RELIABLE VEHICLE-TO-VEHICLE WEIGHTED LOCALIZATION IN VEHICULAR NETWORKS

by

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ABSTRACT

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Vehicular Ad Hoc Network (VANET) supports wireless communication among vehicles using vehicle-to-vehicle (V2V) communication and between vehicles and infrastructure using vehicle-to-infrastructure (V2I) communication. This communication can be utilized to allow the distribution of safety and non-safety messages in the network. VANET supports a wide range of applications which rely on the messages exchanged within the network. Such applications will enhance the drivers' consciousness and improve their driving experience. However, the efficiency of these applications depends on the availability of vehicles real-time location information. A number of methods have been proposed to fulfill this requirement. However, designing a V2V-based localization method is challenged by the high mobility and dynamic topology of VANET and the interference noise due to objects and buildings. Currently, vehicle localization is based on GPS technology, which is not always reliable. Therefore, utilizing V2V communication in VANET can enhance the GPS positioning. With V2V-based localization, vehicles can determine their locations by exchanging mobility data among neighboring vehicles.

In this research work, we address the above challenges and design a realistic

V2V-based localization method that extends the centroid localization (CL) by assigning a weight value to each neighboring vehicle. This weight value is obtained using a weighting function that utilizes the following factors: 1) link quality distance between the neighboring vehicles 2) heading information and 3) map information. We also use fuzzy logic to model neighboring vehicles' weight values.

Due to the sensitivity and importance of the exchanged information, it is very critical to ensure its integrity and reliability. Therefore, in this work, we present the design and the integration of a mobility data verification component into the proposed localization method, so that only verified data from trusted neighboring vehicles are considered. We also use subjective logic to design a trust management system to evaluate the trustworthiness of neighboring vehicles based on the formulated subjective opinions.

Extensive experimental work is conducted using simulation programs to evaluate the performance of the proposed methods. The results show improvement on the location accuracy for varying vehicle densities and transmission ranges as well as in the presence of malicious/untrusted neighboring vehicles.

RELIABLE VEHICLE-TO-VEHICLE WEIGHTED LOCALIZATION IN VEHICULAR NETWORKS

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CHAPTER 1
INTRODUCTION

1.1 BACKGROUND

Vehicular Ad Hoc Networks (VANETs) have attracted the interest of many researchers all over the world. With advances in technologies in wireless networks, vehicles will be able to communicate with each other via vehicle-to-vehicle (V2V) communication and roadside units (RSU) via vehicle-to-infrastructure (V2I) communication.

Wireless Access in Vehicular Environments (WAVE) [1] defines the architecture, protocols, services and interfaces to enable secure V2V and V2I communications. When vehicles are equipped with WAVE, they can exchange beacon messages periodically, including location, mobility and movement characteristics with their neighbors. In addition, safety-related information can also be propagated throughout the network to inform drivers, in advance, so required actions are taken to avoid accidents and save lives. Traffic-related information can also be disseminated to provide efficient driving trips.

Currently, VANET is a major component of the intelligent transportation system (ITS). VANET's main goal is to provide safety and pleasant driving experience for both drivers and passengers. Safety applications are crucial motive for VANET development due to their impact in reducing accidents and saving lives. However, all of these applications [2] [3] [4] demand a real-time accurate position of vehicle and therefore, requires a localization method to determine the physical location of the vehicle [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] [15] [16] [17] [18] [19].

In this work, we study the localization problem in VANET and propose two localization methods that complement GPS by utilizing V2V communication. Both solutions take advantages of using V2V communication to construct a local map of the vehicle and its neighboring vehicles to overcome the GPS outages and errors. We also investigate the impact of incorrect mobility data, exchanged in the beacon messages, on the proposed localization method. To mitigate this impact, we propose a verification system to detect vehicles with untrusted behavior. Isolating untrusted vehicles has improved the performance of the localization method and the network in general.

1.2 PROBLEM STATEMENT

The location of the vehicle is crucial to many VANET applications. In fact, the performance of these applications depend highly on the vehicle's ability to determine its location within the network anytime and anywhere. Therefore, a number of localization methods and protocols have been proposed. For instance, the most popular method for localization is GPS; other techniques include Geographical Information System (GIS), Dead Reckoning (DR), Cellular Phone Technology, V2V-Based Localization, and V2I-Based Localization. However, GPS, which is considered a global positioning system, suffers from outages, especially in areas where signals can be easily interrupted. The GIS method relies on map matching technology, and it is usually combined with other techniques to provide location information. DR can only be used for a short period of time. Cellular phone technology is very expensive since it depends on the used amount of airtime. In V2I-based localization, the accuracy of the location depends highly on the proper configuration of the RSUs, which can be expensive in terms of cost and time. On the other hand, V2V-based localization takes advantages of the VANET environment and utilizes the V2V communication to allow vehicles to determine their locations in relation to other neighboring vehicles. Table 1.1 summarizes the advantages and disadvantages of each localization method.

Table 1.1: Localization Methods

Method	**Advantages**	**Disadvantages**
GPS	Most vehicles are embedded with a GPS receiver and satellites usage is free	Signal interference and outages
Geographical Info System (GIS)	Uses digital maps	Needs to be combined with GPS
Dead Reckoning (DR)	Uses data from the embedded sensors	Reply heavily on the estimated location of the last fixed position
Cellular Phone Technology	Uses cellular base station	Very expensive
V2V-Based Localization	Uses V2V communication	Bandwidth consumptions
V2I-Based Localization	Does not depend on GPS	Requires proper installation of roadside units

Designing a localization technique for VANET involves a number of challenges due to the following factors:

- Dynamic topology due to the high and variable speeds of the vehicles in the network. This causes the connectivity between the vehicles to change frequently and rapidly.
- Objects and other obstacles that exist on roads can interfere with the radio signal and affect its power and strength [20].

Existing V2V-based localization methods do not adequately address the above challenges. Most of them require a certain number of neighboring vehicles for location estimation, which cannot be guaranteed in VANET environment. Moreover, they do not also consider the noise that may affect the received signal strength. In VANET, objects on roads can interfere with the radio signals. Therefore, such interference needs to be taken into account, otherwise, this will affect the accuracy of the results. In addition, since the data is exchanged among vehicles, it is very important to validate the integrity and validity of such data before using it in the location estimation.

Here we propose the development of two V2V-based localization methods, that address the above challenges and satisfy VANET constraints. We also propose a verification system that can effectively verify the mobility data announced by the vehicles in the network to determine if the vehicles information can be considered in the localization method or not.

1.3 CONTRIBUTIONS

The contributions are as follows:

1. Survey and classification of localization techniques in VANET (Chapter 2).

2. Design and evaluation of a V2V-based weighted localization method that uses distance information to estimate the vehicle's location [21].

3. Design and evaluation of a V2V-based weighted localization method that uses distance and heading information to estimate the vehicle's location [22].

4. Design and evaluation of a multi-factor V2V-based weighted localization method [23] (Chapter 3).

5. Design and evaluation of fuzzy logic based localization method [24] (Chapter 4).

6. Design and evaluation of a mobility data verification system for vehicle localization in VANET [25] (Chapter 5).

7. Design and evaluation of a subjective logic based trust management system for vehicle localization in VANET [26] (Chapter 6).

1.4 ORGANIZATION

The remainder of this document is organized as follows. Chapter 2 contains the literature review and classification of the localization methods and related work in verification systems. We introduce our first localization method in Chapter 3. In Chapter 4, we present our second localization method. Chapter 5 presents the proposed mobility data verification system. Subjective logic based management system is presented in Chapter 6. Finally, Chapter 7 presents the conclusion along with future work.

CHAPTER 2
LITERATURE REVIEW

This chapter surveys the proposed solutions and related work in localization techniques in VANET. It also presents a classification of these techniques based on the use of GPS (Global Positioning System), which is the most popular method in localization. The discussion is divided in two sections. The first section focuses on localization methods and the second section discusses the mobility data verification systems that are proposed to validate the integrity of the received location information.

2.1 LOCALIZATION TECHNIQUES

Most VANET applications assume that vehicles can determine their real-time exact position using GPS (Global Positioning System); this requires that each vehicle must have a GPS receiver embedded into it. However, due to nature of VANET and the sensitivity of GPS signals, positions obtained by GPS are inaccurate and insufficient for many VANET applications, especially safety applications. To overcome these limitations many localization techniques have been proposed to either improve GPS or replace it with more reliable methods. We classify these techniques as follow:

1. *GPS-only*: In this class the localization technique uses GPS alone for determining the vehicle location.

2. *GPS-assisted*: In this class the GPS method is combined with other localization techniques to enhance the accuracy of vehicle location.

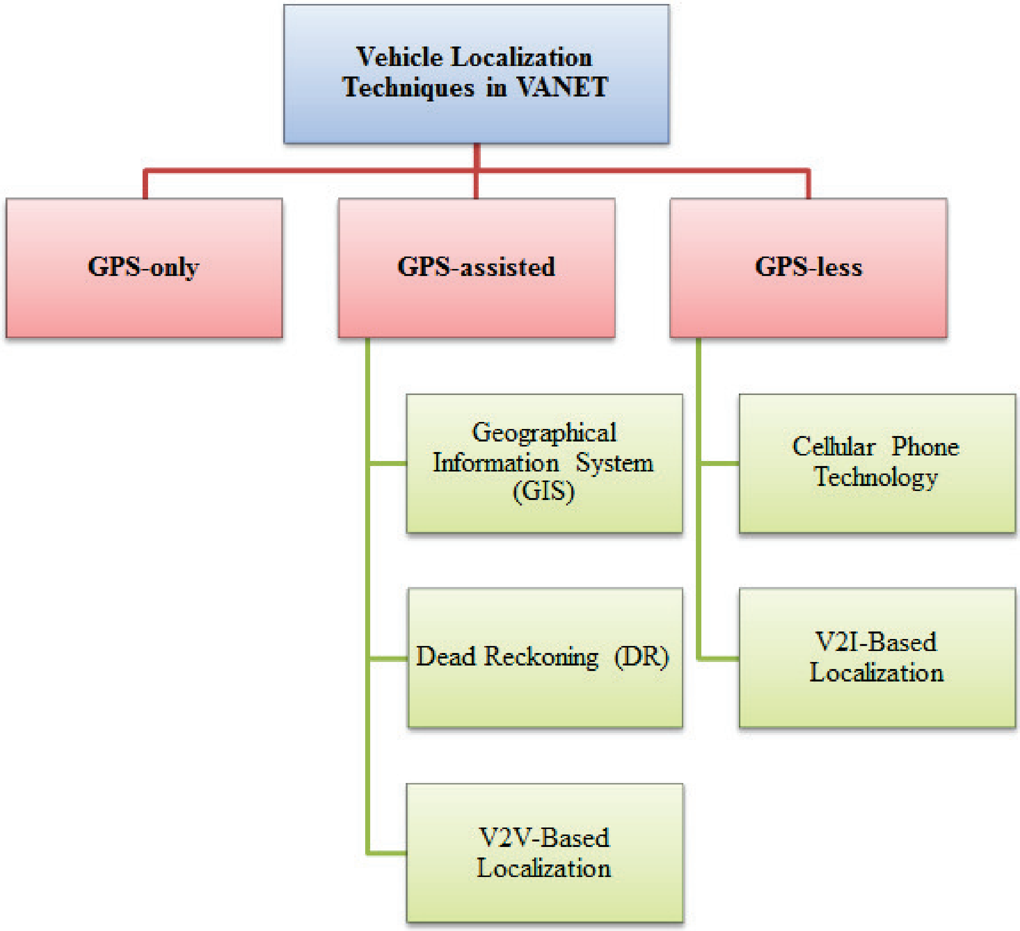

Figure 2.1: Classification of Vehicle Localization in VANET

3. *GPS-less*: In this class the localization techniques do not use or rely on GPS for determining the vehicle location.

Figure 2.1 summarizes the different classification of vehicle localization techniques in VANET.

Although, all of these techniques have their pros and cons, they all aim to provide an accurate localization method that is reliable to be used in any VANET application e.g. safety applications. However, due to the nature of VANET and the importance of precise location of the vehicle, localization is a challenging area for a research. Below are some of the challenges in VANET:

- Vehicles can move really fast and therefore updating their positions must be

Table 2.1: Vehicle Localization Techniques Comparison

Technique	Advantages	Disadvantages	Cost
GPS-only	Most vehicles are embedded with a GPS receiver	Signal interference and outages	Satellites usage is free
GPS-assisted	- Uses vehicle Sensors data - Uses VANET communication media	- Needs to be combined with GPS - Highly demands on the number of vehicles	Bandwidth consumption
GPS-less	Does not rely on GPS	Depends highly on the proper configuration of roadside units	Installation of roadside units

done in a fast and efficient way, otherwise the location information will be obsolete and false information will be propagated through the network, which will eventually affect the performance of VANET.

- Vehicles travel through roads with different structures. For instance, tunnels, highways and urbans. Such infrastructure can easily affect and interfere the accuracy of the localization technique. Therefore, current factors must be considered in determining the accurate position of the vehicle.

Table 2.1 summarizes the advantages and disadvantages of the three different classes of vehicle localization, GPS-only, GPS-assisted and GPS-less.

2.1.1 GPS-Only Localization Techniques

GPS, Global Positioning System, is the most popular method in localization; in fact, it is the universal measurement for positioning objects. In this technique, it is always assumed that the vehicle has an embedded device, receiver, which can read signals from satellite and use that information to calculate its position. The GPS system consists of 29 orbiting satellites, originally designed by the US military in 1970s, where 24 of them are actually needed for global coverage and 5 of them are used as backups. In order for the receiver to discover the position properly, a GPS receiver needs access, in a clear line-of-sight, to at least three satellite signals for a 2D positioning and at least four satellite signals for a 3D position computation. The GPS receiver uses Time of Arrival (TOA) technique to estimate its distance from the satellites and calculates its position (e.g., latitude, longitude and altitude) using trilateration [3].

However, in practice, GPS signals can be easily blocked or interrupted with obstacles such as high buildings, tunnels, forests, and even electronic interference by a different satellite can affect these signals. Therefore, vehicles traveling in these areas, where obstacles persist, are likely to encounter GPS outages. Moreover, observations have shown that GPS errors are propagated between receivers in the same location [19].

To overcome these drawbacks and to increase the accuracy and to resolve delay problems, two advanced techniques have been proposed: Differential GPS (DGPS) and Assisted GPS (A-GPS). In DGPS, The GPS receiver will receive the signal and calculate its position with the standard method. At the same time, the ground station, which is placed in an exact known coordinate, receives the same signal at a known spot. The difference between what is received and the actual known spot is calculated and broadcasted as a DGPS signal. The properly equipped GPS receiver will make the necessary calculations to correct its position [27]. The major issue with DGPS is that it required a special kind of infrastructure, where ground stations must be used to broadcast the DGPS signals. In addition, in urban areas, tall buildings obstruct the GPS signals, so the use of DGPS cannot maintain an accurate position.

On the other hand, A-GPS, suited for mobile devices offers superior accuracy, availability, and coverage at an extra cost. An assistance server is added to help the GPS receiver in determining its position in a quick and efficient way. By the use of A-GPS the position retrieving rate is improved. However, A-GPS relies heavily on cellular network and wireless communication, which makes it expensive to use in vehicle localization. Moreover, some privacy issues are questionable because of the use of third party assistance server [28].

Nevertheless, the use of GPS in vehicle localization is considered unreliable, especially with critical safety application where the precise position plays an important role in avoiding collisions and saving lives. Therefore, a number of solutions have been introduced in the literature, where GPS is combined with other localization techniques, to improve the accuracy of vehicle location.

2.1.2 GPS-Assisted Localization Techniques

Geographical Information System (GIS)

GIS, Geographical Information System, is a tool for managing geographical information. Its database consists of digital maps, which mostly used in navigation systems. With the advance technology in GIS, the spatial information provided by GIS can be used in vehicle localization. In fact, many methods have combined GPS with GIS to enhance the location accuracy. For instance, in [29], the vehicle is equipped with a laser scanner. Therefore, if the GPS location is unavailable, landmarks that are captured are matched against those available in the GIS database and if a matching one is found then the vehicle location will be corrected. The map matching technology, based on pattern recognition, is the main application used in localization when using digital maps stored in GIS database. Map matching process can be divided into two relatively independent processes: First, find the current vehicle traveling road. Second, project current positioning point to the vehicle traveling road [30]. However, map matching technology is usually combined with GPS or other techniques to improve the location accuracy and therefore cannot be considered a localization technique by itself.

Dead Reckoning (DR)

Dead Reckoning technique is used for estimating the position of the vehicle based on the last known location. It also uses data, e.g., direction, speed, distance, time, etc., collected by the vehicle sensors such as wheel odometers, and compass as input factors in determining the new future location [31]. This technique relies on knowing the last determined position, which can be obtained by a GPS receiver (commonly used) or by a known physical location, e.g., road, parking lots. However, DR is subject to errors due to the fact that it relies heavily on the data read from equipped sensors in vehicles, which must be accurate in order to determine the location accurately. Moreover, since DR estimates the position based on the previous position, hence it can produce cumulative errors. In order to resolve such errors, one approach is to reset the location periodically and combine it with other localization methods such as GPS and GIS for determining the position which can be only used for short period of time.

V2V-Based Localization

The main scheme of this technique is that the location of a vehicle is estimated in relation to other vehicle(s). In V2V-based localization, a vehicle can determine its position by exchanging distance information messages among its neighbors. This type of technique takes advantages of VANET environment and uses the vehicle-to-vehicle communication to construct a local map of the vehicle and its neighbors. Nevertheless, this technique was initially used in Wireless Sensor Network (WSNs). Figure 2.2 demonstrates how a vehicle can determine its location using location information from its neighboring vehicles (vehicles within its transmission range).

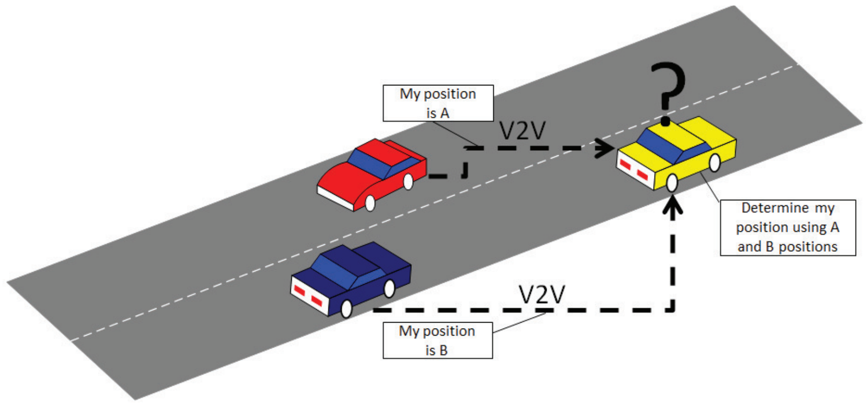

Figure 2.2: V2V-Based Localization

In VANET environment, GPS can be easily interrupted; therefore, V2V communication can be utilized to be combined with GPS to provide a reliable and permanent localization technique for vehicles in the network. Recently a number of solutions have been proposed for the use of V2V-based localization in VANET. The existing schemes are based on the following techniques:

- Trilateration
- Fusion technology using Kalman Filter (KF)
- Geometric pattern matching
- Weighted average

With Trilateration technique, location information is exchanged among neighboring vehicles and used for determining the location of the vehicle. This method is used in [5], [6] and [7]. The issue with this technique is that the accuracy of the location is subject to the number of neighboring vehicles. For instance, the localization method proposed in [5] requires that there should be at least three neighboring vehicles, which are able to communicate and exchange location information, to estimate the location of a vehicle. Due to the odd characteristics of VANET, where topology and mobility are changing frequently and rapidly, having a specific number of neighboring vehicles at a certain time cannot be guaranteed.

The idea behind fusion technology is to combine different sources of information to provide accurate location estimation. With this technique the Kalman Filter (KF) is used in [8] and the Extended Kalman Filter (EKF) and the Particle Filter (PF) are used in [9] to improve the location accuracy. Inter-Vehicle-Communication- Assisted Localization (IVCAL) is proposed in [8]. In this method, the distances between vehicles, along with motion information and GPS measurements are utilized and integrated into a Kalman Filter to enhance the location estimation, specifically in multipath environments. However, inadequate neighboring vehicles and long periods of GPS outage are issues that might affect the proposed localization method and must to be addressed. The authors of [9] have mentioned that in order to increase the accuracy of the location, the cost of computational resources and the calculation time will also increase. While resources are not an issue in VANET, high mobility and varying vehicles speeds require a localization method that is fast to compute.

Grid-based On-road localizaTion system (GOT) is introduced in [10]. In their proposed method, a geometric pattern matching technique is utilized for localization in sparse network. To resolve the issues with sparse networks, they proposed the use of a signal accepting threshold and two fuzzy geometric relationships. Similar to the previously discussed methods, the accuracy of the estimated location depends on the number of neighboring vehicles as well as the proposed signal acceptance threshold value.

In the last technique, weighted average, the location estimation is performed by averaging the location coordinates of the vehicles that are within the transmission range of the vehicle that needs to be localized. The use of weighted average in VANET is proposed in [11], [12] and [13]. In the proposed algorithms, VANET LOCation Improve VLOCI [11] and its extension VLOCI2 [12], the location and distance information exchanged among neighboring vehicles are used by the weighted average function. A weight value is determined and given to each neighboring vehicle, based on distance information. In [11] and [12], the location accuracy is affected by the density of the network and the error in the distance measurement. Another most important issue is that they only considered stationary vehicles and did not consider any mobility in the evaluation of the proposed methods. However, including mobility is an important aspect of VANET. The relative span weighted localization (RWL) is proposed in [13]. In their method, a weighting function is determined by using the received signal strength (RSS) value v within the span of all RSS values. The values of the RSS are obtained from the beacon messages exchanged among vehicles. The minimum RSS v_{min} and the maximum RSS v_{max} are first determined and then RSS span is calculated as follows:

$$v^{\Delta} = v_{max} - v_{min} \tag{2.1}$$

and for node i the proposed weight w_i is computed as shown below:

$$w_i = \frac{v_i - v_{min}}{v^{\Delta}} \tag{2.2}$$

The proposed methods in [13] do only consider the received signal strength. The noise and interference that may affect the strength of the radio signal have not been taken into account in the estimation of the location.

From the discussion above it is clear that there are a number of issues that need to be addressed in the V2V-based localization. Some of these issues are: GPS outages and its commutative errors, the demand on the number of nearby vehicles to estimate the position and the noise that might affect the received signals. Table 2.2 summarizes the previously proposed methods in V2V-based localization.

Table 2.2: V2V-Based Localization Techniques

Method	[5]	[8]	[7]	[10]	[11]
Year	2005	2010	2010	2011	2012
Best case	100% of vehicles obtained their exact location	82% of the vehicle location estimates had errors less than 5m	Location error with less than 4m	All vehicles can calculate their location	Location error with 2.38m
Worst case	0% of vehicles obtained their exact location	N/A	Location error with 8m	Less than 50% of vehicles can calculate their location	Location error with 2.7m
No. of vehicles	GPS-U is 2,4,6,8 vehicles/km/lane GPS-E is greater and less than 3	100	20, 30, 40, 50 and 100	40	10
No. of vehicles required for computation	3	N/A	At least 2	4 - 16	1- 10
Highway environment	10 km with C lanes in two directions	5 km with 2 lanes in one direction	N/A	N/A	N/A
Average Speed	N/A	The right lane contains vehicles that travel at 50 km/h, and vehicles in the left lane travel at a higher speed of 60 km/h	Between 20 km/h and 50 km/h and between 80 km/h and 140 km/h	N/A	N/A
Simulator	ns-2	MATLAB7	ns-2	ns-2	PARAMICS

2.1.3 GPS-Less Localization Techniques

Cellular Phone Technology

Global System for Mobile Communications (GSM), the world most widespread cellular phone technology, can be used in vehicle localization. In GSM, the localization technique uses base stations to find the location of a mobile device in respect to its cell. A GSM base station is typically equipped with a number of directional antennas that define sectors of coverage or cells, each of which has uniquely identifiable cell ID which can provide a rough indication of a position [32].

The geographical position of any device can be determined through various range techniques:

- Received Signal Strength Indicator (RSSI). It works by using the behavior of the signal, basically the strength of the signal, to determine the distance to the closest base station. However, RSSI can be affected and easily changed by obstacles and the surrounding environment, and therefore, a certain technique must be applied to filter such noise on the received signal.

