A Vehicular Positioning Enhancement with Connected Vehicle Assistance Using Extended Kalman Filtering

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Abstract. In this paper, we consider the problem of vehicular positioning enhancement with emerging connected vehicles (CV) technologies. In order to actually describe the scenario, the Interacting Multiple Model (IMM) filter is used for depicting varies of observation models. A CV-enhanced IMM filtering approach is proposed to locate a vehicle by data fusion from both coarse GPS data and the Doppler frequency shifts (DFS) measured from dedicated short-range communications (DSRC) radio signals. Simulation results state the effectiveness of the proposed approach called CV-IMM-EKF.

Keywords: Vehicular positioning enhancement · Target vehicle (TV) GPS · CV-IMM-EKF

1 Introduction

Due to the development of the fifth-generation (5G) mobile communications, this new communicated method attracts more and more attention because of its faster transfer speed, high adaptability and better end-to-end performance [2, 3]. And the more transfer technologies such like the ultra dense cloud small cell network (UDCSNet) [1] are used in the construction of vehicular network. About applications, some of the communications problems in the society have been resolved such as LTE-V systematic and integrated V2X solution [4], software-defined heterogeneous vehicular network (SERVICE) [5], credible RTI sharing mechanism [6], traffic density estimation [7] and

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the physical layer outage performance of information sharing [8], and the effectiveness in the application has improved greatly [9–11].

The availability of high-accuracy location-awareness is essential for a diverse set of vehicular applications including intelligent transportation systems, location-based services (LBS), navigation, as well as a couple of emerging cooperative vehicle-infrastructure systems (CVIS) [12]. Typically, as an important technique, the real-time vehicle positioning system has drawn great attention in the fields of transportation and mobile communications [13]. However, it still faces a big challenge in the areas with inconsistent availability of satellite networks, especially in dense urban areas where the standalone global navigation satellite systems (GNSSs) (e.g., GPS). Even the high precision GNSS equipment associated with a high cost (e.g., DGPS), sometimes provides serious outliers caused by non-line-of-sight (NLOS) (e.g., buildings, walls, trees, vehicles, and more obstructions) and severe multipath issues [14].

The accurate positioning with sub-meter error is significant for vehicles in vehicle ad-hoc networks (VANETs). Because any vehicle with this capability and wireless communications would be able to sense others accurately and simply, which is an extremely essential factor for vehicular collision avoidance, lane change assistance and so on [15, 16]. In [14, 18, 19], the fundamental techniques in positioning systems have been presented based on the real-time measurements of time of arrival (TOA), time difference of arrival (TDOA), direction of arrival (DOA), received signal strength indicator (RSSI), Doppler frequency shift (DFS), fingerprinting, and wireless channel state information (CSI) techniques and so on. Especially, cloud-based wireless network proposed in [20] is expected to provide flexible virtualized network functions for vehicular positioning. Recent researches indicate that these measurements are challenged by some drawbacks varying from complexities of the time synchronization, occupations of the high-bandwidth, to huge costs on the implementations [14]. Although there already exist some location systems, such as those presented in [17], which can achieve lane-level location performance, these systems require the accurate detection on unique driving events through smart phones or the deployment of lane anchors.

To tackle the aforementioned problems, a new class of cooperative positioning (CP) methods that relies on vehicle-to-vehicle (V2V) communications and data fusion filtering [20–22] has been presented in recent years, which can further improve the accuracy of positioning. Actually, such concern raised in CP is the reliability of the localization approaches in heavy multipath and NLOS scenarios, which is similar to that in indoor environment [19, 20].

Because of the low speed of vehicles, the DFS is too difficult to be extracted from noise, and thus for DFS vehicular positioning methods, the standard deviation (STD) of positioning error increases as the relative speed between the target vehicle and the other vehicles decreases. So we will investigate the method to overcome this problem. In this paper, We will focus on the scenario that the neighbor vehicles travel in the opposite direction of the target vehicle (TV), for this case can provide obviously detectable Doppler Effect.

