Multi-Sensor Multi-Vehicle (MSMV) Localization and Mobility Tracking for Autonomous Driving

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***Abstract*—Vehicle localization and mobility tracking are important tasks in autonomous driving. Traditional methods either have insufficient accuracy or rely on additional facilities to reach the desired accuracy for autonomous driving. In this paper, a multi-sensor multi-vehicle localization and mobility tracking framework is developed for autonomous vehicles equipped with GPS, inertial measurement unit (IMU), and an integrated sensing system. Our algorithm fuse the information from local onboard sensors as well as the observations of other vehicles or existing intelligent transportation system infrastructure such as road side units (RSU) to improve the precision and stability of localization and mobility tracking. Specifically, this framework incorporates the dynamic model of vehicles to achieve better localization and tracking performance. The communication delays during the information sharing process are explicitly taken into account in our algorithm development. Simulations manifest that not only the accuracy of localization and mobility tracking could be greatly enhanced in general, but also the robustness can be guaranteed under circumstances where traditional localization and tracking devices fail.**

***Index Terms*—Multi-sensor multi-vehicle (MSMV) localization and mobility tracking, autonomous driving, cooperative sensing, intelligent transportation systems (ITS).**

I. Introduction

Localization and mobility tracking, which are regarded as fundamental tasks in autonomous driving, provide essential information to direct the operation of intelligent transportation systems (ITS), e.g. determination of the accurate positions during multi-vehicle cooperation or multi-vehicle information fusion [2], [3]. In recent years, many researchers have been trying to develop new techniques to provide accurate localization information of vehicles, including the early simple and moderately priced dead reckoning techniques [4], the currently prevailing GPS-based techniques (see e.g. [5]), and the more recent marker and high-precision map based techniques (see e.g. [6], [7]). Compared with GPS-based techniques, which are easily affected by the working environment and cannot provide the required accuracy under certain circumstances, such as crowded urban, under bridges, beside high buildings, in tunnels etc., the map-based techniques are capable of providing more precise positioning. However, the map-based techniques rely on the high-precision maps which incur extra high cost and hence are not the best options for most ITS applications.

In response to the restrictions of techniques based upon individual sensors, researchers have attempted to conduct the localization and mobility tracking using the information provided by multiple sensors for better accuracy. Within this framework, some traditional filtering algorithms, e.g. particle filter and Kalman filter etc., are applied for the fusion of measurements from different sensors and their prior information so as to gain more accurate estimates (see e.g. [8]–[12]). However, for most solutions proposed so far in the literature, information of different sensors can be fused and utilized only if all sensors are located at the same vehicle. Moreover, though various kinds of sensors are involved in the process, the accuracy is still heavily dependent on GPS and hence is sensitive to environment. For example, if the vehicle is operating in areas with limited or no GPS signal, the accuracy will be significantly compromised. In summary, the existing single-vehicle multi-sensor strategies are still not capable of addressing the main challenges. To overcome the above-mentioned limitations, some researchers have come up with solutions to enhance the stability of single-vehicle sensors with the support of other vehicles' information (see e.g. [2], [13]). However, the existing solutions proposed mostly rely on traditional localization sensors and hence requires extra efforts to build other supporting infrastructure in the ITS to assist the localization process. They are incapable of incorporating the information from the new sensing techniques available on the state-of-the-art intelligent vehicles. Furthermore, these techniques based upon traditional localization sensors assume a static model for the vehicles and hence cannot conduct effective

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mobility tracking. In other words, they can only report the localization results based upon single-snapshot observations at each single time instance and cannot utilize the temporal relationship among the observations over a period of time.

With the development of sensing and autonomous driving technologies, light detection and ranging (LiDAR), radar, a variety of camera-based vision sensors and many other new sensors are installed on intelligent vehicles. The data provided by these sensors could be utilized to improve the localization precision and achieve mobility tracking given their capacity of detecting and interpreting the ambient environment, even though their main purpose of installation might not be localization. For example, the digital surface model (DSM) represented by discrete-points is used to describe the LiDAR data, which includes the spatial information needed for localization purposes [14]–[19]. Another example is the camera data, with which the relative position of a vehicle and its surrounding objects can be obtained via the vision-based simultaneous localization and mapping (SLAM) technique [20], [21]. There are other techniques to utilize those latest sensing techniques for localization (see e.g. [22]–[24]), e.g. using the camera for perception in the high-precision map constructed by LiDAR [25].

For the vision of the "Internet of Vehicles" in the future (see e.g. [26]–[28]), it is an important task to find a way to make different vehicles cooperate with each other and combine the information of sensors from these vehicles to improve the accuracy of localization and mobility tracking [29]. The most common technique is V2V multilateration, i.e. vehicles transmit their own positions and calculate distances to other vehicles in cooperation, and then obtain more accurate estimates of self-localization [30]. However, most multilateration-based studies use only GPS, IMU and V2V wireless communication modules, while other sensors such as radar and LiDAR of different vehicles cannot be applied [31]–[35]. In [36], the information provided by radar is combined with the V2V technique to improve localization accuracy of GPS, but the technique did not take into account the dynamic motion of the vehicles and hence cannot achieve good mobility tracking performance. In summary, in the literature, there is no general framework that combines information obtained from traditional localization devices as well as more recent advanced sensing devices to improve the precision of localization and mobility tracking.

In this paper, a multi-sensor multi-vehicle (MSMV) localization and mobility tracking framework is developed. The framework establishes the link between observations that come from multiple vehicles and measurement data acquired from both traditional localization sensors namely the inertia measurement unit (IMU) and GPS, and more advanced sensing systems which may include camera, LiDAR, radar etc. The proposed framework has a novel two-layer structure, consisting of global filtering and local filtering. At the local filters, on the one hand, we use traditional IMU and GPS data to obtain an estimate of the vehicle's self state. On the other hand, the vehicle observes other vehicles and obtain their states by using the integrated sensing system to generate the sensing data through another set of local filters. Then the local estimates related to the same target vehicle from all vehicles are fed into a global filter to obtain the global estimate of this target, which can greatly improve the accuracy of its estimates. The localization process is carried out under the guidance of the dynamic models for vehicles, and as a result, mobility tracking can be achieved. The proposed MSMV framework is general in that it not only works for all types of sensors but also can be implemented by different techniques for local filters to utilize the dynamic motion models. Besides, our framework can also include intelligent infrastructures in ITS such as road side units (RSUs) in the cooperative localization and mobility tracking process to further improve the performance. In addition, a critical practical issue during cooperative localization and mobility tracking, namely the delay during the information sharing via V2V communication links, is considered and addressed well by the proposed framework.

