

Modified RHKF Filter for Improved DR/GPS Navigation against Uncertain Model Dynamics

Seong Yun Cho and Hyung Keun Lee

In this paper, an error compensation technique for a dead reckoning (DR) system using a magnetic compass module is proposed. The magnetic compass-based azimuth may include a bias that varies with location due to the surrounding magnetic sources. In this paper, the DR system is integrated with a Global Positioning System (GPS) receiver using a finite impulse response (FIR) filter to reduce errors. This filter can estimate the varying bias more effectively than the conventional Kalman filter, which has an infinite impulse response structure. Moreover, the conventional receding horizon Kalman FIR (RHKF) filter is modified for application in nonlinear systems and to compensate the drawbacks of the RHKF filter. The modified RHKF filter is a novel RHKF filter scheme for nonlinear dynamics. The inverse covariance form of the linearized Kalman filter is combined with a receding horizon FIR strategy. This filter is then combined with an extended Kalman filter to enhance the convergence characteristics of the FIR filter. Also, the receding interval is extended to reduce the computational burden. The performance of the proposed DR/GPS integrated system using the modified RHKF filter is evaluated through simulation.

Keywords: RHKF filter, EKF, DR/GPS, magnetic compass, varying bias, bias estimation.

Manuscript received June 22, 2011; revised Dec. 13, 2011; accepted Dec. 27, 2011.

This work was supported by the Industrial Strategic Technology Development Program of MKE, [10035250, Development of Spatial Awareness and Autonomous Driving Technology for Automatic Valet Parking].

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<http://dx.doi.org/10.4218/etrij.12.0111.0391>

I. Introduction

Navigation technology has become one of the core technologies in the local based service/telematics industry. The navigation system used in telematics is called a car navigation system (CNS). An off-line CNS is generally comprised of a stand-alone Global Positioning System (GPS) receiver and digital map. The navigation system for on-line CNS uses an assisted GPS (A-GPS) or network RTK-GPS instead of a stand-alone GPS. However, the GPS signal cannot be used continuously in an urban area due to signal blockage. Therefore, the GPS-based CNS cannot provide accurate seamless navigation service in urban environments. To overcome this problem, a dead reckoning (DR)/GPS integrated navigation system has been adopted for the CNS [1]-[3]. For the mass market, the DR system should be implemented using low-cost sensors. Therefore, a magnetic compass module is discussed in this paper. The module usually consists of a 2-axis accelerometer and three magnetic compass sensors for tilt compensation. In this paper, the output of the 2-axis accelerometer and tilt compensated azimuth data are integrated with the GPS data for CNS.

A magnetic compass offers absolute azimuth data by measuring Earth's magnetic flux. Therefore, magnetic compass-based azimuth data does not have increasing errors over time unlike gyro-based azimuth data. However, magnetic compass-based azimuth data can be influenced by the surrounding magnetic sources such as bridges, buildings, cars, as well as by Earth's magnetic field. Therefore, magnetic compass-based azimuth data has a bias error dependent upon the location [4], [5].

To compensate for bias error, a proper filter is necessary in the DR/GPS integrated system. In general, extended Kalman

filter (EKF) is widely used in an integrated navigation system [1]-[3], [6]. When a CNS is used in an urban area, a magnetic compass error varies with a larger bias. It is assumed that the bias error of a magnetic compass is modeled as a random constant error. In this case, the EKF cannot estimate the varying bias exactly, as the EKF has an infinite impulse response (IIR) structure. In this paper, an RHKF filter is adopted to overcome this problem. The RHKF filter estimates the state variables using the measurements only on the current horizon $[t - \Delta T, t]$. This filter has a fast estimation property due to the finite impulse response (FIR) structure [7]-[15]. However, the DR error has nonlinear dynamics, and research on the RHKF filter for nonlinear systems is insufficient. In this paper, the RHKF filter is modified for application in nonlinear systems that have a discrete-time model. The inverse covariance form of the linearized Kalman filter is derived because the RHKF filter has a feed-forward structure in the horizon. This filter has two demerits: one is bad convergence characteristics, and the other is a heavy computational burden. In this paper, the FIR construction is modified to overcome these problems. The inverse covariance form of the linearized Kalman filter is combined with the EKF to enhance the convergence characteristics. Also, the receding interval is extended to ΔT , the size of the horizon of the RHKF filter, to reduce the computational burden. The modified RHKF (MRHKF) filter has several merits. It is robust to the model uncertainty, temporary disturbance, and so on, due to the FIR structure. It also has a fast estimation property. The convergence characteristic is enhanced compared with the conventional RHKF filter. Moreover, the computational burden is reduced. To verify the performance of the MRHKF filter, a DR/GPS integrated system is implemented virtually using MATLAB toolbox.

