Dual Polarization Radio Localization for Vehicular Networks

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***Abstract*—Vehicular networks allow for a variety of applications ranging from platooning to fully automated driving. Most of such applications require the vehicles that constitute the networks to be aware of their relative or absolute position as well as the position of nearby vehicles. To this end, multiple positioning methods can be employed, among such methods are Global Positioning Systems or methods that employ time delay of arrival. This work presents a localization method that employs a dual polarized antenna at the transmitter and receiver side of wireless communications in vehicular networks. The proposed approach does not increase network load as it does not require extra data packets to be sent for localization purposes, and can be used to mitigate position spoofing inside the network. The accuracy and reliability of the proposed method are measured trough a set of numerical simulations, showing sufficient performance for acting as a secondary positioning mechanism capable of providing improved security and reliability to the network.**

***Index Terms*—Radio Localization, Cooperative Localization, Vehicular Networks**

I. Introduction

Vehicular ad hoc networks (VANETs) are a promising technology finding applications that range from traffic control to platooning [1]. Many of such applications require the localization of vehicles that compose the VANET to be known or estimated with a high degree of accuracy. Furthermore, not only must the accuracy be sufficient but also the estimate must be reliable.

These position estimates can be obtained by using a variety of methods. One of the main sources of location information in a VANET is the usage of Global Navigation Satellite Systems (GNSS) so that each vehicle can obtain an estimate of its location, which is then broadcast to the rest of the network. GNSS such as the Global Positioning System (GPS) can provide location information with a nominal accuracy of fifteen meters in urban environments [2]. However, this accuracy is not sufficient for emerging applications in Intelligent Transportation Systems (ITS) such as platooning [3] or for safety of life applications. Real-Time Kinematic (RTK) can be used to enhance GPS performance. However, this method is still susceptible to the presence of multipath and the occurrence of cycle slips, making its application challenging for real-time safety-critical systems [4]. Furthermore, obtaining a position while using GNSS requires that a set of at least four line of sight signals to different satellites is received, this might be impossible in dense urban environments, resulting in outages and general unreliability.

Other means of vehicle position estimation can also be employed. Dead reckoning [5] can be used to estimate the position of a vehicle based on an estimate previously available by using sensors located within the vehicle, such as the speedometer and a compass or gyroscope. While feasible in cases when other system are offline for a short time, these systems cannot be used as a primary method since they drift over time, increasing the positioning error. Recently, with the advances seen in cellular communication, specially with the advent of 5G, cellular localization methods have become a feasible alternative to GPS. In this regard, in [6], authors proposed an algorithm consisting of steps of distributed processing. Those steps requires that individual vehicles measure and receive location information such as the angle of arrival from the neighboring vehicles and absolute position from the GPS.

Recent advances in machine learning have enabled it for a multitude of applications within the scope of VANETs [7]. Computer vision has become another attractive alternative for solving the problem of vehicle positioning inside VANETs. However, the lack of interpretability of most recent machine learning models can become a barrier if they are to be applied in safety of life applications, as outlier results may be inexplicable and even unavoidable given the black box nature of such algorithms.

Other positioning approaches such as Ultra Wide Band (UWB) [8] can be used to achieve sub-meter accuracy when aided by GNSS. Light Detection and Ranging (LiDAR) can also be applied together with machine learning methods to detect other vehicles or pedestrians within a VANET [9].

To overcome those difficulties, hybrid approaches have been proposed for cooperative vehicular localization. The idea behind of those approaches is to fill in the gaps of using GPS, especially in hard environments such as intersections. In that sense, in [10], authors proposed a multi-sensor multi-vehicle localization algorithm based on cooperation among neighboring vehicles for estimation and prediction of vehicle locations. In [11], authors proposed a Bayesian method based on sharing GPS data and inter-vehicle distance measurements with a cluster of vehicles. Likewise, in [12], authors proposed an algorithm that takes the carrier-to-noise ratio of raw pseudorange measurements into consideration for mitigating the noise so that it can improve the accuracy of the distance detection. Another integrated cooperative localization approach was proposed in [13] and [14], the authors used the round trip times ranging technique and integrated it with inertial navigation systems technology to update the neighbors positions during GPS outages. Unfortunately, available GPS devices may not provide sufficient performance, specially in dense urban environments, which make the aforementioned approaches not suitable for many applications.

