Pervasive and Mobile Computing 40 (2017) 139–155

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

journal homepage: www.elsevier.com/locate/pmc

Improved vehicle positioning algorithm using enhanced innovation-based adaptive Kalman filter

Fuad A. Ghaleb [a,*], Anazida Zainal [a], Murad A. Rassam [a,b], Ajith Abraham [c]

[a] Information Assurance and Security Research Group, Faculty of Computing, Universiti Teknologi Malaysia, 81310, Johor, Malaysia
[b] Faculty of Engineering and Information Technology, Taiz University, 6803, Taiz, Yemen
[c] Machine Intelligence Research Labs, Auburn, 2259, WA 98071-2259, USA

ARTICLE INFO

Article history:
Received 13 August 2016
Received in revised form 17 April 2017
Accepted 8 June 2017
Available online 21 June 2017

Keywords:
VANET
ITS
Vehicle positioning
Kalman filter
Adaptive filtering
Error estimation
Innovation-based adaptive filtering

ABSTRACT

Accurate positioning is a key factor for enabling innovative applications to properly perform their tasks in various areas including: Intelligent Transportation Systems (ITS) and Vehicular Ad Hoc Network (VANET). Vehicle positioning accuracy depends heavily on positioning techniques and the measurements condition in its surroundings. Several approaches which can be used for improving vehicle positioning accuracy have been reported in literature. Although some positioning techniques have achieved high accuracy in a controlled environment, they suffer from dynamic measurement noises in real environments leading to low accuracy and integrity for some VANET applications. To solve this issue, some existing positioning approaches assume the availability of prior knowledge concerning measurement noises, which is not practical for VANET. The aim of this paper is to propose an algorithm for improving accuracy and integrity of positioning information under dynamic and unstable measurement conditions. To do this, a positioning algorithm has been designed based on the Innovation-based Adaptive Estimation Kalman Filter (IAE_KF) by integrating the positioning measurements with vehicle kinematic information. Following that, the IAE_KF algorithm is enhanced in terms of positioning accuracy and integrity (EIAE_KF) in order to meet VANET applications requirements. This enhancement involves two stages which are: a switching strategy between dead reckoning and the Kalman Filter based on the innovation property of the optimal filter; and the estimation of the actual noise covariance based on the Yule–Walker method. An online error estimation model is then proposed to estimate the uncertainty of the EIAE_KF algorithm to enhance the integrity of the position information. Next Generation Simulation dataset (NGSIM) which contains real world vehicle trajectories is used as ground truth for the evaluation and testing procedure. The effectiveness of the proposed algorithm is demonstrated through a comprehensive simulation study. The results show that the EIAE_KF algorithm is more effective than existing solutions in terms of enhancing positioning information accuracy and integrity so as to meet VANET applications requirements.

1. Introduction

The Vehicular Ad Hoc Network (VANET) aims to support a wide range of applications such as Intelligent Transportation Systems (ITS) applications for traffic efficiency, road safety, and different entertainment services [1–3]. Current VANET applications research trends include, among others: cooperative collision warning (CCWS) [4]; intersection safety [5]; cooperative

* Corresponding author.
E-mail address: fuadeng@gmail.com (F.A. Ghaleb).

http://dx.doi.org/10.1016/j.pmcj.2017.06.008

driving [6]; cooperative adaptive cross control (CACC) [7]; and driver assistance systems (ADAS) [8]. These applications have huge potential benefits to save tens of thousands of lives and billions of dollars each year [9]. A comprehensive list of innovative VANET application scenarios was analyzed in [2,9]. Vehicle position is vital for the performance of most if not all VANET applications [10–13]. The accuracy requirements of the position information depend on the application under consideration [14,15]. For example, safety applications in smart and unmanned vehicles (UV), CCWS and ADAS demand lane level accuracy in which the acceptable accuracy should not be more than one meter [16]. Other applications such as navigation, traffic efficiency and entertainment applications require road level accuracy with a five meter margin of error [14].

The availability of continuous and accurate positioning information has a direct impact on applications and network performance [15,17]. In order to ensure acceptable VANET performance, three important requirements should be achieved by positioning unit as follows [17–20]. *First*, a vehicle should maintain acquisition of continuous positioning information at all times [18,19]. *Second*, positioning algorithms should be sufficiently robust to accommodate vehicle dynamicity and measurements condition in the surrounding environment [18,20]. *Third*, vehicles should have an immediate and clear indication about positioning accuracy i.e. vehicle should be able to quantify the uncertainty of the acquired position information online [17,18]. The first requirement is related to the availability of the position information, while the second and third requirements are related to the accuracy of the positioning algorithm. While availability can be solved by redundancy and complementary fusion techniques such as incorporating Dead Reckoning (DR) and Global Positioning System (GPS) [14], the accuracy of the positioning algorithms still presents a challenge. The positioning accuracy can be described by the robustness of positioning algorithms under dynamic environments and the integrity of the acquired positioning information. The positioning integrity is a measure of trust that can be placed on the accuracy of the position information [20,21]. The integrity of the positioning information can be measured by quantifying the uncertainty of the acquired position [17,18]. The need for both high positioning accuracy and integrity is principal for VANET applications and services [17,22]. Unfortunately, these two requirements have not been well-investigated in previous positioning algorithms suggested for VANET.

Many approaches have been proposed for positioning, including: GPS-Based; Dead Reckoning-Based; Network-Based; Cellular-Based; Image/Video-Based; and Map Matching-Based [11,14]. However, the positioning accuracy of such approaches is not sufficient to fulfill accuracy requirements for VANET applications [11,14,23]. Integration of GPS with DR or/and Map Matching is a prevailing approach in navigation systems [24–28]. However, most of these integrated approaches are designed for navigation purposes where concern about the availability and accuracy requirements is quite far removed from the requirements of VANET safety applications and other services. Kalman Filter (KF) is the most common fusion algorithm used for integrating positioning approaches for VANET [12,29–31]. KF gives an optimal positioning estimate if prior information about the surrounding noises is known and belongs to Gaussian distributions [32,33]. However, inadequate or poor prior assumption of the process and measurement noise covariance can result in unreliable results and sometimes filter divergence which affects the accuracy and integrity of the positioning algorithms [34–36]. Vehicles in VANET often move in harsh environments in which the positioning techniques are susceptible to stochastic noises which is far from being a Gaussian distribution [20,37]. The use of deterministic noise statistics assumption in data fusion algorithms is a major drawback in stochastic environments [38,39]. The concept of adaptive fusion using the Adaptive Kalman Filter (AKF) was used to solve the problem of a stochastic noise environment by adaptively estimating the process and measurement of noise covariance (Q) and (R) respectively [33,35,36,38]. Several papers have examined the use adaptive Kalman filtering in navigation applications. Most of the reported researches in this regard focus on innovation-based adaptive estimation (IAE). This IAE_KF filter has been adopted for some applications in vehicular navigation and mobile robot control such as in [25,40]. However, most of the algorithms concerned only adapting the process noise covariance (Q) in low cost Inertial Navigation Systems (INS). Meanwhile, it is common assumption that the measurement noise covariance (R) is stationary. In contrast, this paper focuses on adapting the measurement noise covariance (R) for VANET environment. To the best of our knowledge, such adaption has never been intended for positioning accuracy enhancement for VANET environment in which variety of noise types can be expected.

The contributions of this paper can be summarized as follows. *First*, Innovation-based Adaptive Estimation Kalman Filter (IAE_KF) is used to adapt both measurement noise covariance and process noise covariance so as to contain the change in the measurement conditions in VANET environment. *Second*, the IAE_KF filter is further enhanced to produce EIAE_KF. The enhancement involves two stages, specifically: design switching strategy between the Kalman filter correction and dead reckoning based prediction phases; and online estimating the measurement noise covariance using Yule–Walker approach [41]. This provides better control of Kalman gain to switch between the dead reckoning (DR) and Kalman Filter (KF) correction phases and thus enhances the overall performance of the estimation in different types of noises. In contrast to the previous adaptation, the theoretical covariance is substituted by the actual innovation covariance directly. *Finally*, an error model is proposed based on the covariance matrices of the proposed EIAE_KF and DR error models. The error model is used to online estimate the accuracy of the projected position which is an important requirement for many applications in VANET [17]. Unlike previous studies, the proposed solution neither relies on conventional rigid assumptions nor does it need particular sensors, neighbors cooperation or intensive infrastructure.

The rest of this paper is organized as follows. In Section 2, related works are reviewed. Section 3 describes the mathematical preliminaries of standard Kalman filter (SKF) and Adaptive Kalman filter (AKF). Section 4 describes the proposed adaptive algorithm based on enhanced innovation adaptive estimation (EIAE_KF). It also describes an online positioning error estimation model. Section 5 presents a performance evaluation of the proposed algorithms, simulation results, and discussions. The paper is concluded in Section 6.

2. Related work

Significant research efforts have been devoted to data fusion methods for position information accuracy enhancements in VANET. Parker and Valaee [42] proposed a Kalman Filter-based cooperative positioning algorithm in which vehicles obtain their inter-vehicle distances through RSSI and the initial position via GPS. Vehicles then exchange their measurements in order to improve the positioning estimates. In each step, the estimated position is verified through velocity and map constraints so as to provide integrity of the estimation. Alam et al., in [26,43] proposed a positioning approach based on tight integration of Inertial Navigation Sensors (INS) with GPS measurements using Kalman filter and cooperative positioning techniques. Relative distances, GPS measurements and INS sensors were combined using Kalman filter. The cooperative positioning concept introduced by Parker and Valaee [42] was used for the integration. The process noise covariance (Q) was assumed as being a small value since vehicle kinematics is a more accurate technique than the GPS measurements and the GPS noises (R) were assumed to be stationary and known.

Alam et al., in [16,23] showed through simulation that the accuracy of cooperative positioning has a direct relationship with vehicle density [42]. Similar to Parker and Valaee [42], Alam et al. [16] argued that exchanging measurements ranges should not be restricted to vehicles in the same clusters; instead, all information from the neighboring vehicles should be engaged. The ranging measurements of all neighboring vehicles were collected in one time epoch and "piggybacked" to a safety message of the next time epoch. Thus, it is not necessary to concentrate heavily on exchanging ranging measurements within the cluster. In both positioning algorithms [16,42], Kalman Filter was used to minimize the errors of inter-vehicle-distance measurements, while at the same time ensuring that the road and lane constraints were met. However, the measurements noises of both GPS and RSSI were assumed to be stationary and known with normal distribution, while neither RSSI nor GPS measurement noises remain stationary all the time [11,20]. Kalman Filter has also been employed in GPS-Free positioning approaches where vehicles compute their positions based on three references (anchors) such as Road Side Units (RSU) [44,45] or neighboring vehicles [13,16]. Khattab, Fahmy [46] proposed a positioning scheme using single RSU. A process of vehicle kinematics was integrated using Kalman Filter for complementary fusion. The main drawback of the proposed solution is that the lateral position information was neglected, which consequently had a serious effect on VANET safety applications and other security services. In addition to its cost ineffectiveness, the resultant noises were assumed to be stationary and Gaussian.