This paper is organized into five sections. In section II, the MRHKF filter is proposed as an iterative form and batch-process form. In section III, the DR/GPS integrated navigation system using the MRHKF filter is described. In section IV, its performance is verified by simulation, and, finally, some concluding remarks are given in the last section.

II. MRHKF Filter

The RHKF filter, also referred to as a moving horizon filter or moving window filter, has an FIR structure; thus, the RHKF filter estimates current states based on a finite number of measurements over the recent time horizon. It is known that the RHKF filter has a robust property against temporary errors and has a fast estimation property. However, a conventional RHKF filter has three problems:

- 1) It can be applied only in linear systems.

- 2) It has a much heavier computational burden than the conventional Kalman filter, which has an IIR structure.
- 3) The convergence characteristic is not good due to the use of a finite number of measurements.

In this paper, an MRHKF is proposed to overcome these problems. This filter consists of an RHKF filter and an EKF. First, the nonlinear system model is linearized on the propagated nominal points, and the RHKF filter is processed using the linearized model. The filter is then combined with the EKF to enhance the convergence characteristics. Figure 1 shows the concept of the MRHKF filter. The receding interval is set by N , the horizon size of the RHKF filter to reduce the computational burden. In Fig. 1, the dotted line is the hidden horizon and the solid line is the active horizon. The RHKF filter is processed in the hidden horizon. The state variables cannot be estimated in this horizon. After processing the hidden horizon, the active horizon and another hidden horizon are carried out. In the active horizon, the EKF is processed and the state variables are estimated by the EKF. A measurement is used only twice. In this section, the discrete time model of the MRHKF filter is presented.

Consider a nonlinear discrete time system represented by

$$\begin{aligned} x_{k+1} &= f(x_k) + Gw_k, \\ y_k &= h(x_k) + v_k, \end{aligned} \quad (1)$$

where k is the discrete time, $x_k \in \mathfrak{R}^L$ is the state, and $y_k \in \mathfrak{R}^q$ is the output. Moreover, $w_k \in \mathfrak{R}^p$ and $v_k \in \mathfrak{R}^q$ are uncorrelated zero-mean white Gaussian noise processes, and the covariance of the two processes are denoted by Q and R , respectively. The functions f and h are assumed to be continuously differentiable.

The RHKF filter has an inverse covariance form. For this paper, the inverse covariance matrix is defined as

$$\Omega_k = P_k^{-1}. \quad (2)$$

The measurement update and time propagation equations of the inverse covariance and Kalman gain equation are then expressed as follows [16]:

$$\Omega_k = \Omega_k^- + H_k^T R_k^{-1} H_k, \quad (3)$$

$$\Omega_k^- = (I - \Gamma_{k-1} G^T) \Psi_{k-1}, \quad (4)$$

$$K_k = \Omega_k^{-1} H_k^T R_k^{-1}, \quad (5)$$

where

$$\Psi_k = F_k^{-T} \Omega_k F_k^{-1}, \quad (6a)$$

$$\Gamma_k = \Psi_k G (Q^{-1} + G^T \Psi_k G)^{-1}, \quad (6b)$$

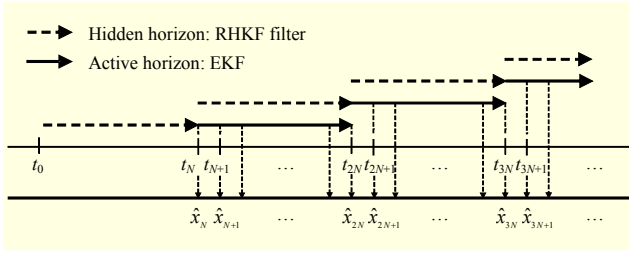


Fig. 1. Concept of MRHKF filter.