The remainder of this paper is organized as follows. System model and problem formulation are presented in Section II. Section III presents the multi-vehicle cooperative localization and mobility tracking algorithm, which includes global filtering and local filter. Then we evaluate the performance of the algorithms in the proposed framework through numerical simulations in Section IV. Finally, conclusions and ongoing research issues are highlighted in Section V.

II. System Model

The physical motion and observation model of a vehicle can be described by a dynamic model as follows [9]:

$$\begin{aligned} \boldsymbol{x}[k] &= \boldsymbol{f}\left(\boldsymbol{x}[k-1], \boldsymbol{u}[k], \boldsymbol{w}[k]\right), \\ \boldsymbol{z}[k] &= \boldsymbol{g}\left(\boldsymbol{x}[k], \boldsymbol{v}[k]\right), \end{aligned} \tag{1}$$

where k is the index of discrete time slot, $\boldsymbol{x}$ is the state of the vehicle including position and speed, $\boldsymbol{u}$ is the command process which is equivalently regarded as the driving input and indicates the acceleration, and $\boldsymbol{w}$ is the command noise (state noise) which comes from the uncertainty of command process; $\boldsymbol{z}$ is the measurement data reported by various sensors such as IMU, GPS, LiDAR, camera etc. and $\boldsymbol{v}$ is the data noise during measurement and transmission; $\boldsymbol{f}$ and $\boldsymbol{g}$ are equations of the state and measurement model which can be obtained by the physical dynamics of the motion and the inherent properties of the sensing devices, respectively.

It is assumed that every vehicle in cooperation is equipped with inertia measurement unit (IMU), GPS, and an integrated sensing system which may include one or more sensing devices, such as camera, radar, LiDAR and so on. Then each of the above vehicles obtains its own estimate of angular velocity, speed, acceleration through wheel encoders and IMU, its own estimate of position through GPS, and estimate of the relative position and speed with respect to other vehicles in cooperation through the integrated sensing system. In order to develop the multi-sensor multi-vehicle localization and mobility tracking framework, here we introduce the observation and state transfer model for moving vehicles in detail as follows:

A. *System State Transfer Model*

We are mostly interested in localizing and tracking an object in the two-dimensional plane using Cartesian coordinate x and

y. For a vehicle V_i, we apply the equation in [9] to describe its mobility in a system state transfer function:

$$\boldsymbol{x}_i[k] = \boldsymbol{A}\boldsymbol{x}_i[k-1] + \boldsymbol{B}_{\boldsymbol{u}}\boldsymbol{u}_i[k] + \boldsymbol{w}_i[k], \tag{2}$$

where

$$\boldsymbol{x}_i = \begin{pmatrix} x_i \\ \dot{x}_i \\ y_i \\ \dot{y}_i \end{pmatrix}, \boldsymbol{u}_i = \begin{pmatrix} F_{i,x} \\ F_{i,y} \end{pmatrix}, \boldsymbol{w}_i = \begin{pmatrix} w_{x_i} \\ w_{\dot{x}_i} \\ w_{y_i} \\ w_{\dot{y}_i} \end{pmatrix},$$

$$\boldsymbol{A} = \begin{pmatrix} 1 & dt & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & dt \\ 0 & 0 & 0 & 1 \end{pmatrix}, \ \boldsymbol{B}_{\boldsymbol{u}} = \begin{pmatrix} \frac{dt^2}{2} & 0 \\ dt & 0 \\ 0 & \frac{dt^2}{2} \\ 0 & dt \end{pmatrix},$$

where $\boldsymbol{x}_i$ is the state vector, in which x_i, y_i are the vehicle i's coordinates in the Cartesian coordinate system, and $\dot{x}_i, \dot{y}_i$ are the velocity of the vehicle i; $F_{i,x}, F_{i,y}$ are the command process of the vehicle that is related to motion acceleration, which is generated form the power system of a vehicle and measured by IMU; $\boldsymbol{w}$ is the state noise, and in general it can be modeled as additive white Gaussian noise (AWGN); matrix $\boldsymbol{A}$ and $\boldsymbol{B}_{\boldsymbol{u}}$ are obtained by the physical dynamics.

B. Observation Model

The observation data at vehicle s consist of two parts which have different information sources: 1) the measurement provided by sensors such as GPS and IMU with information only related to its own position and mobility state, denoted as $\boldsymbol{z}_s$; 2) the measurement provided by the integrated sensing systems on other vehicles, related to both its own and another vehicle i's states, denoted as $\boldsymbol{z}_{i\to s}$.

For $\boldsymbol{z}_s$, we have

$$\boldsymbol{z}_s[k] = \boldsymbol{H}_s\boldsymbol{x}_s[k] + \boldsymbol{v}_s[k], \tag{3}$$

where $\boldsymbol{v}_s$ is the measurement noise and $\boldsymbol{H}_s$ is the measurement matrix, both of which is related to information processing mode and the inherent properties of sensors.

For $\boldsymbol{z}_{i\to s}$, we have

$$\boldsymbol{z}_{i\to s}[k] = \boldsymbol{H}_{i\to s}\boldsymbol{x}_{i\to s}[k] + \boldsymbol{v}_{i\to s}[k], \tag{4}$$

where $\boldsymbol{x}_{i\to s}[k] = \boldsymbol{x}_i[k] - \boldsymbol{x}_s[k]$ is the relative states between vehicle i and vehicle s. The matrix $\boldsymbol{H}_{i\to s}$ and the statistical property of $\boldsymbol{v}_{i\to s}$ are determined by the properties of their sensing devices, the algorithm to extract the spatial information from raw sensor data and the information transmission process. Without loss of generality, we assume that for $\boldsymbol{z}_s$ and $\boldsymbol{z}_{i\to s}$, direct measurement of the state from the sensing devices can be obtained, and the measurement noise is AWGN, whose variance can be provided by the calibration and testings of the sensing devices.

C. Compensation for Delay During Cooperation

Practically, for the information sharing during multi-vehicle cooperation, there is a time delay $\tau_{i\to s}$ when a vehicle i sends information to another vehicle s. The delay $\tau_{i\to s}$ usually consists of three parts: time of information processing at the sender, time of information transmission, and time of information processing at the receiver. Both the first part and the third part can be accurately measured during processing, so only the second part needs to be analyzed. The delay can be assumed to be bounded, e.g. $0 \le \tau_{i\to s} \le \tau_{\max}$ since the communications delay in vehicular network is bounded in most cases [37].

