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Position and Velocity Estimations of Mobile Device Incorporate GNSS

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ABSTRACT Today, the global navigation satellite system (GNSS) is usually integrated into smart mobile devices for necessary communication with the possibility of locating users accurately in the surrounding environment. In contrast to the traditional estimation approaches, this paper proposes a message passing algorithm for position and velocity estimations of the mobile device incorporate GNSS. First, the smart mobile device incorporate GNSS is modeled as a state-space framework. Then the message passing scheme is proposed considering the Bayesian tree structure. In this scheme, the messages are shifted between forward and backward nodes so that the estimation error is minimized. The simulation results show that the proposed algorithm provides significant performance improvement compared with the existing Kalman filter.

INDEX TERMS Bayesian tree structure, position and velocity estimation, global navigation satellite system, message passing algorithm, mobile device.

I. INTRODUCTION

Generally speaking, location tracking plays an important role in many emerging applications such as location-based services and radio resource management [1]–[3]. In order to support these applications, the global navigation satellite system (GNSS) is a key element in today's modern society [4], [5]. Sometimes, the line of sight between the satellite and receiver is impossible [6] due to signal blockage, heavy mountains and high-rise buildings such as New York City. Therefore, the GNSS can be integrated into cellular terminals such as smart mobile phones [2], [7], [8]. The installed software can properly estimate the location and position of the system [9]. For example, aircrafts are equipped with GPS receivers which determine their own positions [10]. Designing the effective software is the challenging task for such applications.

There are many algorithms in the literature that used to estimate the position and velocity of receivers/mobile users. To begin with, the least square technique is proposed in [11] and [12]. Unfortunately, it cannot properly estimate the highly dynamic system states [13]. To solve this problem, an iterative least square approach is presented in [14]. In order to obtain better performance, the Kalmna filter (KF) algorithm is used for system state estimations [15] since 1960. For nonlinear estimation, the extended KF and unscented KF schemes are also widely used for satellite systems [14], [16]. However, the computational complexity of theses algorithms are very high [17]. Moreover, the particle swarm optimization algorithm is adopted in [18], but it requires significant amount of particles to get an accurate estimation.

Specifically, the extended KF (EKF) is used to the vision-based navigation system where GNSS information is not always available due to signal blockage or jammed [19]. When GPS signal is weak, the unmanned aerial vehicle is used for sensing, information collection and data fusion [19]. Afterwards, the EKF is adopted to estimate the distance between the receiver and transmitter. Furthermore, the distributed unscented KF (UKF) based multi-sensor data fusion algorithm for the global navigation satellite system is presented in [20]–[22]. It shows that the UKF provides better estimation performance compared with the EKF. Overall, it can be seen that all of the aforementioned centralized estimation approaches are based on the mean squared error principle and widely used from many years.

Interestingly, the distributed state estimation has received significate attention in recent years. In distributed approach, nodes only share limited information with their neighboring connected nodes to achieve a consistent estimation. First of all, the KF based distributed consensus state estimation algorithm for the GNSS is proposed in [23]. It concludes that using consensus algorithm, the GNSS users can potentially deliver high precision estimations without the need of having a centralized computing center. Unfortunately, it requires to know the exact noise statistics which are very difficult to know. Interestingly, noise covariance matrices for the GPS system are computed from the innovation sequence and Kalman gain [24], [25]. Besides, the multi-sensor navigation system based on an adaptive KF is proposed in [26]. In this framework, the inertial navigation system states are determined using two different measurements from the GNSS and Locata sensors. Moreover, the performance of the GPS system considering measurement errors and delays are investigated in [27]. Based on a smooth receiver clock, a novel strategy to integrity monitoring for the GPS system is proposed in [28]. Technically, the KF like position and velocity estimation algorithms are used in different ways.

Generally speaking, the message passing algorithms are widely used for various applications such as mobile communication, compressed sensing, power systems and social networks. To begin with, the message passing algorithm for localization of mobile wireless sensors networks is proposed in [29]. It shows that combining belief propagation and variational message passing algorithm can provide better estimation accuracy compared with the maximum likelihood scheme. Interestingly, the low computational complexity based message passing algorithm for sparse code multiple access is presented in [30]. It uses the adaptive thresholds and scheduling algorithm to reduce complexity of the message passing algorithm, but it degrades system performance significantly. The message passing algorithm for power systems is proposed in [31] and [32]. In addition, an approximate message passing algorithm for compressed sensing is explored in [33]. This algorithm can effectively reconstruct compressed signals after reducing system uncertainties.

