Distributed Vehicle Selection for Non-Range Based Cooperative Positioning in Urban Environments

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***Abstract*—This paper addresses the challenge of vehicle selection in a Vehicular Ad-hoc Network (VANET) used to assist vehicles with limited satellite visibility in urban environments. In [1], we proposed a Non-Range cooperative positioning system which uses pseudoranges from only one assisting vehicle at any given time. However , many vehicles are within the communication zone of the target vehicle especially in dense urban canyons. In this paper, we elevate the performance of our cooperative system by proposing a distributed vehicle selection criterion named Absolute Sum of Single Differencing (ASOSD). To test the viability of the proposed system, we design a cooperative experiment using three NovAtel receivers and show that the Positioning Accuracy Gain (PAG) of our system has increased by 60% compared to a system that averages Artificial Candidate Pseudoranges (ACPs) from two assisting receivers. Moreover, we study the effect of; the number of assisting vehicles, multipath, receiver noise, satellite clock bias, ionospheric and tropospheric errors on the selectivity of the proposed system. We show that as the number of assisting vehicles increase, the Root-Mean-Square-Error (RMSE) of the generated ACP decreases. Moreover, the selectivity of the ASOSD selector is not affected by the common errors in the shared pseudoranges.**

I. INTRODUCTION

The World Health Organization (WHO) stated that the number of deaths due to traffic accidents reaches 1.24 million annually. Aside from fatalities, traffic congestions cost Americans at least 124 billion dollars a year [2]. Intelligent Transportation Systems (ITS) aim at reducing traffic accidents and congestion. In addition, ITS systems enable many applications including entertainment, driver assistance and many other applications [3], [4]. The recent developments in Vehicular Ad-Hoc Networks (VANETs) and Dedicated Short Range Communication (DSRC) enabled many of the ITS applications. Information about the position of the vehicles are used by many ITS applications and Location-Based Services (LBS). For example, in automated driving modes and safety critical applications, vehicles have to exchange their accurate positions. The required positioning accuracy and availability of the vehicles' positions depends on the application.

In urban environments, the positioning accuracy and availability of land vehicles is limited. Tall buildings block many signals from different Global Navigation Satellite Systems (GNSS). Buildings in urban areas also reflect GNSS signals causing multipath effect. The measured pseudoranges are also contaminated with errors due to uncompensated atmospheric delays and satellite clock biases. There are also many challenges on the receiver side that include:

- A limited number of vehicles employ advanced multipath and jamming detection and mitigation techniques.
- A limited number of vehicles are capable of decoding multi-constellation GNSS signals.
- A limited number of vehicles are capable of removing uncompensated atmospheric errors using corrections from Differential-Global-Positioning Systems (DGPS) or Satellite-Based Augmentation System (SBAS).

Accurate positioning of vehicles is required by most safety critical ITS applications. Positioning systems can be categorized as non-cooperative (conventional) and cooperative systems. Due to the harsh signal environment in urban areas, non-cooperative systems suffer from limited positioning accuracy [5]. Recently, Cooperative Positioning (CP) has been proposed as an ideal solution to the problem of limited positioning accuracy in urban environments. CP takes advantage of the fact that vehicles have different positioning resources and uses DSRC to exchange positioning information between vehicles and subsequently estimate accurate positions. Most of the proposed systems rely on ranging methods such as the work in [6]–[10] to estimate the distance between vehicles or between vehicles and Road Side Units (RSUs). Ranging methods introduce large errors to the estimated distances [11]. These errors propagate to the final computed position and thus the performance of the range based CP systems are also limited. Motivated by the limitations of the Range based CP systems, a Non-Range based CP system was proposed in [1] to enhance the positioning availability and accuracy of target vehicles (i.e., vehicles with limited satellite visibility) in urban environments. However, we only considered the availability of one assisting vehicle which is not a practical scenario in a dense urban area. In this paper, we elevate the performance of our cooperative system by proposing a distributed vehicle selection criterion named Absolute Sum of Single Differencing (ASOSD). Prior to applying the Angle Approximation (AA) concept and subsequently using the Sum of Double Differencing indicator (ASODD) to select the most accurate Artificial Candidate

