UNIVERSIDADE FEDERAL DO AMAZONAS - UFAM

INSTITUTO DE COMPUTAÇÃO- ICOMP

PROGRAMA PÓS-GRADUAÇÃO EM INFORMÁTICA - PPGI

Cooperative Localization Improvement in Vehicular Ad hoc Networks.

Felipe Leite Lobo

Manaus - AM

Fevereiro 2020

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Cooperative Localization Improvement in Vehicular Ad hoc Networks.

Thesis presented to the Graduate Program in Computers Science of the Federal University of Amazonas in partial fulfillment of the requirements for the degree of Doctor in Computers Science.

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Tese submetida à avaliação, como requisito para a obtenção do título de Doutor em Informática no Programa de Pós-Graduação em Informática, Instituto de Computação.

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Manaus - AM

Fevereiro 2020

Ficha Catalográfica

Ficha catalográfica elaborada automaticamente de acordo com os dados fornecidos pelo(a) autor(a).

L799c

Lobo, Felipe Leite

Cooperative Localization Improvement in Vehicular Ad Hoc Networks. / Felipe Leite Lobo. 2020

111 f.: il. color; 31 cm.

Orientador: Horácio Antonio Braga Fernandes de Oliveira

Tese (Doutorado em Informática) - Universidade Federal do Amazonas.

1. Vehicular Ad-hoc Networks. 2. Localization Systems. 3. Data Fusion. 4. Distance Information. I. Oliveira, Horácio Antonio Braga Fernandes de II. Universidade Federal do Amazonas III. Título

FOLHA DE APROVAÇÃO

"Cooperative Localization Improvement in Vehicular Ad Hoc Networks"

FELIPE LEITE LOBO

Tese de Doutorado defendida e aprovada pela banca examinadora constituída pelos Professores:

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Manaus, 21 de Fevereiro de 2020

Dedico esta tese à minha família, que sempre me apoiou e incentivou a trilhar novos caminhos. Em especial, a minha esposa Mayara Lobo pelas palavras de conforto, amor e paciência.

Acknowledgements

Agradeço à Deus por me guiar, iluminar, pela saúde física e mental. Esses aspectos foram primordiais para atingir êxito nessa jornada.

Gostaria de agradecer ao meu orientador, Professor Horácio, pelos ensinamentos, ajuda e incentivo sempre que necessário. Aos Professores Khalil El-Khatib e Abudlaziz Almehmadi pela oportunidade de realizar parte deste trabalho na Ontario Tech University. Aos amigos de Oshawa, Danilo, Thiago, Fernanda, Flávia, Cláudia e Felipe, pelo apoio e companhia durante o doutorado sanduíche. Gostaria de agradecer também aos professores do ICOMP da UFAM, bem como os funcionários, colegas e amigos de laboratórios, em especial ao pessoal do LCMU, ETSS e ANTS (Ontario Tech University). Aos Professores da UFRR, pelo incentivo e auxílio durante esse período.

À minha mãe, Nancy Lobo, minha irmã Fernanda e amigos, que em alguns momentos, mesmo distantes me apoiaram e incentivaram. E finalmente, agradeço à minha esposa pelo apoio incondicional durante todo o período dedicado ao doutorado.

Paciência e perseverança tem o efeito mágico de fazer as dificuldades desaparecerem e os obstáculos sumirem.

John Quincy Adams

Melhoria da Localização Cooperativa em Redes Ad hoc Veiculares.

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Resumo

Em redes veiculares ad hoc (VANets), um sistema de localização preciso é um fator crucial para várias aplicações críticas de segurança. Embora o Sistema de Posicionamento Global (GPS) possa ser usado para fornecer a estimativa de posição de veículos, ele ainda possui erros indesejados que pode aumentar ainda mais em algumas áreas, como túneis e prédios de estacionamento, tornando-o não confiável e inviável para a maioria aplicações críticas de segurança. Neste trabalho, apresentamos uma nova técnica de estimativa de posição através de dois algoritmos, o CoVaLID (melhoria de localização de veículo cooperativa usando informações de distância), que melhora as posições de GPS de veículos próximos e minimiza seus erros usando o Extended Kalman Filter (EKF) para executar a fusão de dados de informações de GPS e distância, e o COLIDAP que utiliza filtro de partículas (PF). Nossa solução também usa informações de distância para avaliar a precisão da posição relacionada a três aspectos diferentes: número de veículos, trajetória do veículo e erro de informações de distância. Para esse fim, usamos um método de média ponderada para aumentar a confiança nas informações de distância fornecidas pelos vizinhos mais próximos do alvo. Implementamos e avaliamos o desempenho dos nossos algoritmos usando cenários do mundo real simulados, além de discutir o impacto de diferentes sensores de distância em nossa solução proposta. Nossos resultados mostram claramente que nossos algoritmos são capazes de reduzir o erro de GPS em 63% e 53% quando comparado ao algoritmo estado da arte Vanet

LOCation Improve (VLOCI). *Palavras-chave*: Redes Veiculares, Sistemas de Localização, Fusão de Dados, Informação de Distância.

Cooperative Localization Improvement in Vehicular Ad hoc Networks.

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Abstract

In Vehicular Ad Hoc Networks (VANets), a precise localization system is a crucial factor for several critical safety applications. Even though the Global Positioning System (GPS) can be used to provide the position estimation of vehicles, it still has an undesired error that can increase even more in some areas, such as tunnels and indoor parking lots, making it unreliable and unfeasible for most critical safety applications. In this work, we present a new position estimation technique by two algorithms, the CoVaLID (Cooperative Vehicle Localization Improvement using Distance Information), which improves GPS positions of nearby vehicles and minimize their errors using Extended Kalman Filter (EKF) to perform Data Fusion of both GPS and distance information, and the COLIDAP that uses Particle Filter (PF). Our solution also uses distance information to assess the position accuracy related to three different aspects: the number of vehicles, vehicle trajectory, and distance information error. For that purpose, we use a weighted average method to put more confidence in distance information given by neighbors closer to the target. We implement and evaluate the performance of CoVaLID using real-world data, as well as discuss the impact of different distance sensors in our proposed solution. Our results clearly show that our algorithms are capable of reducing the GPS error by 63%, and 53% when compared to the state-of-the-art VANet LOCation Improve (VLOCI) algorithm.

Keywords: Vehicular Ad-hoc Networks; Localization Systems; Data Fusion; Distance Information.

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INTRODUCTION

1.1 Motivation

Recently, the increasing number of vehicles in big cities has been drawn the researchers' attention to some issues such as pollution, traffic jam, and vehicle accidents. Thus, the Intelligent Transportation System (ITS) emerges as a possible solution to these problems. The future of ITS will be based on connected vehicles, and they will be equipped with various sensory, communication and computation technologies (SKULIMOWSKI et al., 2018). Some envisioned applications for ITS include driverless vehicles (autonomous vehicles), blind crossing, automatic parking and platoons.

As aforementioned, autonomous vehicles can be a solution for the mentioned problems. However, to work properly, they are based on some functional systems, in particular, the localization system capable of localizing a vehicle within a network area. This system can take advantage of Vehicular Ad Hoc Networks (VANets), in which vehicles can exchange data among themselves (KUUTTI et al., 2018).

VANets also require precise localization information, mainly in critical safety-based applications, such as Driverless Vehicles and Blind Crossing (BOUKERCHE et al., 2008). To deal with this problem, vehicles are commonly equipped with Global Positioning System (GPS) devices that provide location information (BOUKERCHE et al., 2008; BOUKERCHE et al., 2009; XIONG et al., 2015).

However, the problem is that the accuracy of GPS information can be affected by several issues in dense urban areas (i.e. urban street canyons) mainly due to satellite signals refraction or reflection on buildings. Thus, GPS becomes an inaccurate instrument to provide precise location information (BALICO et al., 2015), which is still a problem that needs to be addressed (LOBO et al., 2017).

To tackle this drawback, there are some solutions proposed in the literature that use anchor nodes (GOLESTAN et al., 2015; LIU et al., 2018). In these solutions, anchor nodes are aware of their positions, so the other nodes can compute their relative positions by measuring their distances and using the anchor nodes as references (FRANCO et al., 2017). On the other hand, some approaches use a Cooperative Positioning (CP) technique. These approaches benefit from using vehicle-to-vehicle communication (V2V), in which nearby nodes exchange information about their positions and the relative distance between them and their neighbors (HOANG et al., 2016; NASCIMENTO et al., 2018). It is important to mention that the bigger the number of vehicles the more accurate the current approaches are.

Another known technique used to decrease localization error is Data Fusion (NAKAMURA et al., 2007), which combines location information from different sources to generate a more precise result. In these solutions, data from GPS, Geographic Information Systems (GIS), sensor information, and other sources can be combined using techniques such as Particle Filter (PF), Kalman Filter (KF), or even in Linear Transformation to estimate more precisely the vehicle's location (BARRIOS; MOTAI, 2011; EFATMANESHNIK et al., 2012; STOJKOSKA, 2016). Nowadays, vehicles are commonly equipped with vehicular safety systems that come with several associated sensors such as cameras, radars, and lasers, to mention a few. So, data fusion can be used to fuse all of this extra information to improve vehicle localization. Most current solutions can achieve accuracy between 1 m to 5 m using vectors constituted by several dimensions to describe the vehicle state, which increases the computational cost (KUUTTI et al., 2018).

Thus, this thesis presents a new low computational cost method and techniques to provide up-to-date, accurate position information about vehicles in Vehicular Ad hoc Networks. We propose a novel location data fusion technique that cooperatively gathers GPS and distance information from nearby vehicles to improve their locations. In this work, we are using a weighted average model to put more confidence in distance information provided by vehicles closer to the target. Hence, we take advantage of extra sensors to propose a distance-based data fusion technique to improve the localization provided by GPS. Also, we have applied a set of equations based on the concept of congruent triangles. These equations work with information about the difference between both the sensor and the GPS distance information. The results obtained from these equations feed into our two proposed algorithms, CoVaLID that uses an Extended Kalman Filter (EKF), and the CoLIDAP that utilizes a Particle Filter (PF). Both are used to perform data fusion and estimate the vehicle position. Finally, we used a simple map matching technique to adjust the positions of the vehicles on the road by using only a single anchor node.

1.2 Objectives

This thesis aims at proposing, testing, and validating a novel data fusion technique based on GPS data and distance information to improve the localization process in VANets. To achieve the main goal of this work, some following secondary objectives need to be reached:

- to propose, test, and validate a set of equations based on the concept of congruent triangles to improve the localization provided by GPS;
- to analyze and discuss the impact of sensors used to provide distance information;
- to test and validate a weighted average technique to improve the distance information confidence;
- to evaluate the proposed algorithms, CoVaLID and CoLIDAP using data from real-world maps.

1.3 Research Questions

In (AHAMMED et al., 2010), the authors show that the VLOCI algorithm in a simulated intersection scenario can minimize GPS error. Their results reached 2.38m of mean absolute error (MAE) values using at least 5 vehicles and distance information, which is known as the state-of-art algorithm according to Kutti (KUUTTI et al., 2018). It is worth mentioning that they did not use any statistical model in their solution. Thus, emerges our first research question, is that possible to minimize the GPS positioning error through the use of the concept of the similarity of triangles along with a Bayesian statistical method, using only a single anchor node, GPS data, and distance information better than VLOCI? Furthermore, in this thesis, we are assuming the nature of the problem as nonlinear, this is the reason why we chose an extended Kalman Filter and a Particle Filter to perform data fusion as Bayesian statistical method.

Since we are using only a single anchor node, the second research question is if the increase in the number of vehicles can affect our proposed method? At this point, we will apply a weighted average method, described in Section 5.5.

Another interesting point that we can notice, according to literature, that the vehicles farther away from the target can provide less accurate distance information than closer vehicles. Thus, emerges the third research question, does the use of a heuristic can minimize the effects of distance among nearby vehicles in our proposed solution? Hence, the main idea to put more weight in the distance information given by neighbors closer to the target and less weight for the ones that are farther.

Last, the fourth research question is, does the use of a Bayesian stochastic model can minimize the effects of sensors distance information (i.e. cameras, radars, and lidars) in our proposed method accuracy? According to Muller (MULLER, 2017), each sensor has its strengths and drawbacks and all of them have their accuracy affected by some phenomena, and it will be better described in Section 2.5.

1.4 Main Contributions

The main contributions of this thesis are:

- Our proposed solution reaches a high level of accuracy of estimated positions using just GPS data, distance information, and only a single anchor node. In these evaluations, we developed two new algorithms, CoVaLID and CoLIDAP, that use respectively extended Kalman Filter and Particle Filter to minimize GPS error.
- High level of accuracy of estimated positions even when increased the number of vehicles. We can observe that accuracy of our two proposed algorithms improved due to the use of a weighted average technique.
- We evaluated our proposed solution through simulations using new real-world maps data, such as Dundas St., Yonge St., Church St., Queen St. and Bay St, Highway 401, and Windfields Farm all in the province of Ontario.
- An exploratory analysis of the sensors used to provide distance information. We simulated seven different sensors, one camera, two lasers, and four radars in order to gather distance information in the most like way as in the real-world.

1.5 Thesis Guideline

The remainder of this thesis is organized as follows. The next chapter describes the definitions and concepts that this work is based on, whilst Chapter 3 brings relevant related work present in the literature. In Chapter 4, we present our proposed solution for minimizing the GPS error in VANets. The evaluation of our proposed solution and results are shown in Chapter 5. Finally, the thesis conclusions, future work, as well as the research next steps, and the list of publications during the doctorate period are presented in Chapter 6.

2

Theoretical Foundation

This chapter focuses on presenting the main concepts and definitions addressed in this work, such as the Vehicular Ad hoc Networks overview, as well as some data fusion and localization techniques used to reduce localization errors.

The remainder of this chapter is structured as follows: Section 2.1 covers the VANets overview, such as communication, characteristics and some challenges, Section 2.2 covers the localization techniques, such as GPS, dead reckoning, and map matching. Section 2.3 describes the data fusion techniques: Kalman Filter (KF), Extended Kalman Filter (EKF), and Particle Filter. Section 2.4 shows some localization systems applied in VANets, whereas Section 2.5 covers sensor-based techniques, and last, Section 2.6 gives the chapter conclusions.

2.1 Vehicular Ad-hoc Networks Overview

VANets have attracted the research community's attention as an emerging technology to perform intelligent communication between vehicles and improve road safety (LI; WANG, 2007; BOUKERCHE et al., 2008; PAPADIMITRATOS et al., 2009; BALICO et al., 2018). This section aims at providing a brief overview of VANets, their characteristics, and how communication is accomplished, likewise describe some challenges.

2.1.1 Vehicular Ad-hoc Networks: Communication and Characteristics

According to Vijayakumar (VIJAYAKUMAR et al., 2016), we can classify communication in VANets as follows::

- vehicle-to-vehicle (V2V), where vehicles can communicate directly with each other, as shown in Figure 1; and
- vehicle-to-infrastructure (V2I) or vehicle-to-roadside unit (V2R), where the vehicle can communicate with devices along the roads, seen in Figure 2.

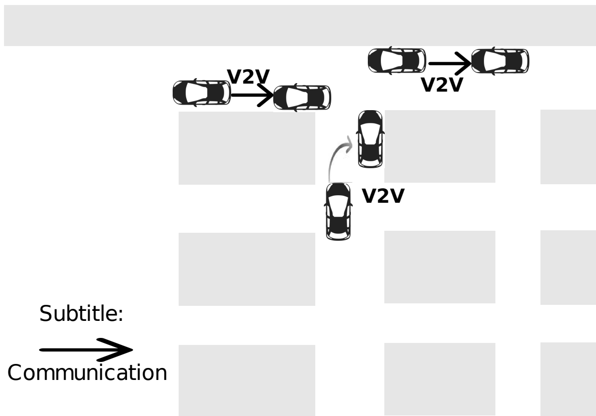


Figure 1 – Vehicle-to-Vehicle Communication.

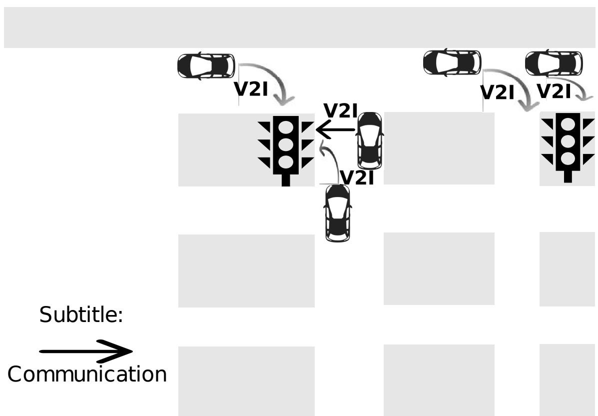


Figure 2 – Vehicle-to-Infrastructure Communication.

The roadside unit (RSU), the on-board unit (OBU) and the application unit (AU) are the components used for the communication of VANETs (BOUKERCHE et al., 2008;

BOUKERCHE et al., 2009; XIONG et al., 2015). Generally, the RSU is fixed along the roads, whilst the OBU and AU are placed inside the vehicle.

The RSU can provide services to vehicles, such as the transmission of information, security applications, and even internet connection. On the other hand, the OBU grants the communication between vehicles and as RSUs. In addition, OBUs communication capability allows AU to take advantage of services over the network, in order to provide a bunch of applications for users (KARAGIANNIS et al., 2011).

Some specific characteristics of VANets are listed below:

- *dynamic topology:* due to high mobility of vehicles;
- *the communication link between vehicles:* due to the high speed of vehicles, they become out of the communication range of the neighboring vehicle;
- *position inaccuracy:* due to high speed and mobility of vehicles, it is a challenge to determine precisely vehicle position.

2.1.2 Challenges

Due to the peculiar characteristics presented in the previous section, VANETs suffer from some limitations. Among these limitations, we can highlight the bandwidth restrictions, delay constraints, and the node precise localization. It is noteworthy that some solutions proposed in the literature wish to address these challenges. However, it is still necessary to find a single solution that can overcome such issues.

- *Bandwidth Limitations*

  It happens mainly when the density of nodes in the network is high, which results in a high number of collisions in the channel. For instance, vehicles equipped with GPS receivers update their positions each time period. Thus, if the communication is performed in real time, which likely leads to constraints regarding bandwidth (MO et al., 2016).

- *Delay Constraints*

  Usually, VANETs applications are delay sensitive (KARAGIANNIS et al., 2011). This is due to the high mobility and speed of the vehicles, sometimes resulting in the link breakdown between a vehicle and its neighboring node, especially when they are moving in opposite directions. Therefore, communication must be performed while one node is within the range of the other. On the other hand, in critical applications there is also the delay constraint, for instance, in a cooperative crossing application, if the location information is delayed, it can cause an accident.

- *Node Precise Localization*

  As aforementioned, there are some applications in VANETs, such as Driverless Vehicles, Blind Crossing, and Collision Warning System (CWS) that require a precise localization system (BOUKERCHE et al., 2008). It was also mentioned that GPS has limitations, become unavailable in some scenarios such as in tunnels, and in dense urban areas. Due to this fact, some localization techniques, such as Dead Reckoning, Cellular Localization, and Map Matching, were created in VANETs in order to overcome these activities (BALICO et al., 2018) . However, because of the characteristics of the VANETs, such as high mobility, driver behavior, high speed changes, and vehicle displacement (YOUSEFI et al., 2006), emerges the possibility of use data fusion techniques to calculate an estimated vehicle position, combining various localization techniques into a single solution more powerful and accurate than any individual approach (BALICO et al., 2015; GOLESTAN et al., 2012; BOUKERCHE et al., 2008; NAKAMURA et al., 2007)

2.2 Localization Techniques

In the survey presented by Monika (MONIKA RAHUL, 2014), the authors detailed some localization techniques using in VANets, as seen in Table 1.

Currently, vehicles are equipped with GPS devices in order to localize themselves. However, these devices have some drawbacks and could not be considered reliable and

Localization Techniques	Description
AOA: Angle of Arrival	Based on angle of arrival information among neighboring vehicles (NICULESCU; NATH, 2003).
TDOA: Time Diference of Arrival	Classical approach, calculates the cross correlation between signals arriving at two base stations (CAFFERY; STUBER, 1995).
RSS: Received Strength Signal	Based on received strength signal, sensitive to the environment, such as the multiple paths problem (EL-NAHRAWY et al., 2004).
Dead Reckoning	The current position of a vehicle can be estimated based on its last known location (KING et al., 2005).
GPS	Calculates the node's position using triangulation between satellites. Once this procedure is performed, the receiver is able to know its latitude, longitude, and altitude (HOFMANN-WELLENHOF H. LICHTENEGGER, 2001).
Cellular Localization	used in most urban environments to estimate the position of an object. Some applications include mobile phones, tracking and positioning of pets, and vehicle location (VARSHAVSKY et al., 2006; CAFFERY; STUBER, 1998).
Map Matching	Several positions obtained over regular periods of time can be used to create an estimated trajectory. This estimate is compared with digital map data, known in advance, in order to find the most appropriate path (JAGADEESH et al., 2004).
Image/Video Processing	Image/video processing techniques are used in data fusion algorithms to estimate and predict a vehicle position (NAKAMURA et al., 2007).

Table 1 – Localization Techniques an their descriptions, respectively.

feasible, mainly in VANets critical applications. The GPS system will be better detailed in the next section.

2.2.1 GPS

The United States Government, more specifically the U.S. Department of Defense designed the GPS system. It is a satellite-based radio navigation system used for locating and tracking objects. Firstly used by military, but thereafter was granted civilian use (HOFMANN-WELLENHOF et al., 2012).

In addition, the GPS system is composed by satellite constellation with 24 satellites organized in six orbital planes, that allow at least four GPS satellites being visible at any time from anywhere on the planet. Each satellite transmits time and position (longitude,latitude, and altitude) information at the speed of light to a GPS receiver. Then, the receiver can calculate both the pseudo-ranges to at least three satellites (how far it is from satellite) and their positions using trilateration (RAZA et al., 2008).