Furthermore, the generalized approximate message passing scheme for fifth generation (5G) mobile communication system is developed in [34]. The algorithm is flexible as it meets the desired performance and involves reasonable computational complexity. Moreover, an improved message passing algorithm for 5G sparse code multiple access is proposed in [35]. The algorithm provides better performance and higher convergence speeds. Additionally, the dynamic message passing algorithm for estimating the origin of an epidemic outbreak is presented in [36]. This framework is very important in different contexts of social and computer networks such as examining the roots and spreading patterns of fake news. Overall, it can be seen that different message passing algorithm are proposed for various applications such as mobile communication, compressed sensing, computer networks and medical applications. There has not been much research carried out about the message passing algorithm for navigation systems. Inspired by [31], [32], and [37], this paper proposes a message passing algorithm for position and velocity estimations of the mobile device. The key contributions of this paper are summarized as follows:

- A state-space framework for position and velocity estimation of the mobile device incorporate GNSS is developed.
- The message passing algorithm is proposed on the Bayesian tree structure. Basically, the estimation error covariance is propagated from the tree root to leaf and vice-versa in the Bayesian structure. Consequently, the positioning estimation errors are minimized leads to reflect the true position and velocity of the mobile device.
- The effectiveness of the developed approach is verified with and without communication delays. It shows that the proposed algorithm can estimate the speed and velocity of the mobile device within a very short time. Basically, the potential applications that could benefit from this approach are those related to the urban mobility information and emergency services.

Organization: This paper is organized in five sections. The system state-space model is described in Section II. The proposed scheme is presented in Section III, and the simulation results are demonstrated in Section IV. Section V draws the concluding remarks and future work.

Notations: The capital and small letters are used for matrix and vector, respectively. $N(\mathbf{x}, \mu, \mathbf{P})$ is the probability density function (PDF) of a Gaussian variable $\mathbf{x}$ whose mean μ and covariance $\mathbf{P}$. Also PDF is expressed as $\pi_{\mathbf{x}(t-1),\mathbf{x}(t)}(\mathbf{x}(t-1)) = N(\mathbf{x}(t-1), \mathbf{x}_{\pi_{x(t-1)}}, \mathbf{\Sigma}_{\pi_{x(t-1)}})$ and $\pi_{\mathbf{x}(t-1)}(\mathbf{x}(t-1)) = N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{l(t-1)}, \mathbf{\Sigma}_{l(t-1)})$. The conditional probability is denoted by $p(\mathbf{x}(t) \mid \mathbf{x}(t-1)) = N(\mathbf{x}(t), \mathbf{F}\mathbf{x}(t-1) + \mathbf{G}\mathbf{u}(t-1), \mathbf{\Sigma}_n)$.

II. STATE-SPACE FRAMEWORK

Location-based services is one of the fastest growing segments in mobile applications. Nowadays, the mobile phone is widely used for personal communication and position estimation. In order to support these services, the smart mobile phone is integrated with the GNSS [7], [8]. So, integration is performed between the GNSS system and cellular mobile phone networks. Using the installed software, it is possible to calculate the position of the satellites, their pseudoranges, and user positioning [38], [39]. The data integration system uses GPS alone when there are at least four satellites in visibility [40]. This kind of scenario is applied for traffic routine, driver-assistance systems, tourist information, electronic toll collection and emergency location.

In this paper, it is considered 2-D Universal Transverse Mercator (UTM) coordinate system for mobile device position and speed estimations [7], [8]. The state-space framework for the mobile user is given by:

$$\mathbf{x}(t+1) = \mathbf{F}\mathbf{x}(t) + \mathbf{G}\mathbf{u}(t) + \mathbf{n}(t), \tag{1}$$

where $\mathbf{F}$ is the system state matrix, $\mathbf{x} = [x\ v_x\ y\ v_y]'$ is the system state, $\mathbf{G}$ is the system input matrix, $\mathbf{u}$ is the system input, t is the time index, and $\mathbf{n}$ is considered the exogenous disturbance (Gaussian distribution) with zero mean and covariance $\mathbf{\Sigma_n}$. Here, symbol x and v_x are the position and velocity in the coordinate system. The system state transition matrix is given by:

$$\mathbf{F} = \begin{bmatrix} 1 & \alpha & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \alpha \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Here, α is the sampling time. Similar to [26], an inertial navigation system (INS) is used to establish the system model. The measurement by the INS sensors are given by [7] and [26]:

$$\mathbf{y}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{w}(t), \quad (2)$$

where $\mathbf{y}$ is the measurement information, $\mathbf{H}$ is the measurement matrix and $\mathbf{w}$ is the zero mean Gaussian process noise whose covariance is $\mathbf{\Sigma}_w$. From equations (1)-(2), it can be seen that the system and measurement are disturbed by noises $\mathbf{n}(k)$ and $\mathbf{w}(k)$. The state estimation algorithm can effectively reduce these uncertainties to extract the system states. In other words, the measurement information is utilized for position and velocity estimations.

III. PROPOSED ESTIMATION ALGORITHM

From the system dynamics in (1) and (2), it can be observed that the current system state depends on the previous state. Based on these dependencies and inspired by [31], [32], and [37], the Bayseian tree is drawn in Fig. 1. Using the forward and backward message update rules, the state estimation and error covariances are computed at each node. Afterwards, the estimated information and it error covariance are rectified at each point in the tree and lead to the true estimated

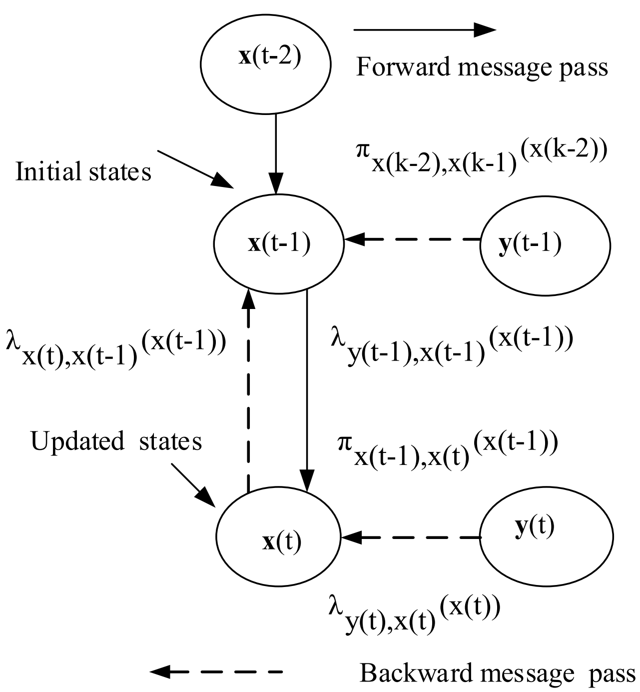

FIGURE 1. Inspired by [31], [32], [37] the Bayesian message passing for GNSS position and velocity estimations.

system states. From the structure, the update order is given by: Step 1) $\mathbf{x}(t-1) \rightarrow \mathbf{y}(t-1)$; step 2) $\mathbf{y}(t-1) \rightarrow \mathbf{x}(t-1)$; step 3) $\mathbf{x}(t-1) \rightarrow \mathbf{x}(t)$; step 4) $\mathbf{x}(t) \rightarrow \mathbf{y}(t)$; step 5) $\mathbf{y}(t) \rightarrow \mathbf{x}(t)$; step 6) $\mathbf{x}(t) \rightarrow \mathbf{x}(t-1)$ and step 7) $\mathbf{x}(t-1)$ is the updated state estimation. Inspired by [31] and [32], the detail process of the proposed scheme is demonstrated as follows [37], [41], and [42]:

A. FORWARD MESSAGE PASSED FROM x(t − 1) to y(t − 1)

According to message passing *rule 1* [32], [41], the prior information at $\mathbf{x}(t-1)$ is given by:

$$\begin{aligned}\pi_{\mathbf{x}(t-1)}(\mathbf{x}(t-1)) &= \int_{-\infty}^{\infty} p(\mathbf{x}(t-1) \mid \mathbf{x}(t-2)) \\ &\quad \times \pi_{\mathbf{x}(t-2),\mathbf{x}(t-1)}(\mathbf{x}(t-2))d\mathbf{x}(t-2) \\ &= p(\mathbf{x}(t-1)) = N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{l(t-1)}, \mathbf{\Sigma}_{l(t-1)}).\end{aligned}$$

