Studies on a Novel TDOA-based Estimation Technique to Improve DOA accuracy for Vehicular Localization

A Thesis Submitted to the Department of Computer Science and Communications Engineering, the Graduate School of Fundamental Science and Engineering of Waseda University in Partial Fulfillment of the Requirements for the Degree of Master of Engineering

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Research guidance: Research on Wireless Network Systems

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Summary

This thesis presents the studies on a 2-dimensional (2D) vehicle localization within an urban highway scenario utilizing a novel combination of the Time Difference of Arrival (TDOA) technique and Trilateration within a Line-of-Sight (LOS) scenario. The research here was undertaken for the purpose to advance the frontier in Vehicle-to-Vehicle (V2V) communication, investigate the utility of localization techniques in an on-road environment, and for the realization of fully autonomous driving in the future. Firstly, different existing vehicular localization methods were researched and evaluated to understand the current dynamic and standards that would need to be met. These standards predominantly center around the regulations of what is to be expected to achieve V2V communication, i.e., URLLC (Ultra-Reliable Low Latency Communications). Along with this, parameters for consideration were contemplated in order to construct a realistic simulation environment within a 2D space. The thesis' proposed method was conceived and investigated on the basis of its usefulness within a vehicular environment. The procedure for this consisted of constructing the simulation environment, designing the transmission and receiver vehicle for the investigation, receiver properties, signal properties, range of simulation, and propagation model. To further improve the technique, a machine learning regression model was also implemented to learn from previous simulation's DOA error margins, to produce a DOA adjustment process and increase the precision of the method. Multiple models were tested in order to use the optimal model for the scenario. A random forest fine-tree model was used within the simulation due to the low root mean squared error (RMSE) as well as

short training time. From the results produced from the experiment setup, the studied novel technique proves to perform better than a conventional TOA method when utilizing the machine learning regression model for DOA adjustments. Along with this, raytracing results show similar results, proving the usefulness of the technique in a free space environments.

Acknowledgements

I would like to express my gratitude towards my academic supervisor, Professor Shigeru Shimamoto, for his continuous support, inputs and help he has provided over the entire duration of my research. Through the group meetings held frequently along with swift replies to urgent emails, it was possible to get regular feedback on my work which was reassuring and at times where I would find it difficult to progress. Furthermore, I would like to thank Dr. Zhenni Pan who has provided me with endless guidance throughout periods of academic break and times when I have been out of the country. Her feedback on my conference papers and on-going research gave me a lot of strength and courage to not be disheartened from rejection and pushed me to strive for better quality and new results. I would also like to thank my peers within the Shimamoto laboratory for their remarks through my research. From constant expression of their thoughts and innovative ideas, I was able to investigate new avenues to include into my research. Finally, I would like to thank my family for their constant support and encouragement they have provided me with over my Masters' studies at Waseda University.

1 Introduction

In this section, the research background along with the motivation behind the research are presented. From there the contribution and the structure of this thesis will be outlined.

1.1 Research Background

V2V communication will become indispensable when the technology to realize fully autonomous driving is achieved. One of the first, and most important, issues necessary to overcome when implementing autonomous vehicles on public roads is the safety of pedestrians and other vehicles to mitigate collisions and fatal accidents. To improve this, research involving the localization of vehicle positions is being conducted [1] as well as the processing of information these vehicles are carrying concerning their next course of action. Knowing the exact location of these surrounding vehicles and their trajectory will greatly enhance road safety and route planning for all parties within the local vicinity.

Using Global Navigation Satellite Systems (GNNS) such as GPS alongside the plethora of on-board sensors such as light detection and ranging (LiDAR), cameras [2] and millimeter-wave (mmWave) radar technology, vehicles can register their current positions and perceive their surrounding environment. An example of this is the use of GPS systems with the capability of delivering an accuracy to centimeter-level accuracy through the use of RTK (Real-time kinematics) GPS [3]. LiDAR's also have the capacity to map road environments through proper installation and orientation on the vehicle and continuous scanning to make every road visible [4]. Incorporating this with Advanced

Driver Assistance Systems (ADAS) provides drivers with further applications such as Active Cruise Control (ACC), Lane Keeping Assistance (LKA) [5] and Collision Avoidance System (CAS) to prevent various causes of accidents. However, the limitation that exist with such system mitigate usage for on-road use. The GPS technology receives constant interference, reducing the overall localization accuracy due to multipathing effects [3], and suffers further lose from clock errors and atmospheric effects [6]. Along with this, LiDAR's are not adaptable to low visibility weather conditions which limits their useability in commonly occurring scenarios [2]. The cost of such technology is another factor to be contemplated. Millimeter wave (mmWave) radars also suffer from similar limitations that restrict the progress of autonomous vehicles towards meeting safety requirements. Within urban environments, mmWave can be affected by interference from nearby BS and cellular hotspots.

As much as these systems are capable of mitigating accidents within the proximity of the installed vehicle, advances in algorithmic-based accident mitigation should be promoted to overcome the previously mentioned issues, while reducing financial and spatial limitations. By transmitting information concerning a vehicle's future actions, neighboring vehicles can act accordingly and optimize their routes to minimize any collisions and reduce energy waste. Whilst understanding what vehicles will do is beneficial for urban street navigation, this information cannot be utilized to its full potential without knowing the transmitter's location. Therefore, the necessity to accurately locate the position of surrounding vehicles will become ever more crucial. Hence by increasing the quantity of solely vehicular links and reducing the reliance on BS and other such infrastructures to act as a midpoint for any transmissions, unnecessary connections and propagation delay can be mitigated, which in turn will bring us closer to achieving the low-latency communication requirements for V2V.

1.2 Research Motivation

The goal of realizing fully autonomous driving has been around for the last two decades as vehicles has evolved from being just simple transportation devices. The installation of computers that can communicate and interact with each other pushes the boundaries of what was thought to be impossible before. Advanced Driver Assistance Systems (ADAS) are being installed into current vehicles to mitigate on-road accidents and prevent fatal crashes from occurring as frequently [7], as well as to ensure the safety of as many people as possible. As shown in Fig. 1. these applications aid drivers through providing parking assistance through Automatic Parking (AP), matching traveling speeds with ahead vehicles through Adaptive Cruise Control (ACC) etc., easing the drivers travel experiences [8]. However, as much as these systems have the capacity of mitigating accidents in specific scenarios, the safety requirements that need to be upheld are yet to be met with the current technology, meaning for the homologation of ADAS to be fully implemented for autonomous driving will need to be revised [9].

For vehicles to maintain an almost perfect performance on live-road scenarios, high-speed communication, and Ultra-Reliable Low Latency Communication (URLLC) will need to be harnessed within the vehicular network. Specified by the 3rd Generation Partnership Project (3GPP), URLLC will need to uphold 99.99% reliability for a single transmission of 32 bytes packet with latency under 1ms (millisecond) [10], [11]. The fifth generation (5G) of broadband cellular networks is the current solution to provide autonomous driving the performance capabilities; showing promise with the rise in popularity as 5G communication is forecasted to account for 20% of connections worldwide by 2025 [12]. Not just for safety of all individuals, the incorporation of 5G in autonomous driving establishes the possibility of platooning, enabling vehicles to drive in close proximity, thus increasing the capacity of roads, reducing fuel use and CO_2 emission reduction by 16% [12].

With 5G pushing the automotive industry to enhance their on-board technology to facilitate it, new innovative solutions are being introduced to power the frontier of autonomous driving. Within this, the precise positioning of vehicles will be essential to construct a close-knit vehicular network, therefore techniques to overcome multipath effects on-road and localization within NLOS (Non-Line-Of-Sight) scenarios will become ever more important.

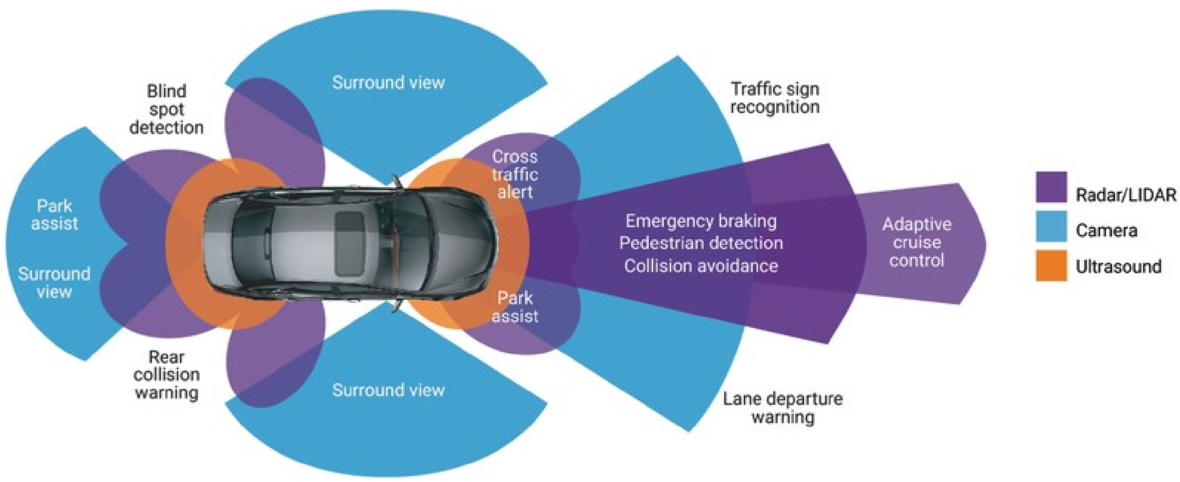


Figure 1. Different ADAS applications and the necessary hardware [8]

1.3 Contribution of the Thesis

Through investigation within the V2X communication fields, and more specifically, the V2V communication, this thesis has undergone the trial and error of attempting to solve some of the current problems within the field. These are:

- Provide an algorithmic, mathematically sound, solution to a problem which would otherwise require further hardware installed on any vehicular unit. Thereby, reducing cost of installation and maximizing use of software solutions.

- Devise a technique that does not require any time synchronization between the transmitter vehicle (TV) and receiver vehicle (RV), as well as with other infrastructures in the close vicinity of the vehicles, while being able to uphold results to an exceptional level. The implementation of this method on on-road vehicle allows the possibility to conduct V2V communication within a variety vehicular scenarios.

1.4 Structure of the Thesis

Chapter 2 will divulge into the V2X communication as well as the specifics of V2I and V2V. An explanation on the field of wireless communications revolving around vehicles will be introduced, followed by a comprehensive look into V2I technology. This will explore the advantages of vehicle-to-infrastructure technology implemented currently as well as the drawbacks that prevent fully autonomous driving. Finally, the field of V2V communication is covered by going through the possibilities of driverless cars and minimizing accidents rates along with the high standards that need to be achieved for the realization of this technology.

Chapter 3 investigates different localization techniques used over time along with their use cases. The (Multiple Signal Classification) MUSIC scheme and the usage within localization problems and frequency estimation are explained along with a comparison of the performance to other existing techniques. Next, the Trilateration approach and how the use of circle equations and the combination of regression analysis procedures such as the least squares method help improve the estimation accuracy from problems that have no exact solution. Time of Arrival (TOA) is research for its implementation of the Trilateration technique utilizing time of arrival measurements between a transmitter and receivers along with its high accuracy due to the time synchronization condition. Lastly, in order to consider scenarios that require independence between transmitters and receivers, the Time Difference of Arrival (TDOA) method is explored and how the use of multiple hyperbolic equations can locate transmission sources with minimal equipment and conditions.

Chapter 4 delves into the proposed localization estimation technique and goes through the step-by-step procedure on how the method is implemented. This includes the arrangement of the receivers and transmitter in order for the TDOA measurements to be accurately recorded along with the necessary circle equations and least squares analysis to make initial estimations. Fundamental characteristics involving the properties of the technique are explained along with a comparison to other existing techniques. For maximum potential of the technique to locate the transmission source, the regression model working alongside the proposed technique is dissected. The implementation strategy of the regression model and the selection process as to why the specific model was chosen is also described. Multiple simulation setups are given in the form of the code implementation to best represent the vehicle bodies and to accurately estimate TDOA measurements within each time frame of simulation. The construction of the environmental setup along with the vehicle motion throughout the simulation is explained, followed by the key differences between the theoretical and ray tracing setups, producing 2 different results that are evaluated.

Chapter 5 expresses the research undertaken over the course of this master's program by demonstrating the DOA estimation accuracy for both test scenarios, the average DOA estimation error for the different tested techniques, as well as the explanation on what caused such results to be produced.

Finally, chapter 6 covers the possible considerations for future work within the field of vehicle localization and how the studies within this research can be furthered with in NLOS scenarios.