$$F_k = \left. \frac{\partial f}{\partial x} \right|_{x=x_k^*}, \quad (6c)$$

$$H_k = \left. \frac{\partial h}{\partial x} \right|_{x=x_k^*}, \quad (6d)$$

where x_k^* is the nominal point for linearization of the nonlinear functions and is defined as

$$x_k^* = x_k - \delta x_k. \quad (7)$$

The nominal point is time propagated in the hidden horizon as

$$x_k^* = f(x_{k-1}^*). \quad (8)$$

The measurement update equation of the error state can be expanded as (9) using (5).

$$\begin{aligned} \delta \hat{x}_k &= \delta \hat{x}_k^- + K_k \left(z_k - h(x_k^*) - H_k \delta \hat{x}_k^- \right) \\ &= \delta \hat{x}_k^- + \Omega_k^{-1} H_k^T R^{-1} \left(z_k - h(x_k^*) - H_k \delta \hat{x}_k^- \right) \\ &= \left(I - \Omega_k^{-1} H_k^T R^{-1} H_k \right) \delta \hat{x}_k^- + \Omega_k^{-1} H_k^T R^{-1} \left(z_k - h(x_k^*) \right) \\ &= \Omega_k^{-1} \left\{ \left(\Omega_k - H_k^T R^{-1} H_k \right) \delta \hat{x}_k^- + H_k^T R^{-1} \left(z_k - h(x_k^*) \right) \right\}, \end{aligned} \quad (9)$$

where z_k is a sensor measurement.

The initial value of the inverse covariance matrix is zero because there is not any information for initial states. This leads to singularities in the calculation of Ω_k^{-1} . Therefore, the error states cannot be updated using (9). To avoid this problem, let us define another pseudo error state as

$$\hat{\xi}_k = \Omega_k \delta \hat{x}_k. \quad (10)$$

The pseudo error state can be written as (11) by substituting (3) and (9) into (10).

$$\begin{aligned} \hat{\xi}_k &= \left(\Omega_k - H_k^T R^{-1} H_k \right) \delta \hat{x}_k^- + H_k^T R^{-1} \left(z_k - h(x_k^*) \right) \\ &= \Omega_k \delta \hat{x}_k^- + H_k^T R^{-1} \left(z_k - h(x_k^*) \right) \\ &= \hat{\xi}_k^- + H_k^T R^{-1} \left(z_k - h(x_k^*) \right). \end{aligned} \quad (11)$$

The time propagation equation of the pseudo error state is

expressed as

$$\begin{aligned} \hat{\xi}_k^- &= \Omega_k^- \delta \hat{x}_k^- \\ &= \left(I - \Gamma_{k-1} G^T \right) \Psi_{k-1} F_{k-1} \delta \hat{x}_{k-1} \\ &= \left(I - \Gamma_{k-1} G^T \right) F_{k-1}^{-T} \Omega_{k-1} F_{k-1}^{-1} F_{k-1} \delta \hat{x}_{k-1} \\ &= \left(I - \Gamma_{k-1} G^T \right) F_{k-1}^{-T} \Omega_{k-1} \delta \hat{x}_{k-1} \\ &= \left(I - \Gamma_{k-1} G^T \right) F_{k-1}^{-T} \hat{\xi}_{k-1}. \end{aligned} \quad (12)$$

The pseudo error state is updated in the hidden horizon using (11). At the end of the hidden horizon, the inverse matrix of the inverse covariance matrix is necessary to estimate the error state variables. To calculate the covariance matrix, the size of the hidden horizon, N , must be larger than or equal to the state dimension, L [7]. If $N \geq L$, then the inverse of Ω_k can be achieved. Therefore, the error state can be estimated as

$$\delta \hat{x}_k = \Omega_k^{-1} \hat{\xi}_k. \quad (13)$$

Now, the inverse covariance form of the linearized Kalman filter is combined with the RH strategy. This filter is applied from t_0 to t_N and estimates the error states at t_N , as can be seen in Fig. 1. Also, EKF is applied from t_{N+1} to t_{2N} , where the initial value of EKF is set by the compensated value (13) at t_N and the initial error covariance matrix is set by the inverse matrix of the inverse covariance matrix. Also, a new hidden horizon is formed from t_N to t_{2N} .