In this paper, we design a CV-enhanced Interacting Multiple Model Extended Kalman filter (CV-IMM-EKF) for vehicular positioning. Firstly a first-order Tylor series expansion is used to transform a nonlinear problem to a linear problem.

Secondly, a multiple-model is used to describe the variation of the DFS measurements. Finally, IMM-EKF is used to estimate the target vehicle's state. The next, we integrate the GPS measurements from both a target vehicle and its neighbors into a vehicular positioning filter and set a relatively conservative number of neighbors for the basic set, which can reduce the dispensable computation complexity. And the information fusion provides a great enhancement compared with GPS-only localization from the simulation results.

The problem to be solved and the analytical models are presented in Sect. 2, the CV-IMM-EKF steps are described in detail in Sect. 3, and the simulation results are revealed and compared in Sect. 4. Finally, Sect. 5 concludes this paper.

2 Problem Statement

The problem to be solved is to estimate the position of a TV moving on a 2-D road, where there are many other neighbors around the TV. All of the vehicles are able to know their own state information, including position, velocity, etc., provided by coarse GPS receiver and they can know the neighbors' state information via vehicular communications as well. Consequently, this case can be treated as a simple but practical CV scenario. A TV is considered as a research object for positioning enhancement based on CV, and a neighbor is considered as the vehicle who is within a certain communication range to the TV and travel in the opposite direction of the TV. Each vehicle is assumed to be with an OBU providing both the DSRC and the DFS measurements [24].

Considering the ith moving vehicle at time instant k with a state vector $\theta_k^i = \left[p_{x,k}^i, p_{y,k}^i, v_{x,k}^i, v_{y,k}^i\right]^T$, $i = 1, \ldots, n_p$, where the $(p_{x,k}^i, p_{y,k}^i)$ and $\left(v_{x,k}^i, v_{y,k}^i\right)$ denote the ith vehicle's position and velocity, respectively, and n_p is the total number of the vehicles driving on the road, and T is a transpose operator. The dynamic state can be modeled by the following system:

$$\theta_k^i = F_{k-1}^i \theta_{k-1}^i + G_{k-1}^i \left(u_{k-1}^i + w_{k-1}^i\right) \tag{1}$$

where F_{k-1}^i is the state transition matrix, and G_{k-1}^i is the noise distribution matrix. u_{k-1}^i is the control vector and w_{k-1}^i is zero-mean white Gaussian noise with covariance matrix Q_{k-1}^i.

For the dynamic model presented by (1), the following observation model can be defined:

$$\Psi_k = h(\theta_k) + \Upsilon_k(r_e) \tag{2}$$

where $h = \left[p_{x,k}^i, p_{y,k}^i, v_{x,k}^i, v_{y,k}^i, \omega_k^1, \ldots, \omega_k^j\right]^T$ is a nonlinear observation vector in terms of θ_k. ω_k^j is the DFS of the received signal from the jth neighbor, $j = 1, \ldots, n_k, n_k < n_p$, and n_k is the total number of the neighbors on the road. $\Upsilon_k(r_e)$ is the observation noise that can be used to describe the M types of observation errors by assuming a set of another covariance matrixes. The transition among M types of the errors is generally modeled as a first-order M-state homogeneous Markov chain r_e, $e = 1, 2, \ldots, M$.