2 Overview of V2X Communication

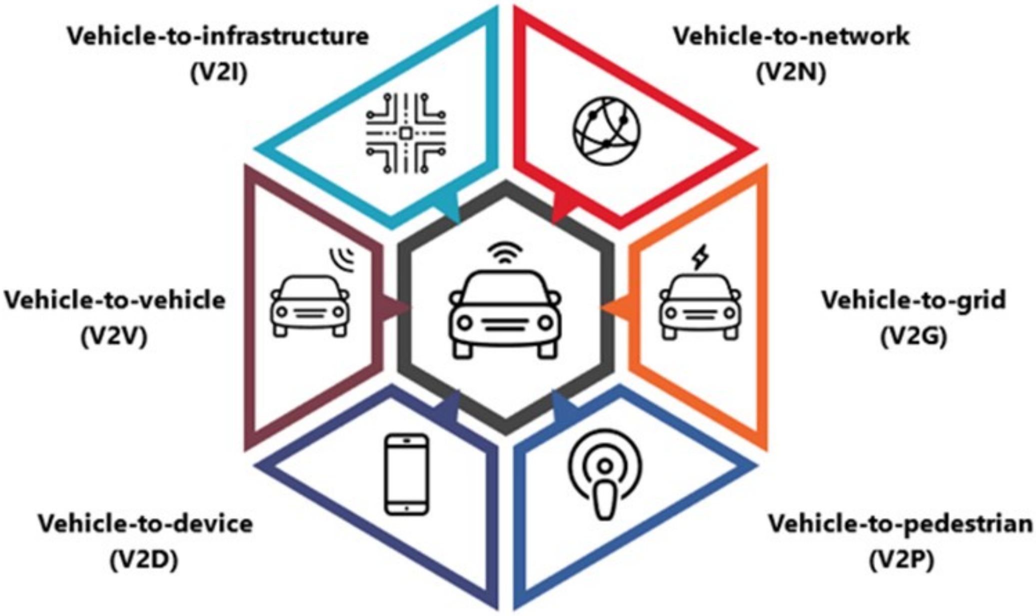


Figure 2. Various V2X systems [11]

2.1 Introduction to V2X Communication

Vehicle-to-everything (V2X) is the field of wireless communication coined for the transmission of data between vehicles and other entities with the purpose of improving road safety, reduction in fuel use, and mitigation of traffic clustering. Examples of these are shown in Fig. 2, where the most common V2X scenarios that are currently implemented are V2I (Vehicle-to-Infrastructure), V2V (Vehicle-to-Vehicle) and V2P (Vehicle-to-Pedestrian). Each of these networks are used to share on-road vehicle statuses to the inform individuals, infrastructures, base stations (BS) etc. regarding one aforementioned reasons or others. As the number of vehicle manufacturers that installed V2X applications in their vehicles increased, the necessity to implement a global standard for this technology became evermore required. Moreover, not all manufacturers would have had the same specifications for their technology, creating inconsistencies in performance and could possibly lead to fatal road accidents. Therefore in 2010, the Institute of Electrical and Electronics Engineers (IEEE) amended their 802.11 to 802.11p, the standard for wireless network products, to include Wireless Access in Vehicle Environments (WAVE). [13]. By creating this standard, a new management system is created for all vehicle manufacturers to ensure a fast and stable communication channel for vehicles to communicate with little to no failure.

Besides standard V2X that focuses connection to other entities through Wireless Local Area Networks (WLAN), but the use of cellular networks to conduct communication, cellular V2X (C-V2X), has been rising in popularity due to advantages over conventional V2X. By utilizing cellular network infrastructures, it is possible to operate all V2V, V2I and V2P since the C-V2X protocol can function without the use of a SIM and network assistance [14]; creating an end-to-end structure that allows for any entity to directly communicate with the vehicle, ensuring the scalability of C-V2X. A further benefit of C-V2X comes exactly from this direct communication, as unlike V2X, C-V2X can operate a Public Key Infrastructure (PKI) to consistently control the flow of data using digital security certificates, maintaining a high-level of security [14].

2.2 V2I

V2I allows the direct communication between vehicles and surrounding infrastructures for the purpose of sharing information consisting of traffic congestion data, road conditions, parking locations etc. Examples of these infrastructures are streetlights, cameras, radio towers, etc. providing close to constant coverage along any road environment. These infrastructures, Road Side Units (RSU's), communicate by using their installed V2X chipsets [15] in order to receive the 5.9GHz bandwidth propagated by the transmission vehicles. As these links are bi-directional, vehicles can receive information transmitted from these RSU's, for the sake of sharing road data and guarantee the functionality of the abundant on-road operations. As shown in Fig. 3, these countless direct links, and functions that V2I are employed is being used to advance the frontier of Intelligent Transportation Systems (ITS), a network structure for improving road management [16], [17]. The technology V2I holds makes realizes the possibility for ITS to reduce workloads associated with driving, improve the road transport safety, create a more efficient traffic management scheme, and contribute to the improvement of quality of life and environmental conservation [16].

The benefits and externalities that are brought about implementing V2I in urban environments produce better health and economical standards, however, the structure of V2I is not the optimal for emergency scenarios where every millisecond can count. The structure of V2V is very discrete, allowing for an undemanding flow of data with less risk of concurring a delay within the system, while V2I utilizes a centralized topology, increasing the change of delay as all nodes require a connection to an individual vehicle, leading to a delayed reaction time [18].

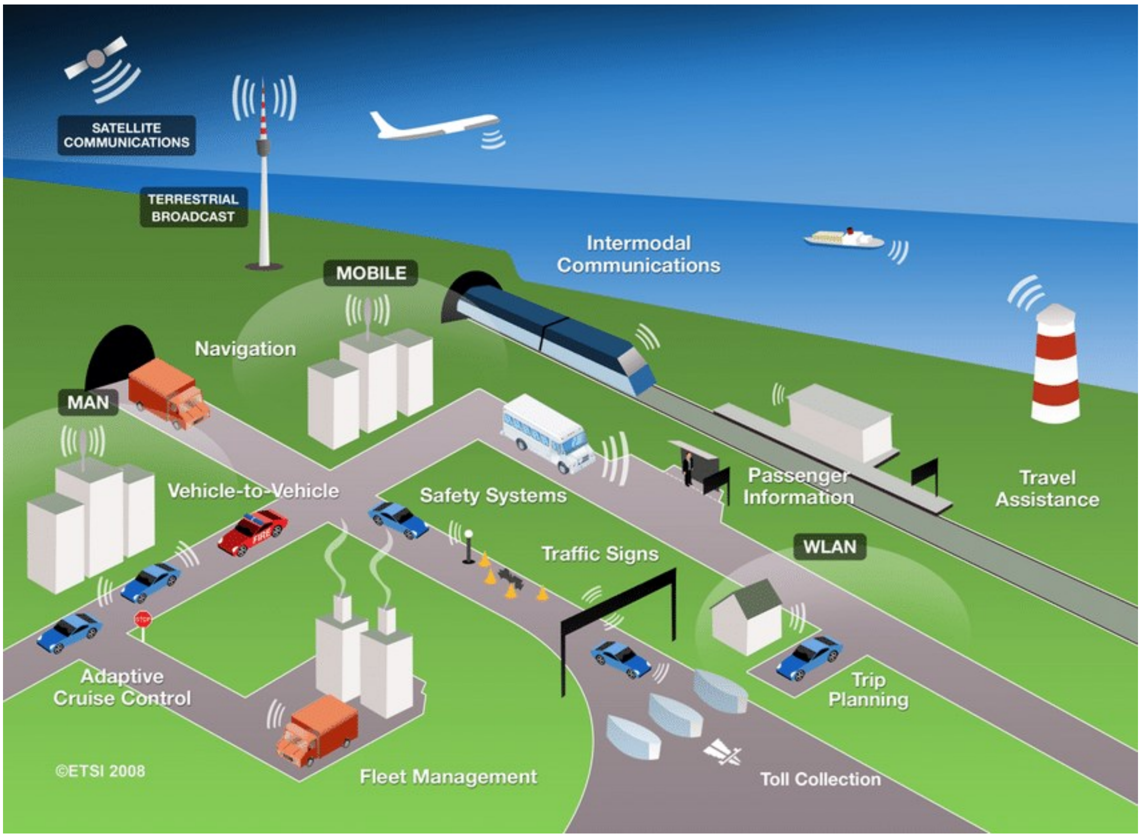


Figure 3. Intelligent Transport Systems [17]

2.3 V2V

Even before the amendment of the IEEE 802.11 to 802.11p, the standard for wireless network products, automotive companies had a focus on installing means for vehicular communications into their products to create a new connected environment on-road. The direct communication between vehicles, V2V, paves a secure path to ensure the future of enhanced road safety, increased efficiency, and superior driver assistance [19]. This can be achieved from sharing information concerning road situations, including road conditions, traffic congestion, delays etc., as shown in Fig. 4. The communication technology that predominantly influences the growth in V2V communication is Dedicated Short Range Communication (DSRC), utilizing wireless radio signals to communicate with nearby vehicles. While DSRC was developed for the advancement in V2V and V2I communication [20], DSRC is mainly used within short to medium range transmissions [21], otherwise the transmission range is too large, reducing the reliability of the technique. Because of these properties, DSRC has also extended its usefulness to assisting in the implementation of Electronic Toll Collection [ETC] along highways gates.

Among the numerous advantages that V2V communication has the potential to offer, the improved safety of vehicles while platooning is very promising. Vehicles would have the capacity to share data seamlessly, allowing for close proximity vehicles to avoid collisions through emergency lane changing, and braking scenarios that would be impossible to steer clear of with human reactions would be mitigated through inter-vehicular communication [22]. Additional information can be acquired through the utilization of Cooperative Adaptive Cruise Control (CACC) in order to further refine platooning, by reducing the employable time headway [23]. Studies from [24] also the significance of the combined use of V2V and CACC within platooning as this allows for the throughput to double within traffic intersections, as long as the vehicles pass through pre-specified nodes within the network. While there a still many constraints for platooning to be implemented on live roads, the technology required to meet expectations are gradually being realized. By efficiently being able to control vehicle navigation, positive externalities are created; for example, the close proximity formation of all vehicles will have trailing vehicles follow the standards of the leader, thereby maintaining a constant formation, with all vehicles adjusting their speed and location to their leader.

This mitigates any abnormal scenarios to be given birth, reducing the likelihood of accidents, as well as improving fuel efficiency [22].

The concerns that come with these new techniques must also be considered before implementing on live road scenarios. With the whole technique requiring absolute trust with V2V communication, a necessity to be absolutely certain that no security breaches occur must be upheld. If these signals can be intercepted and manipulated for personal gain or terrorism, the potential risks could lead to further fatal accidents, instead of mitigating them [25]. The intrusion of driver's privacy is another matter not to be forgotten, as via these V2V links, private data concerning the driver and the vehicle have the possibility of being obtained by third parties; therefore, security requirements are established [26]. By confirming receivers specifically authenticate from legitimate senders, malicious data can be blocked from the system, the use of encryption techniques using secure key management systems can limit access to unauthorized users, and real identities of vehicles are hidden, unless necessary from specific authorities [26].

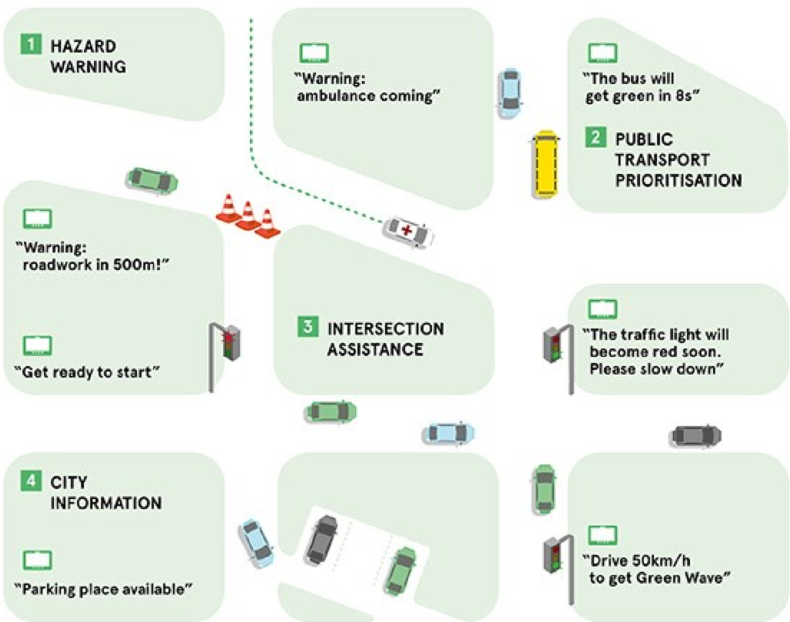


Figure 4. Information sharing via the use of V2V communication [19]

3 Localization Techniques

This chapter expresses some of the prominent methods used for localization problems. The methods approaches are explained along with the limitations to understand their specific uses cases.