Here, the mean value $\hat{\boldsymbol{\mu}}_{l(t-1)}$ and its error covariance $\mathbf{\Sigma}_{l(t-1)}$ derive from the system dynamic (1) as follows:

$$\hat{\boldsymbol{\mu}}_{l(t-1)} = \mathbf{F}\hat{\mathbf{x}}_{\pi_x(t-2)} + \mathbf{G}\mathbf{u}(t-1). \quad (3)$$

$$\mathbf{\Sigma}_{l(t-1)} = \mathbf{F}\mathbf{\Sigma}_{\pi_x(t-2)}\mathbf{F}' + \mathbf{\Sigma}_n. \quad (4)$$

Here, $\hat{\mathbf{x}}_{\pi_x(t-2)}$ and $\mathbf{\Sigma}_{\pi_x(t-2)}$ are the previous mean and covariance values. From Fig. 1, it is observed that $\lambda_{\mathbf{y}(t-1),\mathbf{x}(t-1)}(\mathbf{x}(t-1)) = 1$ as $\mathbf{y}(t-1)$ has no child nodes. Based on this with the message update *rule 5* [32], [37], [41], the information from $\mathbf{x}(k-1)$ *to* $\mathbf{y}(k-1)$ is given by:

$$\begin{aligned}\pi_{\mathbf{x}(t-1),\mathbf{y}(t-1)}(\mathbf{x}(t-1)) &= \pi_{\mathbf{x}(t-1)}(\mathbf{x}(t-1)) \\ &\quad \times \lambda_{\mathbf{y}(t-1),\mathbf{x}(t-1)}(\mathbf{x}(t-1)) \\ &= \pi_{\mathbf{x}(t-1)}(\mathbf{x}(t-1)) \\ &= N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{\pi_{y(t-1)}}, \mathbf{\Sigma}_{\pi_{y(t-1)}}),\end{aligned}$$

where

$$\hat{\boldsymbol{\mu}}_{\pi_{y(t-1)}} = \hat{\boldsymbol{\mu}}_{l(t-1)} = \mathbf{F}\hat{\mathbf{x}}_{\pi_x(t-2)} + \mathbf{G}\mathbf{u}(t-1). \quad (5)$$

$$\mathbf{\Sigma}_{\pi_{y(t-1)}} = \mathbf{\Sigma}_{l(t-1)} = \mathbf{F}\mathbf{\Sigma}_{\pi_x(t-2)}\mathbf{F}' + \mathbf{\Sigma}_n. \quad (6)$$

After updating prior information at $\mathbf{y}(t-1)$, the following step is used to compute likelihood information at $\mathbf{x}(t-1)$.

B. BACKWARD MESSAGE PASSED FROM y(t − 1) to x(t − 1)

After applying *rule 2* [32] to $\mathbf{y}(t-1)$, the likelihood information is given by:

$$\begin{aligned}\lambda_{\mathbf{y}(t-1)}(\mathbf{x}(t-1)) &= \int_{-\infty}^{\infty} \pi_{\mathbf{b}(t-1),\mathbf{y}(t-1)}(\mathbf{y}(t-1)) \\ &\quad \times p(\mathbf{y}(t-1) \mid \mathbf{x}(t-1))d\mathbf{y}(t-1) \\ &= N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{\lambda_y(t-1)}, \mathbf{\Sigma}_{\lambda_y(t-1)}),\end{aligned}$$

Due to notational consistency $\mathbf{y}(t-1)$ is written as $\mathbf{y}_{\lambda_y(t-1)}$, and its parameters are given by.

$$\hat{\boldsymbol{\mu}}_{\lambda_y(t-1)} = \mathbf{H}^{-1}\mathbf{y}_{\lambda_y(t-1)}. \quad (7)$$

$$\mathbf{\Sigma}_{\lambda_y(t-1)} = \mathbf{H}^{-1}\mathbf{\Sigma}_w\mathbf{H}'^{-1}. \quad (8)$$

Using both of the aforementioned step 1 and 2, the update state information is computed as follows.