Generally, the size of the horizon is equal to the state dimension. However, N must be larger than L when the degree of observability is low. The more the horizon size of the RHKF filter increases, the more the filter is affected by uncertainties. If the horizon size of the RHKF filter is set to small, the convergent characteristics of the filter may worsen. Therefore, it is important to set the horizon size properly.

To express the MRHKF filter clearly, the summary of the MRHKF filter is shown in Table 1.

The linearized RHKF filter in the hidden horizon is in an iterative form. This filter can be expressed as a batch form, which utilizes N measurements on the horizon $[t_{k-N}, t_k]$. It can be represented in an FIR structure.

Let us define new variables as

$$A_{k-N+i} = \left(I - \Gamma_{k-N+i} G^T \right) F_{k-N+i}^{-T}, \quad (14a)$$

$$B_{k-N+i} = H_{k-N+i}^T R^{-1}, \quad (14b)$$

and

$$\begin{aligned} C_{k-N+i} &= \left(A_{k-N+i-1} \Omega_{k-N+i-1} F_{k-N+i-1}^{-1} + B_{k-N+i} H_{k-N+i} \right) x_{k-N+i}^* \\ &\quad - A_{k-N+i-1} \Omega_{k-N+i-1} x_{k-N+i-1}^*. \end{aligned} \quad (14c)$$

Table 1. Summary of MRHKF filter.

$t_{jN} \leq t_k \leq t_{(j+1)N}, j = 0, 1, \dots$: Hidden horizon (RHKF filter)	
• Initialization	$x_{jN}^* = \hat{x}_{jN},$ $\Omega_{jN} = 0_{L \times L},$ $\hat{\xi}_{jN} = 0_{L \times 1}$ Let: $h_i = jN + i$
• Time propagation ($1 \leq i \leq N$)	
Initialization	$\Psi_{h-1} = F_{h-1}^{-T} \Omega_{h-1} F_{h-1}^{-1}$ $\Gamma_{h-1} = \Psi_{h-1} G_{h-1} (Q^{-1} + G^T \Psi_{h-1} G)^{-1}$ $x_{h-1}^* = f(x_{h-1}^*)$
Inverse covariance	$\Omega_h = (I - \Gamma_{h-1} G^T) \Psi_{h-1}$
Pseudo error state	$\hat{\xi}_h = (I - \Gamma_{h-1} G^T) F_{h-1}^{-T} \hat{\xi}_{h-1}$
• Measurement update ($1 \leq i \leq N$)	
Inverse covariance	$\Omega_h = \Omega_h + H_h^T R^{-1} H_h$
Pseudo error state	$\hat{\xi}_h = \hat{\xi}_h + H_h^T R^{-1} (z_h - h(x_h^*))$
$t_{(j+1)N} < t_k \leq t_{(j+2)N}, j = 0, 1, \dots$: Active horizon (EKF)	
• Initialization ($t_k = t_{(j+1)N}$)	$P_{(j+1)N} = \Omega_{(j+1)N}^{-1},$ $\delta \hat{x}_{(j+1)N} = \Omega_{(j+1)N}^{-1} \hat{\xi}_{(j+1)N},$ $x_{(j+1)N}^* = x_{(j+1)N}^* + \delta \hat{x}_{(j+1)N}$ Let: $a_i = (j+1)N + i$
• Measurement update ($1 \leq i \leq N$)	
Kalman gain	$K_{a_i} = P_{a_i} H_{a_i}^T (H_{a_i} P_{a_i} H_{a_i}^T + R)^{-1}$
Error state	$\delta \hat{x}_{a_i} = K_{a_i} (z_{a_i} - h(x_{a_i}^*))$
Covariance	$P_{a_i} = (I - K_{a_i} H_{a_i}) P_{a_i}^-$
• Time propagation ($1 \leq i \leq N$)	
State	$x_{a_i+1}^* = f(x_{a_i}^*)$
Covariance	$P_{a_i+1}^- = F_{a_i} P_{a_i} F_{a_i}^T + Q$