In recent years, GPS has been widely used in vehicles in order to help drivers reach in their destinations aided by a map system. Through GPS, for instance, drivers are able to determine which part of the road they are driving. It is possible by calculating an object position in the GPS system, as described in equation 2.1.

$$d_i = (t_i - b - s_i) \cdot c \tag{2.1}$$

where t_i is the true reception time of satellite information, the subscript i denotes the number of satellites, and it varies from 1 to n, b is the receiver clock bias, s_i is the satellite time. The velocity which messages travel is c, the speed of light. Then, d_i is the distance between satellite and receiver, that is given by the equation 2.2 :

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} \tag{2.2}$$

However, the drawback of using GPS in estimating precise a vehicle position in real time is its unavailability in some scenarios, such as tunnels and dense urban areas, where there the GPS information can be affected by several issues, mainly due to satellite signals refraction or reflection on buildings, when GPS has no straight visibility to satellites. Thus, GPS cannot be considered a reliable accurate way to provide precise localization information (BOUKERCHE et al., 2008; BOUKERCHE et al., 2009; BALICO et al., 2015; LOBO et al., 2017). Also, according to Balico (BALICO et al., 2018), localization techniques can be combined to overcome GPS drawbacks.

These techniques aim to provide precisely the node localization. However, each one of them has its drawbacks and still does not reach the required precision. Thus, data fusion emerges as a solution to improve localization accuracy in VANets.

2.2.2 Dead Reckoning

Dead Reckoning (DR) is a navigation technique used by sailors in earlier centuries that through the stars along with a known land position they could determine their own position. Currently, DR has also applied in VANets, which is a good option in GPS outage scenarios. We can determine the current position can be estimated based on a previous last. Although, since DR accumulate errors, it can be used just for brief periods of time (BALICO et al., 2018; NASCIMENTO et al., 2018) . Using DR we can estimate the vehicle's current position using trigonometric calculations. These equations are described as follows:

$$x_2 = x_1 + d \cdot cos\theta \tag{2.3}$$

$$y_2 = y_1 + d \cdot sin\theta \tag{2.4}$$

where d is the vehicle distance, centered at earlier vehicle location, with coordinates $(x1, y1)$. However, it is known that this node makes an angle θ from earlier to the current location in the x-axis, then you can recover the current coordinates $(x2, y2)$.

2.2.3 Map Matching

Map Matching is a technique used in VANets based on navigation systems that can estimate the vehicle position by a digital road map. For instance, if the position estimation goes down off the road boundaries we can adjust the estimated position by combining both the measured GPS position and the past trajectory of the vehicle (PEKER et al., 2011). There are some Map Matching approaches in the literature. Usually, it can be classified such as topological, geometric and advanced (ROHANI et al., 2016).

- *geometric map matching:* the algorithm uses the geometric data from the map by gathering information about road segment shapes.
- *topological:* it uses both the geometric and also the road segment connections information.
- *advanced:* used in GPS outages areas such as dense urban areas, and tunnels. In these scenarios, GPS can be affected by signal outage and multipath error.

Both DR and Map Matching can be used along with data fusion techniques to improve localization accuracy in VANets.

2.3 Data Fusion Techniques

Data Fusion has been applied in diversified areas with different aims, due to that it has several definitions. Nevertheless, these definitions have one characteristic in common that is to improve accuracy information by combining data from multiple sources (HALL; LLINAS, 1997).

Nakamura (NAKAMURA et al., 2007) presented Data Fusion applied in Wireless Sensor Networks (WSN) in order to reduce the amount of data traffic in the network, filtering noise measurements, making predictions and inferences about a monitored entity. Table 2 describes the classification of data fusion according to the inference criterion:

In our proposed solution, we used Bayesian inference based data fusion techniques to reduce localization errors in VANets. For this purpose, we have tested a derivative of Kalman Filter (KF), the extended Kalman Filter (EKF), and a Particle Filter (PF).

Data Fusion Approaches	Description
Bayesian Inference	provides a formalism for combining evidences according to the rules of probability theory.
Dempster-Shafer Inference	based on Dempster-Shafer accumulation (also known as theory of evidence). It is a mathematical theory introduced by Dempster that generalizes Bayesian theory. It deals with beliefs or mass functions, just as the Bayes rule does with probabilities (DEMPSTER, 1968; SHAFER, 1976).
Fuzzy Logic	able to deal with approximate reasoning in order to make decisions based on imprecise information (BELOHLAVEK et al., 2011).
Neural Networks	used for classification and recognition tasks in the field of information fusion.
Semantic Information Fusion	raw data from the sensors are processed and only the resulting semantic interpretations are exchanged by the nodes.

Table 2 – Data fusion classification according to the inferences criterion.

2.3.1 Kalman Filter

The Kalman Filter (KF) is a data fusion method used as a filtering component based on the iteration process divided into two phases: a prediction and an update phase (FASCISTA et al., 2017), as show in Figure 3. It is a linear optimal estimator with Gaussian noise. In addition, it can be suitable even with nonlinear systems due to its variations such as extended Kalman Filter (EKF), and unscented Kalman Filter (UKF) (BALICO et al., 2018).

KF minimizes the mean squared error between the estimated state and the true state. The KF estimates the state x of a process given a sequence of noisy observations for each time step k.

$$x_k = F_k x_{k-1} + B_k u_k + w_k \tag{2.5}$$

where F_k, is the state matrix; H_k is the observation matrix; the covariance of the process noise and the covariance of the observation noise are Q_k, and R_k, respectively; and finally, the B_k is the input control matrix model applied over vector u, whilst w is the

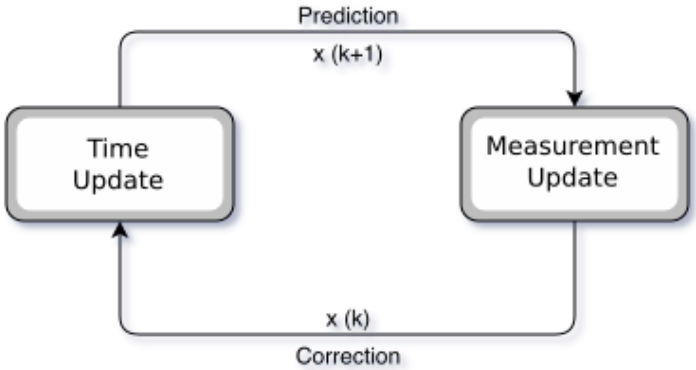


Figure 3 – Filtering Phases.

observation noise.

The measurements z_k of the true state x_k is given by:

$$z_k = H_k x_k + v_k \tag{2.6}$$

the measurement matrix is H_k, and measurement noise is given by v which is assumed to be zero mean Gaussian white noise with covariance R_k.

In the prediction phase, the last time step information is used to produce an estimated state at the current time step.

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \tag{2.7}$$

The predicted error covariance is calculated by:

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{2.8}$$

At the update phase, we calculate the Kalman gain as:

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T R_k)^{-1} \tag{2.9}$$

Finally, the formula for update the estimation is:

$$P_k = (I - K_k H_k) P_{k|k-1} \tag{2.10}$$

where I is the identity matrix.

As aforementioned, the KF is an optimal solution for linear problems. However, the nature of the localization problem can be also nonlinear. To deal with that kind of problem an Extended Kalman Filter (EKF) can be used which through calculating partial derivatives of both state and measurement matrix.

2.3.2 Extended Kalman Filter

The main difference between KF and EKF is that while in KF the state transition and the measurement models must be linear functions, in EKF both of them may be differentiable functions. Then, using the Jacobian matrix of state transition the Equation 2.8 can be rewritten as:

$$P_k = jF * P_{k-1} * jF^T + Q_k \tag{2.11}$$

where jF and jF^T are the Jacobian matrix of the state matrix and its transpose, respectively.

In addition, when applied the Jacobian matrix over the measurement model, the Kalman gain can be calculated by:

$$K = P_{k|k-1} jH_k^T (jH_k P_{k|k-1} jH_k^T + R_k)^{-1} \tag{2.12}$$

Furthermore, the difference between the measurement and state estimation y can be obtained by:

$$y = Z^T - (jH_k * x_k) \tag{2.13}$$

Consequently, the formulas for update both the uncertainty process covariance and the estimation state are expressed by:

$$P_k = (I - K_k jH_k) P_{k|k-1} \tag{2.14}$$

where I is the identity matrix.

$$x_k = x_{k|k-1} + (K * y) \tag{2.15}$$

Sometimes, the series approximation yields to a poor description of the nonlinear functions and the associated probability distributions. In order to deal with these drawbacks, another kind of nonlinear filtering method can be used, such as Particle Filter (PF).

2.3.3 Particle Filter

The Particle Filter (PF) is a Bayesian filtering technique that deals with nonlinear problems to estimate the state of a dynamical system. This technique uses random samples (particles) with non-negative weights in order to define the posterior probability density function (PDF) (ARULAMPALAM et al., 2002). Also, the PF is performed through an iteration process divided into initialization, prediction, sequential sampling, and resampling.

- *initialization:* generating particles randomly over the whole observation area;
- *prediction:* using a state function to predict particles at the next time step;
- *sequential sampling:* using the importance function recursively over time;
- *resampling:* discarding particles that show low posterior probability;

As a result, it aims at estimating recursively in time the distribution $p(X_{0:n}|Z_{0:n})$ (LI et al., 2008).
where the state matrix is x. In the initialization stage, our initial belief state is $p(x_0)$, in the prediction stage, we sample a particle p_i from the previous distribution according to its weight (w_{t-1}). Thus, we sample a new state based on both previous sample x_{t-1} and the process noise u_t:

$$x\prime_t = p(x_t|x_{t-1}, u_t) \tag{2.16}$$

After that, we compute importance weight in sequential sampling phase:

$$w_t^i = p(z_t|x_t^i) \tag{2.17}$$

we also compute the sum of these weights, $n = n + w_t^i$, where n is the normalization factor. Moreover, we add the particle to the set of particles recursively until the total number of particles N. Last, the weights do not sum to 1, so we need to normalize the weights. For that purpose, we can normalize weights recursively, for each particle, N times:

$$w_t^i = w_t^i / n \tag{2.18}$$

Consequently, the new value of the state vector is computed:

$$p(x_t|Z) = \sum_{i=1}^{N} w_t^i p_i(x_t) \tag{2.19}$$

where z is the measurement matrix.

Finally, the resampling stage aims at selecting samples with probabilities proportional to their weights that is used in the next iteration. Thus, the Particle Filter gives a new state estimation of a dynamical system.

In general, the combination of both data fusion techniques and localization in a single solution can be more powerful and accurate, achieving better results than any single approach (BALICO et al., 2015; GOLESTAN et al., 2012; NAKAMURA et al., 2007). In this respect, the following section will illustrate combinations of localization techniques and data fusion techniques as solutions in vehicular networks.

2.3.4 VANets Applications That Require Data Fusion and Localization Techniques

Boukerche (BOUKERCHE et al., 2008) mentions applications in VANETs that require, or may take advantage of, some type of locating technique, such as vehicle collision warning system; safety distance; driver assistance; cooperative driving; cooperative crossover control; dissemination of road information; and Internet access.

An example of an application for VANETs that can take advantage of prediction location is internet access. Packet routing can use predicted vehicle position to forward packets direct to the most appropriate Internet gateways (BALICO et al., 2015). Another application also mentioned by the same author is the vehicle collision warning system (CWS), one of the most interesting in vehicular networks, which can be improved using location prediction. According to the author, this type of application is one of the most important for driver safety as it provides assistance to drivers to avoid danger.

The application in which vehicles arriving at a road intersection and exchanging messages with each other in order to make the safe crossing in intersections is another example of an application in vehicular networks. Besides ensuring safety at the intersection, it is also possible to make a blind crossing where there is no traffic light and the vehicles cooperate with each other to cross (BOUKERCHE et al., 2008).

Furthermore, there some applications that can take advantage of more precisely localization techniques, such as location prediction, driverless vehicles, platoons, and automatic parking. All applications presented clearly try to avoid vehicle collisions, and they can be classified as safety applications.

After presenting some examples of applications that require the use of data fusion and localization techniques, the following section will be describe characteristics of Localization Systems in vehicular networks.

2.4 Localization Systems in VANets

In VANets localization systems, estimating the dynamic state of the vehicle is an essential data fusion task for ITS applications (SHUBERT et al., 2008). Some other data fusion techniques such as Kalman Filter, Particle Filter, and Belief Theory have also been used in order to improve the location estimation in various sensor-based systems (NAKAMURA et al., 2007). Although data fusion techniques can provide reliable location information for most applications in VANets (BOUKERCHE et al., 2008), improvements regarding localization systems are still necessary and desirable.

VANets characteristics such as mobility restrictions, drivers' behavior, and high-speed displacement can cause rapid changes in network topology, which induce to outdated dissemination of location information, more specifically, when packet delay rate is high (YOUSEFI et al., 2006; BALICO et al., 2018). In this context, some solutions that require position information need to increase the frequency of periodic messages as a natural solution to this problem. Another characteristic is the inaccurate position information, once they usually are provided by GPS, and as aforementioned, that can be erroneous or unavailable in urban dense areas or tunnels.

A common solution is a possibility of using data fusion techniques to calculate the precise position of the vehicle by combining various localization techniques in a single solution that is more robust and accurate than using any individual approach (BALICO et al., 2018; GOLESTAN et al., 2012; NAKAMURA et al., 2007). It is worth mentioning that proposed solutions must take into account the constraints imposed by VANets characteristics.

2.5 Sensor-Based Techniques

In order to find the vehicle position in a specified system, the sensor-based techniques use on-board sensors information, such as velocity, orientation, and position. The main sensors utilized are GPS, ultrasonic sensors, RADAR, cameras, LiDAR, and inertial motion units (IMUs) (KUUTTI et al., 2018).

Table 3 provides details of the capabilities of each sensor including advantages and disadvantages likewise the examination of localization techniques using both a single sensor and a sensor combination (KUUTTI et al., 2018).

2.5.1 RADAR-Based Techniques

A Radar sensor is a ranging sensor that uses radio waves to measure relative distance. According to Ponte (MULLER, 2017) there are two radar technologies in ITS. The first one, Frequency-Modulated Continuous Wave (FMCW) radars, emit a signal with constant power. The frequency difference between the transmitted and received waves corresponds to the relative distance to the target. The other one is the impulse radar that distance to the target is measured from the time of arrival of the waves.

Technique	Sensors	Accuracy	Advantage	Disadvantage
GPS standalone	GPS	10m	Low cost.	Low accuracy and poor signal.
GPS and IMU (RÖCKL et al., 2008)	GPS and IMU	7.2m (Rmse)	Low cost.	Low accuracy and cumulative errors.
Vision based localization, road detection(FOIX et al., 2011)	Camera, GPS and IMU	0.58m, lat. and 1.43m, lon. (Mean)	Low cost.	Susceptible to illumination and observation angle.
Microwave Radar SLAM (HSU et al., 2006)	Microwave Radar	10.5m (Mean)	Low cost and low power requirements.	Low accuracy.
Short Range Radar SLAM (ELKHALILI et al., 2006)	Radar, GPS and IMU	0.07m, lat. and 0.38m, lon. (Rmse)	Low cost, low power requirements and high accuracy.	Low robustness to dynamic environments.
LiDAR SLAM (SIVARAMAN; TRIVEDI, 2013)	LiDAR, GPS and IMU	0.017m, lat. and 0.033m, lon. (Rmse)	High accuracy and robust to changes in environment.	High cost, high power and processing requirements; sensitive to weather conditions.

Table 3 – Sensor-Based Localization Techniques. Adapted from (KUUTTI et al., 2018).

Some Radars characteristics and their respective parameters are described in Table 4.

Sensor	Frequency	Bandwidth	Range	Azimute Angle	Accuracy	Cycle
Bosch LRR3	77 GHz	1 GHz	250m	+/- 15°	0.1m	80ms
Delphi ESR	77 GHz	-	174m	+/- 10°	1.8m	50ms
Continental ARS30x	77 GHz	1 GHz	250m	+/- 8.5°	1.5m	66ms
SMS UMRR Type 40	24 GHz	250 MHz	250m	+/- 18°	2.5m	79ms

Table 4 – Commercially Available Radar Sensors gathering from the respective manufacturer's data sheet. Adapted from (MULLER, 2017).

It is important mentioning that we used these parameters in our simulations environment to replicate radars' behavior.

2.5.2 Camera-Based Techniques

Cameras are the sensors used for image-based localization. There are two kinds of cameras used to deal with localization problem in VANets, 3-dimensional and 2-dimensional cameras. The solutions that use cameras have lower costs when compared to the other sensors.

Recently, many solutions using cameras have been developed. For instance, An overview of ego-motion estimation is shown in (KHAN; ADNAN, 2017) . The authors state that is needed time intervals small enough between two continuous images to estimates ego-motion. Also, an overview of image-based camera localization is presented in the Xin's survey, which can provide more details about this kind of solution (XIN et al., 2019) .

2.5.3 LIDAR-Based Techniques

Light Detection and Ranging (Lidar) is used for vision-based localization. It has some interesting characteristics such as long-range, wide field of view, accurate measurements, and insensitive to light conditions.

We can divide Lidar-based localization into two groups, simultaneous localization and mapping (SLAM) and map-based localization (JAVANMARDI et al., 2019). In the first, a map of an unknown environment is constructed and updated while an object is still keep been tracking. In the later, a known map is used to match the observed Lidar scan to the vehicle position. This map is often a high-definition 3D point cloud.

2.6 Chapter Conclusions

In this chapter, we presented an overview of VANets, likewise some important characteristics that must be taken into account in a localization system. In addition, we pointed out the GPS drawbacks and described both the extended Kalman Filter and the Particle Filter used to improve vehicle localization. Furthermore, we presented several sensors, which can provide important information such as distance, acceleration, and velocity, just to mention a few. These sensors' information can aid in filtering techniques.

Then, in the next chapter we will mention the related work regarding the developed research.

3

Related Work

This chapter will describe several localization techniques in VANets that have been proposed to reduce localization errors.

In VANets, localization solutions can be divided in assisted by GPS and GPS-free solutions (NASCIMENTO et al., 2018). That is the reason why we structured this chapter as follows: Section 3.1 covers GPS assisted solutions, while Section 3.2 presents GPS free techniques. Finally, Section 3.3 describes hybrid approaches that take advantage of both.

3.1 GPS Assisted Solutions

In this section, we will highlight some GPS assisted solutions. First, Eric presented a decentralized data fusion system (RICHTER et al., 2009) . It aims at estimating the relative position between vehicles using V2V communications. Nodes exchange messages that contain GPS pseudo-range measurements and ego-motion estimation information. It is worth mentioning that the GPS was the only external data source used. In addition, a curvilinear Constant Turn Rate and Velocity (CTRV) was deployed as a motion model. In order to perform data fusion, Particle Filtering was applied. The results showed that when the GPS error is up to 2m the solution reaches its best accuracy, from 0.88m to 1.15m of root-mean-square error. However, when the GPS error increases up to 8m the RMSE also increases to 5.50m. Hence, the presented approach is dependent on GPS availability.

Another interesting GPS assisted method is presented by Farhan (AHAMMED et al., 2010), where the authors proposed the VLOCI algorithm. Similar to our solution, vehicles exchange GPS position information. Also, they assume that all vehicles are capable of measuring the distances among themselves. They also consider that vehicles are traveling in one lane and following the same direction. Thus, the distance information is used to improve the position only in one axis. On the other axis, they assume there is no error since vehicles are moving in a straight-line trajectory. After the GPS data exchange, the VLOCI algorithm is executed, and a set of neighbors coordinates is computed. A weighted average technique is applied to use the more reliable information from closer vehicles while giving less priority to further vehicles. As a result, the best MAE value was of 2.38m, and at least 5 vehicles are needed to reach this accuracy. It is worth mentioning that, despite its limitations, the VLOCI is a state-of-the-art localization technique that uses only GPS and V2V communication (KUUTTI et al., 2018). For this reason, we chose the VLOCI algorithm to compare our proposed solution. Algorithm 1 summarizes more clearly how the VLOCI algorithm works.

Algorithm 1 VLOCI algorithm

```
while iteration < I do
    transmitMessage(p̂i) M contain received messages
    for each item M_j in M do
        d̂_{i,j} = (1/D) Σ_{k=1}^{D} takeDistMeas(n_j)
        if x̂_i < x̂_j then
            p_i^j = (x̂_i^j, ŷ_i) = (x̂_j - d̂_{i,j}, 0)
        else
            p_i^j = (x̂_i^j, ŷ_i) = (x̂_j + d̂_{i,j}, 0)
        end if
    end for

    x̂'_i = Σ w(n_k)·x̂_i^k / Σ w(n_k) · ŷ'_i = 0
end while
```

Efatmaneshnik et al. (2012) developed an information fusion system that used a Kalman Filter to combine both GPS positions and inter-vehicle distance information shared through Cooperative Positioning (CP) technique. In addition, the presented solution is aided by a MM technique that is divided into two rules. The first is the simple constraint that the vehicle is travelling within road boundaries, and the second rule takes into account intersection scenarios. In these scenarios, the direction of the road segment is the applied rule, since sometimes the nearest road may not be the next vehicle's trajectory. According to the authors, their solution can reach from 2.5 m to 4.5 m on average, the position error. However, the used MM technique need to be improved, since it presented some conflicts in real-world scenarios.

In (GOLESTAN et al., 2012), the authors presented two fusion models to improve vehicle localization by combining V2V communication. Each vehicle has a weight regarding its position proportional to the belief, thus the estimation of vehicles' position can be improved by using an extended Kalman Filter and a Particle Filter to predict the vehicles' location using a pre-defined dynamic motion model. This approach can reach high accuracy, but at least five connected vehicles are needed.