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Pseudorange (ACP), the shared pseudoranges are processed to determine the nearest assisting vehicle. Only the ACP from the nearest assisting vehicle is then used to estimate the position of the target vehicle. The proposed Cooperative positioning (CP) selection method does not require any communication with an infrastructure or the aid of the vehicles on-board sensors. Moreover, ASOSD reduces the complexity of the proposed CP system by computing AA and ASODD only for the selected vehicle. The experimental results verify the superiority of the proposed system. Specifically, the Positioning Accuracy Gain (PAG) of our system increased by 60% compared to a system that averages ACPs from two assisting receivers. Moreover, using the developed MATLAB Orbit Simulator (OS), we study the effect of; the number of assisting vehicles, multipath, receiver noise, satellite clock bias, ionospheric and tropospheric errors on the selectivity of the proposed system. The rest of this paper is divided into four sections. The system proposed in [1] which includes the AA concept and the ASODD indicator are presented in Section 2. In Section 3, the challenge of multiple assisting vehicles in dense areas is introduced and the ASOSD criterion is proposed to guide our CP system in vehicle selection. Section 4 presents the experimental setup and results. Moreover, the simulation results are also depicted. Finally, Section 5 summaries our work and also presents future research directions.

II. Background

In this Section we introduce the concept of Angle Approximation (AA). In addition, the Absolute Sum of Double Differencing (ASODD) method for satellite selection is briefly presented.

A. Angle Approximation Concept

In urban environments, the availability of satellites decreases and therefore only vehicles that are able to decode GNSS signals from multiple constellations (GPS, GLONASS and Galileo constellations) can successfully estimate their position. Vehicles equipped with a single constellation receiver like GPS receivers might have less than four visible satellites and therefore would not be able to estimate their position. Here, we refer to those vehicles as Target vehicles. In [1], we propose a method by which the blocked pseudoranges from the single constellation receivers (target vehicles) are artificially generated using Angle Approximation.

The blocked pseudorange is generated by exchanging all the information of the visible pseudoranges between the target vehicle and all assisting vehicles (receivers equipped with multi-constellation receivers) using DSRC. Using a geometric approach, an artificial pseudorange representing the blocked pseudorange is generated for every visible satellite common to the target and the assisting vehicle. The generated pseudoranges are named Artifical Candidate Pseudoranges (ACP). Finally, the ASODD is used as a selection criterion to choose the most accurate ACP to be used to compute the final position of the target vehicle.

B. Absolute Sum of Double Differencing (ASODD)

ASODD is a selection method that takes as an input all the measured pseudoranges from the target vehicle and the assisting vehicle and all the ACPs representing the blocked pseudorange. For every ACP, ASODD computes a positive indicator. Subsequently, the ACP candidate with the minimum ASODD indicator value is selected. In other words, the ASODD method maximizes the projection of the error due to AA [1].

III. Multiple Assisting Vehicles

In dense urban areas, the target vehicle is probably surrounded by many vehicles within its communication zone. Some of those vehicles can assist the target vehicle in either enhancing positioning availability or accuracy. In this section, we propose a method by which one assisting vehicle is selected from the candidate assisting vehicles. After vehicle selection, AA is applied to generate ACPs and then ASODD is used to select the final ACP. Here, the final ACP refers to the pseudorange which will be used in the final position estimation.

A. Absolute Sum of Single Differencing (ASOSD)

Each assisting vehicle transmits its pseudoranges to the target vehicle. The target vehicle selects only one vehicle and then uses AA method to generate ACPs. Subsequently, the ASODD method selects one of the ACPs. Here, we propose a method for vehicle selection. Assume we have three satellites k, m and n common to vehicles A, B, C and a target vehicle j while satellite f is only available to the assisting vehicles. Figure **??** shows the block diagram of the proposed system where three assisting vehicles are available and can be used to enhance the positioning availability or accuracy of the target vehicle denoted by j. The proposed selector is called Absolute Sum of Single Differencing (ASOSD).

This method acts as a distance indicator for each assisting vehicle using the common pseudoranges between the assisting vehicle and the target vehicle. The accuracy of the AA method is inversely proportional to the distance between the target and the assisting vehicles. Specifically, the probability of generating ACPs with high errors from an assisting vehicle separated from the target vehicle by a large distance is higher than the probability of generating ACPs with high errors from an assisting vehicle at smaller distances. Hence, the distance between the Candidate Assisting Vehicles (CAVs) and the target vehicle is the most important factor affecting the accuracy of the generated ACPs [1]. The ASOSD method uses the difference between the common pseudoranges of the target and the CAVs to calculate a distance indicator for each vehicle. This method assumes that each CAV can estimate its GNSS receiver clock bias and subsequently, the pseudoranges transmitted to the target vehicle are corrected for the error due to the clock bias.

