Cooperative Localization with Distributed ADMM over 5G-based VANETs

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***Abstract*—This paper presents a cooperative localization strategy via a distributed optimization technique known as the alternating direction method of multipliers (ADMM). In a Vehicular Ad hoc Network (VANET) where a vehicle communicates with neighboring vehicles via vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, the developed algorithm utilizes three types of measurements, which are the pairwise relative distance, angle of arrival, and absolute positions for a subset of vehicles in cooperative localization. The proposed algorithm is designed to provide an attractive solution for the localization of autonomous driving vehicle in the GPS-denied (urban) environment. Simulation results confirm the potency of distributed ADMM-based cooperative localization for autonomous driving in 5G-based VANETs.**

***Index Terms*—ADMM, cooperative localization, optimization, V2I, V2V, VANET**

I. Introduction

Autonomous driving is considered to be the major framework for future cooperative intelligent transport systems (C-ITS). The fifth-generation (5G) communication which has numerous high data-rate advantages, such as broadband data transmission, multi-antenna technology, and millimeter wavelength spectra, is expected to enable technology [1]. In addition, since device-to-device communication [2]–[4], which provides decentralized links among vehicles and connectivity information-aided localization [5]–[7], 5G-based Vehicular Ad hoc Networks (VANETs) should enable to develop higher-accuracy and lower-computation cooperative localization techniques by utilizing vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. For satisfying the requirements of location-based services and applications for future C-ITS, cooperative localization techniques [8]–[11] have also been addressed in line with the 5G systems that allow sufficient connectivity information for cooperation.

This paper develops a cooperative localization algorithm via the alternating direction method of multiplier (ADMM) over 5G-based VANETs. The algorithm consists of three steps of distributed processing that handles messages which are the prediction, expectation, and compensation steps over the underlying graphical model for the network [12], [13]. To accomplish these steps, individual vehicles measure and receive location information (e.g., the pairwise relative distance and the angle of arrival from the neighboring vehicles, and absolute position from the global positioning system (GPS) [14] or infrastructures [15]). These types of measurements are obtained at individual vehicles and exchanged via cooperation between the vehicles with V2V and V2I communication. Simulation results show the performance of the proposed algorithm in the aspect of the localization accuracy. The results confirm that the ADMM-based distributed cooperative localization algorithm contributes to the autonomous driving technology in the 5G-based VANETs using V2V and V2I communication.

This paper is organized as follows. Section II defines the vehicular networks model and measurement model for cooperative localization. The proposed algorithm for the ADMM-based cooperative localization is described in Section III. Section IV provides the performance of the proposed algorithm and confirms requirements for autonomous driving in VANETs with V2V and V2I communication, and Section V concludes the paper.

II. System Model

A. Vehicular Networks Model

Consider a vehicular network in an N_x m $\times$ N_y m two dimensional region, where interconnected V vehicles are deployed on the road. Let Ω_V denote the set of vehicles in the network. The location of the i-th vehicle at time instant k is represented by $\mathbf{x}_i^{(k)} = \left[x_i^{(k)}, y_i^{(k)}\right]^T \in \mathbb{R}^2$. The pairwise relative distance between the i-th vehicle and the j-th vehicle (i.e., connected neighbor) is given by

$$d_{i,j}^{(k)} = \|\mathbf{x}_j^{(k)} - \mathbf{x}_i^{(k)}\|, \tag{1}$$

where $\|\cdot\|$ is the Euclidean distance. The angle of arrival between the connected vehicle i and j is expressed by

$$\theta_{i,j}^{(k)} = \arctan \frac{y_j^{(k)} - y_i^{(k)}}{x_j^{(k)} - x_i^{(k)}}. \tag{2}$$

B. Measurement Model

For an individual vehicle, the *relative distance measurement*, *angle of arrival measurement*, and *absolute position measurement* are available. The relative distance and angle of arrival measurements can be obtained from the neighboring vehicles at every time instant. Depending on the receiving signal environment, the location coordinates of the absolute position measurement is determined with either the GPS signal or the uplink time difference of arrival (UTDoA) [15] at every time instant.