A high-cost approach that uses lasers and cameras to localize the vehicle from the environment perception is presented in Schindler (SCHINDLER, 2013). The self-localization approach is performed by Particle Filter to fuse differential GPS, the inertial measurement information, camera images, laser, and digital map data. As a result, high accuracy is reached, and the localization error is below 1 m but requires a high computational cost and several data sources.

Ali and Abu-Elkheir (2015) presented in his work a position error model that incorporates the correlation between successive measurements of position. To establish the degree of correlation between both the past and future vehicles' position, the Yule Walker equations are performed. Since is proved the presence of this correlation a first-order Gauss-Markov model is applied that reaches a high level of accuracy in estimation vehicles' future location. However, results are not reliable since it uses only GPS information to compute distances among the vehicles for cooperative localization.

A new vehicle localization approach using a vehicle motion model and the V2V communication is proposed by Golestan (GOLESTAN et al., 2015). The authors applied an Extended Kalman Filter (EKF) to perform the data fusion of both GPS data and TOA and AOA distance measurements. Furthermore, the vehicles' location estimation is improved by taking a weighted average over the position estimation of all nearby vehicles. The performance of this solution was evaluated by using the Mean-Square-

Error (MSE) technique. The best result was 2.63m of MSE when it used 9 vehicles communicating with each other, although the accuracy of this solution decreased when it used fewer vehicles.

Another solution is proposed in (SURYAWANSH et al., 2015) that improves the Inter-Vehicular Communication Assisted Location (IVCAL) by a path detection algorithm (PPD). The authors take advantage of GPS position information to identify the previous path of the vehicle through a Kalman Filter that reduces signal output. In our proposed solution, we also use GPS position information along with distance information, which both are shared with neighbors by V2V communication. Unlike IVCAL, our proposed algorithms, CoVaLID and CoLIDAP, aim at improving GPS position.

An experimental approach that combines the advantage of both the H-infinity filter and the multiple fading filter was demonstrated in (LIU et al., 2017). Hence, a new robust multiple fading factor approach is proposed at a high computational cost, since the loosely coupled GPS/INS that integrated navigation system requires a 15-dimension state vector. On the other hand, our proposed approach uses only a 5-dimension state vector.

In order to mitigate unbalanced Geometric Dilution of Precision (GDoP), Hoang (HOANG et al., 2016) proposed a data fusion framework derived from a modified Extended Kalman Filter (EKF) capable of removing the gyroscope unbounded noise. In addition, it can achieve accurate location estimation by refining the density of the posterior based on the knowledge of road boundaries. However, this approach suffers from accuracy degradation due to large GNSS errors. To tackle this drawback, in our proposed solution, we use distance information as a key factor for keeping the accuracy almost constant.

Geographical information is used by Luo (LUO et al., 2018) to identify no line-of-sight area. Also, Extended Generalized Approximate Message Passing based Cooperative Localizer (EGAMP-CL) is applied to estimate the vehicle position. The GPS average position error was reduced from 12 m to 6 m, which is still an undesirable accuracy for critical safety applications in VANets.

3.2 GPS Free Solutions

Regarding GPS free solutions, it is common to take advantage of communication devices to gather some information and use them to improve vehicles' localization in GPS free solutions for VANets. Some proposed solutions in the literature make use of radios, for instance, Liu (LIU et al., 2018) used full-duplex radios to propose a localization approach that can compute the inter-node distance among vehicles through two successive transmissions. Although, it is necessary at least three anchor nodes to perform the computation, whereas in the CoLIDAP we can execute it through only one anchor node. Another approach that makes use of radios is proposed by (MENDRZIK et al., 2019). In their work, they demonstrated that NLOS components in 5G MIMO systems could be used to increase the position accuracy, but only if the angle-of-arrival, angle-of-departure, and time-of-arrival of each path can be measured accurately. Also, their solution needs at least three NLOS paths to assist the received signal. Overall, employing more antennas and radio devices can increase the solution cost.

In (KAIWARTYA et al., 2018), the authors tackled the problem of GPS outage using the equation of a circle and the intersection between the circle and a line to improve the estimated vehicle's location. Their solution, named a geometry-based localization (GeoLV), was assessed in a straight, curved, and angular scenarios, the same used to test our proposed solution. However, in contrast to GeoLV, we are using the similarity of triangles concept to deal with GPS inaccuracies.

A different approach is proposed in (NASCIMENTO et al., 2018), in which the authors describe an integrated Dead Reckoning and Cooperative Positioning (CP) approach that is capable of locating a vehicle when GPS is unavailable. In their solution, a multihop V2V communication is used to reinitialize Dead Reckoning periodically, when GPS loses their Line of Sight (LOS) with satellites. Moreover, the Geometric Dilution of Precision (GDOP) concept is applied to obtain the best combination of nodes to operate the multilateration technique. However, the authors did not try any prediction models Bayesian statistics-based, such as Kalman Filter, to improve the accuracy of their solution.

3.3 Hybrid Approaches

In order to take advantage of both GPS assisted and GPS-free solutions, some works in literature proposed hybrid approaches, for instance, Goli presented a Sequential Monte Carlo Probability Hypothesis Density (SMC-PHD) filter to estimate vehicle states (GOLI et al., 2015). The authors combined vehicles' GPS information along with distance information among them, shared through V2V communication to feed the filter. This approach can be used also when GPS is unavailable for short periods of time. The results show that the proposed solution obtained 1.7 m of RMSE values. However, its performance was evaluated using a constant velocity motion model and need to be tested in real-world scenarios, since they just assessed their approach in a straight-line scenario.

Another hybrid approach is a proof of concept demonstrated in (OGUZ-EKIM et al., 2016). In his solution, a data fusion algorithm is proposed that uses TOA from a single RSU, along with acceleration and angular velocity from IMU, and map information to improve vehicles' position. All this information fed an EKF to perform the position estimation. The GPS information is used only to initialize the algorithm, since this solution is deployed in GPS-denied environments. The experiments show that the accuracy between 1 m to 5 m at a high computational cost, since they used an 11-dimensional vector for the vehicle state.

Furthermore, Cruz (CRUZ et al., 2017) also used both V2V and V2I communication along with low-cost smartphone sensors to address the localization problem. A PF is implemented to fuse data such as GPS positions, V2V signal strength measurements, map information, and inertial data from the smartphone. The results show that this solution can provide position information when GPS data is unavailable. However, its performance demonstrated considerable errors in the estimated positions.

The Spatiotemporal Local-Remote Senor Fusion (ST-LRSF) for Cooperative Vehicle Positioning is a hybrid approach presented in (JEONG et al., 2018). This solution is used when GPS information is available or not. When GPS is available, a Kalman Filter is used to fusion this information along with an accelerometer, compass, and/or gyroscope measurements. Furthermore, in outage GPS scenarios, a dead Reckoning approach is used. This solution takes advantage of the aggregated statistical characteristics of nearby vehicles to improve the positioning accuracy of the vehicle itself. However, this approach has a high computational cost. In addition, it requires that vehicles need to run in the opposite direction, which may not be true in real-world scenarios.

Furthermore, our research is aided by some other works found in the literature. For instance, Muller (MULLER, 2017) expressed Cooperative Techniques for Relative Positioning of Vehicles. Interesting information pointed out in this work is that take advantage of both cooperative and non-cooperative approaches, combine both into a single solution is the most promising solution in relative position estimation. Furthermore, radar sensors and vision-based systems can be used along with GNSS measurements, kinematics, and inertial sensor information, to provide the highest accuracy cooperative technology.

The survey of localization prediction in VANets is presented by Balico (BALICO et al., 2018). In their work, the authors describe some proposed solutions for localization that are suitable for estimating the vehicles' future position. The Dead Reckoning, Machine Learning, and Filtering approaches were detailed described, more specifically, Neural Networks, Support Vector Regression, Kalman Filter (and derivative such as Extended KF, and Unscented KF), and Particle Filter. Furthermore, the author evaluated the performance of these approaches. In conclusion, the DR, PF, and KF can be used as solutions for prediction techniques, whereas the machine learning algorithms presented lower accuracy in tested scenarios.

Finally, a survey of the state-o-the-art localization techniques is shown by Kuutti (Kuutti, 2018). In this survey, the localization methods are arranged in on-board sensor-based, V2V, and V2I communication. As a result, their limitations and strengths were described, as we can see in Table 5.

3.4 Chapter Conclusions

Although several recent research efforts have been studied to improve vehicle localization in VANets, as mentioned earlier, this is still an open problem that needs to be

Method (Reference)	Sensors	No. of Vehicles	Accuracy
VANet Multilateration (ROHANI et al., 2015)	GPS and V2V	5	3.30m (Mean)
V2V and on-board sensor localisation (FUJII et al., 2011)	GPS, V2V, and ranging sensors	1800 per hour on 1km of road	0.60m (Mean)
VANet supported by stationary vehicles (ORDÓÑEZ-HURTADO et al., 2015)	GPS and V2V	20	Up to 3.14m
Multilateration with shared position estimates in VANet (GOLESTAN et al., 2012)	GPS, gas and breake pedal and steering wheel sensors, V2V	5	Up to 1.65m (MSE)
Weighted V2V Localisation based on intervehicle distance (AHAMMED et al., 2010)	GPS and V2V	10	2.38m (Mean)

Table 5 – Localization Techniques suitable for Autonomous Vehicles. Adapted from (KUUTTI et al., 2018).

addressed. Thus, in this work, we propose a novel location data fusion technique that cooperatively gathers GPS and distance information from nearby vehicles to improve their locations. In this work, we are using a weighted average model to put more confidence in distance information provided by vehicles closer to the target. Hence, we take advantage of these extra sensors to propose a distance-based data fusion technique to improve the localization provided by GPS. Also, we have applied a set of equations based on the concept of congruent triangles. Our proposed solution will be better detailed in the next chapter.

4

COOPERATIVE LOCALIZATION IMPROVEMENT

In this chapter, we will detail our proposed two localization algorithms. First, the CoVaLID algorithm (Cooperative Vehicle Localization Improvement using Distance Information) that uses an extended Kalman filter (EKF) to perform data fusion. Second, the CoLIDAP algorithm (Cooperative Vehicle Localization Improvement using Distance Information along with the Particle Filter) algorithm, as the name suggests, uses Particle Filter instead. It is important mentioning that our algorithms are totally different from the VLOCI algorithm, that we chose to compare our solutions. Also, we investigate and discuss some of its challenges and limitations in real-world maps implementation.

This chapter is structured as follows: Section 4.1 brings the problem statement, whereas Section 4.2 describes the concept of similarity of the triangles. Section 4.3 shows a weighted average method applied over the vehicles' position. Section 4.4 describes the extended Kalman Filter used in the CoVaLID algorithm, while Section 4.5 presents the used Particle Filter in the CoLIDAP algorithm. Thus, Section 4.6 shows how the vehicles are adjusted onto the road limits through a simple map matching technique. Last, Section 4.7 brings the chapter conclusions.

4.1 Preliminary Definitions

In this work, to simplify the localization problem, we take into account only two dimensions (2D). However, our proposed solution is also suitable for three dimensions (3D) and could be easily adapted.

Definition 1: Let $X = [X_1, \ldots, X_N]$ *be a set of position coordinates,* $\forall X_i \in R^2$*, in a two dimensional plane, where* N *is the number of vehicles, and* $\langle X_i, X_j \rangle \in X$ *if* X_i *is in the communication range of* X_j*;* $\forall X_i \in X,\ X_i = [x_i, y_i]$ *is the position coordinates of vehicle* i*, given by the GPS;*

Definition 2: The GPS accuracy can be affected by some factors, such as atmospheric conditions, satellite positions, and natural barriers to the signal, to cite a few (THIN et al., 2016). Given a set of vehicles V*, where each vehicle* v_i *has its GPS position* Gp_i*, and its true position is* Tp_i*, the GPS error (*E_{gps}*) is defined as:*

$$E_{gps} = ||Gp_i - Tp_i|| \tag{4.1}$$

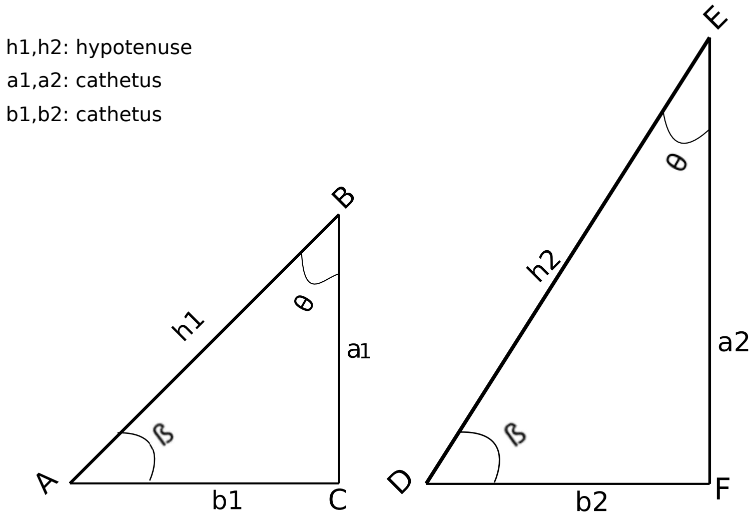
It is important to mention that the bigger E_{gps}, the bigger the GPS distance information error. Thus, our proposed algorithms are directly affected since GPS distance information is used in Equation 4.4 results. These results are a key feature in our proposed solution since it is used to compute the new estimated vehicle position through the concept of similarity of the triangles. However, in our solution, this problem is minimized due to the use of distance information given by sensors, which is more reliable than GPS for these cases. Also, it is important to mention that we have used the Euclidean Distance concept to compute distance values.

In this work, we assume that the distance between each pair of vehicles given by the GPS device is on the same line as the one formed by the one from the sensors. Therefore, we can apply trigonometry concepts in order to minimize GPS error. Thus, we used the concept of similarity of the triangles to deal with the localization problem in VANets, as demonstrated in our previous work (LOBO et al., 2019), which states that:

Definition 3: If two triangles share congruent angles, they are similar, as shown in Figure 4. Hence, the ratios of the corresponding sides of any two triangles are equivalent, no *matter the hypotenuse length.*

$$\frac{h_1}{h_2} = \frac{a_1}{a_2} = \frac{b_1}{b_2} = c, \tag{4.2}$$

where c is the constant of proportionality, h, a and b are the sides of the triangles.



(a) ABC Triangle (b) DEF Triangle

Figure 4 – Two triangles with different sizes but sharing congruent angles (β and θ) are similar.

Due to the demonstrated property above (similarity of the triangles), it supports that the ratio of two sides in one particular triangle is equal to the ratio of two sides in another similar triangle. From Equation 4.2 we can formulate:

$$\frac{a_1}{h_1} = \frac{a_2}{h_2}. \tag{4.3}$$

Definition 4: Since the GPS can provide noisy coordinates, we can compute the difference of the distances between both that information given by the sensor and the one given by the GPS. Hence, we denoted distance error as:

$$tD = Dist_{Gps} - Dist_{Sensor}. \tag{4.4}$$

In this work, we are taking into consideration that near vehicles have related GPS errors. Although the different brands of GPS receptors do result in different errors, it is known that they are spatially auto-correlated, which means that vehicles in similar locations have similar errors (RANACHER et al., 2016). However, it is worth to mention that real-world errors were introduced in our simulation environment to model the difference in GPS receivers brands.

4.2 Applying the Concept of Similarity of the Triangles

Our proposed localization technique is constituted of two equations. We can obtain these equations as follows:

Equation 4.3 gives us the distance information using the GPS coordinates. Whereas, Equation 4.4 provides the difference between both the GPS distance and the sensor distance.

Figure 5 shows that D is the sensor distance information. As explained in the next section, we are using the weighted average information. Here, d is the distance computed based on the GPS positions of both vehicles A and B. Once we have this information, we can calculate the difference ($D - d$) of the distance between the vehicles, the coordinates of vehicle B, centering in vehicle A, are given as x and y. Moreover, we can notice that the β angle is the same in both triangles ACB and triangle $AC'B'$. Hence, taking advantage of the concept of similarity of triangles, our algorithms CoVaLID and CoLIDAP aim at finding the residual values x' and y' to adjust the vehicle's position based on the difference between the sensor and the GPS distances.

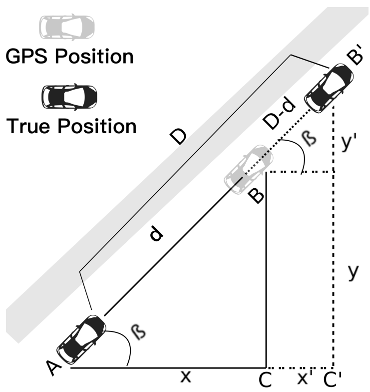


Figure 5 – Vehicles communicating with each other via vehicle-to-vehicle (V2V)—exchange information about its own GPS location and vehicle A sending the distance information given by sensors.

Thus, we can apply the concept of similarity of the triangles to estimate the new vehicle position, through Equations 4.5 and 4.6.

$$\frac{D-d}{x'} = \frac{d}{x} \tag{4.5}$$

$$\frac{D-d}{y'} = \frac{d}{y} \tag{4.6}$$

where the x' and y' are the residual values that must be used to estimate the new vehicle coordinates. The Equations 4.5 and 4.6 can be derived in:

$$x' = \frac{(D-d)x}{d} \tag{4.7}$$

$$y' = \frac{(D-d)y}{d} \tag{4.8}$$

finally, we can obtain the new estimated coordinates through:

$$X_{new} = X_{gps} + x' \tag{4.9}$$

$$Y_{new} = Y_{gps} + y' \tag{4.10}$$

It is worth mentioning that we assume the error in both the x-axis and the y-axis is proportional, which might not be accurate in some real-world scenarios. Moreover, CoVaLID can be used in real-world maps, despite its use of straight lines. For instance, if two vehicles are on the same road (straight line), the sensors can collect distance information even if they are not in the same lane which is a fair assumption since both highways and downtown scenarios are common scenarios.

Sometimes the GPS position may not be on the same line as the one formed by the true positions of vehicles A and B', as shown in Figure 6. In these cases, we can compute the GPS distance (d") between A and B". Also, we still have distance information from both the GPS and the sensor (D), so we can use CoVaLID. Thus, we assume that the GPS position is in the same line as the one formed by the true positions of A and B'. Thus, the distance value d" is equal to d, which may not be true in the real-world. However, the less the angle ∂, the closer d" will be regarding d. Hence, we performed our algorithm as the GPS position was in the same line of the sensor's position, as seen in Figure 5.

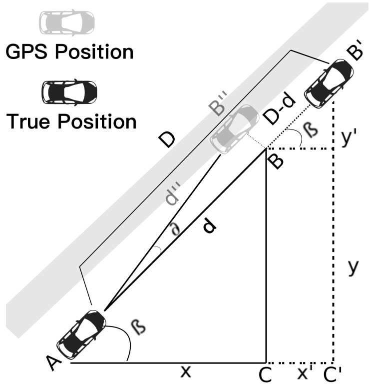


Figure 6 – Vehicles communicating with each other via V2V—exchange information about its own GPS location and vehicle A sending the distance information given by sensors.

We must mention that our proposed solution cannot work properly when the sensors used to provide distance information to lose their line of sight for its nearby nodes. In addition, in some real-world maps such as downtown where some intersections have huge buildings, this can also affect our algorithms as well as GPS signals. Another point is that if the vehicles are traffic in opposite directions they become out of their communication range and since there is no communication among nearby vehicles, our algorithms cannot be applied. On the other hand, in maps such as highways, downtown, and neighborhood (the last two with line-of-sight) our solution can perform well, and reach a high level of accuracy.

4.3 Gathering Distance Information

As mentioned above, each vehicle sends its GPS position along with the distance information every second. Thus, the target vehicle, when it receives the neighbors' information can perform a weighted average on its GPS position and use the sensor's distance information along with the similarity of the triangles method for each pair of vehicles. It is worth mentioning that in this work, we are focused only on distance information that is given by sensors, such as cameras, lasers, or radars. Hence, how these sensors gather this information is not our focus. Also, we can notice in our previous work (LOBO et al., 2019) that vehicles farther away from the target can provide less accurate distance information than closer vehicles. The main idea in this work is to put more weight in the distance information given by neighbors closer to the target and less weight for the ones that are farther. In the VLOCI algorithm (AHAMMED et al., 2010) the authors compute the weighted average for the target's GPS position received from its neighbors using Equation (4.11).

$$x' = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \tag{4.11}$$

where x_i are the GPS coordinates, and w_i is its respective weight.

We compute the weighted average for the target vehicle's position in the same way as in (AHAMMED et al., 2010). Hence, this weighted average position is used to provide the GPS distance information. However, differently from VLOCI, we use different weights for each distance range, according to Table 6. As a result, we get this distance information to feed our extended Kalman filter. It is worth mentioning that if there is more than one node in the same range, it distributes equally the weights for them. Also, the values showed in Table 6 are based on the results of our earlier work (LOBO et al., 2019).

Weights	**Range**
90%	for nodes up to 10 m of distance
80%	for nodes from 10.1 m to 20 m of distance
10%	for nodes from 20.1 m to 30 m of distance
1%	for nodes from 30.1 m of distance

Table 6 – Weights for the weighted average method.

4.4 Extended Kalman Filter (CoVaLID Algorithm)

A Kalman Filter or one of its derivatives can be a suitable method to perform data fusion. The KF is used as a filtering component based on an iteration process that is divided into two phases: a prediction and an update phase (FASCISTA et al., 2017). Moreover, it is an optimal linear estimator for Gaussian noise. Also, it can be used even with nonlinear systems due to its variations such as the extended Kalman filter (EKF) that can linearize the problem by calculating its partial derivative. Due to our proposed solution nature, in the CoVaLID algorithm, we implemented an EKF that is fed by both the GPS coordinates, corrected by Equations 4.9 and 4.10, and the sensor distance information.