In [15], authors proposed an scheme that made use of the roadside units (RSUs) deployed in VANETs to get the position estimates, and then improve their accuracy using cooperation among neighboring vehicles based on the received signal strength indicator ranging technique. Although the suggested method seems useful, the need for the whole road being populated with RSUs raises infrastructure/hardware cost of the system [16]. To the end of position estimation, another technology that can leveraged within the context of VANETs is the usage of Multiple-Input Multiple-Output (MIMO) communication schemes. MIMO is now part of multiple modern wireless communications standards to allow for better spectral efficiency, higher capacity and more robust communication. The usage of MIMO within vehicular network scenarios can be leveraged for multiple ends, such as improving the network performance [17], jamming attacks suppression [18], and increasing network capacity [19] and positioning [20]. The antenna arrays that are used for communication using MIMO can also be employed for the application of signal processing techniques that can provide positioning estimates of vehicles inside the network, without requiring a dedicated infrastructure or hardware. However, due to the additional economical cost and design complexity, the widespread use of antenna arrays in vehicles may not become a reality in the short term. Therefore, positioning approaches that employ a single antenna can also be useful in such a hardware limited context.

This work proposes a cooperative data sharing approach that applies Direction Of Arrival (DOA) array signal processing tools to estimate the position of transmitting vehicles inside a VANET. The proposed alternative relies on the use of a dual polarized antenna element. By exchanging data the vehicles can cooperate to form a distributed antenna array, allowing the position of another vehicle inside the network to be estimated. The proposed approach is specially suitable to deal with spoofers that are transmitting fake position data within to VANET, as it relies on physical layer parameters that are extremely difficult to alter or falsify. Furthermore, the proposed approach can be either used in an ad-hoc manner within the network, or the computation can be offloaded to a central processing location, to minimize computational load inside the network, or the avoid issues regarding the privacy of it's members. In addition, such approach enables low-cost localization since antenna arrays are expensive, complex and consume more power compared to the use of a single antenna element.

The remainder of this paper is divided into four sections. In Section II the mathematical model assumed for the physical layer is presented. Section III presents the proposed dual polarization localization approach. In section IV the results of a set of numerical simulations are presented and analyzed. Finally, conclusions are drawn in section V.

II. Signal Model

A propagating electromagnetic wave can have its electric field written as

$$\boldsymbol{E} = -E_x \boldsymbol{e}_x + E_y \boldsymbol{e}_y, \tag{1}$$

here, E_x and E_y are the horizontal and vertical vectors of the electric field. A polarization ellipse can be defined with such vectors, as shown in Figure 1.

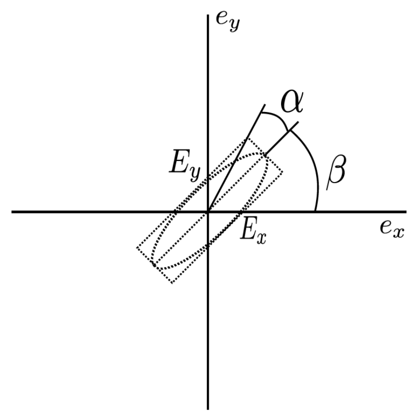

Fig. 1. Polarization ellipse

As observed in Figure 1, the electric field components can be rewritten with respect to the electric angles α and β as:

$$E_x = \boldsymbol{E}\cos(\gamma) \tag{2}$$
$$E_y = \boldsymbol{E}\sin(\gamma)\mathrm{e}^{j\eta}, \tag{3}$$

where

$$\cos(2\gamma) = \cos(2\alpha)\cos(2\beta) \tag{4}$$
$$\tan(\eta) = \tan(2\alpha)\csc(2\beta), \tag{5}$$

as shown in Figure 2.