Adaptive Kalman Filter (AKF) has been developed mainly for adapting the measurement noises (R) and process noise (Q) in order to provide an optimal estimate [22,33]. There are two types of adaptation approaches for implementing Adaptive Kalman Filter (AKF). The first approach focuses on building error models that better describe the characteristics of the error by linking the error with phenomena such as the GPS error model in [16]. This approach is difficult for VANET because the positioning noises have spatial and temporal properties as well as dependency on the ranging techniques. The second approach focuses on online estimation of the error parameters through a proper use of available process and measurement information. In the latter approach, two methods were suggested to the adaptive Kalman filtering problem, namely: Multiple-Model-based Adaptive Estimation (MMAE) and Innovation-based Adaptive Estimation (IAE) [33,38]. In the former, a bank of Kalman filters run in parallel under different assumptions of Q and R. Based on the computed posteriori probabilities of each filter, a weighted sum of the estimated state of each individual filter is considered as the final estimation of the scheme. As measurements evolve with time, the adaptive scheme learns which filter is correct. MMAE is inefficient for real time applications due to its high complexity and resource consuming [47]. In the latter (which is the most adaptive filter reported), the adaptation is done by utilizing the innovation sequence (or the residual) to estimate the statistical information of Q and R. It is reported that the most suitable form of adaptive Kalman Filtering is the Innovation-based Adaptive Estimation (IAE) which belongs to the second approach [33,35,36,38]. The innovation sequence is the difference between the prediction and the real measurements. IAE was originally proposed by Mehra et al., [35] for estimating unknown stationary (Q) and (R). It was modified by Lobies et al., [22] for autonomous underwater vehicle (AUV) navigation using fuzzy logic techniques. Adaptation of covariance's matrices is done based on the sign and value of the last residual. If the sign of the residual is positive and larger than a positive threshold, then the covariance matrices are decreased; otherwise, it is increased.

Hide et al., in [47] compared three adaptive Kalman filtering algorithms namely: process noise scaling, the Adaptive Kalman Filter (AKF), and Multiple Model Adaptive Estimation (MMAE) to improve estimation of process noise (Q) in low cost INS. Process noise scaling is reported as unstable for dynamic noise environment while MMAE is inefficient for real time applications due to its significant time processing. Meanwhile, IAE_KF algorithm showed low performance. In the three algorithms the focus was on adapting the process noise covariance Q in marine trial environment in which all the elements in the state vector are highly uncertain. Similarly, Ding et al., [48] introduced a method for tuning the process noise covariance Q. The main assumption for estimating Q is that the measurement noise R is stationary and known. In contrast, the measurement noise in VANET environment is more dynamic whereas the process noise is more stable than marine trial's environment. Authors in [49,50], proposed adaption methods that utilized the GPS error prediction model to predict R then estimate Q, accordingly. GPS error prediction model uses Horizontal Dilution of Precision (HDOP) to predict the precision of the GPS position. It is very difficult to accurately obtain the positioning error through GPS error model, due to many disturbance sources in VANET environment [25]. Moreover, vehicles may use many positioning techniques based on their availability, therefore it is difficult to build accurate error model for each positioning technique separately.

ZhiWen, XiaoPing [51] proposed a robust algorithm for outlier measurements called RIAE_KF which employs Chi-square to evaluate the innovation sequence normality. The abnormal values of the innovation vector were revised by multiplying these values by small factors. However, reducing the value of abnormal innovations vector in AKF leads to underestimate the actual measurement noises. Thus, the filter produces inaccurate estimations in dynamic noise environments. Chatterjee and Matsuno [40] proposed a neuro fuzzy model for adapting the measurement noises for solving Simultaneous Localization and Mapping (SLAM) problems in mobile robots. Similar to a previous finding [22], an adaptation strategy was performed to reduce mismatching between the theoretical covariance of the innovation sequences and the corresponding actual covariance of the innovation sequence. The previous adaptation approaches such as [22,40] assumed that the noise is stationary and normally distributed but unknown. This assumption is not always true in a vehicular environment where noise statistics rapidly change over time and in relation to the environment [20,52]. In addition, a correlated noise that may cause filter divergence is highly possible in many urban environments [26,43].

To conclude, the existing solutions improved vehicular positioning under controlled environments where the measurement noises can be assumed to be stationary. However, when the measurement noises become stochastic, accuracy varies based on the surrounding conditions which threaten positioning algorithm integrity, and thus decrease applications and services performance. Integration positioning information from infrastructure (such as RSUs) or spatial non-radio-based ranging sensors (such as cameras) are limited to particular areas and are actually inefficient in terms of implementation costs and computational requirements. Most of the solution that use AKF focused mainly on the adapting process noise covariance (Q), because they were intended to be used for navigation applications in marine or airplane environments. A few attention have been focused in VANET environment where the dynamic model is more accurate and the process noise covariance (Q) is more stable comparing with the observation model and the measurement noise covariance which have more stochastic behavior due to the vehicles movement in harsh environment. Moreover, in most previous research the uncertainty of acquired information is ignored, while it is important measure for many applications in VANET. In this paper, to enhance the accuracy and integrity of positioning information, use of the adaptive Kalman filter is suggested to adjust the measurement noise covariance (R) online. Yule–Walker approach is used to estimate the measurement noise covariance (R). It relates the autoregressive model (AR) parameters to the auto-covariance of the innovation sequence. In a scenario where the innovation is totally corrupted, the positioning algorithm uses dead reckoning on a vehicle motion model to predict the positioning information. As a result, the positioning information accuracy and integrity are improved.

3. Kalman filter preliminaries

In this section, the concept of Standard Kalman Filter (SKF) and the Innovation Based Adaptive Estimation Kalman Filter (IAE_KF) which is the focus of improvement in this paper are presented.

3.1. Standard Kalman filter (SKF)

Kalman filter relies on two models, namely: a system or process model that describes the state of transition and it is used for prediction; and an observation or measurement model that describes the relationship between state and observations. To drive Kalman filter algorithm, consider a linear system with a discrete linear state model and a discrete linear measurement model as follows.

$$\begin{aligned} x_k &= F\check{x}_{k-1} + Bu_k + w_k \\ y_k &= Hx_k + v_k, \end{aligned} \tag{1}$$

where x_k is the state vector, with transition matrix F obtained from a vehicle's kinematic model (motion equation) and current forces, Bu_k which represents external forces that act on a vehicle's motion and direction such as driver behaviors, w_k is the system noise with covariance Q, y_k is the measurement model (or observation model) that maps the current vehicle state x_k to the measurement, while v_k refers to the measurement noises with covariance R. SKF algorithm can be derived in four steps as shown in Fig. 1, where $\check{x}^-_{k|k-1}$ is a priori vehicle state vector, $\check{P}^-_{k|k-1}$ is a priori state error covariance, and $\check{y}_k$ is the expected measurement. $\check{y}_k$ is obtained by projecting the up to date prediction state $\check{x}^-_{k|k-1}$ onto the measurement space using mapping matrix H. $\check{z}_k$ is the innovation vector resulted from subtracting the actual measurement y_k and predicted measurement $\check{y}_k$. $\check{x}^+_{k|k}$ is the final estimated state vector (a posteriori state vector) which can be obtained after the Kalman Gain K_k is calculated by utilizing the theoretical covariance S_k and $\check{P}^+_{k|k}$ is a posteriori covariance matrix which is used in the next iteration.

3.2. Innovation-Based Adaptive Estimation (IAE_KF)

SKF assumes the normality and availability of prior knowledge Q and R. However, in dynamic situation, Q and R change dynamically. Innovation-Based Adaptive Estimation (IAE_KF) is the most reported adaptation for dynamic noises in linear systems [38]. IAE_KF utilizes the innovation (or residual) sequence $\check{z}_k$ to estimate noise covariance in order to correct state estimation [35]. The innovation reflects the discrepancy between the predicted value $\check{y}_k$ and the actual measurement y_k. If $\check{z}_k$ is zero, then both the measurement model and the prediction model are in complete agreement [53]. The occurrence of data with statistics different from the a priori information will first show up in the innovation sequence $\check{z}_k$ [22]. Therefore, $\check{z}_k$ can

Algorithm 1: SKF Algorithm

```
// Step 1: Initialization Phase
Initialize x̆⁺_{k|k−1}, Q, R, P̆_{k−1}, F, H
FOR Each Time Epoch k
// Step 2: State Prediction Phase
    x̆⁻_{k|k−1} = F x̆⁺_{k−1|k−1}
    P̆⁻_{k|k−1} = F P̆⁺_{k−1|k−1} F^T + Q
// Step 3: Measurement Update Phase
    Obtain new measurement y_k
    ž_k = y_k − y̆_k = y_k − H x̆⁻_{k|k−1}
    S_k = (H P̆⁻_{k|k−1} H^T + R)
// Step 4: State Correction Phase
    K_k = P̆⁻_{k|k−1} H^T S_k^{−1}
    x̆⁺_{k|k} = x̆⁻_{k|k−1} + K_k ž_k
    P̆⁺_{k|k} = (I − K_k H) P̆⁻_{k|k−1}
LOOP CONTINUE
```

Fig. 1. Pseudocode for the standard Kalman filter (SKF).

reflect the filter status such as optimal, sub-optimal or divergence [33]. The actual covariance is defined as an approximation of the innovation sequence $\check{z}_k$ through averaging inside a moving window of size m [33].

$$\hat{C}_k = \frac{1}{m}\sum_{i=k-m+1}^{k} \hat{z}_i\hat{z}_i^T. \tag{2}$$

The theoretical covariance of the innovation sequence is defined as follows [22].

$$S_k = E\left[\hat{z}_i\hat{z}_i^T\right] = H\check{P}^-_{k|k-1}H^T + R_{k-1}. \tag{3}$$

By matching the estimated covariance with the theoretical covariance of the noise according to Standard Kalman Filter (SKF), the observation noise covariance R_k and process noise covariance $\hat{Q}_k$ can be approximated as follows. Details of the proofs can be found in [33].

$$\hat{R}_k = \hat{C}_k - H\left(\check{P}^-_{k|k-1}H^T\right) \tag{4}$$

$$\hat{Q}_k = K_k\hat{C}_kK_k^T. \tag{5}$$

If the measurement noise w_k is un-stationary or correlated with the time (i.e. the w_k is not Gaussian), KF randomly behaves with high uncertainty according to the relationship between Q and R. This high uncertainty in the filter could be hidden from the filter statistics, i.e. the error covariance $\check{P}^+_{k|k}$ will deceive the filter and bring significant errors [54].