The EKF prediction phase uses the information from the last time step to produce an estimated state at the current time step, as seen in Equations 4.12 and 4.13:

$$x_k = F_k x_{k-1} + B_k u_k \tag{4.12}$$

The predicted error covariance is calculated by:

$$P_k = jFP_{k-1}jF^T + Q_k, \tag{4.13}$$

where F_k, is the transition matrix; the state matrix $x = [xA, yA, xB, yB]$ that are the estimated coordinates of the pair of vehicles A and B, given by the similarity of triangles method; x_{k-1}, is the observation matrix; the covariance of the process noise is Q_k; the B_k is the input control matrix model applied over vector u; P_{k-1} is the initial uncertainty in the process. Finally, both jF and jF^T are the Jacobian matrix of the state matrix and its transpose, respectively.

In the second phase, the update is given by the set of equations as follows. The measurement matrix z is composed of GPS positions of vehicles A and B, and the true distance information (the gathering of distance information):

$$z = [Ax, Ay, Bx, By, trueD]. \tag{4.14}$$

The sensor readings are expressed as the measurement matrix H_k. However, the relationship between the measurements and the state vector is required. To meet that requirement, we can observe two interesting points. First, the GPS measurements have a linear relationship with the state vector, since GPS provides the coordinates of both axes. Second, the distance of the sensor measurements is gathered in polar coordinates, which means that we need to convert them from polar to Cartesian coordinates in the matrix below.

$$h(x') = \begin{Bmatrix} x \\ y \\ \sqrt{x^2 + y^2} \end{Bmatrix} \tag{4.15}$$

It is noticed that the problem described in the matrix above is nonlinear, so we can apply the EKF to linearize it. For that purpose, the Jacobian (partial derivative) is used to estimate jH_k (the Jacobian matrix of H_k), and jH_k^T is its transpose. The measurement's noise is given by v, which is assumed to be zero-mean Gaussian white noise with covariance R_k. Hence, the Kalman gain can be calculated by:

$$K = P_{k|k-1} jH_k^T (jH_k P_{k|k-1} jH_k^T + R_k)^{-1}. \tag{4.16}$$

Furthermore, the difference between the measurement and state estimation y can be obtained by:

$$y = Z^T - (jH_k \cdot x_k). \tag{4.17}$$

Consequently, the formulas for update both the uncertainty process covariance and the estimation state are expressed by:

$$P_k = (I - K_k jH_k) P_{k|k-1}, \tag{4.18}$$

where I is the identity matrix.

Thus, the coordinates are estimated by the equation 4.19:

$$x_k = x_{k|k-1} + (K \cdot y). \tag{4.19}$$

4.5 Particle Filter (CoLIDAP Algorithm)

In the CoLIDAP algorithm, we used a Particle Filter (PF) to perform data fusion, the PF is performed through an iteration process divided into initialization, prediction, sequential sampling, and resampling.

In our solution, the state matrix x is made up of the estimated coordinates of the pair of vehicles A and B:

$$x = [Ax, Ay, Bx, By] \tag{4.20}$$

In the initialization stage, our initial belief state is $p(x_0)$, which is given by the GPS position of vehicles A and B. In addition, in the prediction stage, we sample a particle p_i from the previous distribution according to its weight (w_{t-1}). Thus, we sample a new state based on both previous sample x_{t-1} and the process noise u_t:

$$x\prime_t = p(x_t | x_{t-1}, u_t) \tag{4.21}$$

After that, we compute importance weight in sequential sampling phase:

$$w_t^i = p(z_t|x_t^i) \tag{4.22}$$

we also compute the sum of these weights, $n = n + w_t^i$, where n is the normalization factor. Moreover, we add the particle to the set of particles recursively until the total number of particle N that in this work, we used 100 particles. Last, the weights do not sum to 1, so we need to normalize the weights. For that purpose, we can normalize weights recursively, for each particle, N times:

$$w_t^i = w_t^i/n \tag{4.23}$$

The measurement matrix z is composed of GPS positions of vehicles A and B, and the true distance information (the gathering of distance information):

$$z = [Ax, Ay, Bx, By, trueD] \tag{4.24}$$

Consequently, the new value of the state vector is computed:

$$p(x_t|Z) = \sum_{i=1}^{N} w_t^i p_i(x_t) \tag{4.25}$$

Finally, the resampling stage aims at selecting samples with probabilities proportional to their weights that is used in the next iteration. It is important to mention that in the CoLIDAP algorithm, we apply the low variance resampling method.

It is noticed that the estimated coordinates by both the EKF and PF, sometimes can result in an off-road position. So, they need to be adjusted according to the road boundaries through a simple map matching technique.

4.6 Map Matching

To adjust the vehicle position, we compare the new estimated vehicle position computed by both CoVaLID and CoLIDAP algorithms with the path geometry of the road. We use map information to restrict the estimated vehicle position onto the identified road.

Moreover, we assumed that our proposed solution has access to a digital road map. Thus, we can verify if the vehicle's estimated position is within the road limits. If that is not the case, the algorithm shifts the vehicle position to the nearest point onto the road, as seen in Algorithm 2.

Algorithm 2 Map Matching algorithm

```
1: Input: vehicle estimated position
2: Output: updated vehicle estimated position
3: if (estimatedposition > upperroadlimit) then
4:     estimatedPosition ← upperRoadLimit
5: else if (estimatedposition < lowerroadlimit) then
6:     estimatedPosition ← lowerRoadLimit
7: end if
8: print estimatedPosition
```

4.7 Chapter Conclusions

In this chapter, we present our two localization algorithms. The CoVaLID algorithm (Cooperative Vehicle Localization Improvement using Distance Information) that uses an extended Kalman filter (EKF) to perform data fusion. Second, the CoLIDAP algorithm (Cooperative Vehicle Localization Improvement using Distance Information along with the Particle Filter) algorithm that uses Particle Filter. Also, it described the set of equations geometry-based, which feed both KF and PF to estimate a new vehicle position. Thus, in the next chapter, we will assess our proposed solution.

5

Evaluation and Results

In this chapter, we will evaluate our two proposed algorithms to verify whether they can be a solution for the localization problem in VANets. Thus, we will compare the CoVaLID and CoLIDAP algorithms to VLOCI, GPS, and ground truth coordinates.

The remainder of this chapter is structured as follows: Section 5.1 covers the methodology used to evaluate our proposed solution, Section 5.2 brings the metrics used to measure the error of each localization technique. In Section 5.3 describes the used simulation scenario, and Section 5.4 covers the three different real-world maps, both to compare CoVaLID, VLOCI, and GPS approaches, whereas in Section 5.5 brings the evaluation of CoLIDAP against the CoVaLID, VLOCI, and GPS approaches. Last, Section 5.7 gives the chapter conclusions.

5.1 Methodology

To evaluate the behavior of our proposed solution, we have used the simulation of urban mobility - SUMO (KRAJZEWICZ et al., 2012) for scenario construction, an open source road traffic simulation package projected to deal with large road networks. We also used for vehicles communication and behavior the Omnet++ (VARGA, 2001), a modular discrete event simulator, along with Veins framework (SOMMER et al., 2011), an open source framework for vehicular ad hoc network simulations, and python scripts for statistical computing. Hence, it was possible to define all vehicle mobility and all vehicular network parameters according to the IEEE 802.11p standard. The parameters used in the simulations are described in Table 7.

Parameters	Value
Network Interface	Nic80211p
Communication Range	200 m
GPS error	1, 2, 5, 10 m
Number of Iterations	10
Number of Vehicles	from 2 to 10

Table 7 – Simulation parameters.

Concerning the network topology, we took into account that all vehicles are inside their communication range. Thereby, each vehicle is capable of communicating with each other. Thus, vehicles can exchange both their location information given by GPS and the sensor distance information. When one vehicle receives this information, it can start the computation process by constructing the needed matrices and computing the proposed methods CoVaLID and CoLIDAP.

Moreover, to compare the approaches fairly, we had to make some adjustments to the VLOCI algorithm since in the original approach, the network is static, i.e., vehicles were set to be stationary. Thus, in our simulations, all vehicles were set up with constant velocity in an intersection scenario, we applied the map matching technique in order to estimate vehicle position into the road bouderies. However, the number of iterations was the same as used in (AHAMMED et al., 2010). Hence, we considered that all the vehicles had an acceleration equal to zero. Also, the target vehicle is the one in the front, and its neighbors are lined up, and last, their trajectories were defined in the north/south direction.

We evaluate the accuracy of our proposed solution related to the impact of three different aspects. First, concerning the number of vehicles, to verify the behavior of the presented solution, we used multiple increasing values. Second, to evaluate the impact of the trajectory on the accuracy over the tested approaches, it was divided into two parts, straight-line and curve. Finally, to verify how the noise in distance measurements can affect the proposed solution, we evaluated the impact of distance information error.

5.2 Analysis of the Error

To evaluate our proposed solution, we conducted an analysis using the root-mean-square error (RMSE) method, described in Equation 5.1. This metric is commonly used to measure the error of the localization approaches as seen in (RICHTER et al., 2009; LIU et al., 2017; NASCIMENTO et al., 2018; JEONG et al., 2018), to cite a few.

$$RMSE = \frac{1}{n}\sum_{i=1}^{N}(x - x')^2 + (y - y')^2, \tag{5.1}$$

where (x, y) and (x', y') are respectively the perfect and estimated vehicles' positions, while the latter varies between GPS, VLOCI, CoVaLID, and CoLIDAP.

Furthermore, we used the mean absolute error (MAE) as a metric to evaluate our method since some works in literature (ROHANI et al., 2015; FUJII et al., 2011; KAMIJO et al., 2015; AHAMMED et al., 2010) also use it to assess their results. In Equation (5.2), we compute the MAE for one axis to simplify the explanation. However, it is suitable for as many axes as necessary.

$$MAE = \frac{1}{n}\sum_{i=1}^{N}|(x - x')|, \tag{5.2}$$

where (x) and (x') are respectively the perfect and estimated vehicles' coordinates, while the latter varies between GPS, VLOCI, CoVaLID, and CoLIDAP.

5.3 CoVaLID Evaluation in Simulation Scenario

In this section, we used a simple intersection scenario to evaluate the performance of our proposed localization solution. In this scenario, vehicles can move in a straight-line road. Furthermore, we used RMSE and MAE to assess the accuracy of the GPS, VLOCI, and CoVaLID regarding the impact of GPS error, the increase of the number of vehicles, and distance among vehicles. Then, both the results and discussion about them are presented.

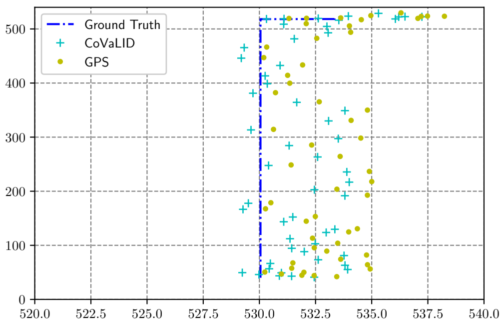
5.3.1 Applying Road Constraints Using Map Matching

In this subsection, we compare the results of our proposed solution to the initial GPS inaccurate coordinates, to the VLOCI algorithm, and also to the perfect position of vehicles. It is worth mentioning that we used a simple map matching technique to adjust the vehicle's positions within road limits. Thus, we plotted graphs with vehicles' positions as a result of each cited approach. In these graphs, the yellow circle represents GPS position, whereas the cyan cross, the red cross, and the blue line denote, respectively, CoVaLID, VLOCI, and the ground truth position.

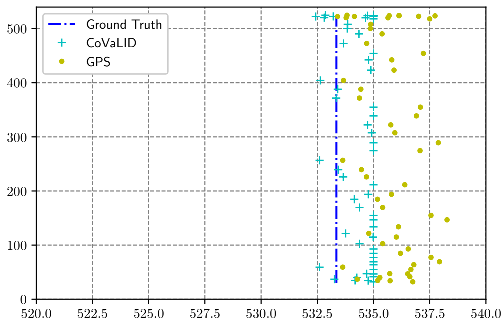
As shown in Figure 7a, our proposed solution was able to improve the GPS positions. However, sometimes, those estimations still put the vehicle outside the road. So, we apply the map matching (MM) technique, as described in Section 4.6, in our data fusion solution, resulting in a more accurate estimation, as seen in Figure 7b. Also, it is noticeable that the trajectory of the vehicle using CoVaLID + MM is similar to the ground truth. According to Table 8, the CoVaLID + MM, called just CoVaLID from now on, is capable of reducing x-axis and y-axis GPS positioning error on average in 62% and 22%, respectively. Another interesting point in Table 8 is that the VLOCI algorithm had better performance when compared to CoVaLID without MM. It can be explained due to the fact that we made some adjustments in the VLOCI original approach, and one of them was to use map matching. So, VLOCI was already using MM, while CoVaLID not.

Localization Techniques	**RMSE**	**MAE**	**RMSE**	**MAE**
	x-Axis	**x-Axis**	**y-Axis**	**y-Axis**
CoVaLID without MM	1.871733 m	1.54864 m	2.633068 m	2.18359 m
CoVaLID + MM	1.006493 m	0.997129 m	2.067209 m	1.64502 m
VLOCI	2.710796 m	2.388535 m	2.238849 m	1.850759 m
GPS	2.710796 m	2.388535 m	2.672965 m	2.2277 m

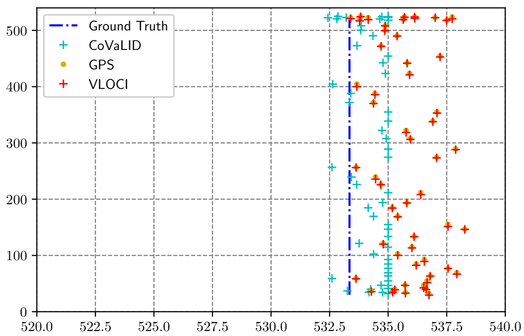
Table 8 – Localization techniques accuracy.



(a) CoVaLID without map matching technique.



(b) CoVaLID along with map matching technique..



(c) Comparison among CoVaLID + MM, Vehicular ad hoc networks LOCation Improve (VLOCI), GPS, and ground truth.

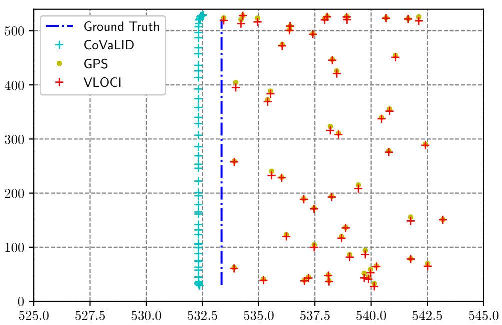
Figure 7 – Comparison among CoVaLID, CoVaLID+MM VLOCI, GPS, and ground truth.

We noticed, for this scenario, that the VLOCI algorithm improved its accuracy when compared to the results presented by Farhan (AHAMMED et al., 2010) due to the adjusts that we made. It is important to mention that the VLOCI approach assumes that vehicles are traveling in one lane and in the same direction. Hence, the values in both, RMSE and MAE are the same in the x-axis for VLOCI and GPS techniques. So, when comparing our CoVaLID solution to the VLOCI, in terms of accuracy in the y-axis, our approach outperforms VLOCI by at least 11%, reducing the error from 1.85m to 1.64m. We can also observe differences between values when the axis changes. It can be explained due to the fact that we assume the error in both axes is proportional, which may not be true in real-world maps.

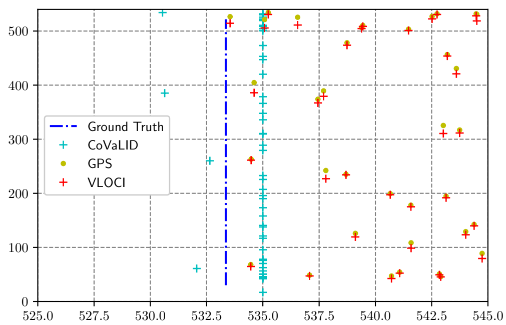
5.3.2 The Impact of GPS Error

To study the impact of GPS error regarding the accuracy of the tested solutions, we varied the GPS error parameter by 1, 5, and 10 m, respectively.

We can see that in the five-meters GPS error scenario, the CoVaLID, VLOCI, and GPS trajectories are almost the same as the ground truth, as shown in Figure 8a. However, our proposed solution is slightly better when compared to the other techniques. When the GPS error increased to 5 and 10 m, respectively, both CoVaLID and VLOCI could still reduce and improve GPS localization. Besides, our proposed solution, CoVaLID reached its best performance in 10 m of GPS error scenario, minimizing it on average of both axes in 58% when compared to GPS, and 51% when compared to VLOCI. It is worth mentioning that when the GPS error increases, the trajectory of the VLOCI algorithm is quite different than the ground truth, as seen in Figure 8b, while the CoVaLID maintained its trajectory similar to the ground truth.



(a) The 5 m of GPS error.



(b) The 10 m of GPS error.

Figure 8 – Impact of GPS error—increasing the GPS error from 5 to 10 m.

In Tables 9 – 11, we can notice that our proposed solution obtained the least RMSE values in all cases when compared to both GPS and VLOCI.

Localization Techniques	**RMSE**	**MAE**	**RMSE**	**MAE**
	x-Axis	**x-Axis**	**y-Axis**	**y-Axis**
CoVaLID	1.007360 m	0.908047 m	0.829160 m	0.660428 m
VLOCI	1.084340 m	0.955464 m	0.882375 m	0.725475 m
GPS	1.084340 m	0.955464 m	1.069160 m	0.891048 m

Table 9 – Localization techniques accuracy for 1 m of GPS error.

Localization Techniques	RMSE	MAE	RMSE	MAE
	x-Axis	x-Axis	y-Axis	y-Axis
CoVaLID	1.000024 m	0.989990 m	4.158237 m	3.266210 m
VLOCI	5.421584 m	4.777160 m	4.588680 m	3.844891 m
GPS	5.421584 m	4.777160 m	5.345863 m	4.455358 m

Table 10 – Localization techniques accuracy for 5 m of GPS error.

Localization Techniques	RMSE	MAE	RMSE	MAE
	x-Axis	x-Axis	y-Axis	y-Axis
CoVaLID	1.256964 m	1.150331 m	7.532818 m	6.169233 m
VLOCI	10.343913 m	8.674089 m	7.802703 m	6.169344 m
GPS	10.343913 m	8.674089 m	10.596546 m	9.417037 m

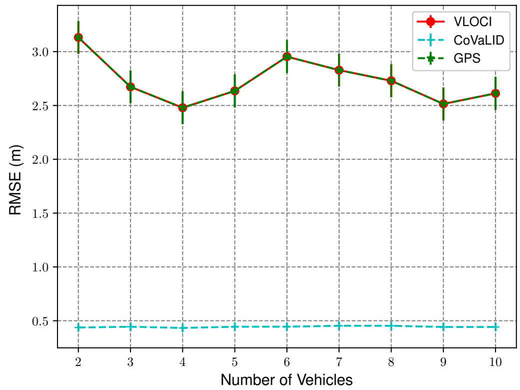
Table 11 – Localization techniques accuracy for 10 m of GPS error.

We can also notice that albeit VLOCI had improved its performance when the GPS error increased from 1 to 10 m, the algorithm depends on the GPS accuracy, in other words, the more accurate the GPS device is, the more efficient VLOCI can be. Our proposed solution demonstrated similar behavior since it is also a GPS assisted approach. However, CoVaLID shows to be efficient in all evaluated scenarios.

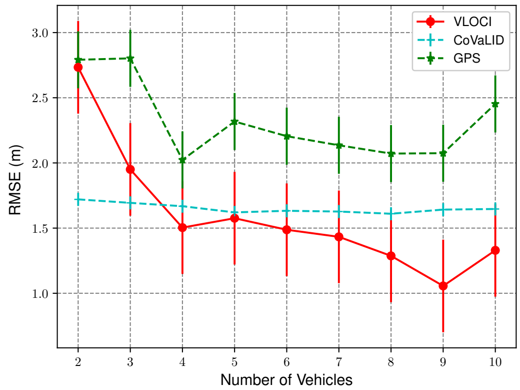
5.3.3 The Impact of Number of Vehicles

To assess the impact of the number of vehicles in all tested approaches, we kept the GPS error constant at 2 m, while the number of vehicles was increased from 2 to 10. Furthermore, we maintained the distance constant among all neighbors regarding the target vehicle in 30 m. To evaluate the performance of each technique, we took into account both the RMSE and MAE values regarding the x-axis and y-axis, separately, as well as the average between both axes. All graphs presented in this section were plotted with 95% confidence interval.

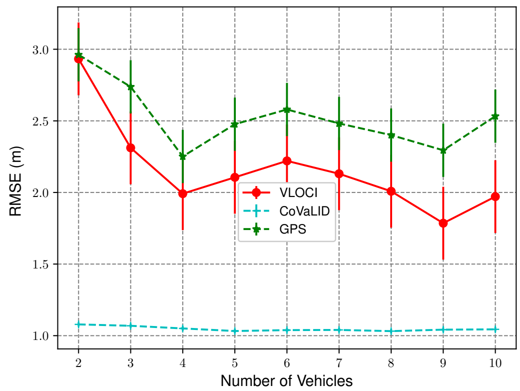
The RMSE and MAE values show that our proposed method had better performance in all evaluated scenarios when compared to both VLOCI and GPS regarding the x-axis. This result is expected since in x-axis both have the same values, as presented in Figures 9a and 10a.



(a) Root-mean-square error (RMSE) in x-axis.



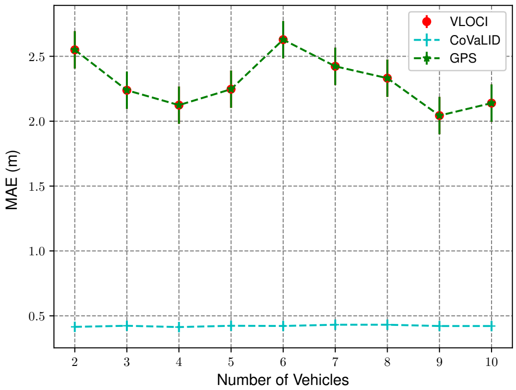
(b) RMSE in y-axis.



