2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)
Windsor Oceanico Hotel, Rio de Janeiro, Brazil, November 1-4, 2016

Cooperative Localization via DSRC and Multi-Sensor Multi-Target Track Association

Ahmed Hamdi Sakr* and Gaurav Bansal⋆
*Department of Electrical and Computer Engineering at University of Manitoba, Winnipeg, Manitoba, Canada
⋆Toyota InfoTechnology Center, Mountain View, California, U.S.A.
Email: ahmed.sakr@umanitoba.ca, gbansal@us.toyota-itc.com

Abstract— **Vehicles in the near future will be equipped with dedicated short-range communications (DSRC) transceiver which holds great promise of significantly reducing vehicle collisions by enabling vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. In addition, modern vehicles will be equipped with different on-board sensors such as GPS receivers and ranging sensors (e.g., cameras, radars, and lidars). Using these technologies, this paper proposes a comprehensive system design to improve the positioning of a host vehicle based on Kalman filters. In this approach, the host vehicle fuses its own position information obtained by the on-board GPS receiver with position information of nearby vehicles collected by the on-board ranging sensor(s) and the messages received via the DSRC transceiver from other equipped vehicles. This process also involves performing track matching using a multi-sensor multi-target track association algorithm. We provide insights on the system design and present simulation results that show significant performance gains of the proposed method in terms of localization accuracy and matching accuracy.**

Keywords: Localization, V2V Communication, DSRC, Track Association, Kalman Filter, Data Fusion, Simulation.

I. Introduction

Vehicle-to-vehicle (V2V) communication is expected to play an important role in intelligent transportation systems in the near future. Most importantly it will enable safety applications that can prevent collisions and save lives. The US Federal Communication Commission (FCC) has allocated a 75 MHz spectrum in the 5.9 GHz band for the dedicated short-range communications (DSRC) use [1]. Vehicles are able to form an ad-hoc network to exchange their core state information (e.g., vehicle speed and location) using DSRC technology. The Society of Automotive Engineering (SAE) has standardized a Basic Safety Message (BSM) which could be periodically broadcasted by vehicles in a 10 MHz safety channel (also referred to as channel 172) [2]. BSM messages contain real-time updates on the status of the vehicle such as position information, speed, heading, acceleration, path history, etc.

The DSRC radio box is equipped with a GPS receiver which provides the positioning information to the transceiver. In addition, modern vehicles are equipped with different on-board sensors such as cameras, radars, and/or lidars that can be used to measure the relative distance to nearby objects to improve the perception of the vehicle to its surroundings. This, in turn, increases the ability of the driver (or the vehicle) to make best decisions while driving. The main limitation of these sensors is the accuracy (i.e., reliability) of the measurements which highly depends on the type and quality of the sensor. For example, the performance of GPS receivers can by highly impacted by the environment. That is, the spatial errors can be very large in urban-like environments with many obstacles and less visibility of the satellites compared to an open sky environment [3]. On the other hand, ranging sensors have their own limitations which vary from cameras, radars, and lidars. For example, the performance of all three mentioned sensors is highly affected by the object occlusion, field of view, and detection range. In addition, the relative distance measurements (i.e., relative range and angle) error depends on the sensor itself. For example, in general, lidars are more accurate compared to radars, while radars are more accurate compared to cameras [4].

Limited accuracy of the on-board sensors often prevents making decisions for actions that require very reliable position information with low probability of error. However, these shortcomings can be overcome via V2V communication between nearby vehicles to exchange local sensors data [5], [6], [7]. In [5], the authors use a likelihood-based weighted average method to discover non-equipped vehicles and estimate the position of nearby equipped vehicles via wirelessly exchanging sensor information. The authors in [6] and [7] propose a track-to-track association algorithm that uses Kalman filters to match the track of an equipped vehicle obtained via DSRC messages to a set of tracks obtained from a ranging sensor which improves the perception of the nearby vehicle. In this paper, we propose a comprehensive system design that utilizes the diversity of position information of multiple nearby vehicles to reduce the uncertainty of the estimate of position of the host vehicle. That is, we use a Kalman filter-based approach to fuse multiple estimates of the position of the host vehicle in order to increase the localization accuracy. These estimates are obtained from:

1) position measurements by the on-board GPS receiver at the host vehicle, and
2) position estimates by adding both the relative distance to nearby vehicles measured by the on-board ranging

*The author is currently an intern with Toyota InfoTechnology Center, Mountain View, California, U.S.A.

sensor and the position information of these nearby vehicles received at the host vehicle via DSRC messages using its on-board DSRC transceiver.