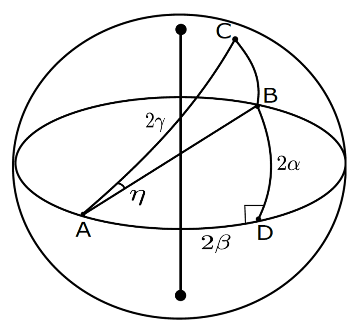

Fig. 2. Poincaré sphere

The received noise free wavefront at a crossed dipole with its antenna elements parallel to the $x-$ and $y-$axis of the polarization ellipse generates an output proportional to the incoming vectors E_x and E_y respectively, and can be written as

$$\begin{aligned} \boldsymbol{E} &= (-E_x)\boldsymbol{e}_x + (E_y \cos(\theta))\boldsymbol{e}_y & (6) \\ &= \boldsymbol{E}\left(-\cos(\gamma)\boldsymbol{e}_x + \sin(\gamma)\cos(\theta)\mathrm{e}^{j\eta}\boldsymbol{e}_y\right), & (7) \end{aligned}$$

here θ is the angle of arrival of the received wavefront with respect to the $y-$axis.

Under the presence of noise at the receiver, the received signal can then be written in matrix form as

$$\boldsymbol{X} = \boldsymbol{us} + \boldsymbol{N}, \tag{8}$$

where $\boldsymbol{X} \in \mathbb{C}^{2\times N}$ is a matrix with measured outputs at each of the dipole elements, N is the number of snapshots, $\boldsymbol{s} \in \mathbb{C}^{1\times N}$ is the vector containing the transmitted signal, $\boldsymbol{N} \in \mathbb{C}^{2\times N}$ is the noise matrix, having its entries drawn from $\mathcal{CN}(0, \sigma_n^2)$, and the polarization vector $\boldsymbol{u} \in \mathbb{C}^{2\times 1}$ is given by

$$\boldsymbol{u} = \begin{bmatrix} -\cos(\gamma) \\ \sin(\gamma)\cos(\theta)\mathrm{e}^{j\eta} \end{bmatrix} \tag{9}$$

according to Eq. (7). For the remainder of this work it is assumed that all polarization components are known at all vehicles of the network.

III. Cooperative dual polarization antenna based localization

Dual polarized antenna is an antenna system with orthogonal polarizations, commonly used in mobile communications [21]. The interest for these antennas is the reduced cost for installation and space needed. As mentioned before, this work makes use of a dual polarized antenna so vehicles can cooperate to form a distributed antenna array. This work assumes a network consisting of K vehicles located at coordinates $S_1, S_2, ..., S_K$ where

$$S_1 = [x_1, y_1]. \tag{10}$$

Furthermore, a set of vehicles $S_i, ..., S_j$, whose position information is known a priori, is also assumed to be present within the global set of K vehicles. The proposed method requires

$$|i, ..., j| \geq 2. \tag{11}$$

Finally, the orientation of all vehicles is known with respect to a common reference.

The proposed approach consists of estimating the angle of arrival of a received signal by looking at the ratio between the different polarization outputs of the crossed dipole. The ESPRIT [22] algorithm can be used to estimate this ratio by constructing the covariance matrix $\boldsymbol{R_{XX}} \in \mathbb{C}^{2\times 2}$ of the received signal

$$\boldsymbol{R_{XX}} = \frac{\boldsymbol{XX}^{\mathrm{H}}}{N}, \tag{12}$$

where $(\cdot)^{\mathrm{H}}$ represents conjugate transposition. Next, an eigendecomposition of $\boldsymbol{R_{XX}}$ is calculated

$$\boldsymbol{R_{XX}} = \boldsymbol{\Gamma\Lambda\Gamma}^{-1}. \tag{13}$$

Assuming that at any given carrier frequency only one vehicle is transmitting during a given time slot, the signal subspace $\boldsymbol{E_s} \in \mathbb{C}^{2\times 1}$ can be reconstructed by selecting the eigenvector related to the largest eigenvalue. An estimate of the ratios between the two polarizations can be obtained by