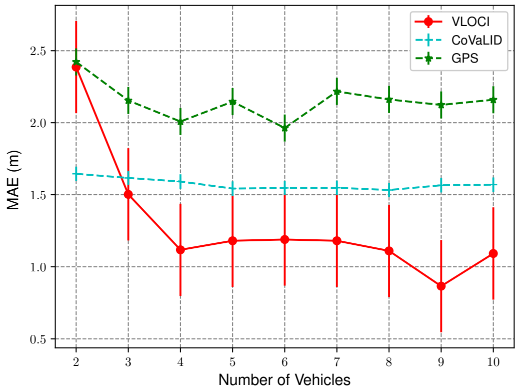
(c) RMSE on average in both axes.

Figure 9 – RMSE Values in x-axis, y-axis, and on average in both axes—regarding the increase in the number of vehicles.

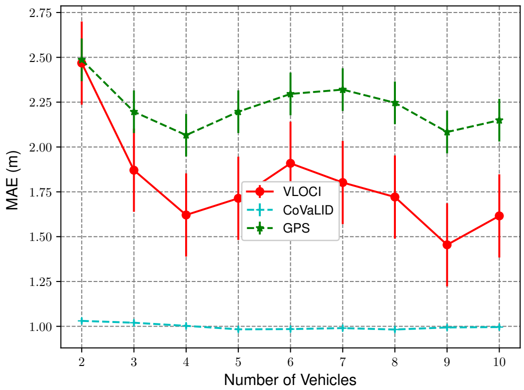
Another interesting point is that when the number of vehicles increases to 3, MAE values demonstrated that the VLOCI algorithm could overcome CoVaLID regarding the y-axis, as shown in Figure 10b. However, according to RMSE values, the VLOCI algorithm overcomes our proposed method only when the number of vehicles is increased to 4, and maintained its better performance for the remainder of the tested scenarios, as seen in Figure 9b. It suggests that when the number of vehicles increases, better accuracy is achieved in the y-axis by VLOCI. Also, it is worth pointing out that although our solution was overcome by VLOCI when the number of vehicles increased, our method maintained RMSE and MAE values almost constant.



(a) Mean absolute error (MAE) in x-axis.



(b) MAE in y-axis.



(c) MAE on average in both axes.

Figure 10 – MAE Values in x-axis, y-axis, on average in both axes—regarding the increase in the number of vehicles.

Figures 9c and 10c show the average error of both axes. We can notice that our proposed method had better results in all tested scenarios when compared to both VLOCI and GPS. It can be explained by the fact that CoVaLID uses distance information to minimize the GPS error in both axes, while the VLOCI algorithm only improves the error in one axis.

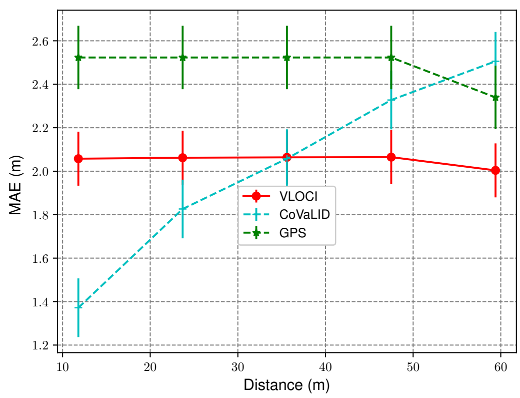
Overall, the results support that the CoVaLID algorithm can be used to circumvent the real time position estimation problem in VANets using fewer vehicles than the VLOCI algorithm.

5.3.4 The Impact of Distance Values

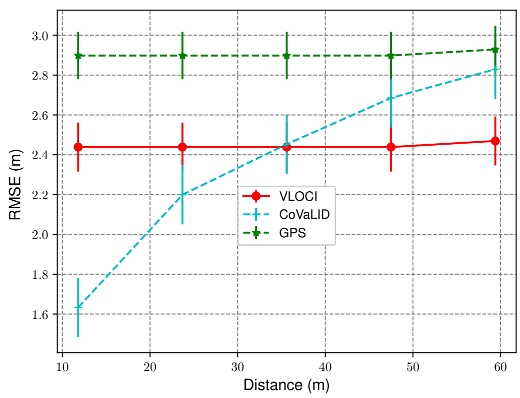
To evaluate the impact of the distance between two vehicles in the RMSE and MAE values, we kept the GPS error at 2 m and increased the distance between them. The distance values used in this scenario were: 11.8, 23.7, 35.6, 47.5, and 59.4 m. All graphs presented in this section were plotted with a 95% confidence interval.

Figures 11a, and 11b show the MAE and RMSE values of the average of both axes. We can notice that CoVaLID is directly affected when the distance between neighbors increases. However, our proposed approach had better performance when compared to the VLOCI for vehicles near the target. Although, for long distances between the vehicles, more specifically when the range is greater than 35 m, the VLOCI overcomes our proposed solution.

An interesting point that we can observe is that when increased distance values, the VLOCI algorithm is not affected. This fact can be explained because this algorithm uses the weighted average technique. VLOCI puts more weight in small distance values while putting less weight for higher distances, which means that VLOCI is capable of keeping its performance constant even with different distances between the target vehicle and its neighbors.



(a) MAE average of both axes.

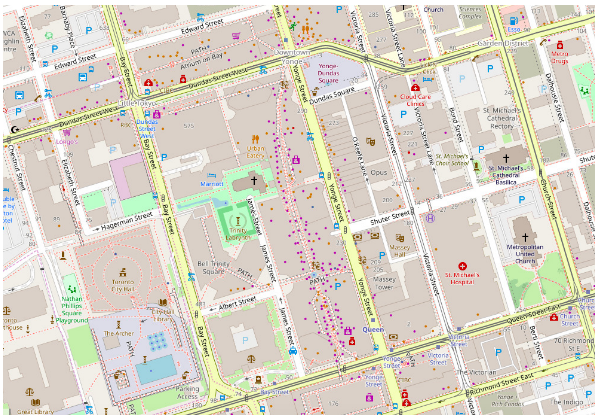


(b) RMSE average of both axes.

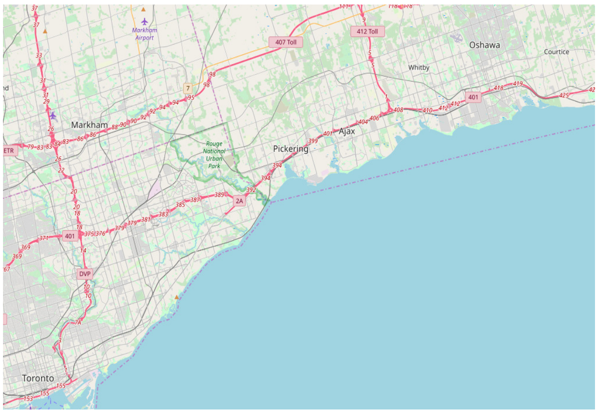
Figure 11 – MAE and RMSE values of the average of both axes—regarding the increase of distance values.

5.4 CoVaLID Evaluation in Real-World Maps

This section aims at evaluating the CoVaLID, VLOCI, and GPS methods in real-world maps. Thus, we used three different scenarios: downtown, highway, and neighborhood. The Figure 12a shows Downtown Toronto, which we took as scenario the most famous streets with a considerable amount of traffic, such as Dundas St., Yonge St., Church St., Queen St. and Bay St. In order to use a highway scenario, we chose Highway 401 (seen in Figure 12b) which has heavy traffic once it does not charge tolls. Finally, as the neighborhood scenario, we took into account the one named Windfields Farm close to the Ontario Tech University north campus, as we can notice in Figure 12c.



(a) Downtown Toronto.



(b) Highway 401.

(c) Neighborhood.

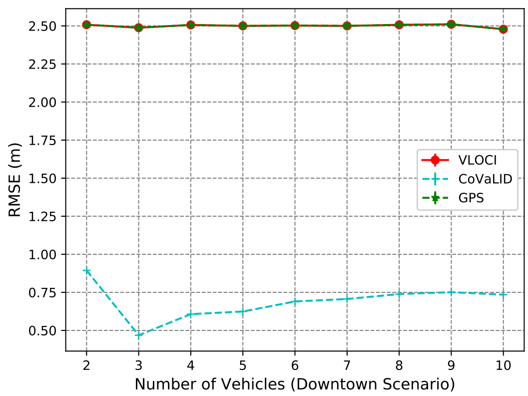
Figure 12 – Real-World Maps.

Furthermore, since the RMSE and MAE values demonstrated similar behavior, we will only use the RMSE values to assess the accuracy of the VLOCI, CoVaLID, and GPS regarding the impact of increasing the number of vehicles, the distance information error, and the distance among vehicles in simulation scenarios. From now on, we are using our proposed solution CoVaLID along with the weighted average from Section 4.3. Also, as before, all graphs presented were plotted with a 95% confidence interval.

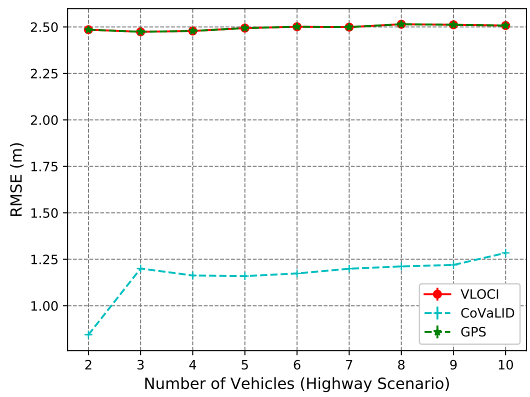
5.4.1 The Impact of Number of Vehicles

In this section, we kept the GPS error constant at 2 m, while the number of vehicles was increased from 2 to 10. Furthermore, both the distance among vehicles and vehicles' velocities were set randomly. To evaluate the performance of each technique, we took into account both the RMSE values regarding the x-axis, the y-axis, as well the average between both axes.

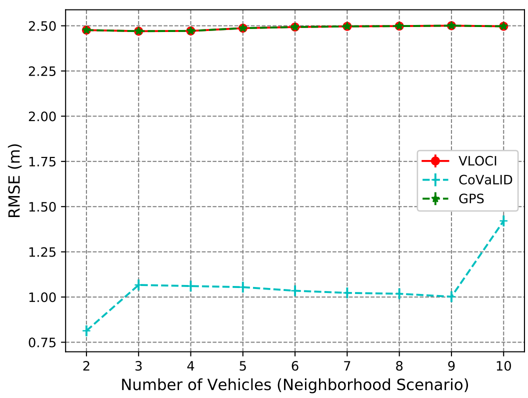
As we can see in Figures 13a, 13b, and 13c, the VLOCI and GPS had the same value as explained in Section 5.3.1. Furthermore, we can notice that the CoVaLID had its best performance regarding the x-axis in the downtown scenario, while in the highway, it performed with accuracy almost constant, as well in neighborhood scenario, except when increased the number of vehicles for 10. The best accuracy in the downtown scenario can be explained because, in a highway scenario, the vehicle velocity is higher. Hence, the higher the velocity, the more affected is our proposed approach in the x-axis.



(a) RMSE in x-axis—downtown scenario.



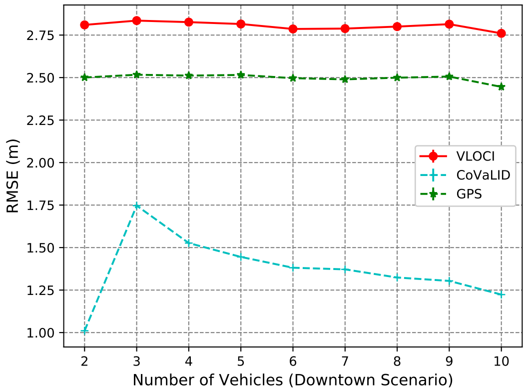
(b) RMSE in x-axis—highway scenario.



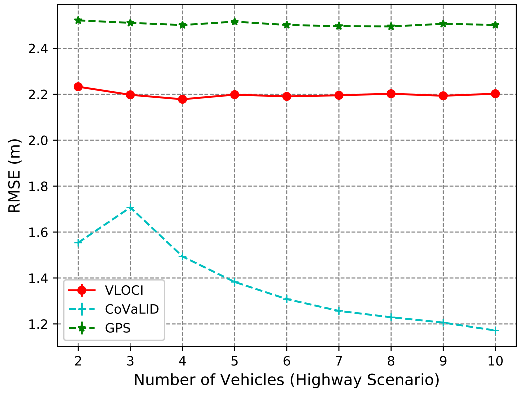
(c) RMSE in x-axis—neighborhood scenario.

Figure 13 – RMSE Values in x-axis in downtown, highway, and neighborhood scenarios—regarding the increase in the number of vehicles.

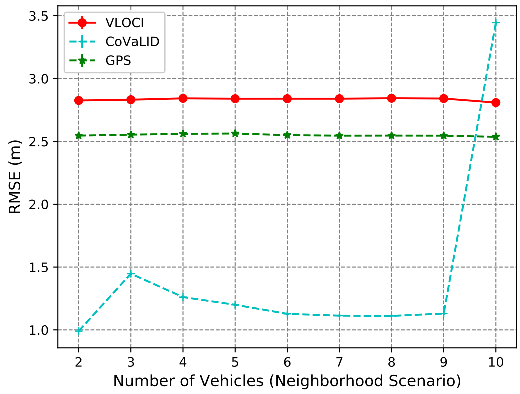
In the y-axis, according to RMSE values described in Figures 14a, 14b, and 14c, our proposed method had better performance when compared to both VLOCI and GPS in downtown, highway, and until 9 vehicles in neighborhood scenario. However, when the number of vehicles increased to 10, it can be noticed that CoVaLID had its performance significantly affected. It is explained because, in scenarios with turns, it is more challenging to apply the similarity of triangles concept, since the communication can be affected by obstacles, such as buildings, and houses. Another interesting point is that contrary to the x-axis, we can notice is that the higher the velocity, the less affected is our proposed approach in the y-axis. Also, in both downtown and neighborhood scenarios, we can notice that VLOCI had the worst performance, it can be explained because VLOCI was developed and tested in straight-line scenarios that is one characteristic of highway scenario, where VLOCI can overcome GPS accuracy.



(a) RMSE in y-axis—downtown ccenario.



(b) RMSE in y-axis—highway scenario.

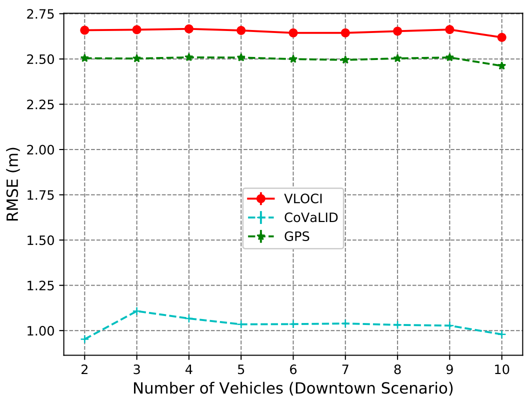


(c) RMSE in y-axis—neighborhood scenario.

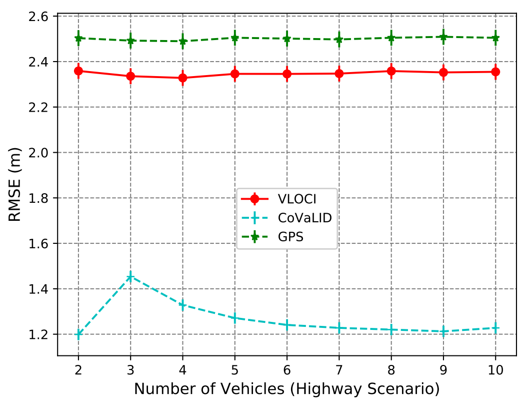
Figure 14 – RMSE values in y-axis in downtown, highway, and neighborhood scenarios—regarding the increase in the number of vehicles.

We can notice that when the number of vehicles increases to 3, according to RMSE values, the CoVaLID algorithm had a slight decrease in its accuracy, which can be explained due to the use of random distance among vehicles, as well some obstacles and turns during the trajectory. These factors can affect our proposed solution since it assumes that the distance information is perfect. In other words, it does not take into account noise in distance information, which is not true in real-world scenarios. Furthermore, the accuracy of the distance information depends on which sensor is used.

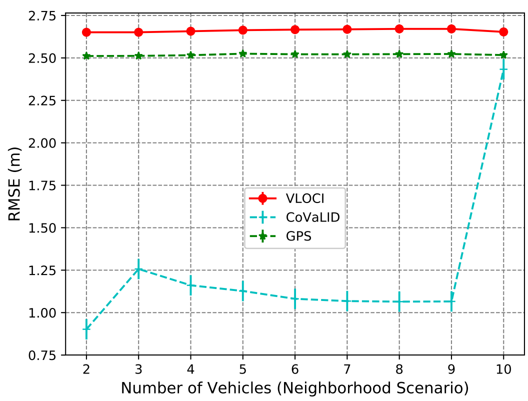
Another interesting point is that when increasing the number of vehicles, the CoVaLID performance improves due to the use of the weighted average method of nearby vehicles' positions. Also, the results suggest that CoVaLID can be used as a solution for localization problem aided by GPS in all tested scenarios, except when the number of vehicles is increased to 10 in neighborhood scenario. In this particular case, the RMSE values, as seen in Figures 13c, 14c and 15c, show that CoVaLID had the worst performance due to the 10th vehicle being farther to the target and as a consequence, its distance information become noisy since in neighborhood scenarios there are only one-lane streets and sometimes the 10th vehicle is not even in the same street as the target vehicle. However, on average of both axes, as seen in Figure 15a, 15b, and 15c , results suggest that our proposed solution is suitable for all tested scenarios. However, in the neighborhood scenario, CoVaLID presented limitations on its performance, when used with 10 vehicles.



(a) RMSE of both axes—downtown scenario.



(b) RMSE of both axes—highway scenario.



(c) RMSE of both axes—neighborhood scenario.

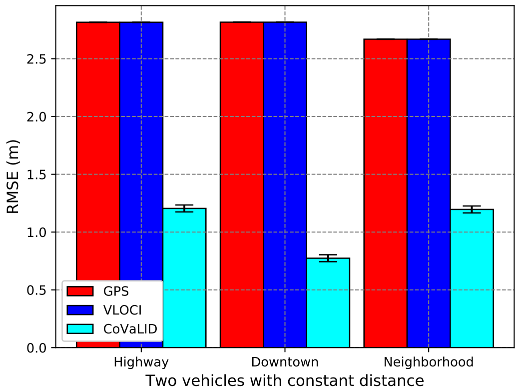
Figure 15 – RMSE values of the average of both axes in downtown, highway, and neighborhood scenarios—regarding the increase in the number of vehicles.

5.4.2 The Impact of the Vehicle Trajectory

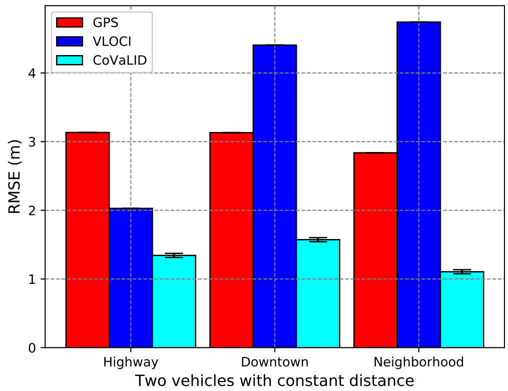
In this section, we divided the target vehicle trajectory into two parts: when vehicles are in a straight line or when they are in a turning scenario. In addition, we kept the GPS error constant at 2 m. We also used two vehicles, and the distance between them was set at 5 m apart. Thus, we can evaluate the impact of the vehicle trajectory regarding the accuracy of tested approaches in real-world maps.

Furthermore, each one of the three real-world maps, was divided into a straight-line and scenarios with curves, as described in Appendix A.

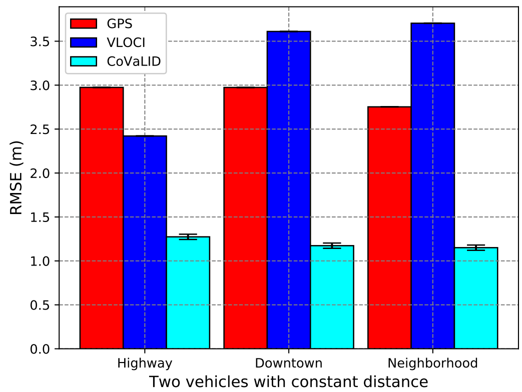
When compared straight-line against trajectory with curves in the downtown scenario, in the x-axis, as depicted in Figures 16a and 17a, we can notice that CoVaLID had better accuracy in the straight-line trajectory. The same occurred in the highway scenario, but with a just slightly better result when compared to the turning trajectory. On the other hand, in the neighborhood scenario, the turning trajectory had almost the same performance as in a straight-line scenario.



(a) RMSE of x-axis—three real-world maps.



(b) RMSE of y-axis—three real-world maps.

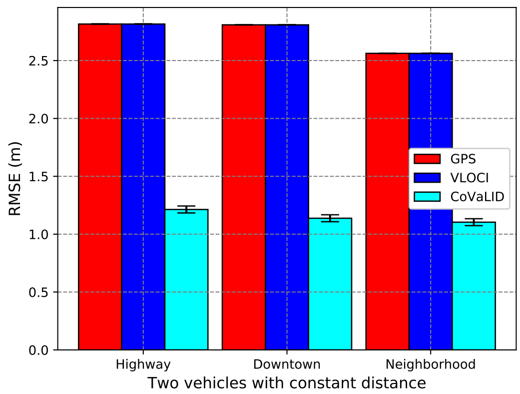


(c) RMSE of both axes—three real-world maps.

