Cooperative Vehicle Localization Base on Extended Kalman Filter In Intelligent Transportation System

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***Abstract*—In this paper, we proposed an Extended Kalman filter (EKF) method for multi-vehicle cooperative localization using Global Positioning System (GPS) data and inter-vehicle position information. Each cooperative vehicle uses its own GPS receiver to estimate its position. And inter-vehicle position information is obtained by the Dedicated Short-range Communication (DSRC). This proposed method includes two processes. Firstly, the GPS positioning information of cooperative vehicles are collected to get the positioning matrix. Then the EKF is applied to the matrix to further improve the positioning accuracy. In the simulation, we analyze the impact of different numbers of neighbor vehicles on positioning accuracy and the performance of the proposed method has been verified.**

Keywords—Cooperation vehicle positioning; GPS receiver; Extended Kalman filter; positioning matrix

I. INTRODUCTION

As vehicles become smart and automated, various applications in the Intelligent Transportation System (ITS), such as real time estimation of traffic conditions, collision warning system, lane departure warning, are all for enhancing the safety and efficiency of driving [1]. Most of such applications rely on the accurate and reliable knowledge of vehicles localization. The vehicle navigation techniques includes the GPS, Global Navigation Satellite System(GLONASS), Galileo and BeiDou system(BDs), which can provide users with location and speed information[2]. But these techniques cannot provide precise location information in the ITS [3,4]. In this paper, we focus on finding some method to further improve the location accuracy of GPS.

One of the most common ways to improve accuracy for localization is called “cooperative positioning (CP)”[5]. Currently, several techniques have been proposed to enhance the performance of GPS in ITS[6]. A classical approach to enhance the GPS localization accuracy is differential GPS (DGPS)[7] which corrects the errors of the measured pseudo-ranges [8]. Although the accuracy can be improved, it requires deploying a large number of stations and additional communication cost between the fixed station and the moving receiver. Another approach to boost the accuracy of GPS localization is map matching[9]. It has been used to estimate the vehicle position on a digital road map, which limits the estimated position of a vehicle in relation to roads [10].

In this article, we aim to improve the target vehicle position estimate by combining the position and velocity of neighbor vehicles. The vehicles use their GPS receiver to estimate their position. Using the Dedicated Short-range Communication (DSRC), the vehicles can sense the motion status of other vehicles and exchange information mutually. The target vehicle obtains the positioning information of neighbor vehicles, and then uses the positioning information to construct a positioning matrix. Then we can obtains the position estimate by using Extended Kalman filter (EKF) and positioning matrix. Finally, the target vehicle gets more accuracy position. The simulation results shows that our proposed method has more accuracy and less uncertainty.

The rest of paper is organized as follows. After introducing the proposed method in Section II, the simulation results are discussed in Section III and in Section IV, we draw the conclusion.

II. PROPOSED METHOD

It is assumed that every vehicle has the GPS receiver and that by using DSRC, all the inter-vehicle distances will be measured. All range sensors and GPS receivers are the same.

A. Motion Model Algorithm Framework

A vehicle motion model is as follow:

$$\mathbf{X_{k+1}} = f(\mathbf{X_k}, \mathbf{U_k}) \tag{1}$$

where position of vehicle $\mathbf{X_k}$=$[x_k\ y_k\ \theta_k]^T$, x_k is the position at the time k in the x direction, y_k is the position at the time k in the y direction and θ_k is the azimuth angle.$\mathbf{U_k} = [v_k\ a_k\ \Phi_k]^T$, v_k is the velocity, a_k is the acceleration and Φ_k is the steer angle at the time k.

We assume that the vehicle moves in a straight line within one sampling period and the a_k is regarded as a fixed value. The error on the GPS positions is a zero mean white Gaussian noise. So the motion model is:

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$$\mathbf{X_{k+1}} = f(\mathbf{X_k}, \mathbf{U_k}) = \begin{cases} x_{k+1} = x_k + (v_k t + \frac{1}{2} a_k t^2)\, cos(\theta_k + \Phi_k) \\ y_{k+1} = y_k + \left(v_k t + \frac{1}{2} a_k t^2\right) sin(\theta_k + \Phi_k) \\ \theta_{k+1} = \theta_k + \Phi_k \end{cases} \quad (2)$$

where t is sampling period, $\mathbf{U_k} = [v_k\ a_k\ \ \Phi_k]^T$ also have a zero mean white Gaussian noise.