C. INITIAL MESSAGE UPDATE FROM $\mathbf{x}(t-1)$ to $\mathbf{x}(t)$

In the aforementioned forward steps, the initial values of $\hat{\mathbf{x}}_{\pi_x(t-2)}$ and $\mathbf{\Sigma}_{\pi_x(t-2)}$ are assumed. Based on these assumptions, the message update at point $\mathbf{x}(t)$ is considered as an initial estimation step. According to message update *rule 3* with Lemma 12 in [43] and [32], the term $\pi_{\mathbf{x}(t-1),\mathbf{x}(t)}(\mathbf{x}(t-1))$ can be written as follows:

$$\begin{aligned}\pi_{\mathbf{x}(t-1),\mathbf{x}(t)}(\mathbf{x}(t-1)) &= \pi_{\mathbf{x}(t-1)}(\mathbf{x}(t-1))\lambda_{\mathbf{y}(t-1),\mathbf{x}(t-1)} \\ &\quad \times (\mathbf{x}(t-1)) \\ &= N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{\pi_x(t-1)}, \mathbf{\Sigma}_{\pi_x(t-1)}),\end{aligned}$$

where,

$$\hat{\boldsymbol{\mu}}_{\pi_x(t-1)} = \mathbf{\Sigma}_{\pi_x(t-1)}[\mathbf{\Sigma^{-1}}_{l(t-1)} \times \hat{\boldsymbol{\mu}}_{l(t-1)} + \mathbf{\Sigma}_{\lambda_y(t-1)}\hat{\boldsymbol{\mu}}_{\lambda_y(t-1)}]. \tag{9}$$

$$\mathbf{\Sigma}_{\pi_x(t-1)} = [\mathbf{\Sigma^{-1}}_{l(t-1)} + \mathbf{\Sigma}_{\lambda_y(t-1)}]^{-1}. \tag{10}$$

The initial state estimation is computed as follows [32]:

$$\begin{aligned}\hat{\mathbf{x}}(t-1) &= \lambda_{\mathbf{y}(t-1),\mathbf{x}(t-1)}(\mathbf{x}(t-1))\pi_{\mathbf{x}(t-1)}(\mathbf{x}(t-1)) \\ &= N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{b(t-1)}, \mathbf{\Sigma}_{b(t-1)}),\end{aligned} \tag{11}$$

where,

$$\hat{\boldsymbol{\mu}}_{b(t-1)} = \mathbf{\Sigma}_{b(t-1)}[\mathbf{\Sigma^{-1}}_{l(t-1)} \times \hat{\boldsymbol{\mu}}_{l(t-1)} + \mathbf{\Sigma}_{\lambda_y(t-1)}\hat{\boldsymbol{\mu}}_{\lambda_y(t-1)}]. \tag{12}$$

$$\mathbf{\Sigma}_{b(t-1)} = [\mathbf{\Sigma^{-1}}_{l(t-1)} + \mathbf{\Sigma}_{\lambda_y(t-1)}]^{-1}. \tag{13}$$

Based on the initial update information, the final estimation is obtained at t. It can be seen that the steps 4 and 5 are similar to the steps 1 and 2, respectively where corresponding mean and covariance come from the sequence of messages.

D. FORWARD MESSAGE PASSED FROM $\mathbf{x}(t)$ to $\mathbf{y}(t)$

Similar to step 1, the updated information for step 4 is given by [32], [37]:

$$\pi_{\mathbf{x}(t),\mathbf{y}(t)}(\mathbf{x}(t)) = N(\mathbf{x}(t), \hat{\boldsymbol{\mu}}_{\pi_{y(t)}}, \mathbf{\Sigma}_{\pi_{y(t)}}),$$

with

$$\hat{\boldsymbol{\mu}}_{\pi_{y(t)}} = \mathbf{F}\hat{\boldsymbol{\mu}}_{b(t-1)} + \mathbf{Gu}(t). \tag{14}$$

$$\mathbf{\Sigma}_{\pi_{y(t)}} = \mathbf{F}\mathbf{\Sigma}_{b(t-1)}\mathbf{F}' + \mathbf{\Sigma}_{\boldsymbol{n}}. \tag{15}$$