4. The proposed positioning algorithm (EIAE_KF)

The proposed positioning algorithm is explained in three sections as follows. In Section 4.1, vehicle kinematic information is integrated with positioning measurements using the Standard Kalman filter (SKF) in a tight coupling approach for provision of position availability, accuracy, and consistency. In doing so, vehicles can maintain continuous knowledge about their positioning information through a process of dead reckoning when the positioning information is not available. Kalman filter is used for both integration and accuracy enhancement by removing the stationary noise. Stationary noise is referred to as Noise Type I in this paper. Then, the SKF is modified to include the Innovation-based Adaptive Estimation algorithm (IAE_KF) to estimate and update process and measurement noise covariance matrices for enhancing accuracy in non-stationary noise variance conditions. This is referred to as Noise Type II in this paper. In Section 4.2, an Enhanced Innovation-based Adaptive Estimation Kalman filter algorithm (EIAE_KF) is proposed based on the innovation property of the optimal filtering for correlated noises and non-stationary noise statistics. This is referred to as Noise Type III in this paper. A switching strategy is designed to switch between Kalman filter prediction (dead reckoning) and a correction model to eliminate the effect of correlated error and enhance the stability of the filter in a dynamic noise environment. In Section 4.3, an uncertainty error model is introduced to monitor the integrity of the positioning information. Fig. 2 shows a sketch of the proposed positioning algorithm components. Each component is described in the subsequent sections.

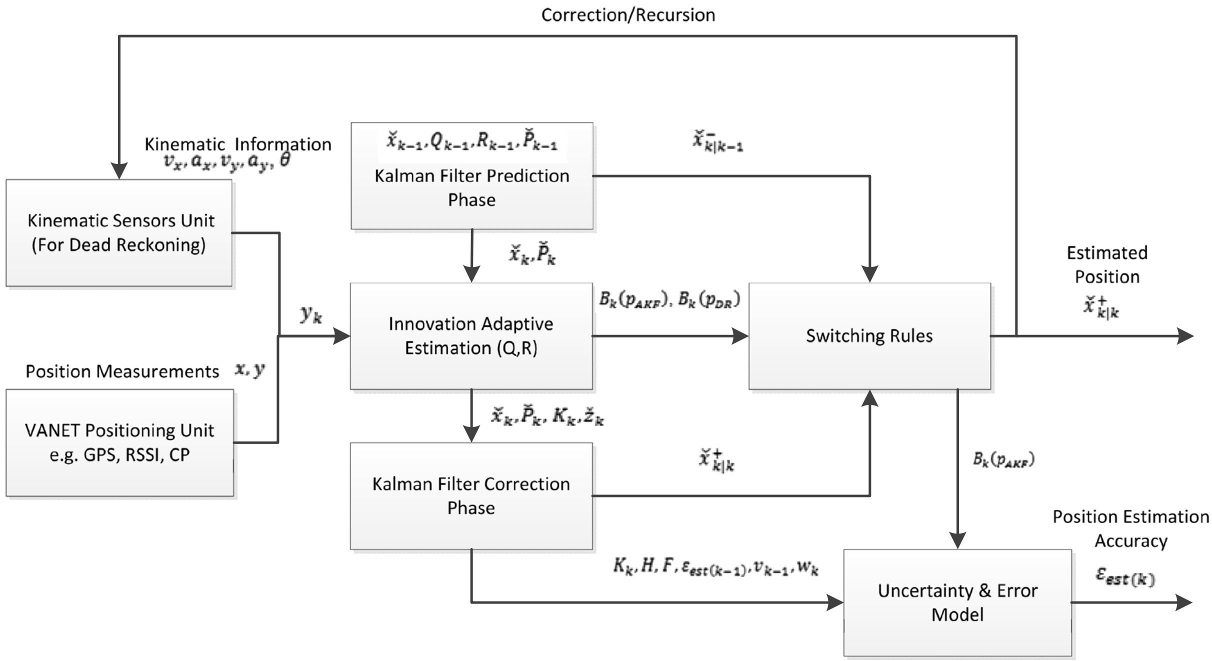


Fig. 2. Components of the proposed positioning algorithm.

4.1. *Integrating kinematic information with positioning information using IAE_KF*

When design Kalman Filter algorithm, many versions of vehicle dynamic or kinematic models can be used as a process model [55]. The process noise covariance (Q) can evolve with time due to the uncertainties in the process model. In this paper, the process model is called "dead reckoning" (DR), because DR is employed for prediction. Similarly, an observation model can be selected based on underline ranging sensors such as Radio-based sensors [42]. The high dynamicity of a vehicular environment causes the measurement sensors to be subject to stochastic noises in which the measurement noise covariance R changes dynamically. According to Drawil and Basir [53], the kinematic information can be pre-processed and then used as input for Kalman filter as linear components. Given that most vehicles are low-maneuvering objects, and driver behavior actions are slower than the updating rate of kinematic information sensors, therefore the kinematic model can be considered as a linear time-invariant system. The kinematic information is usually obtained by way of a vehicle inertial navigation system (INS) or Inertial Management Units (IMU) through sensors such as wheel sensor encoder, odometer, Gyroscopes and other sensors [25,26]. In addition, vehicles VANET in such as passenger's cars are more controllable than aircraft and marine vehicles due to low impact of external forces on the vehicles movement such as wind and water. Eq. (6) demonstrates the kinematic information that was used in the observation model.

$$\text{Observation from vehicle kinematics sensors} \begin{cases} v_x = v * \cos(\theta) \\ v_y = v * \sin(\theta) \\ \theta = \dfrac{v}{L} * \tan(\delta) \\ a_x = dv_x/dt \\ a_y = dv_y/dt, \end{cases} \tag{6}$$

where v_x, v_y, θ, δ, L, a_x and a_y refer to vehicle latitude speed, longitude speed, vehicle direction (angle relative to global axis), wheel angle, vehicle length, latitude acceleration and attitude acceleration, respectively. All this information is assumed to be accurately measured from vehicles sensors. Thus, the position of a vehicle at any point can be described by the model in Eq. (14), namely, the Discrete form of Continues Wiener Process Acceleration Model with Jerk (DWPA-Jerk) [56]. DWPA-Jerk can be considered as the result of a random process described by discrete-time Markov process as follows.

$$\text{DWPA} - \text{Jerk} \begin{cases} p_{x(t)} = p_{x(t-1)} + v_{x(t-1)}\Delta t + \dfrac{a_{x(t-1)}\Delta t^2}{2} \\ p_{y(t)} = p_{y(t-1)} + v_{y(t-1)}\Delta t + \dfrac{a_{y(t-1)}\Delta t^2}{2}. \end{cases} \tag{7}$$

In most cases, a kinematic model can accurately describe the past behavior of vehicle movement. DWPA-Jerk was used as the prediction model and performs dead reckoning. Dead reckoning uses the kinematic model in Eq. (7) to predict vehicle

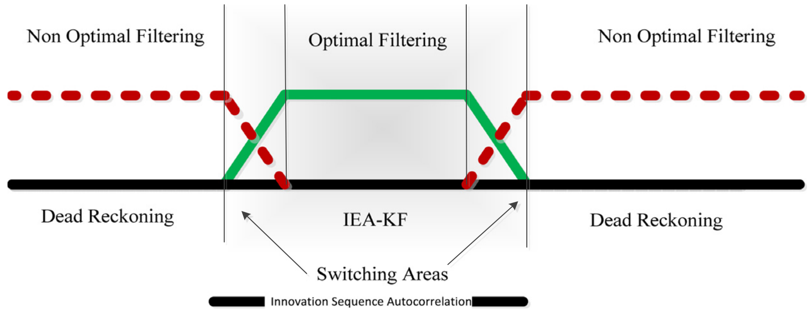


Fig. 3. Switching decision.

future position by projecting its current $p_{x(t)}$ over the time. In this paper, a vehicle system model (Kinematic or Dynamic) is integrated with any positioning unit available on the vehicle board such as GPS, RSUs, or V2V Cooperative Positioning and so on. The vehicle state vector and observations vector can be written as follows.

$$\begin{cases} x_k = \left[p_x, p_y, v_x, v_y, a_x, a_y\right]^T \\ y_k = \left[p_{x(GPS)}, p_{y(GPS)}, v_{x(IMU)}, v_{y(IMU)}, a_{x(IMU)}, a_{y(IMU)}\right]^T. \end{cases} \tag{8}$$

According to Eq. (8), vehicles dynamic sensors and positioning sensors are combined in a single centralized Kalman filter, so that any inconsistency between them will be first showed in the innovation sequence. Thus, the Eqs. (1) in Section 3.1 are used as the process and observation model, respectively. The transition matrix F and the initialization of the process noise covariance Q can be obtain from (DWPA-Jerk) [57]. For vehicles such as passengers' cars, Q is related to driver behavior, vehicle status, and road conditions respectively [57]. External forces such as inertia, winds, and others can be neglected [43]. However, the observation model is limited when a priori statistics are used to model the measurement errors that have time varying characteristics (e.g. non-stationary noise environment). Meanwhile, the mapping matrix H can be assigned to the unity $I_{6\times6}$ as all the elements in the state vector are measured.

4.2. Enhanced Innovation-based Adaptive Estimation (EIAE_KF)

When the actual error covariance $\hat{C}_k$ (see Eq. (2)) is not equivalent to the theoretical error covariance S_k,the innovation sequence will misrepresent the error statistics leading to significant errors or filter divergence. This situation occurs when the error is correlated or is non-Gaussian. The proposed idea by which to solve this problem involves the design of a switching strategy between the prediction model DR and the correction model based on the correlation and the means of the recent innovation sequence. The DR is used whenever the autocorrelation of the innovation sequence become high. Meanwhile, Q should be increased with time until the innovation sequence becomes stationary. When the innovation sequence returns back to its randomness once again, KF adaptively converges to the optimal and so on. During the optimality of KF, Q is fixed on its initial values. Thus, the drifts of dead reckoning are reinitialized to minimum each time the filter is in its optimality state. The stability of main positioning such as GPS over long periods of time provides the perfect complement to correct the dead reckoning DR drift. In contrast, unstable position measurements will result in large errors over longer periods of time due to sensor biases and integration inaccuracies [24]. The process noise covariance is assumed to be known while the measurement noise covariance is unknown. Fig. 3 explains the switching strategy based on the innovation property of the Kalman Filter [35]. The dotted line shows the non-optimal areas of the filter.