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1) Relative Distance Measurement: The relative distance measurement [9] between the vehicle j (subject) and i (object) is defined as

$$z_{d,j\to i}^{(k)} = d_{i,j}^{(k)} + v_d^{(k)}, \tag{3}$$

where $v_d^{(k)}$ is the measured distance error modeled as zero-mean Gaussian random variable with variance σ_d^2.

2) Angle of Arrival Measurement Model: The angle of arrival measurement [16] between vehicle j (receiver) and i (transmitter) is denoted by

$$z_{a,j\to i}^{(k)} = \theta_{i,j}^{(k)} + v_a^{(k)}, \tag{4}$$

where $v_a^{(k)}$ is the measured angle error modeled as a zero-mean Gaussian random variable with variance σ_a^2.

3) Absolute position measurement: The absolute position measurement [14], [15] is defined as

$$\mathbf{z}_{c,i}^{(k)} = \mathbf{x}_i^{(k)} + \mathbf{v}_c^{(k)}, \tag{5}$$

where $\mathbf{v}_c^{(k)} = \left[v_{c,x}^{(k)}, v_{c,y}^{(k)}\right]^T$, and bivariate Gaussian random vector $\mathcal{N}(0, \mathbf{\Sigma})$. Here, the covariance matrix $\mathbf{\Sigma}$ is given by

$$\mathbf{\Sigma} = \begin{bmatrix} {\sigma_c}^2 & 0 \\ 0 & {\sigma_c}^2 \end{bmatrix}.$$

III. Cooperative Localization Algorithm in Vehicular Networks Based Upon ADMM

A. Problem Formulation

In this paper, we propose to cooperatively and distributively localize each individual vehicle in the network by formulating the problem as an optimization problem. In the vehicular network, the location of an individual vehicle is a 2D vector that minimizes an objective function $f_0(\mathbf{x})$. The objective function $f_0(\mathbf{x})$ can be formulated using likelihood functions of measurement models for the parameters introduced in Section II-B. The likelihood functions of the relative distance, relative angle, absolute position measurement are modeled as

$$p(z_{d,j\to i}|\mathbf{x}_i, \mathbf{x}_j) = \frac{1}{\sqrt{2\pi{\sigma_d}^2}} \exp\Big(-\frac{|z_{d,j\to i} - d_{i,j}|^2}{2{\sigma_d}^2}\Big), \tag{6}$$

$$p(z_{a,j\to i}|\mathbf{x}_i, \mathbf{x}_j) = \frac{1}{\sqrt{2\pi{\sigma_a}^2}} \exp\Big(-\frac{|z_{a,j\to i} - \theta_{i,j}|^2}{2{\sigma_a}^2}\Big), \tag{7}$$

$$p(\mathbf{z}_{c,i}|\mathbf{x}_i) = \frac{1}{2\pi\sigma_c} \exp\Big(-\frac{|z_{c,i}^x - x_i|^2 + |z_{c,i}^y - y_i|^2}{2\sigma_c^2}\Big). \tag{8}$$

Thus, the likelihood function for cooperative localization is represented by

$$L(\mathbf{x}) = \prod_{i,j\in\Omega_V} p(z_{d,j\to i}|\mathbf{x}_i, \mathbf{x}_j) \prod_{i,j\in\Omega_V} p(z_{a,j\to i}|\mathbf{x}_i, \mathbf{x}_j) \prod_{i\in\Omega_V} p(\mathbf{z}_{c,i}|\mathbf{x}_i). \tag{9}$$

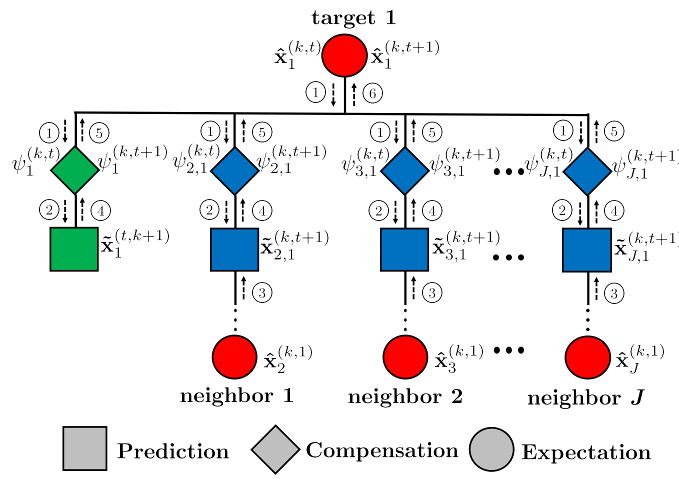

Fig. 1. Message flow for distributed location estimation of target 1 at k-th time instant and $t+1$ iteration.

