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CISTER-TR-240601

2024/09/02

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Abstract

Autonomous driving (AD) is advancing rapidly, but enhancing situational awareness beyond the internal sensors (cameras, radar, and Lidar) requires cooperative perception services enabled by Vehicle-to-Everything (V2X) links. However, some vehicles can inject incorrect information, either intentionally or by hardware malfunction. Wireless positioning offers a set of physical-layer mechanisms, such as Angle-of-Arrival (AoA) and RSS-based ranging, that can verify the correctness of shared data, particularly position data. We introduce Cooperative Wireless Positioning System (CoWiPS), an innovative mechanism in which a set of cooperating vehicles cooperate to estimate the position of a Vehicle-of-Interest. Our positioning solution achieves accurate position estimations, with 70.16% accuracy within a 10m error margin under 0dB amplitude noise variance, and 50.01% accuracy under 5dB variance.

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***Abstract*—Autonomous driving (AD) is advancing rapidly, but enhancing situational awareness beyond the internal sensors (cameras, radar, and Lidar) requires cooperative perception services enabled by Vehicle-to-Everything (V2X) links. However, some vehicles can inject incorrect information, either intentionally or by hardware malfunction. Wireless positioning offers a set of physical-layer mechanisms, such as Angle-of-Arrival (AoA) and RSS-based ranging, that can verify the correctness of shared data, particularly position data. We introduce Cooperative Wireless Positioning System (CoWiPS), an innovative mechanism in which a set of cooperating vehicles cooperate to estimate the position of a Vehicle-of-Interest. Our positioning solution achieves accurate position estimations, with 70.16% accuracy within a $10m$ error margin under 0dB amplitude noise variance, and 50.01% accuracy under 5dB variance.**

***Index Terms*—Cooperative Wireless Positioning, V2X, Angle-of-Arrival, MUSIC**

I. Introduction

Cooperative perception (CP) services enabled by Vehicle-to-Everything (V2X) communication extend the vehicle's awareness beyond the range of its internal sensors (cameras, radar, and Lidar).For example, vehicles transmit their positions via V2X standardized messages to other vehicles and infrastructure. However, this presumes good will or absence of hardware errors from the vehicles sharing their data. Inaccurate position reports from other vehicles could lead to severe accidents, making the detection of misreports a safety-critical matter.

There are solutions to independently verify the position reported by a vehicle of interest (VoI) in a V2X message. Cooperation can be key in this process: a party of vehicles interested in verifying the correctness of a VoI's reported position information and connected via V2X links or an overlaying Information System (IS) can cooperate towards that end. While camera, Lidar or radar data can be shared to attain this goal, another option are (wireless) **physical-layer mechanisms**. Wireless positioning (WP) techniques based on phase difference, referred to as Angle-of-Arrival (AoA), calculate the angle between (ego-)vehicle and target vehicle.

This work was supported by national funds through the FCT/MCTES, Portuguese Foundation for Science and Technology, within the CISTER, ISEP/IPP Research Unit (UIDP/UIDB/04234/2020), and also by project Route 25 (ref. TRB/2022/00061 - C645463824-00000063), funded by the EU/Next Generation, within call N.º 02/C05-i01/2022 of the Recovery and Resilience Plan (RRP).

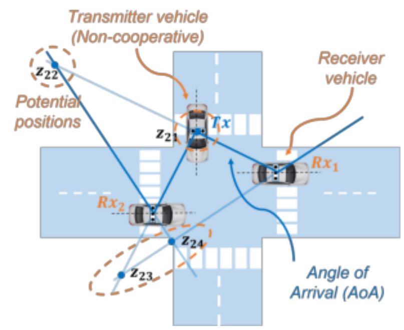


Fig. 1: Scenario showing a Vehicle-of-Interest (VoI) Tx and two cooperating vehicles Rx_1 and Rx_2, that measure AoA of Tx's transmissions using antenna arrays and compute intersections to identify possible locations of Tx.

In this paper we use Uniform Linear (antenna) Arrays (ULAs), that produce two symmetrical solutions. While circular arrays do not have this limitation, we claim that, at the early stages of large-scale deployment of V2X systems, linear arrays will be used in larger scale due to their inferior cost and simpler arrangement. Finally, the AoA technique does not estimate distance, crucial to determine the position of the VoI.