- Time of Arrival (ToA). It estimates the distance from the base station to the receiver by knowing the time of the traveled signal. However, this technique requires a perfect synchronization between the clocks of the base stations and the receivers, which cannot be guaranteed in most cases.

- Time Differences of Arrival (TDoA). It deals with estimating the location using difference time measurement of the traveled signal from the receiver to multiple base stations. This technique is preferable than ToA because synchronization between the clocks of the base stations and the receivers is not required.

- Angle of Arrival (AoA). It estimates the location by measuring the angle of signal arrived from the receiver at multiple base stations by means of antenna array [33].

- Fingerprinting. This is a pattern matching technique that consists of an exhaustive training phase. In the training phase, a database is built to form a mapping from signal characteristics to positions. Then, to find a location, it matches every signal characteristics from the receiver to the position recorded during the training phase [34]. This technique takes into account the noise that may occur and change the received signal. However, the main issue with this is that the database needs to be maintained regularly which is very expensive in term of time and cost.

In GSM, most of the ranging technique such as, Time of Arrival (ToA), Time Differences of Arrival (TDoA) and Angle of Arrival (AoA) can be used to estimate the position. Nevertheless, by knowing the distance to at least three base stations, the position can be calculated using trilateration.

Cellular Phone Technology is very expensive. The cost actually depends on the amount of airtime used. In VANET, the position of the vehicle needs to be maintained continuously, which requires a very expensive continuous amount of airtime. Moreover, this technology depends on the number of base stations, the more base stations we have the more accurate position will be estimated. Similarly, the accuracy of the position is affected by the ranging algorithm in use.

V2I-based localization

In this method the location of a vehicle is estimated in relation to roadside entities (e.g., traffic light, street light, access point, road signs, and wireless sensors). This kind of technique uses the roadside unit (RSU) to provide position that can help vehicle to determine its location. The roadside unit (RSU), which is used in this method, is a fixed road infrastructure that has a fixed known physical location and can accommodate high capacity of wireless transmission range. Figure 2.3 demonstrates

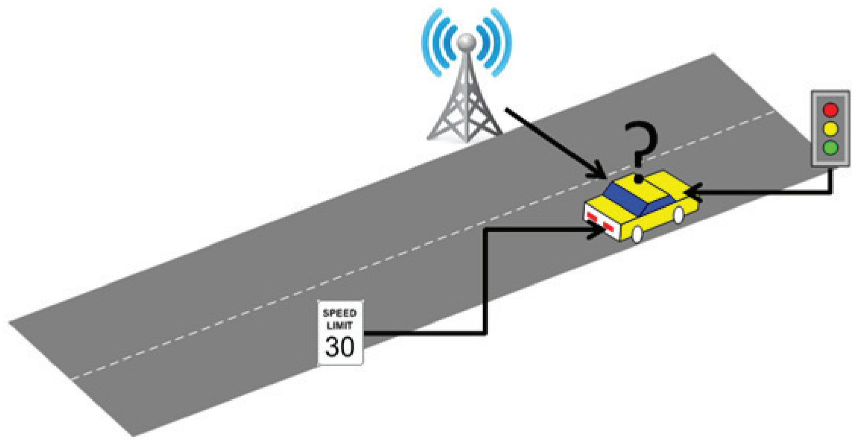

Figure 2.3: V2I-Based Localization

how a vehicle can determine its location using RSUs. V2I-based localization can be classified into two types based on the communication between the vehicles and the road's infrastructure.

A. DSRC Communication

This technique uses vehicle to infrastructure communication (V2I) and therefore, both roadside unit (RSU) and vehicle must be equipped with proper DSRC devices to allow wireless communication and exchanging position information between vehicles and roadside unit (RSU). Some methods were proposed in the literature that use vehicle to infrastructure communication (V2I) to provide localization services to vehicles, nevertheless, they all assume that all the vehicles and roadside unit (RSU) are equipped with DSRC devices.

In [14], sensor nodes are installed on vehicle and roadside sensor nodes are deployed on either side of the highway. These roadside sensors (RSS) nodes have a fixed position coordinate stored initially on their memory. In the proposed method, the vehicle has to send a Location Request Packet (LREQ) to its one-hop neighbors. When a RSS receives LREQ, it creates a Location Reply Packet (LREP), comprising of its current location coordinates (longitude, latitude), and sends it back to the requesting vehicle. To compute the precise location of a vehicle, the vehicle needs to receive LREP from at least three nodes. In the best way, if the vehicle receives three LREQs, then it can obtain the length from itself to the responding nodes based on triangulation and other proposed formulas. If the vehicle received more than there LREQs, it chooses three of them based on Received Signal Strength. However, this method depends highly on the roadside sensors (RSS) which consume a lot of power, and their proper distribution; therefore, in the proposed method the accuracy of the location is very high when the number of well-working sensors on either side of the highway is high.

Another proposed method [15] uses V2I communication to provide initial position for vehicles and Dead Reckoning (DR) to obtain current location at any time after knowing about the initial position. DR uses direction and distance to determine the vehicle's position, nevertheless, DR can fit only on highway traffic environment rather than urban areas, where vehicles usually stop and wait for traffic signals which make it difficult to predict the vehicle's movement. Another issue with this method is the number of messages that are being broadcasted by the RSU; however, the authors have mentioned that reducing the consumption of the wireless communication will be handled in a future work. In addition, the authors have indicated that the error rate in location can be diminished with proper configuration of roadside units.

[16] takes advantages of DSRC devices in the form of on board unit (OBU) installed in vehicles and roadside unit (RSU). In the proposed method, each vehicle estimates its distance to a pair of RSUs located on either side of the road on the basis of the beacon messages broadcast on a periodic basis. By using the position information within the first set of beacon messages received from the two RSUs and its estimated distance from the two RSUs, the vehicle then applies the concept of two intersecting circles to compute its two possible positions. After receiving the second set of beacon messages from the RSUs, the vehicle determines which of these two positions it is actually located at by computing its two possible movement vectors over the broadcast period and comparing the angle between these movement vectors and

that of the known road direction. Similar to the previous proposed techniques, the accuracy of the vehicle location depends on the proper configuration of the roadside unit (RSU); in fact, this technique shows an accurate position in fault-free environment where RSUs are configured and working properly.

As it has been reported above, a number of V2I localization techniques have evolved in recent years. Roadside units (RSU) are essential component of VANET and utilizing them to provide location information for vehicles on road has improved the localization accuracy. Nevertheless, the appropriate configuration of RSUs has a great impact on the location accuracy; however, such configuration can be expensive in terms of time and cost. In addition, the issue with communication overhead and bandwidth consumption must be addressed especially in dense VANETs. Table 2.3 summarizes the previously proposed methods.

B. RFID Communication

RFID-based localization is a sub class of the V2I-based localization. Radio Frequency Identification (RFID) is an automatic identification technology that can be used to track people and even objects. It is composed of three different entities, RFID tag, readers and servers. There are two types of RFID tags, active tag and passive tag. An active tag has an internal battery and can have memory and sensors. The other type is a passive tag and it has no power supply and therefore, has limited capabilities. RFID readers have two interfaces, RF interface to communicate with the RFID tag and retrieve its ID, and a communication interface to communicate with the servers. These servers collect tag IDs from the reader in order to perform some calculation on them [17]. RFID has gained some interest in VANET; in fact, RFID technology has shown an improvement in vehicle localization. The main idea is to install an RFID tag which contains an exact position on road or on roadside unit.

In [18], RFID was incorporated into the navigation system to improve the location accuracy. In the proposed method, RFID tags, along with ID and location

Table 2.3: V2I-Based Localization Techniques with DSRC Communication

Method	**[14]**	**[15]**	**[16]**
Year	2011	2012	2012
Best case	93% of vehicles obtained their exact location	100% of vehicles obtained their exact location	Distance measurement error is 0.6 m
Worst case	73% of vehicles obtained their exact location	92.31% of vehicles obtained their exact location	Distance measurement error 3.3 m
No. of RSU	6, 8, 10 per km	1 at the 6th km of the road	1 at distance 0.5 from the beginning of the road, 1 after 1 km from the first RSU, 1 after 1 km from the second RSU
No. of RSU required for computation	3	1	2
RSU transmission range	100-500 meters	650 meters	500.14 meters
Highway environment	5 km with 2 lanes in two direction (each direction is 7.5 m)	12 km with three lanes in one direction	2.5 km and a width of 12 m with two lanes in two directions
No. of Vehicles	N/A	467	1 to 5 vehicles/km/lane
Average Speed	N/A	120 km/h	Randomly selected
Simulator	GloMoSim	ns-2.34	ns-2

information, are installed on road. Vehicles are equipped with an RFID reader to communicate with the RFID tags on road; GPS and internal sensors are installed as well. The proposed method was not simulated or tested and; therefore, the results of the study are not available. The authors have also studied the feasibility of using RFID for vehicle positioning. Nevertheless, the experiments that were conducted have shown that it is feasible to retrieve the tag ID with high speed and in harsh weather conditions. However, the authors suggested developing a scheme that combines RFID and GPS to produce accurate positioning information. Some issues such as high speed communication and tag operation in harsh environmental conditions are still open for future investigation.

In [19], the proposed technique employs the DGPS concept to improve the GPS accuracy. In this technique, the vehicle obtains two different position data: one from the GPS receiver and the other one from RFID communication. Then, it computes GPS error and shares it with neighbors to help them correct inaccurate GPS coordinates. A GPS equipped vehicle and non-GPS equipped vehicle can both obtained accurate position. The GPS equipped vehicle obtains the exact position data from RFID tag on roadside unit, corrects its position and then broadcasts the calculated GPS error to its neighbors. The non-GPS equipped vehicle estimates its accurate position from the data received from its neighbors using RFID and DSRC communication. The proposed method has been evaluated using simulation and testbed experiments. The simulation has shown that the proposed method can be improved when: (1) the number of vehicles increases, (2) the number of non-GPS vehicles decreases and (3) the number of RFID-enabled vehicle increases. On the other hand, the testbed experiment shows that performance depends highly on the number of RFID tags installed on the roadside unit and the interval between them.

However, in VANET environment such parameters cannot be guaranteed due to the dynamic nature of VANET including number of vehicles and their speed. Therefore, combining the RFID and RSUs provides a cost-efficient way to provide real-time position and hence improve the location accuracy. Some issues regarding RFID needs to be addressed in efficient methods: effective operational in different conditional environments and fast communication and reading speed between the tag and the reader. Other issues related to the proper configuration of the RFID tag on road and roadside unit is less important since RFID deployment is very cheap.

2.2 MOBILITY DATA VERIFICATION METHODS

Verifying the announced position of the vehicle has been an active research area in VANET. To the best of our knowledge, many algorithms, as reviewed below, focus on monitoring and verifying the exchanged data for routing purposes. For instance, they validate the data received from neighboring vehicles to either forward the message or not. In contrast, we focus on assisting vehicles in the network to perform self-localization using verified mobility data received from neighboring vehicles. In this section we review the existing verification systems.

In [35] and [36] the authors proposed the use of independent sensors to evaluate the trustworthiness of the neighboring vehicles. They defined two types of sensors: 1) threshold-based, map-based and overhearing sensors, and 2) cooperative sensors. A different weight value is assigned to all sensors based on its significance and reliable performance. The results from all sensors is combined to evaluate the trustworthiness of the neighboring vehicles. The authors used hard threshold values to verify data; however, VANET environment involves uncertainties; therefore, the use of flexible thresholds will be more suitable.

[37] proposed a mechanism to enhance the position security in VANET by using the on-board radar to detect neighboring vehicles and to confirm their announced coordinates. One of the challenges in this proposed scheme is that it requires direct line-of-sight between two neighboring vehicles. In addition, the radar has a limited

transmission range which is less than the vehicle's transmission range. Therefore, only a limited number of neighboring vehicles can be verified in the network.

A secure location verification scheme is introduced in [38]. This infrastructure-less cooperative scheme is designed to detect incorrect positions by the use of: 1) RF-based distance bounding protocol to estimate the distance by measuring the time-of-flight (ToF), and 2) plausibility checks to verify the correctness of the information received from neighboring vehicles.

In [39] a relative position verification is proposed. It uses two types of directional antennas (f-antenna or b-antenna) along with the beacon messages exchanged among neighboring vehicles. Using this scheme a vehicle can distinguish and divide its neighbors into two groups (front and behind) and then broadcast this information periodically to others. By collecting the shared group information from all neighboring vehicles the vehicle can detect and eliminate messages sent by untrusted vehicles. However, the proposed system depends on density; therefore, more untrusted vehicles can be detected if the density in the network is high.

A trusted neighbor table (TNT) is constructed in each vehicle [40]. The TNT has an entry for each neighboring vehicles that includes the latest location and a trust value. Using TNT can enhance the geographic routing protocols. For instance, a vehicle can forward the message to its neighboring vehicle based on the trust value. The verification process consists of two phases: 1) The start-up phase that excludes neighboring vehicles if their exchanged information are violating the threshold values and if the distance between the two vehicles violates the predefined minimum distance 2) The refinement phase that further verifies the location information by using a common trusted neighbor. At the end of the verification process the TNT will be updated with the result. However, this work has not been verified or validated through simulations or testbeds.

In [41] a set of plausibility checks is proposed to mitigate the effect of attacks on position based routing. The verification is performed based on these checks, communication range, speed, density, traveled distance and map location information.

[42] presented a collaborative multi-hop approach to verify the location of the vehicle when direct communication is not possible due to obstacles. The main objective of this work is to allow a vehicle to verify the location of a neighboring vehicle with which there is no direct communication and hence enhanced neighborhood awareness. This is achieved by broadcasting a request to find the vehicle that has a direct communication with the vehicle that needs to be verified. Upon the receiving of the request the distance will be estimated based on the received signal strength (RSS) and a reply, with distance information, will be sent back to the requesting vehicle.

[43] proposed the use of the Kalman filter to detect untrusted behavior based on past vehicle movements and other sensor information. In this approach the Kalman filter is used to estimate a vehicle's future movements, to be later used for mobility verification. In addition, vehicles local sensors are checked to enhance the verification process.

The authors in [44] proposed the use of a moving vehicle (observer) to verify the claimed position of a vehicle. It uses the V2V environment without the need for any fixed infrastructure (RSUs) or other neighboring vehicles. In this scheme, the observer vehicle receives safety signals from the same vehicle at different locations along the trajectory of that vehicle. The location of the vehicle is then estimated, by the observer, based on TDOA (Time Difference of Arrival) multilateration technique and at least three records of time of arrival and location coordinates. Table 2.4 summarizes related work conducted in verification.

As we have seen, most of the work discussed in the literature focuses on validating the exchanged data to ensure the successful delivery of packets to destinations, which in turn will enhance the underlying routing protocols. However, the objective of our work is to generally detect the incorrect mobility data of single-hop neighboring vehicles. We only focus on assisting vehicles in determining their location. This can be achieved by providing a mechanism to verify the data, received from neighboring vehicles, before using it in the location estimation.

Table 2.4: Summary of Related Works in Mobility Data Verification

Ref	Verification Method	Context in use	Infrastructure	Distributed	Special Hardware
[35] [36]	Combination of autonomous and cooperative sensors	Geographic routing protocols	No	Yes	No
[37]	On-board radar	To calculate the amount of time needed to detect untrusted vehicles	No	Yes	Yes
[38]	RF-based distance bounding and plausibility checks	Greedy forwarding routing protocol	No	Yes	Yes
[39]	Directional antennas	Geographic routing protocols	No	Yes	Yes
[40]	Round trip of challenge-response messages, position and velocity checks	Geographic routing protocols	No	Yes	Yes
[41]	Plausibility checks	Position-based routing	No	Yes	No
[42]	Triangulation calculations	Neighborhood awareness under NLOS conditions	No	Yes	No
[43]	Kalman filter and past vehicle movements	Not specified	No	Yes	No
[44]	Moving observer vehicle	Not specified	No	Yes	No

CHAPTER 3
MULTI-FACTOR VEHICLE-TO-VEHICLE WEIGHTED LOCALIZATION

In this chapter, we propose a new V2V-based localization that extends the centroid localization (CL) by assigning a weight value to each neighboring vehicle. This weight value is obtained using a weighting function that utilizes the following factors: 1) link quality distance between the neighboring vehicles 2) heading information and 3) map information. We develop a simulation program to evaluate our proposed method in terms of average location error, maximum location error and efficiency. The proposed method is shown to improve the location accuracy for varying vehicle densities and transmission ranges. Material in this chapter is published in [21] [22] and [23].

3.1 INTRODUCTION

Over the last decades, wireless communication has become the fastest growing sector in telecommunications. Ad hoc networks, which are examples of advanced technologies in wireless communication, have attracted the interest of researchers all over the world. The vehicular ad hoc network (VANET), a class of mobile ad hoc network (MANET), allows vehicles on the road to communicate via vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) wireless communications. With this communication, vehicles are able to collaborate and exchange information to ensure the safety and comfort of drivers and passengers. Consequently, many applications and services are proposed with the potential to increase the transportation safety and efficiency [2] [4]. However, in order to allow such applications to work effectively and efficiently, a real-time position information must be available. This creates the need for an accurate localization method that can provide vehicles on road with their physical location. Accordingly, a number of methods have been proposed to fulfill this crucial requirement [3].

On the other hand, most VANET applications assume that vehicles can determine their real-time position using GPS (Global Positioning System), this requires each vehicle to have an embedded GPS receiver. In practice, GPS signals can be easily blocked and interrupted. Hence, vehicles are likely to encounter GPS outages in areas where obstacles persist. Therefore, due to the nature of VANET and the sensitivity of GPS signals, positions obtained by GPS may not be adequate for many VANET applications [2] [3] [4]. GPS has become the standard for vehicle localization due to the fact that it is available and all vehicles are powerful enough to operate the embedded GPS receivers. Observations have also shown that basic GPS receivers may produce errors in location estimation especially in areas with high building, tunnels and forests. Therefore, V2V communication can be combined with GPS to achieve higher and more reliable location estimation. This solution is suitable for VANET environment, where each vehicle can communicate with its neighboring vehicles and construct a local map using the exchanged location information. Beacons with neighbor information can be broadcast periodically between vehicles to assist in determining their location. The idea of using beaconing was originally introduced in wireless sensor networks (WSNs), and more recently in VANET [5] [6] [7] [8] [9] [10] [11] [12] [13]. In this chapter, we propose a solution that adapted the use of weighted centroid localization (WCL), so the location of the vehicle can be estimated based on the weighted neighboring vehicles' coordinates. The resulting weighting function will consider three factors: 1) link quality distance 2) heading and 3) map and will produce a weight value. This value will be assigned to all the neighboring vehicles (vehicles within the transmission range of the vehicle that needs to be localized).

3.2 BACKGROUND

In this section we briefly introduce the centroid localization (CL) and the weighted centroid localization (WCL) approaches, which are the base of our proposed method.

3.2.1 Centroid Localization

In Wireless Sensor Networks (WSN), centroid localization (CL) has been used as a range-free localization scheme. It is simple, low complex and robust to the changes in WSN environment [45] [46]. Due to the unique characteristics of VANET environment, high mobility and dynamic topology, the localization method needs to be fast and reliable; therefore, CL is a suitable candidate to be taken into consideration for vehicle localization.

With CL, the location estimation is performed based on the location information received from the neighboring nodes. Such information is exchanged among nodes via beacon messages. They are sent by neighboring nodes, with known locations, and received by nodes that need to be localized. The position is calculated as a centroid of all the neighboring nodes' positions, received from the beacon messages. The intersection of the neighboring nodes transmission ranges is used to construct the areas, where the node with an unknown location can be localized [46]. As shown in Figure 3.1, node A is using its four neighboring nodes to perform CL.

In this chapter, we use:

- loc_{est}= $(x_{est}$,$y_{est})$ to denote the estimated location
- loc_i= $(x_i$,$y_i)$ to denote the location of node i

Therefore, given a set of neighbors n with locations loc_i, the node's estimated location loc_{est} can be calculated from the centroid using Equation 3.1:

$$loc_{est} = (\frac{\sum_{i=1}^{n} x_i}{n}, \frac{\sum_{i=1}^{n} y_i}{n}) \tag{3.1}$$

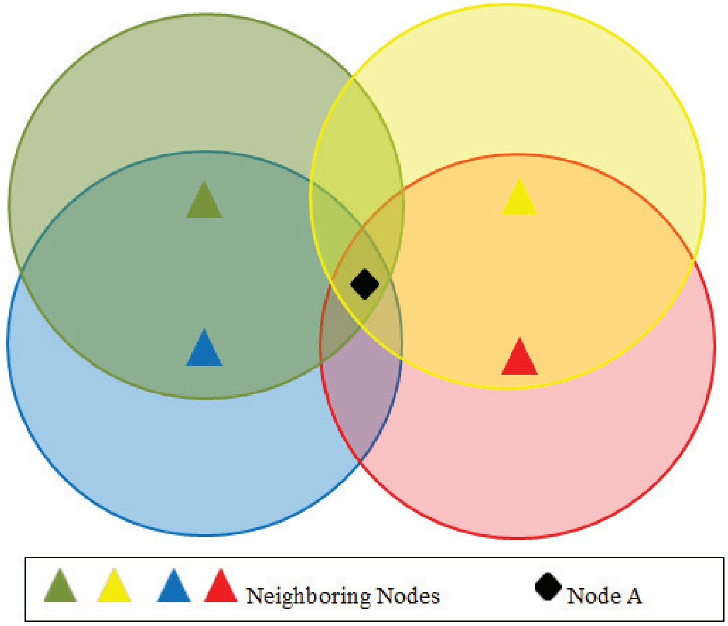

Figure 3.1: Centroid Localization

3.2.2 Weighted Centroid Localization

As discussed previously, CL method can be utilized and used in VANET environment due to its simplicity. However, the issue with CL is that it assumes that all neighboring nodes, within the transmission range of the node that needs to be localized, to be at the same/equal distance from that node, otherwise; the accuracy of the location will be affected. To overcome this limitation, [47] offers an enhancement to the original CL method, by proposing the use of weights. Weighted centroid localization (WCL) aims to improve the location accuracy by giving high weight values to neighboring nodes that are close to the node that needs to be localized. WCL uses the following formula:

$$loc_{est} = \left(\frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}\right) \tag{3.2}$$

Because weight and distance are inversely proportional in WCL, a longer distance will have a weight value that is lower than a shorter distance. Using WCL, w_i for node i can be expressed as follows:

$$w_i = \frac{1}{(d_i)^g} \tag{3.3}$$

where d_i is the distance between neighboring node i and the node that needs to be localized. Exponent g, whose value relies on experimentation, is the degree that influences the impact of the neighboring node in the location estimation of the node.

3.3 THE PROPOSED METHOD

Designing a localization technique for VANET involves a number of challenges due to the following factors:

1. Dynamic topology due to the high and different speeds of the vehicles in the network. This causes the connectivity between the vehicles to change frequently and rapidly.

2. Power and strength of the radio signal, which can be affected by the presence of obstacles, natural power dissipation and existence of multiple paths [20].

In our proposed method we address the above and adopt the use of WCL in location estimations. By using WCL, a weight value will be assigned to the neighboring vehicles based on: 1) link quality distance 2) heading and 3) map information. Therefore, the calculation of the location estimation is fast and the noise and interference in the radio signal is considered by using signal to interference-noise ratio (SINR) in calculating the neighbors' weights. Below is a basic description of our proposed localization method:

1. Every node in the network will broadcast periodic beacon messages with the contents described in Figure 3.2.

```
-----------------------------------------------------------------
|       0       |       1       |       2       |       3       |
0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|     Time      |                  SenderId                     |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                        X - Coordinate                         |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                        Y - Coordinate                         |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                           Heading                             |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                            Speed                              |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                           Road ID                             |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
```

Figure 3.2: Beacon Message Contents

Table 3.1: Positioning Table

Column	**Definition**
$NodeID$	The vehicle's unique identification
$Position$	The current x, y position of the vehicle
$Speed$	The current speed of the vehicle
$RoadID$	The road ID in which the vehicle is traveling on
$Heading$	The direction in which the vehicle is heading to
$Time$	The timestamp of the beacon message
$Weight$	The assigned weight value

2. Upon receiving the beacon messages, every node will construct a positioning table which contains the neighboring vehicles information. Details about the fields of the positioning table are shown in Table 3.1.