3.1 Music

The MUSIC (Multiple Signal Classification) algorithm is a technique used for estimating radio frequency transmission locations through the construction of uniform linear array (ULA) [27], providing transmission signal vector coordinates. The variables for the ULA are as follows. A steering vector array, with each column representing the steering vector for the antennas used for receiving the transmission signal. An amplitude vector for relating the received power level at each of the arranged antennas. Finally, a vector value to represent the Gaussian white noise.

$$\boldsymbol{A}(r,\theta) = [a_1(r,\theta), a_2(r,\theta), \dots, a_M(r,\theta)] \qquad (1)$$

$$a_i(r,\theta) = \frac{r}{r_i}\exp(-jw_0\tau_i)$$

$$\tau_i = \frac{-dsin\theta}{c_{AV}}(i-1) + (-\frac{d^2}{c_{AV}r}cos^2\theta)(i-1)^2$$

(1) defines the array steering vector, where r is the distance from the source to the receiver, θ represents the transmission signal propagation angle, d is the distance between 2 receivers, and c_{AV} is the average velocity of the Lamb waves [27]. By using the signal covariance matrix and eigenvalue decomposition, the MUSIC algorithm looks to obtain the signal and noise subspace to estimate the signal parameter by through the orthogonal value of the 2 subspaces [27].

$$\boldsymbol{P}_{MUSIC}(r,\theta) = \frac{1}{\boldsymbol{A}^H(r,\theta)\boldsymbol{U}_N\boldsymbol{U}_N{}^H\boldsymbol{A}(r,\theta)} \qquad (2)$$

With (2), the orthogonality between the signal and noise subspace is calculated using the spatial spectrum. $\mathbf{U}_\mathrm{N}$ gives the noise subspace constructed using the eigenvector matrix and the superscript $\mathbf{H}$ represents the Hermitian matrix for both $\mathbf{A}$ and $\mathbf{U}$ [27].

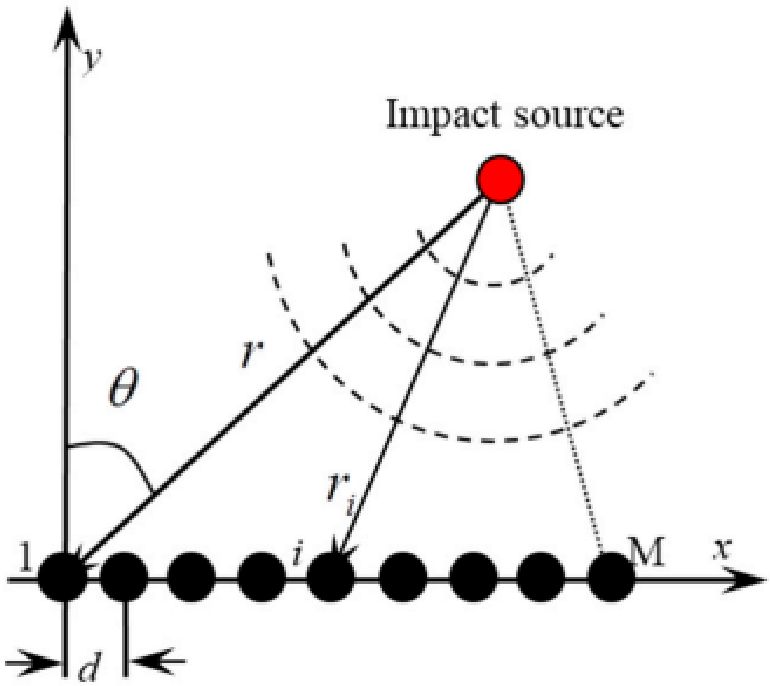


Figure 5. Source to multiple receiver model of MUSIC algorithm [27]

While being one of the dated localization techniques, the advantages signify why the method is still used within many applications. As shown in Fig. 5, the MUSIC algorithm allows for multiple transmission signals to be measured simultaneously, can deliver a high level of precision of the source location, the technique can be used for small datasets, and has a high spatial resolution [28]. The method comes with drawbacks which are linked towards computational-intensive operations. These come from the above-mentioned processes of, correlation matrix computation, eigen value decomposition and pseudo-spectrum function computation [29].

3.2 Trilateration

When expressing most localization scenarios on a 2D plane with a limited number of considered variables, the algebraic method of Trilateration is one of the simplest, yet effective, techniques that will be contemplated. This technique's most fundamental feature is to compute the area covered by multiple circles within a specified region and further calculate the intersection region of all circles [30]. Further implementation of this strategy with regression analysis techniques, such as least squares, can provide higher accuracy results within scenarios that have no definite solutions.

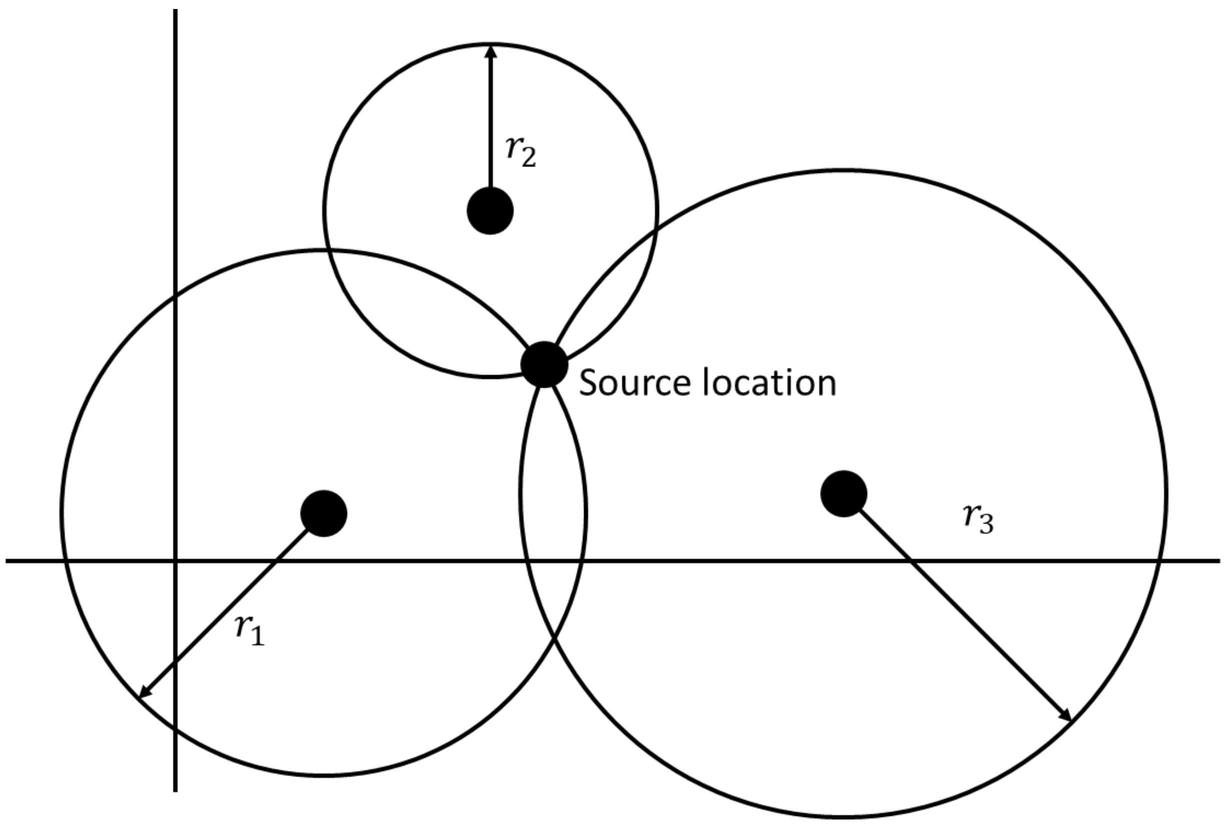


Figure 6. Trilateration diagram on a 2D plane

If intersection coordinates $(x, y) \in \underline{\boldsymbol{x}}$ were to be calculated using three points (x_i, y_i) as centers of 3 circles with respective radius measurements r_i for $i = 1, 2, 3$,this can be easily expressed as 3 simultaneous equations [31]:

$$\begin{aligned}(x - x_1)^2 + (y - y_1)^2 &= {r_1}^2 \\ (x - x_2)^2 + (y - y_2)^2 &= {r_2}^2 \\ (x - x_3)^2 + (y - y_3)^2 &= {r_3}^2\end{aligned} \qquad (3)$$

From Fig. 6, these circle equations represent the use of each of the 3 center coordinates along with their radii to find the singular point in which all 3 circles intersect. In order for Trilateration to be effective within an environment using precise data, at least 3 surrounding circles is necessary to produce reliable results. It is possible to use Trilateration for a minimum of 2 circles, but this will give rise to the possibility of multiple solutions. When considering 2 circles with an intersection between them, the likelihood of the nature of this intersection will be in the form of an overlap. Overlapping scenarios of 2 circles will cause 2 intersection points, resulting in multiple solutions. However, for scenarios that consist of at least 3 circles this likelihood decreases significantly due to the conditions of all 3 intersecting with each other being stricter, resulting in more dilemmas of single solutions. In the expression above, it is possible to solve as it is, although this incurs the calculation procedure for this solution to remain inefficient and will continue to be so if more circle equations were to be added into the scenario. Therefore, to reduce computation time for the current and future models, the equation in (3) can be rearranged into matrix format [31]:

$$\begin{bmatrix} 1 & -2x_1 & -2y_1 \\ 1 & -2x_2 & -2y_2 \\ 1 & -2x_3 & -2y_3 \end{bmatrix} \begin{bmatrix} x^2 + y^2 \\ x \\ y \end{bmatrix} = \begin{bmatrix} r_1^2 - x_1^2 - y_1^2 \\ r_2^2 - x_2^2 - y_2^2 \\ r_3^2 - x_3^2 - y_3^2 \end{bmatrix} \quad (4)$$

$$C = \{(x_0, x_1, x_2)^T \in \mathbb{R}^3 / x_0 = x_1^2 + x_2^2\}$$

The matrix form of $Ax = b$ allows for better manipulation of the equations. As mentioned earlier, as more circles are added into the problem, the likelihood of single intersections increases, however there will always be possibilities of multiple intersections and solutions. To combat this, the use of regression analysis techniques become important as this can provide the optimal solution within problems that have difficulties in expressing as a single solution.

3.3 Time of Arrival (TOA)

TOA takes a practical approach to the trilateration method, being most well-known for applications within indoor positioning systems [32]. This can be expressed by looking at fig (Trilateration), the center points of each circle can be replaced as receivers of a vehicle. These receivers act as nodes for detecting incoming transmission signals to record the earliest arrival time to calculate the distance of the transmission source [33]. These distance measurements are then used as the radius value for constructing the circles. Apart from TOA being used in an acoustic scenario, the transmission signals are propagated at the speed of light, with a slight discrepancy due to diffraction. Since the technique derives the majority of the technique from Trilateration, the conditions for this technique to be upheld are also the same. Therefore, it is necessary that at least 3 nodes must be adopted to confidently find a solution, since in 2-node scenarios, unless these circles only touch, 2 possible solutions will always be present.

The primary advantage of the TOA technique is it can provide highly accurate results. This is because the technique revolves around the use of transmitter to receiver time synchronization, therefore there can be no error when concerning the arrival time. Depending on the precision of the clocks used within the transmitter and receiver vehicle, the localization estimation can be improved. However, there are numerous limitations that hinder the method from being useful in a vehicular scenario. The major requirement being that all the receivers on the RV must be synchronized with the transmitter on the TV to record the arrival time to a sufficient degree of accuracy. Even if this condition is satisfied, the time for signal processing of the information source at the TV will still need to be accounted for, otherwise this will cause significant errors in distance calculations and lead to incorrect estimations of the DOA.

In [34], a two-way TOA localization technique was proposed by taking multiple TOA measurements for a moving user device (UD). Their results conveyed that, depending on the traveling velocity, root mean squared error (RMSE) values of under 0.1m can be achieved, providing very precise estimations. However, this comes under the condition of needing 2 one-way transmission, taking up communication time, as well as needing the UD to be encompassed by the surrounding BS's. Within a tunnel scenario, [35] looks into the conducting vehicle localization through the use of Kalman Filtering (KF) and Extended Kalman Filtering (EKF) on TOA and Doppler Shift measurements and analyze the performance of the filtering methods. Their motivation for this research stemmed from improving position monitoring of vehicles within tunnel environments which is strongly susceptible to period spatial fading. Results of their experiments show that the EKF method was able to reduce the estimation errors standard deviation more than the KF method, as well as estimate the TV position better by 10m. The results acquired from a closed environment involving in-tunnel propagation loss and fading provide evidence that further improvements can be attained.