The resulting objective is obtained by taking the logarithm of (9) and is given by

$$f_0(\mathbf{x}_i) = \sum_{i,j\in\Omega_V} \frac{|z_{d,j\to i} - d_{i,j}|^2}{2{\sigma_d}^2} + \sum_{i,j\in\Omega_V} \frac{|z_{a,j\to i} - \theta_{i,j}|^2}{2{\sigma_a}^2} + \sum_{i\in\Omega_V} \frac{|z_{c,i}^x - x_i|^2 + |z_{c,i}^y - y_i|^2}{2\sigma_c^2}. \tag{10}$$

B. Distributed Cooperative Localization Based Upon ADMM

In this paper, the minimum of (10) is determined by the ADMM, which consists of three steps: the prediction, compensation, and expectation step. Each step is performed over $K_{\max}$ time instant, where the vehicle location at the first iteration of the k-th time instant is determined by the mobility model in [17].

Fig. 1 shows the message flow for distributed location estimation of a target 1 when the target 1 receives measurements and location information from J neighbors and infrastructures with V2V and V2I communication. There are $J+1$ branches under expectation of the target 1. The leftmost branch is modeled from receiving the absolute position measurement, from the remaining J branches are modeled from the relative distance and angle of arrival measurement. Messages ① include the location of the target 1 at the t-th iteration. Each compensation value at the t-th iteration is additionally included in messages ②. Messages ③ include each location of the neighbors at the first iteration. In the each prediction step, each prediction value is obtained by each measurement and included in messages ④. Each compensation value, which is included in messages ⑤, is determined from messages ④. The message ⑥ includes all messages ⑤. In the expectation step, the location of the target 1 at the $t+1$-th iteration is estimated.

$$\begin{aligned}\tilde{x}_{d_{ji}}^{(k,t+1)} =& \frac{\sigma_d^2}{\frac{1}{\rho}\epsilon_{dx}^2+\sigma_d^2}(\hat{x}_{d_{ji}}^{(k,t)}-\psi_{x,d_{ji}}^{(k,t)}) - \frac{\frac{1}{\rho}\epsilon_{dx}}{\frac{1}{\rho}\epsilon_{dx}^2+\sigma_d^2}(z_{d,ji}-\hat{d}-\epsilon_{dx}\hat{x}_{d_{ji}}^{(k,t)}),\\ \tilde{y}_{d_{ji}}^{(k,t+1)} =& \frac{\sigma_d^2}{\frac{1}{\rho}\epsilon_{dy}^2+\sigma_d^2}(\hat{y}_{d_{ji}}^{(k,t)}-\psi_{y,d_{ji}}^{(k,t)}) - \frac{\frac{1}{\rho}\epsilon_{dy}}{\frac{1}{\rho}\epsilon_{dy}^2+\sigma_d^2}(z_{d,ji}-\hat{d}-\epsilon_{dy}\hat{y}_{d_{ji}}^{(k,t)}),\end{aligned} \tag{11}$$

$$\begin{aligned}\tilde{x}_{a_{ji}}^{(k,t+1)} =& \frac{\sigma_a^2}{\frac{1}{\rho}\epsilon_{ay}^2+\sigma_a^2}(\hat{x}_{a_{ji}}^{(k,t)}-\psi_{x,a_{ji}}^{(k,t)}) + \frac{\frac{1}{\rho}\epsilon_{ay}}{\frac{1}{\rho}\epsilon_{ay}^2+\sigma_a^2}(z_{a,ji}-\hat{\theta}+\epsilon_{ay}\hat{x}_{a_{ji}}^{(k,t)}),\\ \tilde{y}_{a_{ji}}^{(k,t+1)} =& \frac{\sigma_a^2}{\frac{1}{\rho}\epsilon_{ax}^2+\sigma_a^2}(\hat{y}_{a_{ji}}^{(k,t)}-\psi_{y,a_{ji}}^{(k,t)}) - \frac{\frac{1}{\rho}\epsilon_{ax}}{\frac{1}{\rho}\epsilon_{ax}^2+\sigma_a^2}(z_{a,ji}-\hat{\theta}-\epsilon_{ax}\hat{y}_{a_{ji}}^{(k,t)}),\end{aligned} \tag{12}$$