3. Based on the neighboring vehicles information, a weight will be assigned to each of the neighboring vehicle.

4. Every node will estimate its location using WCL (Equation 3.2).

A weight value is assigned to every vehicle i in the positioning table using the following:

$$w_i = \sum_{j=1}^{k} factor_{ij} * parameter_{ij} \tag{3.4}$$

Where $factor_{ij}$ is the weighting factor for $parameter_{ij}$ and k is the number of parameters in the weighting function. The value of the weighting factor can be set to either 0 or 1. If it is set to 1, then the corresponding parameter is considered in the weight calculation, otherwise the parameter is not taken into consideration.

The advantage of designing the weighting function as in Equation 3.4, is to allow each parameter to be investigated separately and to study its impact on location accuracy. In addition, more parameters can be added in the future to the weighting function, to enhance the estimation, providing flexibility and strength to our proposed method. The detailed localization procedure for a vehicle is shown in Figure 3.3 and the proposed system modules are depicted in Figure 3.4. Next we discuss the different parameters used in the proposed weighting function.

3.3.1 Link Quality Distance (LQD)

This parameter represents the distance and the link quality between the vehicle and its neighboring vehicles. The performance of the localization method can be enhanced by measuring the distance and the link quality between vehicles. Therefore, we propose the use of distance and SINR for location estimation. The link quality distance parameter for a neighboring vehicle i can be defined as:

$$LQD_i = \frac{SINR_i}{d_i} \tag{3.5}$$

Including the link quality distance parameter, the weighting function (Equation 3.4) will change to:

$$w_i = \alpha * LQD_i \tag{3.6}$$

Where α is the weighting factor for the link quality distance parameter (LQD).

```
α ← 1, β ← 1, μ ← 1                                  ▷ include LQD, heading and map
function RECEIVE(BeaconMessage)
    for each received beacon i do
        DeletePreviousRecord(SenderID)
        Obtain SINR using Equation 3.7, Calculate distance using Equation 3.11
        LQD_i ← SINR_i / d_i
        if same direction then
            Heading_i ← 1
        else
            Heading_i ← 0
        end if
        if same road then
            Map_i ← 1
        else
            Map_i ← 0
        end if
        w_i ← α * LQD_i + β * Heading_i + μ * Map_i
        InsertIntoTable(SenderID,w_i)
    end for
end function
function LOCALIZE(PositioningTable)
    x_total ← 0, y_total ← 0, w_total ← 0
    for each entry j do
        x_total ← x_total + (x_j * w_j), y_total ← y_total + (y_j * w_j) , w_total ← w_total + w_j
    end for
    if w_total = 0 then
        x_est ← 0, y_est ← 0
    else
        x_est ← x_total / w_total, y_est ← y_total / w_total
    end if
    return x_est, y_est
end function
```

Figure 3.3: Localization Algorithm

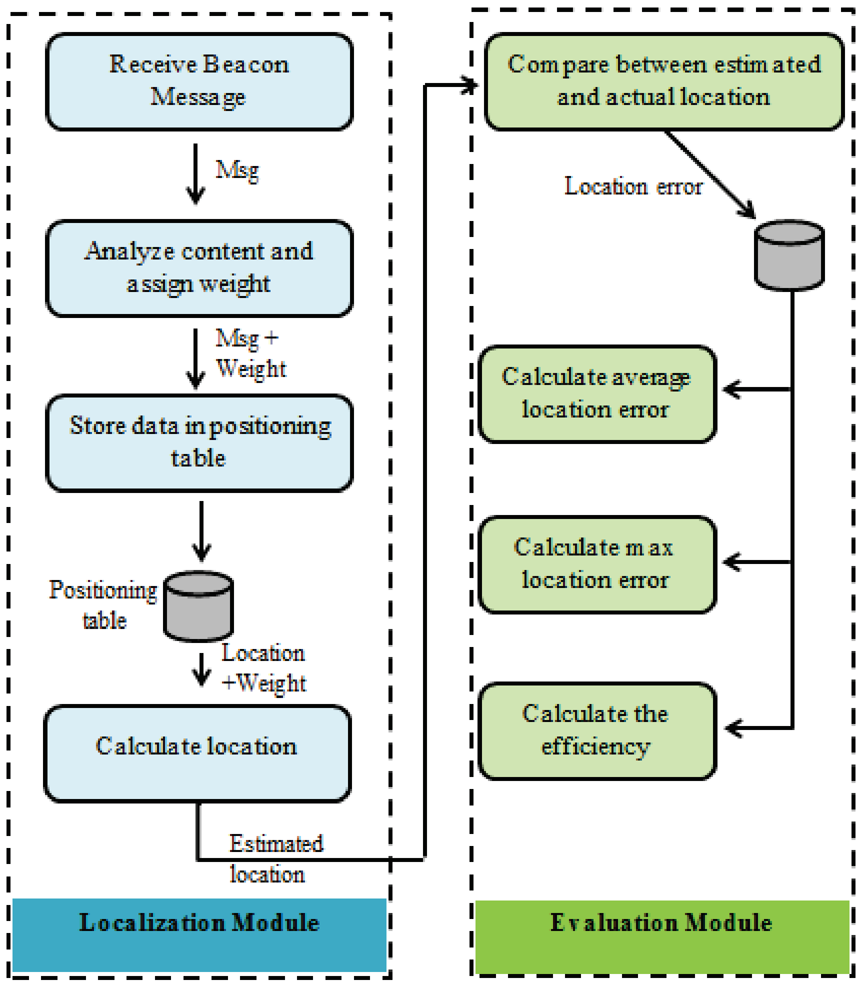

Figure 3.4: The System Modules

When a vehicle receives a beacon message from its neighboring vehicles, the SINR value is obtained to estimate the quality of the link. As in [20], SINR is calculated using the following equation:

$$SINR = \frac{S}{I + N} \tag{3.7}$$

where S is the received signal power, I is the cumulative power of interfering signals and N is noise power.

RSS measurements can be used to obtain or estimate the distance between vehicles [47]. According to Friis free space transmission the RSS decreases as a quadric power law of distance [20]. The power of the received signal P_r can be determined using the following formula:

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{3.8}$$

In Equation 3.8, P_t is the transmission power of the sender (transmitter), λ is the wavelength, d is the distance between the sender and receiver, G_t and G_r are antenna gains, and L is the system loss factor. We set G_t=1, G_r=1 and L=1 as defaults. The wavelength λ is calculated as follows:

$$\lambda = \frac{C}{f} \tag{3.9}$$

where C is the speed of light in vacuum (299,792,458 meters per second) and f is the frequency. Equation 3.8 gives us the power in watts. To obtain the power in decibels (dB), we use the following equation:

$$P_r(dB) = P_t(dB) + 10log_{10}(\frac{\lambda^2}{(4\pi)^2 d^2}) \tag{3.10}$$

Using Equation 3.10, we can derive and calculate the distance as follows:

$$d = \sqrt{\frac{\lambda^2}{16\pi^2 10^{\frac{P_r - Pt}{10}}}} \tag{3.11}$$

Including the link quality distance parameter in the weighting function has improved the proposed localization method (details about the results will be discussed in Section 3.4). Next, we investigate the use of heading information to further enhance the location accuracy.

3.3.2 Heading

The movements of the vehicles can be relatively predictable because they are restricted to roads on which they travel. In this chapter, we use the Manhattan mobility model, which is a grid road topology proposed for movement in an urban area. In this model, a vehicle can move along a grid consisting of horizontal and vertical streets. At each intersection, a vehicle chooses to keep moving in the same direction with probability 1/2 and to turn left or right with probability 1/4 in each case [48]. Figure 3.5 shows this topology and the movement of the vehicles.

Moreover, the heading of the vehicle can be determined from the velocity. Using the Manhattan mobility model, the vehicle can move in four different angles, e.g., 0°, 90°, 180° and 270°. Figure 3.6 shows the different angles. If two vehicles are traveling in the same direction, they will have the same x or y coordinates, depending on the direction. Utilizing the heading information of the neighboring vehicles, higher weights will be assigned to vehicles that are traveling in the same direction of the vehicle that needs to be localized. For instance, vehicles that are traveling east or west with angles 0° and 180° will have the same y coordinates. Vehicles that are traveling north or south with angles 90° and 270° will have the same x coordinates. Heading parameter for a neighboring vehicle i is calculated as follows:

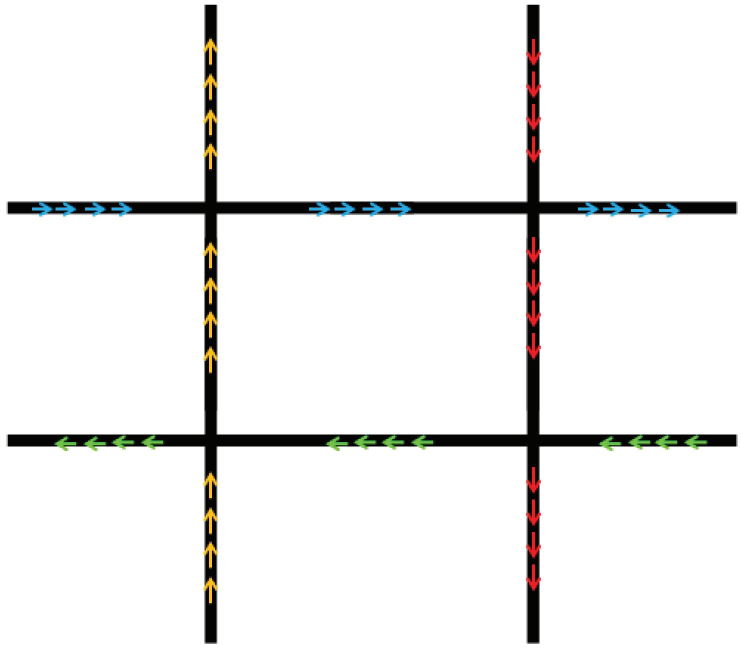

Figure 3.5: Manhattan Mobility Model

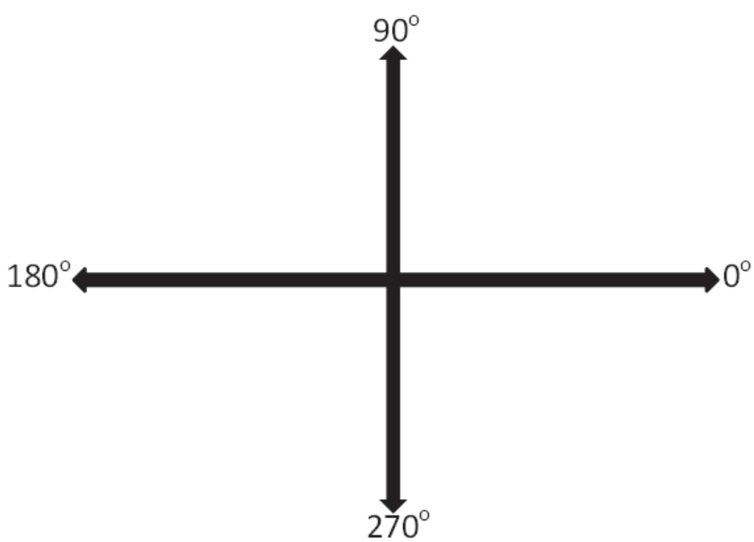

Figure 3.6: Heading Different Angles

$$Heading_i = \begin{cases} 1 & \text{if vehicles are moving in same direction} \\ 0 & \text{if vehicles are moving in different direction} \end{cases} \tag{3.12}$$

To study the impact of the heading information on location accuracy, we present the weighting function as:

$$w_i = \alpha * LQD_i + \beta * Heading_i \tag{3.13}$$

Where α is the weighting factor for the link quality distance parameter (LQD) and β is the weighting factor for the $Heading$ parameter. Simulation results (discussed in Section 3.4) show that including heading information in the weighting function improves the performance of the proposed method, specifically when transmission range is set to 250m. However, when the transmission range is increased to 500m, the location error increased and the overall performance of the localization method decreased. The reason for this is because vehicles traveling in the same direction but on roads farther away are being given a high weight value for the heading parameter. Including heading information is expected to give close and nearby vehicles, traveling in the same direction, high weight values. However, vehicles traveling on different roads, with same direction, should not be given the same high weight values. This problem can be mitigated if map information is included in the proposed weighting function, which will be investigated in the next section.

3.3.3 Map

Knowing the road segment on which the vehicles are traveling has a great impact on the location estimation. Therefore, vehicles that are traveling on the same road must be highly considered by the localization method. Since the network simulator (ns-3) [49] does not provide direct access to map information, we have implemented our own map parser class that can identify the road ID, during the simulation, based on the position provided by SUMO [50] mobility traces. However, map information, including the edges and junctions of each road, must be stored at the beginning of the simulation and before the actual movement of the vehicles. Vehicles that are traveling on the same road along with the vehicle that needs to be localized will get high weight values and will contribute more in the location calculation. In the weighting function, the map parameter for a neighboring vehicle i is calculated as follows:

$$Map_i = \begin{cases} 1 & \text{if vehicles are moving on the same road} \\ 0 & \text{if vehicles are moving on different roads} \end{cases} \tag{3.14}$$

Including LQD, heading and map parameters, our proposed weighting function is expressed as follows:

$$w_i = \alpha * LQD_i + \beta * Heading_i + \mu * Map_i \tag{3.15}$$

Where α is the weighting factor for the link quality distance parameter (LQD), β is the weighting factor for the $Heading$ parameter, and μ is the weighting factor for the Map parameter. As stated above, weighting factors can be set to either 0 or 1. If it is set to 1, then the corresponding parameter is considered in the weight calculation, otherwise the parameter is not taken into consideration.

3.4 SIMULATION AND RESULTS ANALYSIS

In this section, we present the simulation environment parameters and the assumptions used in this chapter. We also define metrics to evaluate the performance of our proposed method, and finally we discuss the results and present our findings based on the simulation results.

3.4.1 Simulation Environment

In order to assess the performance of our proposed method, we simulate scenarios of different vehicle traffic densities using ns-3.19 [49] and SUMO [50]. The road network,

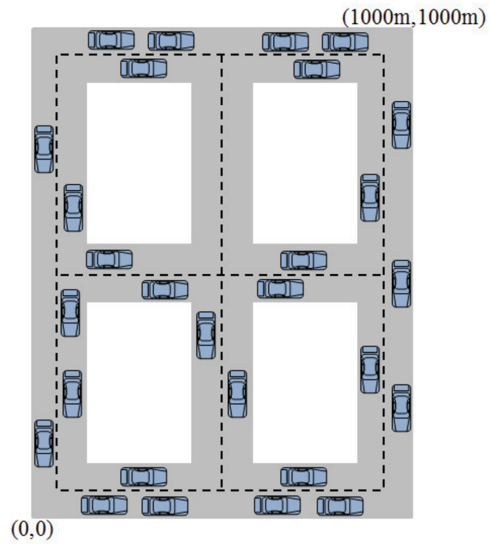

Figure 3.7: 3x3 Manhattan Grid Road Network

shown in Figure 3.7, uses a 3 x 3 Manhattan Grid with an edge length of 1000m (1km) and a distance of 500m (0.5km) between any two neighboring intersections.

The simulations were run with the parameters shown in Table 3.2. Using the car-following model, the speed of a vehicle is adapted to the speed of the leading vehicle. Vehicles in the simulation are randomly distributed and routes are randomly generated. Mobility traces of these scenarios, generated by SUMO, are used by ns-3 to generate node mobility. We used the WAVE model [51], which is the overall system architecture for vehicular communications in ns-3.

3.4.2 Simulation Assumptions

The following is assumed in our proposed system:

1. Every vehicle in the network has a unique identification.

2. Communication and data exchanging are secured as per the IEEE 1609.2 [1].

3. Vehicles can move at any speed without exceeding the predefined speed limit on roads.

Table 3.2: The Simulation Parameters

Parameter	Value
Number of vehicles	20,30,40,50,100,150
Vehicle movement	Intelligent Driver Model
Vehicle speeds	Car-following model
Max road speed	14 m/s
Duration	1800 seconds (30 minutes)
Warm up	20 seconds
Localization update interval	1 seconds
Beacon interval	1 second
Packet size	48 bytes
Signal propagation	Two-ray ground
MAC/PHY protocol	IEEE 802.11p
Transmission range	500m
Layer 3 addressing	IPv6

4. Every vehicle is equipped with a digital map.

3.4.3 Evaluation Metrics

In order to evaluate our proposed localization method, we use the following metrics:

(1) Location Error. This is the error between the actual location (x_{iact}, y_{iact}) and the estimated location (x_{iest}, y_{iest}) for each vehicle v_i in the network of N vehicles. LE_{vi} is defined as follows:

$$LE_{vi} = \sqrt{(x_{iest} - x_{iact})^2 + (y_{iest} - y_{iact})^2} \tag{3.16}$$

(2) Average Location Error. The average location error is the average of all vehicle's location errors. By aggregating the individual location error (LE_{vi}) of each vehicle, the average location error in the network ALE can be formulated as follows:

$$ALE = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_{iest} - x_{iact})^2 + (y_{iest} - y_{iact})^2} \tag{3.17}$$

or

$$ALE = \frac{1}{N}\sum_{i=1}^{N} LE_{vi} \tag{3.18}$$

Location error and average location error metrics are used to measure the performance and the accuracy of the proposed localization method. This can be achieved by matching the ground truth location, obtained from the mobility traces, with the estimated location, generated by the proposed method.

(3) Maximum Location Error. We introduce the maximum location error metric as shown in Equation 3.19.

$$MaxError = \max_{i=1..N}\sqrt{(x_{iest} - x_{iact})^2 + (y_{iest} - y_{iact})^2} \tag{3.19}$$

Knowing the maximum location error exhibited in the network can be beneficial, in fact, the objective of any localization method is to decrease the maximum location error and improve the location accuracy.

(4) Efficiency. We introduce the efficiency as a fraction of the successful runs, in which a vehicle in the network can localize itself, during the entire simulation.

$$Efficiency = \frac{NSR}{NR} \tag{3.20}$$

where NSR is the number of successful runs and NR is the total number of runs. Successful localization will take place when there is at least one neighboring vehicle within the vehicle's transmission range, otherwise; the location update will fail. In our simulation, the location update is performed every second, after the warm up period (20 sec), until the end of the simulation time (1800 sec).

The efficiency metric measures the overall coverage of the localization method. This can be achieved by calculating the percentage of the vehicles that can be localized, regardless of the accuracy of the estimated location. However, coverage is related to the number of the neighboring vehicles, for instance, in the case of a dense network that has high number of vehicles, the efficiency will be 100%.

An overview of the evaluation module is shown in Figure 3.4 and the detailed process is explained in Figure 3.8.

3.4.4 Simulation Results

Effect of Density

This set of results assess the impact of the density (number of vehicles per unit area) on the performance of the proposed localization method (MWL). In order to study the effect of density, we vary the number of vehicles in the network from 20 to 150, while keeping the network area fixed. For each density, we calculate the average location error, using Equation 3.17. To measure the impact of each parameter in the proposed weighting function (Equation 3.15), we first start with the LQD parameter by setting its weighting factor α to 1 and the other weighting factors β and μ to zero. Next,

$LE_{total} \leftarrow 0$
$MaxError \leftarrow 0$
$NSR \leftarrow 0$
$NR \leftarrow DurationTime - WarmUpTime$
for each vehicle v in N **do**
    get x_{est}, y_{est}
    GetActualPosition(MobilityTraces)
    $LE_v \leftarrow \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2}$
    $LE_{total} \leftarrow LE_{total} + LE_v$
    if $LE_v > MaxError$ **then**
        $MaxError \leftarrow LE_v$
    end if
    if $(x_{est} \neq 0) \wedge (y_{est} \neq 0)$ **then**
        $NSR \leftarrow NSR + 1$
    end if
end for
$ALE \leftarrow \frac{LE_{total}}{N}$
$Efficiency \leftarrow \frac{NSR}{NR}$

Figure 3.8: Evaluation Algorithm

we consider the heading parameter in the weighting function by setting its weighing factor β to 1, while the LQD weighting factor α is set to 1 and the map weighting factor μ is set to zero. Finally, we take into account all the parameters by setting their weighting factors to 1, so $\alpha = \beta = \mu = 1$. The results are shown in Figure 3.9.

When the number of vehicles increases, the number of the neighboring vehicles increases as well. More neighboring vehicles generate more information, which improves the performance of the localization method and increases the location accuracy. Our proposed method, MWL, produced more accurate location information when all the three factors are considered ($\alpha = \beta = \mu = 1$). MWL with $\alpha = \beta = \mu = 1$ has decreased the location error to an average of 24% compared to MWL where only LQD factor is considered ($\alpha = 1, \beta = 0, \mu = 0$). On the other hand, MWL where LQD and heading factors are considered ($\alpha = 1, \beta = 1, \mu = 0$), produced the highest location errors for all densities. The reason for that, as discussed in Section 3.3, is because vehicles on farther roads, traveling in the same direction of the vehicle that needs to be localized, are given a high weight value for the heading parameter. However, with MWL where all factors are considered ($\alpha = \beta = \mu = 1$), the location error has decreased to an average of 56% compared to MWL where LQD and heading factors are considered ($\alpha = 1, \beta = 1, \mu = 0$). As suggested by the results, combining the three factors, has definitely enhanced the localization accuracy for all densities.

In Figure 3.10, we evaluate our proposed method, MWL, against the relative span weighted localization (RWL) [13]. It is observed that MWL, where all three factors are considered ($\alpha = \beta = \mu = 1$), offers improvement in location accuracy ranging from 9% (for low densities) to 48% for (high densities).