We introduce CoWiPS, an innovative approach to vehicular positioning aiming to mitigate the impact of vehicles equipped with malfunctioning or malicious positioning systems. In CoWiPS, individual vehicles estimate the AoA and measure the Received Signal Strength (RSS) from the VoI, and exchange this data via an information system reachable via V2X messages. Each cooperating vehicle can compute the position of the VoI by computing the intersection of the AoA observed by each participating vehicles, as shown in Fig.1. As there are multiple possible angles, there are also multiple positions for the VoI. We investigate two RSS-based methods for resolving position solution ambiguities. We analyze the impact of amplitude noise on the received signal during positioning, as well as the effects of received power noise on the disambiguation of potential positions. We can accurately position the transmitter vehicle with an average error margin of $34.102m$ under 0dB amplitude noise variance and $66.469m$

under 5dB variance. CoWIPS will enable the development of trust mechanisms in vehicular context, by observing how often a particular node is providing correct information.

The remainder of this paper is structured as follows. Section II reviews the relevant literature. Section III presents the Cooperative Wireless Positioning System (CoWiPS). In Section IV, we report the positioning accuracy of our system. Section V presents the final remarks.

II. State of the Art

Wireless positioning (WP) offers a cost-effective solution by utilizing existing communication equipment, notably antennas in vehicles, used for V2X communication. WP for channels between mobile devices, known as Device-to-Device (D2D) channels, encompasses methods such as Angle-of-Arrival (AoA) [1], Time-of-Arrival (ToA) [2], and Ranging (distance estimation from Received Signal Strength) [3], [4].

Our research focuses on Angle of Arrival (AoA). The conventional approach to AoA involves outfitting a receiving node with an antenna array, typically in a linear or circular arrangement. This array is linked to a radio transceiver with Multiple-Input Multiple-Output (MIMO) capabilities. The transceiver captures signals received by the antennas, computing differences in amplitude and phase. Algorithms such as MUSIC [5] and ESPRIT [6] utilize this information to estimate AoA.

Multiple works have shown the ability of performing AoA in commercial wireless devices using channel sounding mechanisms and their output, typically known as the Channel State Information (CSI) [7].

AoA does not provide a distance estimate. Ranging can be used to that end but it is typically highly unreliable due to various propagation phenomena that affect a signal's amplitude. Another popular option is Time-of-Flight (ToF), that measures the Round-Trip Time (RTT) and subtracts the turn-around time with dedicated hardware. In the IEEE 802.11 ecosystem, IEEE 802.11mc specifies ToF through the Fine Timing Measurements (FTM) mechanism, but it is only available from IEEE 802.11ac onwards. IEEE 802.11az [8] bundles the beamformers' inherent AoA estimation with the IEEE 802.11mc's ToF mechanism to effectively produce a position estimate; it is available on some 802.11ax devices.

Recent studies on AoA-based WP in vehicular contexts for safety and security fall short in addressing our specific use case. In [9], cooperative positioning is discussed, but AoA from Device-to-Device (D2D) channels is not utilized; instead, reliance is on data from cellular base stations. In [10], the focus is on improving positioning accuracy using GPS positions and AoA information between node pairs within communication range. However, this assumes constant cooperation between transmitting and receiving nodes, with data integrity always maintained, contrasting our scenario. IEEE 802.11p, currently the most established vehicular communication protocol, is based on the old IEEE 802.11a, and therefore does not support MIMO nor the ToF-enabling FTM mechanism. Its successor, the 802.11bd standard [11], is likely to have 2x2 MIMO; support for ToF is uncertain to the best of our knowledge.

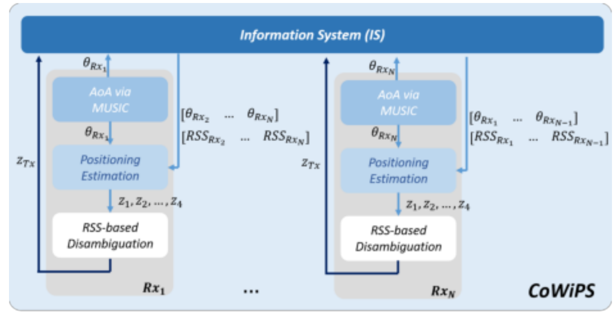


Fig. 2: CoWiPS. Individual vehicles (grey box identified by Rx) estimate AoA to VoI and share angle to participating vehicles via an existing information system (e.g., V2V or cloud-based) to perform positioning by projection intersection.

III. CoWiPS

CoWiPS utilizes cooperation and wireless positioning (AoA and Ranging) to detect the position of a transmitting vehicle, considered non-cooperative or reporting a false position to its V2X neighbours and infrastructure. It has three stages:

1) Individual vehicles measure AoA and RSS to VoI;
2) Vehicles share their position and observed AoA/RSS;
3) Vehicles compute independently the position of VoI.

As depicted in Fig. 2, the IS facilitates the exchange of necessary information among the cooperating vehicles.