$$r = \left|\frac{\boldsymbol{E_s}[2]}{\boldsymbol{E_s}[1]}\right|. \tag{14}$$

Considering that the ratio is given by

$$\frac{-\cos(\gamma)}{\sin(\gamma)\cos(\theta)\mathrm{e}^{j\eta}}, \tag{15}$$

the angle θ can be obtained by

$$\theta = \cos^{-1}\left(\frac{-\cos(\gamma)}{r\sin(\gamma)\mathrm{e}^{j\eta}}\right). \tag{16}$$

The DOA obtained is given with respect to the reference of the receiving vehicle's $\boldsymbol{x}-$axis, as shown in Figure 3. From Eq. (15), it is clear that, if the polarization of the transmitted signal is known, the ratio is only a function of $\cos(\theta)$. Therefore, since the cosine is an even function, it is impossible to pinpoint, without ambiguity, the quadrant from which the signal is received, as the only known parameter is $\cos(\theta)$. Thus, each vehicle has two line estimates in the ground plane that represent possible positions for the transmitting vehicle.

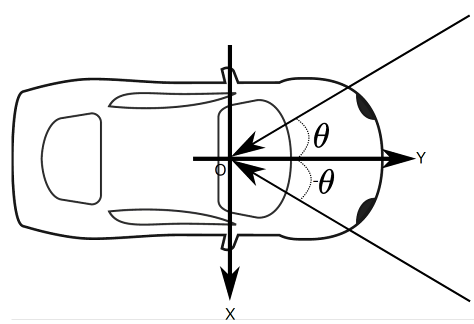

Fig. 3. Ambiguity of DOA estimation

Since each vehicle will have a different yaw angle, in order to obtain a position estimate of the transmitter it is necessary to translate all estimated signal into a common reference system. Assuming that the vehicles are moving over a flat surface, the vertical component of the crossed dipole will remain parallel to the z-axis. However, the horizontal component will have its orientation shifted with respect to x-axis based on how the vehicle turns to maneuver and the yaw angle changes. Thus, it is necessary to correct for the yaw angle to bring all estimates to the same frame of reference. This can be done by

$$\phi = \begin{cases} \tan^{-1}\left(\frac{\tan(\theta) - \frac{-1}{\tan(\psi)}}{-1 - \tan(\theta)\frac{-1}{\tan(\psi)}}\right), & \theta > 0 \\ \tan^{-1}\left(\frac{\tan(\theta) + \frac{-1}{\tan(\psi)}}{1 - \tan(\theta)\frac{-1}{\tan(\psi)}}\right), & \theta < 0 \end{cases} \tag{17}$$

where ψ is the yaw angle of the vehicle at hand.

With ϕ and the coordinates x_{rx} and y_{rx} of the receiver at hand, the pair of lines representing the signal received at a given vehicle can be written as

$$y^{+} = \tan(\phi^{+})x - \tan(\phi^{+})x_{\mathrm{rx}} + y_{\mathrm{rx}}, \tag{18}$$

$$y^{-} = -\tan(\phi^{-})x - \tan(\phi^{-})x_{\mathrm{rx}} + y_{\mathrm{rx}}, \tag{19}$$

where ϕ^{+} and ϕ^{-} represent the values of ϕ for $\theta > 0$ and $\theta < 0$ respectively.

Once a set of such lines has been acquired by at least two different receiving vehicles, an estimate of the transmitting vehicles position can be obtained. Ideally, a set of the estimated signal lines for all receiving vehicles would intersect at the coordinates of the transmitter. However, in practice, due to the present of noise and other sources of error, the estimated signal lines will often not intersect at the same point. Figure 4 presents a graphical example of this imprecision, where estimates from three vehicles are employed to estimate the position of a single transmitting vehicle.