The maximum location error for the proposed method, MWL, is shown in Figure 3.11. For each density, three different cases are investigated: 1) LQD parameter is only considered ($\alpha = 1, \beta = 0, \mu = 0$) 2) LQD and heading parameters are only considered ($\alpha = 1, \beta = 1, \mu = 0$) and 3) LQD, heading and map parameters are

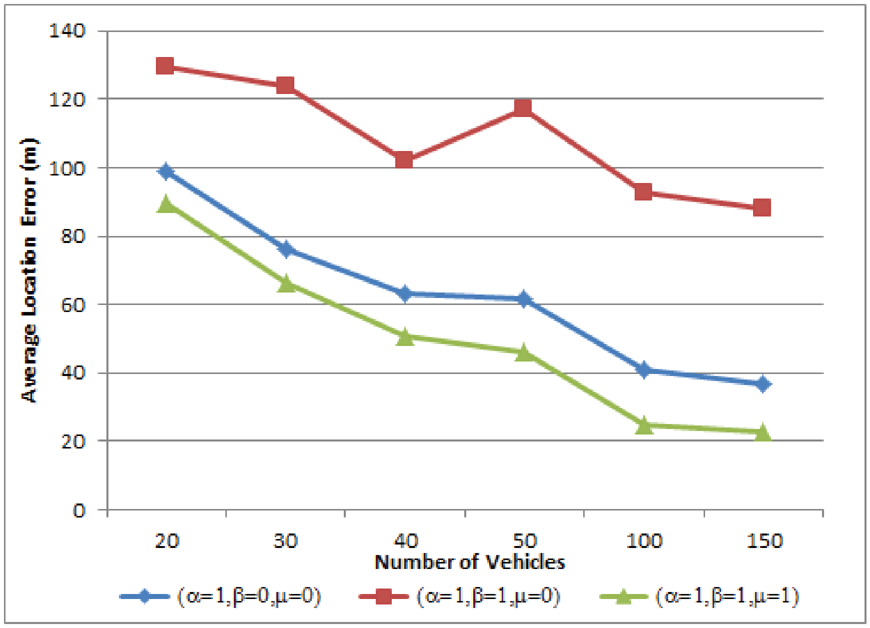

Figure 3.9: MWL Average Location Error vs. Number of Vehicles

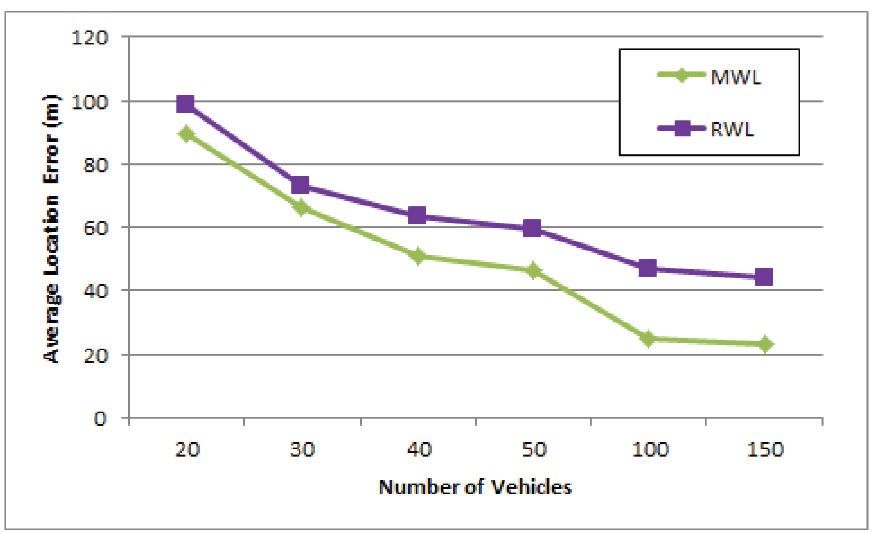

Figure 3.10: Average Location Error vs. Number of Vehicles

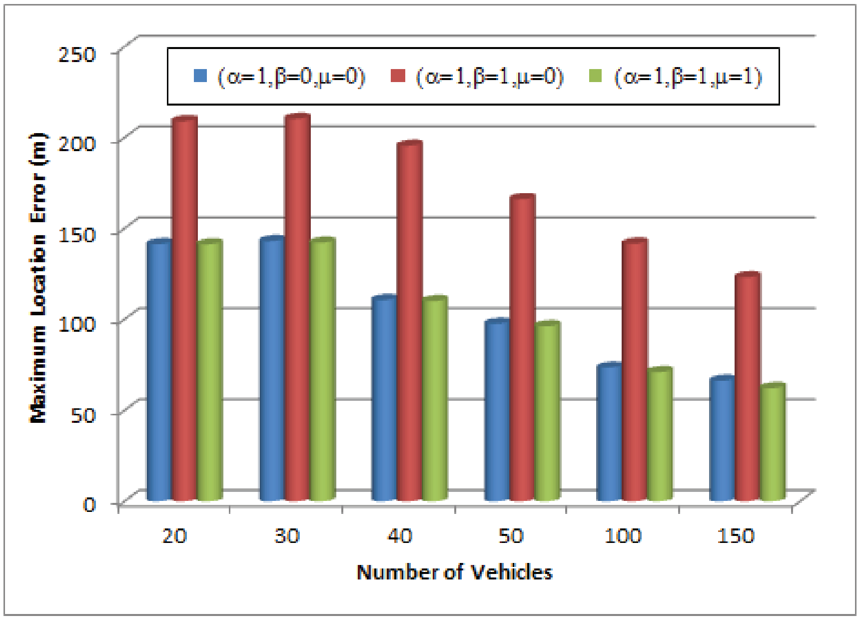

Figure 3.11: MWL Maximum Location Error vs. Number of Vehicles

considered ($\alpha = \beta = \mu = 1$). For higher densities, the maximum location error decreases. The reason is that the maximum location error depends on the number of neighboring vehicles that contribute to the location estimation.

Figure 3.12 shows the maximum location error obtained using MWL and RWL localization methods. Although MWL, where all factors are considered ($\alpha = \beta = \mu = 1$), has high maximum location error values compared to RWL for low densities, with high densities (50,100,150) MWL outperforms RWL.

In this set of results, all the vehicles in the network are able to successfully run the localization method during the simulation time. As a result the overall effectiveness of the proposed localization method is 100%.

Confidence Interval

We compute the average location error and the confidence interval for the proposed method, MWL with ($\alpha = \beta = \mu = 1$),under different densities ranging from 20 to 150. Figure 3.13 shows the results with 95% confidence intervals represented in error

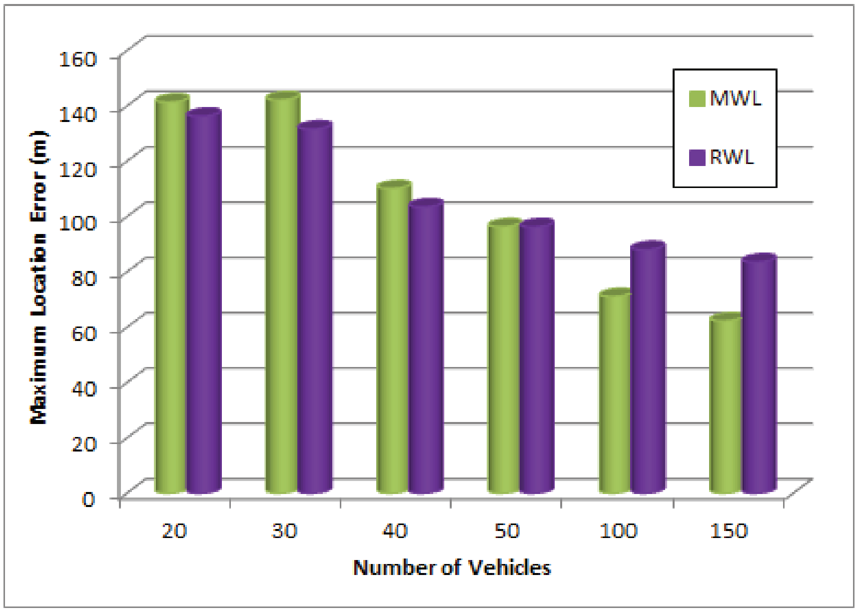

Figure 3.12: Maximum Location Error vs. Number of Vehicles

bars. As observed the obtained confidence intervals are very narrow, especially with high densities.

Effect of Transmission Range

The second set of results investigates the performance of the proposed localization method (MWL) for different transmission ranges (250m and 500m). Changing the transmission range is likely to change the number of neighboring vehicles. This can also affect the performance of the localization method with respect to location error.

Figure 3.14 shows the average location error under different transmission ranges. Here we see that for low densities (20,30,40, and 50) the average location error increases when increasing the transmission range to 500m. The reason is that with the increasing of transmission range, the connectivity increases as well, which is reflected in the number of neighboring vehicles. On the other hand, for high densities (100 and 150) and 500m transmission range, MWL, where all factors are considered ($\alpha = \beta = \mu = 1$), has slightly decreased the average location error. However,

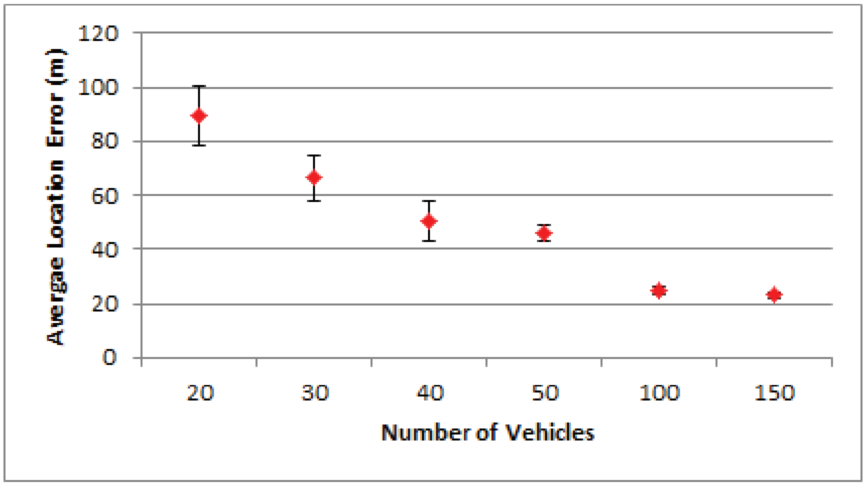

Figure 3.13: MWL Average Location Error with 95% Confidence Interval

MWL, where all factors are considered ($\alpha = \beta = \mu = 1$), performs well for the two different transmission ranges compared with MWL, where LQD is only considered ($\alpha = 1, \beta = 0, \mu = 0$), and MWL, where LQD and heading are considered ($\alpha = 1, \beta = 1, \mu = 0$). Furthermore, in the case of MWL with $\alpha = \beta = \mu = 1$ the difference in the average location errors for the two transmission ranges is relatively small for different densities.

Figure 3.15 shows the performance of MWL and RWL localization methods. For different transmission ranges, we can see that the average location error is lower for MWL, where all factors are considered ($\alpha = \beta = \mu = 1$), compared to the average location error for RWL method.

The impact of the transmission range on the maximum location error for MWL is shown in Figure 3.16. As observed, decreasing the transmission range has decreased the maximum location error for all three cases. Moreover, increasing the transmission range has a potential of increasing the number of neighboring vehicles, which will increase the maximum location error in the network.

In Figure 3.17, we can see that MWL, where all three factors are considered ($\alpha = \beta = \mu = 1$), performs better in all cases compared to RWL in terms of maximum

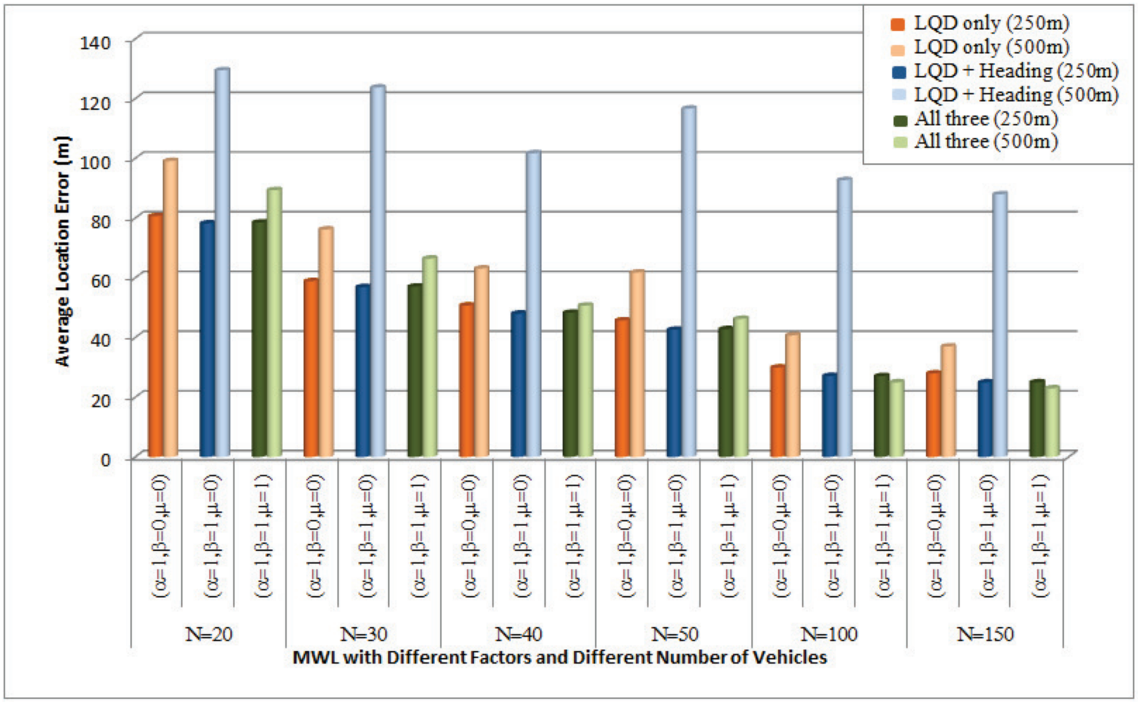

Figure 3.14: MWL Average Location Error for Different Densities and Transmission Ranges

location error.

On the other hand decreasing the transmission range to 250m has affected the efficiency of the proposed localization method, MWL with ($\alpha = \beta = \mu = 1$), for low densities. Figure 3.18 shows the impact of the transmission range on the efficiency of the proposed localization method. As seen in the figure, increasing the transmission range to 500m results in increasing the efficiency and the percentages of vehicles which can be localized within the network. It has been observed that for the 500m transmission range, all the vehicles in the network are able to successfully self-localize using the proposed method.

3.5 SUMMARY

We have proposed a V2V-based localization method that utilizes the exchanged information between neighboring vehicles and use this to estimate the location of the

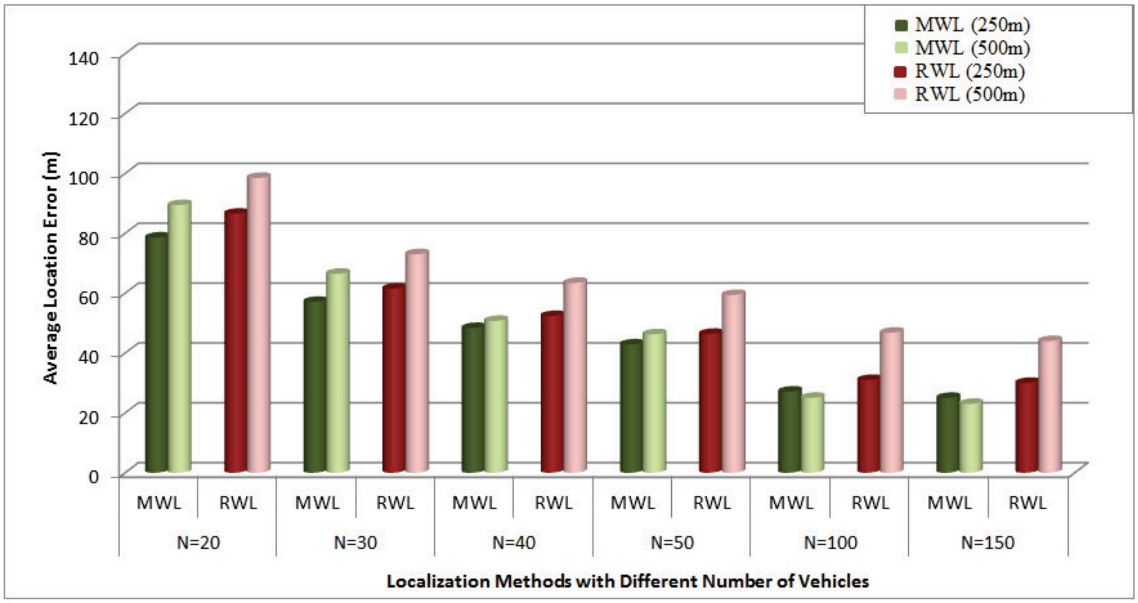

Figure 3.15: MWL and RWL Average Location Error for Different Densities and Transmission Ranges

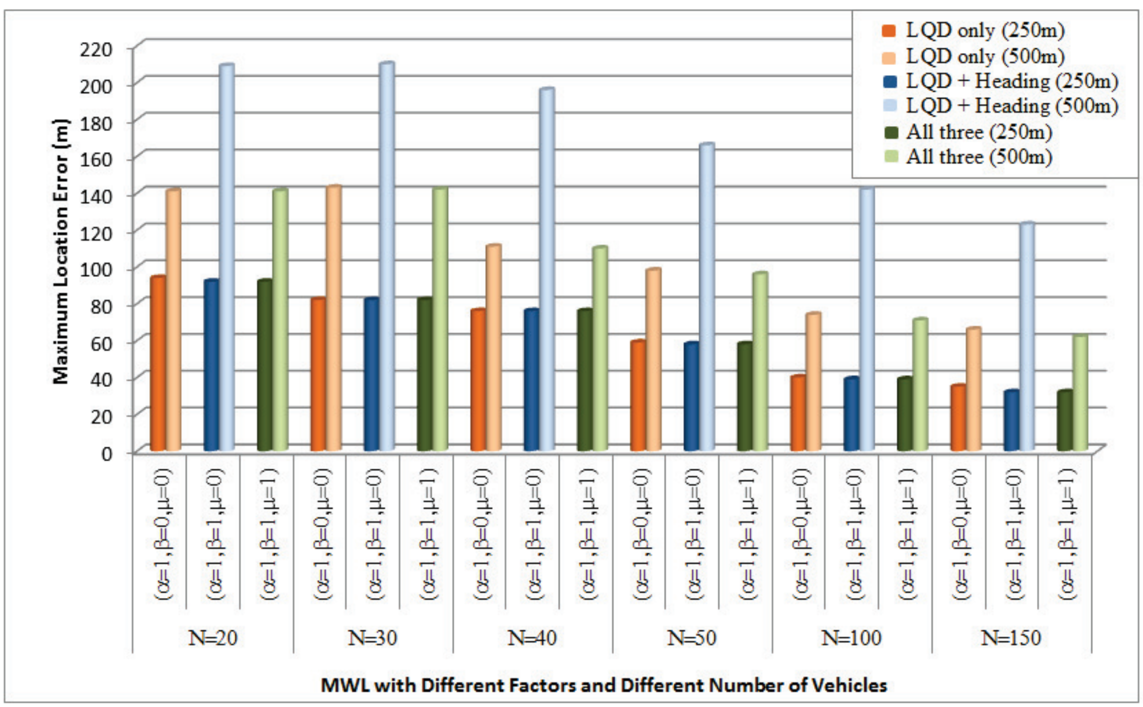

Figure 3.16: MWL Maximum Location Error for Different Densities and Transmission Ranges

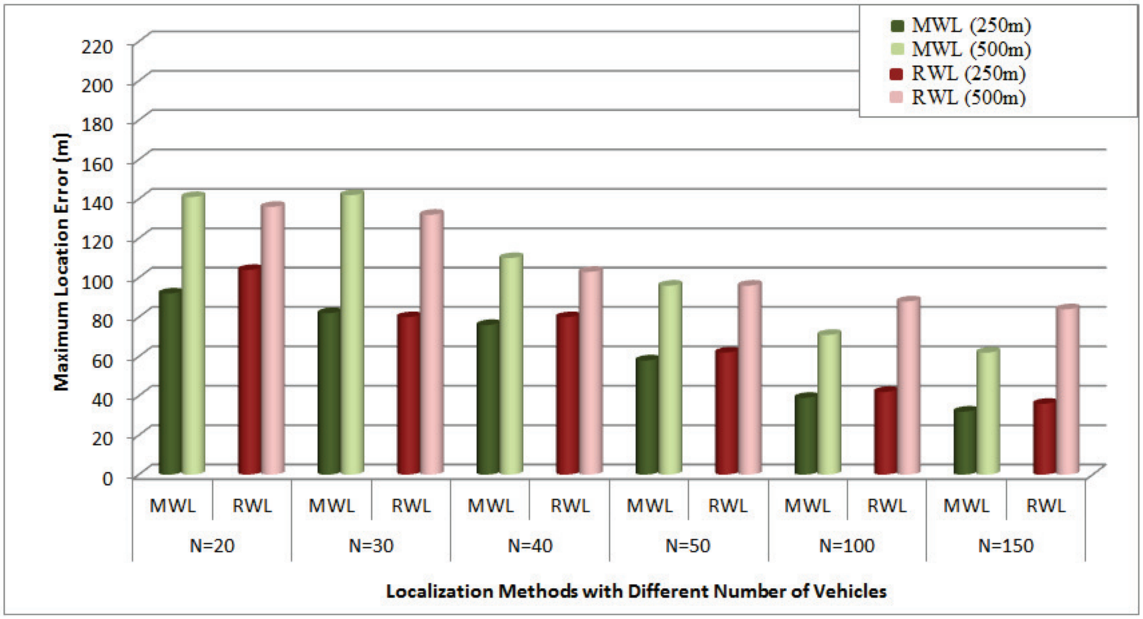

Figure 3.17: MWL and RWL Maximum Location Error for Different Densities and Transmission Ranges

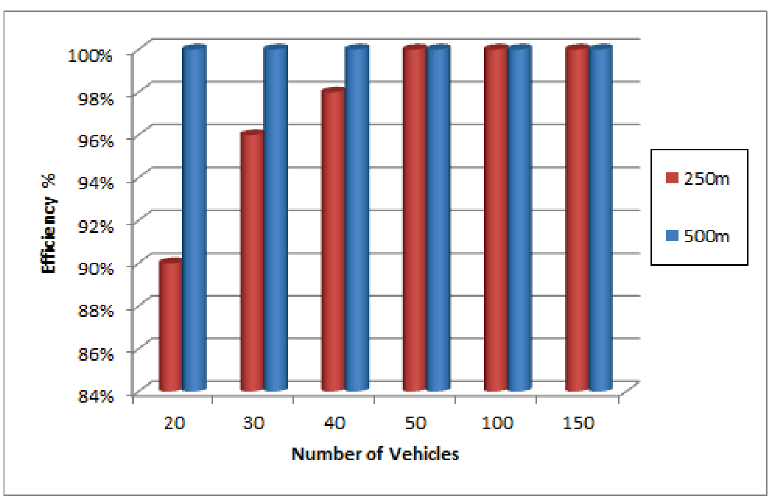

Figure 3.18: MWL Efficiency vs. Transmission Ranges

vehicles in VANET. Designing a V2V-based localization method is challenged by the high mobility, dynamic topology of VANET and the interference noise due to objects and buildings. Current solutions do not adequately address these challenges. In this chapter, we presented the design of a V2V-based localization method that addresses these challenges. We extended the concept of weighted centroid localization (WCL) by introducing a new weighting function that considers the following parameters: 1) link quality distance between the neighboring vehicles 2) heading information 3) map and road information. The proposed method is infrastructures-less and does not rely on any dedicated hardware. It only utilizes currently exchanged data among vehicles through beaconing.

Simulation results are compared by varying the different values of the weighting factors in the proposed weighting function. We have evaluated our proposed method in a wide variety of densities and transmission ranges. In all cases, the results demonstrate that combining the three factors improves the location accuracy. In fact, when considering all the proposed weighting factors, the location error decreased to 24%, compared to the case where only LQD weighting factor is considered, and decreased to 56%, compared to the case where LQD and heading weighting factors are considered.

A future direction of this work is to explore more parameters and factors to include in the proposed weighting function to increase the location accuracy. Although this can increase the overall complexity of the localization method, VANET has relatively adequate resources.

CHAPTER 4

FUZZY LOGIC BASED LOCALIZATION

In this chapter, we propose an intelligent localization method, which is based on fuzzy logic and neighbors' location information. The main objective of our proposed method is to estimate the location of a vehicle by utilizing the location information of its neighboring vehicles. To achieve accurate localization, we model vehicles' weights using fuzzy logic system, which utilizes the distance and heading information in order to obtain the weight values. By assigning weights to neighboring vehicles' coordinates, we expand the concept of centroid localization (CL). We evaluate our proposed method via simulation and compare its performance against CL. Results obtained from the simulation are promising and demonstrate the effectiveness of the proposed method in varying traffic densities. Material in this chapter is published in [24].

4.1 INTRODUCTION

Soft computing, such as fuzzy logic technique, is an important tool for solving problems for systems with rapidly changing characteristics and uncertainties. In VANET, fuzzy logic has been used to improve the decision making process and reduce delays in computation. Some of the areas that it has been applied to include:

- Cluster head selection
- Routing algorithms
- Data aggregation

- Beaconing
- Broadcasting

In cluster head selection [52], cluster heads are elected and reelected according to their speeds and distance from their cluster members. The fuzzy logic inference system is used to predict the future speed and position of the cluster members, resulting in high average cluster head lifetime and more stable topology with less communication. A novel Stability and Reliability Routing protocol (SRR) is discussed in [53]. SRR uses fuzzy logic with geographical routing in making packet forwarding decisions. Direction and distance are considered as inputs of the fuzzy decision making system so that the best neighbor around the vehicle is selected. The results show that SRR has less control overhead compared to the state of the art protocols, Greedy Perimeter Coordinator Routing (GPCR) and Dynamic Source Routing (DSR). Data aggregation using fuzzy logic system is introduced in [54] to reduce the number of sent messages in VANETs. This solution uses two parameters, space and time distances. The output parameter is the decision to aggregate the information or not with two possible values: YES and NO. A fuzzy logic approach for beaconing has been proposed in [55]. The Adaptive Beaconing Rate (ABR) considers the percentage of vehicles traveling in the same direction and the status of vehicles as inputs to the fuzzy logic system. The determined output is an adaptive beaconing rate that is tuned to the vehicular traffic characteristics. FUZZBR (FUZZy BRoadcast) is proposed in [56], which is a fuzzy logic based multi-hop broadcast protocol for information dissemination in VANETs. Multiple metrics of distance, mobility and signal strength are used as inputs to the fuzzy logic system in order to choose the best selection of the relay nodes.