In this paper we focus on Uniform Linear (antenna) Arrays (ULA). ULAs lead to a position solution ambiguity, as there are two potential angles at which the VoI can be. This is not the case, e.g., of Uniform Circular (antenna) Arrays (UCA), in which their circular arrangement allows to unambiguously identify the arrival angle in the $[0°, 360°]$ range. We focus on the ULA configuration as it is the simplest arrangement of multiple antennas and can operate with a minimum of two antennas, hence being natural that it takes dominance at the early deployment stages of multi-antenna (i.e., multi-stream) setups in vehicles. UCAs, in turn, require sufficient antennas to create a circle (minimum of 4); resolution improves as the number increases. We plan to address UCAs in future work.

As ULAs produce two potential angles, position uncertainty becomes compounded as the AoAs are used to compute intersections with AoA from other nodes. E.g., for two vehicles, as each produces two angles, 4 possible intersection points are possible. We present two variations of a Received Signal Strength (RSS)-method to disambiguate the correct position. In the first, we equip vehicles with two additional antennas positioned at the front and back of the vehicle to perform differential RSS analysis. In the second, trusted vehicles exchange their measured RSS to the VoI, and select the potential location that is the most coherent with the observed RSSs. The first option allows vehicles to identify individually the correct angle, meaning that they need to share that angle only. The former requires that both angles are shared, all intersections to be computed, and a mechanism to find the position that is most consistent with the observed RSSs. We compare the performance of these two techniques.

A. Angle-of-Arrival Estimation at Individual Vehicle

Consider three vehicles: one transmitter Tx (the VoI), and two receivers Rx_1 and Rx_2. The transmitter emits signals isotropically. The receiving vehicles are equipped with an ULA of $M = 3$ antennas, spaced at distance d_{ant} (inferior to wavelength λ). The incident signals from the D transmitters, along with their amplitude and phase, are represented by complex quantities $s_1, s_2, ..., s_D$. For simplicity, we set $D=1$.Incoming signals vary over time, and therefore we take k samples over time of the incoming signal.

The incident signals are represented by the steering vector $\vec{\mathbf{a}} = a(\theta_i)$, where the first column, $a(\theta_1)$, corresponds to the steering vector for the first user, and so on.

$$a(\theta_1) = \begin{bmatrix} 1 \\ e^{j\beta d_0 cos(\theta_1)} \\ e^{j2\beta d_0 cos(\theta_1)} \\ ... \\ e^{j(M-1)\beta d_0 cos(\theta_1)} \end{bmatrix}$$

where $\beta = \frac{2\pi}{\lambda}$, with λ being the signal wavelength.

Then, the received signal $\vec{\mathbf{x}}$ is expressed as:

$$\vec{\mathbf{x}} = \vec{\mathbf{a}}s + \vec{\mathbf{n}}_{\mathrm{AoA}} \tag{1}$$

$$\vec{\mathbf{x}} = \begin{bmatrix} a(\theta_1) & ... & a(\theta_D) \end{bmatrix} \begin{bmatrix} s_1(k) \\ s_2(k) \\ ... \\ s_D(k) \end{bmatrix} + \vec{\mathbf{n}}_{\mathrm{AoA}}(k) \tag{2}$$

where $\vec{\mathbf{n}}$ identifies noise components affecting the signals received at each antenna independently (discussed in detail below). Under this signal model, the MUltiple SIgnal Classification (MUSIC) algorithm is able to estimate the direction of the impinging signal. MUSIC decomposes the signal correlation matrix into two orthogonal matrices: the signal-subspace and noise-subspace. Direction estimation can be performed from either subspace, with the assumption of uncorrelated noise within each channel.

The noise component $\vec{\mathbf{n}}$ incorporates various sources of fading, such as shadowing (attenuation by obstacles), and interference from similar-frequency signals, notably multipath reflections. Multipath is a phenomenon of particular concern that can be modelled as attenuated, delayed copies of the original transmitted signal. In (urban) vehicular scenarios, where there are many reflective surfaces and obstacles impeding LoS, this can lead to complex power delay profiles (that make $\vec{\mathbf{n}}_{\mathrm{AoA}}$ more intricate). In this paper, we do not consider shadowing (i.e., all links are in Line-of-Sight) or interference, from the same signal (multipath) or others. We acknowledge the relevance of these propagation phenomena and plan to address them in future work; in the present work, we focus mostly on proving the concept of cooperative WP and the suitability of the ranging mechanisms to complement AoA towards position estimation. Therefore, for simplicity, we model $\vec{\mathbf{n}}_{\mathrm{AoA}}$ as white Gaussian noise, i.e., $\vec{\mathbf{n}}_{\mathrm{AoA}}(k) \sim \mathcal{N}(\mu_{\mathrm{n_{AoA}}}, \sigma_{\mathrm{n_{AoA}}})$ for each k.