3.4 Angle of Arrival (AOA)

The AOA technique is the most reliant on hardware out of the different localization techniques investigated throughout this research. The technique focuses on receiving the transmission signal on 2 or more antennas in order to measure the signal arrival angle, and to construct a line of bearing (LOB), As demonstrated in Fig. 7. The combination of at least two LOBs can produce an estimation on the location of the transmitter [36], [37]. Compared to the previous methods, AOA has the advantages of only needing 2 receivers to determine the transmission source along with not requiring the receivers to be synchronized, thus not being restricted by any time constraints.

Like the MUSIC algorithm, AOA has the capability of localizing multiple transmission sources to a satisfactory level of accuracy, while maintaining a low computational complexity [29]. The setup defines the antennas to be multiple synchronized receivers with a unified control point, as well as the AOA being set on the azimuth plane, therefore allowing the incoming signal direction to be calculated as the perpendicular to the receiver plane. The estimation errors within the mentioned setup are capable of estimating the location of the source to a 1.31-0.98-degree error [29]. From this research, the results show current AOA techniques cannot meet expectations for V2V localization. The limitations of this technique also lie in the expensive cost of the antenna array necessary [37] and their quantity to be feasible in a vehicular environment. Due to the requirement for calculating the signal arrival angle, the technique cannot be applied within multipathing scenarios, thus requiring Line-of-Sight (LOS).

Hybrid localization techniques such as Received Signal Strength (RSS) with TDOA and AOA/RSS were contemplated for the use in this research as they utilize the advantages of each approach to increase the estimation precision [36] and with proper installment, could be a practical approach in vehicle scenarios. However, while RSS has been used for localization in many Wireless Sensor Networks (WSN) due to the simplicity and inexpensiveness of the approach, the model requires a well-defined, accurate propagation model to estimate the distance measurements otherwise the accuracy of the final result does not satisfy the requirements for V2V communication [36].

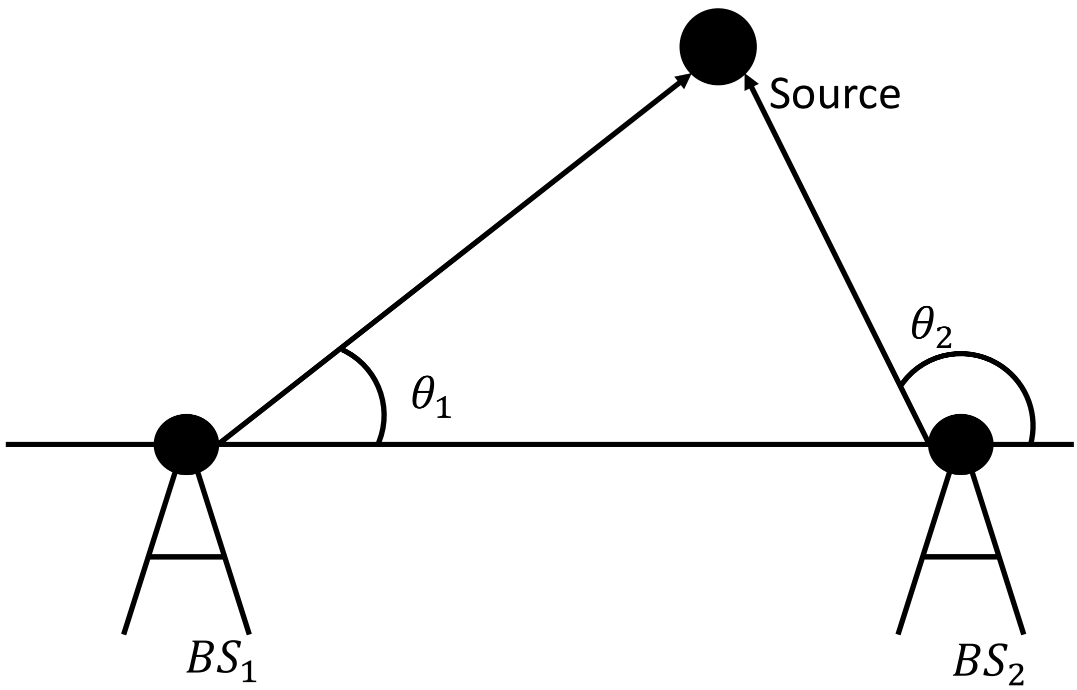


Figure 7. AOA technique using 2 BS's and a Mobile Source (MS)

3.5 Time Difference of Arrival (TDOA)

Unlikely the previously mentioned TOA technique, TDOA is not held back by TOA limitations, such as time synchronization between the transmitter and receiver, since the method focuses on calculating the location of the transmission source through the differences in signal arrival times at the receivers [36], [38], [39], [40]. Once the signal transmission begins, surrounding receivers record the signal arrival time to calculate the TDOA between the receiver obtaining the signal first, the reference receiver, and the other receivers. Since the positions of the receivers is assumed to be known, along with the distances between each receiver, hyperbolic equations that act as possible solutions can be constructed and represented as hyperbolas. The intersection of multiple hyperbolas provides the location of the transmission source as shown in Fig. 8.

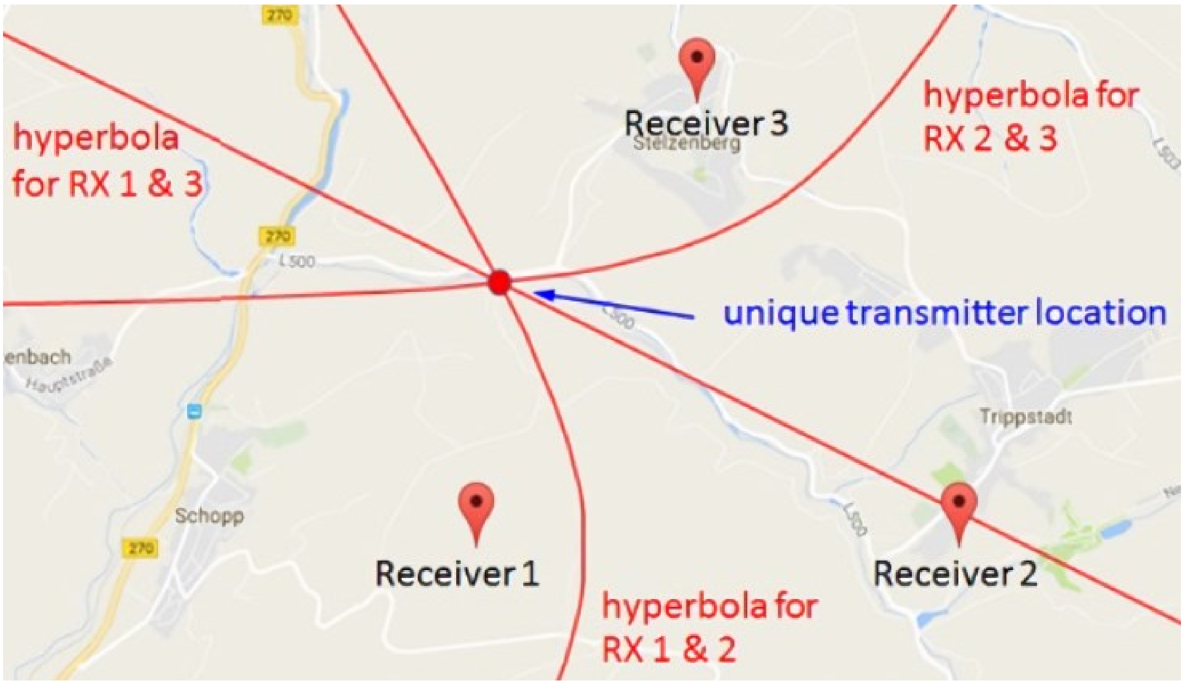


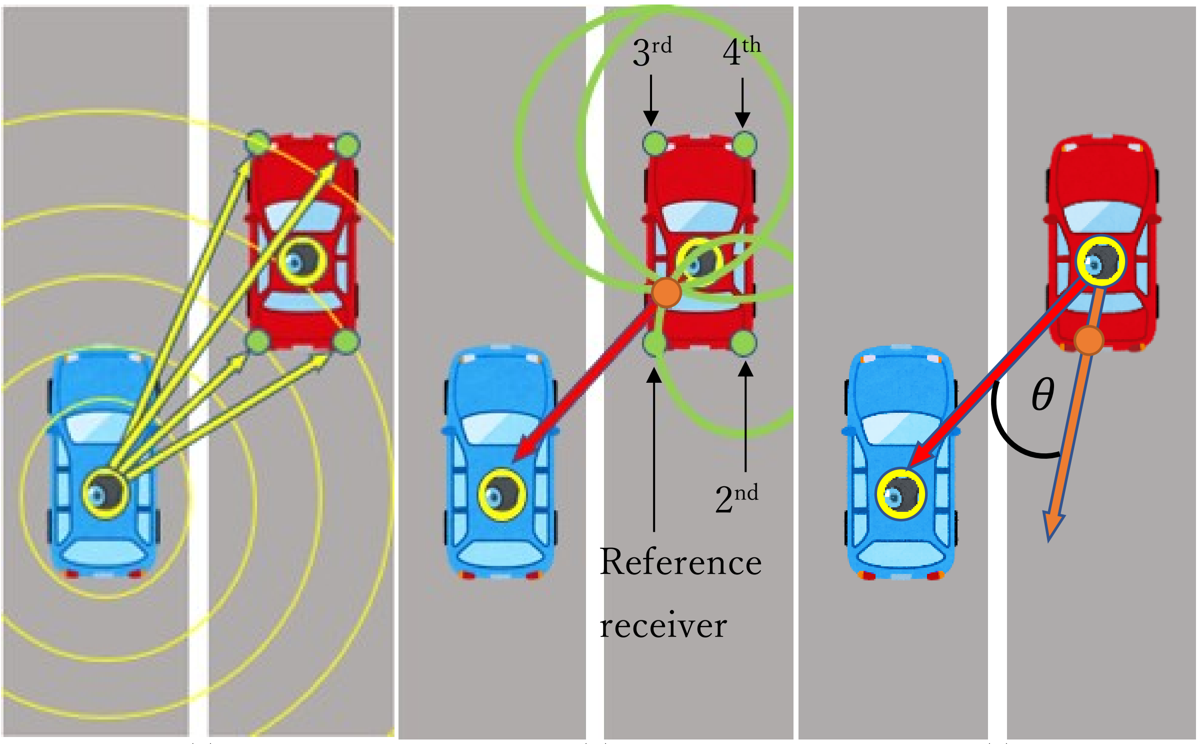
Figure 8. TDOA diagram using 3 BS's [40]

Although this method can reduce the restrictions to be considered, TDOA cannot be executed on a single vehicle due to the relative positions of the receivers to the TV. When conducting TDOA on BS, their positions are established in an orientation that encompasses the transmission source. Hyperbolas in this manner will overlap and produce a viable solution, but in a vehicular scenario, the distance between each receiver is inadequate, thus only producing hyperbolic curves over the receiving vehicle.

The TDOA technique boosts numerous merits over the other techniques studied within this research. AOA receiver locations need to minimize the wave front distortion from local obstacles, as well as needing to be calibrated to reduce resulting frequency and direction dependent errors [41]. While with TDOA, the location of setting up antennas is less restrictive as the TDOA method can overcome shadowing effects of infrastructures by simply installing more receivers within the close proximity, along with not needing to calibrate after installation [41]. TDOA techniques are also able to reject uncorrelated noise and interference due to the correlation processing used for suppressing co-channel signals, making the technique to locate signals with low signal to interference noise ratios (SINR) [41].

In [42], a vehicle localization method involving a single signal transmission from a BS to 2 receivers on a vehicle is considered, using the Cramér-Rao lower bound (CRLB) to measure the TDOA measurement likelihood at a specific location. While this takes an interesting look at minimizing equipment and achieving accurate results within a narrow range, the accuracy degrades rapidly due to the positioning of the vehicle getting worse relative to the BS's, leading to inaccurate TDOA measurements.

4 Proposed Technique



(a) (b) (c)

Figure 9. Diagram of the proposed method, (a) transmitter vehicle propagates a signal, for receivers to record the arrival time, (b) proposed method is used to estimate the DOA position, and (c) represents the DOA error.

Within this section, the specifics of the novel Trilateration-TDOA based localization method is covered. This will explain how the method is conducted within a live motion environment, the advantages of the technique compared to other methods investigated, as well as the drawbacks. To support the proposed technique, a machine learning regression model is introduced to the initial estimation and further improve the final localization angle. The details of the model used for the technique and the selection process of this will be introduced.