$$\begin{aligned}\tilde{x}_{c_i}^{(k,t+1)} =& \frac{\sigma_c^2}{\frac{1}{\rho}+\sigma_c^2}(\hat{x}_{c_i}^{(k,t)}-\psi_{x,c_i}^{(k,t)}) + \frac{\frac{1}{\rho}}{\frac{1}{\rho}+\sigma_c^2}z_{c,ix},\\ \tilde{y}_{c_i}^{(k,t+1)} =& \frac{\sigma_c^2}{\frac{1}{\rho}+\sigma_c^2}(\hat{y}_{c_i}^{(k,t)}-\psi_{y,c_i}^{(k,t)}) + \frac{\frac{1}{\rho}}{\frac{1}{\rho}+\sigma_c^2}z_{c,iy}.\end{aligned} \tag{13}$$

1) Prediction Step: At the t-th iteration of the k-th time instant, the prediction step is performed separately considering each measurement. By considering the relative distance, angle of arrival, and absolute position measurement, each prediction step is respectively performed as

$$\begin{aligned}\tilde{x}_{d_{ji}}^{(k,t+1)} =& \operatorname*{argmin}_{x_i}[f_{d_{ji}}(x_i,y_i,x_j,y_j)+\frac{\rho}{2}(x_i-n_{x,d_{ji}})^2],\\ \tilde{y}_{d_{ji}}^{(k,t+1)} =& \operatorname*{argmin}_{y_i}[f_{d_{ji}}(x_i,y_i,x_j,y_j)+\frac{\rho}{2}(y_i-n_{y,d_{ji}})^2],\end{aligned} \tag{14}$$

$$\begin{aligned}\tilde{x}_{a_{ji}}^{(k,t+1)} =& \operatorname*{argmin}_{x_i}[f_{a_{ji}}(x_i,y_i,x_j,y_j)+\frac{\rho}{2}(x_i-n_{x,a_{ji}})^2],\\ \tilde{y}_{a_{ji}}^{(k,t+1)} =& \operatorname*{argmin}_{y_i}[f_{a_{ji}}(x_i,y_i,x_j,y_j)+\frac{\rho}{2}(y_i-n_{y,a_{ji}})^2],\end{aligned} \tag{15}$$

$$\begin{aligned}\tilde{x}_{c_i}^{(k,t+1)} =& \operatorname*{argmin}_{x_i}[f_{c_i}(x_i,y_i)+\frac{\rho}{2}(x_i-n_{x,c_i})^2],\\ \tilde{y}_{c_i}^{(k,t+1)} =& \operatorname*{argmin}_{y_i}[f_{c_i}(x_i,y_i)+\frac{\rho}{2}(y_i-n_{y,c_i})^2],\end{aligned} \tag{16}$$

where ρ is the penalty coefficient and each $n_{(\cdot)}$ is obtained by each message ②. Each function for prediction $f_{d_{ji}}(x_i,y_i,x_j,y_j)$, $f_{a_{ji}}(x_i,y_i,x_j,y_j)$, and $f_{c_i}(x_i,y_i)$ is respectively defined as

$$f_{d_{ji}}(x_i,y_i,x_j,y_j) = \frac{(z_{d,j\to i}-\sqrt{(x_i-x_j)^2+(y_i-y_j)^2})^2}{2\sigma_d^2}, \tag{17}$$

$$f_{a_{ji}}(x_i,y_i,x_j,y_j) = \frac{(z_{a,j\to i}-\arctan\frac{y_j-y_i}{x_j-x_i})^2}{2\sigma_a^2}, \tag{18}$$

$$f_{c_i}(x_i,y_i) = \frac{(x_i-z_{c,ix})^2+(y_i-z_{c,iy})^2}{2\sigma_c^2}. \tag{19}$$