B. Position Determination & Solution Ambiguity

By exchanging AoAs and positions of receiving vehicles, signal trajectories can be described as lines on the world map, as shown in Fig.1. When using ULAs, the application of the MUSIC algorithm produces two symmetrical angles of arrival $\theta_{ij} = \{\theta_{i,1}, \theta_{i,2}\}$ per transmitted signal, where $\theta_{i,2} = 360° - \theta_{i,1}$, of which only one is correct. Here, i denotes the receiving vehicle, and j represents the AoA and its estimated symmetric counterpart. We exclude scenarios where all three vehicles are aligned. The arriving angles $\theta_{i,j}$ measured by the cooperating vehicles need to be mapped into a Common (world) Referential, resulting in $\theta_{i,j,(CR)}$. Defining the orientation of a receiver vehicle in the Common Referential as $\alpha_{\mathrm{i,(CR)}}$, we use $\alpha_{\mathrm{i,(CR)}}$ as an Euclidean rotational operator via the expression $\theta_{i,j,(CR)} = \theta_{i,j} + \alpha_{\mathrm{i,(CR)}}$.

Equations for linear curves can be extracted using $m_{ij} = \tan\theta_{ij,(CR)}$, and calculating the y-intercept b from a known position of the receiver vehicle in the Common Referential. To compute the set of intersections $\mathbf{Z}$, the curve equations from Rx_1, Rx_2,...Rx_n are paired with each other. For instance, when $N_{\mathrm{RX}} = 2$, the system yields $|\mathbf{Z}| = 4$ solutions. This is the scenario of Fig. 3, in which the equations apply:

$$m_{1,1}x + b_{1,1} = m_{2,1}x + b_{2,1} \;; \quad m_{1,1}x + b_{1,1} = m_{2,2}x + b_{2,2}$$
$$m_{1,2}x + b_{1,2} = m_{2,1}x + b_{2,1} \;; \quad m_{1,2}x + b_{1,2} = m_{2,2}x + b_{2,2}$$

With $N_{\mathrm{RX}} = 3$, the two-by-two pairings produces $|\mathbf{Z}| = 12$ solutions. When $N_{\mathrm{RX}}=4$, $|\mathbf{Z}|=24$. For $N_{\mathrm{RX}}=n$ receiver vehicles, the number of intersections $|\mathbf{Z}|$ is given by $\mathbf{2n(n-1)}$.

Some solutions can be discarded as they fall on a half-plane that we know not to be eligible. The two MUSIC solutions $\{\theta_{i,1}, \theta_{i,2}\}$ always fall on the same half-plane $\mathcal{H}$ of the trigonometric circle, and any solutions not located on that half-plane can be discarded. In fact, the space for eligible solutions will actually be the intersection of all eligible half-planes (each one defined by each vehicle), i.e., $\mathcal{H}_{\mathrm{viable}} = \cap_{i=1}^{N_{\mathrm{RX}}} \mathcal{H}_{\mathrm{viable},i}$. In Fig. 3, this is the case of z_2 and z_3; the eligible half-planes are shown in light blue, with the final eligible being indicated in darker blue. As for the remaining solutions, the use of maps may help eliminate improbable locations, but this is not guaranteed.

C. RSS-based Disambiguation Mechanisms

We propose two RSS-based approaches to disambiguate the location indetermination:

- Method 1: **Individual Differential RSS Mechanism**: vehicles are equipped with extra antennas and use RSS to determine antenna closest to TX.
- Method 2: **Cooperative RSS Mechanism**: vehicles exchange their observed RSS and determine the potential location of TX that minimizes the distance error.

1) Individual Differential RSS Mechanism: We propose receiving vehicles to feature two RSS disambiguation (RSS-D) antennas besides those of the ULA. We assume the ULA to be deployed at the middle of the vehicle's roof, while the two RSS-D antennas would be placed at the roof extremities

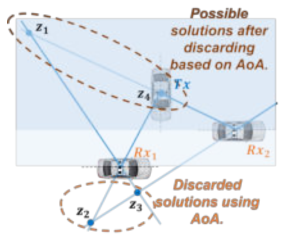


Fig. 3: Discarded potential positions of Tx

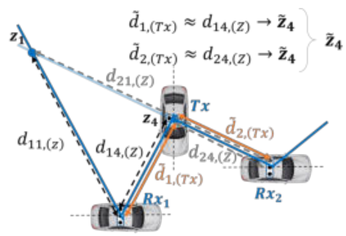


Fig. 4: RSS-based and geometrical distances

along the longitudinal axis of the vehicle (at the *front* and at the *back*). We denote by $P_{\mathrm{rx,front}}$ the power received at the front RSS-D antenna, and by $P_{\mathrm{rx,back}}$ at the back.