Equation 1 depict the model for the measured pseudorange before blockage.

$$\rho_j^f = R_j^f + \beta_j + \alpha^f + \varepsilon_j^f \tag{1}$$

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where :

- R_j^f is the true range from vehicle j to satellite f.
- β_j is the clock bias of vehicle j and the receiver noise.
- α^f is the clock bias of satellite f , the ionosphere and troposphere errors.
- ε_j^f is the error due to multipath.

Equation 2 is used to calculate the ASOSD distance indicator for assisting vehicle i denoted by $ASOSD_i$. Assuming S is the number of common satellites between the target and assisting vehicle.

$$\begin{aligned} ASOSD_i &= \sum_{s=1}^{S} |\rho_j^s - \rho_i^s - \beta_i| \\ &= \sum_{s=1}^{S} |(R_j^s + \beta_j + \alpha^s + \varepsilon_j^s) - \\ &\quad (R_i^s + \beta_i + \alpha^s + \varepsilon_i^s) - \beta_i| \end{aligned} \tag{2}$$

Removing the assisting vehicle clock bias denoted by β_i in (2) is very important as it is not common to all assisting vehicles. However, the target's clock bias does not have to be removed since the all ASOSD indicators are referenced to the target vehicle. In other words, the target vehicle clock bias equally affects the ASOSD indicator for all assisting vehicle. Moreover, all common errors between pseudoranges to the same satellites are removed. These commmon errors are due to the uncompensated satellite clock bias, and atmospheric delays. Equation3 shows the ASOSD indicator for assisting vehicle i after removing the common errors and the assisting vehicle clock bias.

$$\begin{aligned} ASOSD_i &= \sum_{s=1}^{S} |(R_j^s + \beta_j + \alpha^s + \varepsilon_j^s) - \\ &\quad (R_i^s + \beta_i + \alpha^s + \varepsilon_i^s) - \beta_i| \\ &= \sum_{s=1}^{S} |(R_j^s - R_i^s) + \beta_j + (\varepsilon_j^s - \varepsilon_i^s)| \end{aligned} \tag{3}$$

The difference between the non-common errors affecting pseudorange s at the target vehicle j and the assisting vehicle i is denoted by $(\varepsilon_j^s - \varepsilon_i^s)$. Let us assume that the non-common errors like multipath or receiver noise at the assisting vehicles are approaching zero. This occurs for example when assisting vehicles are capable of mitigating short delay multipath signals or are not affected by multipath at all (i.e., common visible satellites are at high elevation angles). Hence, Equation 3 can be expressed as :

$$ASOSD_i = \sum_{s=1}^{S} |(R_j^s - R_i^s) + \beta_j + \varepsilon_j^s| \tag{4}$$

The effects of the target's clock bias denoted by β_j and the non-common errors of the pseudoranges of the target vehicle denoted by ε_j^s does not affect the accuracy of the ASOSD distance indicator, because all other ASOSD indicators are computed referenced to the pseudoranges at the target vehicle. Assuming the common satellites are denoted k, m and n, the ASOSD indicator for the assisting vehicle i can be expressed as :

$$\begin{aligned} ASOSD_i &= \sum_{s=1}^{S} |(R_j^s - R_k^s) + \beta_j + \varepsilon_j^s| \\ &= |(R_j^s - R_n^s) + \beta_j + \varepsilon_j^s| + |(R_j^s - R_i^s) + \\ &\quad \beta_j + \varepsilon_j^s| + |(R_j^s - R_m^s) + \beta_j + \varepsilon_j^s| \end{aligned} \tag{5}$$

By selecting the nearest assisting vehicle, the AA becomes more valid and the errors in the ACPs are minimized. Furthermore, using the ASOSD method reduces the complexity of the overall system and enables system scalability. When selecting one assisting vehicle based on the distance indicator, the AA and the ASODD selection method are applied only to one vehicle instead of N assisting vehicles. Hence, a practical real-time system can be implemented.

IV. Performance Evaluation

Here we use three evaluation criteria to assess the performance of the proposed system.

1) The Root-Mean-Square Error (RMSE) of the ACP from the target vehicle j to satellite s for T samples is given by:

$$RMSE = \frac{\sum_{t=1}^{T} \sqrt{(R_j^s - \rho_j^s)^2}}{T} \tag{6}$$

2) The RMSE of the 2D position error is given by:

$$RMSE = \frac{\sum_{t=1}^{T} \sqrt{(E_j - \hat{E}_j)^2 + (N_j - \hat{N}_j)^2}}{T} \tag{7}$$

where E_j, $\hat{E}_j$ are the true and estimated position of the receiver along the Eastern axis. Moreover, N_j, $\hat{N}_j$ are the true and estimated positions of the receiver along the Northern axis.