In this chapter, we propose an intelligent localization method, which incorporates fuzzy logic with exchanged neighbors location information to estimate the location of a vehicle in the network. Localization metrics, including distance and heading, which are obtained from the periodic beacons, are considered as inputs to the fuzzy logic system in order to obtain weight values for all neighboring vehicles within the transmission range. In our proposed method, a weight is assigned to neighboring vehicles, so that closer neighboring vehicles will have great weights, and vehicles that are farther will get fewer weights. Using the weighted centroid localization (WCL), the weighted coordinates of all the neighboring vehicles is used to estimate the location of a specific vehicle in the network. Our proposed method is evaluated through simulations, and the results are compared with the original centroid localization (CL).

4.2 BACKGROUND

This section gives a brief background about the fuzzy logic system which has been utilized in our proposed method.

4.2.1 Fuzzy Logic

Fuzzy logic, introduced by Zadeh in 1965, accepts a range of values (logic) and returns estimated results. A fuzzy logic system consists of the following [57]:

- Fuzzifier
- Inference engine
- Defuzzifier

Fuzzifier uses predefined linguistics variables and memberships functions to map the crisp inputs into fuzzy values.

Inference engine maps the fuzzy values (from the fuzzifier) into fuzzy values using the combination of the predefined IF-THEN rules. Rules can be determined from numerical data or provided by experts in the area. For example, **IF** *temperature* is very high, **THEN** turn the fan to high.

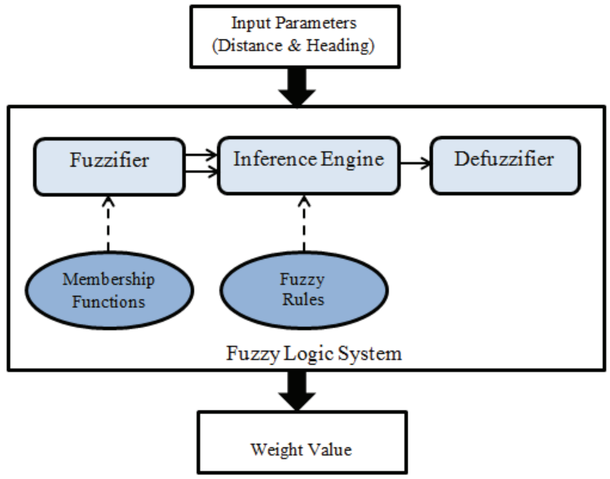

Figure 4.1: Fuzzy Logic System to Generate Weight Values

Defuzzifier refers to mapping the fuzzy values to crisp outputs. The obtained results are produced based on output membership functions. Figure 4.1 depicts the above elements of the fuzzy logic system.

4.3 THE PROPOSED METHOD

We propose a novel localization method that utilizes the fuzzy logic system by employing the calculated distance between vehicles using the measured received signal strength (RSS) value from the received messages and the heading information of neighboring vehicles.

4.3.1 Motivation

The use of the fuzzy logic theory is motivated by the fact that it has been proposed for locating nodes with unknown location in WSNs [58] [59] [60] [61] [62] [63]. It provides fast data processing without the need for any additional hardware. In addition, in reality, it has been accepted by the industry and used in many control applications. For example, in the auto industry, fuzzy systems have been used by key car makers, such as Nissan and Subaru, for cruise control, automatic transmission, anti-skid steering and anti-lock braking systems [57] [64].

Due to the odd characteristics of VANET, including high mobility and dynamic topology, fuzzy logic system can be applied to determine the weight values of neighboring vehicles. These weights are then used in the location estimation using WCL (Equation 3.2). In addition, RSS measurements are usually inaccurate and can be affected by the presence of obstacles, natural power dissipation and the existence of multiple paths [20].

4.3.2 Fuzzy Logic for Localization

In WSN, the use of fuzzy logic has improved the decision making process, reduced the computational resources, and thus, increased the performance [58]. The main advantage of using fuzzy logic is to minimize the errors and consider measurements from real world scenarios [59].

The proposed method is designed to adopt the V2V communication, in which vehicles can communicate without the use of roadside infrastructure. A vehicle can keep track of its neighboring vehicles, within its transmission range, by using beacons. These beacons are periodically broadcasted "hello" messages that contain information regarding the vehicle's position and heading. Using beacons will increase the level of awareness between vehicles in the network, and hence, increase the accuracy of the localization method.

The localization process is composed of five steps, as listed in Table 4.1. It starts when vehicles send beacons, containing location and heading information. Upon receiving the message, the vehicle will construct a positioning table filled with neighboring vehicles information. The localization method uses the measured RSS to determine the distance between the two vehicles. According to Friis free space propagation model, which assumes that there is one clear line-of-sight(LOS) path between the sender (transmitter) and the receiver, RSS decreases as a quadratic power law of distance [20]. The power of the received signal P_r can be determined using the following formula:

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{4.1}$$

In Equation 4.1, P_t is the transmission power of the sender (transmitter), λ is the wavelength, d is the distance between the sender and receiver, G_t and G_r are antenna gains, and L is the system loss factor. We set G_t=1 , G_r=1 and L=1 as defaults. The wavelength λ is calculated as follows:

$$\lambda = \frac{C}{f} \tag{4.2}$$

where C is the speed of light in vacuum (299,792,458 meters per second) and f is the frequency. Equation 4.1 gives us the power in watts. To obtain the power in decibels (dB), we use the following equation:

$$P_r(dB) = P_t(dB) + 10log_{10}(\frac{\lambda^2}{(4\pi)^2 d^2}) \tag{4.3}$$

Using Equation 4.3, we can derive and calculate the distance as follows:

$$d = \sqrt{\frac{\lambda^2}{16\pi^2 10^{\frac{P_r - Pt}{10}}}} \tag{4.4}$$

Once the distance is calculated, the localization method employs the fuzzy logic system to calculate the weight values based on the distance and heading of the neighboring vehicles. A weight value is assigned to each of the neighboring vehicle. Then, location estimation is performed using the WCL (Equation 3.2).

As demonstrated in Figure 4.1, the first step in designing a fuzzy logic system is to define the input and output values. The second step is determining the set of membership functions. The third step is designing the fuzzy rules, which are used in the inference engine. More details are elaborated in the next sections.

Table 4.1: Localization Process

Step 1	Broadcast beacon messages to all neighboring vehicles
Step 2	Construct positioning table based on the information received from the beacon message
Step 3	Determine the distance between the vehicle and its neighboring vehicles using RSS
Step 4	Employ fuzzy logic to determine the weight value for each neighboring vehicle
Step 5	Estimate the location using WCL (Equation 3.2)

Fuzzifier

As illustrated in Figure 4.2 and Figure 4.3, the two input parameters that must be fuzzified are: 1) distance 2) heading. The membership function with values VVClose, VClose, Close, Med, Far and VFar are used to represent the distance parameter. The range begins at zero and ends at 250, which has been chosen based on the maximum transmission range that is set to 250m in this work. The heading is represented as a discrete value because the neighboring vehicle would be either traveling in the same or in the opposite direction of the vehicle. The membership function utilizes same and opposite to represent the heading parameter. The previously discussed membership functions are derived based on the experience and the trails of the localization requirements.

Rules and Inference Engine

The design of the knowledge based rules is based on our understanding of the characteristics of VANETs. The fuzzy values of the distance and heading uses the IF-THEN rules, defined in Table 4.2, to determine the rank of the weight to be assigned to the neighboring vehicle. The linguistics variables are defined as: VVHigh, VHigh, High,

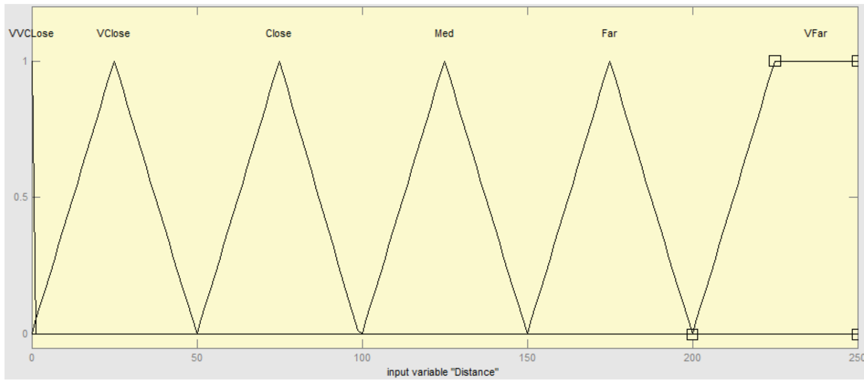

Figure 4.2: Membership Function for Distance

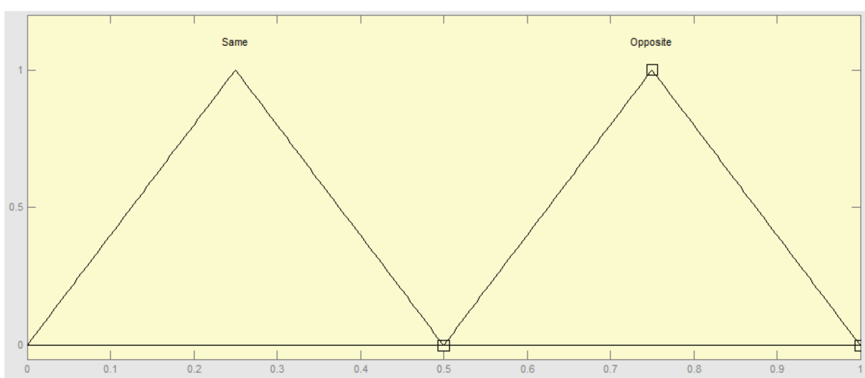

Figure 4.3: Membership Function for Heading

Table 4.2: Rule Base

	Distance	Heading	Rank
Rule 1	VVClose	Same	VVHigh
Rule 2	VVClose	Opposite	VVHigh
Rule 3	VClose	Same	VVHigh
Rule 4	VClose	Opposite	VHigh
Rule 5	Close	Same	High
Rule 6	Close	Opposite	Med
Rule 7	Med	Same	Med
Rule 8	Med	Opposite	Low
Rule 9	Far	Same	Low
Rule 10	Far	Opposite	VLow
Rule 11	VFar	Same	Low
Rule 12	VFar	Opposite	VLow

Med, Low and VLow. For instance, Rule 1 in Table 4.2 can be expressed as:

IF *Distance* is Large and *Heading* is Same

THEN *Rank* is VVHigh

Defuzzifier

The output membership function, defined in Figure 4.4, is used to produce the numeric result representing the weight value. In our proposed method, a weight value is assigned to each neighboring vehicle. Weight value represents the contribution of the neighboring vehicle in the localization estimation. The higher the value, the greater is the contribution. The correlation between the input and output variables is shown in Figure 4.5.

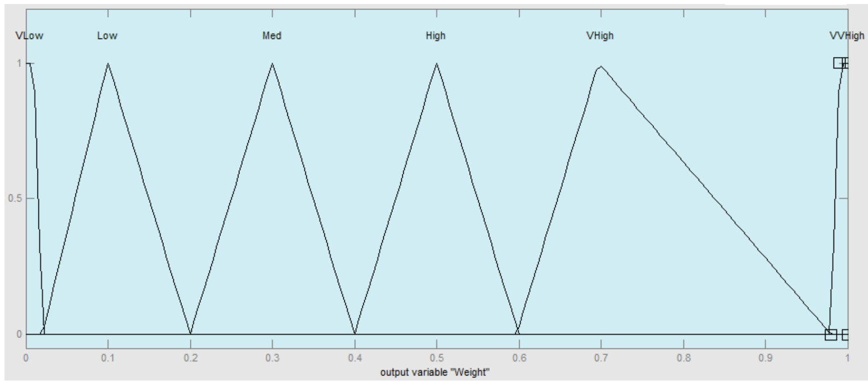

Figure 4.4: Output Membership Function

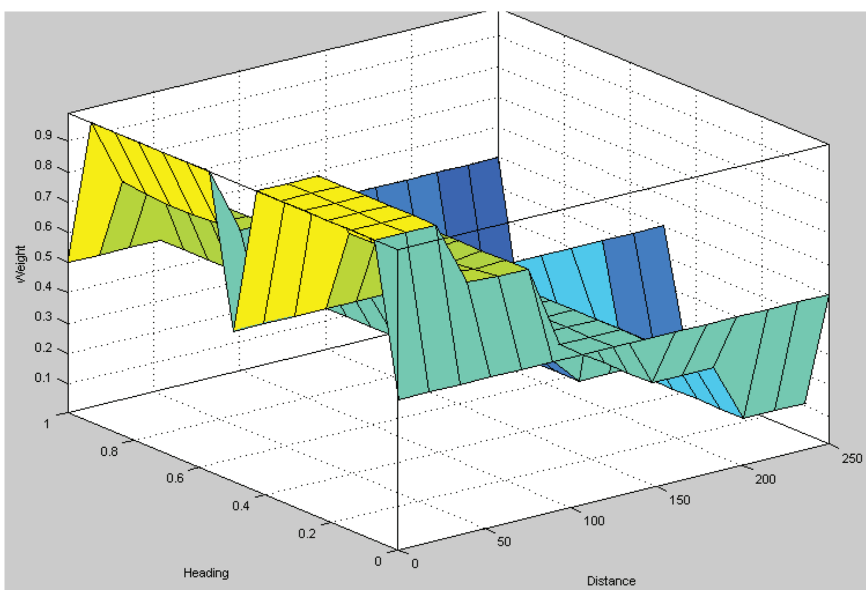

Figure 4.5: Correlation Between the Input and Output Variables

4.4 SIMULATION AND RESULTS ANALYSIS

4.4.1 Performance Evaluation

Network location error [11] is used to evaluate the performance of our proposed method.

Definition 1: Location error (LE_v) is the error between the actual location and the estimated location for each vehicle v_i in the network of N vehicles. LE_v is defined as follows:

$$LE_{vi} = \sqrt{(x_{iest} - x_{iact})^2 + (y_{iest} - y_{iact})^2} \tag{4.5}$$

Definition 2: Average location error (ALE) is the average of all vehicles' location errors. Using the location error (LE_v), the ALE can be formulated as follows:

$$ALE = \frac{\sum_{i=1}^{N} \sqrt{(x_{iest} - x_{iact})^2 + (y_{iest} - y_{iact})^2}}{N} \tag{4.6}$$

or

$$ALE = \frac{\sum_{i=1}^{N} LE_{vi}}{N} \tag{4.7}$$

4.4.2 Network and Mobility Model

We simulate scenarios of different vehicle traffic densities using ns-3.19 [49] and SUMO [50]. In our simulation, the road network uses a 3 x 3 Manhattan Grid with an edge length of 1000m and a distance of 500m between any two neighboring intersections. The road network is shown in Figure 4.6.

The simulations are run with the parameters shown in Table 4.3. The vehicle's mobility is generated using SUMO. In the car-following model, which is used in SUMO, the speed of a vehicle is adapted to the speed of the leading vehicle. Vehicles in the simulation are randomly distributed and routes are randomly generated using the

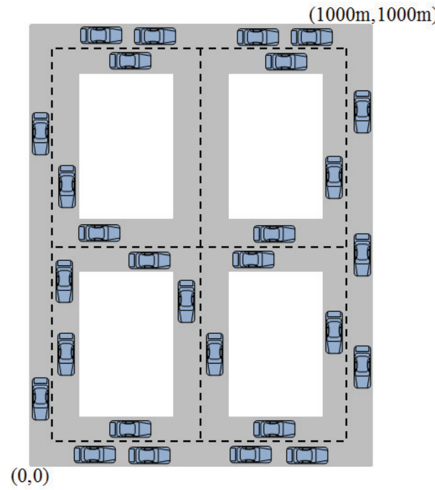

Figure 4.6: 3x3 Manhattan Grid Road Network

Table 4.3: The Simulation Parameters

Parameter	Value
Number of vehicles	20,30,40,50,100,150,200
Vehicle movement	Intelligent Driver Model
Vehicle speeds	Car-following model
Max road speed	14 m/s
Duration	1800 seconds (30 minutes)
Beacon interval	1 second
Packet size	48 bytes
Signal propagation	Two-ray ground
MAC/PHY protocol	IEEE 802.11p
Transmission range	250m
Layer 3 Addressing	IPv6

randomTrips utility in SUMO. The generated mobility traces of these scenarios are imported into ns-3 to generate node mobility using Ns2MobilityHelper class. We use the WAVE model [51], which is the overall system architecture for vehicular communications implemented in ns-3. The performance of our proposed method is compared with centroid localization (CL), and the results are presented below.

4.4.3 Results and Analysis

In Figure 4.7, the average location error is calculated using Equation 4.6 for all the methods. For both CL and our proposed method, the location accuracy increases consistently with higher densities. However, the location information is more accurate in our method. In addition, it is observed that CL got the highest location errors in all densities compared to our method. This is because it assumes that all neighboring vehicles are of equal distance from the vehicle that needs to be localized. In contrast, adding weight values to neighboring vehicles, based on their distance and heading information, has reduced the location error and improved the accuracy. An important parameter that affects the improvement of the proposed method is the local density, which is the number of the neighboring vehicles that can communicate and exchange massages within the transmission range. Therefore, the performance of our proposed method is influenced by the number of available neighboring vehicles.

4.5 SUMMARY

Safety applications are crucial to VANETs due to their impact in reducing accidents and saving lives. However, these applications require accurate localization methods to determine the location of the vehicle in the network. We proposed an intelligent localization method that combines fuzzy logic and weighted centroid localization (WCL). Two input parameters are fed to the fuzzy logic system, distance between the neighboring vehicles and heading information. Periodic messages (beacons) are used to

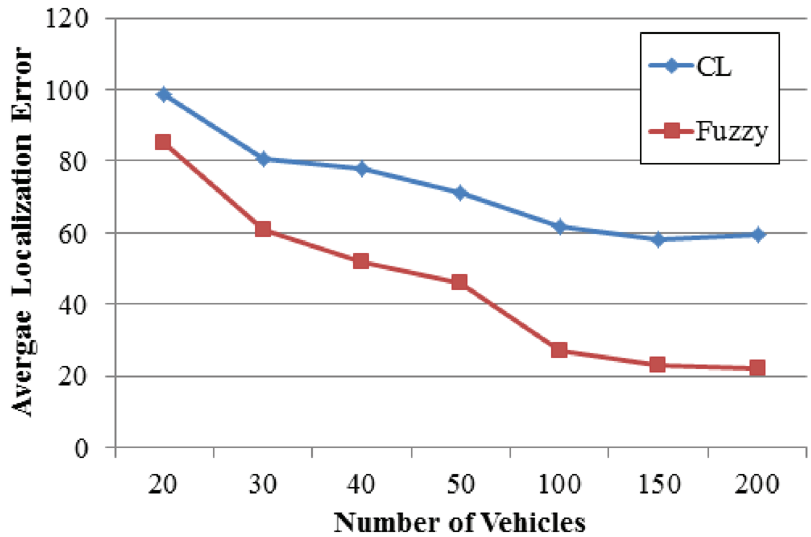

Figure 4.7: Average Location Error vs. Number of Vehicles

exchange such information. The output of the fuzzy logic system is weight values. Using WCL, each neighboring vehicle will be assigned a weight value. The weighted coordinates of the neighboring vehicles are then used to estimate the location of the vehicle. Compared to CL, our method demonstrates significant improvement in reducing location errors as density increases. However, the performance of our method can be improved by adding different parameters as inputs to the fuzzy logic system.

CHAPTER 5

MOBILITY DATA VERIFICATION FOR VEHICLE LOCALIZATION

In this chapter, we address this issue of exchanging invalid mobility data and propose a solution to mitigate the impact of such data in vehicle localization. We develop simulations to evaluate and validate our proposed verification system. We apply the proposed system to our previously developed localization method, optimized weighted localization (OWL) [22]. The results show that our solution has successfully detected untrusted vehicles and hence improved the performance of the localization method. Material in this chapter is published in [25].

5.1 INTRODUCTION

Wireless communication has been an active research area in the past decade. Vehicular Ad Hoc Network is an example of such network whose main focus is to increase the safety on roads. In VANET, vehicles are equipped with OBU to facilitate the communication between vehicles and between vehicles and RSUs. A wide range of services and applications are expected to be supported using vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. Therefore, this technology is being standardized as Wireless Access in Vehicular Environments (WAVE) [1], to secure the communications in the VANET environment.

Knowing the location of the vehicle is a key component in many VANET applications and services [2] [3] [4]. Therefore, a number of methods and protocols have been proposed to determine the accurate physical location of the vehicle in VANET [5] [8] [15] [19] [16]. For instance, the most popular method for localization is GPS; other techniques include Geographical Information System (GIS), Dead Reckoning (DR), Cellular Phone Technology, V2V-based localization, and V2I-based localization [21].

In VANET, the location of the vehicle is crucial to many applications. In fact, the performance of these applications depend highly on the vehicle's ability to determine its location within the network anytime and anywhere. GPS, which is considered as a global positioning system, suffers from outages, especially in areas where signals can be easily interrupted [19]. Therefore, combing V2V communication and GPS can solve this problem. In V2V-based localization each vehicle can estimate its location in relation to other neighboring vehicles (vehicles within its transmission range). This can be achieved by using the information exchanged via periodic beacon messages.

However, there is a critical issue when a vehicle sends incorrect information about its position in the beacon messages. This can impact the performance of many position based VANET applications. Our objective is to design a verification system that can effectively verify the mobility data announced by the vehicles in the network to determine if the vehicle's information can be considered in the localization method or not. With our solution, the error in the location estimation will decrease and the overall performance of many applications and services will improve.

5.2 THE PROPOSED MODEL

Providing a reliable and secure information is a challenging area in VANET; therefore, it is very important to understand the limitation and the nature of this network. Localization methods must be designed to be adaptive to VANET environment but also must be aware of the existence of malicious vehicles that can change the characteristics of the environment, or interrupt the entire network by disseminating incorrect information through beaconing or broadcasting. Taking this into account, the localization system can be divided into three different components (Figure 5.1):

Figure 5.1: Localization System Components

1. *Data Gathering*: This component is responsible for gathering and recording the received data from neighboring vehicles.

2. *Data Verification*: This component is responsible for verifying and checking the reliability of data.

3. *Localization Method*: This is the core component of the localization system. It utilizes the available verified data and use them in location estimation.

Localization methods have been the focus of our previous two chapters. In this chapter, we focus on data verification, which is the second component in the localization system.

5.2.1 Assumptions

The following is assumed in our proposed system:

1. Vehicles in the network can estimate their locations using any of the existing localization methods.

2. Each vehicle broadcast beacons that contain its mobility data as shown in Figure 5.2 to all vehicles within its transmission range.

3. Communication and data exchanging are secured as per the IEEE 1609.2 [1].

4. Vehicles can move at any speed without exceeding the predefined speed limits on roads.

5. Every vehicle is equipped with a digital map.

```
-----------------------------------------------------------------
|       0       |       1       |       2       |       3       |
0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|     Time      |                   SenderId                    |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                        X - Coordinate                         |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                       Y - Coordinate                          |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                           Heading                             |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                            Speed                              |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                           Road ID                             |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
```

Figure 5.2: Beacon Message Contents

5.2.2 Verification Model

Our proposed model consists of two distinct units as shown in Figure 5.3. In this section, we discuss the different units in details.

A. Parameters Check

Upon the receiving of a beacon packet, the analysis of its contents will be started to detect the inconsistency in the received information. The check is basically performed based on predefined rules and physical attributes as explained below. The outcome of these checks are modeled as binary values (0 and 1) to simplify the computation. In the following we discuss the different parameters used in this unit.

- *Position*:

  When a new packet is received from a neighboring vehicle, the current position of that vehicle can be estimated using the previously received position information and the current speed. This estimated position is then compared with the current stated position. If the two positions are different, then the vehicle information is considered to be incorrect.

