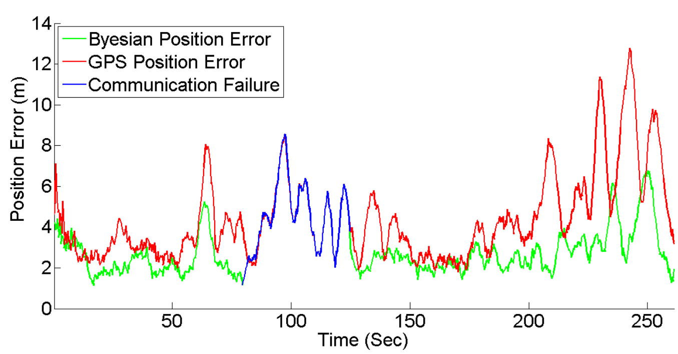

Figure 6-14. Position error of the Kalman with the GPS (red) comparing to the Kalman with the proposed method (green) during communication failure (blue).

this algorithm in the cases that the GPS errors are different between vehicles with respect to the case that vehicles have similar GPS offsets.

6.6 Conclusion & Future work

In this article we proposed a Bayesian method for multi-vehicle cooperative localization in a cluster of vehicles using GPS data and inter-vehicle distance measurements. Each vehicle uses its own GPS receiver to estimate its position and shares this information with other vehicles in the cluster by using a VANET protocol. In addition we assumed that each vehicle is also equipped with a proper VANET based range measurement method which is capable to measure its distance to other vehicles. Figure 6-1 provides an overview of the system. We also proved that this method doesn’t have the over convergence problem of the similar methods.

In order to investigate the efficiency of the proposed method, we used the new estimated positions produced by our algorithm as the measurements and applied a Kalman filter to them and compared the result with the result of the same Kalman filter using the GPS measured positions of the target vehicle as the measurements. The obtained result indicates that using this procedure, reduces the positioning uncertainty significantly and makes the positioning error decrease considerably. Consequently a vehicle is positioned with a greater accuracy. Using this method with more complicated tracking filters or using Map matching could greatly increase the performance of a tracking system. Also the results of the sensitivity analysis confirms that using more accurate range measurement methods and more vehicles in the fusion algorithm can better improve the localization performance. We consider as future work, to extend this method to vehicles with more proprioceptive sensors and to use this method in a collision avoidance system.

6.7 Acknowledgment

This work is part of CooPerCom, a 3-year international research project (Canada-France). The authors would like to thank the National Science and Engineering Research Council (NSERC) of Canada and the Agence nationale de la recherche (ANR) in France for supporting the project STP 397739-10.

Chapter 7 Experimental Validation

In this chapter we describe the experimental results of the cooperative map matching (CMM) algorithm using real sensory data acquired in the Satory road in France provided by LIVIC-IFSTTAR (Figure 7-1). The chapter is organized as follow. In the first section we describe the structure of sensors' data that we used in this experiment. The second section introduces the dynamic model and the Extended Kalman filter equations. The Synchronization process of the sensors' data is discussed in the third section followed by the CMM data validation and algorithm in the fourth section. Finally in the last section the results of the CMM algorithm is discussed.

7.1 Data Structure

The dataset used in this experiment is acquired by a test vehicle in Satory road, France. This dataset consists of a GPS receiver, RTK solution, Odometer which is mounted on the front wheels, INS data with acceleration and gyroscope and a sensor to measure the angle of the vehicle's front wheels.

- GPS and RTK data: Each sample of the GPS and RTK data consists of the position measurement *[x,y,z]*, UTC time stamp and HDOP acquired on 5Hz.
- Odometer and wheel angle data: Each sample of these sensors consists of the value of these sensors and an UTC time stamp.

Figure 7-1. Satory Road.

- INS data: each sample of INS data consists of the acceleration in three axis and the roll, yaw and pitch measured by the gyroscope. In addition to this, similar to the other sensors data, INS data also has an UTC time stamp for each sample.

7.2 Extended Kalman Filter

In this experiment we used an Extended Kalman Filter which is one of the most popular filters for vehicle localization [43, 81, 95]. We have used the result of CMM as measurements instead of GPS position in the EKF and compared the estimated position to the EKF with the GPS. The model used in this experiment is the three wheels kinematic model [1, 82, 86, 87]. In this model it is assumed that the vehicle has two back wheels and one director front wheel (Figure 7-2). The state vector is $[x, y, \psi]^T$ where $[x, y]$ represents the position of the vehicle and ψ is the heading angle. The origin of the mobile frame is at the center of the front wheel. The v_{lon} and v_{lat} are the longitudinal and lateral velocities respectively.