3) The Positioning Accuracy Gain (PAG) measures how much the CP system gains in terms of accuracy by employing the ASOSD selector. PAG is given by:

$$PAG(\%) = \frac{|RMSE_{ASOSD} - RMSE_{Avg}|}{RMSE_{Avg}} \times 100 \tag{8}$$

where $RMSE_{ASOSD}$ is the RMSE of the 2D position estimated using the ACP generated by the ASOSD selected vehicle. Moreover, $RMSE_{Avg}$ is the RMSE of the 2D position estimated using the averaged ACP from all assisting vehicles.

A. Experiments

We design a cooperative experiment using 3 GPS NovAtel receivers to demonstrate the gain achieved in positioning accuracy by selecting one of the assisting vehicles using ASOSD criterion. Denote to the 3 GPS NovAtel receivers by R_a, R_b and R_c. Here, R_a is the target receiver, while R_b is an assisting receiver at a relative distance of 10m from R_a and $R_c$is another assisting receiver at a relative distance of 25m

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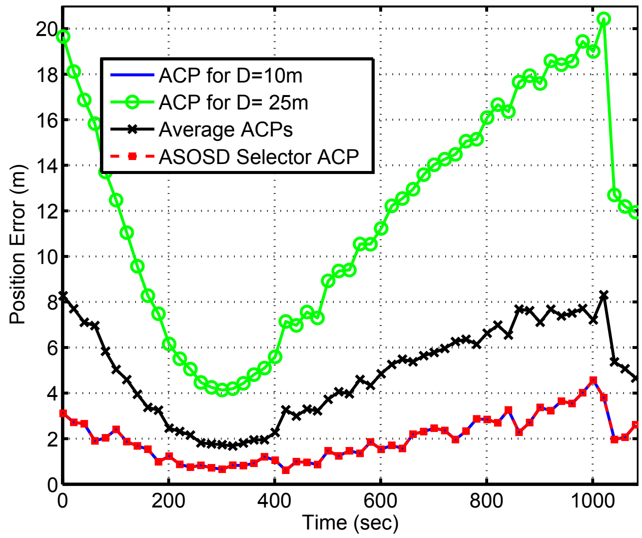

Fig. 1: Comparison between averaging ACPs from assisting receivers and selecting an ACP based on the ASOSD criteria in terms of 2D position error.

from R_a. The three receivers were positioned on a straight line to ensure the same geometry of the assisting vehicles relative to the target vehicle and the visible satellite. The duration of the experiment was around 15 minutes.

In order to mimic the high elevation mask in an urban environment, the elevation angle of each visible satellite was computed. Subsequently, the four highest-elevation angle satellites were considered visible while the other satellites were blocked. After collecting pseudoranges from all receivers, one of the four visible satellites was blocked only at R_a. In MATLAB, ASOSD was employed to compute a distance indicator for the two assisting receivers. AA and then ASODD were applied to the assisting receiver selected by ASOSD to generate one ACP. This ACP was used to estimate the position of R_a. On the other hand, the average of the selected ACPs was also used to estimate the position of R_a. Both positions were then compared in terms of mean position error and PAG. Here, the final position is estimated using Least Squares (LS) algorithm. Figure 1 shows the 2D position error in meters for the duration of the experiment. The position error computed using assistance from R_b (D=10m) and R_c (D=25m) are shown. Moreover, the position error computed by averaging the selected ACP from each assisting receiver is also shown. Finally, the position error computed after employing the ASOSD distance indicator is also depicted. Here it is clear that the ASOSD selector was successful at selecting the nearest receiver (at D=10m) for the whole duration. The $RMSE_{ASOSD}$ is 1.8m and the $RMSE_{Avg}$ is 4.87m, thus, the PAG is 60%.

In our experiments, we are limited by a specific number of receivers and the current satellite geometry relative to the position of the receivers. To overcome this constraint, we use our developed Orbit Simulator (OS) to study the performance of our system.