To apply the previous idea, one needs to collect the innovation sequence that best describes the measurement noises. Assuming $\widehat{p_{GPS}}_k$ is the position of the vehicle according to GPS measurement, at the same time epoch k and $\widehat{p_{DR}}_k$ refer to the position of the vehicle calculated through DR using real time vehicle kinematic information and previous known true position. The following equation can be obtained.

$$\forall \Delta T, \widehat{p_{GPS}}_k = p_{GT(k)} + \varepsilon_{GPS(k)} \tag{9}$$

$$\forall \Delta T, \widehat{p_{DR}}_k = p_{GT(k)} + \varepsilon_{DR(k)}. \tag{10}$$

Hence $p_{GT(k)}$ is the true position of the vehicle while $\varepsilon_{GPS(k)}$, and $\varepsilon_{DR(k)}$ refer to the associated error of the positioning techniques. For example, GPS and Dead Reckoning are located respectively in the time epoch k; whereas $p_{GT(k)}$ denotes the ground truth position information. A vehicle can obtain both positions and GPS error through the DR by taking the difference between DR and GPS output. Assuming $p_{(k-1)}$ is the ground truth position at the time epoch $(k-1)$ then the current position $p_{DR(k)}$ can be obtained using the Eq. (7). Where Δt is assumed to be the sampling rate of vehicles kinematic sensors, it is assumed to have a rating of 0.1 s in this paper according to the positioning update standards [58,59]. Thus, the real kinematic information can be employed to accurately track vehicle positions. Hence, the innovation $\check{z}_k$ can be obtained by differencing $p_{DR(k)}$ and $p_{GPS(k)}$ as follows.

$$\check{z}_k = p_{TRUE(k)} + \varepsilon_{DR(k)} - p_{TRUE(k)} - \varepsilon_{GPS(k)} = \varepsilon_{DR(k)} - \varepsilon_{GPS(k)}. \tag{11}$$

Hence $\varepsilon_{DR(k)}$ is very small at the beginning of the period. Thus, the innovation $\check{z}_k$ at time epoch k can be approximated by $\varepsilon_{GPS(k)}$. After $\check{z}_k$ is obtained, three steps should be completed in order to improve the positioning accuracy. The first step is to test the randomness of the innovation sequence $\check{z}_k$ (the optimality test). The second step is maintaining the switching strategy between the DR prediction model and the AKF correction model. The former can be achieved by timely fitting of the measurements on the vehicle trajectories starting from assumption of known and accurate position and measurement noises with Gaussian distribution. The most accurate position was obtained from previous estimation using either DR or AKF in their optimal situations. The switching rules work according to the innovation property of Kalman Filter, the estimation is optimal if the innovation sequence is Gaussian white noise sequence [35]. The third step aims to estimate the measurement noise covariance (R). The estimation of the covariance considers the correlation between the innovation sequences. If the correlation is high, the measurement noise covariance should be maximized to decrease the effect of measurement noises on the final estimation.

Step 1: Testing innovation randomness

Testing for optimality of the Kalman Filter can be achieved using many different statistical test methods of innovation sequence. Such methods include: Durbin–Watson, Pearson, Kendall rank, or Spearman rank [41]. The purpose of this test is to answer the null hypothesis whether $\check{z}_k$ is the result of white noise process or not. According to Chatfield in [41], the autocorrelation coefficient of the error sequence summarizes the strength of the linear relationship between present and past error values. If 95% of the ρ_k is bounded by $\pm 2/\sqrt{m}$, then the time series will comprise completely random white noise with zero mean; hence, m is the sample size. In that case, the innovation sequence $\check{z}_k$ is a stationary random process with zero mean (white noise).

$$\rho_k = \frac{\sum_{k=1}^{m-1}(\check{z}_k - \mu_\varepsilon)(\check{z}_{k+1} - \mu_\varepsilon)}{\sum_{k=1}^{m}(\check{z}_k - \mu_\varepsilon)^2} \tag{12}$$

ρ_k is the sample autocorrelation coefficients which measure the correlation between observations at different times (lags). According to Mehra [36], if ρ_k greater than $-2/\sqrt{m}$ or ρ_k smaller than $+2/\sqrt{m}$, then the filter is unbiased and the estimation is optimal. Thus, the auto-covariance can be calculated by estimating the variance of the sample according to the Eq. (21) [33].

$$\sigma_\varepsilon^2 = \hat{C}_k = \frac{1}{m} \sum_{i=k-N+1}^{k} \hat{z}_i \hat{z}_i^T \tag{13}$$

In this situation, the dead reckoning drift can be re-initialized and the vehicle will then have strong belief (high certainty) of the correctness of its location estimation accuracy. In contrast, if ρ_k is smaller than $-2/\sqrt{m}$ > or ρ_k greater than $+2/\sqrt{m}$, this implies that the error is correlated (precision biased). In this case, AKF localization should be eliminated. Correlation in the innovation sequence indicates either the KF in its sub-optimality or divergences. In both cases, there will be high uncertainty for vehicles regarding the correctness of location estimation accuracy. The following rules represent the switching strategy between dead reckoning and AKF according to error statistics analysis.

Step 2: Trigging switching rules

Let us assume that the $B_k(p_{AKF})$ is the vehicle belief regarding the correctness of the vehicle position information obtained from AKF at time epoch k. Then, vehicle belief can be defined according to the following function.

$$B_k(p_{AKF}) = \begin{cases} 1 & -2/\sqrt{m} < \rho_k < +2/\sqrt{m} \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

Similarly, let us assume that $B_k(p_{DR})$ is the vehicle belief about the correctness of the position information that was obtained from DR at time epoch k. The belief $B_k(p_{DR})$ can be modeled as follows.

$$B_k(p_{DR}) = \begin{cases} 1 & |\rho_k| > +2/\sqrt{m} \text{ and } \sigma_{DR(k)} < \alpha \\ 0 & \sigma_{DR(k)} \geq \alpha. \end{cases} \tag{15}$$

where α is the square root of the measurement covariance norm. The norm of the measurements covariance is used to expend the switching interval of the AKF as long as AKF is more effective than the DR. The drift $\sigma_{DR(k)}$ could be a function of many parameters, including environmental conditions, such as: weather; wind; precision of Kinematic Sensor; driver behavior; vehicle state and so on. However, it can be approximated through a function of time. According to [11], the standard deviation of the error will take the form of the following equation:

$$\sigma_{DR} = \sqrt{\sigma_{p_i}^2 + t^2 * \sigma_v^2}. \tag{16}$$

Step 3: Estimating measurement noise covariance

In VANET, information about measurement noise statistics (R) is usually unknown and stochastic, because it depends on the environmental noises that hit the measurement device. The information about process noise statistics (Q matrix) is known, because it depends on the well-known motion models created for the vehicle dynamic system with known inputs. Moreover, the performance of a Kalman filter does not depend on the selection of absolute levels of Q and R but on their relative relationship. By considering the Eq. (6), noise adaptation works according to the relation between Q and R and not on their independent values, as follows. If $Q \gg R$, then K_k approaches unity ($K_k \to I$), while if $Q \ll R$ then K_k approaching zero ($K_k \to 0$). $K_k \to I$ implies that the estimator trusts the measurement more than the prediction output. In contrast, if $K_k \to 0$, then the estimator trusts the prediction output more than the measurements. Therefore, the reasonable way to analyze the influence of noise statistics on the estimation errors is based on R influence explanation when Q is fixed. For consistency switching between DR and AKF, the following procedure is applied. The process noise covariance Q is fixed to a small value; whereas measurement noise covariance are adaptively approximated according to the correlation between the measurements. Ignoring the autocorrelation of the innovation sequence can lead to underestimating the measurement noise covariance, and thus ensure more belief in their correctness. Thus, the innovation sequence is modeled in the context of first order autoregressive $AR(1)$. Then, the Yule–Walker approach for parameter estimation is used to estimate the innovation sequence parameters, as follows. Let us assume that z_k is the current measurement error; accordingly, the model can be written as follows.

$$z_k = \rho * z_{k-1} + u_k. \tag{17}$$

Hence, u_k can be assumed to be white noise process with zero mean in the sense of first order autoregressive representation of serial correlation; therefore, the actual variance and covariance can be approximated as follows.

$$var(z_k) = \frac{\frac{1}{m}\sum_{i=k-m+1}^{k} \hat{z}_i \hat{z}_i^T}{1-\rho_k^2} \tag{18}$$

$$cov(z_k) = \check{C}_k = \frac{\hat{C}_k}{1-\rho_k^2} * \begin{bmatrix} 1 & \rho & \rho^2 & \rho^3 & . & \rho^{n-1} \\ \rho & 1 & \rho & \rho^2 & . & \rho^{n-2} \\ . & . & . & . & . & . \\ \rho^{n-1} & \rho^{n-2} & . & . & . & 1 \end{bmatrix}. \tag{19}$$

Then, similar to [38], Kalman Gain K_k can be directly estimated as follows.

$$K_k = \check{P}^-_{k|k-1} H^T \check{C}_k^{-1}. \tag{20}$$

Therefore, during sub-optimality of the AKF, the gain for K_k will be small, letting DR dominate the estimation process. If the innovation sequence covariance remains smaller than the process noise covariance, AKF is governing the estimation process. One important characteristic of the innovation sequence that should be checked before being used is the actual covariance of innovation sequence $\hat{C}_k$ which must be a positive definite matrix. A matrix is said to be positive definite if its' symmetric (or Hermitian) part contains all positive eigenvalues. The determinant of a positive definite matrix is always positive, hence, a positive definite matrix is always non-singular. Thus, estimation of the K_k as always optimal as well as $\check{C}_k^{-1}$ is found, i.e., $\check{C}_k$ is a positive definite matrix. This condition is only true if there is no linear dependence among innovation sequences, otherwise the filter diverges.

4.3. Online error estimation model

It is fairly common that the evaluation of the position estimation accuracy is achieved by testing the positioning algorithm with samples of ground truth information during testing phase. In such cases, the integrity of the estimation is taken based on the prior known situations. Due to dynamic noise environment in VANET, the accuracy of positioning algorithms is change according to the space and the time [20]. For example, the accuracy of the GPS differs based on where and when the measurements were taken [20,25]. The vehicle experiences uncertainty concerning the accuracy of the positioning algorithm which may lead to poor application performance. In Kalman filter-based estimation, the error statistics can be readily available from the posterior estimation covariance matrices $\check{P}^+_{k|k}$ [17,26]. However, the accuracy of $\check{P}^+_{k|k}$ is dependent upon the optimality of the filter. Therefore, based on previous switching, the expected positioning error can be obtained by the help of the switching rules detailed in Section 4.2. The estimated error that is associated with the Kalman filter can be obtained directly by subtracting the model that describes the corrected state $\check{x}^+_{k|k}$ from the model that describes the truth model x_k in Eq. (1) which represents the real state as follows.

$$\varepsilon_{est(k)} = \check{x}^+_{k|k} - x_k. \tag{21}$$

As long as the model in Eq. (1) is correct and linear, it can be shown that the behavior of the estimation error $\varepsilon_{est(k)}$ can be obtained by substituting Eq. (8) and Eq. (1) as follows.

$$\sigma_{AKF}(k) = \varepsilon_{est(k)} = (I - K_k H)F\varepsilon_{est(k-1)} + (I - K_k H)R_{k-1} - K_k Q_k. \tag{22}$$

Similarly, the error that is associated with dead reckoning can be approximated using the following step error of Kinematic Sensors.

$$\sigma_{DR}(k) = \sqrt{\sigma^2_{\varepsilon_{est(0)}} + \tau^2 * \sum \sigma^2_{Kinematic\ Sensors}}. \tag{23}$$

Hence τ is the time divergence between the current epoch and past time epoch where the dead reckoning using a prediction model is selected. This formula is a generalized form of [16,16]. Generalization is done using the variance sum law statistic of random variables $\sigma^2_{x\pm y} = \sigma^2_x + \sigma^2_y$. Since the dead reckoning fuses measurements obtained from different independent sensors, the total variance will be the summation of the individual sensor variance. Accordingly, the estimation error model can be obtained as follows.

$$\varepsilon_{est(k)} = \begin{cases} \sigma_{AKF}(k) & \text{if AKF is Optimal} \\ \sigma_{DR}(k) & \text{if AKF is not Optimal.} \end{cases} \tag{24}$$

5. Performance evaluation

Five positioning algorithms (SKF, IAE_KF, FQ_IAE_KF, RIAE_KF, and EIAE_KF) have been implemented in MATLAB. Next Generation Simulation (NGSIM) Trajectory Dataset (I-80) has been used to evaluate the effectiveness of the proposed algorithms. NGSIM datasets are a collection of real-world vehicles' trajectories which were collected for understanding driver behavior [56]. The NGSIM provides high-quality and publicly available trajectory datasets that describe realistic kinematic information and driver behaviors [60]. It is an open source that was used for constructing simulation models, as well as evaluating and testing driver behavior models in transportation and VANET [56,61,62]. Similar to the findings of Thiemann et al. in [63], an exponential weight moving average method (sEMA) is used to smooth the speed measurements. The acceleration is derived directly from the derivative of speed over time. In addition, the heading angle is derived from the derivative of position displacement in one axis over the displacement in the second axis. The dataset is categorized into four different clusters using K-Means clustering algorithm based on driver behavior regime, specifically: free flowing, random flowing, car flowing, and lane changing behavior. A total of 44 vehicles were selected for the evaluation. Eleven vehicles were selected from each category. Each category is ordered based on the distance to its cluster center. Each k order is selected from each cluster, where k is the cluster size over sample size.