We define:

$$\mathbf{A_k} = \frac{\partial f(\mathbf{X_k}, \mathbf{u_k})}{\partial \mathbf{X_k}} = \begin{bmatrix} 1 & 0 & -\left(v_k t + \frac{1}{2} a_k t^2\right) sin(\theta_k + \Phi_k) \\ 0 & 1 & (v_k t + \frac{1}{2} a_k t^2)\, cos(\theta_k + \Phi_k) \\ 0 & 0 & 1 \end{bmatrix} \quad (3)$$

where $\mathbf{A_k}$ is the Jacobi matrix of $f(\mathbf{X_k}, \mathbf{U_k})$ at $\mathbf{X_k}$.

$$\mathbf{B_k} = \frac{\partial f(\mathbf{X_k}, \mathbf{U_k})}{\partial \mathbf{X_k}}$$

$$= \begin{bmatrix} t\, cos(\theta_k + \Phi_k) & \frac{1}{2} t^2 cos(\theta_k + \Phi_k) & -\left(v_k t + \frac{1}{2} a_k t^2\right) sin(\theta_k + \Phi_k) \\ t\, sin(\theta_k + \Phi_k) & \frac{1}{2} t^2 sin(\theta_k + \Phi_k) & (v_k t + \frac{1}{2} a_k t^2)\, cos(\theta_k + \Phi_k) \\ 0 & 0 & 1 \end{bmatrix} \quad (4)$$

where $\mathbf{B_k}$ is the Jacobi matrix of $f(\mathbf{X_k}, \mathbf{U_k})$ at $\mathbf{U_k}$.

Now we can get the motion model for the target vehicle V_0 at the time k :

$$\mathbf{X_{0(k+1)}} = f(\mathbf{X_{0k}}, \mathbf{U_{0k}}) = \begin{cases} x_{0(k+1)} = x_{0k} + (v_{0k} t + \frac{1}{2} a_{0k} t^2)\, cos(\theta_{0k} + \Phi_{0k}) \\ y_{0(k+1)} = y_{0k} + \left(v_{0k} t + \frac{1}{2} a_{0k} t^2\right) sin(\theta_{0k} + \Phi_{0k}) \\ \theta_{0(k+1)} = \theta_{0k} + \Phi_{0k} \end{cases} \quad (5)$$

And the motion model for the neighbor vehicle V_j at the time k is:

$$\mathbf{X_{j(k+1)}} = f\left(\mathbf{X_{jk}}, \mathbf{U_{jk}}\right) = \begin{cases} x_{j(k+1)} = x_{jk} + (v_{jk} t + \frac{1}{2} a_{jk} t^2) \cos(\theta_{jk} + \Phi_{jk}) \\ y_{j(k+1)} = y_{jk} + \left(v_{jk} t + \frac{1}{2} a_{jk} t^2\right) \sin(\theta_{jk} + \Phi_{jk}) \\ \theta_{j(k+1)} = \theta_{jk} + \Phi_{jk} \end{cases} \quad (6)$$

B. Observation Model Algorithm Framework

1) The 2 Vehicle Case

Now, we think about the 2-vehicle case. There is one vehicle V_j around the target vehicle. At the time k, the vehicle V_j is observed by the target vehicle V_0. The observation model of the position is expressed as:

$$\mathbf{Z_{jk}} = h\left(\mathbf{X_{0k}}, \mathbf{X_{jk}}\right) \quad (7)$$

The relative measurement between two vehicles is the distance d_{0j} between vehicle V_0 and vehicle V_j and the azimuth angle φ_{0j} that vehicle V_0 relative to vehicle V_j. The relative measurement is shown in Fig.1.