The i-th vehicle performs the prediction step with one of its neighbors, the j-th vehicle. The resulting messages obtained by the prediction step are (11)-(13). Here, $\epsilon_{dx}, \epsilon_{dy}, \epsilon_{ax}$, and ϵ_{ay} are defined as

$$\epsilon_{dx} = \frac{\hat{d}_x}{\hat{d}},\quad \epsilon_{dy} = \frac{\hat{d}_y}{\hat{d}},\quad \epsilon_{ax} = \frac{\hat{d}_x}{\hat{d}^2},\quad \epsilon_{ay} = \frac{\hat{d}_y}{\hat{d}^2}. \tag{20}$$

For simplicity, the following parameters are introduced as

$$\begin{aligned}\hat{d} = \sqrt{\hat{d}_x^2+\hat{d}_y^2},\quad \hat{\theta} = \arctan\frac{\hat{d}_y}{\hat{d}_x},\\ \hat{d}_x = \hat{x}_j^{(k,t)}-\hat{x}_i^{(k,t)},\\ \hat{d}_y = \hat{y}_j^{(k,t)}-\hat{y}_i^{(k,t)}.\end{aligned} \tag{21}$$

2) Compensation Step: The i-th vehicle performs the compensation step, which acts as, for all neighbors j as

$$\begin{aligned}\psi_{x,d_{ji}}^{(k,t+1)} =& \psi_{x,d_{ji}}^{(k,t)}+\tilde{x}_{d_{ji}}^{(k,t+1)}-\hat{x}_i^{(k,t)},\\ \psi_{y,d_{ji}}^{(k,t+1)} =& \psi_{y,d_{ji}}^{(k,t)}+\tilde{y}_{d_{ji}}^{(k,t+1)}-\hat{y}_i^{(k,t)},\end{aligned} \tag{22}$$

$$\begin{aligned}\psi_{x,a_{ji}}^{(k,t+1)} =& \psi_{x,a_{ji}}^{(k,t)}+\tilde{x}_{a_{ji}}^{(k,t+1)}-\hat{x}_i^{(k,t)},\\ \psi_{y,a_{ji}}^{(k,t+1)} =& \psi_{y,a_{ji}}^{(k,t)}+\tilde{y}_{a_{ji}}^{(k,t+1)}-\hat{y}_i^{(k,t)},\end{aligned} \tag{23}$$

$$\begin{aligned}\psi_{x,c_i}^{(k,t+1)} =& \psi_{x,c_i}^{(k,t)}+\tilde{x}_{c_i}^{(k,t+1)}-\hat{x}_i^{(k,t)},\\ \psi_{y,c_i}^{(k,t+1)} =& \psi_{y,c_i}^{(k,t)}+\tilde{y}_{c_i}^{(k,t+1)}-\hat{y}_i^{(k,t)}.\end{aligned} \tag{24}$$

$$\begin{aligned}\hat{x}_i^{(k,t+1)} =& \frac{1}{2J+2}\{\hat{x}_i^{(k,t)}+\Sigma_{j=1}^{j=J}(\tilde{x}_{d_{ji}}^{(k,t+1)}+\psi_{x,d_{ji}}^{(k,t+1)})+\Sigma_{j=1}^{j=J}(\tilde{x}_{a_{ji}}^{(k,t+1)}+\psi_{x,a_{ji}}^{(k,t+1)})+(\tilde{x}_{c_i}^{(k,t+1)}+\psi_{x,c_i}^{(k,t+1)})\},\\ \hat{y}_i^{(k,t+1)} =& \frac{1}{2J+2}\{\hat{y}_i^{(k,t)}+\Sigma_{j=1}^{j=J}(\tilde{y}_{d_{ji}}^{(k,t+1)}+\psi_{y,d_{ji}}^{(k,t+1)})+\Sigma_{j=1}^{j=J}(\tilde{y}_{a_{ji}}^{(k,t+1)}+\psi_{y,a_{ji}}^{(k,t+1)})+(\tilde{y}_{c_i}^{(k,t+1)}+\psi_{y,c_i}^{(k,t+1)})\}.\end{aligned} \tag{25}$$