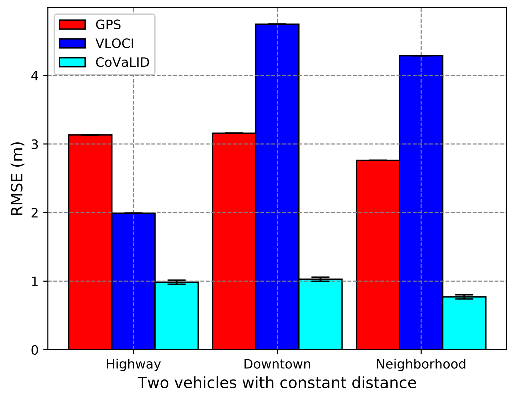
Figure 16 – RMSE values in downtown, highway, and neighborhood scenarios—regarding the vehicle in a straight-line trajectory.

In the y-axis, we can notice that the behavior of CoVaLID in a straight-line trajectory was the opposite presented in the x-axis. As shown in Figure 16b, the RMSE values show that in the downtown scenario, the CoVaLID performance decreased, whereas, in both highway and neighborhood scenarios, the accuracy was improved. Regarding the VLOCI algorithm, only in highway scenarios, it can overcome the GPS accuracy. Surprisingly, in y-axis simulations and using trajectory with turns, the accuracy of CoVaLID was improved, as shown in Figure 17b. It can be explained because usually, the vehicle position given by GPS does not lie in the same line as the distance information provided by sensors, which implies in an automatic triangle rotation when triangle similarity concepts are performed.

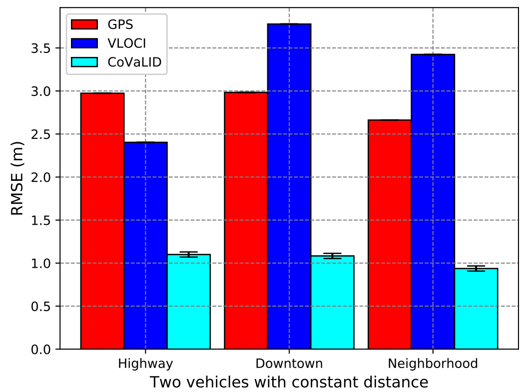
Overall, we can notice that all tested approaches presented similar behaviors for both trajectories simulated. As we can see in Figures 16c and 17c, on average in both axes, CoVaLID had the best performance when compared to VLOCI and GPS. On the other hand, VLOCI was able to overcome GPS only in highways scenarios. However, it is worth mentioning that the CoVaLID approach is dependable on the high quality of sensor information about distance among vehicles.



(a) RMSE of x-axis—three real-world maps.



(b) RMSE of y-axis—three real-world maps.



(c) RMSE of both axes—three real-world maps.

Figure 17 – RMSE values in downtown, highway, and neighborhood scenarios—regarding the vehicle in a turn trajectory.

5.4.3 The Impact of Distance Information Error

This section aims at analyzing and assessing the sensors that are suitable to provide the distance information in all tested scenarios. We used the sensor's specifications provided in the literature (MULLER, 2017). The used parameters and their respective sensors are described in Table 12.

Moreover, all simulations in this section were conducted using 10 vehicles with both distance and velocity set randomly, 2 m of GPS error, and the scenarios were divided into random, straight-line, and trajectories with turns.

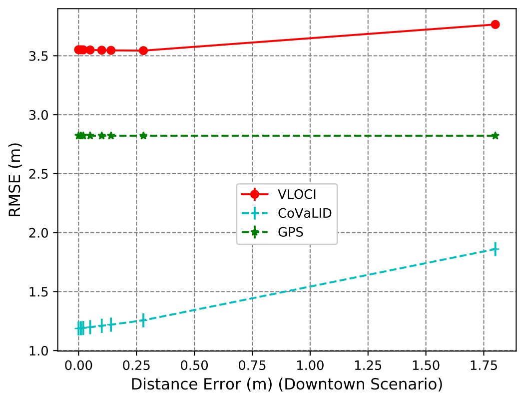
Sensor Type	Sensor (Brand)	Range	Distance Measuring Accuracy
Camera	SwissRanger SR4000	10 m	± 0.01 m
Laser	Velodyne HDL-64E S2	120 m	± 0.02 m
Laser	Quanergy M8-1	150 m	± 0.05 m
Radar	Bosh LRR3	250 m	± 0.10 m
Radar	Continental ARS30x	250 m	± 0.14 m
Radar	SMS UMRR Type40	250 m	± 0.28 m
Radar	Delphi ESR	174 m	± 1.80 m

Table 12 – Sensors Specification.

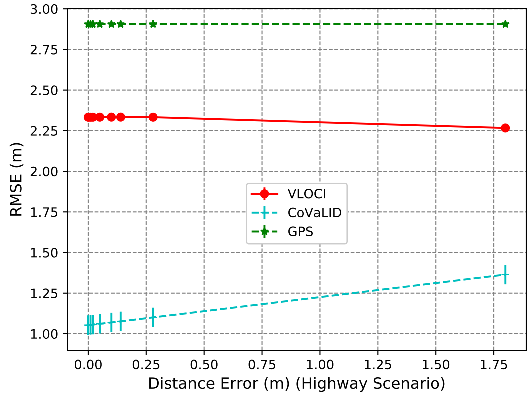
In a random trajectory scenario, the results presented in the x-axis show that CoVaLID had a similar behavior for all three tested scenarios. We can observe that the higher is the distance information error, the worse is the CoVaLID performance. The same behavior can be seen in the y-axis, and as a consequence, on average of both axes. However, the CoVaLID accuracy just decreased its performance around 32 cm in the downtown scenario.

Also, y-axis overall, we noticed that in both downtown and neighborhood scenarios, the VLOCI behavior was affected similarly as CoVaLID, whereas in highway scenario the VLOCI kept its accuracy almost constant due to the distance measurement model used in VLOCI algorithm along with vehicles' skewed position treatment. Another interesting point is that in downtown scenario was also the worst CoVaLID performance as expected since the buildings and other obstacles can affect the sensors' measurements.

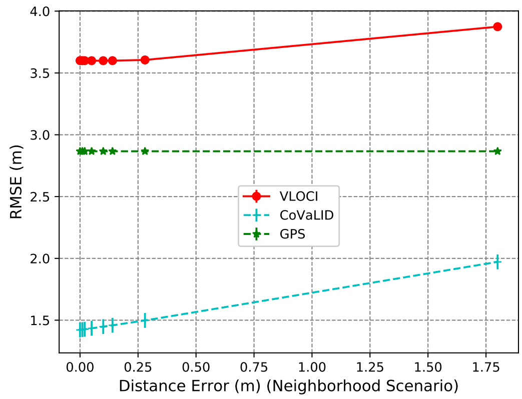
The RMSE values on average of both axes, seen in Figures 18a, 18b, and 18c, can summarize the behavior of the tested approaches. Overall, we can notice that the best accuracy was reached in the highway scenario that is due to its characteristics: a scenario with no buildings or obstacles, and mostly a straight-line scenario. Moreover, results suggest that the EKF works well using the velocities of the vehicles in this scenario.



(a) RMSE of both axes—downtown scenario.



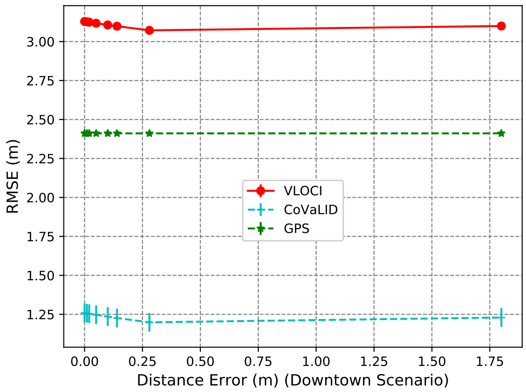
(b) RMSE of both axes—highway scenario.



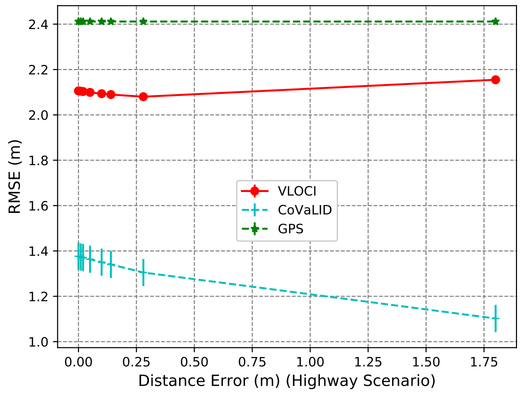
(c) RMSE of both axes—neighborhood scenario.

Figure 18 – RMSE values of the average of both axes in downtown, highway, and neighborhood scenarios—regarding the distance error information.

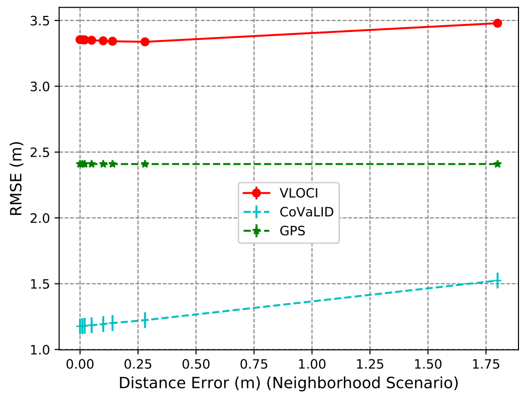
Using the straight-line trajectory, we can notice that, according to Figures 19a, 19b, and 19c, in both downtown and highway scenarios, the CoVaLID improved its performance due to two reasons. First, because of the trajectory characteristics (a straight-line). Second, because the EKF deals well with noises in distance information in these scenarios along with higher velocities, as seen in the highway case. However, as expected, in the neighborhood scenario, the CoVaLID had the worst performance due to the lower vehicles' velocity.



(a) RMSE of both axes—downtown scenario.



(b) RMSE of both axes—highway scenario.

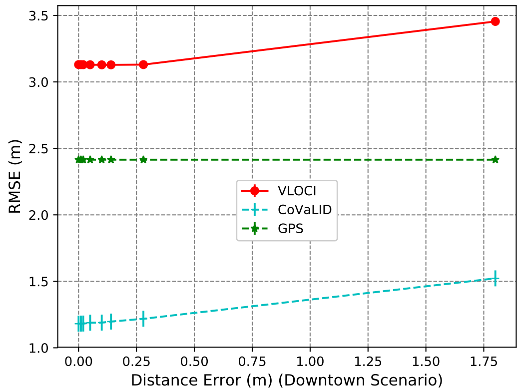


(c) RMSE of both axes—neighborhood scenario.

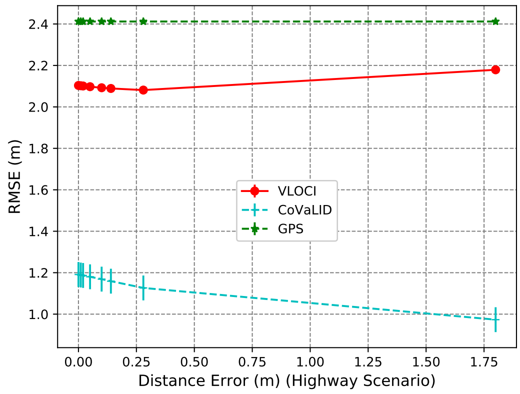
Figure 19 – RMSE values of the average of both axes in downtown, highway, and neighborhood scenarios—regarding the distance error Information in a straight-line trajectory.

From trajectories with turns, we can observe, according to Figures 20a, 20b, 20c that CoVaLID presented the same behavior as in the highway scenario, improving its performance. Whereas, in the downtown scenario, its accuracy was affected by the scenarios' characteristics such as obstacles, lower vehicles' velocity, and sensors' field of view. On the other hand, in the neighborhood scenario, the CoVaLID kept RMSE values almost constant. It can be explained due to the combination of lower vehicles' velocities and scenario characteristics.

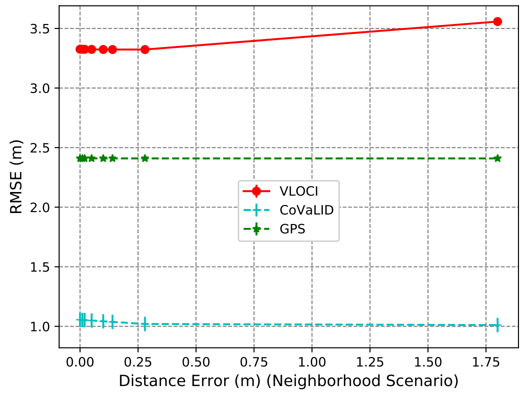
Hence, we detailed the impact of the sensors used to provide distance information, and the results presented in this section suggest that either the trajectories and the noisy distance information can affect our proposed solution in some way.



(a) RMSE of both axes—downtown scenario.



(b) RMSE of both axes—highway scenario.



(c) RMSE of both axes—neighborhood scenario.

Figure 20 – RMSE values of the average of both axes in downtown, highway, and neighborhood scenarios—regarding the distance error information in a trajectory with curves.

5.5 CoLIDAP Evaluation in Real-World Maps

We assess the CoLIDAP, CoVaLID, VLOCI, and GPS methods in real-world maps. For that purpose, we used downtown, highway, and neighborhood scenarios. Moreover, all presented graphs were plotted with a 95% confidence interval.

5.5.1 Impact of the Number of Vehicles

This section aims at evaluating the CoLIDAP, CoVaLID, VLOCI, and GPS methods when increasing the number of nearby vehicles. Therefore, we maintain the GPS error constant at 2 meters, and both the vehicles' velocities and distance are randomly set. We assess each technique's performance concerning the x-axis, y-axis, as well as the average between both axes. We decided to evaluate these axes separately since they can have different behaviors depending on the technique and scenario.

First, it is important to mention that for all tested scenarios, the VLOCI algorithm considers that vehicles travel in both the same direction and lane. Thus, the RMSE values in the x-axis are the same for the VLOCI and GPS approaches, as shown in Figures 21a, 21b, and 21c. The CoLIDAP algorithm reached the best accuracy in the downtown scenario when compared to the others. Also, its performance was almost constant even when increasing the number of vehicles (shown in Figure 21c). Regarding the accuracy, CoLIDAP performed better than the CoVaLID.

On the other hand, the CoVaLID algorithm had its accuracy slightly affected when the number of vehicles increased. In the highway scenario, our proposed solution had the worst accuracy due to the vehicles' higher velocities. In addition, the increasing number of vehicles also affected CoLIDAP, as shown in Figure 21b). However, we can notice that when the number of vehicles increases, the CoLIDAP algorithm can be more accurate than CoVaLID. In other words, the more vehicles, the more accurate the CoLIDAP is. This behavior can also be observed in the neighborhood scenario, except when the number of vehicles was 10, which can be explained since the distance information becomes noisier when the neighbor vehicle is farther from the target.

Overall, regarding the x-axis, we can notice that the CoLIDAP reached is best results in the downtown scenario due to nearby vehicles being closer to the target and traveling in lower velocities. Thus, in scenarios where vehicles travel in higher velocities, such as in the highway scenario, the CoLIDAP algorithm can be more affected. Furthermore, in general, the CoLIDAP had the best accuracy when compared to CoVaLID, VLOCI, and GPS.

On the other hand, in the y-axis, the RMSE values show that CoLIDAP had

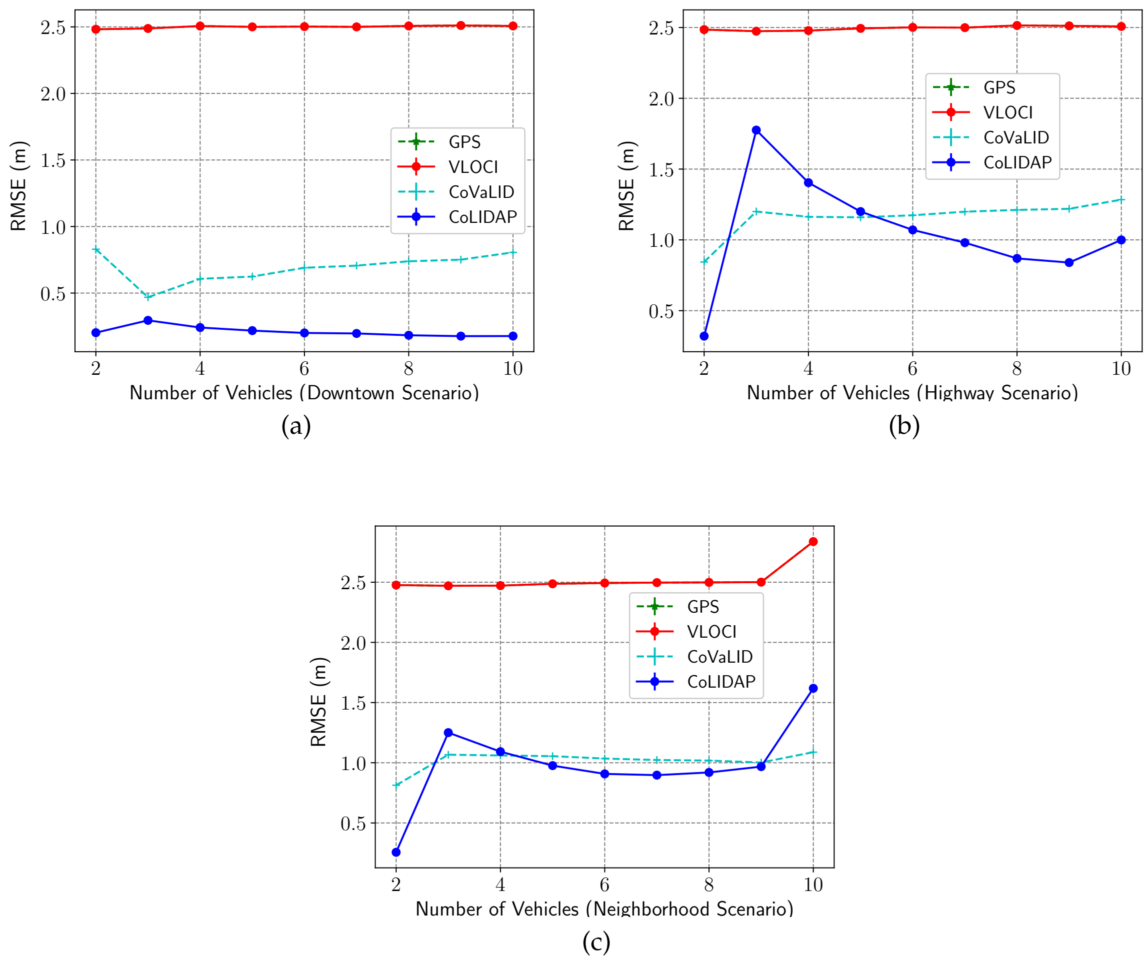
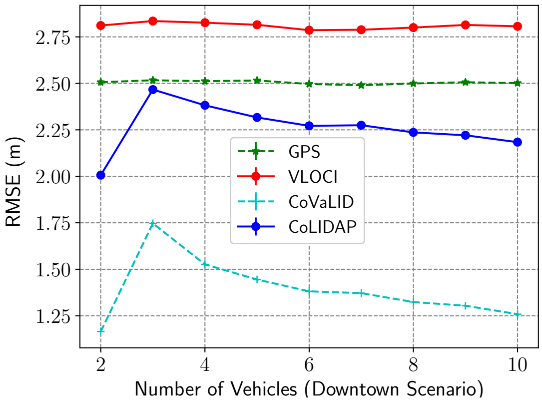
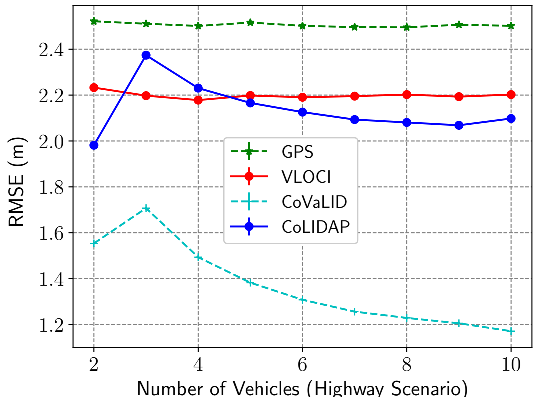


Figure 21 – RMSE values regarding the impact of increasing the number of vehicles in the x-axis in (a) downtown, (b) highway, and (c) neighborhood scenarios.

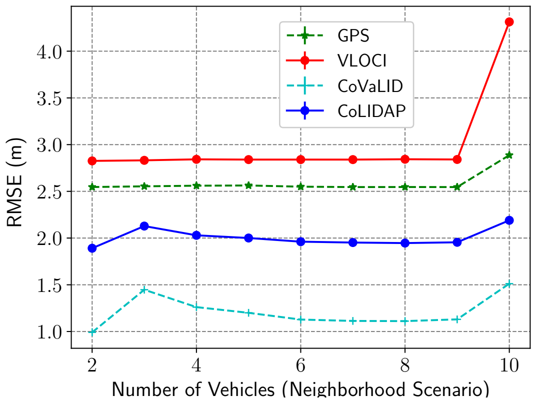
a similar behavior in both highway and downtown scenarios, as demonstrated in Figures 22a and 22b. Also, in both scenarios, the CoLIDAP algorithm performed better than VLOCI and GPS, except in the highway scenario where the VLOCI algorithm overcomes CoLIDAP when the number of vehicles is increased to 3 and 4, as shown in Figure 22b. It can be explained due to the fact that VLOCI was proposed and assessed in a straight-line scenario, which is similar to the highway. Furthermore, we can notice that differently from the x-axis, the higher velocities do not affect our proposed solution in the y-axis. In the neighborhood scenario, the CoLIDAP performance is almost constant. However, it is important to mention that the CoVaLID had the best performance in all tested scenarios regarding the y-axis. The results suggest that the CoLIDAP algorithm suffers from across-track error, especially in urban canyon areas, such as the downtown



(a)



(b)



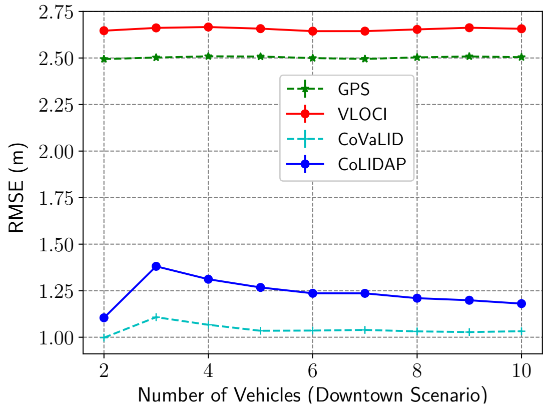
(c)

Figure 22 – RMSE values regarding the impact of increasing the number of vehicles in the y-axis in (a) downtown, (b) highway, and (c) neighborhood scenarios.