As the odometer is mounted on the front wheel we have:

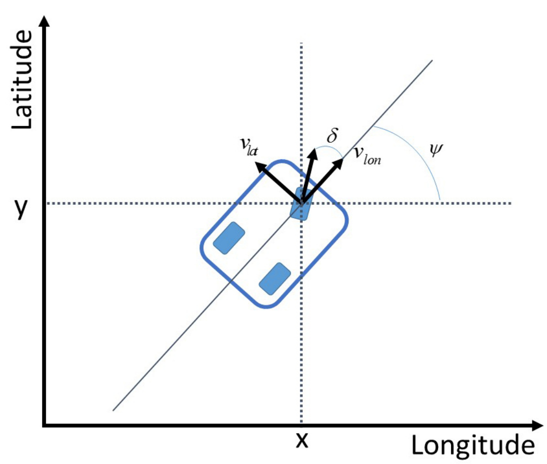

Figure 7-2. Three wheels kinematic model.

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} \cos(\psi)\cos(\delta) \\ \sin(\psi)\sin(\delta) \\ \tan\dfrac{\delta}{l} \end{bmatrix} \qquad 7\text{-}1$$

where l is the distance between two axles and δ is the angle of the front wheel with respect to the vehicle's body. Having the angular velocity measured by the gyroscope, the prediction equations become:

$$\begin{gathered} x_k = x_{k-1} + \Delta T v_k \cos(\psi_{k-1} + \Delta T\, \omega_k / 2) \\ y_k = y_{k-1} + \Delta T v_k \sin(\psi_{k-1} + \Delta T\, \omega_k / 2) \\ \psi_k = \psi_{k-1} + \Delta T \omega_k \end{gathered} \qquad 7\text{-}2$$

where ΔT is the time step.

Also the update equation is as follow,

$$\begin{gathered} x_k = X_{GPS} \\ y_k = Y_{GPS} \end{gathered} \qquad 7\text{-}3$$

7.3 Data Synchronization

Since the data acquired from the sensors are not synchronized we use their time stamp to apply them in the Kalman filter. The algorithm checks the time stamps of the valid data and selects the data with the less time stamp. If the selected data was from odometer it uses the prediction equations (7-2) to predict the state vector and if the selected data was GPS it uses the update equation (7-3) to update the predicted position.

7.4 CMM

In order to test the performance of the CMM method we have used the result of CMM as measurements instead of GPS position in the EKF and compared the estimated position to the EKF with the GPS. In this experiment we have 5 vehicles which can communicate and cooperate with the target vehicle. A typical formation of the vehicles is shown in . The algorithm procedure is as follow:

- The target vehicle uses the odometer and director wheel angle data to predict the position.
- Whenever the target vehicle receives a GPS position from other vehicles it record it in the memory.
- When the target vehicle measures its GPS position it uses this measurement along with the previously received valid GPS position of other vehicles in the CMM algorithm to generate the CMM estimated position.
- Then the target vehicle uses this CMM position in the update stage of the EKF to update its predicted position.

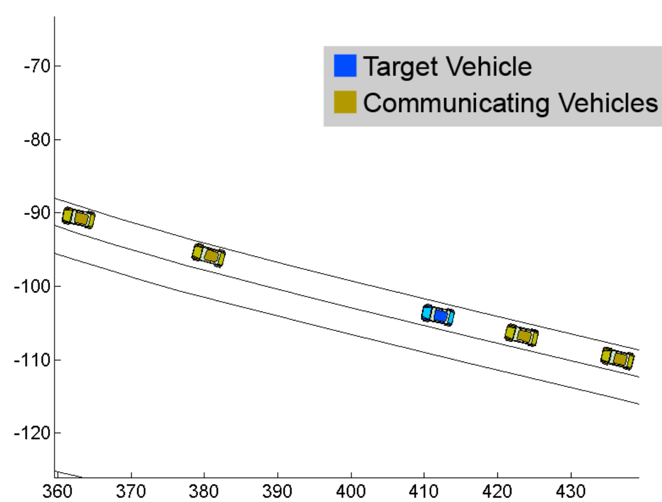

Figure 7-3. A typical formation of the vehicles in Satory road.