The proposed approach involves three main steps: (1) synchronization of all data, (2) performing multi-sensor multi-target track association in order to match different tracks from different sensors to their corresponding source, and (3) fusing information from different sensors. Note that these three steps take place at the host vehicle and do not require any modifications to other vehicles or the vehicular network.

The remainder of the paper is organized as follows. In Section II, we provide an overview of the proposed system and an application example. More details on the system design and the main challenges are presented in Section III. In Section IV, we describe the simulation scenario and the performance metrics, and present the simulation results. Finally, Section V concludes the paper.

II. Overview of the Proposed System

In order to achieve V2V communication, vehicles will be equipped with DSRC transceivers which act as an interface to other nearby vehicles. A DSRC transceiver enables the vehicle to form a wireless ad hoc network with other equipped vehicles in its vicinity to exchange their own state information (e.g., via BSM messages). Typically, each vehicle is required to broadcast its current position information using an on-board GPS receiver every time slot T_s (which is typically 100 msec). Note that the accuracy of the position information highly depends on the environment and the GPS receiver quality. That is, a GPS receiver in general gives more precise readings in an open-sky environment because of availability of more satellites as compared to urban environment that can suffer from severe signal propagation conditions.

In addition to a GPS receiver, we also assume that the vehicle of interest is equipped with a ranging sensor (RS) that measures the relative position (i.e., range and angle) of different objects (including pedestrians, cyclists, vehicles, etc.) in its surroundings. Then, points belonging to the same object are clustered together, filtered, classified, and given a unique identification. In practice, a ranging sensor can be a camera, a radar, or a lidar where the accuracy of the measurements and the complexity of the algorithms involved in the aforementioned process vary from one type of sensor to another. For example, a camera (such as Mobileye) can have an accuracy of less than 2.25 m at 45 m and 9 m at 90 m [8], a radar (such as Delphi ESR) can have an average accuracy of less than 0.5 m and $0.5°$, and a lidar (such as Velodyne HDL-32E and HDL-64E) can have a range accuracy of less than 2 cm. Hereinafter, the vehicle of interest (i.e., equipped with both a DSRC transceiver and an RS) is called a *host vehicle* (HV) and its nearby *detected* vehicles (either via RS or DSRC messages) are called *remote vehicles* (RVs).

A. Positioning Improvement

As shown in Fig. 1, the HV receives BSM messages that are transmitted by nearby RVs containing their position

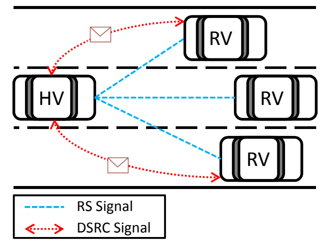

Fig. 1. Basic scenario with a three-lane street.

information over the DSRC links (i.e., dotted red lines in Fig. 1). Upon receiving these messages, the HV extracts the position information and keep track of each RV's position using the unique identifier (e.g., a MAC address) given to each detected vehicle. In addition, the HV uses an on-board RS that detects nearby RVs and measures their relative distances and angles (i.e., dashed blue lines in Fig. 1). The RS also creates a unique identifier to keep track of range measurements belonging to the same RV using its own unique identifier. It is worth mentioning that the unique identifier given to each detected RV by the RS is not necessarily the same unique identifier used to keep track of the received BSM messages since both systems operate independently. Note also that an HV does not necessarily receive BSM messages from all vehicles detected by the RS which could happen due to either bad propagation conditions or that vehicle is not equipped with a DSRC transceiver. For example, although the vehicle in the middle land ahead of the HV in Fig. 1 is not communicating with the HV, it is detected by the RS. Hence, the number of RVs detected by the RS is not necessarily the same number of RVs detected by the DSRC transceiver.