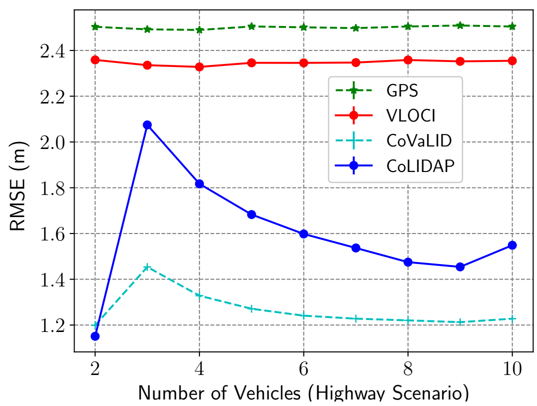
scenario.

Another interesting point is that when increasing the number of vehicles to 3, the CoLIDAP algorithm accuracy is affected, which can be explained by the use of random distance values among nearby vehicles. Also, some obstacles and different trajectories can affect our proposed algorithm since it does not consider noise on distance information. Moreover, the distance information accuracy varies according to the used sensor.

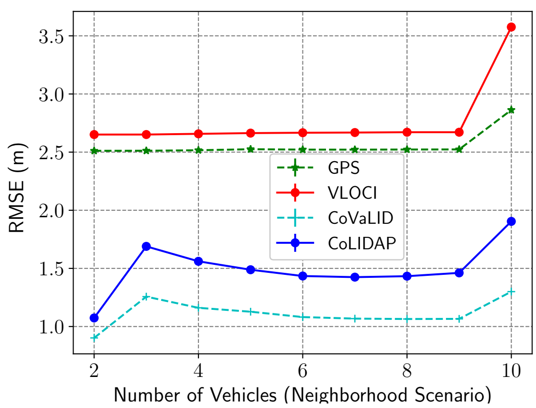
We can notice in the neighborhood scenario, as shown in Figures 21a, 22c, and 23c that when the number of vehicles is increased to 10, our proposed solution is severely disturbed. It can be explained since the distance information becomes noisier when the neighbor vehicle is farther to the target. Regarding the average of both axes, the CoLI-



(a)



(b)



(c)

Figure 23 – RMSE values regarding the impact of increasing the number of vehicles, on average of both axes in (a) downtown, (b) highway, and (c) neighborhood scenarios.

DAP algorithm best performed in the downtown scenario, following by the highway, and neighborhood scenarios, respectively, as seen in Figures 23c, 23c, and 23c.

Overall, results support that our data fusion technique aided by GPS (CoLIDAP algorithm) is suitable as a solution to localization problems in VANets for all tested scenarios. However, it presents restrictions in the neighborhood scenarios when tested with 10 vehicles. Also, CoVaLID overcomes the CoLIDAP algorithm, on average of both axes in all tested scenarios.

5.5.2 The Impact of the Vehicle Trajectory

To assess the impact of the vehicle trajectory, we divided each real-world map in both straight-line and turning trajectories, as shown in Appendix A. Also, we simulated all scenarios with 2 vehicles and 5 meters of distance apart between them, and a constant GPS error at 2 meters.

According to Figures 24a and 25a, the RMSE values show that in the x-axis, in the downtown scenario with straight-line trajectories, our proposed solution has the best accuracy when compared to CoVaLID, VLOCI, and GPS, whereas in highway scenario using the same trajectory, it is better than VLOCI, and GPS, as expected since straight-line is more suitable to apply the concept of similarity of triangles. In the neighborhood scenario, the CoLIDAP has its worst performance in straight-line trajectories because of the noisier distance information when vehicles are farther to the target since, in this scenario, vehicles travel lined up on the one-lane street. Overall, the CoLIDAP algorithm has its best performance in the downtown scenario where it is better when compared to all the other approaches. In contrast, in both highway and neighborhood scenarios, the CoVaLID overcomes CoLIDAP due to the fact that in these scenarios, vehicles can travel faster than in downtown, which can deteriorate the CoLIDAP performance in the x-axis. Also, in all tested scenarios using trajectories with curves, the CoLIDAP has its accuracy affected by the trajectory, yet it still better accuracies when compared to VLOCI and GPS.

On the other hand, in the y-axis, the CoLIDAP behavior is almost the same for all tested scenarios using both trajectories. However, when compared to the x-axis in both highway and downtown scenarios, our proposed solution has its accuracy deteriorated, whereas, in the neighborhood, its accuracy keeps the same performance. Overall, in the y-axis, the CoLIDAP algorithm can improve the CoVaLID performance in the highway scenario using both trajectories. It is worth mentioning that in the highway scenario, the VLOCI algorithm overcomes our proposed solution. It can be explained because, in this scenario, the vehicles' velocities are higher, which can affect the applied PF since it uses nearby vehicles as references.

On average, in both axes, in the highway scenario using a straight-line trajectory,

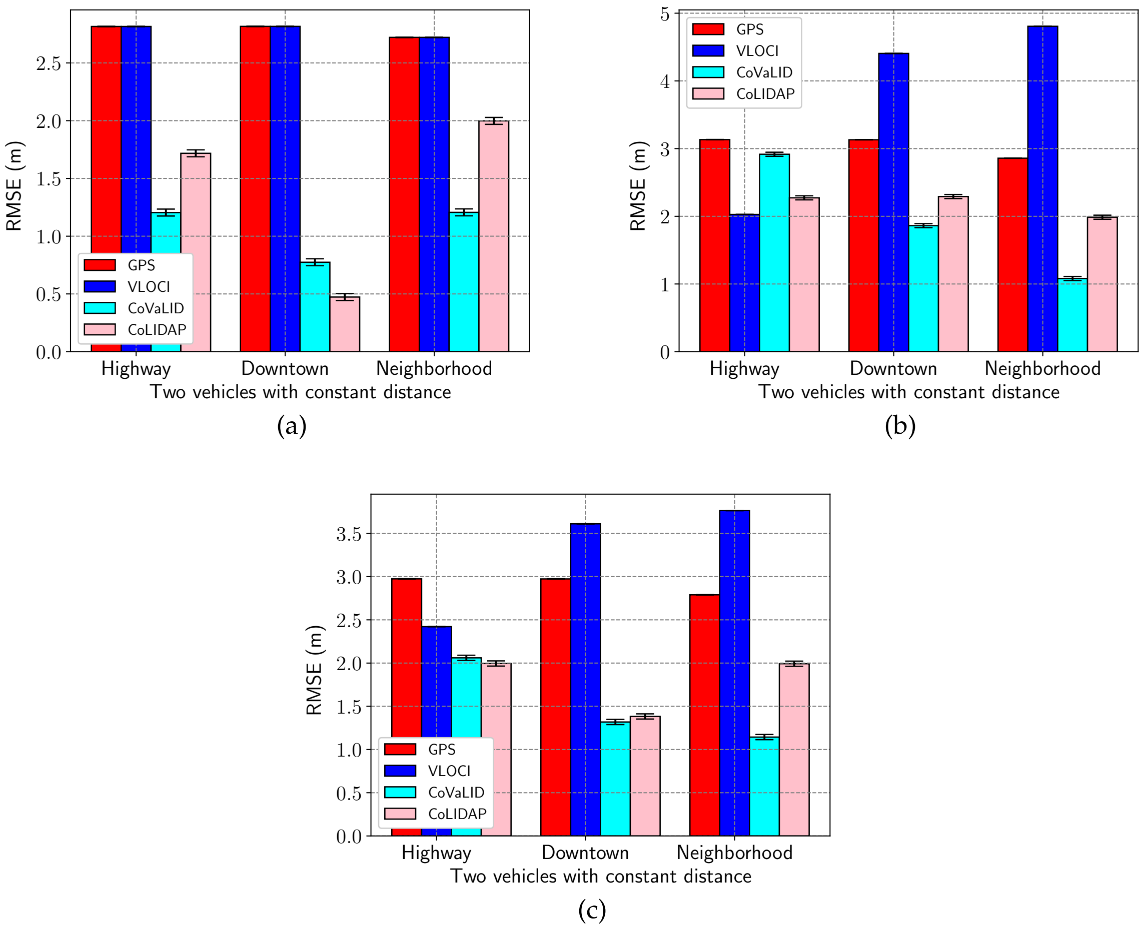


Figure 24 – RMSE values regarding the impact of a straight-line trajectory in downtown, highway, and neighborhood scenarios for the (a) x-axis, (b) y-axis, and (c) both axes.

the CoLIDAP algorithm has better accuracy when compared to CoVaLID, VLOCI, and GPS. Moreover, in the downtown scenario using the same trajectory, our proposed solution presents almost the same accuracy as CoVaLID, and both overcome VLOCI and GPS approaches. However, in this scenario, the CoLIDAP reaches its best accuracy. It can be explained due to the scenario characteristics, such as lower mean velocities when compared to highway scenarios, and more than one lane streets where the nearby vehicles are closer to the target. As a result, distance information is more reliable, which improves CoLIDAP accuracy. In the neighborhood scenario using both trajectories, the CoLIDAP algorithm has almost the same behavior and performed better than VLOCI, and GPS, whereas CoVaLID reaches the best accuracy in this scenario, on average in both axes. Another interesting point is that the VLOCI algorithm can minimize GPS

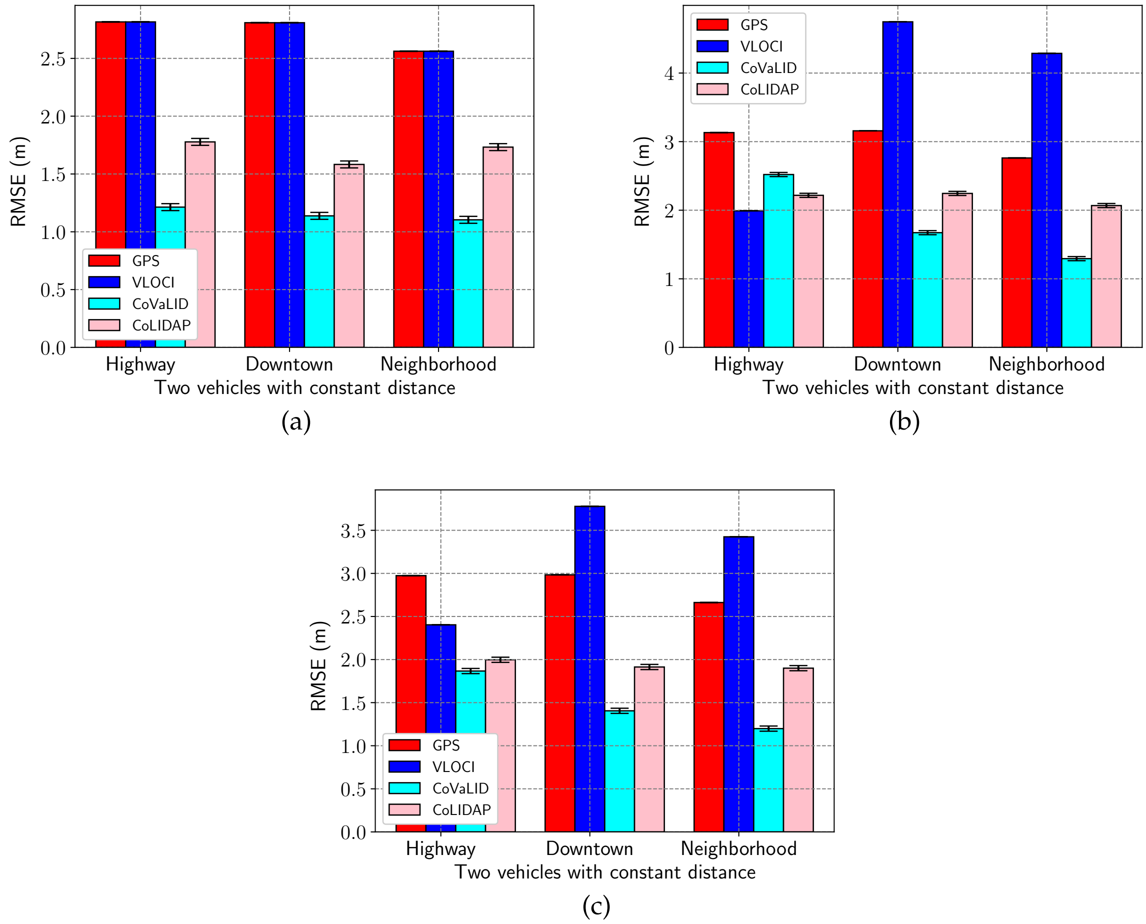


Figure 25 – RMSE values regarding the impact of a trajectory with curves in downtown, highway, and neighborhood scenarios for the (a) x-axis, (b) y-axis, and (c) both axes.

error only in the highway scenario, since it was developed and assessed in this type of scenario.

Overall, the presented results support that the CoLIDAP algorithm can be affected by vehicle trajectory, especially in trajectories with curves. Also, CoLIDAP overcomes the CoVaLID algorithm, on average of both axes in the highway scenario using a straight-line trajectory, whereas, in downtown, both have almost the same accuracy. Furthermore, the CoLIDAP can improve both VLOCI and GPS accuracy for all tested scenarios.

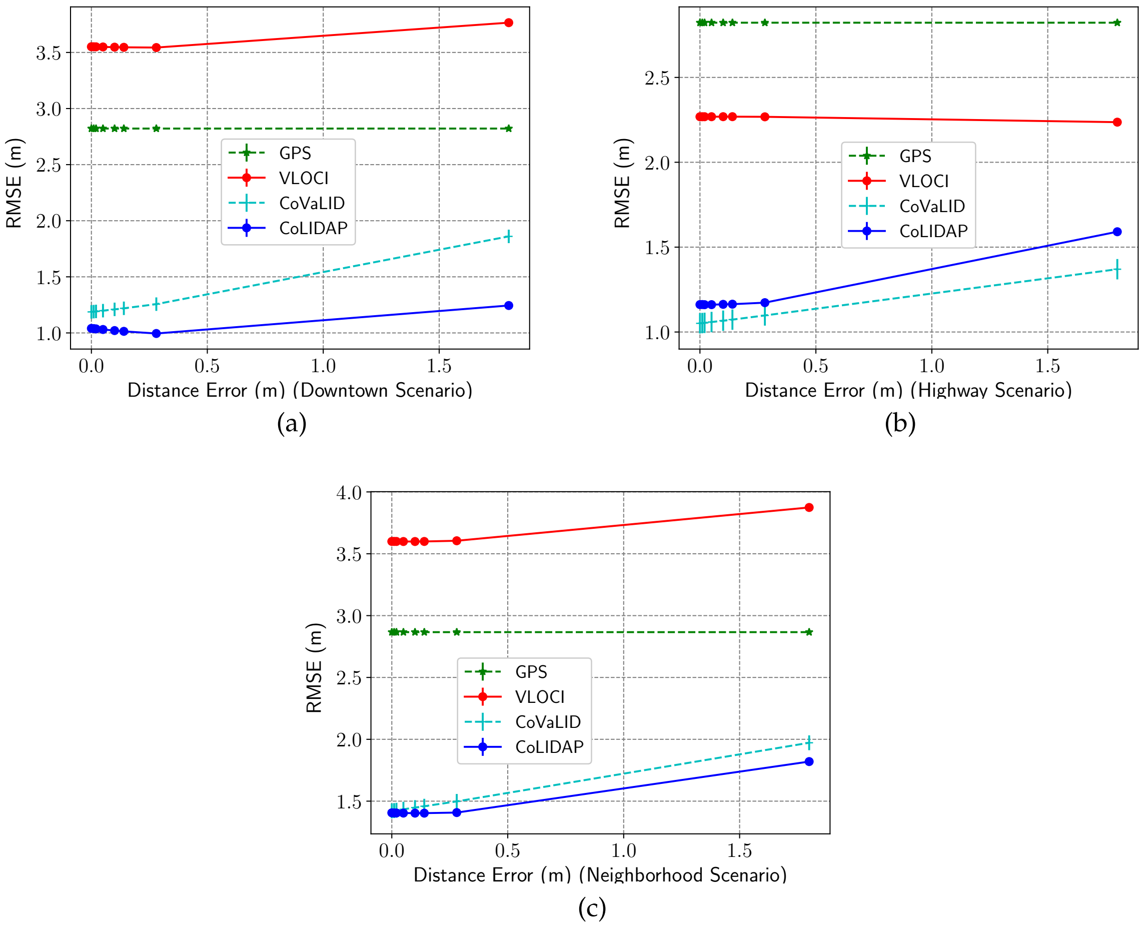


Figure 26 – RMSE values regarding the impact of distance information error, on average of both axes, in a random trajectory for (a) downtown, (b) highway, and (c) neighborhood scenarios.

5.5.3 Impact of Distance Information Error

To evaluate the impact of the distance information as reported by the sensors, we are taking into account the specifications presented in (MULLER, 2017), shown in Table 12. Furthermore, we simulated all scenarios with 10 vehicles with random velocity and distance, and a constant GPS error at 2 meters. We divided all scenarios into random, straight-line, and trajectories with turns. Finally, for the sake of simplification, we are using the RMSE values on average of both axes.

The results described in Figures 26a, 26b, and 26c, suggest that CoLIDAP has the same behavior in all 3 different scenarios using a random trajectory. It is interesting to note that the bigger the distance information error, the more our proposed solution accuracy is affected, mainly in the highway and neighborhood scenario. In the first, can

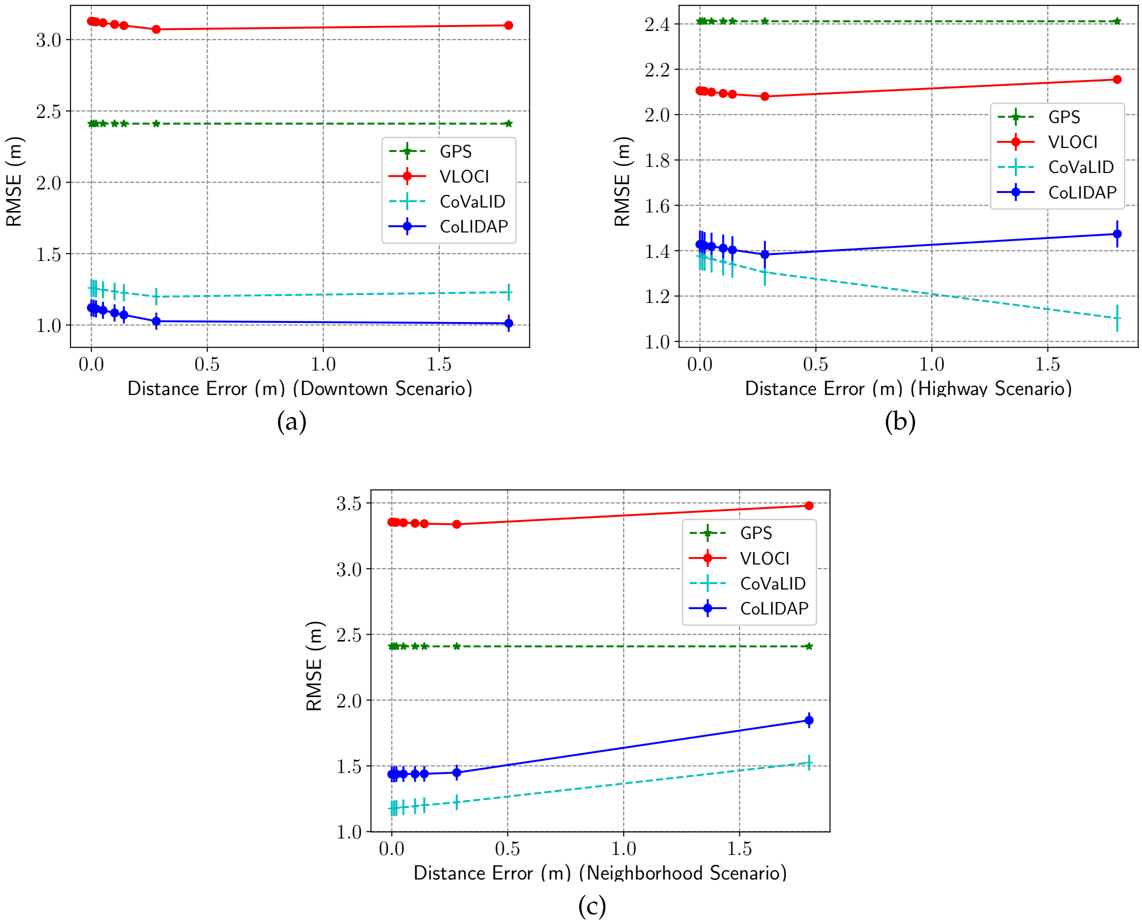


Figure 27 – RMSE values regarding the impact of distance information error, on average of both axes, in a straight-line trajectory in (a) downtown, (b) highway, and (c) neighborhood scenarios.

be affected due to higher vehicle velocities, whereas the latter can be affected due to the higher distances among nearby vehicles regarding the target.