E. BACKWARD MESSAGE PASSED FROM $\mathbf{y}(t)$ to $\mathbf{x}(t)$ AND $\mathbf{x}(t) \rightarrow \mathbf{x}(t-1)$

Similar to step 2, the information for step 5 is given by [32], [37]:

$$\lambda_{\mathbf{y}(t),\mathbf{x}(t)}(\mathbf{x}(t)) = N(\mathbf{x}(t), \hat{\boldsymbol{\mu}}_{\lambda_y(t)}, \mathbf{\Sigma}_{\lambda_y(t)}),$$

with

$$\hat{\boldsymbol{\mu}}_{\lambda_y(t)} = \mathbf{H}^{-1}\mathbf{y}_{\lambda_y(t)}. \tag{16}$$

$$\mathbf{\Sigma}_{\lambda_y(t)} = \mathbf{H}^{-1}\mathbf{\Sigma}_{\boldsymbol{w}}\mathbf{H}'^{-1}. \tag{17}$$

For step $\mathbf{x}(t) \rightarrow \mathbf{x}(t-1)$, we have:

$$\begin{aligned}\lambda_{\mathbf{x}(t)}(\mathbf{x}(t-1)) &= \int_{-\infty}^{\infty} \lambda_{\mathbf{y}(t),\mathbf{x}(t)}(\mathbf{x}(t))p(\mathbf{x}(t) \mid \mathbf{x}(t-1))d\mathbf{x}(t) \\ &= N(\mathbf{x}(t), \hat{\boldsymbol{\mu}}_{\lambda_y(t)}, \mathbf{\Sigma}_{\lambda_y(t)})p(\mathbf{x}(t) \mid \mathbf{x}(t-1))d\mathbf{x}(t) \\ &= N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{\lambda_y(t-1)}, \mathbf{\Sigma}_{\lambda_y,(t-1)}),\end{aligned}$$

where,

$$\hat{\boldsymbol{\mu}}_{\lambda_y(t-1)} = \mathbf{F}^{-1}\hat{\boldsymbol{\mu}}_{\lambda_y(t)} - \mathbf{F}^{-1}\mathbf{Gu}(t). \tag{18}$$

$$\mathbf{\Sigma}_{\lambda_y(t-1)} = \mathbf{F}^{-1}(\mathbf{\Sigma}_{\lambda_y(t)} + \mathbf{\Sigma}_{\boldsymbol{n}})\mathbf{F}'^{-1}. \tag{19}$$

Using step 1, 2, and 6, information at $\mathbf{x}(t-1)$ is updated as follows.

F. UPDATED STATE ESTIMATION

Similar to step 5, the estimated system state $\hat{\mathbf{x}}_b(t-1)$ is determined by [32] and [37]:

$$\begin{aligned}\hat{\mathbf{x}}_b(t-1) &= \lambda_{\mathbf{x}(t),\mathbf{x}(t-1)}(\mathbf{x}(t-1))\lambda_{\mathbf{y}(t-1),\mathbf{x}(t-1)} \\ &\quad \times (\mathbf{x}(t-1))\, \pi_{\mathbf{x}(t-1)}(\mathbf{x}(t-1)) \\ &= N(\mathbf{x}(t-1), \hat{\boldsymbol{\mu}}_{b(t-1)}, \mathbf{\Sigma}_{b(t-1)}),\end{aligned} \tag{20}$$

where,

$$\hat{\boldsymbol{\mu}}_{b(t-1)} = \mathbf{\Sigma}_{b(t-1)}[\mathbf{\Sigma^{-1}}_{\lambda_y(t-1)} \times \hat{\boldsymbol{\mu}}_{\lambda_y(t-1)} + \mathbf{\Sigma^{-1}}_{l(k-1)} \times \hat{\boldsymbol{\mu}}_{l(t-1)} + \mathbf{\Sigma^{-1}}_{\lambda_x(t-1)} \times \hat{\boldsymbol{\mu}}_{\lambda_x(t-1)}]. \tag{21}$$

$$\mathbf{\Sigma}_{b(t-1)} = [\mathbf{\Sigma^{-1}}_{\lambda_y(t-1)} + \mathbf{\Sigma^{-1}}_{l(t-1)} + \mathbf{\Sigma^{-1}}_{\lambda_x(t-1)}]^{-1}. \tag{22}$$

It can be seen that the mean and error covariance are propagated from one node to another to achieve the true system states. Based on the propose algorithm, the simulation results are presented in the following section.