In our framework, we assume that the time delay $\tau_{i\to s}$ can be measured by extra time stamp reported by the sender. When a vehicle i send the information, a time stamp $t_{i,\text{send}}$ is also sent at the same time [38]. By comparing with the time stamp $t_{s,\text{receive}}$ at the receiver, say vehicle s, the delay can be obtained

$$\tau_{i\to s} = t_{s,\text{receive}} - t_{i,\text{send}}. \tag{5}$$

Then, during the cooperation, at time instant t, the vehicle s actually receives vehicle i's observations at the time instant $t - \tau_{i\to s}$. So, the measurement equation (4) should be rewritten as

$$\boldsymbol{z}_{i\to s}[t-\tau_{i\to s}] = \boldsymbol{H}_{i\to s}\boldsymbol{x}_{i\to s}[t-\tau_{i\to s}] + \boldsymbol{v}_{i\to s}[t-\tau_{i\to s}]. \tag{6}$$

And the measurement at time instant t is

$$\boldsymbol{z}_{i\to s}[t] = \boldsymbol{H}_{i\to s}\boldsymbol{x}_{i\to s}[t] + \boldsymbol{v}_{i\to s}[t]. \tag{7}$$

The state transfer equation (2) can be used to account for the measurement $z_{i\to s}[t]$:

$$\begin{aligned} \boldsymbol{z}_{i\to s}[t] = {} & \boldsymbol{H}_{i\to s}\boldsymbol{A}^{dt=\tau_{i\to s}}\boldsymbol{x}_{i\to s}[t-\tau_{i\to s}] \\ & + \boldsymbol{H}_{i\to s}\boldsymbol{B}_{\boldsymbol{u}}^{dt=\tau_{i\to s}}\boldsymbol{u}_s[t] \\ & + \boldsymbol{H}_{i\to s}w_s[t] + \boldsymbol{v}_{i\to s}[t]. \end{aligned} \tag{8}$$

In particular, time delay τ is less than $0.1\,s$ [38], and the acceleration is assumed to be approximately constant during $\tau_{i\to s}$. That is, the command process of the vehicle can not be suddenly change in a short time, i.e.

$$\boldsymbol{u}_s[t] \simeq \boldsymbol{u}_s[t-\tau_{i\to s}] \tag{9}$$

Substitute (6) and (9) into (8), then we have:

$$\begin{aligned} \boldsymbol{z}_{i\to s}[t] = {} & \boldsymbol{H}_{i\to s}\boldsymbol{A}|_{dt=\tau_{i\to s}}\boldsymbol{H}_{i\to s}^{-1}\boldsymbol{z}_{i\to s}[t-\tau_{i\to s}] \\ & + \boldsymbol{H}_{i\to s}\boldsymbol{B}_{\boldsymbol{u}}|_{dt=\tau_{i\to s}}\boldsymbol{u}_s[t-\tau_{i\to s}] + w^*, \end{aligned} \tag{10}$$

where

$$\begin{aligned} w^* = {} & \boldsymbol{H}_{i\to s}w_s[t] + \boldsymbol{v}_{i\to s}[t] \\ & - \boldsymbol{H}_{i\to s}\boldsymbol{A}|_{dt=\tau_{i\to s}}\boldsymbol{H}_{i\to s}^{-1}\boldsymbol{v}_{i\to s}[t-\tau_{i\to s}] \end{aligned} \tag{11}$$

is a Gaussian variable, so the estimate of $\boldsymbol{z}_{i\to s}[t]$ is

$$\begin{aligned} \hat{\boldsymbol{z}}_{i\to s}^{\tau_{i\to s}}[t] = {} & \boldsymbol{H}_{i\to s}\boldsymbol{A}|_{dt=\tau_{i\to s}}\boldsymbol{H}_{i\to s}^{-1}\boldsymbol{z}_{i\to s}[t-\tau_{i\to s}] \\ & + \boldsymbol{H}_{i\to s}\boldsymbol{B}_{\boldsymbol{u}}|_{dt=\tau_{i\to s}}\boldsymbol{u}_s[t-\tau_{i\to s}]. \end{aligned} \tag{12}$$

When $\boldsymbol{H}_{i\to s}$ is an identity matrix, the estimate $\hat{\boldsymbol{z}}_{i\to s}[t]$ can be written as

$$\hat{\boldsymbol{z}}_{i\to s}^{\tau_{i\to s}}[t] = \boldsymbol{A}|_{dt=\tau_{i\to s}}\boldsymbol{z}_{i\to s}[t-\tau_{i\to s}] + \boldsymbol{B}_{\boldsymbol{u}}|_{dt=\tau_{i\to s}}\boldsymbol{u}_s[t-\tau_{i\to s}]. \tag{13}$$

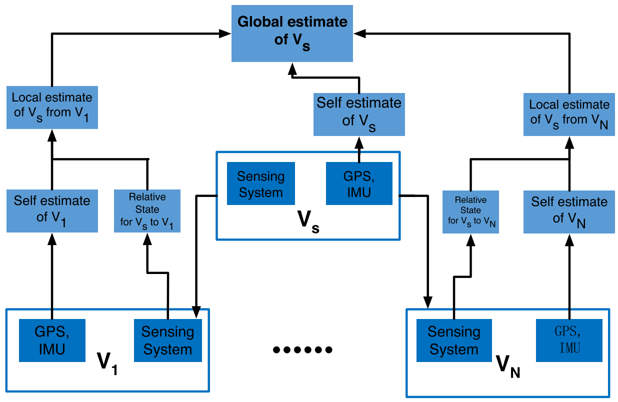

Fig. 1. Framework of the MSMV cooperative localization and mobility tracking algorithm.

III. Multi-Sensor Multi-Vehicle (MSMV) Localization and Mobility Tracking

An illustration of our proposed multi-sensor multi-vehicle (MSMV) localization and mobility tracking framework is shown in Fig. 1. The ego-vehicle is denoted as V_s which can conduct self estimation of its own state from its own onboard sensors, and there are N other vehicles $(V_1, V_2, \ldots, V_N)$ cooperating in the Internet of Vehicles, all of which can make an observation on V_s to measure the state of V_s. Based on V_s's own onboard sensor data namely the commonly used traditional localization devices such as IMU and GPS, it can obtain a local estimation $\hat{\boldsymbol{x}}_s$ of its state through local filtering. At the same time, each of other vehicles in cooperation can also observe V_s, and they can obtain an estimate of V_s's state $\hat{\boldsymbol{x}}_{1\to s}, \hat{\boldsymbol{x}}_{2\to s}, \ldots, \hat{\boldsymbol{x}}_{N\to s}$ through local filters, which are the relative states between V_s and themselves based upon their measurements through sensing devices. Together with the estimate of their own localization $\hat{\boldsymbol{x}}_i$, they can obtain the estimate of the state of V_s as $\hat{\boldsymbol{x}}_{s,i} = \hat{\boldsymbol{x}}_{i\to s} - \hat{\boldsymbol{x}}_i$. These independent estimation results of local filters can be shared with V_s, and then a global estimate of $\boldsymbol{x}_s$ is obtained by fusing all the local estimates using a global filter at V_s. The same story applies to all vehicles, which forms a decentralized framework.