Specifically, assuming that the DFS measurements from the OBU can be modeled in a derivative form of the DSRC carrier frequency, f, as follows:

$$\omega_k^j = -\frac{f}{c} \nabla_t \left(d_k^j + \vartheta_k^j r_e \right) \tag{3}$$

$$d_k^j = \sqrt{\left(p_{x,k} - p_{x,k}^j\right)^2 + \left(p_{y,k} - p_{y,k}^j\right)^2} \tag{4}$$

where c is the speed of light, d_k^j is the relative distance between the TV and its neighbor j, and ϑ_k^j is the DFS observation noise of neighbor j. Substituting (4) into (3) yields

$$\omega_k^j = -\frac{f}{c} \left[\frac{\left(p_{x,k} - p_{x,k}^j\right)\left(v_{x,k} - v_{x,k}^j\right) + \left(p_{y,k} - p_{y,k}^j\right)\left(v_{y,k} - v_{y,k}^j\right)}{\sqrt{\left(p_{x,k} - p_{x,k}^j\right)^2 + \left(p_{y,k} - p_{y,k}^j\right)^2}} \right] + \Upsilon_k(r_e) \tag{5}$$

where $(p_{x,k}^i, p_{y,k}^i)$ and $\left(v_{x,k}^i, v_{y,k}^i\right)$ is the position and velocity vector of the neighbor j. To solve this nonlinear observation function, with the first-order Taylor expansion of (5) around an arbitrary state vector, h can be transformed to a fixed form of matrix, in which all of the components are supposed to obtain from both the GPS and OBU. As a result, the observation model of the TV can be reformulated as a linear one:

$$Z_k = H_k \theta_k + \Upsilon_k(r_e) \tag{6}$$

and with the observation transition matrix:

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ h_k^{11} & h_k^{12} & h_k^{13} & h_k^{14} \\ \vdots & \vdots & \vdots & \vdots \\ h_k^{j1} & h_k^{j2} & h_k^{j3} & h_k^{j4} \end{bmatrix} \tag{7}$$

where

$$\begin{aligned} h_k^{j1} = \nabla_{p_{x,k}}\left(\omega_k^j\right) = -\frac{f}{c} \frac{\left(p_{y,k} - p_{y,k}^j\right)}{\left(d_k^j\right)^3} \\ \left[\left(p_{y,k} - p_{y,k}^j\right)\left(v_{x,k} - v_{x,k}^j\right) + \left(p_{x,k} - p_{x,k}^j\right)\left(v_{y,k} - v_{y,k}^j\right)\right] \end{aligned} \tag{8}$$

$$h_k^{j2} = \nabla_{p_{y,k}}\left(\omega_k^j\right) = -\frac{f}{c}\frac{\left(p_{x,k} - p_{x,k}^j\right)}{\left(d_k^j\right)^3} \left[\left(p_{x,k} - p_{x,k}^j\right)\left(v_{y,k} - v_{y,k}^j\right) + \left(p_{y,k} - p_{y,k}^j\right)\left(v_{x,k} - v_{x,k}^j\right)\right] \tag{9}$$

$$h_k^{j3} = \nabla_{v_{x,k}}\left(\omega_k^j\right) = -\frac{f}{c}\frac{\left(p_{x,k} - p_{x,k}^j\right)}{d_k^j} \tag{10}$$

$$h_k^{j4} = \nabla_{v_{y,k}}\left(\omega_k^j\right) = -\frac{f}{c}\frac{\left(p_{y,k} - p_{y,k}^j\right)}{d_k^j} \tag{11}$$

Based on the aforementioned models from (1) and (6), it is reasonable to assume that F_{k-1}^i and G_{k-1}^i in the system model are invariable at both each time instant and vehicle. Therefore, the position estimation of the TV can be formulated as the problem of linear filtering for M-state jump Markov systems and the model can be simplified as:

$$\begin{cases} \theta_k^i = F\theta_{k-1}^i + G\left(u_{k-1}^i + w_{k-1}^i\right) \\ Z_k = H_k\theta_k + \Upsilon_k(r_e) \end{cases} \tag{12}$$

Because H_k can be estimated by data fusion from both the GPS and OBU at each time instant k, a CV-enhanced Interacting Multiple Model Extended Kalman filter (IMM-EKF) can be deployed.

3 Connected Vehicles-Enhanced Interacting Multiple Model Extended Kalman Filtering for Vehicular Positioning

In this section, we adopt the IMM approach to propose a vehicular positioning enhancement algorithm based on CV. The structure of the vehicular positioning system is illustrated in Fig. 1.