In addition to the position information reported by the on-board GPS receiver at the HV, knowing the global position of nearby RVs (from the BSM messages) and their relative position (from the RS) enables the HV to obtain additional estimates of its own location. These multiple estimates of the position (which have different levels of spatial error) can then be fused altogether to improve the localization accuracy of the HV. Hereinafter, we use $\mathcal{D} = \{\mathrm{RV}_1, \mathrm{RV}_2, \ldots, \mathrm{RV}_N\}$ to denote the set of RVs whose BSM messages are received by the DSRC transceiver at the HV where RV_i is a unique identifier given to the DSRC messages received from the same RV. Also, we use $\mathcal{R} = \{\mathrm{RV}'_1, \mathrm{RV}'_2, \ldots, \mathrm{RV}'_K\}$ to denote the set of RVs detected by the RS at the HV where RV'_j is a unique identifier given to each detected RV.

B. Illustration

As an illustration, Fig. 2 shows an example for the true positions (i.e, without measurements error) for all vehicles in the scenario shown in Fig. 1 in a Cartesian coordinate system $\mathbb{R}^2$. The on-board GPS receiver may measure the position of the HV to be $(1.25, -0.9)$ including the spatial error. There are also two RVs communicating with the HV and their positions may be reported via BSM messages as $\mathrm{RV}_1 = (-4.1, 6.25)$ and $\mathrm{RV}_2 = (3.5, 9)$. In addition, three vehicles are detected by the RS at $\mathrm{RV}'_1 = (6.9, -28.5°)$, $\mathrm{RV}'_2 = (8.93, 2°)$, and $\mathrm{RV}'_3 = (8.25, 23°)$ measured from

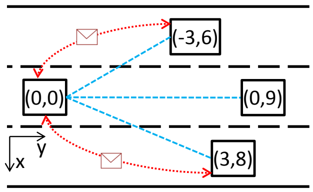

Fig. 2. True positions of vehicles in Fig. 1 in $\mathbb{R}^2$.

the heading of the HV. Therefore, based on this information, the following estimates can be calculated for the position of the HV:

1) $(1.25, -0.9)$ as reported by the on-board GPS receiver.
2) $(-4.1, 6.25) - (6.9, -28.5°) = (-0.81, 0.19)$ after matching RV_1 and RV'_1.
3) $(3.5, 9) - (8.25, 23°) = (0.27, 1.4)$ after matching RV_2 and RV'_3. Note that vehicle RV_2 (indexing over received BSM) is same as vehicle as RV'_3 (indexing over tracks received by RS). RV'_2 is only reported by the on-board RS

Now instead of using only $(1.25, -0.9)$ to be an estimate of the position of the HV, the HV can fuse the three estimates altogether to improve the uncertainty that exist in the on-board GPS measurements. As an example, if HV takes a simple average of all the estimates, the new position estimate would be $(0.24, 0.23)$. Knowing that the true position of the HV is $(0, 0)$, the new obtained position estimate has a spatial error of $\sqrt{0.24^2 + 0.23^2} = 0.33$ m which is 78% more accurate than position information reported by the on-board GPS receiver with a spatial error of $\sqrt{1.25^2 + 0.9^2} = 1.54$ m. Note that, the above is only an illustration to provide the overview of proposed system and show the potential of cooperative localization. Our fusion technique is based on Kalman Filters and is described in the next Section.

III. Positioning Improvement System

Each HV obtains multiple estimates for its own position from the following sources: (1) an estimate from on-board GPS receiver and (2) the other estimates using the global positioning of nearby RVs received by the DSRC messages and the relative position of these RVs measured by the on-board RS. The HV fuses these estimates to reduce the uncertainty (i.e., spatial error) of its position estimation and improve its localization accuracy. However, there are three main challenges present in the aforementioned system:

- Tracking and Synchronization.
- Multi-sensor Multi-target Track Association (MTA).
- Data Fusion.

Our system model is shown in Fig. 3 and presented in details in the following subsections.

A. Tracking and Synchronization

We use a Kalman filter (KF) based approach for the DSRC transceiver at the HV to be able to track the position of detected RVs [9]. That is, the DSRC transceiver has a number of KFs dedicated to track and filter the position of all RVs where each filter tracks one RV at a time. As shown in Fig. 3, the system has a maximum of N KFs while the number of

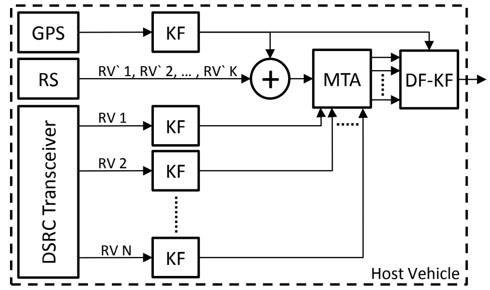

Fig. 3. Positioning improvement algorithm design.

detected RVs varies. If the number of RVs transmitting BSM messages is greater than N, the system prioritizes DSRC messages based on the closeness to the HV. In addition, the system defines an *age threshold* which is used to decide if an RV can be considered absent and should not be tracked anymore if the recent message received from that RV is older than the defined threshold. HV uses an additional KF to track and filter its own position.