Also, we can notice that in the downtown scenario, the CoLIDAP reached its best performance due to the scenario characteristics that vehicles are closer to the target which yields better cooperation among nearby vehicles with more reliable distance information. Moreover, the CoLIDAP algorithm has the best accuracy when compared to all other approaches, in both downtown and neighborhood scenarios, whereas in the highway scenario, CoVaLID overcomes the CoLIDAP algorithm for the same reasons mentioned before.

Working with the straight-line trajectory, the RMSE values show that in both highway and downtown scenarios, the CoLIDAP algorithm presented an almost constant accuracy, as seen in Figures 27a, and 27b. However, the best performance is in the downtown scenario because of trajectory characteristics, straight-line, and the PF capability to deal with noisy distance information. In this scenario, CoLIDAP overcomes all the evaluated approaches. On the other hand, the worst CoLIDAP performance was in the neighborhood scenario (as shown in Figure 27c) because of the higher distance among nearby vehicles and the lower vehicles' velocities. Furthermore, in the highway scenario, the CoVaLID reaches better accuracy when compared to the others. However, when the distance information error is small, the CoLIDAP and CoVaLID have the same accuracy. Another interesting point is that the VLOCI algorithm improved GPS coordinates only in the highway scenario for the same reasons mentioned in 5.4.2.

According to RMSE values, in trajectories with curves, we can notice that when increasing distance information error, our proposed solution accuracy, in both highway and neighborhood scenarios (seen in Figures 28b and 28c), was almost not affected because of two reasons. First, when using trajectories with turns in the highway scenario, the velocities decrease, helping to maintain the CoLIDAP accuracy almost constant. Second, in the neighborhood scenario, nearby vehicles can become closer to the target, since all vehicles should minimize their velocities to make the turn. However, in the downtown scenario (as shown in Figure 28a), CoLIDAP was severely affected since buildings and other obstacles can disturb the sensors' measurements. Moreover, CoLIDAP has better results when compared to all other approaches in the downtown scenario, until 0.25m of distance information error, for all other tested cases, the CoVaLID performed better.

Overall, in scenarios using trajectory with curves, CoVaLID has the best performance when compared to all other tested approaches. In contrast, in random trajectories, which is similar to the ones used in the real-world, the CoLIDAP algorithm has the best accuracies when compared to CoVaLID, VLOCI, and GPS.

In this section, we depict the impact of each type of sensor that can be used to gather distance information. Also, the results support that both trajectories and noisy distance information can disturb the CoLIDAP algorithm somehow.

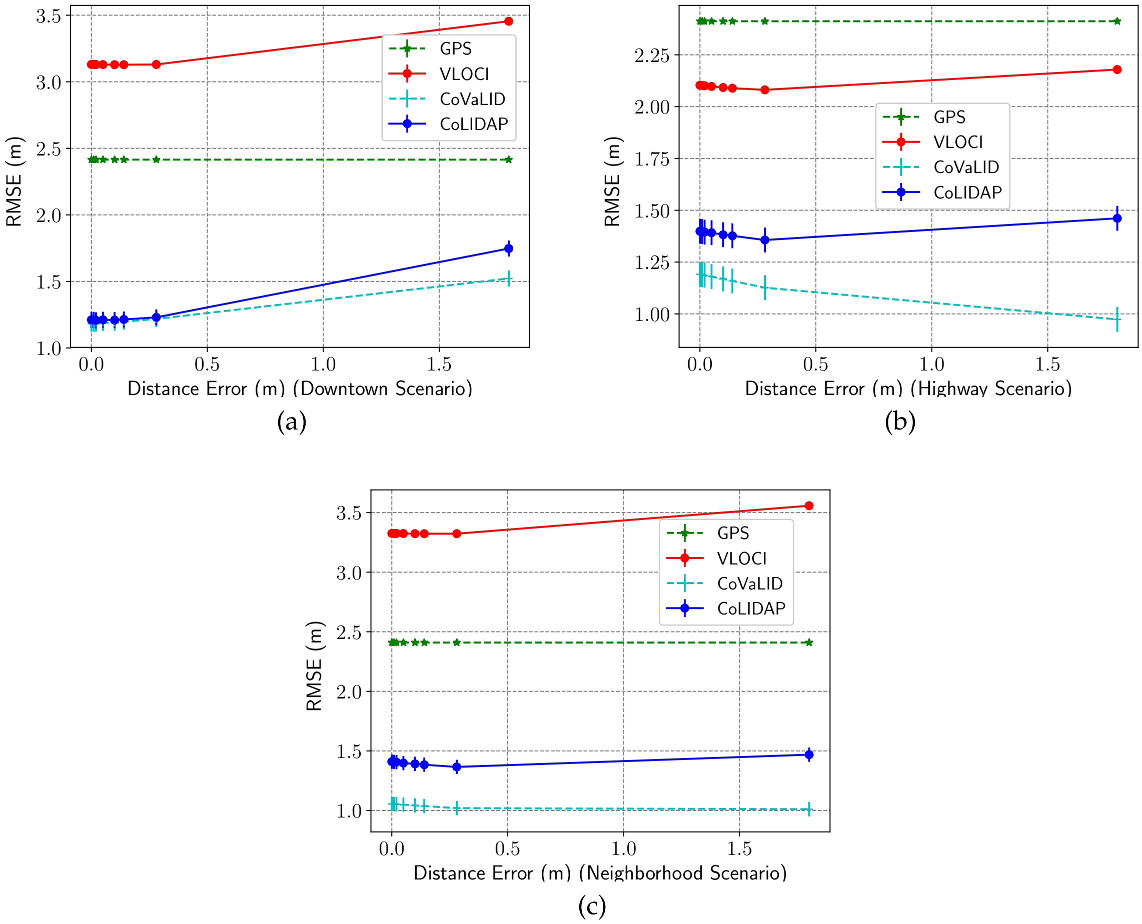


Figure 28 – RMSE values regarding the impact of distance information error, on average of both axes, in a trajectory with curves in (a) downtown, (b) highway, and (c) neighborhood scenarios.

5.6 Sensors Analysis

In this work, we assessed cameras, lasers, and radars as sensors that give us the distance information. This distance information is key information used in the CoLIDAP algorithm to improve the vehicles' localization. Thus, in order to suggest which sensor is more suitable to gather distance information, we highlighted the pros and cons of each one, as follows.

Cameras are equipment that can provide distance information with accuracy about 0.01m and high update rates. However, the camera's range is limited to 10m (MULLER, 2017). Moreover, the camera's efficiency can be disturbed when in contact with lights, such as sunlight and other vehicles' lights. In our simulations, we can notice that cameras can provide a reliable distance information when the neighbors are up to 10m from the target. However, we did not assess the shortcoming condition using cameras exposed to lights.

Laser sensors can also give the distance information, although it is necessary two consecutive scans to give the relative speed information. The lasers are considered a reliable tool to measure distance. However, they can be severely disturbed when exposed to rain, fog, and snow to cite a few. In our simulations, we used two different brands of lasers, and the RMSE values show that they did not significantly impact CoLIDAP regarding its accuracy. As a limitation, we did not assess the laser in such unfavorable situations, as earlier mentioned, which can disturb the lasers' distance information.

Alternatively, the radar sensors can measure the relative distance and speed of an object with a range of up to 250m. These sensors are typically used to tackle localization problems in VANets since they perform well when exposed to unfavorable environmental conditions. However, most radar sensors have static pieces, which affects the across-track accuracy, as seen in the previous section results, where CoLIDAP had its accuracy impacted more in the y-axis than in the x-axis.

In general, when comparing the three sensors, we can notice that lasers and cameras need a considerable amount of data due to the use of a 3D environmental description at a high computational cost, whereas radars can detect an object but with a lower resolution. Regarding the prices, the lasers are the most expensive, while the cameras are the cheapest. This information is important since it can affect the total cost of a solution. Also, it is possible to combine information of all three sensors using the advantages of each one and apply a data fusion technique to improve the localization accuracy.

5.7 Chapter Conclusions

The presented results support that our proposed algorithms can be used as a solution to the localization problem in VANets. Also, we can notice that both the CoVaLID and CoLIDAP can overcome the VLOCI algorithm, and improve GPS position. The main contribution of this work is that we can achieve a high level of accuracy using only a single anchor node.

Still, regarding to the use only a single anchor node, the CoLIDAP performs better than the CoVaLID algorithm only in the highway scenario, whereas, regarding straight-line trajectories impact we can observe that the CoLIDAP overcomes the CoVaLID also only in the highway scenario. In contrast, in trajectories with curves, the CoVaLID has better performance when compared to the CoLIDAP algorithm. Last, concerning the distance information error, using random trajectories, the CoLIDAP shows better accuracy in both downtown and neighborhood, whereas, in trajectories with curves, the CoVaLID performed better.

Overall, our proposed algorithms can improve GPS error. The results lead us to think the CoVaLID is more suitable for lower vehicles velocities scenarios, such as downtown and neighborhood scenarios. On the other hand, the CoLIDAP is more appropriated to higher velocities scenarios, such as on the highway scenario.

6

CONCLUSIONS

This chapter summarizes the thesis conclusions and future work directions. We first present the thesis conclusions in Section 6.1. Then, in Section 6.2, we describe the future directions of this work. Last, we show the list of publications achieved during the development of this thesis, in Section 6.3.

6.1 Thesis Conclusions

In this thesis, we have proposed a new position estimation technique for VANets that based on trigonometry concepts combined with data fusion technique to improve GPS positions. Our solution improves the GPS position of nearby vehicles and minimizes their errors through an extended Kalman filter (CoVaLID algorithm), and a Particle Filter (CoLIDAP) that perform the data fusion of both GPS and distance information to provide a precise estimation for the vehicle's positions within the network area. Also, our solution takes advantage of a weighted average method to put more confidence in distance information given by neighbors closer to the target. We evaluated and tested our solution through simulations in three real-world maps, such as highway, downtown, and neighborhood.

Our results show that the CoVaLID algorithm can minimize the average error between the perfect position and the position given by GPS by 63%. In addition, CoVaLID can estimate the node position better than when compared to the state-of-the-art VLOCI algorithm, in all real-world-tested maps using a less quantity of nodes as verified by RMSE and MAE values. Regarding the CoLIDAP algorithm (using a Particle Filter), the simulation results show that our proposed solution can minimize the GPS error, on average, about 57%. Whereas, when compared to the VLOCI algorithm, in the highway scenario where VLOCI had better performance than GPS, the CoLIDAP also can improve the VLOCI algorithm by 51%. It is worth mentioning that we can achieve those accuracies using only one anchor node along with both GPS and sensor distance information. Hence, these presented results answer our first research question and support that it is possible to minimize GPS error using our proposed solution. Also, our focus is to improve the GPS errors. In this work, we are not dealing with scenarios where GPS signal is not available.

When increasing the number of vehicles we can observe that it did not severely affect our both algorithms, CoVaLID and CoLIDAP due to the weighted average method applied. Moreover, it is noticed that in a straight-line trajectory CoVaLID presented a better performance in the highway scenario, in the x-axis, whereas, in the y-axis, it had similar RMSE values for all three tested scenarios. Furthermore, results support that the CoLIDAP can improve CoVaLID in all tested scenarios, especially when increasing the number of vehicles. Moreover, CoLIDAP overcomes CoVaLID in the highway scenario regarding the straight-line trajectory, one of the main drawbacks of CoVaLID algorithm.

Furthermore, the results presented in Sections 5.4 and 5.5 support that despite both CoVaLID and CoLIDAP can be affected by the distance information error, the use of a heuristic to put more weight in the distance information given by neighbors closer to the target and less weight for the ones that are farther can minimize these effects in our proposed algorithms, which answers our third research question.

Concerning our fourth and last research question, we can observe that the distance information error affects the accuracy of our proposed algorithm, mainly in the highway and neighborhood scenario, as shown in Sections 5.4.3, and 5.5.3. The first can be affected due to higher vehicle velocities, whereas the latter can be affected due to the higher distances among nearby vehicles regarding the target. which is provided by sensors such as radars, lidars, and cameras. However, results support that the use of a Bayesian stochastic model, such as an Extended Kalman Filter, and a Particle Filter are able to minimize these effects, which answers our fourth research question.

Overall, the performance of both CoVaLID and CoLIDAP is dependable on which sensor is used to provide the distance information. Also, regarding the impact of the distance information error when using random trajectories, the CoLIDAP also performed better than CoVaLID. Thus, results suggest that in scenarios using trajectory with curves, CoVaLID has the best performance when compared to all other tested approaches. In contrast, in random trajectories, which is similar to the ones used in the real-world, the CoLIDAP algorithm has the best accuracies when compared to CoVaLID, VLOCI, and GPS.

Last, we presented an exploratory analysis of the sensors used to provide distance information. We simulated seven different sensors: one camera, two lasers, and four radars in order to gather distance information in the most like way as in the real-world. We analyze each sensor behavior and described their advantages and drawbacks, and how they could be used in different real-world maps. As consequence, it is noticed that our proposed algorithms CoVaLID and CoLIDAP are suitable as a solution for localization problems in VANets.

6.2 Future Work

As future work, we can point out some interesting directions. For instance, we can use some other trigonometry concept to tackle the limitation when the nearby vehicles lose their line-of-sight or even use some other technique such as MM or dead reckoning.

Another interesting direction is that we can assume the nature of the localization problem as linear, which can be a fair assumption, especially in straight-line trajectory scenarios. So, we can test a Kalman Filter and compare it to CoVaLID and CoLIDAP algorithms and verify if it can improve their accuracies in these scenarios.

We can also extend and evaluate the performance of CoVaLID, and CoLIDAP in GPS outage scenarios. For that purpose, we aim at combining our proposed solutions with V2I communication to gather the distance information from the target vehicle to roadside units. We also aim at combining dead reckoning data from nearby vehicles in the same way we combine GPS data in order to cooperatively improve the localization in areas with no GPS signals.

Another possible future work is to perform data fusion in more than one source of distance information. We can gather distance information from a camera, a radar, and a laser. Then, to make the fusion in order to get less noisy information and use it to feed CoVaLID and CoLIDAP algorithms.

Finally, we can test and analyze the behavior of other methods for data fusion such as Maximum Entropy (ME), Maximum Likelihood (ML), and Multidimensional Scaling (MDS).

6.3 List of Publications

Publications by the author during the doctorate:

- **Conference Papers:**

- Felipe Leite Lobo, Moyses Lima, Horacio Oliveira, Khalil El-Khatib, and Joshua Harrington. 2017. SoLVE: A Localization System Framework for VANets using the Cloud and Fog Computing. In Proceedings of the 6th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications (DIVANet '17). Association for Computing Machinery, New York, NY, USA, 17–22. DOI:https://doi.org/10.1145/3132340.3132350.

- Joshua Harrington, Jesse Lacroix, Khalil El-Khatib, Felipe Leite Lobo, and Horácio A.B.F. Oliveira. 2017. Proactive Certificate Distribution for PKI in VANET. In Proceedings of the 13th ACM Symposium on QoS and Security for Wireless and Mobile Networks (Q2SWinet '17). Association for Computing Machinery, New York, NY, USA, 9–13. DOI:https://doi.org/10.1145/3132114.3132730.

- Felipe Leite Lobo, Danilo Carvalho Grael, Horacio A.B.F. de Oliveira, Leandro Aparecido Villas, Abdulaziz Almehmadi, and Khalil El-Khatib. 2019. A Distance-based Data Fusion Technique for Minimizing GPS Positioning Error in Vehicular Ad Hoc Networks. In Proceedings of the 15th ACM International Symposium on

QoS and Security for Wireless and Mobile Networks (Q2SWinet'19). Association for Computing Machinery, New York, NY, USA, 101–108. DOI:https://doi.org/10.1145/3345837.3355956

- **Periodical Papers:**

- Lobo, F.; Grael, D.; Oliveira, H.; Villas, L.; Almehmadi, A.; El-Khatib, K. Cooperative Localization Improvement Using Distance Information in Vehicular Ad Hoc Networks. Sensors 2019, 19, 5231.

- Lobo, F.; Grael, D.; Oliveira, H.; Villas, L.; Almehmadi, A.; El-Khatib, K. Cooperative Localization Improvement using Particle Filter in Vehicular Ad Hoc Networks. Computer Communications. (**Submitted**)

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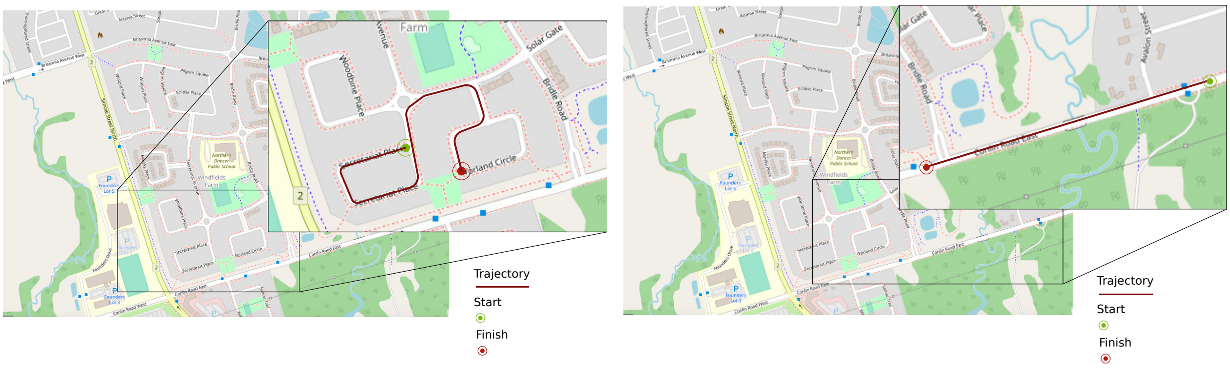
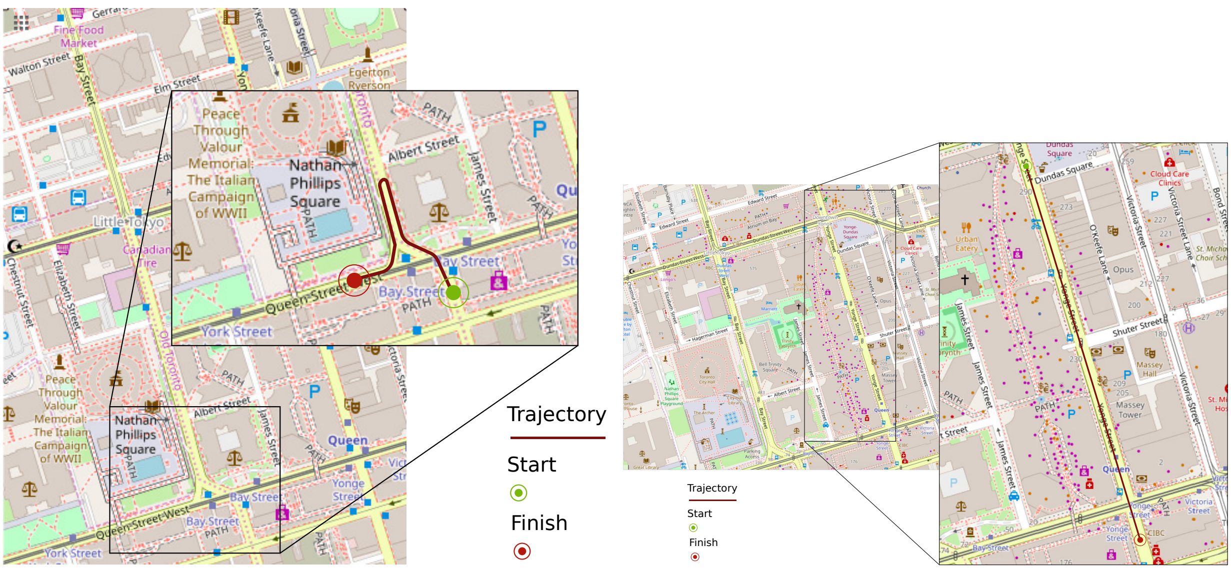
A

This appendix describes the trajectories used in Sections 5.4.2 and 5.5.2.



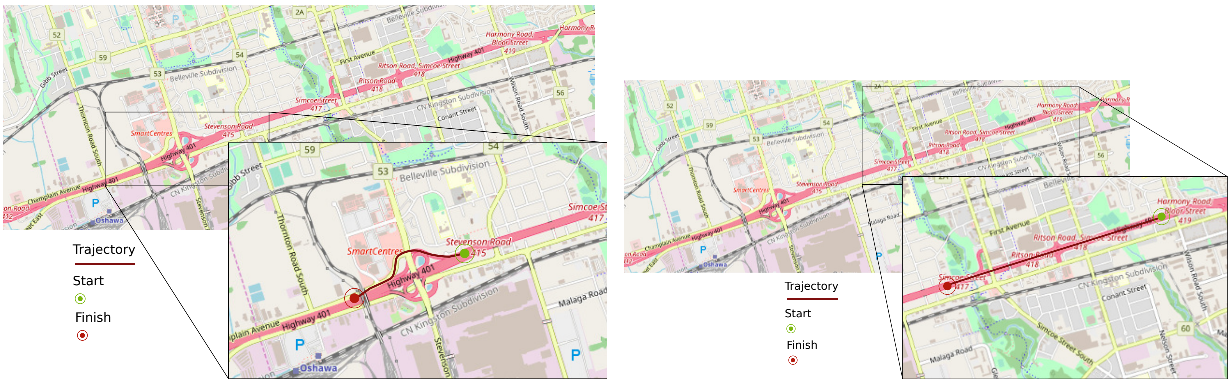
(a) Neighborhood Scenario with Curves. (b) Straight-Line Neighborhood Scenario.

Figure 29 – Trajectories in the Neighborhood Scenario.



(a) Downtown Scenario with Curves. (b) Straight-Line Downtown Scenario.

Figure 30 – Trajectories in the Downtown Scenario.



(a) Highway Scenario with Curves.
(b) Straight-Line Highway Scenario.

Figure 31 – Trajectories in the Highway Scenario.