A. Local Filtering for Single-Vehicle Local Estimation

The function of local filtering is to obtain the local estimates of the state of the vehicle V_s at observing vehicles. An observing vehicle can be either V_s itself or other vehicles equipped with sensing devices that can observe V_s, e.g. $V_1, V_2, \ldots, V_N$. According to Eqs. (2), (3) and (4), various kinds of filtering algorithms can be applied to solve the localization and mobility tracking problem. The well-known and most commonly filtering technique in mobility tracking are Kalman filtering [12], [39], Kalman-like filtering (such as extended Kalman filtering and unscented Kalman Filtering) [11], particle filter [9], Rao-Blackwellised particle filter [9] and so on. Our proposed framework has general technical architecture and any filtering technique can be adopted for a local filter here. Because of the limited space, we will just elaborate on the local filtering technique based on Kalman filtering.

Algorithm 1: Kalman Filtering Based Local Filter.

Initialize: the estimation value $\hat{\boldsymbol{x}}(1 \mid 1)$, and its co-variance $\boldsymbol{P}(1 \mid 1)$.
For $t = 1 : T$ **do**
Receive: the measurement value $\boldsymbol{z}(t+1)$ from GPS, sensing devices of other vehicle.
Measure: Acquire the command process $\boldsymbol{u}(t)$ of V_s.
Filtering:
Prediction Step:
$$\hat{\boldsymbol{x}}(t+1 \mid t) = \boldsymbol{A}\hat{\boldsymbol{x}}_g(t \mid t) + \boldsymbol{B}_{\boldsymbol{u}}\boldsymbol{u}(t)$$
$$\boldsymbol{P}(t+1 \mid t) = \boldsymbol{A}\boldsymbol{P}(t \mid t)\boldsymbol{A}^T + \boldsymbol{B}_w\boldsymbol{Q}\boldsymbol{B}_{\boldsymbol{w}}^T$$
Kalman Gain:
$$\boldsymbol{K}(t+1) = \boldsymbol{P}(t+1 \mid t)\boldsymbol{H}^T(\boldsymbol{H}\boldsymbol{P}(t+1 \mid t)\boldsymbol{H}^T + \boldsymbol{R})^{-1}$$
Update Step:
$$\hat{\boldsymbol{x}}(t+1 \mid t+1) = \hat{\boldsymbol{x}}(t+1 \mid t) + \boldsymbol{K}(t+1)[\boldsymbol{z}(t+1) - \boldsymbol{H}\hat{\boldsymbol{x}}(t+1 \mid t)]$$
$$\boldsymbol{P}(t+1 \mid t+1) = \boldsymbol{P}(t+1 \mid t) - \boldsymbol{K}(t+1)\boldsymbol{H}\boldsymbol{P}(t+1 \mid t)$$
End For

Kalman filtering is one of the most traditional and low-complexity methods for tracking the evolution of a dynamic system and can be applied here for localization and mobility tracking of moving vehicles. A local filtering algorithm based on Kalman filtering designed for multi-vehicles is shown in Algorithm I. In order to accommodate multi-vehicle cooperation, some modifications on the filtering processes are needed. Here, we consider the information sharing process between multiple vehicles during the cooperation. At each iteration, a vehicle obtain the measurement $\boldsymbol{z}$ through GPS and IMU or other sensing devices. The information from GPS and IMU provides the measurement of the vehicle's own state, and the information from other sensing devices provides the measurement of other vehicles' state. Then the prediction and the update procedures are conducted to estimate the state of the tracked vehicle. If the tracked vehicle is not itself, then the estimation would be sent to the target vehicle via communication links. It is worth noting that, in the prediction step of the algorithm, we use the global estimation $\hat{\boldsymbol{x}}_g$ at the previous time instance as the benchmark for prediction to obtain the predicted estimate at the current instance. It is different from the traditional Kalman filtering, which uses the local estimates for prediction. Here, in our framework, the global optimal estimate can be used as the initial value of the filter at each iteration of local filtering. In this way, each local filter is no longer independent, and the information shared among all vehicles are utilized to the maximum extent.

The global estimate, which closely links all local filtering processes at cooperating vehicles, is generated by the optimal global filtering. In the following, we will develop the rule for the optimal global filtering.

B. Global Filtering for Local Estimate Fusion

As mentioned in Section III-A, when Kalman filtering, Kalman-like filtering or Particle Filtering, etc. are applied for a local filter, generally, the output value of the local filters above consists of the state estimate $\hat{\boldsymbol{x}}_*$, i.e. the mean value, and the second-order statistics of the estimate, i.e., the variances and covariances. These statistical information are very important to global filtering that combines the results of local filters to obtain the optimal global state estimate.

The objective for global filtering is to calculate the optimal estimate of vehicle V_s from the outputs of local filters. The self-estimate of the vehicle V_s's state is denoted as $\hat{\boldsymbol{x}}_s$ with covariance matrix $\boldsymbol{P}_s$ and the local estimate from vehicle V_i is denoted as $\hat{\boldsymbol{x}}_i$ with covariance matrix $\boldsymbol{P}_i$. For most data of sensing devices, it is true that the measurement is Gaussian and hence the local filtering results are Gaussian. Then accordingly the global optimal state estimate can be expressed as a linear combination of local estimates. That is to say, the problem becomes a data fusion problem under a linear Gaussian system, which is similar to data fusion for single-vehicle multi-sensor [3], [40], [41]. Then we modify the multi-sensor optimal data fusion method for navigation system in [40], and make it applicable to our setup of multi-sensor multi-vehicle information fusion.