4.1 Trilateration-TDOA Based Technique

The proposed method takes the combined use of TDOA between receivers on a RV and Trilateration to calculate the DOA of the signal relative to the RV position. As shown in Fig. 9(a), the TV propagates a signal using an omnidirectional antenna located at the center of the TV. Surrounding RVs within range will record the time of arrival of the signal at each of the receivers situated on the four corners of the RV. A reference point is set to one of the receivers, considering a Line-of-Sight (LOS) scenario, this is the receiver which records the signal arrival time the earliest out of the four receivers. This is to reduce the signal transmission range, minimize the signal attenuation, as well as reduce the likelihood of the transmission signal being subject to surrounding noise. Using reference receiver, (x_1, y_1), and the respective signal arrival time, τ_1, the TDOA values, distance to the transmission source from the i^{th} receiver, and the range difference between the N receivers and the reference point, $R_{i,1}$, are given as [43]:

$$\Delta\tau_i = \tau_i - \tau_1 \tag{5}$$

$$R_i = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{6}$$

$$\begin{aligned} R_{i,1} = v \cdot \Delta\tau_i = &\sqrt{(x_i - x)^2 + (y_i - y)^2} \\ &- \sqrt{(x_1 - x)^2 + (y_1 - y)^2} \\ i = &\ 1,2, \dots, N \end{aligned} \tag{7}$$

where v is the speed of light. To simplify the problem around the reference receiver, (x_1, y_1) is set as the origin. Therefore $|x_1|, |y_1| = 0$ and the distance to the transmission source is $R_1 = |\boldsymbol{x}|$ [34] . By rearranging equation (7) we can obtain:

$$R_{i,1}^2 + 2R_{i,1}R_1 = x_i^2 + y_i^2 + x_1^2 + y_1^2 - 2(x_{i,1}x + y_{i,1}y) \tag{8}$$

where $x_{i,1} = x_i - x_1$ and $y_{i,1} = y_i - y_1$ [43].

By using (8), the distance between a receiver and the reference point can be calculated, providing us with all the necessary variables. Instead of advancing with the conventional TDOA method involving the construction and solving of hyperbolic equations, circle equations are constructed for each of the receivers, except for the reference receiver, by modifying (3):

$$\begin{aligned}(a-x_2)^2+(b-y_2)^2&=R_{2,1}^2\\(a-x_3)^2+(b-y_3)^2&=R_{3,1}^2\\(a-x_4)^2+(b-y_4)^2&=R_{4,1}^2\end{aligned} \tag{9}$$

This composes circle equations which operate as possible solutions to the DOA estimation. $(a,\ b)$ represents the solution relative to the RV position, as shown in Fig. 9(b) with the orange dot for the estimated solution, and the yellow dot representing the center of the RV. From here, the proposed method uses a similar approach to the trilateration technique, by finding the intersection point of all the circles. To manipulate (9), the same way as (4), effectively, matrix notation will be used:

$$\begin{bmatrix}1 & -2x_2 & -2y_2\\1 & -2x_3 & -2y_3\\1 & -2x_4 & -2y_4\end{bmatrix}\begin{bmatrix}a^2+b^2\\a\\b\end{bmatrix}=\begin{bmatrix}R_{2,1}^2-x_2^2-y_2^2\\R_{3,1}^2-x_3^2-y_3^2\\R_{4,1}^2-x_4^2-y_4^2\end{bmatrix} \tag{10}$$

The solution will also be bound by the same constraint C.

As estimating the precise DOA is strenuous, calculating the DOA error is also necessary to understand the error boundaries for specific scenarios. The calculation of this involves constructing a straight line through the RV and TV to know the true DOA and constructing a straight line through the RV and initial DOA estimation for the estimated DOA. The difference between these 2 DOA values is the DOA estimation error, θ, as shown in Fig. 9(c). The proposed method modifies the traditional TDOA method for application in a vehicular environment to calculate the DOA of a TV with minimal cost and space taken up with the installation of equipment on the RV. As only the time difference between each receiver is considered, no synchronization with the transmission source is needed to conduct the estimation. Since there are situations where not all the circles intersect, this can cause the proposed method to estimate the DOA based on the intersection of the remaining two circles, providing a false estimation. This is particularly common in scenarios involving the TV being a considerable distance apart from the RV along the y-axis, causing the second receiver to have a similar arrival time to the reference receiver. In order to mitigate this, a least squares method is implemented to consider the non-intersecting circle.

$$\boldsymbol{x} = (\boldsymbol{A}^T\boldsymbol{A})^{-\mathbf{1}}\boldsymbol{A}^T\boldsymbol{b} \qquad (11)$$

Where $\boldsymbol{x}$, is the estimation point, $\boldsymbol{A}$, is the rightmost matrix in (10), and $\boldsymbol{b}$ is the leftmost matrix in (10). To know the distance between the TV and RV directly is not possible, however by observing the TDOA between the third and reference receiver, an approximation on whether the transmission signal is approaching from in front or sideways can be made, since the distances between the receivers are constant.

4.2 Advantages of studied technique

One of the largest problems with achieving autonomous driving is satisfying the condition of Low-Latency Communication (LLC) to ensure reliable information sharing. Most techniques utilize infrastructure such as BSs as a midpoint to provide transmissions over larger distances. For different implementations, this method suffices and meets most constraints set. However, this extra step within the data delivery makes it almost impossible to achieve the LLC condition. This is because the delay created from transmitting to the extra infrastructure, as well as propagating from the midpoint increases the latency, making it not sufficient for vehicular communication. The extra processing of the signal at each receiver and transceiver node within the transmission consumes more time. The technique proposed in this research mitigates this problem by only requiring transmission from the source straight to the receiver, reducing overall latency involved in the localization, as well as decreasing the reliance of other infrastructures.

4.3 Regression model

4.3.1 Reasons for implementation

In most scenarios involving discrete data, the proposed approach would be sufficient enough to calculate the location of the transmission source with high accuracy. However, with the use of time sensitive measurements as well as considering continuous motion of the vehicles, the use of a regression model helps adjust for any erroneous situations that can appear. Increasing the distance between the TV and RV makes the precision of the DOA estimation ever more important. An example of this is when time registration at the receiver isn't accurate enough due to distance, larger errors cascade along with this, eventually causing dilution of precision (DOP) and make the final DOA estimation error too high to turn a blind eye.

The regression model was implemented to work along with the least squares analysis and reduce the DOA estimation error that would be caused through undesired increases in the TDOA measurements. In order for the regression model to effectively reduce such errors, the predictor and response variables were chosen accordingly.

Originally the regression model incorporated 2 predictor variables and 1 response variable for testing the usefulness of the idea. These variables were the time difference between the reference receiver and 2nd receiver (T21) and the estimated bearing of the transmission signal. This provided adjustment results that improved the DOA estimation, however for the degree of accuracy that would be considered successful, the results were still underperforming.

Four predictor variables were chosen for the regression model. The time difference between the reference receiver and the 2nd receiver (T21), the time difference between the reference receiver and the 3rd receiver (T31), the estimated bearing of the transmission signal and the Doppler shift were chosen. T21 was chosen as there are only a limited number of values that are possible. Based on the value of T21, the regression model can get an understanding on whether the transmission signal is propagated vertically or horizontally, with respect to the RV's orientation. The T31 value further refines this transmission direction by narrowing down the diagonality of the signal. The estimated bearing of the transmission signal is used since this gives the regression model data on the original estimation the proposed technique calculated. Finally, the Doppler Shift was included since this provides information on the difference in velocity between the transmitter and receiver vehicle. The velocity of the TV and RV is not directly inputted as a predictor variable because, within a real-world environment, it is not possible to exactly determine the velocity of the TV. Therefore, by using the Doppler Shift formula it is possible to get an estimate of this. The transmission from the source is propagated at 5.9GHz consistently until the signal is received by the RV. Since the RV has information on its own vehicle's velocity as well as the original propagation frequency, the doppler shift is known. Depending on whether the value of the doppler shift is negative or positive as well as the size of this value, this indicates the difference in speed between the 2 vehicles. For the response variable, the DOA error was chosen. By making this the response variable, future DOA estimations can be adjusted appropriately by taking the DOA bearing error.

4.3.2 Selection Process

In order to select the best regression model for the DOA adjustment process, multiple models were trained and tested using 2 separate collections of data. 10,000 scenarios were constructed in order to use 5000 for training the regression model, and 5000 to test. In order to avoid overfitting due to the large dataset, cross-validation of 10 folds was used to partition the data into smaller groups and estimate the accuracy of each partition. The regression models chosen for testing were a selection of the best models that were available on the MATLAB Regression Learner Application. These models are the:

- Linear Regression Model
- Random Forest Regression Model
- Support Vector Machines (SVM)
- Gaussian Process Regression Model
- Neural Networks

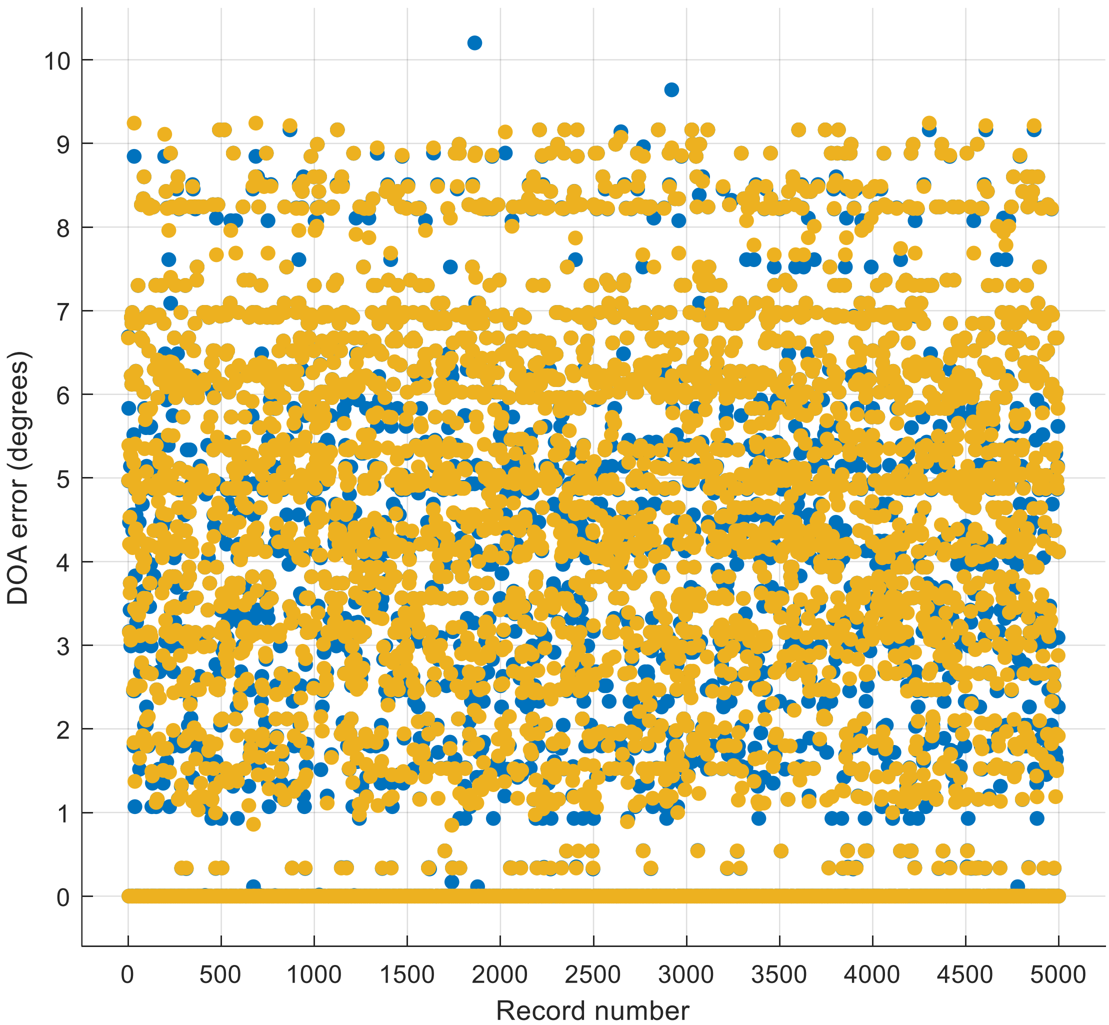


Figure 10. Random forest fine tree regression model

The model producing the lowest root mean square error (RMSE) and requiring the lowest training time were considered for implementation. Overall, it was concluded that the Random Forest Regression Model was the best candidate for the DOA adjustment procedure. Particularly, the Fine Tree model was able to boast a consistent RMSE value of 0.5394 as well as taking approximately 2.22 seconds to train. Through adjusting hyperparameters such as the minimum leaf sizes, the RMSE value was lowered to 0.1744, producing the lowest RMSE possible in the testing of each regression model. Fig. 10 shows the true values (blue) and predicted values (yellow) of the Random Forest regression model. Looking at the other models, the Linear regression model performed poorly, resulting in a RMSE of 2.7679 and having double the training time of the Random Forest model. Looking back at the properties of a Linear regression model, the model investigates a positive or negative proportionality of the predictor inputs to the response value. This does exist in segments of our data, such as when deviation from the front, back and sides of the vehicle increases, larger DOA errors can be witnessed. However, when approaching one of these positions again, this error decreases. The Linear regression model predicts along the average of true responses in order to minimize the sum of square differences, which in turn would lower the RMSE.