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Discretization time period k	100 [ms]
Time duration $K_{\max}$	1300
Iteration duration $T_{\max}$	50
Max. and Min. speed of vehicle: $S_{\max}, S_{\min}$	120, 80 [km/h]
Std. of distance measurement error σ_d	1 [m]
Std. of angle measurement error σ_a	4 [°]
Std. of GPS measurement error α	0.45/$\sqrt{2}$ [m]
Std. of UTDoA measurement error β [15]	0.7/$\sqrt{2}$ [m]

Algorithm 1 Proposed ADMM-based cooperative localization algorithm

```
given x_i^(0), ∀i
for k = 1 to K_max do {time index}
    for i = 1 to V in parallel do
        vehicle movement, according to [17]
        for t = 1 to T_max do {interation index}
            prediction step, according to (11)-(13)
            compensation step, according to (22)-(24)
            expectation step, according to (25)
        end for
    end for
end for
```

3) Expectation Step: Each vehicle i performs the expectation step in parallel. Each expectation step is (25), as shown at the bottom of this page, where J is the number of neighbor vehicles.

IV. PERFORMANCE EVALUATION

A. Simulation Scenario and Environment

In our 5G VANETs scenario-based evaluation, we assume that four connected vehicles are moving for $K_{\max}$ time instant from left $x = 0$ to the right $x = 3600$ on a straight road, which is divided into four lanes shown in Fig. 2. We consider a scenario where the vehicles enter an urban area from a rural area at $0 < x < 300$ m, and moving to a rural again from the urban environment at $x = 3300$ m. Based on $x = 300$ m and $x = 3300$ m, we divide the network into two cases. In the first case, the left area of the road based on $x = 300$ is an rural environment ($\sigma_c = \alpha$) in which the absolute position measurement is obtained from global positioning system (GPS) signal, whereas in the second case, the area between $300 < x < 3300$ m of the road is the urban environment ($\sigma_c = \beta$) in which the position is obtained from UTDoA by using V2I scenario as proposed in [15]. The period of the observed measurements and the communication is equal to the discretization time period k. Each vehicle has a speed that varies in accordance to the mobility model in [17] with time, and the standard deviation of noise in each x- and y-axis of the mobility model is 0.5 and 0.1 $\mathrm{m/s^2}$ respectively. The minimum and maximum speed are $S_{\min}$ and $S_{\max}$. The vehicular network size is 3600 m × 14.5 m, and the width of each lane is 3.5 m. The main simulation parameters are summarized in Table I. The pseudocode of the proposed algorithm is described in Algorithm 1.

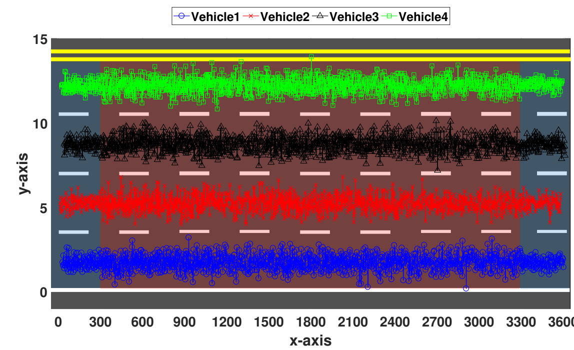

Fig. 2. Trajectory of each vehicle.

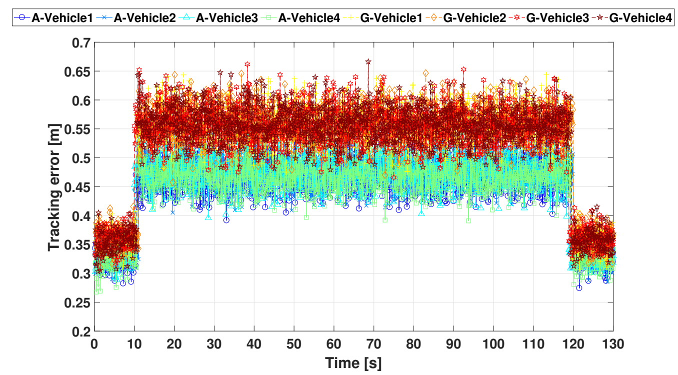

Fig. 3. Tracking errors of cooperative localization with the ADMM.