In practice, DSRC messages arrive at the HV at different times and might not be synchronized. In order to synchronize all position information, we use an open-loop KF to predict the position of the HV and tracked RVs at any given time instant. Note that all data synchronization and position prediction use the timestamp attached to each measurement and are triggered by the RS updates. The rationale is that the rate of the RS updates can be much higher than the update rate of the DSRC transceiver and GPS receiver. For example, measurements update rate of a radar (such as Delphi ESR) can be up to 20 Hz and of a camera can be up to 30 fps. Note also that for implementation all KFs which are used for tracking and synchronization have the same number of dimensions.

B. Multi-sensor Multi-target Track Association (MTA)

This step is to perform a track-to-track association for the data coming from two independent sources: RS and DSRC transceiver. In general each of them detects a different set of RVs (i.e., targets), $\mathcal{R}$ and $\mathcal{D}$, where the size of these two sets are not necessarily the same (i.e., $N \neq K$). The main challenge is to obtain the intersection between these two sets which represents RVs that are detected by the RS and communicating with the HV at the same time. We achieve this by matching the list of detected RVs by the DSRC transceiver to the list of detected RVs by the RS.

In our solution, we propose a multi-sensor multi-target track association (MTA) based on the minimum Mahalanobis distance and Chi-square test. Let $\mathbf{x}_i^k \in \mathbb{R}^2$ denote the position of $\mathrm{RV}_i \in \mathcal{D}$ at time k and $\mathbf{x}_j'^k \in \mathbb{R}^2$ denote the position of $\mathrm{RV}'_j \in \mathcal{R}$ at time k.

We first calculate the distance between each two RVs from the two sets at time k as follows [10]:

$$D^k(\mathrm{RV}_i, \mathrm{RV}'_j) = \frac{1}{W} \sum_{i=0}^{W-1} d^{k-i}(\mathrm{RV}_i, \mathrm{RV}'_j), \qquad (1)$$

Algorithm 1: Multi-target Multi-sensor Association with Validation Gate Test

1. Extract and store position information from DSRC messages in $\mathcal{D} = \{\mathrm{RV}_1, \mathrm{RV}_2, \ldots, \mathrm{RV}_N\}$ and from GPS receiver and RS in $\mathcal{R} = \{\mathrm{RV}'_1, \mathrm{RV}'_2, \ldots, \mathrm{RV}'_K\}$.
2. Create $N \times K$ matrix $D^k = \{D^k(\mathrm{RV}_i, \mathrm{RV}'_j)\}$ for $i = 1, 2, \ldots N$ and $j = 1, 2, \ldots, K$ using (1).
3. **for** $i^* = 1$ **to** N
   find $j^* = \min_j D^k(\mathrm{RV}^*_i, \mathrm{RV}'_j)$
   if condition (2) is **true**
      match track RV_{i^*} to track RV_{j^*}
      delete row i^* and column j^* from matrix D^k
   end
end

where W is the history window size and

$$d^k(\mathrm{RV}_i, \mathrm{RV}'_j) = \ln |\mathbf{P}^k| + (\mathbf{x}^k_i - \mathbf{x}'^k_j)^T \mathbf{P}^k (\mathbf{x}^k_i - \mathbf{x}'^k_j), \quad (2)$$

such that $\mathbf{P}^k = P^k_i + P^k_j$ and P^k_i is the error covariance matrix of the state estimation at time k. Note that the distance in (1) depends on the distances from the recent W updates. This helps to smooth the track matching decisions.