And the steps of this algorithm is as followed:

Step (1) Mixing Probabilities and State Estimates

$$\mu_{k+1,s|t} = \pi_{st}\mu_{k,s}/c_t \tag{13}$$

where $\mu_{k+1,s|t}$ is known as the mixing probability in the IMM estimator, $\mu_{k,s}$ is the probability of the event that the sth motion model is in effect at time step k, $s, t = 1, 2, \ldots, M$, correspond to the s, tth mode of the Markov chain r_e, and

$$c_t = \sum\nolimits_{s=1}^{M} \pi_{st}\mu_{k,s} \tag{14}$$

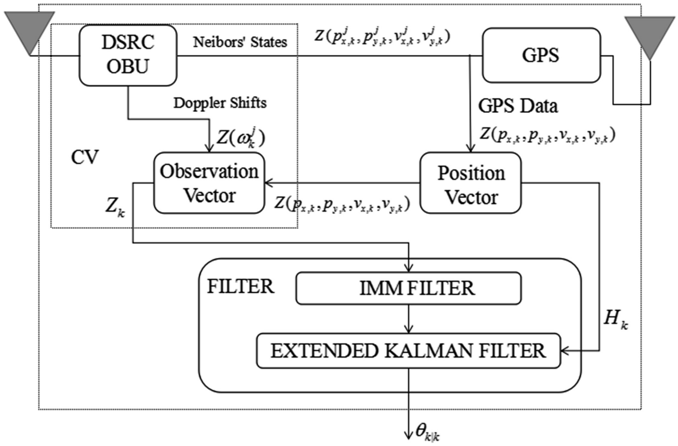

Fig. 1. Vehicular positioning system with information fusion of the DFS and GPS measurements from both itself and the other neighbors

where c_t is a normalization constant and

$$\theta^0_{k|k,t} = \sum\nolimits_{s=1}^{M} \mu_{k+1,s|t}\theta^{0,0}_{k|k,t} \tag{15}$$

$$P^0_{k|k,t} = \sum\nolimits_{s=1}^{M} \mu_{k+1,s|t} \times \left\{ P^{0,0}_{k|k,t} + \left[\theta^{0,0}_{k|k,t} - \theta^0_{k|k,t}\right]\left[\theta^{0,0}_{k|k,t} - \theta^0_{k|k,t}\right]^T \right\} \tag{16}$$

Step (2) Mode Update and Prediction Steps

Calculate $h^{j1}_k, h^{j2}_k, h^{j3}_k, h^{j4}_k$, according to the Eqs. (8)–(11) and then update the observation transition matrix H_k defined in (7).

The CV-IMM-EKF advanced prediction is given by

$$\theta_{k|k-1,t} \approx F_k\theta_{k-1|k-1,t} = F\theta_{k-1|k-1,t} \tag{17}$$

and the State prediction error covariance matrix is as follows:

$$P_{k|k-1,t} \approx F_k P_{k-1|k-1,t}(F_k)^T + Q_{k-1} = FP_{k-1|k-1,t}F^T + Q_{k-1} \tag{18}$$

From the previous data, the CV-IMM-EKF gain is given by

$$\begin{aligned} K_k = {} & P_{k|k-1,t}H^T_k(\varphi_k(N)) \\ & \times \left\{ H_k(\varphi_k(N))P_{k|k-1,t}H^T_k(\varphi_k(N)) + R_k(r_e(N)) \right\}^{-1} \end{aligned} \tag{19}$$

where $\varphi_k(N)$ and $r_e(N)$ are functions of N and can change the dimension of the observation transition matrix H_k and the covariance matrix R_k, respectively.