The fundamental modelling of received electromagnetic signal strength P_{RX} (in log scale) is:

$$P_{\mathrm{RX}} = P_{\mathrm{TX}} - L_{\mathrm{PL}}(d) + N_{\mathrm{f}} \tag{3}$$

where P_{TX} is the transmitting signal power, $L_{\mathrm{PL}}(d)$ is a (deterministic) path loss component as a function of transmitter to receiver distance d, and N_{f} is a (stochastic) noise component, that we model as a Gaussian distribution $\mathcal{N}(\mu_{\mathrm{PL}}, \sigma_{\mathrm{PL}})$ with mean $\mu_{\mathrm{PL}} = 0$ and some variance $\sigma^2_{\mathrm{PL}} > 0$, an assumption for which we present the same justification as for n_{AoA} (see Sec.III-A). A ranging estimate can be produced by re-arranging Eq. 3, distances d_1 and d_2 from transmitter to the two RSS-D antennas can be estimated by:

$$d = L^{-1}_{\mathrm{PL}}(P_{Rx} - P_{Tx} - N_{\mathrm{f}}) \tag{4}$$

Using this equation, estimates for the Euclidean distances $\tilde{d}_{j,(Tx)}$ between each antenna (identify by j) and the transmitter position can be produced. Determining the closest antenna will provide indication of which of the vehicle's half-plane (sectioned by the ULA axis) contains the transmitter position. In practice, a simpler approach can be pursued. Depending on their relative position to the transmitter, RSS-D antennas will likely observe different received power, notably $P_{\mathrm{rx,front}}$ and $P_{\mathrm{rx,back}}$. If $P_{\mathrm{rx,back}} \leq P_{\mathrm{rx,front}}$, the correct solution is in the half-plane (sectioned by the ULA axis) that includes the vehicle's front.

There are issues with this strategy. The distance between the RSS-D antennas may not be large enough to observe RSS differences larger than the noise variance σ_{PL}. Furthermore, this mechanism requires additional antennas besides those of the ULA. It could be argued that, if additional antennas are available, a circular antenna array could be used. Recognizing this limitation, we propose next an alternative approach that does not require additional antennas.

2) Cooperative Differential RSS Mechanism: In this second setup, vehicles rely solely on their ULA to measure RSS, and exchange their position and observed AoA and RSS. Using the received RSS values, each vehicle estimates the distance $\tilde{d}_{i,(Tx)}$ of vehicle i to the transmitter vehicle Tx using the ranging equation shown in Eq. 4. Using the received positions, each receiving vehicle independently computes the exact distance $d_{ik,(\mathbf{Z})}$ between each receiving vehicle i and the set of potential locations $z_k \in \mathbf{Z}$, with $k = \{1, ..., |\mathbf{Z}|\}$. For $N_{\mathrm{Rx}} = 2$ and $|\mathbf{Z}| = 2$, depicted in Fig. 4, this results in two distance estimates to the transmitter vehicle $\tilde{d}_{i,(Tx)}$, and four geometrically-calculated values for the distances of each vehicle to the set of potential transmitter locations $d_{ik,(\mathbf{Z})}$.

The location $\tilde{z}_k$ that shows the minimum absolute error (MAE) ε_{d} between RSS-based distance estimate $\tilde{d}_{i,(Tx)}$ and geometrically-calculated distances $d_{ik,(\mathbf{Z})}$, following equation $\varepsilon_{\mathrm{d}_{ik}} = min|\tilde{d}_{i,(Tx)} - d_{ik,(\mathbf{Z})}|$ is elected as the *likely* location of the transmitter. Again, for $N_{\mathrm{Rx}} = 2$ and $|\mathbf{Z}| = 2$, there are four errors being computed, with pairings according to i.

$$\varepsilon_{\mathrm{d}_{1,1}} = |\tilde{d}_{1,(Tx)} - d_{11,(\mathbf{Z})}| \qquad \varepsilon_{\mathrm{d}_{1,2}} = |\tilde{d}_{1,(Tx)} - d_{12,(\mathbf{Z})}|$$
$$\varepsilon_{\mathrm{d}_{2,1}} = |\tilde{d}_{2,(Tx)} - d_{21,(\mathbf{Z})}| \qquad \varepsilon_{\mathrm{d}_{2,2}} = |\tilde{d}_{2,(Tx)} - d_{22,(\mathbf{Z})}|$$

There are also limitations to this approach. First, there is the issue of consensus. Vehicles should independently arrive at the same solution, or exchange additional messages to converge. This solution requires vehicles to exchange, besides their position and estimated AoA to target vehicle, also their observed RSS. We consider this not to be a major limiting aspect, as RSS data is short. Finally, there is the impact of circumstantial relative positioning of the vehicles, that may not be suited to produce an fitting estimate (e.g., both potential locations are at similar distance from both vehicles).