7.5 Results

The experimental results of the CMM algorithm confirms the simulation results presented in chapter 3. Table 7-1 shows the estimated vehicle position error of the EKF using GPS, single vehicle map matching and the cooperative map matching with various number of cooperative vehicles. We can interpret from this table that although using map matching with EKF can improve the position estimation accuracy, using CMM with more communicating vehicles can improve the positioning accuracy even more. Also Figure 7-4 compares the position error of the EKF with GPS and EKF with CMM with 5 communicating vehicles. It shows that using CMM approach can increase the accuracy of the position estimations.

Table 7-1. Comparison of the position error (m) between the GPS, single vehicle map matching and the CMM with various number of cooperative vehicles.

	GPS	**Single Vehicle MM**	**CMM – Number of Cooperative Vehicles**			
			2	**3**	**4**	**5**
Position Error	5.11	4.15	4.02	3.84	3.57	3.06

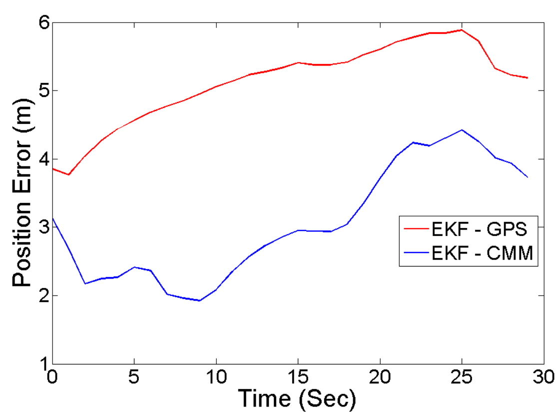

Figure 7-4. Estimated position error with respect to the time.

7.6 Computation Time Requirements in Implementation

One of the most important issues that we have to consider while developing localization algorithms for vehicular applications is the computation time of the algorithms. In many localization applications in robotics, the robots doesn't move very fast or depending on their assigned task they can wait between each movement to receive the proper instruction from the algorithm. In these cases, the computation time is not very restrictive. However in the cases such as vehicle localization, where vehicles can move with high speeds the computation time becomes more important.

The computation time limits of the localization algorithms depends on the application of the vehicle localization in terms of desired localization accuracy and algorithm execution frequency. For example assume that for a specific application such as lane level vehicle positioning an accuracy of 30cm is needed and the maximum speed of the vehicle is 70 km/h. Therefore the total delay of the system (including the data acquisition, communication and etc.) can't exceed of 4ms.

However it is important to mention that these kind of delays in the system can be compensated by projecting the position estimation in time (for example using a Kalman filter) by having a good estimation of the system delay. So these kind of delays may decrease the algorithm efficiency and increase the uncertainty (due to the projection in time) but it is not very restrictive.

What is really restrictive and defines the highest limit of the computation time is the frequency of the algorithm execution. In other words, how many times in a specific period of time the algorithm must run. The algorithm computation time cannot take more than this time.

For example if we assume a 5Hz sampling rate for GPS, the algorithm which treats these GPS data cannot exceed 200ms computation time. Otherwise the delays will accumulate in time and an infinite memory is needed in order to hold all the received and non-treated GPS data.

As described in 6.5 , we have implemented a fast C++ code to test the algorithm proposed in Chapter 6 . As the calculation time of the exponential function is relatively high we used a lookup table to increase the speed of the algorithm. Our experiments shows that each iteration of the algorithm having 5 vehicles in the cluster with 1000 particles around each vehicle takes approximately 20ms. By increasing the number of algorithm iterations to 5 the computation time increases to 100ms. In order to speed up the algorithm it is possible to reduce the number of particles from 1000 to 500 which decreases the calculation time of each iteration for each vehicle in the cluster to 1ms which is an acceptable computation time for localization algorithms while it doesn't make a noticeable difference in the positioning accuracy. However a better implementation and optimization of the C++ code can still improve the speed of the algorithm.

Our Cooperative map matching method described in Chapter 5 , and tested with real data in this Chapter is another algorithm which uses particle filter. This algorithm is less computational extensive in comparison to the method described in Chapter 4. Our experiments shows that each iteration of the algorithm for each vehicle using 1000 particles takes 2ms. However it is still possible to increase the speed of the code by better optimization of the code.

Chapter 8 Conclusions and Future works

The principal objective of this study was to propose cooperative approaches for vehicle localization using the communication capability of the vehicles. This objective was covering the understanding of the different sensors and devices which are used in vehicular localization along with a depth understanding of the most common data fusion methods. In order to reach this goal, we have proposed three different cooperative localization methods. In this chapter we have a conclusion on each proposed method and we suggest some perspectives for the future works.