- *Heading*:

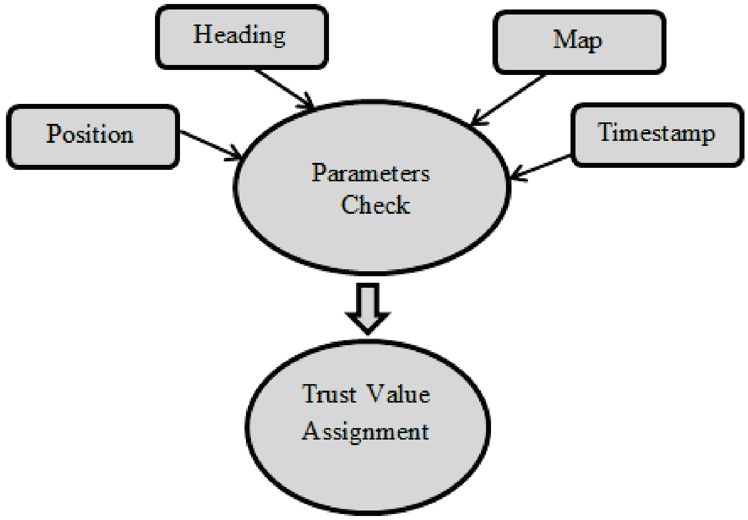

Figure 5.3: Verification Model

Mobility in VANET is constrained by the road; therefore, based on the road network, the exchanged heading values should be within the specified domain. For example, negative values and values greater than 360° are not acceptable.

- *Map*:

  By accessing road map information, the road information in the beacon packet can be verified. This is done by getting the road information from the current stated position and comparing it with the exchanged road information. The aim here is to verify whether the vehicle is moving on the claimed road or not. If not then, the vehicle is considered to be untrusted.

- *Timestamps*:

  Time information should be current; therefore, expired or future timestamps should be ignored. Whenever a vehicle receives a packet with a timestamp that is not current, that vehicle will be marked as untrusted.

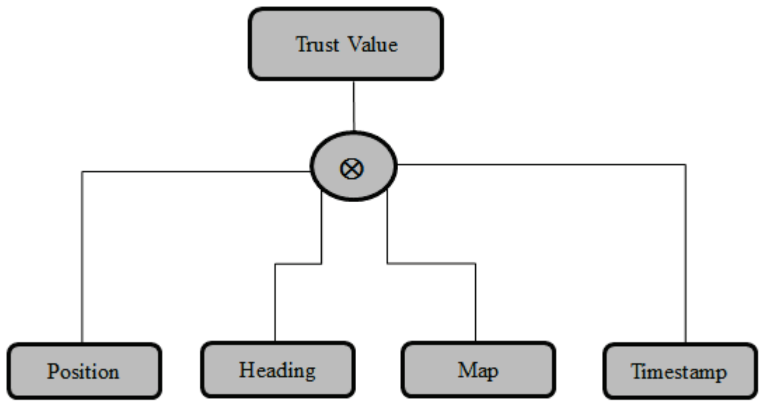

Figure 5.4: Trust Value

Table 5.1: Notation

Symbol	**Definition**
T_p	Position Parameter
T_h	Heading Parameter
T_m	Map Parameter
T_t	Timestamp Parameter
T_r	Trust Value

B. Trust Value Assignment

The key objective of this unit is to obtain the trustworthiness of a vehicle in the network. This can be achieved by measuring the trust value as a discrete quantified value (0 and 1). The overall design of this unit is presented in Figure 5.4. As mentioned above, by analyzing the recent and previous data of every neighboring vehicle, each vehicle can verify and evaluate its neighbors and hence the trustworthiness can also be evaluated. The trust value is calculated as follows:

$$T_r = T_p \otimes T_h \otimes T_m \otimes T_t \tag{5.1}$$

The notation is summarized in Table 5.1 and the detailed procedure is shown in Figure 5.5. The computed trust value will be added to the neighbor table. When

Receive(Beacon)
function CalculatePosition(PrevPosition,CurrSpeed)
    return EstimatedPosition
end function
if EstimatedPosition = CurrentStatedPosition **then**
    $T_p \leftarrow 1$
else
    $T_p \leftarrow 0$
end if
if Heading $\in$ PredefinedHeadingValues **then**
    $T_h \leftarrow 1$
else
    $T_h \leftarrow 0$
end if
function IdentifyRoadID(MapInfo,CurrPosition)
    return EstimatedRoadID
end function
if EstimatedRoadID = CurrentStatedRoadID **then**
    $T_m \leftarrow 1$
else
    $T_m \leftarrow 0$
end if
if (PacketTime = CurrentTime) **then**
    $T_t \leftarrow 1$
else
    $T_t \leftarrow 0$
end if
$T_r \leftarrow T_p \otimes T_h \otimes T_m \otimes T_t$

Figure 5.5: Verification Algorithm

running the localization method, the vehicle will look into the constructed neighbor table, and those vehicles that have trust values equal to zero will be eliminated from the location estimation process.

5.3 SIMULATION AND RESULTS ANALYSIS

In order to evaluate our proposed system, we need to select an application in which it can be applied. Therefore, we use our previous localization method optimized weighted localization (OWL) [22] which has been previously explained. We also simulate different scenarios using ns-3.19 [49] and SUMO [50]. In this section, we discuss the evaluation of our verification system and the simulation environment.

5.3.1 Adversary Model

In our work, we use this model to change the mobility data that is sent through beaconing in order to show the impact and the influence of the incorrect exchanged mobility data on the underlying localization method. We only focus on the following data: 1) Position 2) Heading 3) Map and 4) Time. The implementation of false positioning model is as follows:

1. Before sending a beacon message, the vehicle will run a random positioning function that will select a position within the subject vehicle's maximum transmission range. If R is the maximum transmission range, then D_{pr} which is the distance between the present and the random position should be less than or equal to R.

2. After generating the random position, the vehicle can then attach the data to a packet and broadcast it.

Figure 5.6 illustrates the steps used in our simulation for false positioning.

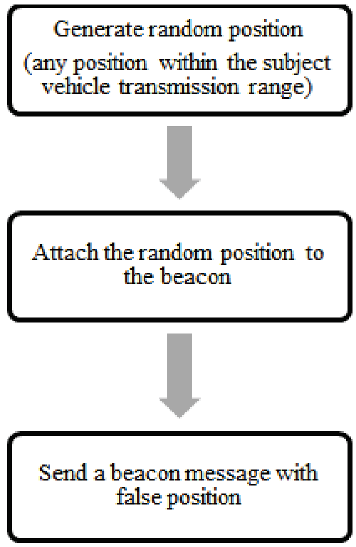

Figure 5.6: False Positioning Implementation

Other mobility data can be similarly altered before broadcasting the packet. We omit the details of this implementation.

5.3.2 Mobility and Simulation Environment

Vehicles in the simulation are randomly distributed and routes are randomly generated. Mobility traces of these scenarios, generated by SUMO, are used by ns-3 to generate node mobility. We used the WAVE model [51] which is the overall system architecture for vehicular communications in ns-3. We also varied the percentage of vehicles that propagate incorrect mobility data ranging from 0% to 50%.

The road network, shown in Figure 5.7, uses a 3 x 3 Manhattan Grid with an edge length of 1000m (1km) and a distance of 500m (0.5km) between any two neighboring intersections. The simulations were run with the parameters shown in Table 5.2.

5.3.3 Evaluation Metrics

To evaluate the efficiency of our proposed verification system, we use the following metrics:

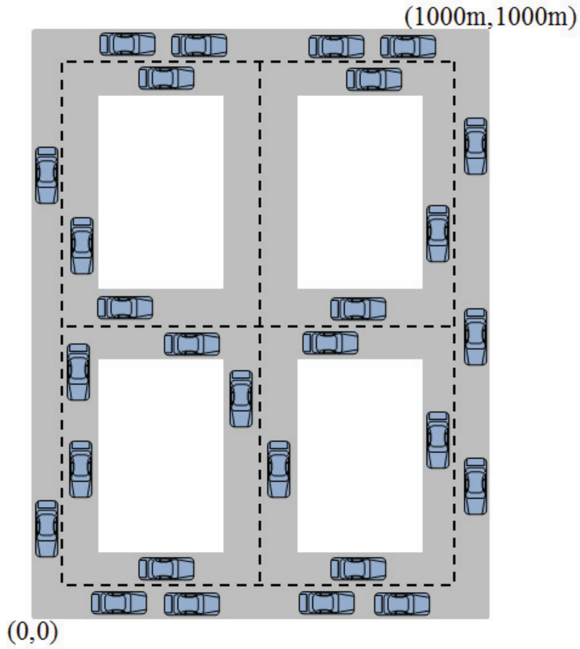

Figure 5.7: 3x3 Manhattan Grid Road Network

Table 5.2: The Simulation Parameters

Parameter	Value
Vehicle movement	Intelligent Driver Model
Vehicle speeds	Car-following model
Max road speed	14 m/s
Duration	1800 seconds (30 minutes)
Beacon interval	1 second
Packet size	48 bytes
Signal propagation	Two-ray ground
MAC/PHY protocol	IEEE 802.11p
Transmission range	250m
Layer 3 addressing	IPv6

(1)Location Error. This will measure the location error between the actual location (x_{act}, y_{act}) (ground truth) and the estimated location (x_{est}, y_{est}) (localization algorithm) of vehicle v in the network of N vehicles. The location error is defined as follows:

$$LocationError = \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2} \tag{5.2}$$

(2)Average Location Error. Using Equation 5.2, the average location error can be formulated as follows:

$$AvgError = \frac{\sum_{i=1}^{N} \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2}}{N} \tag{5.3}$$

(3) Maximum Location Error. This will measure the maximum location error obtained using the localization method. Accuracy can be improved by decreasing the maximum location error.

$$MaxError = \max \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2} \tag{5.4}$$

5.3.4 Results

Figure 5.8 shows the simulation results before and after applying our verification system. The figure clearly shows that identifying and excluding the untrusted neighboring vehicles result in decreasing the location error and hence, improve the overall performance of the localization method.

From the figure, it can been seen that varying the percentage of the untrusted neighboring vehicles from 0% to 50% increased the location error from 0% to 24%. On the other hand, using the proposed system, which eliminates beacons received from untrusted neighboring vehicles, reduced the location error by 7%.

The impact of applying the proposed verification system on the maximum location error is shown in Figure 5.9. As observed, using the verification system has decreased the maximum location error to 48%, when the percentage of untrusted neighboring vehicles is 25%. In addition, the maximum location error has decreased to 50%, when

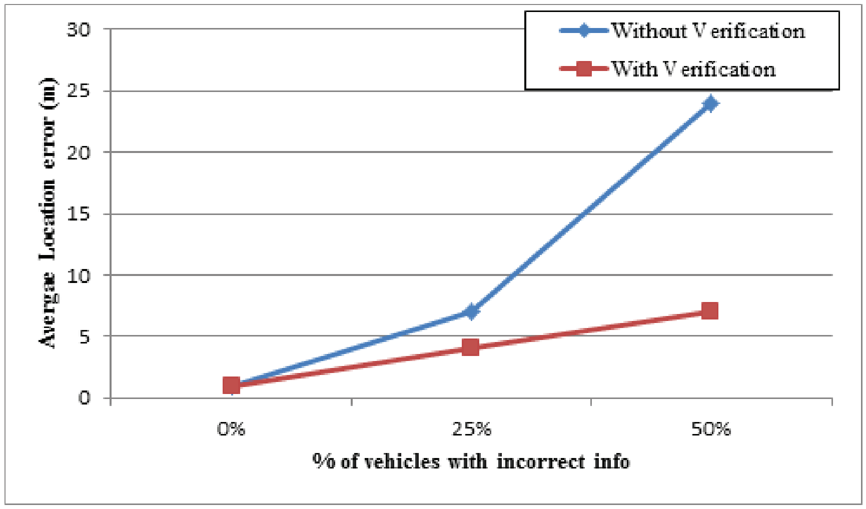

Figure 5.8: The Effect of Verification System on Average Location Error

the percentage of untrusted neighboring vehicles is 50%. As suggested by the results, excluding the untrusted neighboring vehicles has decreased the maximum location error, and hence, improved the performance of the underlying localization method.

The V2V-based localization method that is used in this chapter [22] depends highly on the number of neighboring vehicles. In other words, the performance depends on density, the more neighboring vehicles we have the more accurate the location estimation is. However, by applying the proposed verification system, the number of neighboring vehicles will eventually decrease and the performance of the localization methods will be affected.

5.4 SUMMARY

Dissemination of incorrect data through beaconing can have a negative effect on many VANET applications and services. Localization methods, which provide location information, depend highly on the mobility data exchanged among neighboring vehicles. Therefore, broadcasting incorrect mobility data will result in wrong location estimation that might affect the overall performance of the network. In this chapter, we have studied the negative effect of incorrect mobility data on our previous localization

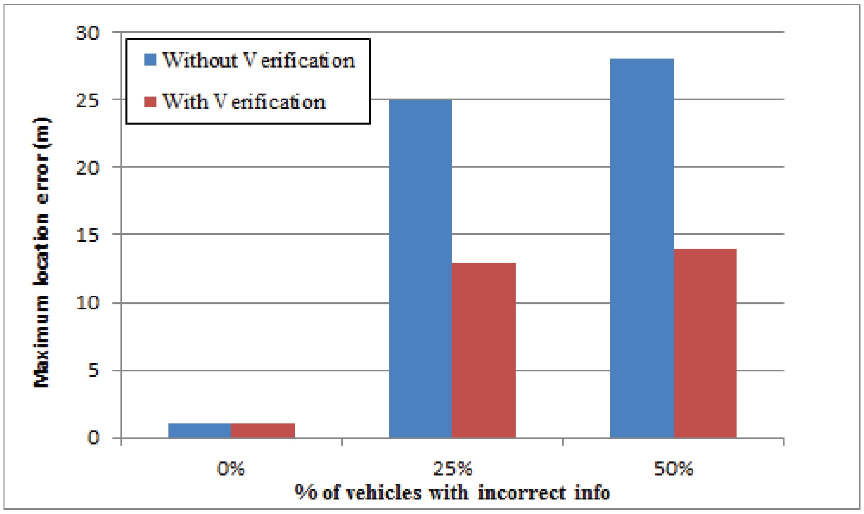

Figure 5.9: The Effect of Verification System on Maximum Location Error

method. We have also presented a verification system that is capable of detecting and evaluating the neighboring vehicles to mitigate the impact of these incorrect data on the localization method. The proposed approach is infrastructures-less and does not rely on any dedicated hardware. It only uses previously and currently exchanged mobility data so that the evaluation of a vehicle in the network can be performed as quickly as possible. We have conducted simulations to evaluate the effectiveness of our proposed system. The results showed that our proposed verification system has successfully detected and excluded untrusted neighboring vehicles and has decreased the location error. Future work will enhance the current solution by adding more parameters to the parameter check unit and investigate alternative approaches that use continuous trust values rather than the binary discrete trust values. In addition, sophisticated attackers will be considered in the adversary model.

CHAPTER 6

SUBJECTIVE LOGIC BASED TRUST MANAGEMENT SYSTEM FOR VEHICLE LOCALIZATION IN VANET

In this chapter, we introduce a subjective logic based trust management system that consists of three main components: 1) direct trust module 2) indirect trust module and 3) decision making module. The proposed solution allows each vehicle in the network to evaluate the trustworthiness of other vehicles based on opinions formulated from either direct interactions or derived from indirect interactions with other vehicles. To demonstrate the utility of the proposed system, we incorporate it with our previously proposed localization method. We develop several simulations, using ns-3, to evaluate the performance and the efficiency of the proposed system. Our simulation results indicate that in the presence of untrusted neighboring vehicles, the performance of the underlying application has improved in terms of average location error. Material in this chapter is published in [26].

6.1 INTRODUCTION

The evolution in the wireless communication and automotive industry has defined the Vehicular Ad Hoc Networks, VANETs. With wireless communication capabilities, vehicles in VANET can exchange and share up-to-date information about road and traffic conditions. Vehicle-to-vehicle communication (V2V) enables such kind of information to be disseminated among vehicles within the network. Consequently, a number of applications and protocols have been developed with the intent to ensure a reliable information delivery and message handling between vehicles [65] [66] [67] [68].

On the other hand, less effort has been spent on evaluating the quality and the integrity of the information sent by vehicles.

For instance, vehicle localization is crucial to VANET. In fact, many applications, especially safety related applications, require an accurate location information in order to operate efficiently and effectively [2] [3] [4]. V2V-based localization is a localization technique that helps vehicles in the network to determine their location in relation to other neighboring vehicles [21] [22]. This can be achieved by allowing neighboring vehicles to exchange position and other mobility information via beacon messages. However, if the exchanged information is incorrect or inaccurate, this will result in wrong location estimation, which in turn will affect the performance of the network.

Therefore, trust can be used as a mechanism to evaluate the reliability and the integrity of the received information based on the behavior of the sender. The objective of the trust management system is to continuously observe and evaluate the interactions between vehicles. This can be achieved by analyzing the content of the beacon messages to quantify the behavior of a vehicle and then establish the trust relationship. Based on the trust relationship and the application policies, a decision can be made to accept or reject the received information.

In VANET, the development of the trust management system is still in its early stages. In addition, due to the nature and the characteristics of VANET, modeling trust relationships among vehicles becomes challenging. The following are some of the challenges [69] [70]:

- Dynamic topology: vehicles can move fast at different speeds which results in rapid changes in the topology and frequent changes in the vehicle's neighbor table. In fact, new vehicles can join and existing vehicles can leave the network at any time.

- Communication channel: many environmental factors can affect the wireless communication between vehicles which cause unreliable transmission of messages. These factors can influence the degree of uncertainty and affect the overall trust evaluation.

- Diversity: many applications and systems have been developed with different specifications and requirements. Therefore, they require a certain level of trust with different degrees of uncertainty to operate efficiently.

- Decentralized network: the environment is open and there is no centralized infrastructure. In addition, it does not rely on a central authority to mange the network.

In order to address the above challenges, we propose the use of subjective logic [71]. Modeling trust relationships using subjective logic is suitable for VANET because:

- It is well-suited for managing uncertainty when a new vehicle joins the network and when the transmission is not reliable in the wireless communication.

- It allows the modeling and quantitation of the positive, negative as well as uncertain observations based on interactions between vehicles and the application requirements.

- It offers different types of operators from binary logic and probability calculus as well as specific operators for combining and merging different opinions. This variety of operators make it possible to support wide range of different applications and systems.

- It provides a flexible framework to accommodate different sources of information to improve the overall efficiency of the trust management system.

- It enables each vehicle in the network to independently evaluate the trustworthiness of other neighboring vehicles. Therefore, it does not rely on a central authority for trust evaluation.

In this chapter, we introduce the design of a subjective logic based trust management system that can be incorporated with localization methods to provide a reliable location estimation. Furthermore, we demonstrate how each vehicle in the network can formulate their opinions about others based on the evidences captured from either direct or indirect interactions. We later discuss how vehicles use these subjective opinions to evaluate the trustworthiness of other vehicles. We also implement simulations to evaluate our proposed system using the localization method discussed in [23]. We compare the performance of the proposed system against our previous mobility data verification system [25], which is binary rules based. The simulation results show that incorporating the proposed system has decreased the error in the location estimation and has improved the overall performance of the localization method.

6.2 BACKGROUND

Subjective logic [72] combines the probability values and uncertainty level to represent the concept of opinion. In turn, the opinion itself is a composite of: 1) belief 2) disbelief and 3) uncertainty [73]. The belief and disbelief are determined from the evidences that are captured from both trusted and untrusted behaviors. On the other hand, uncertainty represents the confidence level about the evidence. An opinion is represented as an ordered tuple with the following format:

$$w_x = (b_x, d_x, u_x) \tag{6.1}$$

In the context of VANET b_x, d_x and u_x represents the following:

- b_x holds the belief that vehicle x is honest and sending correct information based on the captured observations.
- d_x holds the disbelief that vehicle x is honest and supports that vehicle x is sending false information based on the captured observations.

- u_x holds the uncertainty in the captured observations and supports that vehicle x's behavior is uncertain and unsure about the accuracy of the information that is being sent.

In addition, the above components should satisfy these two conditions: 1) $b+d+u=1$ and 2) $b, d, u \in [0.0, 1.0]$.

Subjective logic has a set of operators that allows operations to be performed on opinions. The input and output of these operators are opinions. Details about the full list of operators is discussed in [71]. For our proposed trust management system, we utilize the use of consensus ($\oplus$) and discount ($\otimes$) operators. The consensus ($\oplus$) operator is used to combine the different types of opinions into a single final opinion. The discount ($\otimes$) operator is used to derive opinions from recommenders by knowing the opinion about the recommenders and the recommender's opinion about the recommended vehicle. Using the consensus ($\oplus$) operator will result in reducing uncertainty and using discount ($\otimes$) operator will result in increasing the uncertainty because it is derived from indirect opinions [74]. Next we discuss details about these two operators.

1)Consensus Operator

Given the distance opinion ${}^{dis}w^i_j = ({}^{dis}b^i_j, {}^{dis}d^i_j, {}^{dis}u^i_j)$ and the map opinion ${}^{map}w^i_j = ({}^{map}b^i_j, {}^{map}d^i_j, {}^{map}u^i_j)$ we get ${}^{dis:map}w^i_j = {}^{dis}w^i_j \oplus {}^{map}w^i_j$ such that

$$\begin{aligned} {}^{dis:map}b^i_j &= \frac{{}^{dis}b^i_j\,{}^{map}u^i_j + {}^{map}b^i_j\,{}^{dis}u^i_j}{z} \\ {}^{dis:map}d^i_j &= \frac{{}^{dis}d^i_j\,{}^{map}u^i_j + {}^{map}d^i_j\,{}^{dis}u^i_j}{z} \\ {}^{dis:map}u^i_j &= \frac{{}^{dis}u^i_j\,{}^{map}u^i_j}{z} \end{aligned} \tag{6.2}$$

where $z = {}^{dis}u^i_j + {}^{map}u^i_j - {}^{dis}u^i_j\,{}^{map}u^i_j$.

In the case of ${}^{dis}u^i_j = 0$ and ${}^{map}u^i_j = 0$, the values of ${}^{dis:map}b^i_j, {}^{dis:map}d^i_j$ and ${}^{dis:map}u^i_j$ will be respectively equivalent to the average values of the belief, disbelief and uncertainty.

2)Discount Operator

This operator is used to derive the indirect opinion based on: 1) the subject vehicle's opinion about the recommender vehicle and 2) the recommender vehicle's opinion about the target vehicle. Let's assume that the subject vehicle's (i) direct opinion about recommender vehicle (k) is denoted by ${}^{dir}w_k^i$ and the recommender vehicles direct opinion about target vehicle (j) is denoted by ${}^{dir}w_j^k$. By using the ($\otimes$) operator we can derive i's indirect opinion about j, ${}^{indir}w_j^{i:k} = {}^{dir}w_k^i \otimes {}^{dir}w_j^k$ such that

$$\begin{aligned} {}^{indir}b_j^{i:k} &= {}^{dir}b_k^i \, {}^{dir}b_j^k \\ {}^{indir}d_j^{i:k} &= {}^{dir}b_k^i \, {}^{dir}d_j^k \\ {}^{indir}u_j^{i:k} &= {}^{dir}d_k^i + {}^{dir}u_k^i + {}^{dir}b_k^i \, {}^{dir}u_j^k \end{aligned} \tag{6.3}$$

6.2.1 Related Work

By understanding the nature and the unique characteristics of VANET, we can see that an effective trust management system is crucial for the efficiency of its applications and services. Therefore, a variety of VANET's trust management systems have been studied in the literature [75] [76]. In this section, we only focus on the existing trust and reputation systems that utilize subjective logic in mobile and vehicular ad hoc networks.

[77] proposes the incorporation of uncertainty based on subjective logic into the reputation computation for nodes in ad hoc networks. As per the authors, uncertainty can rise when a new node joins the network or when the behavior of a node is changing in a way that is some how suspicious. The results show that the proposed system is able to maintain the functionality of the nodes while discriminating between the cooperative and the malicious behavior in the ad hoc network. However, the simulation was implemented in a simple way, which allows only certain scenarios to be tested and evaluated. With VANET, simulation should be designed to be more realistic.

In [78], a trust model is proposed based on subjective logic. The aim of this work is to enhance routing in MANET. Similar to [77] uncertainty, which is represented in terms of ignorance, is used in building trust relationships between nodes. Each node in the network computes its opinion of others using: 1) direct interactions 2) observed interactions and 3) recommendations from other nodes. Decision policies, that use a predefined threshold, are specified to enhance the routing protocol by excluding the malicious nodes and using the other nodes in the communication. Compared to their work, where nodes are evaluated by monitoring the successive forwarding of packets, our proposed system evaluates the node based on the data received via beacon messages. In addition, in VANET it is more suitable to use an adaptive threshold to facilitate the decision making process and enhance the overall performance of the application.