3) Trade-offs between Approaches: The first method is self-contained in the sense that vehicles would be able independently disambiguate the correct angle-of-arrival to the transmitting vehicle. However, it presumes the existence of two additional antennas. In turn, the second method does not require more hardware than the ULA, but it is much more susceptible to the circumstantial configuration of transmitter and receivers. Both methods rely heavily on the ranging procedure, which is well-known to be unreliable and therefore only outputting accurate distance estimates at a fraction of samples. This limitation can be overcome by the use of circular antenna arrays, that we will address in future work.

IV. Experimental Evaluation

We report performance results over our technique in a simulated scenario. We investigate the impact of noise on angle estimation and on the determination of the correct solution.

A. System Model

We use a 5x5 Manhattan mobility model, with distances between intersections set to 100m. We consider $N_{\mathrm{TX}} = 1$ and $N_{\mathrm{RX}} = 2$. Both the initial and final positions for each vehicle are selected randomly (respecting uniform distribution) from the list of grid corners, using Python's *random.choice()* function. Vehicles navigate along random trajectories. At each intersection, the simulator randomly selects the next intersection to go to from the set of immediately neighbouring intersections (given the small size of the scenario, few loops occur). The transmitter's movement is set at $60km/h$ and the receiver vehicles at $40km/h$ (thus having more travel time in the scenario). The simulation time step is 1s, and vehicles

TABLE I: Simulation Parameters

Parameter	Value
k: Number of time snapshots	2000
f: Signal frequency	2.442×10^9 Hz
M: Number of antennas	3
D: Number of incoming signals	1
d_{ant}: Spacing between antennas	10^{-1} m
P_{TX}: Transmitting power	20 dBm

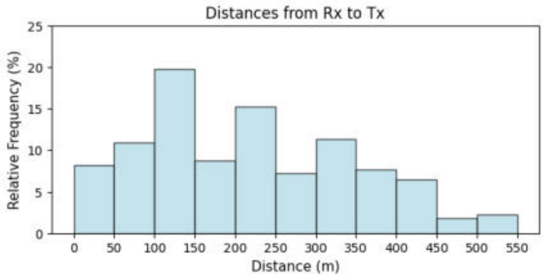


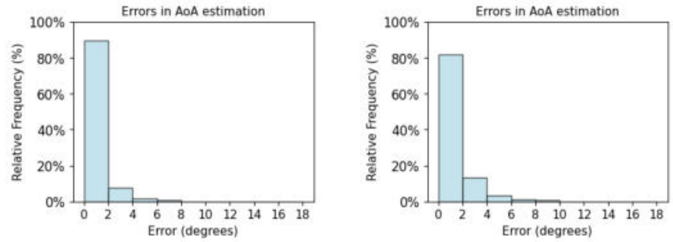
Fig. 5: Distances between Tx and Rx vehicles (500 samples).

produce one AoA and RSS estimate per (simulated) second. We performed 7 experimental runs, yielding an average of 74 AoA & RSS samples per run with a standard deviation of 13.24 samples, and totalling 500 samples. The length of traversed trajectories vary across runs due to their stochastic generation process nature of vehicle trajectories. Fig. 5 plots the distribution of distances between TX and RXs.

For RSS simulation purposes, vehicle-to-vehicle channel is modelled using a free-space path loss model (FSPL). In FSPL, received power P_{Rx} can be calculated using the equation [12]:

$$P_{\text{RX}} = P_{\text{TX}} - 20\log\left(\frac{4\pi d}{\lambda}\right) - \mathcal{N}(\mu_{\text{PL}}, \sigma_{\text{PL}}) \tag{5}$$