Various environmental noises have been considered to evaluate the robustness of the proposed algorithms. Since the noise of positioning measurements changes with a particular environment, three common types of noises were injected into vehicles' trajectories to represent the environment noises that affect ringing techniques and positioning information. Noise injection is widely used as a tool to simulate measurement noises and evaluate the robustness of positioning algorithms [11,42,53]. A combination of stationary white noises with zero mean (Noise Type I), non-stationary white noise with time-varying variance (Noise Type II), and correlated errors (Noise Type III) were reported by many researchers in VANET positioning context and used for simulating environmental error conditions in VANET [11,12,25,42,52,53,64,65]. Noise Type I usually occurs under Line of Sight (LoS) measurement conditions such as the GNSS-based positioning in an open sky environment. It appears on limited conditions such as highways or rural environments. However, it is widely used for evaluating the performance of most proposed positioning algorithms in VANET such as [11,42,53]. Noise Type II occurs in a stochastic environment when vehicles travel through different regions in harsh environments (such as trees), and clouds in which water bodies absorb the positioning signal [11]. It was used for evaluating the positioning algorithms that were proposed in [11,12]. Noise Type III occurs in specific places such as mid-town areas, particularly beside skyscrapers, under bridges, tunnels or earth features. Noise Type III comprises correlated errors and it has been modeled as a random walk process according to [11,25,52,64,65]. Another Noise scenario is simulated which represents mix of the three scenarios as shown in Fig. 4. The road is divided into three parts. In each part, random noise types are injected. Table 1 shows the three noise models in addition to the mixed noise model that were used in the simulation.

Table 1
Noise models and testing scenarios.

Noise type	Error model	Distribution	Time change
Noise Type I	$\mu = 0, \sigma = 10\ m$	$N(\mu, \sigma^2)$	No change
Noise Type II	$\mu = 0\ m$, $\sigma = 20 * rand()\ m$	$N(\mu, \sigma^2)$	every 5 s
Noise Type III	$\sigma, \mu = f(t)\ m$	$\varepsilon_t = \alpha\varepsilon_{t-1} + u$	every 1 s
Mixed noise	$\begin{cases} \sigma = 20 * rand()\ m \\ \sigma, \mu = f(t)\ m \end{cases}$	$\begin{cases} N(0, \sigma^2) & d < \frac{1}{3}l \text{ or } d > \frac{2}{3}l \\ \varepsilon_t = \alpha\varepsilon_{t-1} + u & d \geq \frac{2}{3}l \text{ and } d \leq \frac{2}{3}l \end{cases}$	

The standard error of velocity, acceleration, and vehicle direction measurement sensors are assumed to be 3 m/s, 1 m/s and 3 degree respectively. The sampling period is 100 ms for both position information and Kinematic information as it is required in VANET standards for a positioning update rate [66,67].

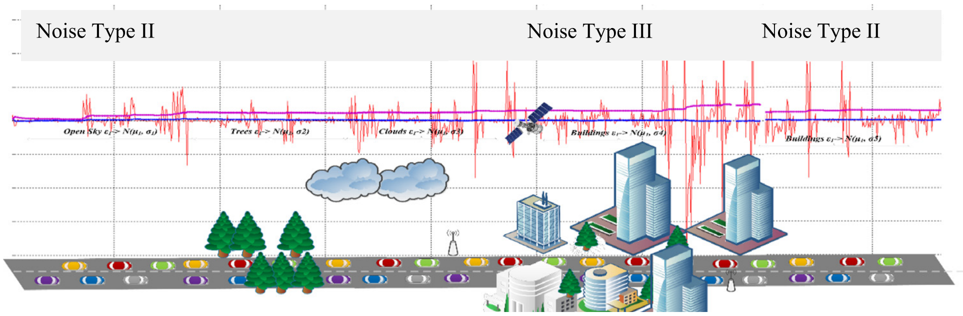


Fig. 4. Mixed noise scenario.

5.1. Performance metrics

Four main metrics have been chosen to evaluate the effectiveness of the positioning algorithms. The first metric is the Root Mean Square Error (RMSE) which can be calculated as follows.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{k}(x_k - \check{x}_{k|k}^{+})^2}{k}}, \tag{25}$$

where x_k, $\check{x}_{k|k}^{+}$ are the actual and the estimated states at time epoch $\boldsymbol{k}$ respectively.

The second metric to evaluate the positioning accuracy satisfaction for VANET applications is the positioning success ratio. This is the number of times by which the positioning error exceeds the application accuracy thresholds ($\boldsymbol{\tau}$) divided by total samples ($\boldsymbol{l}$).

$$\frac{1}{k}\sum_{t=1}^{k}\mathrm{I} : \mathrm{I} = \begin{cases} 1 & \check{x}_{k|k}^{+} \le \tau \\ 0 & \text{otherwise.} \end{cases} \tag{26}$$

where (k) is the number of samples in vehicle trajectories and (τ) is the application accuracy threshold.

The third evaluation metric is the algorithm divergence ratio which represents the number of times that the filter fails and needs to be reinitialized. The divergence ratio is calculated based on the number of times that the filter state covariance matrices grow without bounds divided by the total number of samples. Finally, the fourth evaluation metric is dedicated to evaluating the positioning accuracy error model which shows the difference between the expected error by the algorithm and the actual error. The error model reflects the integrity and the uncertainties of the estimated position.

5.2. Evaluating the positioning accuracy performance

For comparison purposes, a simulation procedure is conducted to estimate the positioning information of vehicles under the four noise scenarios that presented in Table 1 by the proposed algorithms, (EIAE_KF), (IAE_KF), (IAE_FQ_KF), (RIAE_KF) and (SKF) respectively. SKF was used as a benchmark algorithm by which to evaluate the proposed adaptive algorithm as it is widely used in previous positioning algorithms for VANET such as in [12,26,42,55]. EIAE_KF also compared to the RIAE_KF that was proposed by ZhiWen, XiaoPing [51]. RIAE_KF is selected for comparison because it was proposed for localization of autonomous vehicles.

Fig. 5 highlights the accuracy of the proposed algorithms, (EIAE_KF), and the implemented ones (RIAE_KF), (IAE_KF), (IAE_FQ_KF), as well as (SKF) in terms of the average RMSE. X-axis represents the noise type scenario while Y-axis represents the corresponding RMSE values. Each bar chart represents the average RMSE of forty-four vehicles of particular algorithm tested under one noise type. The algorithm with the lowest RMSE has the best accuracy. Accordingly, EIAE_KF achieved the best accuracy while SKF achieved the lowest accuracy in most tested noise types. Meanwhile, IAE_FQ_KF and RIAE_KF shows better accuracy performance than IAE_KF. However, the accuracy different is not high. RIAE_KF revises the innovation sequence element that deviates from normal distribution. The revision include multiplying the outlier value in the innovation vector by small factor to reduce its effect on the estimation. This cause underestimating the measurement noise covariance of the abnormal sequence. In addition, it is difficult to estimate the exact expected noises in dynamic noise environment as the expected one also change.

The results in Table 2 shows the average estimation error statistics of samples containing different vehicle behaviors tested under the four simulated noise scenarios. The error statistics give insight about the overall performance of the algorithm in terms of RMSE means and standard deviation. The numbers in bold indicate best achieved performance. SKF achieved the lowest accuracy and stability in a dynamic noisy environment among all implemented algorithms. The error significantly increases in the correlated noise scenario such as in Noise Type III. This implies that SKF is not robust enough

Table 2
RMSE error statistics.

Algorithm	RMSE statistics							
	Noise Type I		Noise Type II		Noise Type III		Mixed noise	
	μ_{RMSE}	σ_{RMSE}	μ_{RMSE}	σ_{RMSE}	μ_{RMSE}	σ_{RMSE}	μ_{RMSE}	σ_{RMSE}
SKF	2.8	0.67	4.56	1.99	13.21	7.49	4.69	2.42
IAE_KF	0.59	0.26	1.32	2	4.14	3.06	3.86	2.5
IAE_FQ_KF	**0.49**	**0.19**	1.33	1.92	3.57	3.01	1.76	2.19
RIAE_KF	0.59	0.39	1.02	1.62	2.86	3.45	2.27	3.5
EIAE_KF	0.62	0.22	**0.34**	**0.11**	**0.73**	**0.5**	**1.07**	**0.43**

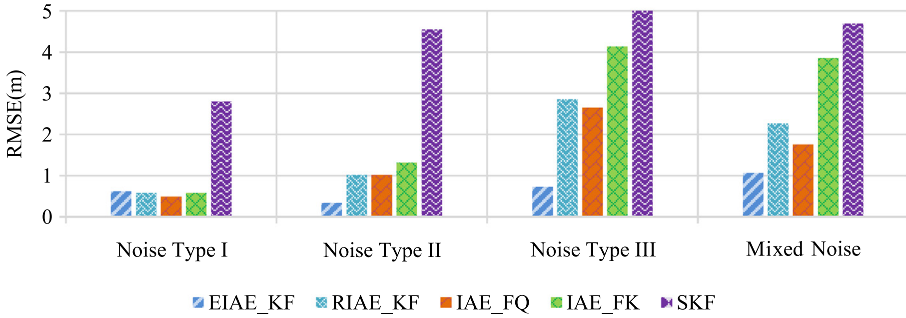
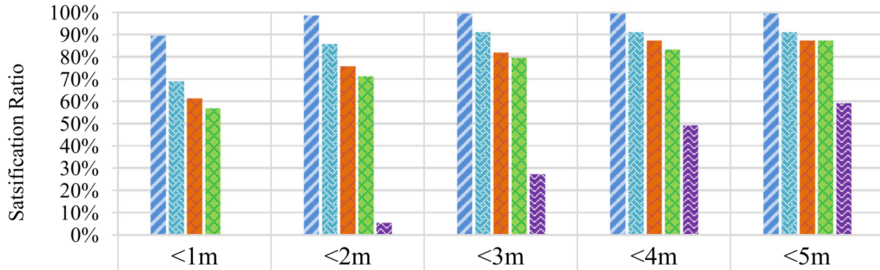


Fig. 5. Positioning accuracy under different noise types.