Substituting (12) and (14) into (11) yields

$$\hat{\xi}_{k-N+i} = A_{k-N+i-1} \hat{\xi}_{k-N+i-1} + B_{k-N+i} z_{k-N+i} + C_{k-N+i}. \quad (15)$$

At the end of the horizon, the variable is estimated as

$$\begin{aligned} \hat{\xi}_k = & \prod_{j=1}^N A_{k-j} \hat{\xi}_{k-N} \\ & + \sum_{n=1}^{N-1} \left(\prod_{j=1}^{N-n} A_{k-j} B_{k-N+n} (z_{k-N+n} - h(x_{k-N+n}^*)) \right) \\ & + B_k z_k + \sum_{n=1}^{N-1} \left(\prod_{j=1}^{N-n} A_{k-j} C_{k-N+n} \right) + C_k. \end{aligned} \quad (16)$$

The error state is then calculated as (17) using (13).

$$\begin{aligned} \delta \hat{x}_k = & \Omega_k^{-1} \prod_{j=1}^N A_{k-j} \hat{\xi}_{k-N} \\ & + \Omega_k^{-1} \sum_{n=1}^{N-1} \left(\prod_{j=1}^{N-n} A_{k-j} B_{k-N+n} (z_{k-N+n} - h(x_{k-N+n}^*)) \right) \\ & + B_k z_k + \Omega_k^{-1} \sum_{n=1}^{N-1} \left(\prod_{j=1}^{N-n} A_{k-j} C_{k-N+n} \right) + C_k. \end{aligned} \quad (17)$$

Since the variable of $\hat{\xi}_{k-N}$ is zero, (17) can be expressed in an FIR form as follows:

$$\hat{x}_k = \sum_{m=0}^{N-1} \mathbf{H}_m (z_{k-m} - h(x_{k-m}^*)) + \sum_{m=0}^{N-1} \mathbf{L}_m C_{k-m}, \quad (18)$$

where the last term is produced from the time propagation of the nominal point; also

$$\mathbf{L}_m = \Omega_k^{-1} A_{k-1} A_{k-2} \cdots A_{k-m} \quad (19a)$$

and

$$\mathbf{H}_m = \mathbf{L}_m H_{k-m}^T R_{k-m}^{-1}. \quad (19b)$$

III. DR/GPS Integrated Navigation Using MRHKF Filter

The typical CNS consists of a GPS receiver, digital map, and navigation computer. However, a GPS signal cannot be used continuously in an urban area due to signal blockage. To provide seamless position information, a CNS can adopt a DR/GPS integrated system, which can be accomplished using an odometer, magnetic compass, accelerometer, gyro, and so on. In this paper, a magnetic compass module is used for the DR system. Generally, the magnetic compass module consists of an MEMS-type 2-axis accelerometer and three magnetic compass sensors. The accelerometers are used for tilt compensation of the magnetic compass sensors. It is easy to extract the sensor signals from the module for integrating signals with the GPS data. The module is aligned such that the accelerometer measures the forward and lateral accelerations of the vehicle and the magnetic compass provides the azimuth angle of the vehicle.

Using the DR system, the velocity and position of the vehicle are calculated as follows:

$$(V_x^b)_k = (V_x^b)_{k-1} + (A_x^b)_k \Delta k, \quad (20)$$

$$P_k^n = P_{k-1}^n + (C_x^n)_k (V_x^b)_k \Delta k, \quad (21)$$

where the Coriolis effect is ignored for simplicity as a low-grade accelerometer is used. Also, Δk is the discrete time interval, A_x^b is the x-axis accelerometer output on the body

frame, V_x^b is the x -axis velocity, P^n is the position on the navigation frame (N - E), and C_x^n denotes the direction cosine matrix from the x -axis on the body frame to the navigation frame denoted as

$$C_x^n = \begin{bmatrix} \cos \psi \\ \sin \psi \end{bmatrix}, \quad (22)$$

where ψ is the tilt compensated azimuth angle obtained from the magnetic compass module.