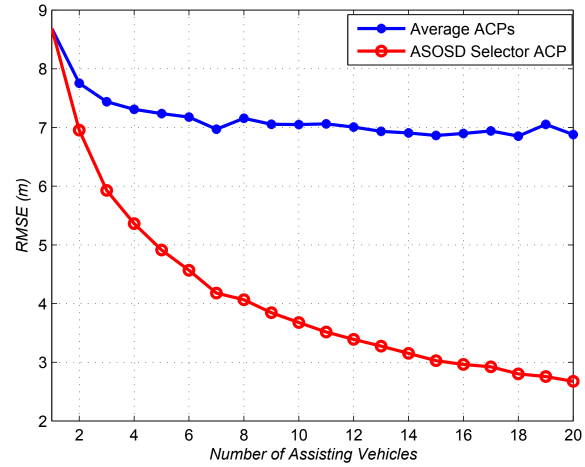

Fig. 2: Performance of the ASOSD method compared to averaging ACPs as a function of the number of assisting vehicles.

B. *Simulations*

Here we will investigate the effect of the number of assisting vehicles on the performance of the proposed cooperative system. Moreover, the effect of common and non-common errors in the measured pseudoranges on the ability of the ASOSD method to detect the nearest assisting vehicle will be investigated.

1) Effect of Number of Assisting Vehicles

First of all, the performance of the ASOSD is assessed in comparison with a simpler method. This method relies on averaging the selected ACPs by the ASODD method for all CAVs. In other words, all the assisting vehicles are treated equally regardless of their distance from the target vehicle. The number of assisting vehicles was varied from 1 to 20 vehicles. The generation of the position of the CAVs was random and covered an area of $100m$ around the target vehicle. To determine the RMSE of the generated ACP for a specific number of assisting vehicles, 10,000 scenarios were generated for a fixed number of assisting vehicles. The elevation mask was set to 67.5 degrees for all scenarios.

Figure 2 shows the performance of two vehicle selection methods as a function of the number of assisting vehicles. The RMSE of the averaged ACPs from all assisting vehicles decreases as the number of assisting vehicles increases from one to six vehicles. After that the RMSE of the averaged ACP seems to stay at around $7m$ regardless of the increase in the number of assisting vehicles. The gain from averaging the error in ACPs is reduced by the effect of increasing the number of assisting vehicles. These assisting vehicles can either be close or far away from the target vehicle. The proposed ASOSD method infers the nearest assisting vehicle and AA and ASODD is only applied to the selected assisting vehicle. Obviously, selecting the nearest assisting vehicle significantly reduces the RMSE of the final ACP as the number of assisting vehicles increase. Specifically, The RMSE of the

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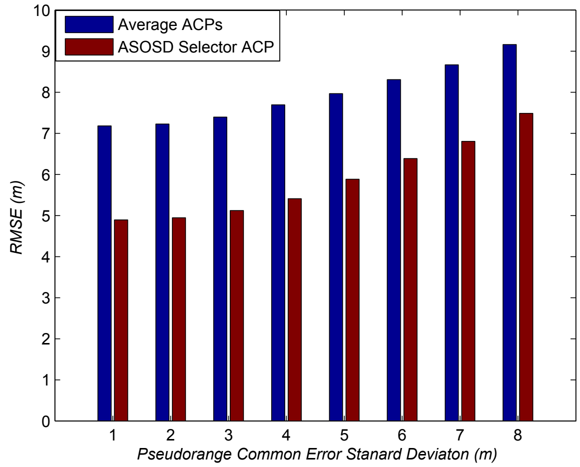

Fig. 3: Performance of the ASOSD method compared to averaging ACPs as a function of the measured pseudorange common errors (satellite clock bias, ionospheric and tropospheric errors).

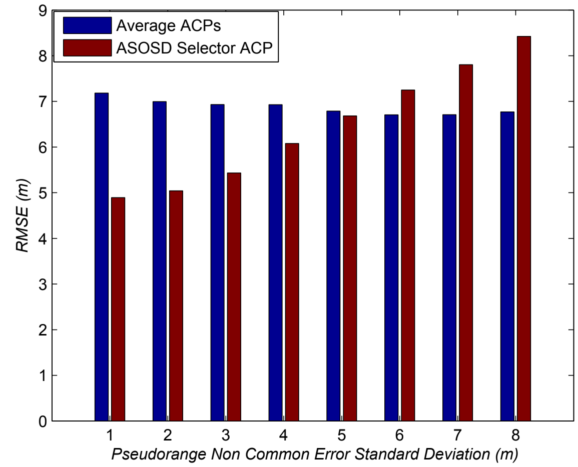

Fig. 4: Performance of the ASOSD method compared to averaging ACPs as a function of the measured pseudorange non-common errors (i.e., multipath and receiver noise).

final ACP selected by ASOSD drops from $8.5m$ to $2.7m$. The assisting vehicles are generated randomly (following a uniform distribution in $100m$ communication range) and therefore, as the number of assisting vehicles increase, the probability of generating a vehicle near the target vehicle increases.