The next step is to use the $N \times K$ matrix that has $D^k(\mathrm{RV}_i, \mathrm{RV}'_j)$ as its entries to find the nearest neighbor (i.e., the track with the minimum distance) from $\mathcal{D}$ to each track in $\mathcal{R}$ and remove the corresponding row and column. We repeat this process until one of the two sets is empty. The number of matches obtained from this step is *equal* to $\min\{N, K\}$. However, this can suffer from a drawback that all tracks in $\mathcal{R}$ will have a corresponding nearest neighbor from $\mathcal{D}$ even if the two tracks do not necessarily originate from the same RV. Therefore, we add a third step which acts as a validation gate. That is, we use a Chi-square statistic test such that a match is *only* accepted if the distance statistic is greater than a predefined threshold $\chi^2_{2W}(\alpha)$ [6]. In other words, we accept a matching between two tracks if

$$\frac{1}{W} \sum_{i=0}^{W-1} (\mathbf{x}^k_i - \mathbf{x}'^k_j)^T \mathbf{P}^k (\mathbf{x}^k_i - \mathbf{x}'^k_j) \leq \chi^2_{2W}(\alpha), \quad (3)$$

where $1 - \alpha$ is the confidence region. Note that the number of matches obtained after the validation gate test is *less than or equal* to $\min\{N, K\}$. The whole process is summarized in Algorithm 1.

C. Data Fusion

The last stage of the proposed system design is to combine the different estimates of the position of the HV into one solution. In this work, we use a higher-dimension KF as shown in Fig. 3. The input to the data fusion KF (DF-KF) is: (1) the position information of the HV obtained by its on-board GPS receiver and (2) the position estimates of the HV derived from the position of nearby RVs that are detected by the on-board RS and communicating with the HV at the same time (i.e., the matching output of the MTA). Note that the number of inputs to the DF-KF is less than or equal to $1 + \min\{N, K\}$ where all these inputs are synchronized to the RS updates. In the worst case, the DF-KF has only one input from the on-board GPS receiver which could happen in the following scenarios:

1) no RVs are detected by the RS,
2) no BSM messages are received by the DSRC transceiver,
3) no matching is obtained between the RVs detected by the RS and the RVs communicating with the HV.

This case is equivalent to the case where the HV only uses its on-board GPS receiver to obtain an estimate for its own current position. This case will be used for comparison as a *baseline* to evaluate the performance of the proposed algorithm.

IV. Performance Evaluation and Results

In this section, we describe the simulation scenario used to evaluate the performance of the proposed algorithm. We also define three performance metrics to evaluate both the error performance and matching accuracy. Then, we present simulation results for different scenarios and system parameters.

A. Simulation Scenario

We have used MATLAB software for our simulations, where we have created a scenario as depicted in Fig. 1. For the microscopic traffic modeling, we use a car-following model where the acceleration of a vehicle is evaluated based on the current position and velocity of the vehicle ahead which is referred to as a *leading vehicle*. The aim of this traffic model is to maintain *desired* separation (i.e., bumper-to-bumper) distance and relative velocity between each vehicle and its leading vehicle. That is, the acceleration of a vehicle at position $\mathbf{x}$ and moving with velocity $\dot{\mathbf{x}}$ is characterized by the following policy [11]:

$$\ddot{\mathbf{x}} = A_1(\mathbf{x}_L - \mathbf{x} - D) + A_2(\dot{\mathbf{x}}_L - \dot{\mathbf{x}}), \quad (4)$$

where $\mathbf{x}_L$ and $\dot{\mathbf{x}}_L$ are the position and velocity of the leading vehicle, respectively. D is the desired separation between the two vehicles. A_1 and A_2 are weights given to the error of distance and velocity, respectively. These weighting factors should be chosen carefully as they play an important role in controlling the stability of the system. For KF design, we use a nearly constant velocity implementation which is best suited for roads without sharp turns. For more details about KF design, please refer to [7], [9, Chapter 6]. Although we assume a loss-less wireless channel, DSRC losses can be easily considered in the current framework. For example, [12] provides curves on packet delivery ratios (PDR) for DSRC safety channel 172 which could be included in our results.