The azimuth is calculated by measuring Earth's magnetic flux using the magnetic compass sensors. Unfortunately, the measured signal can be influenced by the surrounding magnetic field caused by the several magnetic sources such as steel structures, electric/electronic devices, and communication devices. Therefore, the azimuth information may have bias errors dependent upon the location. This causes navigational errors in the DR system. In this paper, the DR system is integrated with a GPS receiver to compensate the DR errors using the proposed MRHKF filter as described in Fig. 2. The MRHKF filter can estimate the varying bias errors of the magnetic compass more effectively than the conventional EKF.

First, the DR error model is derived. A low-grade accelerometer has several errors such as bias errors, scale factor errors, and non-linearity. However, in this paper, it is assumed that the accelerometer has a dominant bias error. Also, other minor errors are treated as noise. So, the accelerometer output is modeled as

$$(\tilde{A}_x^b)_k = (A_x^b)_k + \nabla_x + (w_{\text{accel}})_k, \quad (23)$$

where A_x^b is the true acceleration, ∇_x is the bias, and w_{accel} is white Gaussian noise. Bias errors are modeled as

$$\begin{aligned} (\nabla_x)_k &= (\nabla_x)_{k-1}, \\ (\nabla_x)_0 &\sim N(0, P_\nabla), \quad (w_{\text{accel}})_k \sim N(0, Q_{\text{accel}}). \end{aligned} \quad (24)$$

An azimuth angle computed in the magnetic compass has the following error characteristics.

$$\tilde{\psi}_k = \psi_k + (b_{mc})_k + (w_{mc})_k, \quad (25)$$

where ψ_k is the true azimuth, b_{mc} is a bias error, and w_{mc} is white Gaussian noise. The bias error is modeled as follows:

$$\begin{aligned} (b_{mc})_k &= (b_{mc})_{k-1}, \\ (b_{mc})_0 &\sim N(0, P_{mc}), \quad (w_{mc})_k \sim N(0, Q_{mc}). \end{aligned} \quad (26)$$

Using the linear perturbation method, a velocity error is derived from (20).

$$(V_x^b)_k + (\delta V_x^b)_k = (V_x^b)_{k-1} + (\delta V_x^b)_{k-1} + \left\{ (A_x^b)_k + \nabla_x \right\} \Delta k. \quad (27)$$

Therefore, velocity error is modeled as follows:

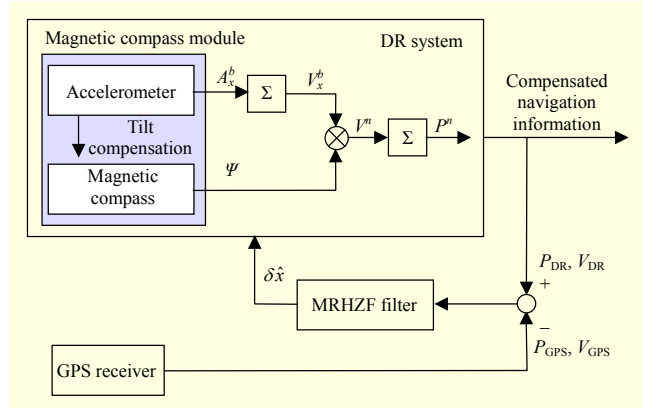


Fig. 2. Block diagram of DR/GPS using MRHKF filter.

$$(\delta V_x^b)_k = (\delta V_x^b)_{k-1} + \nabla_x \Delta k. \quad (28)$$

Finally, position errors can be derived from (21).