A reputation computation model based on subjective logic for MANET is presented in [79]. The proposed scheme aims to classify and recognize selfish nodes early enough in order to decrease the convergence time for excluding selfish nodes. It combines familiarity value, which represents the node's familiar degree with other nodes, with the subjective opinions. This familiarity value is used to compute a weight factor, so that nodes that interact more frequently will have a higher impact on the reputation computation result. In this scheme, some parameters are introduced, e.g., the rating and the threshold parameters; however, the authors did not study the impact of varying these parameters on the performance of the network .

In [80], the probabilistic asymmetric key pre-distribution (PAKP) method is enhanced by using subjective logic in MANET. The enhanced PAKP method is able to detect malicious nodes and hence, choose paths that are more reliable and trustful. Their simulation results have shown that incorporating subjective logic has decreased the traffic in the network and enhanced the security. However, their proposed scheme has been designed in the context of MANET and it may not be feasible to use it in

VANET.

The use of subjective logic for inter-vehicular communication trust model has been discussed in [81]. Each vehicle in the network computes its opinion about other vehicles based on three properties: 1) their competence 2) their predictability and 3) their reputation. These properties are obtained from direct interactions and recommendations through indirect interactions. Opinions are combined using average fusion and priority fusion operators. The resulting opinion is then transferred to single trust value used for decision making. Their proposed trust model focuses on computing trust based on the received traffic reports. However, in our proposed trust system we focus on validating the mobility data received from other vehicles in order to enhance the overall performance of the localization method [23].

[82] introduces the design of a misbehavior detection framework for VANET based on subjective logic. In their work, data received from other vehicles as well as data read from sensors is stored in the world model. Once data is stored in the world model, such information can be evaluated and annotated with subjective logic opinions. Although the authors have shown some examples to prove the applicability of their proposed scheme, they did not provide any details about the implementation and the evaluation.

In contrast to the above proposed schemes, our proposed system aims to assist the vehicles in the network to localize themselves using the reliable and verified information received from trusted neighboring vehicles. To the best of our knowledge, utilizing subjective logic to design trust management systems is new to VANET and hence, requires thorough investigations and analysis.

6.3 THE PROPOSED FRAMEWORK

Trust management system can be used to evaluate the reliability and the integrity of the information exchanged among vehicles. However, it is very important to take

Figure 6.1: Localization System Components

into account the unique characteristics of VANET environment. Therefore, the applications and services must be designed to be adaptive to the environment and also be aware of the existence of the untrusted vehicles. For instance, disseminating and exchanging incorrect information through beaconing can affect the overall performance of the localization method. Taking this into account, we divide the localization system into three different components (Figure 6.1):

1. Data Gathering: This component is responsible for gathering and recording the received data from neighboring vehicles.

2. Data Verification: This component is responsible for verifying and checking the reliability of data.

3. Localization Method: This component utilizes the available verified data and use them in location estimation.

Localization methods have been previously discussed in our previous work [21] [22] [24]. In this chapter, we focus on building a trust management system for the data verification component. Next we outline the assumptions and describe the system operation.

```
-----------------------------------------------------------------
|       0       |       1       |       2       |       3       |
0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|     Time      |                   SenderId                    |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                        X - Coordinate                         |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                        Y - Coordinate                         |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                            Heading                            |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                             Speed                             |
|                                                               |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
|                            Road ID                            |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
```

Figure 6.2: Beacon Message Contents

6.3.1 Assumptions

The following is assumed in our proposed system:

1. Vehicles in the network can estimate their locations using our proposed weighted localization method [23].

2. Every vehicle in the network has a unique identification.

3. Based on the recommendation of the wireless access in vehicular environments (WAVE) standard [1], each vehicle will periodically broadcast a beacon message to all vehicles, within its transmission range, 10 times per second. The content of the beacon message is shown in Figure 6.2.

4. Trust evaluation and location estimation is performed every second.

5. Vehicles can move at any speed without exceeding the predefined maximum speed limit on roads.

6. The vehicle's average speed is calculated each time a beacon message is received. Details about the average speed calculation is provided in the next section.

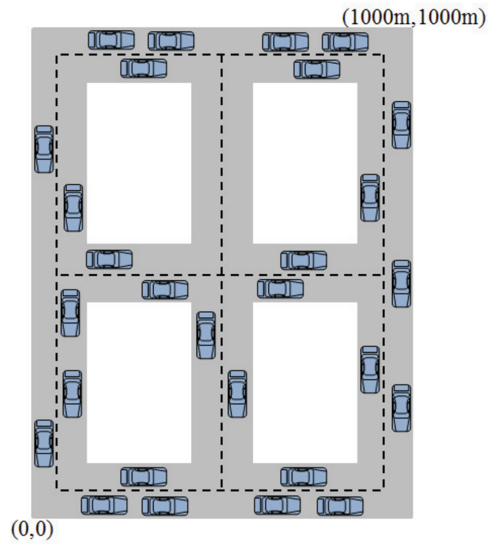

Figure 6.3: The Road Network

7. Every vehicle is equipped with a digital map as in Figure 6.3. Each road consists of two lanes with traffic moving in opposite directions.

8. The digital map provides navigation information, such as the x, y points that define the boundaries of the road and the road ID which contains road number, road orientation and road direction as illustrated in Figure 6.4.

9. The movement of the vehicles is constrained to the Manhattan mobility model. Figure 6.5 shows the four different angles in which a vehicle can move.

6.3.2 System Operations

The proposed system will assist the localization method [23] in making decision whether to accept or reject the mobility information received from neighboring vehicles and use such information in the location estimation for a given vehicle. The decision will depend highly on the trust evaluation, which relies on the opinion formulated for neighboring vehicles based on observations collected during either direct interactions or derived from indirect interactions with other vehicles.

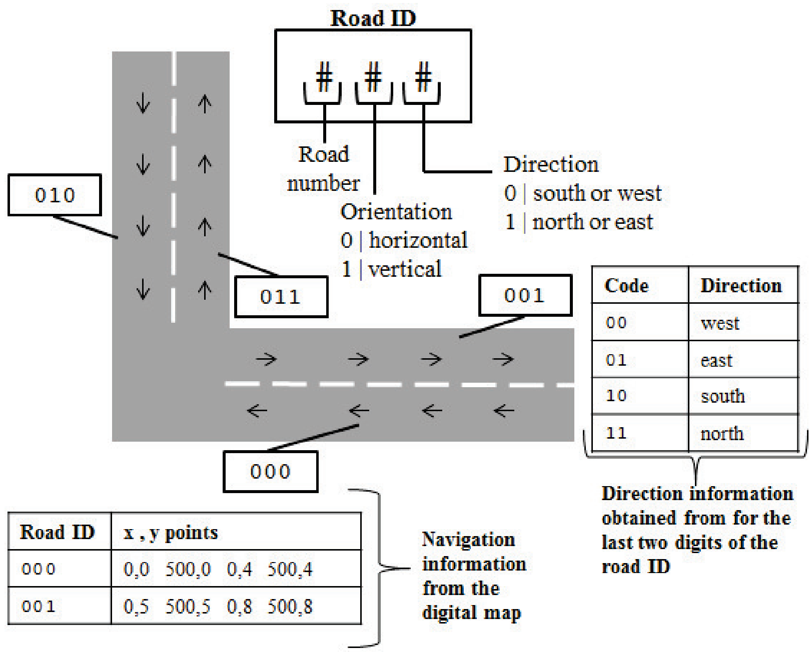

Figure 6.4: Digital Maps Information

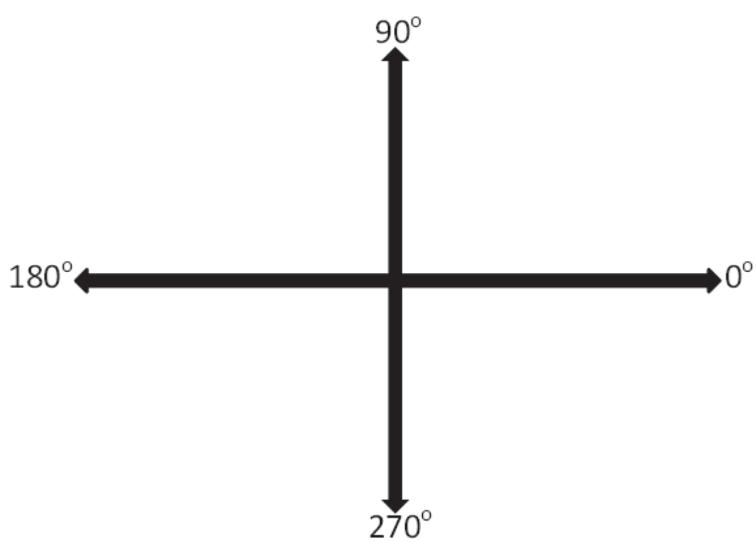

Figure 6.5: Heading Different Angles

We consider untrusted vehicles to be those who have modified and disseminated false or incorrect mobility information including: 1) position 2) speed 3) road ID and 4) heading. Such vehicles must be identified and their mobility information must be eliminated from the location estimation.

In order to understand the overall system operations, let's consider a scenario where vehicle j is a neighboring vehicle of vehicle i. Vehicle i needs to determine its location using the mobility information sent by vehicle j. The mobility information is sent through beacon messages. It is assumed that the beaconing frequency is 10 times per second; therefore, vehicle i will receive 10 beacon messages per one second, we use $M1, M2, ..., M10$ to denote the received beacon messages.

Considering a one second interval, at the end of that interval, the localization method will be activated to estimate the location of vehicle i. Vehicle i will assign a weight value to vehicle j and will use the weight value along with vehicle j's position information to estimate its current location [23]. However, before performing the estimation, vehicle i must evaluate the trustworthiness of vehicle j. Therefore, upon the reception of the first beacon message ($M1$) from vehicle j, vehicle i will check its neighbor table for any previous interaction. The content of the neighbor table is summarized in Table 6.1. If no entry is found, then vehicle i will evaluate the trust based on the recommendation from other vehicles. Details about indirect trust evaluation is provided in Section 6.4.2. On the other hand, if the last received beacon from vehicle j is recorded in vehicle i's neighbor table then direct trust evaluation is started. Direct trust evaluation is discussed in Section 6.4.1.

Once the trust evaluation is completed and the opinion is formulated, either direct or indirect, vehicle j will be classified as 1) trust or 2) distrust based on the decision making module (discussed in Section 6.4.3). After the classification, the localization method will be executed and the location will be estimated using only trusted neighboring vehicles.

Table 6.1: Neighbor Table

Column	**Definition**
$NodeID$	The vehicle's unique identification
$Position$	The current x, y position of the vehicle
$Speed$	The current speed of the vehicle
$RoadID$	The road ID in which the vehicle is traveling on
$Heading$	The direction in which the vehicle is heading to
$Time$	The timestamp of the beacon message
r	The number of position observations
s	The number of negative observations
q	The number of uncertain observations
b	The probability of the belief
d	The probability of the disbelief
u	The probability of the uncertainty

6.4 TRUST EVALUATION

In our work, trust is defined as a mechanism to evaluate the reliability and the integrity of the exchanged beacon messages based on the behavior of the sender. We consider the following three types of vehicles in the network:

- Subject vehicle is the opinion owner
- Target vehicle is the vehicle to be evaluated
- Recommender vehicle is the vehicle that is able to communicate and exchange opinions with both subject and target vehicles

Our trust management system consists of three main components:

1. Direct trust module
2. Indirect trust module
3. Decision making module

When a subject vehicle wants to evaluate the trust value of a target vehicle, it first checks if the target vehicle has an entry in its neighbor table. If found then the direct trust module is initiated. Otherwise, the indirect trust module is triggered. However, in the case where direct and indirect trust cannot be performed, for example, if there was no previous interaction between the subject and the target vehicle and there was no recommender vehicle to communicate with, we use the following default opinion:

$$ {}^{def}w_j^i = ({}^{def}b_j^i, {}^{def}d_j^i, {}^{def}u_j^i) = (0, 0, 1) \tag{6.4} $$

The reason for modeling the default opinion as complete uncertainty, is that our application (vehicle localization) is very conservative and only considers neighboring vehicles with trust evaluation. After formulating the opinion, either direct or indirect,

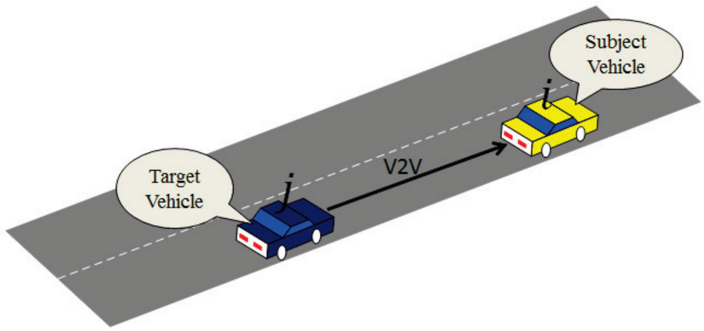

Figure 6.6: Evaluation of Direct Trust

the target vehicle will be classified as either trust or distrust based on the rules specified in the decision making module. Next we discuss the details of each module.

6.4.1 Direct Trust Module

This kind of trust is evaluated based on direct communication between the subject and the target vehicles as shown in Figure 6.6. The output of this module is a direct opinion which can be denoted as ${}^{dir}w_j^i$ where i is the subject vehicle and j is the target vehicle. Three different types of trusts are considered in the evaluation: 1) distance 2) map and 3) heading. Based on the distance opinion ${}^{dis}w_j^i$, the map opinion ${}^{map}w_j^i$ and the heading opinion ${}^{head}w_j^i$, direct opinion between two neighboring vehicles can be obtained as:

$$ {}^{dir}w_j^i = {}^{dis}w_j^i \oplus {}^{map}w_j^i \oplus {}^{head}w_j^i \tag{6.5} $$

When evaluating the three different types of direct trust, we analyze different sources of information to ensure that the performance of the trust management system is efficient and the output is rational. Table 6.2 summarizes the three types of direct trust and the different sources of information used in their evaluations.

For instance, in *distance trust evaluation*, we utilize both speed and time information to get the distance traveled. The evaluation and verification is done based on the following assumptions:

Table 6.2: Three Different Types of Direct Trust

Type	**Data from Beacon Message**	**Estimated Data**	**Resources for Data Estimation**	**Verify Against**
Distance	Speed and Time	Distance traveled	Two timestamps from two consequent beacon message and speed from last received beacon message	Predefined maximum distance and calculated average distance
Map	Position information	Road ID	Map information	Road ID from beacon message
Heading	Road ID	Road direction	Map information	Heading information from beacon message

1. The distance traveled cannot exceed a predefined maximum distance (obtained from the predefined maximum speed limit on road)

2. The distance traveled should be within a range that is close to its average distance traveled (obtained from its average speed which is calculated and updated each time a beacon message is received)

Upon the reception of two consequent beacon messages, the distance traveled is calculated using the difference between the two timestamps and the given speed. Then, it will be compared against the maximum distance and the average distance to ensure that the data in the beacon message is consistent. If the following two conditions are satisfied, then the exchanged data is considered to be valid.

$$DistanceTraveled \leq MaxDistance$$
$$AvgDistance + \delta \geq DistanceTraveled \leq AvgDistance - \delta$$

where δ is a percentage value that denotes the deviation from the average distance.

In *map trust evaluation*, we assume that each vehicle is equipped with a digital map that provides navigation information as in Figure 6.4. Therefore, once a beacon message is received, the trust system will access the navigation information from the digital map and use the stated position information (from the beacon message) to obtain the road ID in which the vehicle is claiming to be traveling on. After that, the obtained road ID will be verified against the stated road ID (from the beacon message) to check whether the vehicle is actually traveling on the road that it claims or not. Therefore, if the following condition is met, the data will be marked as valid.

$$RoadID_{beacon} = RoadID_{estimated}$$

Finally, in *heading trust evaluation*, we also assume that each vehicle is equipped with a digital map that provides navigation information as in Figure 6.4. However, in the heading trust evaluation we only take into consideration the direction of the road

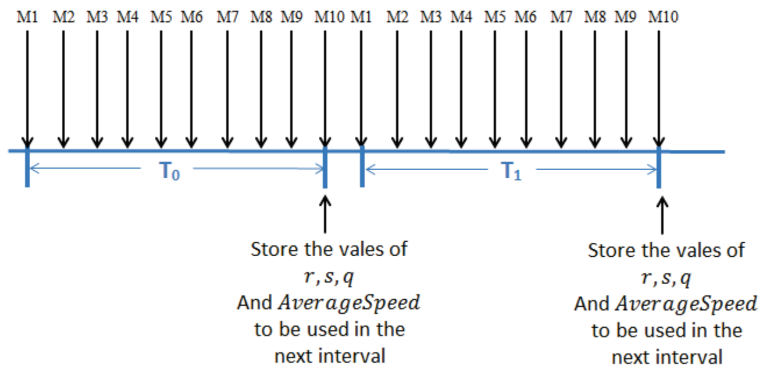

Figure 6.7: Beaconing Interval

which can be determined from the road ID. Once a beacon message is received, the direction of the road will be obtained from the road ID and later will be compared to the heading information (from the beacon message) to verify the validity of the received heading information by ensuring that both values are equal as follows:

$$Heading_{beacon} = Direction_{obtained}$$

In our direct trust module, the values of r, s, q, which represent the total number of positive, negative and uncertain observations respectively, and $AverageSpeed$ will be continuously evaluated and updated whenever there is a direct interaction between the subject and the target vehicles. The reason for that is to keep track of history data and previous interactions. A sample timeline for two consecutive one second time intervals T_0 and T_1 is shown in Figure 6.7.

Next we discuss in details how the three different types of direct trust can evaluate the trust and formulate an opinion.

Distance Trust Evaluation

Upon the reception of a beacon message, the analysis of its content is started to ensure that the received data is consistent. The procedure of evaluating the distance trust is as follows:

1. Get the latest values for r, s and q which denote the total number of positive, negative and uncertain observations, respectively.

2. Get current stated speed $S_{BeaconCurr}$ from beacon message.

3. Update the total speed using $S_{BeaconCurr}$:

$$\Sigma S = \Sigma S + S_{BeaconCurr} \tag{6.6}$$

4. Calculate the average speed as follows:

$$AverageSpeed = \frac{\Sigma S}{\#ofReceivedBeacons} \tag{6.7}$$

5. Get current timestamp $T_{Beaconcurr}$ from beacon.

6. Get the previous timestamp from last received beacon T_{prev}.

7. Calculate the difference between the two timestamps ΔT.

8. Based on $S_{BeaconCurr}$ and ΔT calculate the distance traveled by the vehicle.

9. Set distance to dx.

10. Using the road's maximum speed limit obtain the maximum distance that the vehicle can travel D_{max}.

11. Using the vehicle's average speed obtain the average distance that the vehicle can travel D_{avg}.

12. Set the value of δ, which represents the possible deviation from the average distance D_{avg}. In this chapter the value of δ is set to 10% of D_{avg} value.

13. Get the values of dr, ds and dq which are the possible range values of the positive, negative and uncertain observations, respectively. Figure 6.8 shows the different possible range values.

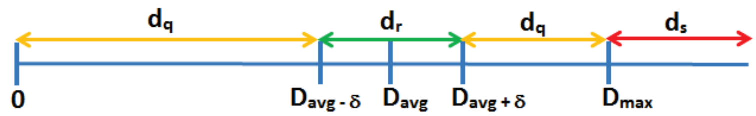

Figure 6.8: Interactions Mapping for Distance Trust

14. Revise r which denotes the number of positive observations as follows:

$$\begin{cases} D_{avg} + \delta \geq dx \geq D_{avg} - \delta & r = r + 1 \\ \text{else} & r = r + 0 \end{cases} \tag{6.8}$$

15. Revise s which denotes the number of negative observations as follows:

$$\begin{cases} dx > D_{max} & s = s + 1 \\ \text{else} & s = s + 0 \end{cases} \tag{6.9}$$

16. Revise q which denotes the number of uncertain observations as follows:

$$\begin{cases} 0 \leq dx < D_{avg} - \delta & q = q + 1 \\ D_{avg} + \delta < dx \leq D_{max} & q = q + 1 \\ \text{else} & q = q + 0 \end{cases} \tag{6.10}$$

17. Check if the beacon is the last received one in the time interval T, which we denote as $M10$. If it is not, repeat steps 1 to 16. Otherwise, 1) store the final values for r, s, q, and $AverageSpeed$ to be used in the next time interval 2) formulate i's distance opinion ${}^{dis}w^i_j = (b, d, u)$ of j as follows:

$$\begin{aligned} b &= \frac{r}{r+s+q} \\ d &= \frac{s}{r+s+q} \\ u &= \frac{q}{r+s+q} \end{aligned} \tag{6.11}$$

Map Trust Evaluation

The aim here is to verify whether the vehicle is moving on the road it claims or not. Map trust is initiated once a beacon message is received and is evaluated by the following:

1. Get the latest values for r and s which denote the total number of positive and negative observations, respectively.

2. Get current stated position (x, y) from beacon.

3. Get current road information $roadID_{BeaconCurr}$.

4. Using map information from the navigation system and current stated potion (x, y) estimate the road information $roadID_{est}$.

5. Revise r which denotes the number of positive observations as follows:
$$\begin{cases} roadID_{BeaconCurr} = roadID_{est} & r = r + 1 \\ \text{else} & r = r + 0 \end{cases} \tag{6.12}$$

6. Revise s which denotes the number of negative observations as follows:
$$\begin{cases} roadID_{BeaconCurr} \neq roadID_{est} & s = s + 1 \\ \text{else} & s = s + 0 \end{cases} \tag{6.13}$$

7. Check if the beacon is the last received one in the time interval T, which we denote as $M10$. If it is not, repeat steps 1 to 6. Otherwise, 1) store the final values for r and s to be used in the next time interval 2) formulate i's map opinion ${}^{map}w_j^i = (b, d, u)$ of j as follows:

$$\begin{aligned} b &= \frac{r}{r+s+q} \\ d &= \frac{s}{r+s+q} \\ u &= \frac{q}{r+s+q} \quad ; q = 0 \end{aligned} \tag{6.14}$$

Heading Trust Calculation

Mobility in VANET is constrained by the road; therefore, based on the road network used in the simulation, the exchanged heading values should follow the same road's direction specified in the map information. The process is as follows:

1. Get the latest values for r and s which denote the total number of positive and negative observations, respectively.

2. Get current stated heading $H_{BeaconCurr}$ from beacon.

3. Get current road information $roadID_{BeaconCurr}$.

4. Using map information from the navigation system and current road information $roadID_{Beaconcurr}$ obtain the lane's direction in which the vehicle is traveling on $roadDir$.

5. Revise r which denotes the number of positive observations as follows:

$$\begin{cases} H_{BeaconCurr} = roadDir & r = r + 1 \\ \text{else} & r = r + 0 \end{cases} \tag{6.15}$$

6. Revise s which denotes the number of negative observations as follows:

$$\begin{cases} H_{BeaconCurr} \neq roadDir & s = s + 1 \\ \text{else} & s = s + 0 \end{cases} \tag{6.16}$$

7. Check if the beacon is the last received one in the time interval T, which we denote as $M10$. If it is not, repeat steps 1 to 6. Otherwise, 1) store the final values for r and s to be used in the next time interval 2) formulate i's heading opinion ${}^{head}w_j^i = (b, d, u)$ of j as follows:

$$
\begin{aligned}
b &= \frac{r}{r+s+q} \\
d &= \frac{s}{r+s+q} \\
u &= \frac{q}{r+s+q} \quad ; q = 0
\end{aligned}
\tag{6.17}
$$

6.4.2 Indirect Trust Module

This kind of trust evaluation is used when there is no previous direct communication between the subject and the target vehicles. Since trust is transitive, recommender vehicles can disseminate their direct opinion about the target vehicle and subject vehicle can use that information to evaluate the indirect opinion as shown in Figure 6.9. Let's consider three vehicles i, j and k, where i is the subject vehicle, j is the target vehicle and k is the recommender vehicle. The indirect opinion can be evaluated using the discount operator ($\otimes$) such that ${}^{indir}w_j^{i:k} = {}^{dir}w_k^i \otimes {}^{dir}w_j^k$ However, if there are many recommender vehicles we can use the consensus operator ($\oplus$) to combine the different indirect opinions from different recommender vehicles into one single opinion. The indirect trust module is divided into the following steps:

1. When the subject vehicle i receives a beacon message from target vehicle j, it will first check its neighbor table for any previous records or interactions.