	<1m	<2m	<3m	<4m	<5m
EIAE_KF	89.39%	98.48%	100.00%	100.00%	100.00%
RIAE_KF	68.94%	85.61%	90.91%	90.91%	90.91%
IAE_FQ	61.36%	75.76%	81.82%	87.12%	87.12%
IAE_FK	56.82%	71.21%	79.55%	83.33%	87.12%
SKF	0.00%	5.30%	27.27%	49.24%	59.09%

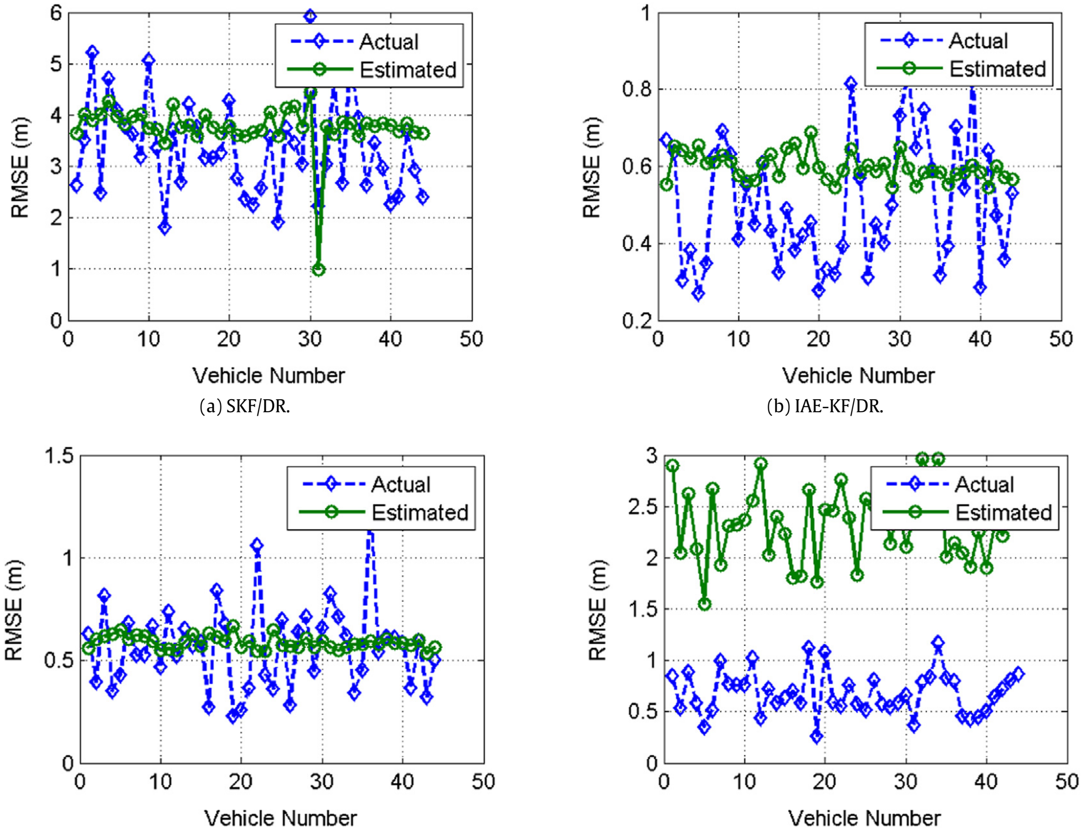
Fig. 6. Comparison based on applications accuracy requirement.

for dynamic noise environment. The error statistics of IAE_KF show that IAE_KF performance is much better than the SKF. This is because the adaptive filtering has the capability to contain the disturbance of the process and measurement error. The worst positioning accuracy of IAE_KF is 4.14±3.06 m, as shown for Noise Type III; but yet, it is still better than SKF which is 13.21±7.49 m. However, this accuracy is not acceptable for some applications (especially safety applications and security services). The accuracy statistics of IAE_FQ_KF show that there is enhancement in terms of decreasing the variability of the errors compared with full adaptation in IAE_KF. The variability of the estimation accuracy is decreased due to fixing the certainty of the process noise Q. This implies that the adaptation of process noise is not necessary to be adapted if a good approximation is available. This is because the uncertainty of the process model remains constant as long as the measurement noise is stationary [57]. RIAE_KF achieved similar accuracy of IAE_FQ_KF but lower stability in dynamic noise environment. This is because revising the innovation vector during abnormal situation leads to underestimating the measurement noise covariance which consequently yields inaccurate results. RIAE_KF, IAE_KF, and IAE_FQ_KF tend to produce high error in dynamic noise environment. Meanwhile, EIAE_KF achieved the best accuracy and stability as compared to the other implemented positioning algorithms.

Fig. 6 illustrates the overall positioning performance in terms of VANET applications satisfaction ratio (τ) (e.g. <1 and <2 m for safety and security services and <5 m for navigation application). As shown in the figure, the accuracy satisfaction

Table 3
Divergence ratio.

Noise type	EIAE_KF	IAE_FQ_KF	IAE_KF	RIAE_KF
Noise Type I	**0%**	0%	0%	5%
Noise Type II	**0%**	18%	60%	18%
Noise Type III	**0%**	5%	64%	20%
Mixed noise	**0%**	18%	64%	23%

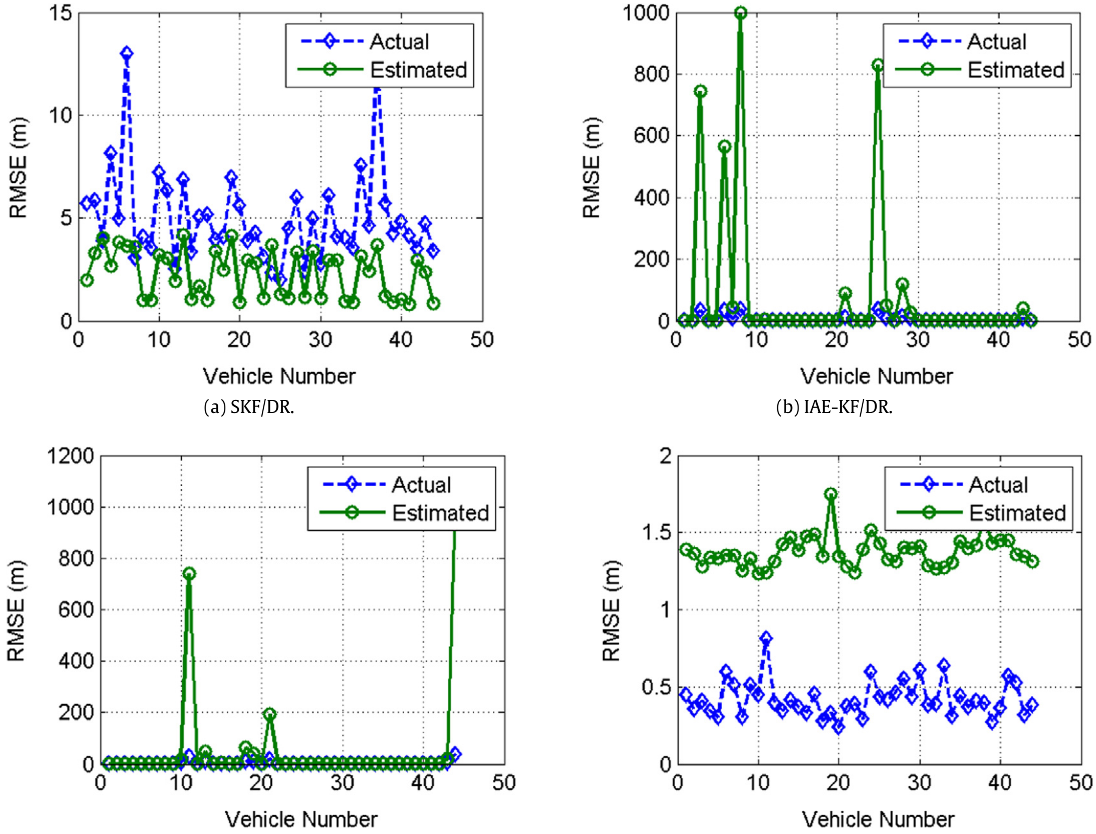


(a) SKF/DR.
(b) IAE-KF/DR.
(c) IAE-FQ-KF/DR.
(d) EIAE-KF/DR.

Fig. 7. Actual and expected error with Noise Type I.

ratio that is achieved by the proposed positioning algorithm EIAE_KF outperforms the other positioning algorithms. In most cases, more than 77.27% of the residual errors that are generated by EIAE_KF are located under 1 m accuracy, while 95.45% of the errors are located under 2 m accuracy. Meanwhile, 100% of the errors are located under 3 m accuracy. This will has positive impact on the performance of VANET applications and service such as safety applications and security performance.

The filtering performance of the EIAE_KF algorithms has been evaluated using covariance analysis. It is common to check the stability of Kalman Filter and predict the filter performance during the design phase of conventional SKF [57]. When the covariance matrix of the state continuously grows, it indicates the presence of filter divergence. Table 3 shows a comparison between divergences of adaptive Kalman Filter of the three proposed algorithms. Full estimation of process noise covariance and measurement noise covariance is more likely to cause divergence than other adaptations of either process noise covariance or measurement noise covariance. The positive definite condition of theoretical covariance of process noise may not be held every time. Positive definite matrix means that the determinant of a positive definite matrix is always positive, so a positive definite matrix is always non-singular. As shown in Table 3, the EIAE_KF outperforms the other algorithms in terms of divergence ratio. This is because the switching decision between a prediction and correction model ensures that the theoretical covariance always remains in a positive definite state. In contrast, RIAE_KF, IAE_KF, and IAE_FQ_KF are not stable for dynamic environment such as VANET. Besides, one observed limitation of existing adaptive Kalman filters is that IAE_KF, IAE_FQ_KF, and RIAE_KF are sensitive to correlated noises and changes in measurement noise distribution.



(a) SKF/DR.

(b) IAE-KF/DR.

(c) IAE-FQ-KF/DR.

(d) EIAE-KF/DR.