IV. SIMULATION RESULTS AND DISCUSSIONS

After modeling the system (1) and measurement (2), the proposed estimation algorithm is applied. From these dynamics, it can be seen that current state depends on the previous step. Based on these iterative dependencies, the Bayseian tree is sketched as shown in Fig. 1. Using the forward and backward message update rules, the state estimation and error covariances are computed using (3)-(22). Basically, the estimated information and it error covariance are rectified at each step and lead to the true estimated system states. In order to see the performance of the proposed algorithm, the simulation is conducted using MATLAB software. The considered process and measurement Gaussian noise covariance matrices are $\mathbf{\Sigma}_{\boldsymbol{n}} = 0.0001\mathbf{I}$ and $\mathbf{\Sigma}_{\boldsymbol{w}} = 0.03\mathbf{I}$, respectively. The sampling time is α=0.09 seconds. For simplicity, we consider an unregulated system, i.e., $\mathbf{u} = \mathbf{0}$.

The performance of the proposed algorithm is compared with the existing Kalman filter for example [44]. Specifically, the mean squared error (MSE) between the true and estimated system states is illustrated in Fig. 2. It can be seen that the proposed approach provides significant performance improvement compared with the existing Kalman filter approach.

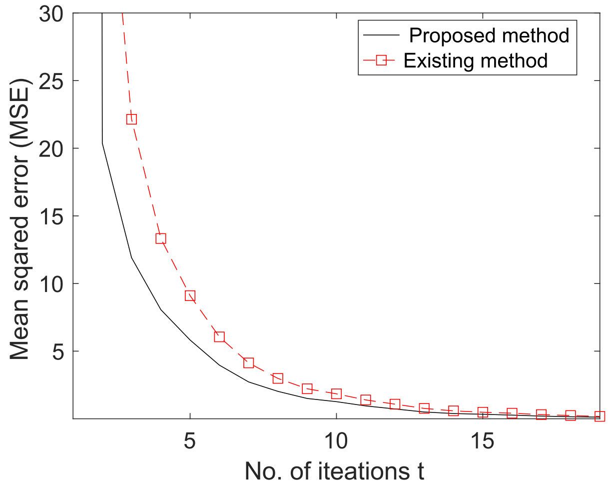

FIGURE 2. Mean squared error performance comparison.

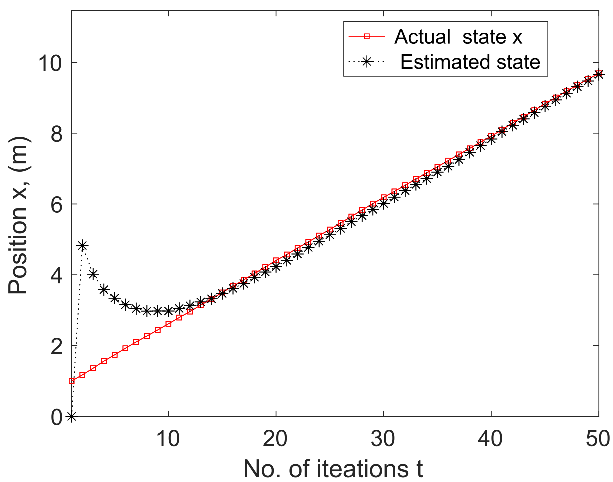

FIGURE 3. Position x and its estimation without delay.

This is due to the fact that the state estimation errors are rectified in the forward and backward directions of the Bayesian network. Consequently, the estimated states converge to the true system states within a very short period of time. Furthermore, 329 dynamics behavior of the system state and it estimation are presented in Figs. 3-4. It can be seen that the proposed algorithm requires approximately 0.36 seconds ($t \times \alpha$) to estimate the position and velocity.