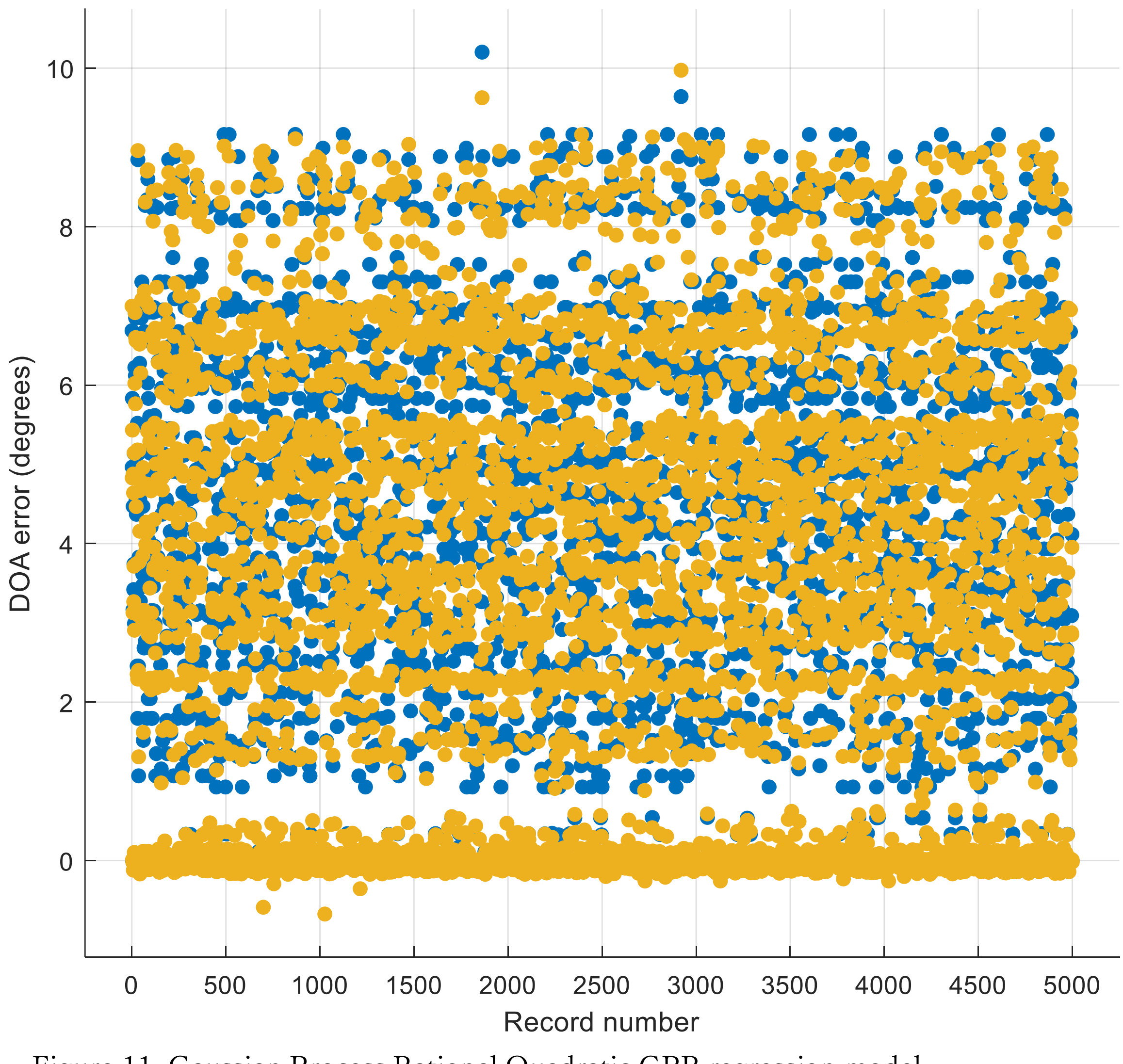


Figure 11. Gaussian Process Rational Quadratic GPR regression model

The SVM models provided interesting results depending on the preset type. The Linear SVM produces similar results to the ordinary Linear regression model, which would make sense as they conduct a like analysis. However, the results for a Quadratic SVM produce lower RMSE results of 1.792 and are able to predict the response variable closer to the true value, rather than placing the new predictions along the average. However, the Quadratic SVM also takes close to 30 seconds to train and does not have many opportunities for tweaking hyperparameters for optimization.

Through multiple testing, the use of the Gaussian Process model was thoroughly considered to be used over the Random Forest as the model consistently produced the lowest RMSE value of 0.3582 without any modifications to kernel hyperparameters. However, the training time necessary to achieve these results is over 263 seconds, taking

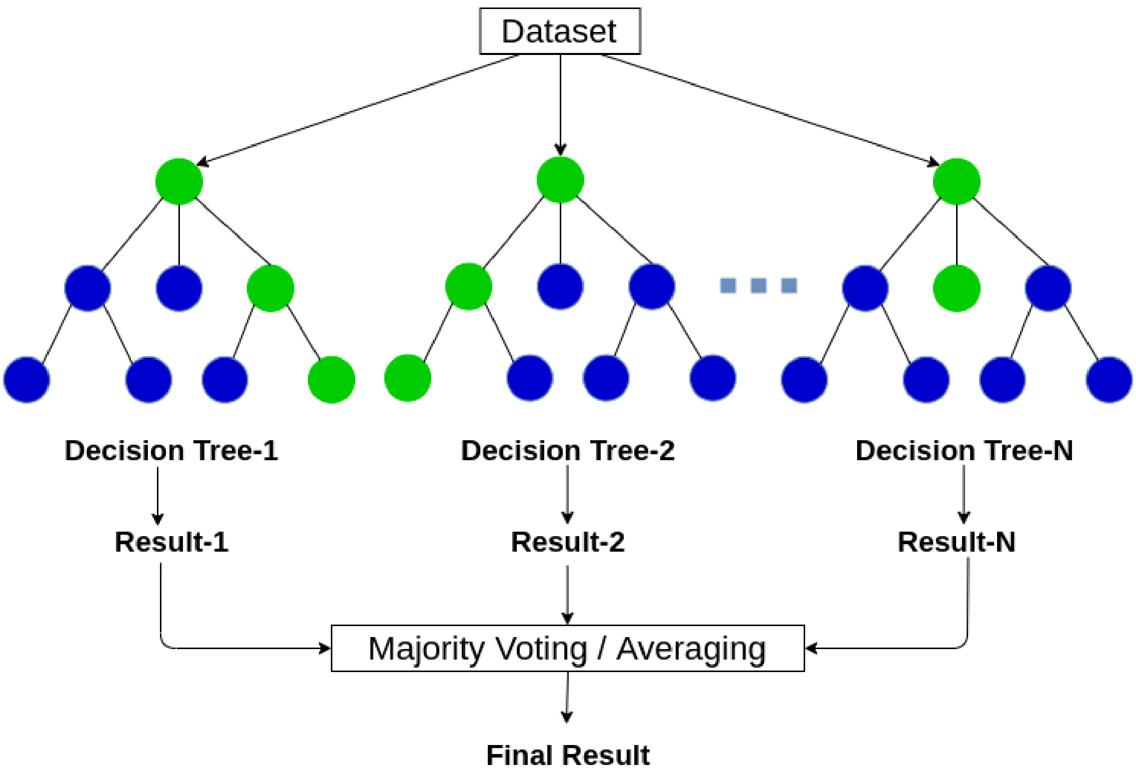


Figure 12. Random forest decision tree model [46]

over 118-fold the time for the Random Forest technique to finish. Fig. 11. represents this as the predictions overall the true and predicted values are more aligned than in Fig. 10.

4.3.3 Random Forest regression model

Out of the different regression models that were contemplated for the localization technique, the random forest fine tree model performed the best by producing the lowest RMSE value as well as having a significantly lower training time comparatively. However, the main reason the random forest models provide relatively strong results is because of its adaptability to include multiple different features and data points. This makes the model applicable to a diverse range of problems and the method of doing so provides a comprehensible explanation of this.

The random forest prediction model is constructed by utilizing multiple decision trees and taking the average of these trees for its prediction, as shown in Fig. 12. Within the training phase, the model will use the dataset provided as the initial tree leaves to construct these decision trees and output the mean. The number of decision trees that are constructed at the beginning is chosen by the user, therefore enabling the choice of benefits between accuracy and speed. Once the training of the random forest regression model is completed, test data can be used to see if the predictions made by the model are of suitable accuracy.

Within the random forest regression model, there are multiple selections of coarseness that are available, them being coarse, medium, and fine. The coarse and medium trees, as their name suggests, provide more clustered results compared to the fine tree. This is because the evaluation process at each decision tree ends at an earlier leave compared to the fine tree model, leading to a less refined analysis. For scenarios that do not consist of large variation in results, coarse and medium trees would be more appropriate due to their training speed being substantially lower and requiring less leaves for consideration. However, for the use of vehicle localization, there are significantly more variables that need to be taken into account due to the continuous change in the environment. Therefore, a fine tree model provides a better prediction compared to the other contenders.

4.4 DOA Adjustment

The implementation strategy of the DOA adjustment process had to be considered in order to define the second DOA estimation most effectively. Originally the process revolved around converting the adjustment value, calculated by the regression model, into (x, y) coordinates. These coordinates are then used for a shifting process where they are added to the preexisting DOA estimation coordinates to perform the adjustment process. While the implementation of this was not so difficult, the representation of the shift was not as accurate. When comparing the adjustment degree with test results, it became apparent that the shift would in most cases be too small. Because of this, the method to adjust the DOA estimation was reconsidered. However, through further research of reliable and practical methods of adjustment processes, a simple solution of utilizing a rotation matrix to definitively represent the necessary modification.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \qquad (12)$$

In order to conduct the modification, the center of rotation is shifted to the origin. Without doing this operation first, information on the original center points as well as the initial DOA estimation point needs to be added to the rotation matrix. By shifting the center of rotation first, this reduces further calculations. Within this scenario, the center of the RV is shifted to the origin and the degree of adjustment is inserted into the rotation matrix. After the operation is completed, the center of the RV is shifted back to its original position, along with the newly revised DOA estimation.

4.5 Considerations

Within this model, the proposed method is conducted on a 2D plane to investigate the effectiveness of the model in a straightforward environment. However, implementing this in a 3D environment would not be very demanding as there are no complications incorporating the z-axis within any of the above-mentioned equations. Since the receivers require recording the earliest time of arrival of the signal, situations which do not align to these essential conditions, such as reflections, can severely distort the final DOA estimation, thus are not considered within this model. To mimic the effects of the transmission signal in a road environment, a ray tracing propagation model is also used to compute the propagation paths of the isotropic signal. This provides a more realistic analysis of the proposed method in common road scenarios. This propagation model implements the Shooting and Bouncing Rays (SBR) method to approximate the propagation paths of the signal. In order to accurately calculate the TDOA between the receivers, it is essential to precisely log the time at which the signal is received, thus time synchronization across all receivers is required. The level of time precision is fairly influential within this model since small variations in arrival time can change the circle radii constructed around each receiver, leading to unreliable results due to Dilution of Precision (DOP). For example, if a TV is marginally to the right of being directly in front of a RV, depending on the time precision, the first and second receiver records the same time of arrival, leading to the DOA being estimated directly ahead of the RV.