Under the assumptions described above, the global estimation $\hat{x}_g$ is denoted to be

$$\hat{\boldsymbol{x}}_g = \sum_{i=1}^{N} \boldsymbol{A}_i \hat{\boldsymbol{x}}_i + \boldsymbol{A}_s \hat{\boldsymbol{x}}_s \ , \tag{14}$$

where $\boldsymbol{A}_i$s and $\boldsymbol{A}_s$ are the unknown weights for linear combination that need to be solved to determine, in which $\boldsymbol{A}_i$ is the weight of other vehicle' estimate and $\boldsymbol{A}_s$ is the weight of self estimate. And the variance of $\hat{\boldsymbol{x}}_g$ is

$$\boldsymbol{P}_g = \sum_{i=1}^{N} \boldsymbol{A}_i \boldsymbol{P}_i \boldsymbol{A}_i^T + \boldsymbol{A}_s \boldsymbol{P}_s \boldsymbol{A}_s^T \ . \tag{15}$$

In order to ensure the global estimation is unbiased, the mean of the estimates cannot be changed. Then we have the constraint on $\boldsymbol{A}_i$s:

$$\sum_{i=1}^{N} \boldsymbol{A}_i + \boldsymbol{A}_s = \boldsymbol{I} \ , \tag{16}$$

According to Gaussian assumption above, the maximum likelihood estimate of $\hat{\boldsymbol{x}}_g$ would be the one that minimizes the variance. Therefore, the global filtering becomes an optimization problem:

$$\begin{aligned} &\min_{\boldsymbol{A}_1,\boldsymbol{A}_2,\ldots,\boldsymbol{A}_N,\boldsymbol{A}_s} \operatorname{tr}(\boldsymbol{P}_g) = \operatorname{tr}\left(\sum_{i=1}^{N} \boldsymbol{A}_i \boldsymbol{P}_i \boldsymbol{A}_i^T + \boldsymbol{A}_s \boldsymbol{P}_s \boldsymbol{A}_s^T\right), \\ &s.t. \sum_{i=1}^{N} \boldsymbol{A}_i + \boldsymbol{A}_s = \boldsymbol{I}, \\ &\boldsymbol{A}_i \text{ and } \boldsymbol{A}_s \text{ are positive semidefinite matrix} . \end{aligned} \tag{17}$$

Lagrange multiplier method can be applied here to solve the convex optimization problem, and accordingly we can formulate the objective function:

$$\begin{aligned} L(\boldsymbol{A},\alpha) = \operatorname{tr}&\left(\sum_{i=1}^{N} \boldsymbol{A}_i \boldsymbol{P}_i \boldsymbol{A}_i^T + \boldsymbol{A}_s \boldsymbol{P}_s \boldsymbol{A}_s^T\right) \\ &+ \alpha^T \left(\sum_{i=1}^{N} \boldsymbol{A}_i + \boldsymbol{A}_s - \boldsymbol{I}\right) \alpha \ . \end{aligned} \tag{18}$$

Finally, the optimal weights for the linear combination at the global filter can be obtained as

$$\begin{aligned} \boldsymbol{A}_s &= {\boldsymbol{P}_s}^{-1} \left(\sum_{i=1}^{N} {\boldsymbol{P}_i}^{-1} + {\boldsymbol{P}_s}^{-1}\right)^{-1}, \\ \boldsymbol{A}_i &= {\boldsymbol{P}_i}^{-1} \left(\sum_{i=1}^{N} {\boldsymbol{P}_i}^{-1} + {\boldsymbol{P}_s}^{-1}\right)^{-1}. \end{aligned} \tag{19}$$

Basically, one can see that the weights are inversely proportional to the local filtering performance.

Hence, the final result of global optimal estimate is

$$\hat{\boldsymbol{x}}_g = \sum_{i=1}^{N} \boldsymbol{A}_i \hat{\boldsymbol{x}}_i + \boldsymbol{A}_s \hat{\boldsymbol{x}}_s \ . \tag{20}$$

In summary, the overall flow of the multi-sensor multi-vehicle (MSMV) localization and mobility tracking is shown in Algorithm 2. At each time slot, there are four steps: measurement, communications, local filtering and global filtering. Delay compensation is conducted before the local filtering of other vehicles according to the discussions presented in Section II-C.

Algorithm 2: Cooperative Localization of V_s.

Initialize: the estimation value
$\hat{\boldsymbol{x}}_{self}(1 \mid 1), \hat{\boldsymbol{x}}_i(1 \mid 1), i = 1:N$, and its co-variance
$\boldsymbol{P}_{self}(1 \mid 1), \boldsymbol{P}_i(1 \mid 1), i = 1:N$.
For $t = 1:T$ **do**
Measure: Get the measurement value of V_s $\boldsymbol{z}_{self}(t+1)$ and the command process $\boldsymbol{u}(t)$ through GPS, IMU and sensing devices. And get the measurement value of other vehicles $\boldsymbol{z}_{other}$.
Send: Send $\boldsymbol{z}_{other}$ to other vehicles.
Receive: the measurement value from sensing devices and GPS of other vehicles $\boldsymbol{z}_i(t+1), i = 1:N$.
Filtering:
$\hat{\boldsymbol{x}}_{self}(t+1 \mid t+1), \boldsymbol{P}_{self}(t+1 \mid t+1) =$
LocalFilter$(\boldsymbol{z}_{self}(t+1), \boldsymbol{u}(t), \hat{\boldsymbol{x}}_{self}(t \mid t), \boldsymbol{P}_{self}(t \mid t))$
For $i = 1:N$
$\hat{\boldsymbol{z}}_i^{\tau}(t+1) = \boldsymbol{A}^{dt=\tau} \boldsymbol{z}_i(t) + \boldsymbol{B}_{\boldsymbol{u}}^{dt=\tau} \boldsymbol{u}(t)$
$\hat{\boldsymbol{x}}_i(t+1 \mid t+1), \boldsymbol{P}_i(t+1 \mid t+1) =$
LocalFilter$(\hat{\boldsymbol{z}}_i^{\tau}(t+1), \boldsymbol{u}(t), \hat{\boldsymbol{x}}_i(t \mid t), \boldsymbol{P}_i(t \mid t))$
End For
$\hat{\boldsymbol{x}}_{global}(t+1 \mid t+1), \boldsymbol{P}_{global}(t+1 \mid t+1) =$
GlobalFilter$(\hat{\boldsymbol{x}}_{self}(t+1 \mid t+1), \boldsymbol{P}_{self}(t+1 \mid t+1),$
$\hat{\boldsymbol{x}}_i(t+1 \mid t+1), \boldsymbol{P}_i(t+1 \mid t+1)$, i = 1:N)
End For

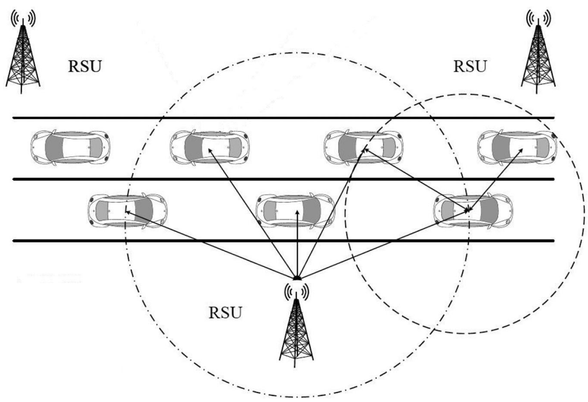

Fig. 2. Internet of Vehicles with RSU.