8.1 Conclusions

GPS receiver is an important component of automotive navigation systems as it provides an estimate of the absolute position of the vehicle. Commercial GPS is subject to several sources of noises and offers insufficient accuracy for most ADAS and ITS applications. The major sources of error in the pseudo-range detection process are highly correlated between the receivers which are close to each other.

In the fifth chapter, we have proposed a new cooperative map matching method which can estimate and compensate the effect of the common error component of the GPS pseudorange errors by exploiting the similarity in the GPS positioning bias of different vehicles. This CMM method is based on applying the road constraint of the neighbor vehicles to the target vehicle in order to reduce the uncertainty of the positioning and improving its accuracy. Unlike other cooperative map matching method this method only relies on exchanging the GPS measurements of different vehicles and having a precise digital road map. In addition to this the effect of non-common pseudorange error which can lead to over converging to a wrong position in the cooperative map matching has been considered and circumvented in our approach. The results indicates that by using the cooperative approach, the map matching task significantly improves and a better positioning can be performed.

In addition to this, a decentralized Dynamic base station DGPS method (DDGPS) has been proposed, which can generate GPS pseudorange corrections and takes advantage of the communication capability of the vehicles in order to exchange the pseudorange corrections in a

VANET. Unlike the DGPS, our method does not require a network of static base stations with precisely known positions to generate pseudorange corrections. These corrections are generated by each vehicle from their ego position estimate and the received corrections from other vehicles. Since the position of the vehicles are not known exactly, a parameter describing the confidence level of each pseudorange correction is introduced, which is calculated based on the uncertainty of the ego position estimate and the confidence level of the received corrections.

In the sixth chapter, we proposed a Bayesian method for multi-vehicle cooperative localization in a cluster of vehicles using GPS data and inter-vehicle distance measurements. In this method each vehicle uses its own GPS receiver to estimate its position and shares this information with other vehicles in the cluster by using a VANET protocol. In addition we assumed that each vehicle is also equipped with a proper VANET based range measurement method which is capable to measure its distance to other vehicles.

The obtained result indicates that using this procedure, reduces the positioning uncertainty significantly and makes the positioning error decrease considerably. Consequently a vehicle is positioned with a greater accuracy.

In chapter 7, experimental validation for the Cooperative Map Matching method has been performed based on real data acquired from test vehicles. As we expected the experimental results confirms the efficiency of the CMM method and proves the simulation results presented in chapter 5.

8.2 Future works

In this section we suggest some perspectives for the future work. The suggestions are classified as follow:

- For the CMM method, investigating a vehicle selection procedure can be useful in the case of having a large number of communicating vehicles in order to have a good performance for the map matching algorithm while keeping the computation time at a reasonable level. Also we can study the effect of imperfect digital maps on the CMM method.
- For the DDGPS method, we intend to study the interdependency of the pseudorange corrections generated by each vehicle. We also consider that the fusion method for merging the received corrections can also be improved. In addition to this a method for considering the life time of the corrections must be used to help the vehicles detect the expired corrections and not to broadcast them to other vehicles.
- For the Bayesian approach, using this method with more complicated tracking filters or using map matching could greatly increase the performance of a tracking system. Also the results of the sensitivity analysis confirms that using more accurate range measurement methods and more vehicles in the fusion algorithm can better improve the localization performance. Therefore we consider as future work to combine this method with the CMM and DDGPS methods which potentially can improve the positioning performance.

Chapter 9 Conclusions et Les Travaux Futurs

L'objectif principal de cette étude était de proposer des approches collaboratives pour la localisation véhiculaire en utilisant la capacité de communication entre les véhicules. Cet objectif portait sur la compréhension des différents capteurs et dispositifs qui sont utilisés dans la localisation des véhicules et une étude en profondeur des méthodes de fusion de données les plus courantes. Afin d'atteindre cet objectif, nous avons proposé trois méthodes de localisation coopérative. Ce chapitre présente une conclusion sur chacune des méthode développée propose quelques perspectives pour les futurs travaux.

1.1 Conclusions

Le récepteur GPS est un composant important dans les systèmes de navigation automobile, car il fournit une estimation absolue de la position du véhicule. Un GPS commercial est soumis à plusieurs sources de bruits et offre une précision insuffisante pour la plupart des ADAS et autres applications des STI. Les principales sources d'erreur dans le processus de détection de pseudo-distance sont fortement corrélées entre des récepteurs qui sont proches.