where, in addition to Eq. 3, λ is the wavelength. The last term models an instantaneous stochastic variation in received power strength (see Sec. III-C1).For the purpose of AoA estimation, the signal reception at multiple antennas is modelled according to Eq. 2. We assume that sufficient power is received over the path for signal phase determination. The MUSIC procedure relies on the ability to separate the signal and noise sub-spaces, hence signal-to-noise ratio SNR_{AoA} is the most relevant metric. SNR is defined by $\text{SNR}_{\text{AoA}}[\text{dB}] = 10\log\left(\frac{E[P_{\text{signal}}]}{E[P_{\text{noise}}]}\right)$, where $E[\cdot]$ is the expected value, $E[P_{\text{signal}}]$ is considered constant, and $E[P_{\text{noise}}]$, if the noise has expected value of zero, takes the value of its variance, $\sigma^2_{\text{n}_{\text{AoA}}}$. As explained in Sec. III-A, in our work we model noise n_{AoA} as following a Gaussian distribution with parameter values $\mu_{\text{PL}} = 0$ and some $\sigma^2_{\text{n}_{\text{AoA}}}$. In the following discussion, we define a set of target SNR values (25dB and 30dB), for which we compute the corresponding $\sigma^2_{\text{n}_{\text{AoA}}}$. Values for the system world parameters are detailed in Table I. All the above details were implemented in a mobility and wireless channel simulator, and paired with a code version of the MUSIC algorithm. Implementation uses Python v3.12.0. Position errors are reported as Euclidean distance to true location.



(a) $\text{SNR}_{AoA} = 30\text{dB}$ (b) $\text{SNR}_{AoA} = 25\text{dB}$

Fig. 6: Error of estimated AoA.

B. Results

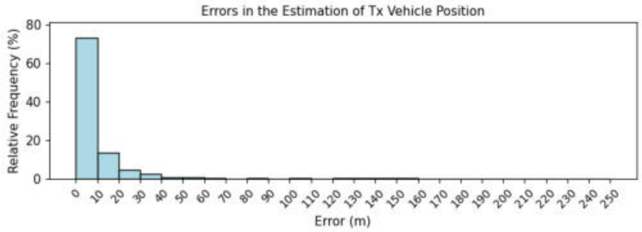
1) Accuracy of AoA Process: We evaluate the impact of Gaussian noise on the various antennas of the ULA in accurately determining the angle of arrival of the signal. For $\text{SNR}_{AoA} = 30\text{dB}$, illustrated in Fig.6a, the average error of estimated angles is $0.570°$ with standard deviation of $1.023°$. For $\text{SNR}_{AoA} = 25\text{dB}$, illustrated in Fig.6b, the AoA estimation yields an average error of $0.945°$, with a standard deviation of $1.311°$. Maximum errors are $7°$ and $9°$, respectively. While average values are relatively small, positioning accuracy will vary also as a function of Tx-Rx distance (Fig. 5).

2) Positioning Accuracy using Individual RSS Method: In this mechanism, RSS-D antennas are added to each vehicle to independently determine the correct location solution. Given a set of potential locations $z > 2$, excluding those that do not fall in an eligible half-plane, we evaluate how often the mechanism determines the correct solution. We set $\mu_{\text{PL}} = 0$, and tested with $\sigma^2_{\text{PL}} = 0\text{dB}$ and $\sigma^2_{\text{PL}} = 5\text{dB}$. Under $\sigma_{\text{PL}} = 0\text{dB}$, the mechanism determines the correct solution in 99.25% of the samples. Considering the angle error, this translates into an average error in position estimation of $13.529m$, with a standard deviation of $33.266m$ when $\text{SNR}_{AoA} = 30\text{dB}$ (Fig.7a). 73.16% of the estimates exhibited errors below $10m$. These values must be considered against the range of distances (Fig. 5), with average $214.31m$. If $\sigma_{\text{PL}} = 5\text{dB}$, accuracy in selecting the correct location decreases to 24.15%. If $\text{SNR}_{AoA} = 25\text{dB}$, the average error in position estimation increases to $83.195m$, with a standard deviation of $149.75m$ (Fig.7b). 36.66% of the estimates show an error below $10m$.

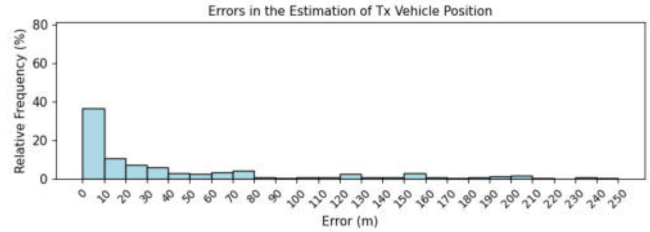
3) Positioning Accuracy using Cooperative RSS Method: We also tested the cooperative RSS-based disambiguation mechanism. If $\sigma^2_{\text{PL}} = 0\text{dB}$, 74.53% of selected solution positions were correct. If $\sigma^2_{\text{PL}} = 5\text{dB}$, the accuracy is 46.60%. If $\text{SNR}_{AoA} = 30\text{dB}$, the average error in position estimation is $34.102m$, with a standard deviation of $98.04m$ (Fig.8a). Among the estimations, 70.16% of the estimations exhibited errors below $10m$. If $\text{SNR}_{AoA} = 25\text{dB}$, the average error in position estimation increases to $66.469m$, with a standard deviation of $126.52m$ (Fig.8b). 50.01% of the estimates showed errors below $10m$.