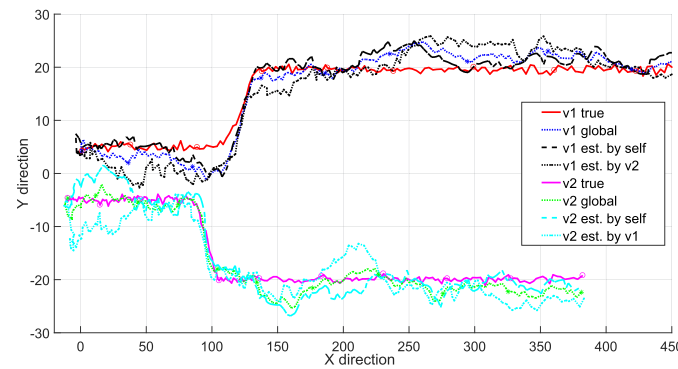

Fig. 3. Trajectory of two vehicles.

C. Inclusion of RSU in Cooperation

In ITS, road side units (RSU) are usually introduced in the infrastructure to provide information to the vehicle and assist the vehicle in driving as shown in Fig. 2. In the Internet of Vehicles, there are not only communications among vehicles (V2V), but also communications among vehicles and RSUs (V2X).

RSU can be treated as a communicable facility with a very precise *a priori* location information and can be recognized by the vehicle sensing device. During the vehicle localization and mobility tracking process, the vehicle sensing system recognizes a RSU and obtains a relative position from the RSU to the vehicle, and meanwhile the RSU broadcasts its own absolute position coordinates to the vehicles within its communication range. Combining these information, the vehicle can obtain its own absolute position estimate. Since the position information of the RSU is trustworthy and accurate, error only comes from the vehicle sensing devices. Therefore, a RSU can greatly improve the accuracy of localization if it is included in the cooperation.

To include RSUs in the cooperative localization and mobility tracking, similar to Eq. (4), we can obtain the relationship between the state and the vehicles' sensing measurement on a RSU as

$$\boldsymbol{z}_{r\to s}[k] = \boldsymbol{H}_{r\to s}\boldsymbol{x}_{r\to s}[k] + \boldsymbol{v}_{r\to s}[k]\ , \tag{21}$$

where $\boldsymbol{x}_{r\to s}$ and $\boldsymbol{v}_{r\to s}$ are the noise and the state of V_s, respectively. Similar local filtering can be applied to obtain the state estimate. For the vehicles that can sense a RSU and communicate with the RSU, the global optimal estimation incorporating measurements on the RSU is

$$\hat{\boldsymbol{x}}_g = \sum_{i=1}^{N} \boldsymbol{A}_i\hat{\boldsymbol{x}}_i + \boldsymbol{A}_s\hat{\boldsymbol{x}}_s + \boldsymbol{A}_r\hat{\boldsymbol{x}}_r\ , \tag{22}$$

where

$$\boldsymbol{A}_s = \boldsymbol{P}_s{}^{-1}\left(\sum_{i=1}^{N} \boldsymbol{P}_i{}^{-1} + \boldsymbol{P}_s{}^{-1} + \boldsymbol{P}_r{}^{-1}\right)^{-1},$$

$$\boldsymbol{A}_i = \boldsymbol{P}_i{}^{-1}\left(\sum_{i=1}^{N} \boldsymbol{P}_i{}^{-1} + \boldsymbol{P}_s{}^{-1} + \boldsymbol{P}_r{}^{-1}\right)^{-1},$$

$$\boldsymbol{A}_r = \boldsymbol{P}_r{}^{-1}\left(\sum_{i=1}^{N} \boldsymbol{P}_i{}^{-1} + \boldsymbol{P}_s{}^{-1} + \boldsymbol{P}_r{}^{-1}\right)^{-1}. \tag{23}$$

As discussed, RSUs can improve the positioning accuracy of the vehicles within the RSU communication range due to the trustworthy and accurate location information of the RSUs. On the other hand, thanks to the cooperation among the vehicles, the vehicles assisted by RSUs can in turn help the vehicles that cannot directly sense and communicate with the RSUs to also improve the positioning accuracy, thus improving the positioning and tracking performance of the vehicles in the entire network. This will be validated by simulations presented in the next section.

IV. Simulation Results

Simulation experiments are conducted to evaluate the performance of our proposed multi-sensor multi-vehicle localization and mobility tracking framework in different cases. Without loss of generality, the most commonly used classical Kalman filter is selected for all local filters, and the simulation parameters are summarized in Table I, which are identical to the parameter settings in [9] and [14]. It should be noted that in order to show the advantage of our MSMV framework, the measurement noise is set at a relatively high level, i.e., we assume fair performance for individual sensors.

In order to thoroughly test the performance and show the advantages of our proposed multi-vehicle multi-sensor framework, we set up three simulation scenarios: a road with fair GPS signal but without RSU, a road with fair GPS signal and with RSU and a tunnel where the GPS signal is very poor.

A. Case 1: A Road Without RSU

To show the performance improvement of our proposed framework over the single-vehicle strategy, we first present the results of localization and mobility tracking for two vehicles in Fig. 3. The figure shows the true and estimated trajectories of the two vehicles without the help of RSU. The vertical and horizontal axises represent the y and x coordinates, respectively. It can be seen that the two vehicles are changing lanes from the trajectories in the figure. And we can see that the trajectory of the global estimate is between the local estimates from itself and

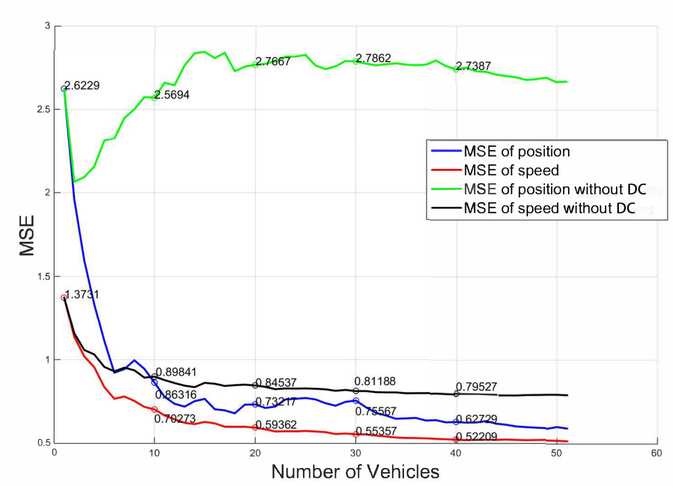

Fig. 4. RMSE vs the number of vehicles in cooperation with delay compensation(DC) or not.