4.6 Environment Setup

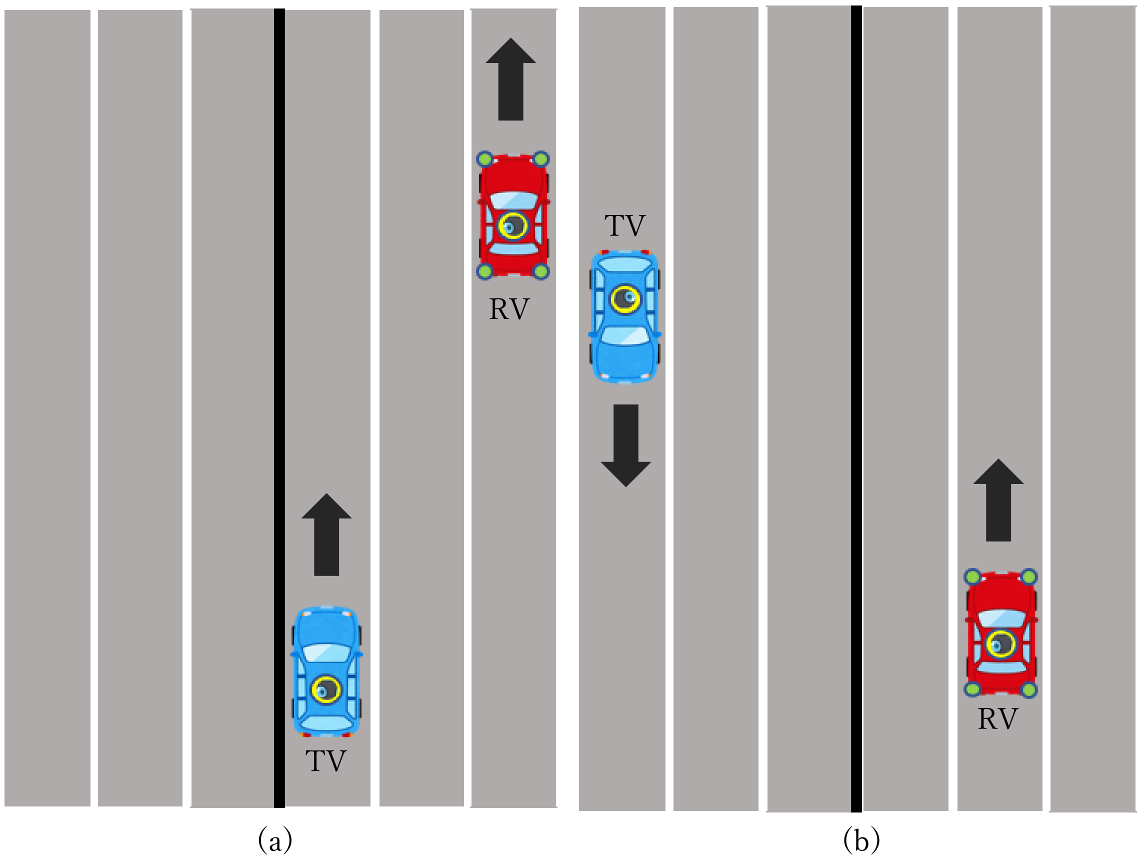


Figure 13. Experiment setup evaluating the (a) Same side scenario (b) Opposing side scenario

4.6.1 Simulation Coding

Originally, the coding language of choice to simulate the vehicle localization technique was Python3 due to the author's previous experience with the natural language along with the vast number of available libraries that can improve the quality of the environment setup. However, through initial testing of early-stage progress, it became quickly apparent the computation time was too long as well as the memory allocation being inefficient. While memory efficiency can be improved to some degree, improving computation time slightly, this was not enough to provide a good analysis on a problem revolving around time sensitive measurements. To mitigate this problem, the best course of action was to change the natural language for this simulation, therefore the coding language was changed to MATLAB. One of the main reasons for the specific switch to MATLAB was due to the realization of the number of matrix manipulations and calculations that were necessary to be conducted throughout the localization estimation. After re-coding from Python to MATLAB, a significant decrease in computation time could be seen for each scenario being tested.

4.6.2 Environment Setup

Out of the many road situations that a vehicle can find itself on a daily basis, urban roads are the most common locations where accidents occur. In 2019, 60% of on-road fatalities occurred on these urban roads [44], with the remaining 40% on rural roads (37%) and motorways (3%). Therefore, situating our environment setup on urban roads seemed the most appropriate. The experiment was set up into 2 different scenarios in order to simulate the effectiveness of the proposed approach - Same side DOA and Opposing side DOA.

Same side DOA: Shown in Fig. 13(a), the TV and RV moved in the same direction in a straight line along an urban highway. 3 lanes were used within this experiment, each with an equal width of 3m, with all lanes extending to 100m in length. Both vehicles were placed on the road using uniform distribution to fully randomize the positions of the TV and RV. The speed of both vehicles was chosen by uniform distribution between 60km/hr to 80km/hr to mimic the environment of an urban highway. For the sake of simplicity, the vehicles in this experiment were set to the same size, 4.55m x 1.75m (Toyota Prius), while the receiver positions on the RV were set to the 4 corners of the vehicle. The signal is propagated from the center of the TV omnidirectionally, increasing the propagation radius by 30cm (1ns time step) or 3cm (0.1ns time step). Receivers on the RV tracked the time step in which the signal arrived. Based on ascending recorded time, the receivers were ordered to determine a reference point. The proposed method was used to calculate the DOA relative to the RV position. Using the method mentioned in section III, the TV speed and distance traveled throughout the elapsed time was calculated and incorporated into the DOA calculation along with the positions of the TV and RV. Finally, two lines were constructed, one through the final RV position and estimated DOA position, the second through the final RV and TV position. The angle between these lines provides the DOA accuracy of the proposed method.

Opposing side DOA: From Fig. 13(b), the TV and RV were moving in opposite directions in a straight line along an urban highway. The structure of the lanes was set the same as the Same side DOA scenario, however there were a total of 6 lanes in which the TV position was placed using uniform distribution on one of the left most 3 lanes, while the RV position was placed using uniform distribution on one of the rightmost 3 lanes. The speed of the vehicles was chosen by uniform distribution between 60km/hr to 80km/hr to mimic the environment of an urban highway. The dimensions of the vehicle used within the experiment were kept the same along with positions of the receiver positions on the RV. The procedure involved signal propagation until the DOA estimation was unchanged to keep the experiment impartial. The vehicle speed and distance traveled throughout the DOA estimation were incorporated in the final positions of the TV and RV. Finally, two lines were constructed, one through the final RV position and estimated DOA position, the second through the final RV and TV position. The angle between the lines provided the DOA accuracy of the proposed method.

4.6.3 Theoretical Setup

In this section, the overall set up for the proposed method is explained, along with the setups for data construction and storage for use in the machine learning regression model and to test it.

For the results to be perfectly representative of the proposed techniques usefulness in various scenarios and the ease of installing to vehicles, it is necessary to test the technique with the same coordinates for both the Same side and Opposing side scenarios. By doing so, the results for using the TOA comparison, proposed method with the regression model, and the ray tracing method with the regression model can be fairly compared. Therefore, it was necessary to set up a dataset to record 1000 random locations for the TV and RV for both Same side and Opposing side scenarios. This was done by constructing multiple zero matrices in order to record the vehicle coordinates for each loop of the simulations. While doing so, the variables used for the machine learning regression model were also recorded using the same manner. The coordinates of the TV and RV were selected using uniform distribution for both their lane position and the distance along the road. Using the position of the vehicles as well as the vehicle dimensions mentioned above, the receiver coordinates for the RV were set. From here a control terminal is set up before the start of the for loop in order to efficiently change the testing scenario, time-step step size, etc. This also includes variable values that are consistently used within the testing such as speed of light, transmission frequency, transmission power, and number of receivers. Other adjustments involving the inclusion of specific considerations such as testing using the ray tracing, doppler shift effect, enabling the DOA adjustment procedure as well as the method being tested against (TOA, proposed method, etc.) can be preset.

At this point in the simulation, all of the variables necessary to use the proposed method are set. The technique commences the theoretical setup by propagating a signal omnidirectionally with the isotropic antenna from the center of the vehicle, with the radius of this signal increasing as the time step of the simulation increases. In order to calculate the maximum number of TDOA values, the V2V transmission continues the signal propagation until all receivers on the RV intercept the signal. The TDOA values are calculated by using the receiver that intercepted the signal first as a reference receiver. The time step values are subtracted from the reference receiver, enabling each of the 4 receivers to have their own TDOA value. To keep the matrices organized as well as to automate the steps to come, the matrix of TDOA values and the receivers intercepting the signal are reordered in ascending order of the TDOA values. The TDOA matrix is used to calculate the radii for each of the receivers except the reference receiver as this value will always be zero since this was the first receiver to intercept the transmission signal.

Using the reordered receiver matrix, the left most matrix, A in equation (10), is constructed with the receiver x coordinates in the second column and the y coordinates in the third. A weighting factor is implemented from the values of the radii in order to normalize the effect each of the receivers have on the final result. Without this weighting factor, the results skew towards the location of the receiver that intercepted the transmission signal the second fastest, reducing the accuracy of the initial DOA estimation results. The rightmost matrix, b, in equation (10) is built using the known distances between each receiver to the reference receiver, and the x and y coordinates of these respective receivers. The inverse of matrix $\boldsymbol{A}$ is taken to conduct matrix multiplication with b to provide the initial DOA estimation. Looking back at equation (10), the solution matrix is a 3x1 matrix, with the solution existing solely in the second and third element. The first element calculates the Pythagorean distance of the x and y coordinate from the center of the RV, therefore this value is not necessary for the DOA estimation. This step is taken further by using the least-squares equation in (11) to find for solutions where not all circles intersect. Depending on whether adjusted results are desired, the regression model analysis is conducted as all the predictor variables are now available, described in section 4.5.1. The regression model calculates a prediction on the DOA error value for the specific scenario, in the form of a degree shift around the center of the RV. The DOA adjustment is performed using the rotation matrix mentioned in (12), allowing the calculation for the revised DOA estimation point, which in turn is the final DOA estimation.

4.6.4 Ray tracing Setup

After the setup of the original theoretical simulation, a more realistic model was also considered to incorporate the physical properties of the transmission signal within the estimation procedure.

This was done by using the MATLAB ray tracing propagation model and using cartesian coordinates to initialize the transmitter and receiver locations for each scenario. There were 2 propagation methods within the model that could be chosen, the shooting and bouncing rays (SBR) method and the image method. Between the two, the SBR method was selected as it was faster at computing the propagation paths than the image method. In order to mimic the behavior and propagation pattern of a signal being transmitted from an omnidirectional antenna, the transmitter antenna was set to isotropic. This made sure that the transmission signal propagated uniformly in all directions. The transmission frequency emitted from the source is 5.9GHz as this is within the bandwidth for Intelligent Transport Systems (ITS) [41]. This frequency is never changed throughout the course of the research as this frequency is used to calculate the doppler shift as well as the vehicle velocity of the transmission vehicle.

Using the cartesian coordinates previously set up, the receivers are set up on the 4 corners of the RV. Same as the transmitter, the antennas on the RV are set to be in an isotropic orientation in order to receive the transmission signal from all directions. The propagation model is conducted under cartesian coordinates. The angle separation of the launched rays was set to high, launching 40,962 rays [45] as this provided the lowest computation time compared to the medium and low angle separation, them being 163,842 and 655,362 rays respectively. From here, the procedure is the same as the theoretical setup, as the TDOA values are obtained and the proposed Trilateration-TDOA technique can be implemented.

Originally within the MATLAB code, the setup for the ray tracing propagation model was incorporated after the position of the vehicles and their receivers were set. The information was fed straight into the ray tracing function to define the antenna position along with the receiver coordinates and their characteristics. However, this entire process was incorporated within the for loop that runs the entire simulation. When conducting the full operation for each of the ray tracing scenarios, the computation time for each individual run was approximately 0.035 seconds. While this doesn't sound very long at first glance, this test is run 1000 times in order to collect data for each of the vehicle coordinates preset, overall requiring 35 seconds. Along with this, the experiment is run in real-time, meaning the calculation time of each run affected how much the vehicles have moved at the same time. Reducing the computation time of each run became a high priority to fix as this directly affects the overall DOA estimation. Therefore, the setting of the receiver and transmitter antennas was conducted at the beginning of the simulation setup so the process would not be involved within the for loop. By doing so the computation speed was improved by 71%, with the average run-time for each scenario being roughly 0.014 seconds.

Table 1. Parameters for simulation

Parameters	Values
Time-interval [ns]	1 / 0.1
Vehicle speed range [km/h]	60 - 80
Vehicle size [m]	4.55 x 1.75
Transmission Frequency [GHz]	5.9
Road dimensions [m] (Same side/Opposing side)	100 x 9 / 100 x 18
Transmit Power [W]	30

5 Results

The performance of the proposed method on its own, the proposed method utilizing the regression model, and the proposed method within a raytracing environment utilizing the regression model are compared to the TOA method.