The CV-IMM-EKF update steps are given by

$$\theta^0_{k|k,t} = \theta^0_{k|k-1,t} + K_k\left\{Z_k - H_k(\varphi_k(N))\theta^0_{k|k-1,t}\right\} \tag{20}$$

$$P^0_{k|k,t} = P^0_{k|k-1,t} - K_k\left\{Z_k - H_k(\varphi_k(N))\theta^0_{k|k-1,t} + R_k(r_e(N))\right\}K_k^T \tag{21}$$

The CV-IMM-EKF prediction steps are given by

$$\theta^0_{k+1|k,t} = F\theta^0_{k|k,t} + G\mu_{k,t} \tag{22}$$

$$P^0_{k+1|k,t} = F\theta^0_{k|k,t}F^T + GQG^T \tag{23}$$

The likelihood function $\Lambda_{k,t}$ and predicted mode probability $\mu_{k,t}$ are given by

$$\Lambda_{k,t} = \mathcal{N}\left(\begin{matrix} Z_k - H_k(\varphi_k(N))\theta^0_{k|k-1,t}; \\ 0, H_k(\varphi_k(N))P^0_{k|k-1,t}H_k^T(\varphi_k(N)) + R_k(r_e(N)) \end{matrix}\right) \tag{24}$$

$$\mu_{k,t} = \Lambda_{k,t}c_t/c \tag{25}$$

where c is a normalizing constant defined as follows:

$$c = \sum\nolimits_{t=1}^{M} \Lambda_{k,t}c_t \tag{26}$$

Step (3) Estimates Combination

$$\theta_{k|k} = \sum\nolimits_{t=1}^{M} \mu_{k,t}\theta_{k|k,t} \tag{27}$$

$$P_{k|k} = \sum\nolimits_{t=1}^{M} \mu_{k,t} \times \left\{P_{k|k,t} + \left[\theta_{k|k,t} - \theta_{k|k}\right]\left[\theta_{k|k,t} - \theta_{k|k}\right]^T\right\} \tag{28}$$

4 Numerical Study

4.1 Simulation Scenario

A basic set with N neighbors for the TV can be formed through Algorithm CV-IMM-EKF. Considering a section of urban roads, which is with a width of four lanes (each one is 3.5 m wide) and a length of one kilometer. It is assumed that the traffic density of the road section is 20 vehicies/km and the average speed of traffic is generated stochastically in duration from 50 km/h to 60 km/h following a uniform distribution. The initial positions of the neighbors are generated stochastically on the road following a uniform distribution as well. The vehicle dynamics described in (12) is with

$$F = \begin{bmatrix} I & \Delta tI \\ O & I \end{bmatrix}, G = \begin{bmatrix} \frac{1}{2}\Delta t^2 I \\ \Delta tI \end{bmatrix} \tag{29}$$

where I is a 2×2 identity matrix, O is a 2×2 zero matrix, and Δt is the sampling period. The control vector in (12) is $u^i = [0\ 0.01]^T$. The noise vector $w^i_{k-1} = \left[\sigma_{ax,k-1}, \sigma_{ay,k-1}\right]^T \sim \mathcal{N}(0, Q)$, with covariance matrix $Q = diag\left[\sigma^2_{ax}, \sigma^2_{ay}\right]$, where the elements $\sigma_{ax,k-1} = \sqrt{0.99/2}$ and $\sigma_{ay,k-1} = \sqrt{0.01/2}$ are the acceleration noises along the X and Y-axis, respectively, with standard deviation (STD) in $\mathrm{m/s^2}$. The covariance matrix $R(r_e)$ of observation noise $\Upsilon_k(r_e) \sim \mathcal{N}(0, R(r_e))$ is described as a first-order Markov chain switching between two models $R(r_1) = diag\left[\sigma^2_{px}, \sigma^2_{py}, \sigma^2_{vx}, \sigma^2_{vy}, \sigma^2_{\omega 1}(r_1), \ldots, \sigma^2_{\omega N}(r_1)\right]$ and $R(r_2) = diag\left[\sigma^2_{px}, \sigma^2_{py}, \sigma^2_{vx}, \sigma^2_{vy}, \sigma^2_{\omega 1}(r_2), \ldots, \sigma^2_{\omega N}(r_2)\right]$, of which the elements are with STDs in units of $\mathrm{m}, \mathrm{m/s^2}$ and Hz. The transition probability for this Markov chain is $\pi_{r_1 r_2} = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}$ and their initial probability is $\mu_0 = [0.5\ 0.5]$. According to the achievable performance discussed in [12, 19], as the number of the neighbors is increasing, the performance enhancement can be less obvious and lead to more additionally computational burden. Therefore, we set $N = 4$, which is a relatively conservative number of the neighbors for the basic set, which is mentioned in Algorithm CV-IMM-EKF.