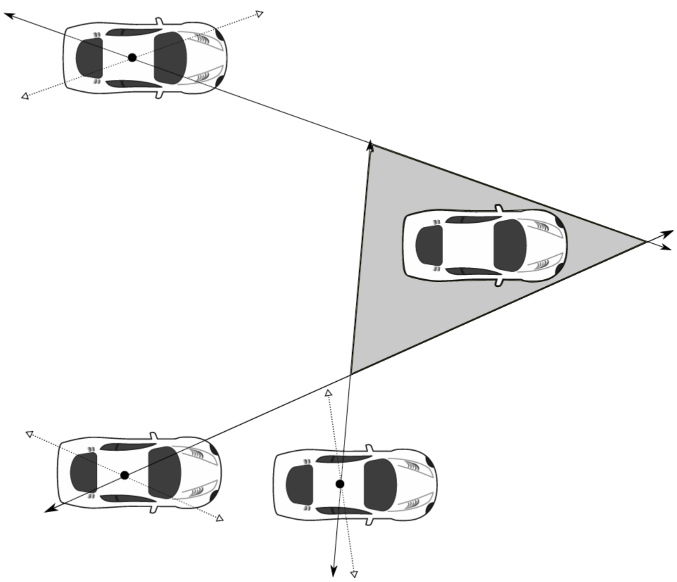

Fig. 4. Sensor triangulation example using only the DOAs of the reference vehicles

Under noise and other sources of error, the problem of estimating the position of the transmitter can be split into two steps. The first step consists of finding the points where pairs of the multiple line estimates for each vehicle intersect. To obtain these points, the intercept of the pair of signal lines estimated at the i-th vehicle can be obtained as

$$b_i^{-} = -\tan(\phi_i^{-})x_i + y_i \tag{20}$$

$$b_i^{+} = -\tan(\phi_i^{+})x_i + y_i \tag{21}$$

Following this step, the intercept between all estimated signal lines can be calculated. Let $\boldsymbol{y}_i = (y_i^{+}, y_i^{-})$ be a set containing both line estimates for the i-th vehicle. The intercept between the signal lines estimated at vehicles a and b can be calculated as

$$x_{a^\circ,b^\circ} = \frac{b_b^\circ - b_a^\circ}{-\tan(\phi_a^\circ) + \tan(\phi_b^\circ)} \tag{22}$$

$$y_{a^\circ,b^\circ} = -\tan(\phi_a^\circ)x_{a^\circ,b^\circ} + b_a^\circ \tag{23}$$

where $b_i^\circ \in [b_i^{+}, b_i^{-}]$, and $\phi_i^\circ \in [\phi_i^{+}, \phi_i^{-}]$. Therefore, in a network composed of M receiving vehicles with known position, a total of $4\frac{M!}{2!(M-2)!}$ transmitter position estimates will be calculated.

The next step to obtain the position of the transmitter is to cluster the position estimations obtained for the transmitter vehicles. This can be done by applying the mean shift algorithm [23]. The mean shift algorithm has the advantage of automatically selecting the number of clusters. The transmitter position can finally be estimated by selecting the cluster center of the cluster with the largest number of elements.

IV. Simulation Results

In the first set of simulations the performance of the proposed localization method is studied with respect to the Signal-to-Noise Ratio (SNR) of the received signal. Here, we assume three vehicles are receiving the signal of a fourth vehicle, whose position is to be estimated following the method in this paper. The position of the vehicles in this simulation is shown in Figure 5. For this set of simulations $N = 100$ snapshots, consisting of 4 QAM symbols, are used for the position estimation. The distance between all vehicles is assumed to remain fixed during the collection of the transmitted data snapshots. The results shown are the average of 5000 Monte Carlo runs. The SNR is defined as

$$\mathrm{SNR} = \frac{\sigma_{\mathrm{s}}^2}{\sigma_{\mathrm{n}}^2}, \tag{24}$$

where $\sigma_s^2 = \sqrt{2}$.