2. If no entry is found, then vehicle i will add an extra information element to the beacon message that contains the ID of vehicle j. The reason for adding this extra byte to the beacon message is to allow vehicle i to collect recommendations, regarding vehicle j, from its neighboring vehicles. This ID information of vehicle j will be broadcasted once and discarded in the next beacon message.

3. Upon the reception of the beacon message, sent by vehicle i, the neighboring vehicles will check if they have a recent direct interaction with vehicle j. If a record is found, then the recommender vehicle will broadcast its recent direct

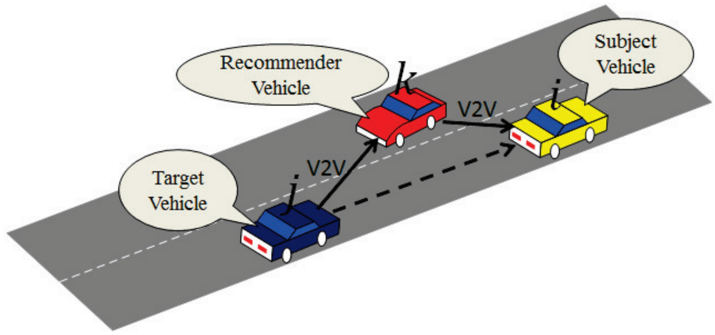

Figure 6.9: Evaluation of Indirect Trust

opinion about vehicle j. Once this information is sent by the recommender vehicle, its following beacon messages will be sent without these additional information.

4. Once the beacon messages, which include the recommendations, are received by vehicle i, the received recommendations will be discounted by the opinion about the recommender. This is done by using the discount operator ($\otimes$).

5. If more than one recommendation is being received, the discounted opinions will be combined using the consensus operator ($\oplus$).

6. The final output of this whole process will be a single opinion about the trustworthiness of the target vehicle j.

6.4.3 Decision Making Module

The objective of designing a trust system is to assist the underlying application in making decisions that in turn can help in maximizing its performance and satisfying its requirements. This can be achieved by defining a threshold value β. In this module, opinions of neighboring vehicles can be evaluated against this threshold value β, and hence, neighboring vehicles can be classified as follows:

- The vehicle is trustful if only $b \geq \beta$, where b is the belief value from the subjective opinion.

- The vehicle is distrustful if only $d \geq \beta$, where d is the disbelief value from the subjective opinion.

After the evaluation and the classification of the neighboring vehicles, the localization method will be executed and only trusted neighboring vehicles will be considered in the location estimation.

To identify the best threshold value β that can optimize the overall performance of the underlying localization method [23], we ran several simulations to establish the relationship between the best application performance (in terms of location error), the percentage of untrusted neighboring vehicles and the threshold value β. From our observation, the best threshold value β can be expressed as follows:

$$\beta = \frac{M}{N} \tag{6.18}$$

where M is the total number of untrusted neighboring vehicles and N is the total number of neighboring vehicles. However, in reality, the total number of untrusted neighboring vehicles cannot be known in advance, thus determining the best threshold value under different conditions needs to be researched. The design of the threshold value that is adaptive to the dynamic environment of VANET will be addressed in the future work.

6.5 SIMULATION AND RESULTS ANALYSIS

We evaluate our proposed system using our previously proposed localization method [23], which will be briefly explained next. We simulate different scenarios using ns-3.19 [49] and SUMO [50]. In this section, we discuss the simulation results and highlight our findings.

6.5.1 Underlying Localization Method

In our weighted V2V-based localization method [23], we proposed a weighting function that utilizes the following factors: 1) link quality distance between the neighboring vehicles 2) heading information and 3) map information. A weight value, which is output of the weighting function, is used to estimate the location of the vehicle using the weighted centroid localization (WCL) formula:

$$(x_{estimated}, y_{estimated}) = (\frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}) \tag{6.19}$$

Where n is the number of neighboring vehicles, w is the weight and (x, y) is the coordinate of the neighboring vehicle's location. Since our proposed localization method is based on V2V communication, it depends highly on the data exchanged among vehicles through beacon messages. Therefore, when a neighboring vehicle disseminates incorrect information, this can result in wrong position estimation and impact the overall performance of the localization method.

6.5.2 Adversary Model

This model is used to modify the mobility data exchanged through beacon messages. The reason for developing this model in the simulation is to demonstrate the influence and the impact of exchanging false and incorrect mobility data on the performance of the underlying localization method. In this chapter, we only focus on introducing false data for the following: 1)Position 2)Speed 3)Road ID and 4) Heading.

The implementation of false positioning is as follows:

1. Before sending a beacon message, the vehicle will run a random positioning function that will select a false position within the subject vehicle's maximum transmission range. If R is the maximum transmission range, then D_{pr} which is the distance between the present and the random position should be less than or equal to R.

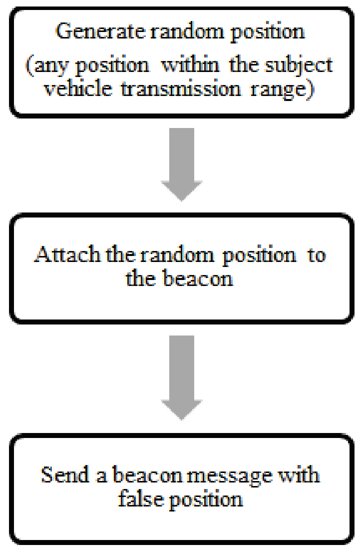

Figure 6.10: False Positioning Implementation

2. After generating the random position, the vehicle can then attach the data to a packet and broadcast it.

Figure 6.10 illustrates the steps used in our simulation for false positioning. Other mobility data can be similarly altered before broadcasting the packet. We omit the details of this implementation.

6.5.3 Mobility and Simulation Environment

Vehicles in the simulation are randomly distributed and routes are randomly generated. Mobility traces of these scenarios, generated by SUMO, are used by ns-3 to generate node mobility. We used the WAVE model [51] which is the overall system architecture for vehicular communications in ns-3. We also varied the percentage of vehicles that propagate incorrect mobility data ranging from 0% to 75%.

The road network, shown in Figure 6.3, uses a 3 x 3 Manhattan Grid with an edge length of 1000m (1km) and a distance of 500m (0.5km) between any two neighboring intersections. The simulations were run with the parameters shown in Table 6.3.

Table 6.3: The Simulation Parameters

Parameter	Value
Vehicle movement	Intelligent Driver Model
Vehicle speeds	Car-following model
Number of vehicles	40
Max road speed	14 m/s
Duration	1800 seconds (30 minutes)
Beacon interval	10 second
Location update interval	1 second
Signal propagation	Two-ray ground
MAC/PHY protocol	IEEE 802.11p
Transmission range	250m
Layer 3 addressing	IPv6

6.5.4 Evaluation Metrics

To evaluate the efficiency of our proposed system, we use the following metrics, which have been introduced in [23]:

(1)Location Error. This will measure the location error between the actual location (x_{act}, y_{act}) (ground truth) and the estimated location (x_{est}, y_{est}) (localization method) of vehicle v in the network of N vehicles. The location error is defined as follows:

$$LocationError = \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2} \tag{6.20}$$

(2)Average Location Error. Using Equation 6.20, the average location error can be formulated as follows:

$$AvgError = \frac{\sum_{i=1}^{N} \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2}}{N} \tag{6.21}$$

Location error and average location error metrics are used to measure the performance and the accuracy of the localization method. This can be achieved by matching the ground truth location, obtained from the mobility traces, with the estimated location, generated by the proposed method.

(3) Efficiency. We introduce the efficiency as a fraction of the successful runs, in which a vehicle in the network can localize itself, during the entire simulation.

$$Efficiency = \frac{NSR}{NR} \tag{6.22}$$

Where NSR is the number of successful runs and NR is the total number of runs. Successful localization will take place when there is at least one trusted neighboring vehicle within the vehicle's transmission range, otherwise; the location update will fail. In our simulation, the location update is performed every second, after the warm up period (20 sec), until the end of the simulation time (1800 sec).

6.5.5 Results and Findings

We applied our proposed subjective logic trust management system to the localization method as an application. As previously discussed, in the localization method each vehicle can determine its location in relation with its neighboring vehicles. To analyze the performance of the underlying application, we vary the percentage of the untrusted neighboring vehicles from 0% to 75%. In addition, the experimental results are averaged over three different simulation runs. This is because we observed that increasing the simulation runs to more than three does not change the average results.

Figure 6.11 shows the effect of threshold value β on the average location error of the localization method with varying the percentage of the untrusted neighboring vehicles. From the same figure we can also identify the optimum threshold value β for the underlying localization method. For instance, when the percentage of the untrusted vehicles (the Y coordinate of Figure 6.11) is increasing, the optimum threshold value β (the X coordinate of Figure 6.11) can be selected to optimize the performance of

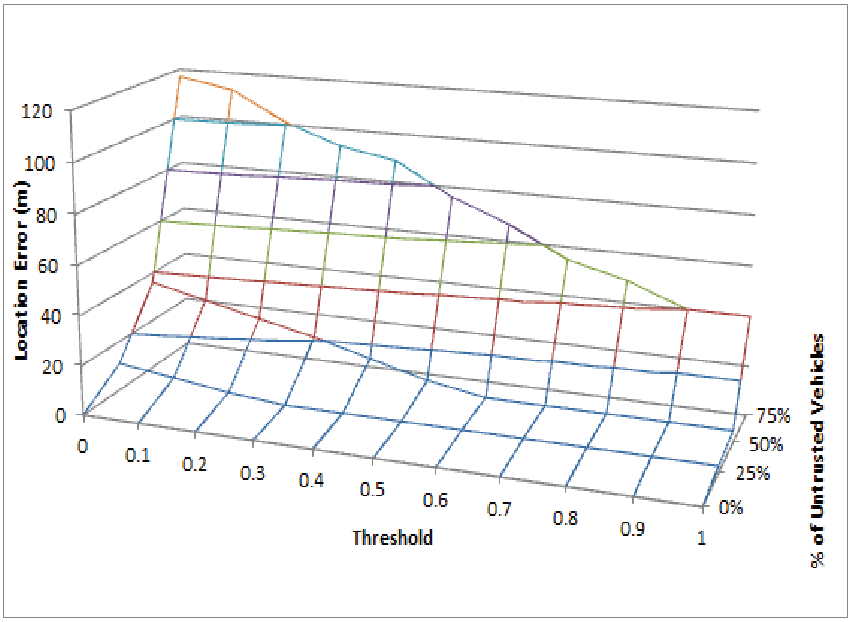

Figure 6.11: Effect of Threshold Value β on Location Error

the localization method in terms of average location error (the Z coordinate of Figure 6.11). Equation 6.18 was determined from the analysis of these results.

Figure 6.12 shows the average location error of the underlying localization method before and after applying our proposed subjective logic (SL) trust management system. The optimum threshold value β is obtained using Equation 6.18. The figure clearly shows that the use of the proposed SL trust management system has improved the overall performance of the localization method by decreasing the average location error and excluding the untrusted neighboring vehicles in the location estimation. From the figure, we observe that increasing the percentage of the untrusted vehicles has increased the location error. On the other hand, using the proposed trust system has reduced the location error up to 73 percent, when the percentage of the untrusted vehicles is 25%, and 66 percent reduction, when the percentage of untrusted vehicles is 75%. We can also see that the proposed SL trust management system approaches the performance of our previous proposed verification system, which is based on binary rules [25].

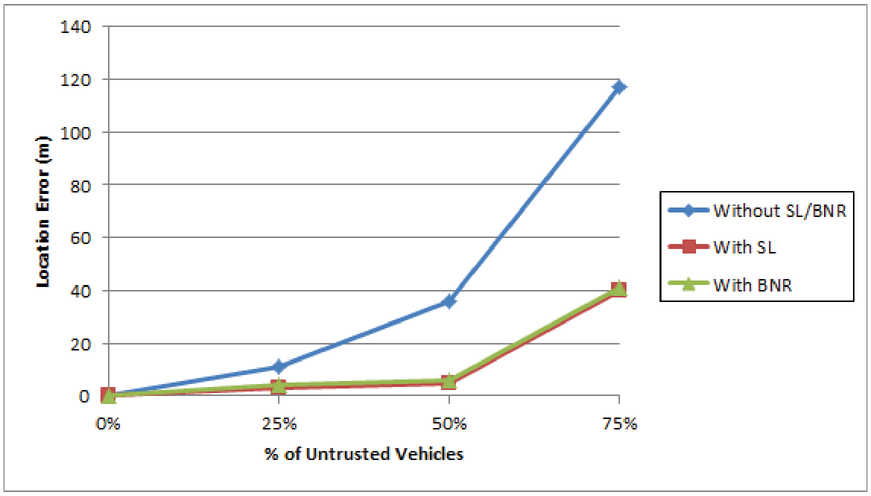

Figure 6.12: The Effect of SL Trust Management System on Location Error

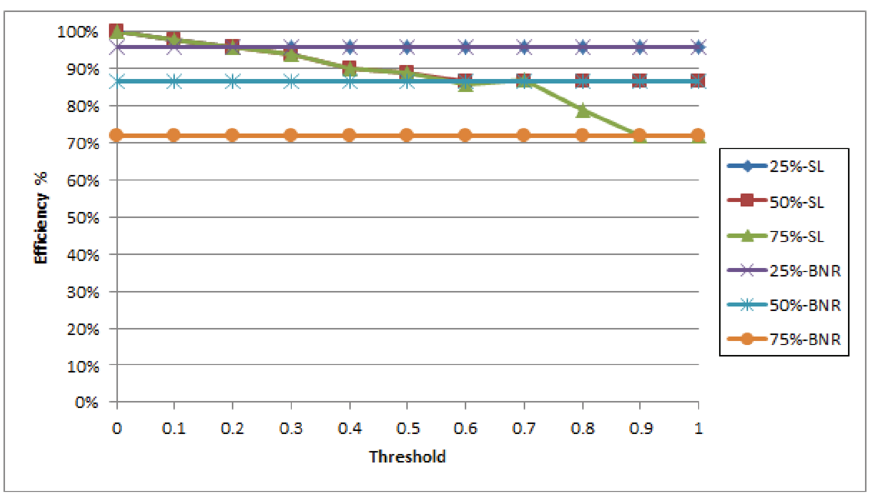

Figure 6.13: The Effect of Threshold Value β on Localization Efficiency

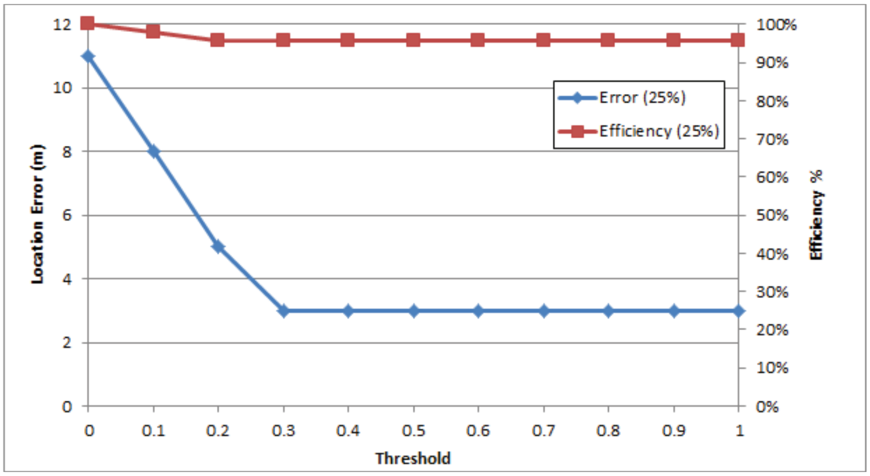

Figure 6.14: The Location Error and Efficiency Percentage of Untrusted Vehicles is 25%

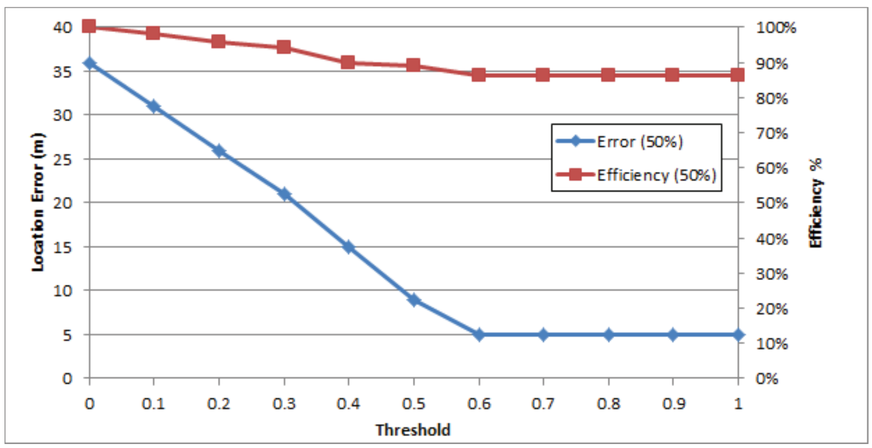

Figure 6.15: The Location Error and Efficiency Percentage of Untrusted Vehicles is 50%

We also conduct a performance analysis in terms of the efficiency of the localization method to compare the proposed SL trust management system with our previously proposed verification system. In this set of results, we vary the percentage of the untrusted neighboring vehicles and also the threshold value β. The results is shown in Figure 6.13. Here we can see that SL trust management system outperforms the binary based verification system. However, the performance is equal when the optimum threshold value β is selected.

Figures 6.14, 6.15 and 6.16 demonstrate the trade-off between the performance,

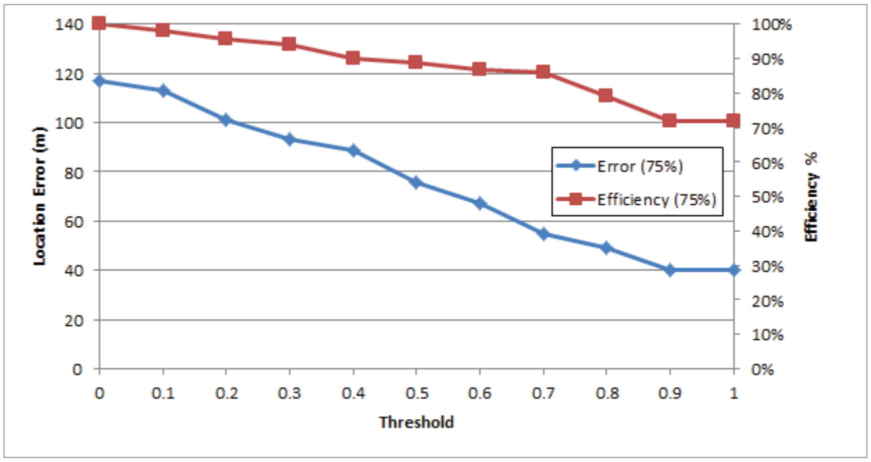

Figure 6.16: The Location Error and Efficiency Percentage of Untrusted Vehicles is 75%

in terms of average location error, and the efficiency of the underlying localization method under the proposed SL trust management system. Overall, we can conclude that increasing the threshold value β will decrease the average location error as well as the efficiency. We also observe that increasing beyond the optimum threshold value β, the value of the average location error and the percentage of the efficiency remain constant and do not further decrease or increase. However, increasing the performance of the localization method, by decreasing the average location error, results in decreasing its efficiency. The reason is that efficiency is related to the number of the trusted neighboring vehicles.

6.6 SUMMARY

The exchange of incorrect information can result in poor performance of many VANET applications and services. For instance, V2V-based localization, which provides location estimation for each vehicle in the network, can be highly impacted because it depends on the information exchanged through beaconing. In this chapter, we have presented the use of a trust management system as a mechanism to evaluate the integrity and the reliability of the received information. With the proposed system, each vehicle can independently model the trust relationship in terms of subjective opinions. Such opinions are formulated based on the direct and indirect interactions among neighboring vehicles. By utilizing subjective logic and its operations, both direct and indirect opinions can be obtained for each neighboring vehicle. The decision making module evaluates the opinions of the neighboring vehicles against the threshold value and only trusted neighboring vehicles will be considered in the location calculation. We have conducted simulations to evaluate the feasibility of applying the proposed method on our previously proposed localization method. The results showed that in the existence of untrusted neighboring vehicles, the use of the proposed trust system has assisted the vehicles in successfully detecting and later excluding the untrusted neighboring vehicles, and hence, enhancing the performance of the underlying application. For future work, we plan to implement the dynamic threshold value that is adaptive to VANET environment. We also intend to investigate the feasibility of applying the proposed system to other VANET applications.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

Vehicle location is a key factor in many VANET applications and services. GPS, which is the commonly used localization technique, may not provide the required location for the different applications in various situation. Therefore, sharing location information among neighboring vehicles can complement the GPS position and hence, improve the applications and the overall performance of the network. However, there are several factors that may affect the exchanged information among vehicles. First, is the network connectivity due to the high and variable speeds of the vehicles. Second, the existence of different objects on roads that can affect and interfere with the radio signal. Finally, the integrity and validity of the data announced by vehicles in the network.

The main objective of this research work is to tackle these different factors and create a V2V-based localization technique that takes advantages of V2V communication to complement the GPS positioning technique. As a result, the location accuracy is improved by utilizing only verified data exchanged among vehicles via beaconing.

In Chapter 2, we present and survey a variety of localization techniques and classify them, based on GPS utilization, to: 1) GPS-only 2) GPS-assisted and 3) GPS-less. We also summarize the pros and cons of these three different classes. Survey of related work in data verification is also discussed in this chapter.

Chapter 3 describes the design of the multi-factor V2V-based weighted localization (MWL) that extends the centroid localization (CL) by assigning a weight value to each neighboring vehicle. This weight value is obtained using a weighting function that utilizes the following factors: 1) link quality distance between the neighboring vehicles 2) heading information and 3) map information. The chapter also presents the simulation results that compare and evaluate the performance of MWL and RWL in a wide variety of densities, transmission ranges and weighting factors' values. As suggested by the results, combining the three different factors in MWL improves the location accuracy by decreasing the location error to 9% (in low densities) and to 48% (in high densities).

Chapter 4 presents the development and evaluation of an intelligent localization method that combines fuzzy logic and WCL. In the proposed method, distance between neighboring vehicles and heading information are fed to the fuzzy logic system and the output is weight values. Using WCL, the location is estimated using the neighboring vehicles weighted coordinates. Compared to CL, the proposed method demonstrates significant improvement in reducing location error as density increases.

The negative effect of the incorrect mobility data on the underlying localization method is studied in Chapter 5. In order to mitigate this impact, the mobility data verification framework is proposed to effectively verify the mobility data announced by the vehicles in the network. Once the data is verified, the underlying localization method will determine if the vehicle's information can be considered in the location estimation or not. We use simulation to evaluate this scheme. The results show that the solution has successfully detected untrusted vehicles and hence improved the performance of the localization method.

Chapter 6 presents the design and development of a subjective logic based trust management system that allows each vehicle in the network to evaluate the trustworthiness of other vehicles based on opinions formulated from either direct interactions or derived from indirect interactions with other vehicles. The results, from the simulation, indicate that in the presence of untrusted neighboring vehicles, the performance of the underlying localization method has improved in terms of average location error.

7.2 FUTURE WORK

Several potential research topics and extensions can enhance the work presented in this dissertation. The following is a listing of some of them:

- Incorporation of different sources of information. Due to the nature of VANET, combining the different sources of information available in the surrounding environment can increase the accuracy of the estimated location. A degree or weight of truthiness can be assigned to every source based on some mathematical logic that consider all the available input along with the current environment parameters to obtain a precise real-time position. The different sources may include: GSM, embedded sensors, embedded GPS and RSUs.

- Real testbed evaluation. The performance evaluation of the proposed solutions was based on simulations. However, conducting some real testbed experiments can validate the simulation results and hence, improve the development of the proposed solutions.

- The development of a more sophisticated adversary model. In this work only trivial attackers were addressed, however, a more complicated adversary model can assist in determining the robustness of the proposed trust management system.

- Incorporation with location-based applications and services. The performance of the proposed solution can be further evaluated by integrating it with any VANET location-based application.

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