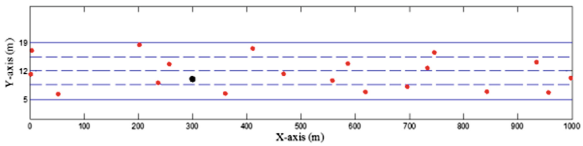

Fig. 2. Initial scenario (Color figure online)

The vehicles that start at the first two lanes from the bottom move towards the positive direction of the X-axis in Fig. 2. On the contrary, the vehicles that start at the first two lanes from the top move towards the negative direction of the X-axis. The 'black dot' and 'red note' denote the initial positions of the TV and the neighbors, respectively. The TV starts at position (300,5) in m, with the initial velocity vector (60,0) in $\mathrm{m/s^2}$. However, because of the system noise and control vector set in the dynamics model, the actual velocity is changing slightly over the sampling period.

In the simulations, the sampling period and length are taken to be 0.2 s and 100, respectively, and the communication range of the DSRC is 300 m. As the DFS measurements presented in [19, 22], the Probability Density Function (PDF) of the DFS is approximately zero-mean asymmetric Gaussian with the left and right STDs of 100 Hz and 120 Hz, when the vehicles travel at the speed of 60 km/h, broadcasting the DSRC packets with a frequency of 5.89 GHz and a rate of 100 packets/s. It is worth noting that the PDF of the DFS remains a fairly consistent estimation from LOS to NLOS.

Considering the noise of the DFS measurements as zero-mean Gaussian with two states of STDs: $\sigma_{wN}(r_1) = 100\,\text{Hz}$ and $\sigma_{wN}(r_2) = 120\,\text{Hz}$. Specifically, the state of the observation noise remains unchanged in r_1 between 0 to 6 s, and changes in the following 10 s to r_2. Finally, the state changes back to r_1 for another 4 s. The position and velocity measured by GPS are assumed to be added noise with the variance $\left(\sigma_{px} = \sqrt{200/2m}, \sigma_{py} = \sqrt{200/2m}\right)$ and $\left(\sigma_{vx} = \sqrt{15/2m}, \sigma_{vy} = \sqrt{15/2m}\right)$, respectively.

4.2 Simulation Results

From the Fig. 3, the Mean-CV-EKF has a higher order of magnitude than the Mean-CV-IMM-KF and the Mean-GPS, and change curve fluctuates greatly. So the interacting multiple model is necessary and we should ignore the huge error on numerical value and put the next two in the Fig. 4 to compare the errors.