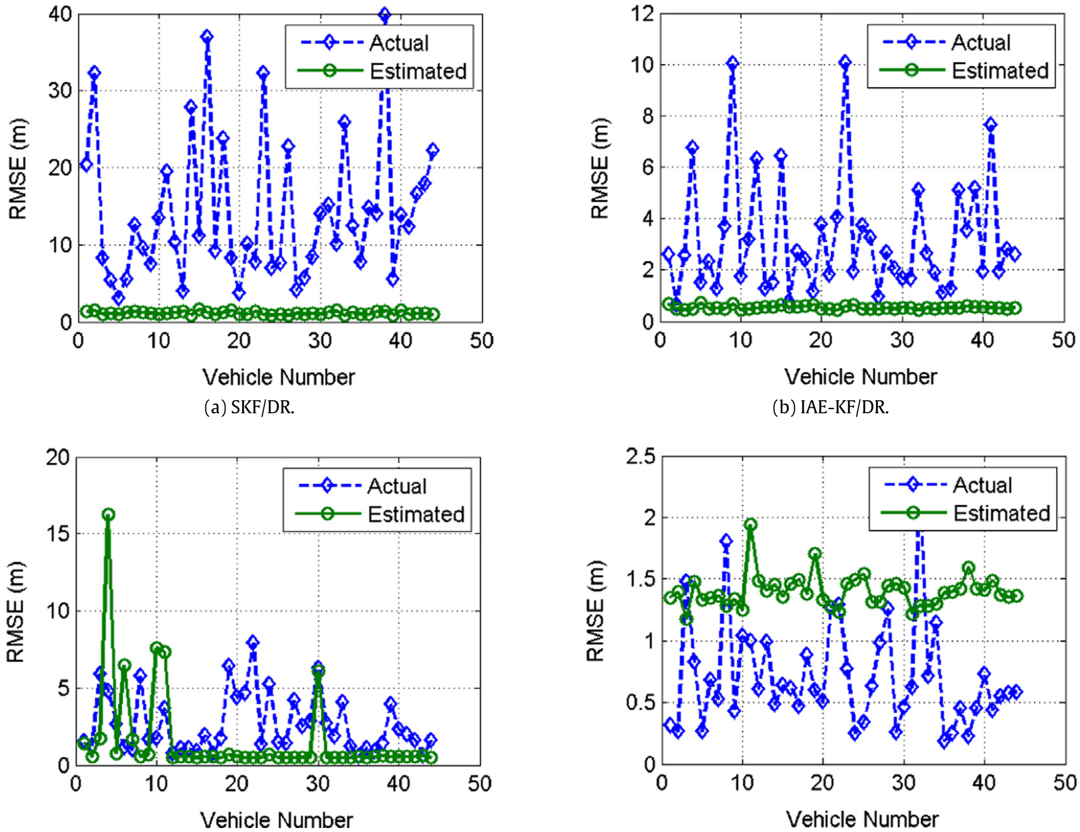
Fig. 8. Actual and expected error with Noise Type II.

The EIAE_KF algorithm is further tested under different speeds and driver behaviors so as to measure the stability of accuracy under VANET dynamicity. In most cases the positioning errors remain small and within the application accuracy requirements. However, it is noted that the estimation error slightly arises when the vehicle speed changes rapidly. Thus, the influence of different driver behaviors on EIAE_KF accuracy is tested. The test results reveals that the EIAE_KF is stable and works well with different driving regimes.

Due to fast movement of vehicles, position information has short lifetime. Therefore, the recurring cost should not affect the information validity period. Consequently, the complexity of the proposed algorithms are important for performance comparison. To do so, the computational complexity is approximated through big O notations. The most time consuming part in SKF, is the calculation of the Kalman Gain due to the inverse of the theoretical covariance matrix (S^{-1}) which take $O(r^{2.4})$ where r the dimension of the state vector. The complexity of IAE_KF is $O(r^{2.4} + 2d) = O(r^{2.4})$ where d is the dimensions of the process and measurement noise covariance matrix. Similarly, the computational complexity of EIAE_KF $O(r^{2.4} + rl^{2.4}) = O(rl^{2.4})$ where l the size of Yule–Walker equation matrix and r the dimension of the state vector. As l and r are small values, therefore, EIAE_KF is time efficient and suitable for vehicles' computational resources in VANET.

5.3. Evaluating the proposed error model

An important requirement for enhancing application and other services in VANTE is that a vehicle should monitor the accuracy of its positioning algorithms. The ability of the positioning algorithm to do an online estimate of the accuracy of the projected position is referred to as a position integrity measure. Vehicles trust positioning information of the applications and services based on the accuracy level of the position information. Therefore, the proposed error model has been employed to estimate the accuracy of the positioning algorithm online. If the estimated error is high, then a vehicle will place a small trust value on the positioning information that is produced in that particular time. In contrast, if the estimated error is low the trust value will increase accordingly. The proposed error model has been evaluated by comparing the actual and estimated error of the proposed algorithms. Each of the results shown in Figs. 7(a)–(d), 8(a)–(d), and 9(a)–(d) depicts comparisons between estimated and actual positioning errors which have been obtained from forty-four samples of vehicles' trajectories



(a) SKF/DR. (b) IAE-KF/DR. (c) IAE-FQ-KF/DR. (d) EIAE-KF/DR.

Fig. 9. Actual and expected error with noise Type III.

with different driver behaviors under the three different noise types. As shown in previous section, RIAE_KF, IAE_KF, and IAE_FQ_KF are not stable in dynamic noise environment, therefore the estimation error covariance is different from the actual error. Thus, RIAE_KF is not included in the comparison due to the similarity of its achievement with IAE_FQ_KF.

Fig. 7 (a), (b), (c) and (d) show comparisons between the actual and expected errors of the proposed algorithms discovered under Noise Type I. As shown in Fig. 7(a), (b) and (c) with Noise Type I, SKF, IAE_KF, and IAE_FQ_KF show that the actual error and the estimated error converge; while in Fig. 7(d), EIAE_KF clearly denotes a separation between the estimated and the actual errors. With this separation, applications in VANET can ensure that the actual error is always considerably smaller than the estimated.

Fig. 8(a), (b), (c) and (d) depict comparisons between the actual and expected errors of the proposed algorithms under Noise Type II. Fig. 8(a) shows that SKF estimated error is less than the actual error. This incorrect estimation threatens the integrity of positioning information and leads to low application and service performance. This arises in terms of false alarms and low accuracy due to the introduction of inaccurate information regarding safety applications and services. Fig. 8(b) and (c) show that IAE_FQ_KF, and IAE_KF failed to estimate the actual error under Noise Type II scenario. In most cases, the difference between the estimated and actual error is high. This element of danger will increase if the estimated error is smaller than the actual error. In such situations, a vehicle may take a serious control decision based on an unexcited event. Fig. 8(d) shows that EIAE_KF has better error estimation than other discussed position algorithms.

Fig. 9(a), (b), (c) and (d) depict comparisons between the actual and expected errors of the proposed algorithms under Noise Type III. In Fig. 9(a) (b) and (c), SKF, IAE_FQ_KF, and IAE_KF underestimate the actual errors which will have serious implications on the application performance in the case of Noise Type III. The accuracy of the position information is higher than the vehicle's belief about the correctness of the information. In such a case, vehicles over-trust the positioning information, which then leads to reduction of the application performance. In comparison with EIAE_KF, the actual error and the expected one by the error model are almost matched with a small ratio of variation.

As seen in Figs. 7–9, the accuracy of the estimated position can be accurately estimated online with the proposed positioning algorithm under all simulated noise types. In contrast with other proposed positioning algorithms, the accuracy of estimation depends on the type of the measurement errors. The achieved quality of accuracy estimation shows potential enhancement in the application performance in terms of accuracy and integrity. Based on this study, Enhanced Innovation-based Adaptive Estimation Kalman filter algorithm (EIAE_KF) can meet VANET applications requirements where the accuracy and the integrity is the main concern. With EIAE_KF, an application can choose the required position information based on the accuracy that is associated with the estimated position using the error model. This procedure will lead to enhancement of the performance of many applications, as well as network and other VANET services.

6. Conclusion

In this paper, the concept of adaptive estimation using innovation-based adaptive estimation Kalman Filter (IAE_KF) has been used to improve the performance of vehicle positioning algorithms. Unlike other adaptive Kalman filtering, the Yule_Walker approach is employed in order to estimate the measurement noise covariance (R) from the innovation sequence. It is then fed back into the estimation process instead of randomly adjusting the theoretical noise covariance. To prevent the filter from producing high uncertainty estimation, switching rules are designed to switch between the prediction and correction estimation based on innovation properties of the optimal filter. In addition, using the proposed error model, vehicles will have a clear indication of the accuracy of positioning information online. Thus, the integrity of the location information is known. Unlike other previous solution simulations based on evaluation of vehicle trajectories, a real world dataset contains many vehicle trajectories that reflect different vehicle behavior. This method has been used for evaluation and testing. Three types of noises are injected into vehicle trajectories to simulate measurement conditions and environment noises. All the efforts are combined in order to evaluate the proposed algorithms under a realistic VANET environment. The results show superior improvement in accuracy and integrity of position information under stochastic noises environment.

Acknowledgments

This work is supported by the Ministry of Higher Education (MOHE) and Research Management Centre (RMC) at the Universiti Teknologi Malaysia (UTM) under Fundamental Research Grant (FRGS) (VOT R.J130000.7828.4F809). We also would like to express our appreciation to Malaysian International Scholarship Department (MIS-MOHE) for sponsoring the first author.