C. Discussion

The individual RSS method is highly susceptible to amplitude noise. We posit that RSS-D antennas in individual vehicles are too close to each other (a vehicle's roof length)

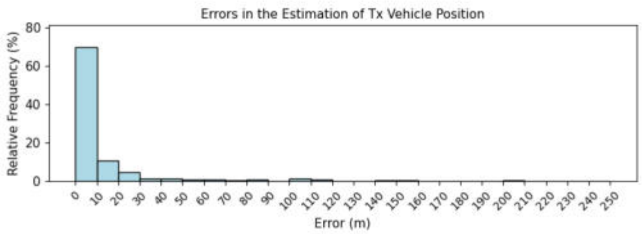


(a) $\mathrm{SNR}_{AoA}=30\mathrm{dB}$, $\sigma^2_{\mathrm{PL}}=0\mathrm{dB}$

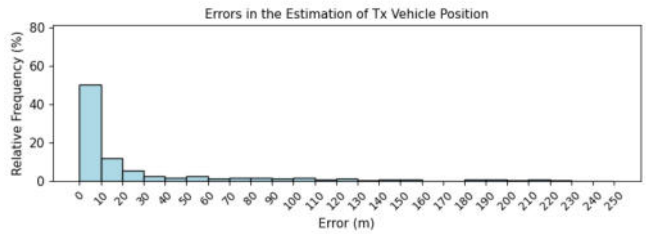


(b) $\mathrm{SNR}_{AoA}=25\mathrm{dB}$, $\sigma^2_{\mathrm{PL}}=5\mathrm{dB}$

Fig. 7: Error in Tx vehicle position using individual RSS method.



(a) $\mathrm{SNR}_{AoA}=30\mathrm{dB}$, $\sigma^2_{\mathrm{PL}}=0\mathrm{dB}$



(b) $\mathrm{SNR}_{AoA}=25\mathrm{dB}$, $\sigma^2_{\mathrm{PL}}=5dB$

Fig. 8: Error in Tx vehicle position using cooperative RSS method.

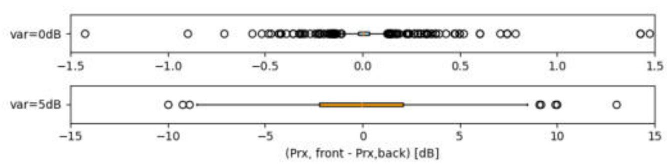


Fig. 9: Boxplots of difference in RSS observed by the (2) RSS-D antennas (note the different scales).

for a RSS difference that can abstract from the noise. We plot in Fig. 9 the difference between the power received at front ($P_{\mathrm{rx,front}}$) and back antennas ($P_{\mathrm{rx,back}}$). While the samples spread for $\sigma^2_{\mathrm{PL}}=0\mathrm{dB}$ is very small, as σ^2_{PL} increases to $5\mathrm{dB}$ the differences between $P_{\mathrm{rx,front}}$ and $P_{\mathrm{rx,back}}$ also increase, not necessarily as expected by their proximity to Tx (hence the inferior accuracy in selecting the right solution of 24.15%).

V. Conclusions and Future Work

CoWiPS is a cooperative wireless positioning mechanism that allows participating vehicles to determine the position of a Vehicle-of-Interest. In our study, CoWiPS achieves at best a rate of 70.16% position estimates with an error under $10m$ w.r.t. the true location when $\sigma_{\mathrm{PL}} = 0\mathrm{dB}$ and $\mathrm{SNR}_{AoA} = 30\mathrm{dB}$. This value drops to 50.01% when $\sigma_{\mathrm{PL}} = 5\mathrm{dB}$ and $\mathrm{SNR}_{AoA} = 25\mathrm{dB}$. We consider that this value is competitive and may support the goal of identifying whether other vehicles are reporting incorrect positions.

Future work will involve the use of Uniform Circular Arrays (to simplify AoA determination), more sophisticated path loss models (e.g., two-ray), simulation of shadowing by urban obstacles (e.g., buildings), and modelling of multipath in the reception at the multiple antennas. The improvement in accuracy as N_{Rx} increases will also be analyzed, and an average of RSS samples will be used (as opposed to the one-shot approach used in this work). Machine learning (ML) techniques will be explored as they can assist the detection of LoS vs NLoS conditions.

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