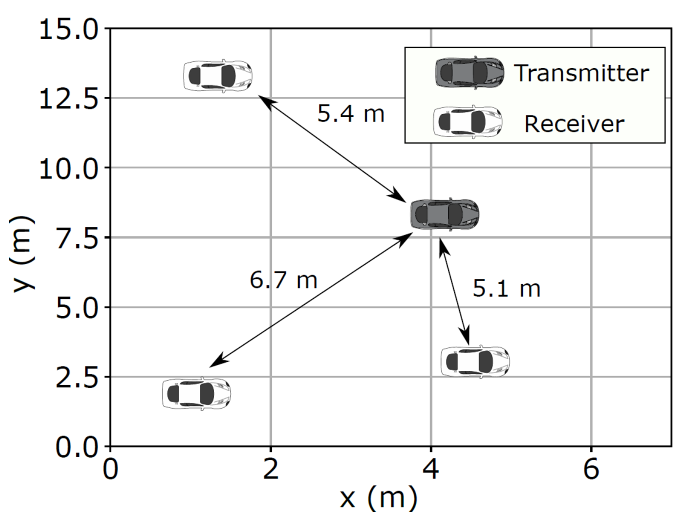

Fig. 5. Simulation scenario

Figure 6 presents the effects of the SNR on the performance of the proposed positioning method. For SNRs between 10 and 15 dB the error is kept close to 1 meter. This level of accuracy is sufficient for acting as a spoofing deterrent, as an adversary vehicle broadcasting a fake position could be identified via the proposed positioning scheme.

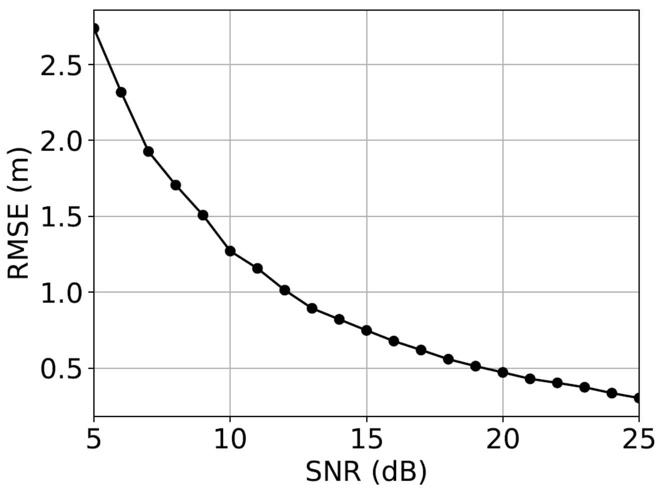

Fig. 6. Positioning error for the proposed scenario

The second metric analyzed during the simulations is the reliability of the proposed method. Due to the Cartesian geometry involved in the positioning estimation, singularities may occur when applying tangents and inverse tangents during the calculation. This will result in the proposed method not being able to estimate the position of the transmitter for the given data frame. Furthermore, if the errors in the DOA estimation at the receiving vehicles are too large, the estimated signal lines may not intersect at any point, which will also lead to not being able to estimate the position of the transmitter. Figure 7 presents the failure rate of the proposed method for a set of 5000 Monte Carlo runs where $N = 100$ snapshots are used for positioning. The failure rate is calculated as:

$$\text{Failurerate} = \frac{\mathrm{T_{success}}}{\mathrm{T_{failures}}}, \tag{25}$$

where T_{success} is the number of simulations where an estimated position could be obtained, and T_{failures} is the number of simulations where the proposed method was not capable of obtaining a position estimate due to singularities in the calculation or due to estimated signal lines not intercepting.

Figure 7 presents the results for the proposed positioning method with respect the the failure rate. For SNRs between 10 and 15 dB the failure rate ranges from approximately 15% to 10%. Therefore, the proposed method is probably not suitable for safety of life applications. However, if the SNR is large enough, it can still be used as a secondary safety and security mechanism.

Lastly, the cluster selection algorithm performance is analyzed. For the sake of clarity, a random sample of 500 runs out of the 5000 Monte Carlo runs is selected.