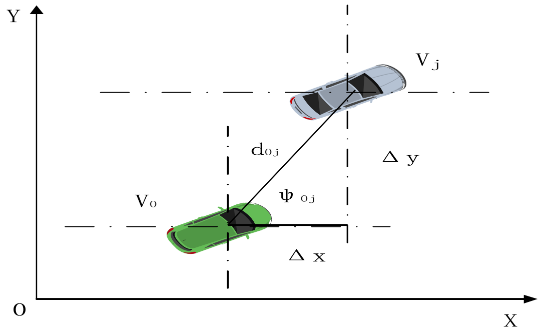


Fig. 1. Vehicle moves from time k to time k+1

The relative measurement is expressed as

$$\mathbf{Z_{jk}} = h(\mathbf{X_{0k}}, \mathbf{X_{jk}}) = \begin{bmatrix} d_{0jk} = \sqrt{(x_{jk} - x_{0k})^2 + (y_{jk} - y_{0k})^2} \\ \varphi_{0jk} = tan^{-1}\left(\frac{y_{jk} - y_{0k}}{x_{jk} - x_{0k}}\right) \end{bmatrix} \quad (8)$$

These observations are affected by the zero mean white Gaussian noise, and the observations are independent of each other and have the same variance. The relative distance is measured as the variance σ_d^2, and for the relative azimuth measurement, the variance is σ_a^2.

Let us define, $\mathbf{H_{jk}}$is the Jacobi matrix of $h\left(\mathbf{X_0}, \mathbf{X_j}\right)$ at $\mathbf{X_0}$. It is expressed as

$$\mathbf{H_{jk}} = \begin{bmatrix} \frac{-(x_{jk} - x_{0k})}{\sqrt{(x_{jk} - x_{0k})^2 + (y_{jk} - y_{0k})^2}} & \frac{-(y_{jk} - y_{0k})}{\sqrt{(x_{jk} - x_{0k})^2 + (y_{jk} - y_{0k})^2}} & 0 \\ \frac{y_{jk} - y_{0k}}{(x_{jk} - x_{0k})^2 + (y_{jk} - y_{0k})^2} & \frac{-(x_{jk} - x_{0k})}{(x_{jk} - x_{0k})^2 + (y_{jk} - y_{0k})^2} & 1 \end{bmatrix} \quad (9)$$

2) The N Vehicles Case

We consider the situation of N vehicles now. The key idea is to fuse the different vehicle information, so that the target vehicle can use those information to get a more accurate location. We treat N neighbor vehicles and target vehicle as a system.

Let us define:

$$\mathbf{X_k} = \left[X_{01k} \cdots X_{0jk} \cdots X_{0Nk}\right]_{N*1}^T \quad (10)$$

$$\mathbf{U_k} = \left[U_{01} \ \cdots U_{0jk} \cdots U_{0Nk}\right]_{N*1}^T \quad (11)$$

where, $\mathbf{X_{0jk}}$ is the position of the target vehicle V_0 when V_0 observes V_j at time *k*. and $\mathbf{U_{0jk}}$ is the velocity information of the target vehicle V_0 when V_0 observes V_j at time *k*.

So we have:

$$\mathbf{A_k} = \begin{bmatrix} A_{X_{1k}} & 0 & \cdots & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 \\ \vdots & 0 & A_{X_{jk}} & 0 & \vdots \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & A_{X_{Nk}} \end{bmatrix}_{N*N} \tag{12}$$

Similarly ,we get

$$\mathbf{B_k} = \begin{bmatrix} B_{U_{1k}} & 0 & \cdots & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 \\ \vdots & 0 & B_{U_{jk}} & 0 & \vdots \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & B_{U_{Nk}} \end{bmatrix}_{N*N} \tag{13}$$

We define $\mathbf{Z_k}$ is the observation model of *N* neighbor vehicles, which is expressed as:

$$\mathbf{Z_k} = \left[Z_{1k}, Z_{2k} \cdots Z_{jk} \cdots Z_{Nk}\right]^T \tag{14}$$

where,

$$\mathbf{Z_{jk}} = h(\mathbf{X_0}, \mathbf{X_j}) = \begin{bmatrix} d_{0j} = \sqrt{\left(x_{jk} - x_{0k}\right)^2 + \left(y_{jk} - y_{0k}\right)^2} \\ \varphi_{0jk} = tan^{-1}\left(\frac{y_{jk} - y_{0k}}{x_{jk} - x_{0k}}\right) \end{bmatrix}$$

$$(j = 1,2,\dots,N) \tag{15}$$

Let us define, $\mathbf{H_k}$ is the Jacobi matrix of $\mathbf{Z_k}$ at $\mathbf{X_0}$. And using our (9), we can obtain:

$$\mathbf{H_k} = \begin{bmatrix} H_{1k} & 0 & \cdots & 0 & 0 \\ 0 & \ddots & 0 & 0 & 0 \\ \vdots & 0 & H_{jk} & 0 & \vdots \\ 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & H_{Nk} \end{bmatrix}_{N*N} \tag{16}$$