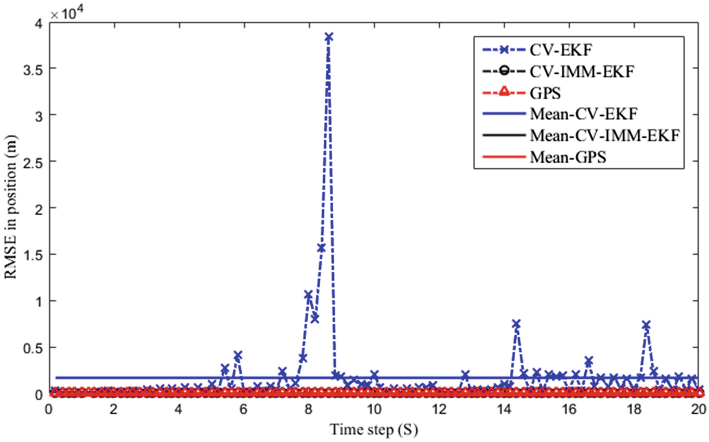

Fig. 3. CV-EKF, CV-IMM-EKF and GPS performance in positioning error

To quantify the performance of the proposed approach, the root mean square error (RMSE) of vehicular positioning is calculated to assess the closeness of the estimated trajectory $\left(\hat{p}_{x,k}, \hat{p}_{y,k}\right)$ to the true trajectory $\left(p_{x,k}, p_{y,k}\right)$ at each time instant over $N_m =$ 500 Monte Carlo simulations. In (28), $\left(\hat{p}_{x,k}(m), \hat{p}_{y,k}(m)\right)$ denotes the estimated position vector in the mth Monte Carlo run at the kth step.

$$RMSE = \sqrt{\frac{1}{N_m}\sum\nolimits_{m=1}^{N_m}\left[\left(\hat{p}_{x,k}(m) - p_{x,k}\right)^2 + \left(\hat{p}_{y,k}(m) - p_{y,k}\right)^2\right]} \tag{30}$$

The performance comparison between the proposed CV-IMM-EKF and the GPS-only approach is shown in Fig. 3 with respect to the RMSE in distance. It is obvious that the proposed CV-IMM-EKF method outperforms the GPS alone

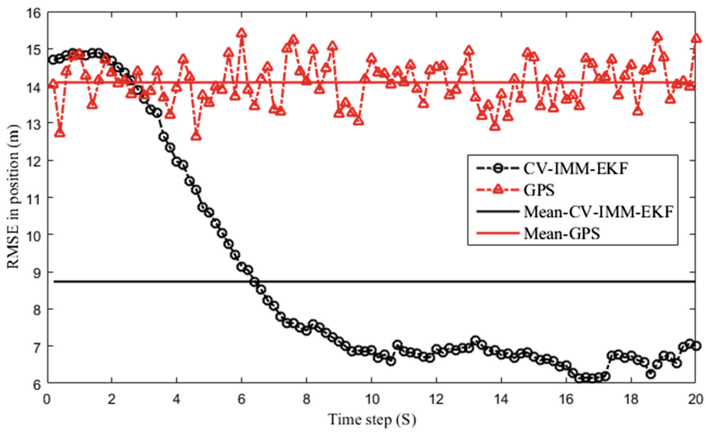

Fig. 4. CV-IMM-EKF and GPS performance in positioning error

localization. In order to indicate the enhancement of vehicular positioning of the proposed approach, the enhancement indicator μ is calculated as follows:

$$\mu = \left(1 - \frac{A\_RMSE}{B\_RMSE}\right) \times 100\% \tag{31}$$

The enhancement of vehicular positioning is shown in Table 1. Compared to the GPS-based localization, the proposed CV-IMM-EKF approach achieves the enhancement of $\mu = 40.15\%$.

Table 1. CV-IMM-EKF and GPS error comparison

Method	RMSE	Enhancement
GPS	14.3268	N/A
CV-IMM-EKF	8.5032	40.15%

If *A_RMSE* is better than *B_RMSE*, μ will be greater than zero. And the increase of μ is link to the good performance of *A_RMSE*. By describing the transition of the measurement noise as a first-order M-state jump Markov chain, the proposed CV-IMM-EKF approach has been proved to achieve better performance in a scenario that is similar to a practical one.

5 Conclusion

In this paper, a vehicular positioning algorithm has been proposed. The observation transition matrix and the covariance matrix of observation noise are updated by the fusion data at each time instant with the assistance of CV, which provide additional useful information compared to the traditional filtering approach. Finally, the simulation results show that the proposed approach outperforms the GPS-based localization.

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