2) Effect of Shared Pseudoranges Common and Non Common Errors

There are two types of measured pseudorange errors, common errors between vehicles like satellite clock bias and atmospheric errors and non-common errors like multipath and receiver's noise. Here we investigate the effect of both types of errors on the ASOSD ability to detect the nearest assisting vehicle. Moreover, averaging ACPs from assisting vehicles is compared to the ASOSD performance. The number of assisting vehicles is set to five and the elevation mask is set to 67.5 degrees. Pseudorange errors are modeled as two Gaussian random variables representing the standard deviation of the common and non-common errors. For every type of error, 10,000 scenarios are randomly generated and the RMSE of the final ACP is computed by averaging the selected ACPs from five assisting vehicles. Moreover, the ASOSD method is used to select the nearest assisting vehicle and the final ACP is also computed. Figure 3 shows the performance of the ASOSD method compared to averaging ACPs as a function of the measured pseudorange common errors. Common errors are simulated by varying the standard deviation of the measured pseudoranges from $1m$ to $8m$. In order to simulate common pseudorange errors, the same generated random variable is added to each pair of pseudoranges (to the same satellite) of the assisting vehicle and the target vehicle. As the standard deviation of the common errors increases, the RMSE of the ACP resulting from averaging ACPs from the five assisting vehicles and the RMSE of the ACP resulting from the assisting vehicle selected by ASOSD increases. However, the RMSE of the ACP generated from the vehicle selected by ASOSD is less compared to the ACP resulting from averaging. Since the errors are common to both pseudoranges of the target and assisting vehicles, the ASOSD removes the common errors and then infers which vehicle should be used to generate the ACPs. The RMSE of the final ACP increases as the standard deviation of the common errors increase because the generated ACPs contain larger errors. The ability of the ASOSD to infer the nearest assisting vehicle is not affected by the pseudorange common errors.

Figure 4 depicts the performance of the ASOSD method compared to averaging ACPs as a function of the measured pseudorange Non Common Errors. The RMSE of the final ACP generated by averaging ACPs from assisting vehicles is around $7m$ and is not significantly affected by the increase in the pseudorange error standard deviation. Since the Non Common pseudorange error is modeled as a Gaussian random variable with mean zero and the errors in pseudoranges from the vehicles to different satellites are uncorrelated, the effect of averaging ACPs from the five assisting vehicles is on average, canceling the errors due to non-common pseudorange errors. On the other hand, the RMSE of the ACP generated from the assisting vehicle selected by ASOSD increases as the pseudorange non-common error standard deviation increases. ASOSD is not able to remove non-common errors and hence the ASOSD distance indicator becomes less meaningful as the standard deviation of the non-common pseudorange errors increase. Beyond a standard deviation of $5m$, the performance of the ASOSD becomes worse than averaging ACPs. Therefore, if the standard deviation of the pseudorange non-common errors increase beyond a certain threshold detected by existing multipath detectors [12], ASOSD should not be used.

V. Conclusion

In this paper, we elevate the performance of the system proposed in [1] by proposing a distributed vehicle selection criterion named Absolute Sum of Single Differencing

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(ASOSD). The proposed selection method does not require any communication with an infrastructure or the aid of the vehicles' on-board sensors. Moreover, ASOSD reduces the complexity of the proposed CP system by computing AA and ASODD only for the selected assisting vehicle vehicle. In addition, experimental results show that the PAG is enhanced by 60% compared to averaging ACPs from the two assisting receivers. Using extensive MATLAB simulations, we show that as the number of assisting vehicles increase the RMSE of the generated ACP decreases. Moreover, the selectivity of the ASOSD selector is not affected by the common errors in the shared pseudoranges, however, if not mitigated or ignored, non-common errors (i.e., severe multipath effects) could affect the performance of the proposed system. Our future work includes considering the measurement noise of the shared pseudoranges (indicated by each receiver) when selecting the assisting vehicle. When complexity is not an issue, a weighted average based on ASOSD and the measurement noise of the shared pseudoranges of each assisting vehicle can be developed and compared to the proposed system.

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