The GPS spatial errors are assumed to follow a Gaussian distribution with zero mean and a constant standard deviation $\sigma_{\mathbf{x}}$. However, in practice, the standard deviation of the GPS error changes over time. The dynamics of this change can be derived from the dilution of precision (DOP) values. In addition, we have conducted several experiments to evaluate the correlation between the spatial errors of nearby GPS receivers. The results show that spatial errors from GPS receivers are correlated only if they are very close to each other. This correlation drops significantly by increasing the separation distance. For example, in an 18-hour experiment in an open-sky environment, it was observed that the correlation coefficient between the spatial errors is 0.11 at $10m$ separation. Whereas in an 8-hour experiment in a suburban scenario, the correlation coefficient was 0.17. Note that correlation coefficient does not incorporate systematic errors such as constant offsets. For all experiments, we used two identical GlobalSat BU-353S4 GPS receivers with a 2.5 m accuracy specified in the device manual. We present results for both scenarios with GPS errors being uncorrelated and correlated. We also assume that the RS error follows a Gaussian distribution with zero mean and a standard deviation σ_r.

Unless otherwise stated, simulation parameters are summarized in the following table:

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Simulation time (T)	$10,000$ sec
DSRC Message rate	10 Hz
Desired speed	30 m/s
Desired distance (D)	50 m
Weight parameters (A_1, A_2)	4, 4
GPS accuracy ($\sigma_{\mathbf{x}}$)	2 m
RS accuracy (σ_r)	0.5 m
Confidence region ($1-\alpha$)	0.99
History window size (W)	4
Age threshold	1 sec

B. Performance Metrics

We evaluate the performance of the proposed system design using the following metrics:

- **Mean Squared Error (MSE):** represents average of the squares of the deviations between the true position and the estimated position of the HV. MSE of each solution over an observation period T can be expressed as:

$$\text{MSE} = \frac{1}{T}\sum_{t=0}^{T-1} \|\mathbf{x}_{\text{est}}^t - \mathbf{x}^t\|^2.$$

- **MSE reduction:** represents reduction of MSE gained by using the proposed approach compared to the baseline case. It is expressed as:

$$\text{MSE reduction} = \frac{\text{MSE (Before)} - \text{MSE (After)}}{\text{MSE (Before)}} \times 100.$$

- **Track matching accuracy (TMA):** is defined as the percentage of correct matching decisions taken by the MTA algorithm from the total number of matching tests executed by the matching algorithm.

C. Simulation Results

Fig. 4 shows the effect of the number of DSRC equipped nearby RVs on the MSE performance of the proposed algorithm. It can be seen that the proposed algorithm outperforms the case when no information about nearby RVs are involved in the solution. It is also evident that having more DSRC equipped RVs helps to reduce the spatial errors and improve the localization accuracy. For example, having only one nearby RV can improve the MSE performance by 43.8%, having two nearby RVs provides 57.8% performance improvement, and having five nearby RVs is 74.2% more accurate compared to the baseline case.

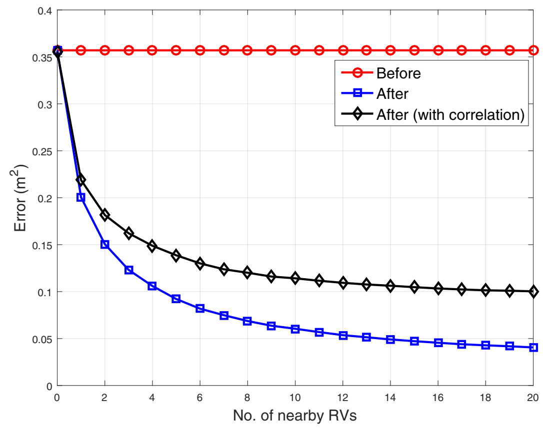

Fig. 4. MSE (m^2) vs. Number of nearby DSRC equipped RVs.

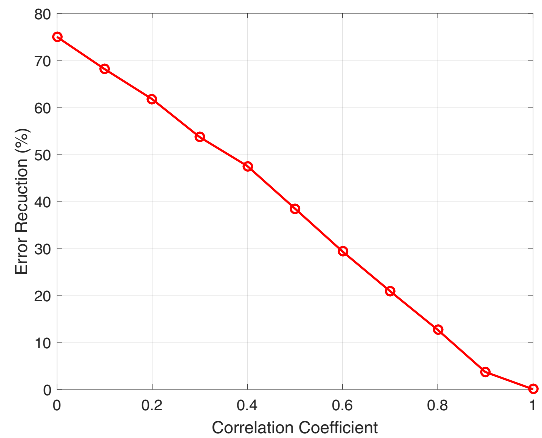

Fig. 5. MSE reduction (%) vs. Correlation coefficient.