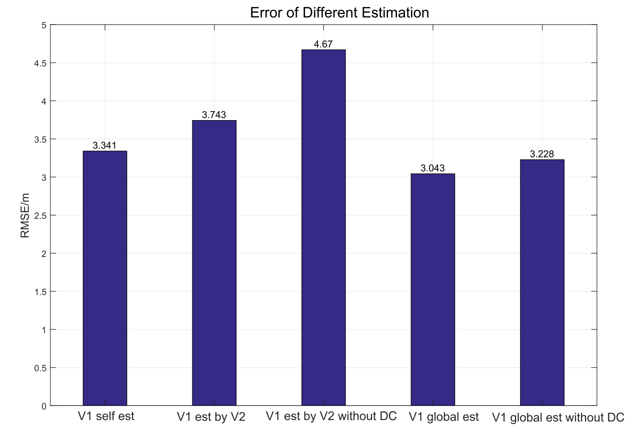

Fig. 5. RMSE in the estimate of V1's position from different information sources with delay compensation(DC) or not.

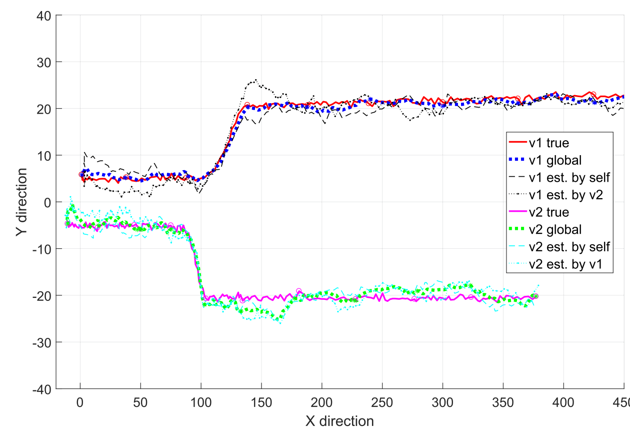

Fig. 6. Trajectory of two vehicles with RSUs.

the other vehicle, and is closer to the true trajectory. For vehicle V_1, the root mean squared error (RMSE) of its self position estimation is 3.341 m and the RMSE of V_2's estimation of V_1's position is 3.743 m. By combining the two estimates, the RMSE of the global estimate of V_1's position is reduced to 3.043 m (a 8.9% reduction in RMSE); for vehicle V_2, the RMSE of its self position estimation is 3.1790 m and the RMSE of V_1's estimation of V_2's position is 4.0945 m. By combining the two estimates, the RMSE of the global estimate of V_2's position is reduced to 2.9175 m (a 8.2% reduction in RMSE).

To show the influence of the number of vehicles that participate in cooperation on the performance improvement, we gradually increase the number of vehicles in the simulations and calculate the RMSE in the estimate of the position and the speed with and without time delay compensation, and plot the results in Fig. 4. We assume that each vehicle added can sense the vehicle being measured and can establish communications with the vehicle being measured. First of all, it can be seen that when the number of vehicles in cooperation is small (less than 30), the proposed MSMV localization and mobility tracking algorithm can greatly improve the performance (e.g., a 67.09% reduction of RMSE for position estimation and a 48.82% reduction of RMSE for speed estimation with 10 vehicles). However, when the number of vehicles in cooperation is large, the improvement of accuracy would be less obvious if the number of vehicles continues to increase. At the same time, the communication burden of system always gets heavier when more vehicles participate in the cooperation. Therefore, it is necessary to choose specific vehicles that participate in the cooperation.

1) Effect of Delay Compensation: In this part, we want to compare the effect of delay compensation on accuracy. As can be seen from Eq. (6), the time delay error mainly comes from the time delay generated by vehicle V_1 measured by other vehicles. When delay compensation is not applied, vehicle V_1 mistakenly treats $\boldsymbol{z}_{i\to s}[t-\tau_{i\to s}]$ as $\boldsymbol{z}_{i\to s}[t]$ during the tracking process, which introduces higher error.

Fig. 5 shows the RMSE of V_1's self position estimate, V_2's estimate of V_1's position with delay compensation, V_2's estimate of V_1's position without delay compensation, global estimate of V_1's position with delay compensation and global estimate of V_1's position without delay compensation. From the simulation results, it can be seen that the delay compensation can significantly reduce the error (a 19.6% reduction in RMSE) introduced by the communication delay between different vehicles, and hence also improve the accuracy of the global estimate (a 5.7% reduction in RMSE).

In Fig. 4, it can be seen that as the number of vehicles participating in cooperative localization increases, the communication delay has a more significant impact on the accuracy. The reason for this phenomenon is that the increase in the number of vehicles reduces the weight of the GPS in forming the final estimate, making the global estimate more affected by the error caused by the delays during the information sharing process.

B. Case 2: A Road With RSUs

We show the performance in localization and mobility tracking under the help of RSU in Fig. 6. We assume that RSUs are only placed on one side of the road and their communication ranges cover only the upper half and do not overlap with each

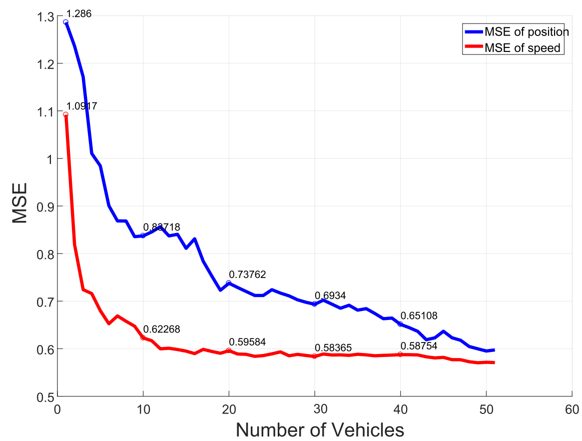

Fig. 7. RMSE vs the number of vehicles in cooperation with RSUs.