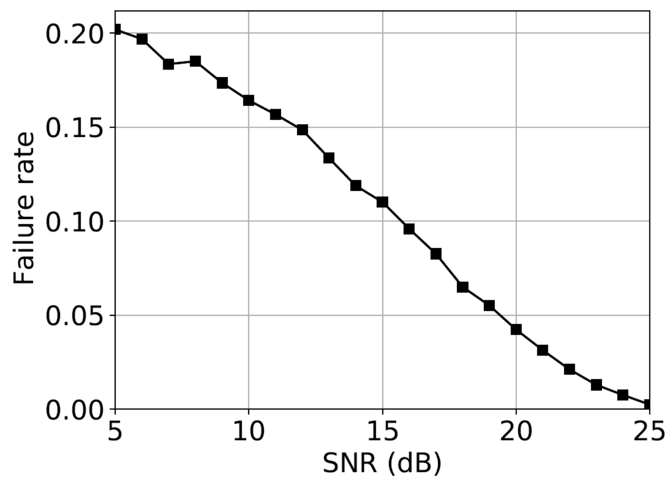

Fig. 7. Failures rate of the proposed positioning method

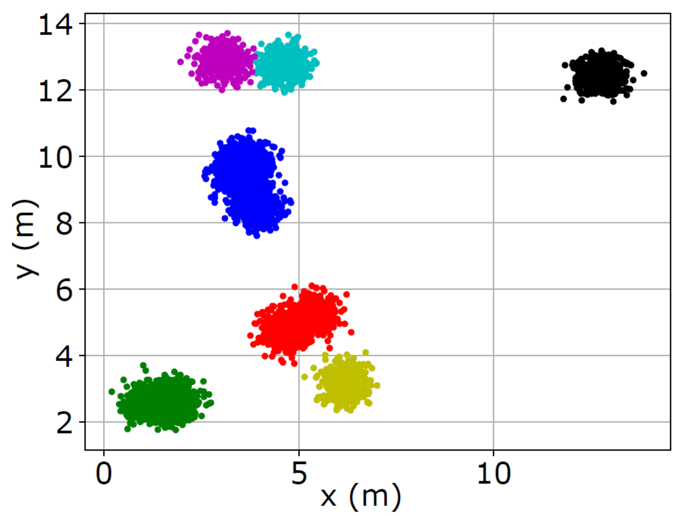

Fig. 8. Clustering performance of the mean shift algorithm over estimated positions

Figure 8 highlights the outcome of the mean shift algorithm for clustering. Furthermore, the figure also highlights the problem of the presence of "ghost" transmitters that arise from the ambiguity present when estimating the DOA of the transmitter, given that the quadrant of the transmitter cannot be uniquely identified. However, once all estimated positions are clustered, the real transmitter position can be easily determined by choosing the cluster with the largest number of elements, as all combination of vehicle pairs should contain at least one position estimation that belong to this cluster. For the figure, the blue cluster is the one containing the real transmitter, and is composed of 2000 elements. The green, red, cyan, magenta, yellow, and black clusters have 1000, 999, 503, 501, 500, and 497 elements, respectively.

V. Conclusion

This work presented a direction of arrival based localization method for vehicular networks. The proposed approach leverages a single dual polarized antenna at different vehicles for performing DOA estimation. The distributed DOA estimates at multiple receivers can be used to cooperatively estimate the relative position of a transmitter inside the network. The performance of the proposed approach was measured with a set of numerical simulations, highlighting a position accuracy of approximately 1 meter for SNRs in the range of 10 dB. The reliability of the proposed method was also measured, with the proposed method being able to estimate the position of a transmitter around 90% of the available data frames. The performance along with the reliability of the proposed method make it an interesting candidate for tackling the problem of position spoofers inside a vehicular network, as a broadcast position can then be crosschecked against the estimated position. The proposed method has the advantage of not requiring specific positioning data to be transmitted, and the computational load can be offloaded to a central system to alleviate the load on the network members or to address privacy concerns.

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