In real-time situation, there may be delay in the system measurements due to senor faults and link failures, i.e., $\mathbf{y}(t) = \mathbf{H}\mathbf{x}(t-\tau) + \mathbf{w}(t)$, where τ is the number of sample delays [45]. Considering ten sample delays in the system measurements, the numerical simulation results are depicted in Figs. 5-6. It can be observed that the simulation results are greatly affected by communication delays but the proposed algorithm needs approximately 5.4 seconds to estimate the speed and velocity of the mobile user as expected. Other states have similar

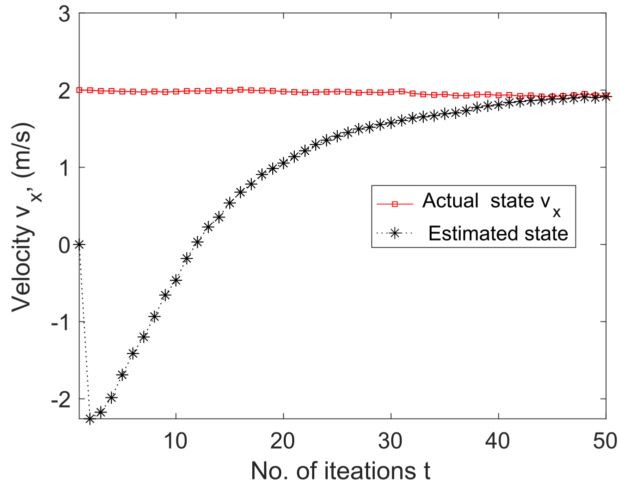

FIGURE 4. Velocity v_x and its estimation without delay.

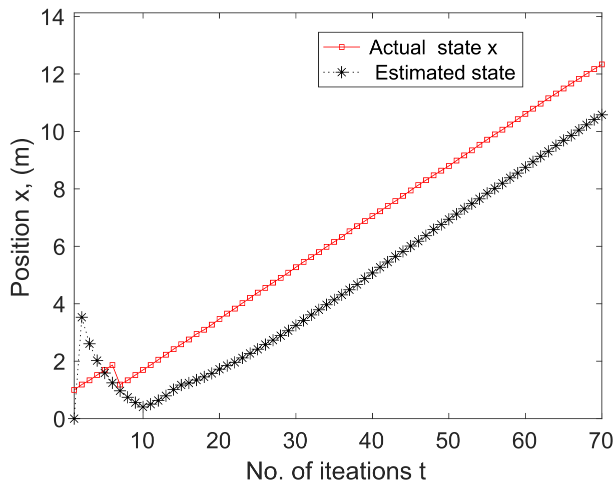

FIGURE 5. Position x and its estimation with delay.

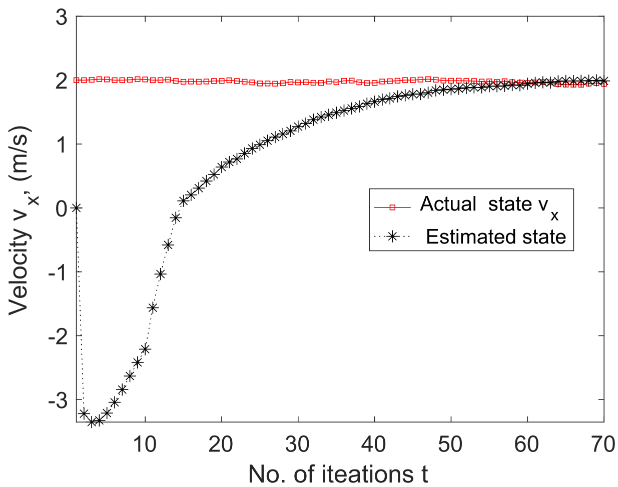

FIGURE 6. Velocity v_x and its estimation with delay.

estimation accuracy. It concludes that to get an accurate estimation results, the delay must be consider to develop the algorithm [45].

V. CONCLUSION AND FUTURE WORK

In this paper, the message passing scheme is proposed and verified for position and velocity estimations of the mobile device incorporate GNSS. After representing the mobile device in a state-space framework, the message passing algorithm is proposed. The design approach is based on the Bayseian structure to rectify system errors. As a result, the proposed algorithm can estimate the position and velocity within a very short time. It can also be seen that the presented algorithm can also be applied if there are communication delays in the measurement. Essentially, this type of scheme can be applied for accurately determining the position of vehicles, for purposes of fleet management (public buses and express couriers) and traffic flow optimization (from public agencies). In future, we will analyze the convergence of the proposed scheme with noise covariance estimation [25].

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