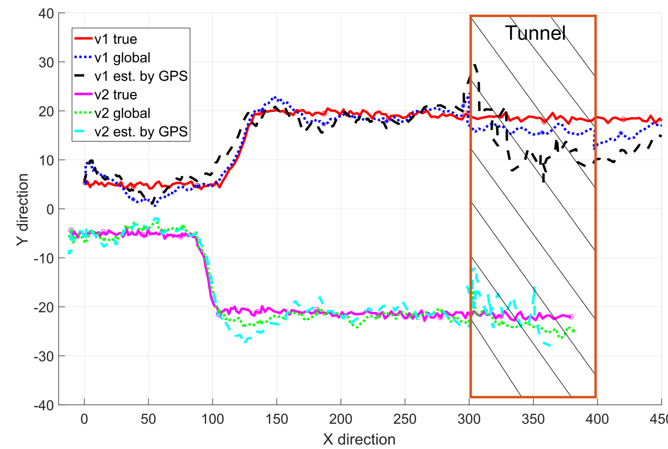

Fig. 8. Trajectory of two vehicles on the road with a tunnel.

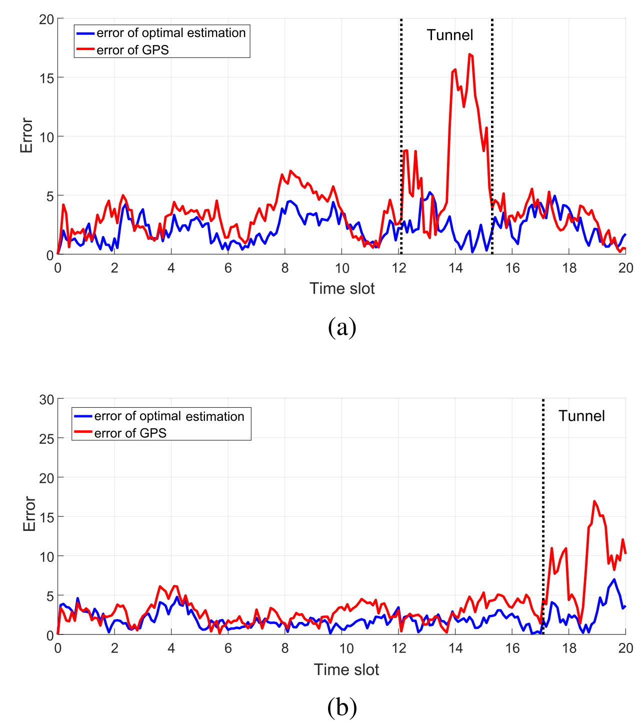

Fig. 9. Error vs time. (a) Error of V_1. (b) Error of V_2.

other. This is the simplest setup where the help provided by RSUs to the vehicles is minimum. In this setup, only V_1 can obtain the information of the RSU and V_1 can only receive one RSU information at any particular time.

From the trajectory, we can see that the estimated trajectory of V_1 is closer to the ground truth than V_2. This shows that the vehicle under the direct helps of RSUs achieves a higher tracking accuracy than the vehicle under the indirect helps of RSUs. Specifically, for vehicle V_1, the root mean squared error (RMSE) of its self position estimation is 2.1265 m and the RMSE of V_2's estimation of V_1's position is 2.3904 m. By combining the two estimates and the estimate from RSU, the RMSE of the global estimate of V_1's position is reduced to 1.0671 m (a 50% reduction in RMSE). For vehicle V_2, the RMSE of its self position estimation is 3.1442 m and the RMSE of V_1's estimation of V_2's position is 4.3466 m. By combining the two estimates, the RMSE of the global estimate of V_2's position is reduced to 2.1887 m (a 30.4% reduction in RMSE). Compared with the results in the scenario without RSUs, it can be seen that even when the vehicle is out of the RSU's communication range, it can be indirectly helped to improve the accuracy. Note that this is the performance gain obtained by cooperations between only two vehicles. If more vehicles are participated in, more significant improvements are expected.

We also conduct an experiment to illustrate the relationship between RMSE and the number of vehicles in cooperation in the case of RSUs, as shown in Fig. 7. It can be seen that in this case the improvement of the positioning from more vechilce cooperations is not as significant as the case without the RSU. This is because that the RSU has already provided the vehicle with a higher tracking accuracy and the increase in the number of vehicles contribute little to the estimation performance.

C. Case 3: A Road With a Tunnel

We have also set up a more challenging and realistic scenario, where multi-vehicle cooperations are more desirable. Based upon the previous road, we set up a tunnel which extends from the 300th meter to the 400th meter along the x direction. In order to model the poor performance of GPS in the tunnel, the GPS positioning error is set to be ten times larger. As shown in Fig. 8, for both vehicles, the self-estimated tracking results based on GPS deviate significantly from the ground truth when the vehicles are traveling in the tunnel. However, the errors of the global estimates are still maintained within an acceptable range. Fig. 9 shows the tracking error of V_1 and V_2 during driving. After the vehicle enters the tunnel, the error of GPS positioning is large, but the vehicle can achieve an accurate positioning with the help of the other vehicle. This indicates that our proposed MSMV localization and mobility tracking can successfully address the issue of unstable GPS signals in various environments.

TABLE I
SIMULATION PARAMETERS

Discrete time step	$0.1\ [s]$
Duration of simulation	$20\ [s]$
Covariance of v in Eq. (4)	$74\ [m/s^2]^2$
Covariance of v in Eq. (3)	$64\ [m/s^2]^2$
Variances of w	$(0.1, 0.15, 0.2, 0.2)'$

V. CONCLUSION

In this paper, a multi-sensor multi-vehicle (MSMV) localization and mobility tracking framework was presented for autonomous driving. We designed a local filter and a global filter to form a two-layer structure for the cooperation localization and tracking. Most traditional filtering techniques, such as Kalman filters, Kalman-like filters and particle filters etc., can be applied to the framework. Compared with single-sensor or single-vehicle multi-sensor solutions, the scheme we proposed uses the information that vehicles obtained for each other. By sharing information, the vehicle in the Internet of Vehicles not only improves its own tracking accuracy, but also helps others.

Simulations verify that the accuracy of localization and tracking has been obviously improved by cooperations among multiple sensors with low cost and high efficiency, especially when RSUs are available. Besides, we have also shown that thanks to the cooperation, the problem of the GPS sensitivity to environments can be largely solved.

In the future, we will look for a strategy to select vehicles to participate in the cooperation to optimize the tradeoff between performance and efficiency. On the other hand, identifying and correcting error messages from vehicles in cooperation is also under consideration.

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