C. The Algorithm Based On Extended Kalman Filter

According to the motion and observation equations, the extended Kalman filter algorithm makes an estimate of the signal required to be processed. Extended Kalman filter equations is[11]:

$$\mathbf{\hat{P}_{k+1}} = \mathbf{A} * \mathbf{P_k} * \mathbf{A^T} + \mathbf{B} * (\mathbf{T} * \mathbf{Q}) * \mathbf{B^T} \tag{17}$$

$$\mathbf{K_{k+1}} = \mathbf{\hat{P}_{k+1}} * \mathbf{H} * \left(\mathbf{R} + \mathbf{H} * \mathbf{\hat{P}_{k+1}} * \mathbf{H^T}\right)^{-1} \tag{18}$$

$$\mathbf{P_{k+1}} = \left(\mathbf{I} - \mathbf{K_{k+1}} * \mathbf{H_k^T}\right) * \mathbf{\hat{P}_{k+1}} \tag{19}$$

$$\mathbf{\hat{X}_{k+1}} = \mathbf{A} * \mathbf{\bar{X}_k} + \mathbf{B} * \mathbf{U_k} \tag{20}$$

$$\mathbf{\bar{X}_{k+1}} = \mathbf{\hat{X}_{k+1}} + \mathbf{K_{k+1}} * (\mathbf{Z_{k+1}} - \mathbf{\hat{Z}_{k+1}}) \tag{21}$$

where **A** is the state transition matrix; **Q** is the noise covariance matrix; **P** is the system variance matrix; **H** is the observation matrix; **R** is the noise covariance matrix of the observation; **Z** is the observation vector at current moment; **K** is the Kalman gain matrix; and **I** is the unit matrix.

We assume that the initial state of target vehicle V_0 and the initial variance $\mathbf{P_0}$, the sampling interval **S**, vehicle GPS error variance **Q**, and observation error variance **R**.

So ,we can obtain that:

$$\mathbf{\hat{P}_{k+1}} = \mathbf{A_k} * \mathbf{P_k} * \mathbf{A_k^T} + \mathbf{B_k} * (\mathbf{S} * \mathbf{Q}) * \mathbf{B_k^T} \tag{22}$$

$$\mathbf{K_{k+1}} = \mathbf{\hat{P}_{k+1}} * \mathbf{H_k} * \left(\mathbf{R} + \mathbf{H_k} * \mathbf{\hat{P}_{k+1}} * \mathbf{H_k^T}\right)^{-1} \tag{23}$$

$$\mathbf{\hat{X}_{k+1}} = \mathbf{A_k} * \mathbf{\bar{X}_k} + \mathbf{B_k} * \mathbf{U_k} * \mathbf{S} \tag{24}$$

$$\text{where, } \mathbf{\hat{X}_{k+1}} = \left[\hat{X}_{0(k+1)}, \hat{X}_{0(k+1)} \cdots \hat{X}_{0(k+1)}\right]_N^T \tag{25}$$

The prediction of observation is expressed as

$$\mathbf{\hat{Z}_{k+1}} = \left[\hat{Z}_{1(k+1)}, \hat{Z}_{2(k+1)} \cdots \hat{Z}_{j(k+1)} \cdots \hat{Z}_{N(k+1)}\right]^T$$

$$(j = 1,2,\dots,N) \tag{26}$$

$$\text{where, } \mathbf{\hat{Z}_{j(k+1)}} = h_j(\mathbf{\hat{X}_{0(k+1)}}, \mathbf{X_{j(k+1)}}) \tag{27}$$

Finally, we can obtain the system state update,

$$\mathbf{\bar{X}_{k+1}} = \mathbf{\hat{X}_{k+1}} + \mathbf{K_{k+1}} * (\mathbf{Z_{k+1}} - \mathbf{\hat{Z}_{k+1}}) \tag{28}$$