References

[1] Q. Xu, et al., Vehicle-to-vehicle safety messaging in DSRC, in: Proceedings of the 1st ACM International Workshop on Vehicular ad hoc Networks, ACM, Philadelphia, PA, USA, 2004, pp. 19–28.
[2] S. Al-Sultan, et al., A comprehensive survey on vehicular ad hoc network, J. Netw. Comput. Appl. 37 (0) (2014) 380–392.
[3] M. Amadeo, C. Campolo, A. Molinaro, Enhancing IEEE 80211p/WAVE to provide infotainment applications in VANETs, Ad Hoc Netw. 10 (2) (2012) 253–269.
[4] C.M. Huang, S.Y. Lin, Cooperative vehicle collision warning system using the vector-based approach with dedicated short range communication data transmission, IET Intell.Transp. Syst. 8 (2) (2014) 124–134.
[5] L. Le, et al., Vehicular wireless short-range communication for improving intersection safety, IEEE Commun. Mag. 47 (11) (2009) 104–110.
[6] S. Kato, et al., Vehicle control algorithms for cooperative driving with automated vehicles and intervehicle communications, IEEE Trans. Intell. Transp. Syst. 3 (3) (2002) 155–161.
[7] V. Milan, et al., Cooperative adaptive cruise control in real traffic situations, IEEE Trans. Intell. Transp. Syst. 15 (1) (2014) 296–305.
[8] L. Li, et al., Cognitive cars: a new frontier for ADAS research, IEEE Trans. Intell. Transp. Syst. 13 (1) (2012) 395–407.
[9] Administration, NHTS, *Vehicle safety communications project task 3 final report, identify intelligent vehicle safety applications enabled by DSRC*, in *US Department of Transportation* 2005.
[10] K. Ghafoor, et al., Beaconing approaches in vehicular ad hoc networks: a survey, Wirel. Pers. Commun. 73 (3) (2013) 885–912.
[11] K. Liu, et al., Improving positioning accuracy using GPS pseudorange measurements for cooperative vehicular localization, IEEE Trans. Veh. Technol. 63 (6) (2014) 2544–2556.
[12] K. Golestan, et al., Localization in vehicular ad hoc networks using data fusion and V2V communication, Comput. Commun. 71 (2015) 61–72.
[13] H. Wymeersch, J. Lien, M.Z. Win, Cooperative localization in wireless networks, Proc. IEEE 97 (2) (2009) 427–450.
[14] A. Boukerche, et al., Vehicular ad hoc networks: a new challenge for localization-based systems, Comput. Commun. 31 (12) (2008) 2838–2849.
[15] T. Williams, et al., Evaluation of GPS-based methods of relative positioning for automotive safety applications, Transportation Research C 23 (2012) 98–108.
[16] J. Yao, et al., Improving cooperative positioning for vehicular networks, IEEE Trans. Veh. Technol. 60 (6) (2011) 2810–2823.
[17] J. Huang, H.S. Tan, Error analysis and performance evaluation of a future-trajectory-based cooperative collision warning system, IEEE Trans. Intell. Transp. Syst. 10 (1) (2009) 175–180.
[18] I. Skog, P. Handel, In-car positioning and navigation technologies–2014; a survey, IEEE Trans. Intell. Transp. Syst. 10 (1) (2009) 4–21.
[19] F Malandrino et al., Verification and Inference of Positions in Vehicular Networks through Anonymous Beaconing.
[20] N.M. Drawil, H.M. Amar, O.A. Basir, GPS localization accuracy classification: a context-based approach, IEEE Trans. Intell. Transp. Syst. 14 (1) (2013) 262–273.
[21] S. Hewitson, H.K. Lee, J. Wang, Localizability analysis for GPS/Galileo receiver autonomous integrity monitoring, J. Navig. 57 (02) (2004) 245–259.
[22] D. Loebis, et al., Adaptive tuning of a Kalman filter via fuzzy logic for an intelligent AUV navigation system, Control Eng. Pract. 12 (12) (2004) 1531–1539.
[23] N. Alam, A.G. Dempster, Cooperative positioning for vehicular networks: facts and future, IEEE Trans. Intell. Transp. Syst. 14 (4) (2013) 1708–1717.
[24] D.M. Bevly, B. Parkinson, Cascaded Kalman filters for accurate estimation of multiple biases, dead-reckoning navigation, and full state feedback control of ground vehicles, IEEE Trans. Control Syst. Technol. 15 (2) (2007) 199–208.
[25] Y. Zhang, K.T. Chong, An GPS/DR navigation system using neural network for mobile robot, Int. J. Precis. Eng. Manuf. 15 (12) (2014) 2513–2519.
[26] N. Alam, A. Kealy, A.G. Dempster, An INS-aided tight integration approach for relative positioning enhancement in VANETs, IEEE Trans. Intell. Transp. Syst. 14 (4) (2013) 1992–1996.
[27] J.A. Farrell, T.D. Givargis, M.J. Barth, Real-time differential carrier phase GPS-aided INS, IEEE Trans. Control Syst. Technol. 8 (4) (2000) 709–721.

[28] M. Rohani, D. Gingras, D. Gruyer, A novel approach for improved vehicular positioning using cooperative map matching and dynamic base station DGPS concept, IEEE Trans. Intell. Transp. Syst. 17 (1) (2016) 230–239.
[29] K. Hyunwoo, K. Binhee, K. Seung-Hyun, GNSS multipath-resistant cooperative navigation in urban vehicular networks, IEEE Trans. Veh. Technol. 64 (12) (2015) 5450–5463.
[30] Y. Kim, Motion state estimation for an autonomous vehicle-trailer system using Kalman filtering-based multi-sensor data fusion, Asia Life Sci. (2015) 81–92.
[31] J. Jyh-Ching, L. Ching-Fu, A sensor fusion scheme for the estimation of vehicular speed and heading angle, IEEE Trans. Veh. Technol. 64 (7) (2015) 2773–2782.
[32] M.S. Grewal, A.P. Andrews, Kalman Filtering: Theory and Practice, Prentice-Hall, Inc, 1993, p. 381.
[33] A. Mohamed, K. Schwarz, Adaptive Kalman filtering for INS/GPS, J. Geodesy 73 (4) (1999) 193–203.
[34] G.M Abdalla et al., Space-Orthogonal Frequency-Time Medium Access Control (SOFT MAC) for VANET, 2009 Global Information Infrastructure Symposium, 2009, pp. 73-80.
[35] R.K. Mehra, Approaches to adaptive filtering, IEEE Trans. Automat. Control 17 (5) (1972) 693–698.
[36] R.K. Mehra, On the identification of variances and adaptive Kalman filtering, IEEE Trans. Automat. Control 15 (2) (1970) 175–184.
[37] N. Alam, A.T. Balaei, A.G. Dempster, A DSRC Doppler-based cooperative positioning enhancement for vehicular networks with GPS availability, IEEE Trans. Veh. Technol. 60 (9) (2011) 4462–4470.
[38] F. Jiancheng, Y. Sheng, Study on innovation adaptive EKF for in-flight alignment of airborne POS, IEEE Trans. Instrum. Meas. 60 (4) (2011) 1378–1388.
[39] W. Li, et al., A survey on multisensor fusion and consensus filtering for sensor networks, Discrete Dyn. Nat. Soc. 2015 (2015) 12.
[40] A. Chatterjee, F. Matsuno, A neuro-fuzzy assisted extended Kalman filter-based approach for simultaneous localization and mapping (SLAM) problems, IEEE Trans. Fuzzy Syst. 15 (5) (2007) 984–997.
[41] C. Chatfield, The Analysis of Time Series: An Introduction, in: Chapman & Hall/CRC Texts in Statistical Science, 2004 Ca. Hall/CRC.
[42] R. Parker, S. Valaee, Vehicular node localization using received-signal-strength indicator, IEEE Trans. Veh. Technol. 56 (6) (2007) 3371–3380.
[43] N. Alam, A.T. Balaei, A.G. Dempster, Relative positioning enhancement in VANETs: a tight integration approach, IEEE Trans. Intell. Transp. Syst. 14 (1) (2013) 47–55.
[44] S. Joo-Han, V.W.S. Wong, V.C.M. Leung, Secure location verification for vehicular ad-hoc networks, in: Global Telecommunications Conference, 2008 IEEE GLOBECOM 2008, IEEE, 2008.
[45] J.-P. Hubaux, S. Capkun, J. Luo, The security and privacy of smart vehicles, IEEE Security & Privacy Magazine 2 (LCA-ARTICLE-2004-007) (2004) 49–55.
[46] A. Khattab, Y.A. Fahmy, A. Abdel Wahab, High accuracy GPS-free vehicle localization framework via an INS-assisted single RSU, Int. J. Distrib. Sens. Netw. 2015 (2015) 16.
[47] C Hide, T. Moore, M. Smith, Adaptive Kalman filtering algorithms for integrating GPS and low cost INS, in: Position Location and Navigation Symposium, 2004, PLANS 2004, 2004.
[48] W. Ding, et al., Improving adaptive Kalman estimation in GPS/INS integration, J. Navig. 60 (03) (2007) 517–529.
[49] A Fakharian, T. Gustafsson, M. Mehrfam, Adaptive Kalman filtering based navigation: An IMU/GPS integration approach, in: 2011 International Conference on Networking, Sensing and Control, 2011.
[50] A Werries, J.M. Dolan, Adaptive Kalman Filtering Methods for Low-Cost GPS/INS Localization for Autonomous Vehicles. 2016.
[51] X ZhiWen, H. XiaoPing, L. JunXiang, Robust innovation-based adaptive Kalman filter for INS/GPS land navigation, in: 2013 Chinese Automation Congress, 2013.
[52] A. Santamaría-Gómez, et al., Correlated errors in GPS position time series: implications for velocity estimates, J. Geophys. Res. Solid Earth (1978–2012) 116 (B1) (2011).
[53] N.M. Drawil, O. Basir, Intervehicle-Communication-Assisted localization, IEEE Trans. Intell. Transp. Syst. 11 (3) (2010) 678–691.
[54] S Rezaei, R. Sengupta, Kalman filter based integration of DGPS and vehicle sensors for localization, in: IEEE International Conference on Mechatronics and Automation, 2005, 2005.
[55] S. Rezaei, R. Sengupta, Kalman filter-based integration of DGPS and vehicle sensors for localization, IEEE Trans. Control Syst. Technol. 15 (6) (2007) 1080–1088.
[56] Y. Hou, P. Edara, C. Sun, Modeling mandatory lane changing using bayes classifier and decision trees, IEEE Trans. Intell. Transp. Syst. 15 (2) (2014) 647–655.
[57] Y. Bar-Shalom, X.R. Li, T. Kirubarajan, Estimation with Applications To Tracking and Navigation: Theory Algorithms and Software, John Wiley & Sons, 2004.
[58] ETSI, Technical Specification: Intelligent Transport Systems (ITS); Security; Security Services and Architecture. European Telecommunications Standards Institute, 2010, ETSI TS 102 731 V111 (ETSI TS 102 731 V111 (2010-09)).
[59] ETSI, T, Intelligent transport systems (ITS); vehicular communications; basic set of applications; definitions, 2009, Tech. Rep. ETSI TR 102 638.
[60] FHWA Next Generation Simulation (NGSIM) Vehicle Trajctories Dataset 2006 17/12/2015; 2006: [Available from: http://ngsim-community.org/].
[61] X. Chen, L. Li, Y. Zhang, A Markov model for headway/spacing distribution of road traffic, IEEE Trans. Intell. Transp. Syst. 11 (4) (2010) 773–785.
[62] K. Abboud, W. Zhuang, Stochastic analysis of a single-hop communication link in vehicular ad hoc networks, IEEE Trans. Intell. Transp. Syst. 15 (5) (2014) 2297–2307.
[63] C. Thiemann, M. Treiber, A. Kesting, Estimating acceleration and lane-changing dynamics from next generation simulation trajectory data, Transportation Research Record: Journal of the Transportation Research Board 2088 (2008) 90–101.
[64] J.P. Montillet, et al., Extracting white noise statistics in GPS coordinate time series, IEEE Trans. Geosci. Remote Sens. 10 (3) (2013) 563–567.
[65] J. Langbein, H. Johnson, Correlated errors in geodetic time series: implications for time-dependent deformation, J. Geophys. Res. Solid Earth 102 (B1) (1997) 591–603.
[66] IEEE Standard for Wireless Access in Vehicular Environments Security Services for Applications and Management Messages. IEEE Std 16092-2013 (Revision of IEEE Std 16092-2006), 2013, p. 1-289.
[67] 2013, ETSI, Intelligent Transport Systems (ITS); Users and applications requirements; Part 1: Facility layer structure, functional requirements and specifications, in Part1, 2013, European Telecommunications Standards Institute 2013.