B. Performance Analysis

Fig. 2 shows the trajectory of each vehicle with cooperative localization with the ADMM. Each estimated location of the trajectory is the optimal value of x and y over $T_{\max}$ iterations. For the first 300 meters from starting location, each vehicle estimates its location using the relative distance, angle of arrival, and GPS measurement. When each vehicle enters the urban area, location estimation is performed by the UTDoA instead of the GPS measurement. After exiting the urban area, each vehicle estimates the location using the relative distance, angle of arrival, and GPS measurement again. From the result of the trajectory, it is clearly shown that autonomous driving is possible in both rural and urban area.

Fig. 3 shows the tracking errors of each vehicle with the proposed algorithm. The results can be segregated into two sections. In the first section, all vehicles are in the rural environment, error of cooperative localization with the proposed ADMM and conventional absolute position measurement is 35 and 40 cm respectively. In the second section, in the urban environment, each error with the ADMM and absolute position measurement increases to 55 and 65 cm, respectively.

Fig. 4 shows the average tracking errors of the proposed cooperative localization with the ADMM and with only the

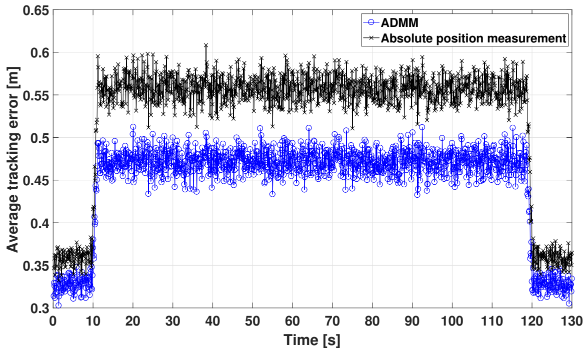

Fig. 4. Average tracking error of the cooperative localization with the ADMM and absolute position measurement.

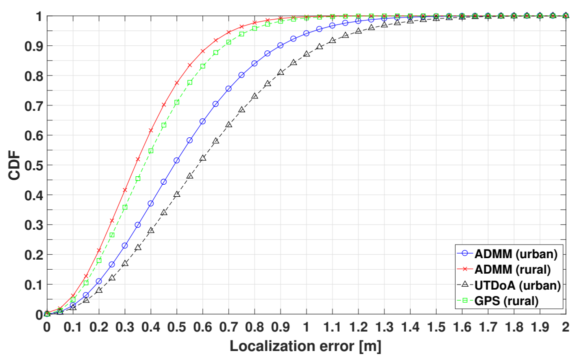

Fig. 5. Cumulative distribution function for localization error.

absolute position measurement. The average tracking errors has similar tendency as the results shown in Fig. 3. The average tracking error of the proposed algorithm is always less than the absolute position measurement, specially, 10 cm less than the UTDoA measurement in the urban environment. From this result, we can confirm that cooperative localization with the ADMM is capable of performing well in both urban and rural environment.

Fig. 5 shows the cumulative distribution function for the localization error of the proposed algorithm compared to the CDF only absolute position measurement. The solid graph and dashed graph show the results of cooperation and non-cooperation, repsectively. Each graph is obtained by 100 Monte Carlo simulation. Results show that the cooperative localization with the ADMM always has performance gain in the aspect of the localization accuracy.

V. Conclusion

This paper presents a cooperative localization via a distributed optimization technique as known as the ADMM. In VANETs the developed algorithm utilizes three types of measurements, which are the pairwise relative distance, angle of arrival, and absolute positions for a subset of vehicles in cooperative localization. The proposed algorithm is designed to provide an attractive solution for autonomous driving vehicle localization under the GPS-denied environment. Simulation results confirm the potency of distributed ADMM-based cooperative localization for autonomous driving in 5G-based VANETs.

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