After extended Kalman filtering, we get the matrix $\mathbf{\bar{X}_{k+1}}$ containing *N* position estimation information of target vehicle at the time k +1. The final position estimation $\bar{X}_{0(k+1)}$ of target vehicle at the moment *k*+1 is expressed as:

$$\mathbf{\bar{X}_{0(k+1)}} = \frac{\mathbf{\bar{X}_{(k+1)}}}{N} \tag{29}$$

III. SIMULATION RESULTS

In this section, in order to evaluate the performance of the proposed method, we considered there are 4 vehicles around the target vehicle V_0 at the time *k*, which is shown in Fig.2. Each vehicle equipped with a GPS receiver, and used DSRC to obtain position information of neighbor vehicles. These vehicles are moving along a road in a straight line and their acceleration a_{jk} are constant but not the same, so their relative positions are changing. We also assume that there are no communication failures and communication delays. The results presented in this article are based on Monte Carlo simulations. The simulation is repeated 500 times.

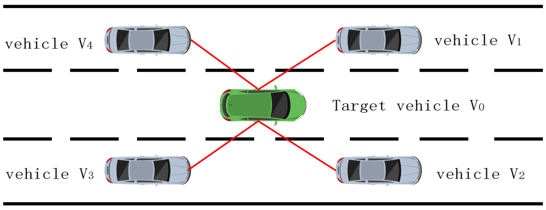
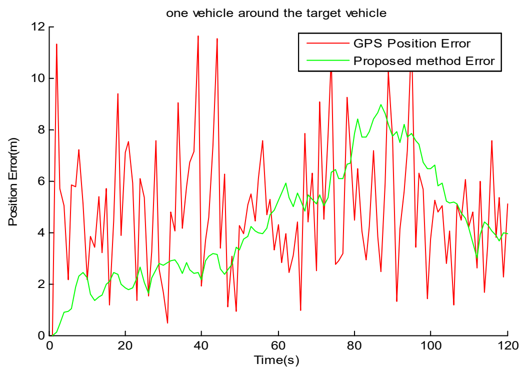


Fig. 2. Neighbor vehicles V_1, V_2, V_3, V_4 communicate with the target vehicle V_0 by DSRC.

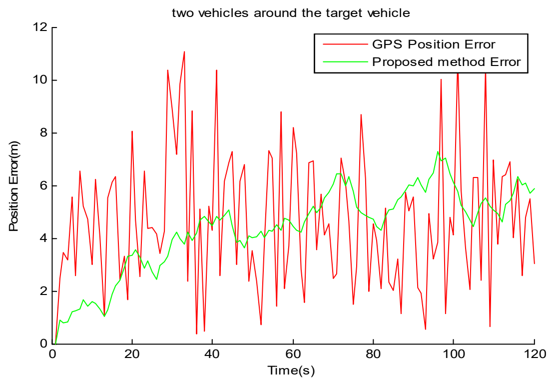
To investigate the effect of the number of adjacent vehicles on position error, we applied the proposed method to the target vehicle with different number of neighbor vehicles. Fig.3 shows the position errors change with time when the number of neighbor vehicles is different. We can find that the position error of the proposed method is much smaller than GPS. As surrounding vehicles increase, the position error is getting smaller and smaller obviously. Comparing the two methods, with the increase of the neighbor vehicles, the position error of proposed method drops significantly while the GPS error hardly changes. Therefore, the performance of proposed method is far superior to the GPS method. And the more surrounding vehicles it has, the better performance it improves.

IV. Conclusions

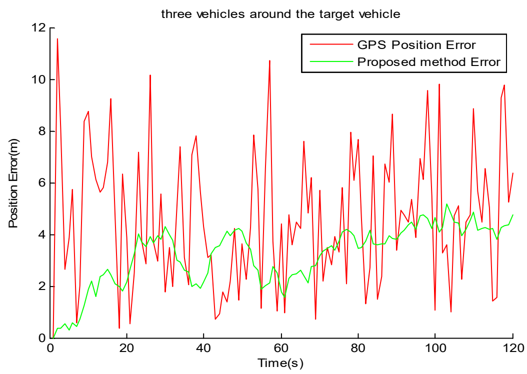
In this paper, we proposed a cooperative vehicle localization