5.1 Performance Evaluation

From the proposed method, in Table 2, we can see that the average DOA accuracy of the proposed method is inferior to the theoretically pure TOA method. This is due to the TOA method relying on synchronization between the transmitter and receiver enabling retrieval of more precise readings while the proposed method cannot. Therefore, the TOA method approach can get an initial better estimation. This improves fractionally when considering the 0.1ns step size as the time granularity provides a more precise reading. However, compared to the impractical transmitter-receiver synchronization condition of TOA, the proposed method combined with the regression model adjustment yields better results and is more easily implementable. As for both scenarios with the 0.1ns time step, the results border around the 0.1-degree level of precision, improving the accuracy by 35% for the Same side and 32% for the Opposing side scenario from the TOA method. Judging from the differences between the 1ns and 0.1ns results the time granularity takes a significant role within the regression model training. While there are improvements between the proposed model and the proposed method with the regression model, there is not much difference between the Same and Opposing side DOA error.

Table 2. Average DOA estimation error results summary

Method	Time step	Same side	Opposing side	Difference
TOA	1ns	1.9885°	2.1616°	0.1731°
	0.1ns	0.1326°	0.2139°	0.0813°
Proposed method	1ns	4.7362°	7.0549°	2.3187
	0.1ns	3.1511°	6.5918 °	3.4407°
Proposed + regression model	1ns	1.9239°	2.1211 °	0.1972°
	0.1ns	0.0866°	0.1458°	0.0592°
Proposed raytracing + regression model	1ns	2.4624°	2.6568°	0.1944°
	0.1ns	0.1498°	0.2744°	0.1246°

This could be an indication that there are other factors that could be incorporated within the input variables of the regression model to introduce a yet more refined DOA adjustment. Looking at the ray tracing model with the regression model, the errors are marginally larger compared to the proposed method with the regression model. A significant cause of this could be due to the increased simulation time to imitate the signal properties, measuring a less accurate initial DOA estimation. This led to the adjustment value from the regression model to not be as accurate as expected. Other causes of error for the DOA estimation arise from DOP through the manipulation of measurement sensitive data. In all scenarios, the Same side estimations are more accurate than the Opposing side, this could be a consequence of the influence of increasing the range of the x-axis used when conducting the simulations for the Opposing side scenario since the RV must consider a larger sample space, inevitably increasing the likelihood of an error.

Fig. 14. visualizes the results of rounding the DOA bearing to the nearest degree and plotting the largest DOA error for each bearing from the 1000 iterations. Curve fitting is used to appropriately represent the trend in DOA error results.

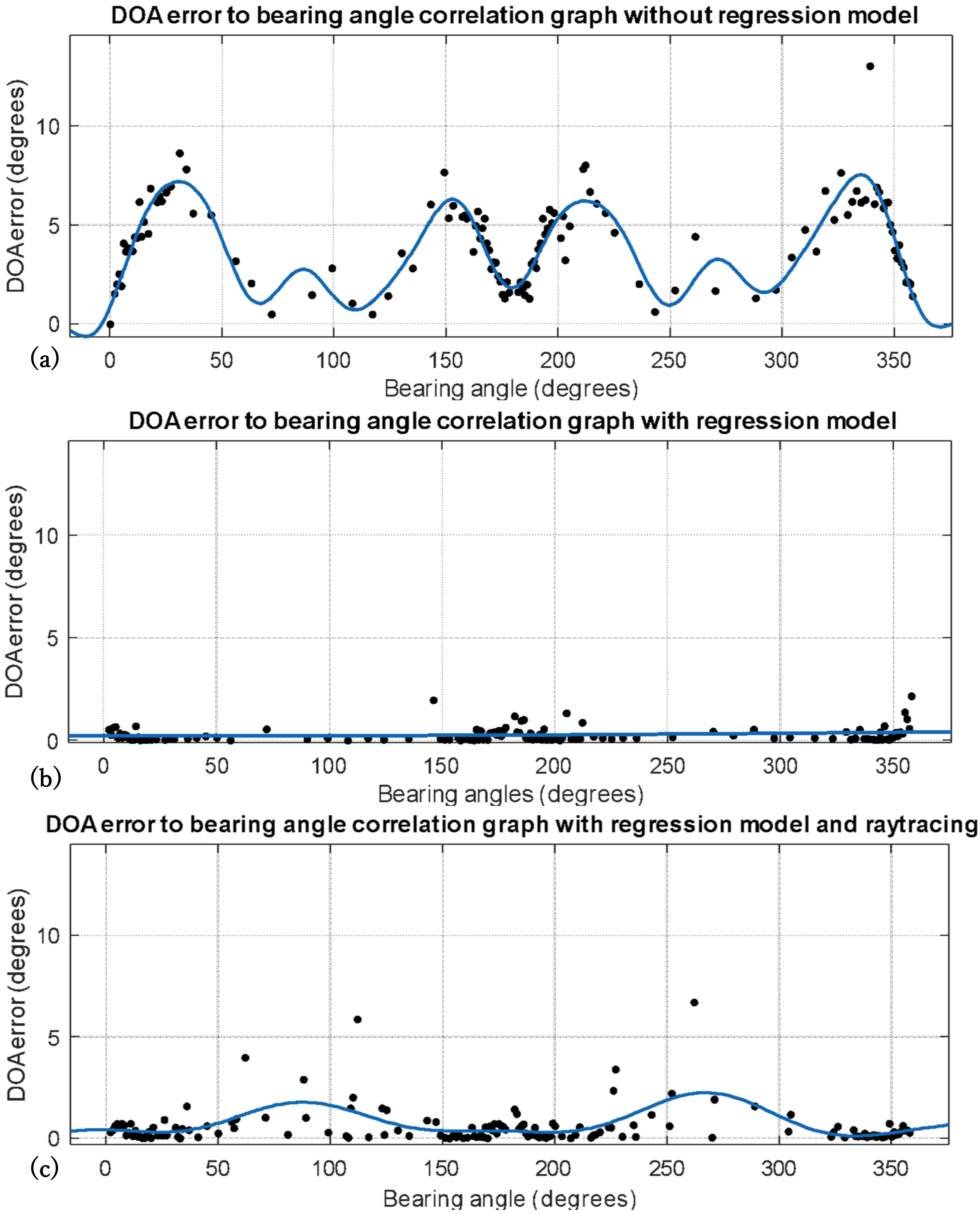


Figure 14. Comparison of DOA error to bearing angle for Same side scenario with 0.1ns time step (maximum DOA error values for each bearing were used). (a) without the regression model (b) with the regression model (c) with the regression model involving raytracing.

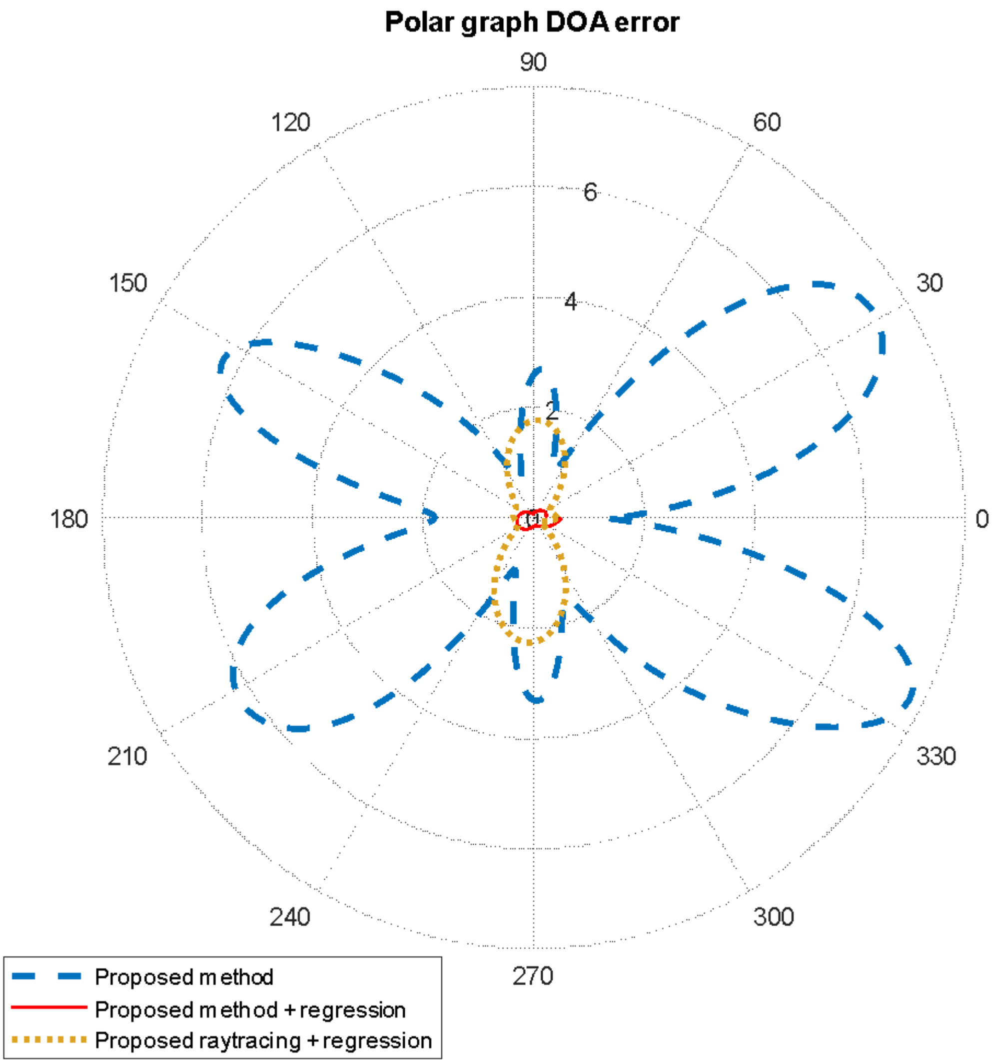


Figure 15. Polar graph comparison of each proposed method

Within Fig. 14(a), a trend can be seen that shows the DOA error increases as the bearing deviates from the front (0 degrees) and back (180 degrees) of the RV. The data points are focused on these bearings between the vehicles, since in a road scenario there is a higher likelihood of receiving a signal ahead or behind. The DOA error improves slightly as the bearing approaches the sides of the RV (90 and 270 degrees). With the incorporation of the regression model, as shown in Fig. 14(b), the DOA error substantially decreases with few results having errors over the 1-degree mark. From these results, we can visualize that the regression model focuses more on adjusting the DOA error closer to the front and back of the vehicle while there are only small improvements made for bearings equivalent to the left and right of the RV. This is also seen in Fig. 14(c), as the DOA error at the front and rear of the vehicle are minimal while the errors corresponding to the sides of the vehicle have only been reduced fractionally. Fig 15. represents the results from Fig. 14 and their improvements in polar coordinates to better visualize estimation accuracy. With the proposed method, frequent fluctuations can be observed when the angles diverge from 0 and 180 degrees for the non-regression plot. These fluctuations occur in correlation to the receiver orientation on the RV since the trajectory of the transmission signal to the closest receiver creates a diagonal line in line with the transmission source. However, the regression model has an overwhelmingly lower DOA error shown by the minimal deviation from the origin as well as having a stable error result which is represented by the limited fluctuations in the inner plot. The ray tracing model has undergone improvements mainly in the diagonal regions of the estimated bearing, while small refinements have been made on the side sections. The slight overlaps between the proposed method and ray tracing model are due to the different initial bearing estimations and the regression model predicting an adjustment value too small.

6 Conclusion and Future Work

Application of vehicular localization will significantly reduce the gap in achieving reliable V2V communication and fully autonomous driving. Research in the field to improve the accuracy and reliability of the technology will need to be undergone for any system involving the safety of the user. This research discussed the merits of using a hybrid method involving trilateration by TDOA for DOA estimation of an incoming signal within a vehicular environment. The method reduces cost, has limited equipment-space needs, minimizes energy waste, and crucially, does not require any time synchronization with the transmission source compared to traditional localization methods. To further enhance DOA accuracy and trustworthiness, the use of other TDOA measurements (received power, TDOA from reference to the other receivers etc.) within the regression model training would be promising. Along with this, changing the orientation or increasing the number of the receivers to minimize error fluctuations in diagonal regions could reduce the DOA error significantly. The implementation of this technique within public urban roads has the potential of improving the V2V communication for autonomous vehicles and mitigating on-road accidents. The experiment showed that, within the setup parameters and assumed conditions, the implementation of the proposed localization technique in a vehicular environment is possible without the need of expensive equipment. Approaches to incorporate signal reflection within the environment would increase the versatility of the method as well as allow the possibility of location estimation within a Non-Line-of-Sight (NLOS) environment.

One such method is the use of FDTD (Finite-Difference Time-Domain) for modeling the propagation patterns exhibited from the transmission antenna of the TV. By defining a set boundary for the simulation setup along with material properties of vehicles and concrete walls, it is possible to experiment on NLOS scenarios for V2V localization.

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