Dans le cinquième chapitre, nous avons proposé une nouvelle méthode de correspondance cartographique coopérative (CMM, Cooperative Map Matching) qui peut estimer et compenser l'erreur de pseudo distance GPS qui est une erreur commune en exploitant la similitude du biais des GPS dans différents véhicules. Cette méthode de CMM est basée sur l'application de la contrainte de la route des véhicules proches du véhicule cible dans le but de réduire l'incertitude sur le positionnement et l'amélioration de la précision. Contrairement à d'autres méthodes correspondance cartographique coopérative cette approche ne repose que sur l'échange des mesures GPS de différents véhicules et ayant une carte routière numérique précise. De plus l'effet de l'erreur de pseudo distance non-commune, qui peut conduire à un phénomène de sur-convergence et tendre vers une mauvaise position pour la correspondance sur la carte coopérative, a été considéré et contourné dans notre approche. Les résultats indiquent que l'utilisation de l'approche collaborative, améliore la correspondance cartographique tâche de manière significative et un meilleur positionnement peut être obtenu.

En plus de cela, un procédé DGPS dynamique décentralisée (DDGPS) a été proposé, afin de générer des corrections de pseudo distance GPS et utilise la capacité de communication des véhicules afin d'échanger les corrections de pseudo distance dans un VANET. Contrairement au DGPS, notre méthode ne nécessite pas un réseau de stations de base fixe avec des positions connues avec précision pour générer des corrections de pseudo-distance. Ces corrections sont générées par chaque véhicule grâce à l'estimation sa position et des corrections provenant d'autres véhicules. Étant donné que la position des véhicules ne sont pas connus exactement, un paramètre décrivant le niveau de chaque correction de pseudo de confiance est introduit est calculé sur la base de l'incertitude de l'estimation de la position et du niveau de confiance des corrections reçues.

Dans le sixième chapitre, nous avons proposé une méthode bayésienne de localisation coopérative pour un groupe de véhicules utilisant des données GPS et des mesures de distance inter-véhiculaire. Dans cette méthode, chaque véhicule utilise son propre récepteur GPS pour évaluer sa position et partage cette information avec les autres véhicules du groupe en utilisant un protocole de VANET. En outre, nous avons supposé que chaque véhicule est également équipé d'une méthode de mesure de la distance sur la base des VANET appropriée qui est capable de mesurer la distance inter-véhiculaire.

Le résultat obtenu montre que l'utilisation de cette procédure réduit l'incertitude de positionnement de manière significative et diminue l'erreur de position considérablement. Par conséquent, chaque véhicule est localisé avec une grande précision.

Dans le chapitre 7, une validation expérimentale de la méthode de correspondance cartographique collaborative a été effectuée sur la base des données réelles acquises à partir de véhicules d'essai. Comme on pouvait s'y attendre, les résultats expérimentaux confirment l'efficacité de la méthode CMM et prouvent les résultats de simulation obtenus dans le chapitre 5.

1.2 Les travaux futurs

Dans cette section, nous proposons quelques perspectives pour les travaux futurs. Les suggestions sont classées comme suit:

• Pour la méthode CMM, une enquête sur la procédure de sélection d'un véhicule peut-être utile dans le cas où on a un grand nombre communication entre véhicule afin d'avoir une bonne performance de l'algorithme tout en gardant le temps de calcul à un niveau raisonnable. Aussi, nous pouvons étudier l'effet de cartes numériques imparfaites sur la méthode.

• Pour la méthode DDGPS, nous avons l'intention d'étudier l'interdépendance des corrections de pseudo distance générées par chaque véhicule. Nous estimons également que la méthode de fusion peut également être améliorée. En plus de cela une méthode pour considérer la durée de vie des corrections doit être utilisée pour aider les véhicules afin de détecter les corrections périmées et de ne plus les diffuser à d'autres véhicules.

• Pour l'approche bayésienne, en utilisant cette méthode avec des filtres de pistage plus complexes ou en utilisant une correspondance cartographique, les performances d'un système de pistage pourraient être grandement augmentées. Aussi les résultats de l'analyse de sensibilité confirment que l'utilisation de méthodes de mesure de la distance inter-véhiculaire plus précises et du nombre de véhicules dans l'algorithme de fusion pourrait améliorer la performance de la localisation. Par conséquent, nous considérons que le travail futur sera de combiner cette méthode avec les méthodes CMM et DDGPS ce qui pourrait potentiellement améliorer les performances du système de positionnement.

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