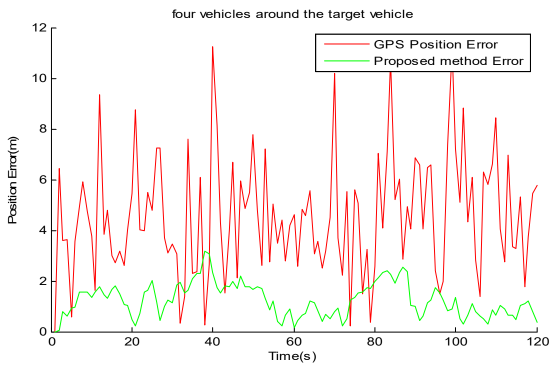
(a)



(b)



(c)



(d)

Fig. 3. The relation of the position error with the number of vehicles around the target vehicle: (a) one vehicle around the target vehicle, (b) two vehicles around the target vehicle, (c) three vehicles around the target vehicle, (d) four vehicles around the target vehicle

using Extended Kalman filter for GPS data. Every vehicle uses their GPS receiver to estimate its position and uses DSRC to obtain relative position information including inter-vehicle distance and relative orientation of neighboring vehicles, then fusing those information to get more accuracy position. To evaluate the efficiency of the proposed method, we simulate our algorithm to estimate positions of target vehicle and compare the result with GPS. The results of proposed method makes the positioning error reduce greatly, and significantly decreases the positioning uncertainty. The results of different number of vehicles around the target vehicle indicates that with the number of vehicles around the target vehicle increases, the corresponding position error of our estimate decrease. Therefore, by adding more vehicles in our algorithm, we can achieve higher accuracy and less uncertainty.

References

[1] A.Arghavan, M.V.Reza, M. G.Jesus, and R.Michael Buehre, "Improving GPS-based vehicle positioning for Intelligent Transportation Systems," *IEEE Intelligent Vehicles Symposium Proceedings*, pp.1023-1029, Jun 2014.

[2] L.JoonHoo, H.C.Kwang, K.LaWoo, K.L.Hyung, "Land vehicle positioning in urban area by integrated GPS/BeiDou/OBD-II/MEMS IMU," *Proceedings of the International Conference on Intelligent Transportation Engineering*, pp.176-180,Aug 2016.

[3] T.M.Rafael, A.Z.I.Miguel, U.M.Benito, and F.G.S.Antonio, "High-integrity IMM-EKF-based road vehicle navigation with low-cost GPS/SBAS/INS," *IEEE Transactions on Intelligent Transportation Systems*, vol.8, no.3, pp.491-511, Sep2007.

[4] L.Kai, B.L,Hock, F.Emilio, J.Houling, and C.S.L.Victor,"Improving positioning accuracy using GPS pseudorange measurements for cooperative vehicular localization," *IEEE Transactionson Vehicular Technology*, vol.63, no.6, pp.2544-2556, Jul 2014.

[5] A.Nima, T.B.Asghar, and G.D.Andrew, "Relative Positioning Enhancement in VANETs: A Tight Integration Approach," *IEEE Transactions on Intelligent Transportation Systems*, vol.14, no.1, pp.47-55, Mar 2013.

[6] A.Nima, and G.D.Andrew ,"Cooperative Positioning for Vehicular Networks: Facts and Future," *IEEE Transactions on Intelligent Transportation Systems*, vol.14, no. 4, pp.1708-1717, Dec 2013.

[7] R.Mohsen, G.Denis, and G.Dominique," Dynamic base station DGPS for cooperative vehicle localization," *Proceedings of the International Conference on Connected Vehicles and Expo*, pp.781-785,Nov 2014.

[8] W.C.Lie, W.S. Hsiang, and F.T.Ming, "Finding Lane Positions of Vehicles: Infrastructure-Less Cooperative Lane Positioning Based on Vehicular Sensor Networks, " *IEEE Vehicular Technology Magazine*, vol. 10, no.4, pp.70-80, Dec 2015.

[9] R.Mohsen, G. Denis, and G.Dominique, "Vehicular cooperative map matching," *Proceedings of the International Conference on Connected Vehicles and Expo*, pp.799-803, Nov 2014.

[10] U.P.Ali, T.Oguz, and A.Tankut, "Particle filter vehicle localization and map-matching using map topology," *Proceedings of the Intelligent Vehicles Symposium*, pp.248-253, Jun 2011.

[11] J.Saeed, L.Cristian, and F.M. Sami, "State estimation of induction motor drives using the unscented Kalman filter," *IEEE Transactions on Industrial Electronics*, vol.59, no.11, pp. 4207-4216, Nov.2012.