Note also that the rate of this improvement is high at the beginning when the number of nearby RVs is relatively small. However, the improvement rate saturates after some point and having more nearby RVs has a marginal effect on the performance. For example, the performance gain difference in the cases when there are one and two nearby RVs is 14%. On the other hand, this difference is only 2.9% when comparing the cases with five and six nearby RVs. This observation can help us designing the system in Fig. 3. For example, if the target MSE is 10 cm^2, using positioning information from only 5 nearby RVs could be sufficient.

Fig. 4 also shows the impact of the correlation between errors at nearby GPS receivers on the level of performance improvement that can be achieved using the proposed algorithm. Correlation coefficient between nearby GPS receivers is set to 0.2. Fig. 5 shows the reduction in the MSE as a

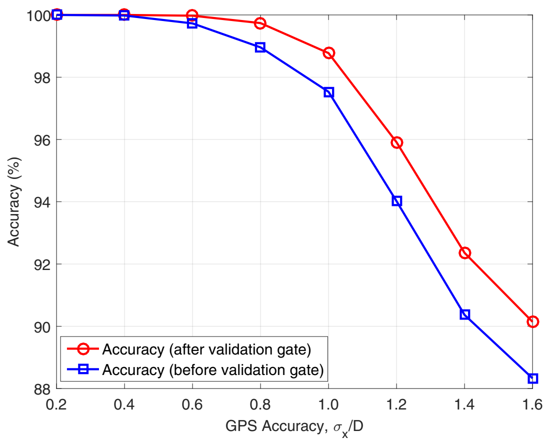

Fig. 6. TMA vs. Ratio of standard deviation of GPS error to the desired separation.

function of the correlation coefficient between spatial errors at nearby GPS receivers. When spatial errors are totally independent, correlation coefficient is 0 and the correlation coefficient is 1 when the errors are perfectly correlated. Both of these scenarios are very rare in practice. Very low correlation could represent the performance in environments where different GPS signals experience independent multipath fading and the visibility of satellites is limited. Whereas, higher correlation could happen when there are multiple visible satellites and less multipath fading. Based on our experiments, the correlation value of nearby GPS receivers is likely to be on the left side of the curve even in open-sky scenarios because of other independent sources of errors than the ionospheric propagation effects. Although performance improvement degrades with correlation, it is shown in Fig. 4 that with the correlation coefficient of 0.2 (which is higher than the observations in the experimental results), our proposed approach outperforms the baseline case.

Fig. 6 depicts the relation between the TMA and the standard deviation of the GPS receiver error relative to the desired separation distance. It can be seen that the matching algorithm achieves high accuracy even in severe situations. For example, TMA is higher than 98.77% even when the standard deviation of the error is equal to the separation distance which is 20 m. As expected, the matching accuracy deteriorates with less-accurate GPS receivers which could have higher values of positioning errors. It can also be seen that the validation gate using Chi-square statistic test in (3) helps to improve the matching accuracy compared to only using the $N \times K$ distance matrix $D^k(\mathrm{RV}_i, \mathrm{RV}'_j)$. Rejecting matching decisions that do not pass the test condition, increases the probability that any two matched tracks (DSRC and RS) are originating from the same source before accepting a match between them.

In this work, we have collected data to evaluate the correlation coefficient of the spatial errors at nearby GPS receivers in an open-sky and a suburban environment. In the future, we plan to collect more data to evaluate the performance in urban environments such as downtown areas. Another limitation of the current work is that we have relied on simulations to evaluate the performance of the proposed approach to improve localization. In the future, we plan to conduct field validation of our proposed method. The main challenge in experimentation is obtaining the ground truth for a moving vehicle. We plan to use a high-grade experimental GPS receiver with high accuracy to provide a good estimate on ground truth.

V. Conclusion

The paper proposes an algorithm to improve the positioning using BSM messages received from nearby DSRC equipped vehicles and information gathered from on-board GPS receiver and ranging sensor(s). After performing a multi-sensor multi-target track association, the host vehicle fuses the information from various sensor and DSRC equipment using Kalman filters. Insights on the system design are presented and results show that our algorithm significantly improves the positioning accuracy without any modifications to the DSRC network. The effect of correlation is also discussed and it is shown that the proposed system is beneficial even when correlation exists between measurements at nearby GPS receivers.

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