$$P_k^n + \delta P_k^n = P_{k-1}^n + \delta P_{k-1}^n + \left(\tilde{C}_x^n \right)_k \left\{ (V_x^b)_k + (\delta V_x^b)_k \right\} \Delta k, \quad (29)$$

where

$$\begin{aligned} \tilde{C}_x^n &= \begin{bmatrix} \cos(\psi + \delta\psi) \\ \sin(\psi + \delta\psi) \end{bmatrix} \\ &\cong C_x^n + \begin{bmatrix} -\sin \psi \\ \cos \psi \end{bmatrix} \delta\psi. \end{aligned} \quad (30)$$

Position error is modeled as

$$\delta P_k^n \cong \delta P_{k-1}^n + C_x^n \Delta k \cdot (\delta V_x^b)_k + \begin{bmatrix} -\sin \psi \\ \cos \psi \end{bmatrix} (V_x^b)_k \Delta k \cdot \delta\psi. \quad (31)$$

The derived DR error model is used to design the system model of the error compensation filter. The state variables are set as position errors on the navigation frame, velocity error, accelerometer bias, and magnetic compass bias as in (32).

$$\delta x = [\delta P_N \quad \delta P_E \quad \delta V_x \quad \nabla_x \quad b_{mc}]^T \quad (32)$$

The corresponding system model is designed as

$$F_k = \begin{bmatrix} I_{2 \times 2} & (C_x^n)_k \Delta k & 0_{2 \times 1} & f_{pmc_k} \\ 0_{1 \times 2} & 1 & \Delta k & 0 \\ & & 0_{2 \times 5} & \end{bmatrix}, \quad (33)$$

where

$$f_{pmc_k} = \begin{bmatrix} -(V_x^b)_k \sin \psi_k \\ (V_x^b)_k \cos \psi_k \end{bmatrix} \Delta k. \quad (34)$$

The position and velocity information obtained from a GPS receiver is used as a measurement. The measurement model is designed as

$$H_k = [I_{3 \times 3} \quad 0_{3 \times 2}]. \quad (35)$$

The system dimension is five. Therefore, the hidden/active horizon size and interval between the horizons are set by five.

IV. Simulation Results and Analysis

To analyze the performance of the MRHKF filter in the DR/GPS integrated system for car navigation, a simulation is conducted. The simulation trajectory is denoted in Fig. 3(a). The accelerometer bias is set as a random constant as

$$P_v = (1 \text{ m/s}^2)^2, \quad Q_{\text{accel}} = (0.1 \text{ m/s}^2)^2. \quad (36)$$

It is assumed that the magnetic compass bias varies as follows, due to the surrounding magnetic field:

$$(b_{mc})_k = (b_{mc})_{k-1} + \alpha_k + \beta_k, \quad Q_{mc} = (0.3^\circ)^2, \quad (37)$$

where

$$\alpha_k \sim (0, (0.1^\circ)^2), \quad (38)$$

$$\beta_k = \begin{cases} 10^\circ, & k = 6, \\ -10^\circ, & k = 20, \\ -10^\circ, & k = 40, \\ 10^\circ, & k = 60, \\ 0.2^\circ \Delta k, & 80 \leq k \leq 85, \\ -0.2^\circ \Delta k, & 95 \leq k \leq 100, \\ 0, & \text{otherwise.} \end{cases} \quad (39)$$

Figure 3(b) shows a sample of the sensor biases. The magnetic compass bias includes a step-type bias and a ramp-type bias. However, the magnetic compass bias is modeled as a random constant bias denoted in (26). Therefore, the corresponding value of the process noise covariance matrix in the filters is set by zero. In other words, there is a model uncertainty. In this case, the capability of estimating the varying magnetic compass bias is evaluated based on the EKF and MRHKF filter. GPS data is generated using the GPS toolbox for MATLAB. GPS data includes various errors such as ionospheric errors, tropospheric errors, multipath errors, and thermal noise.

Simulation results under the environment denoted in Fig. 3 are shown in Fig. 4. Figure 4(a) denotes estimated accelerometer bias. It can be seen that the convergence characteristics of the EKF are better than those of the MRHKF filter. However, the variance of the estimated accelerometer bias in the MRHKF filter is less than that of the white Gaussian noise of the accelerometer output. Consequently, the estimated accelerometer bias in the MRHKF filter is reasonable.

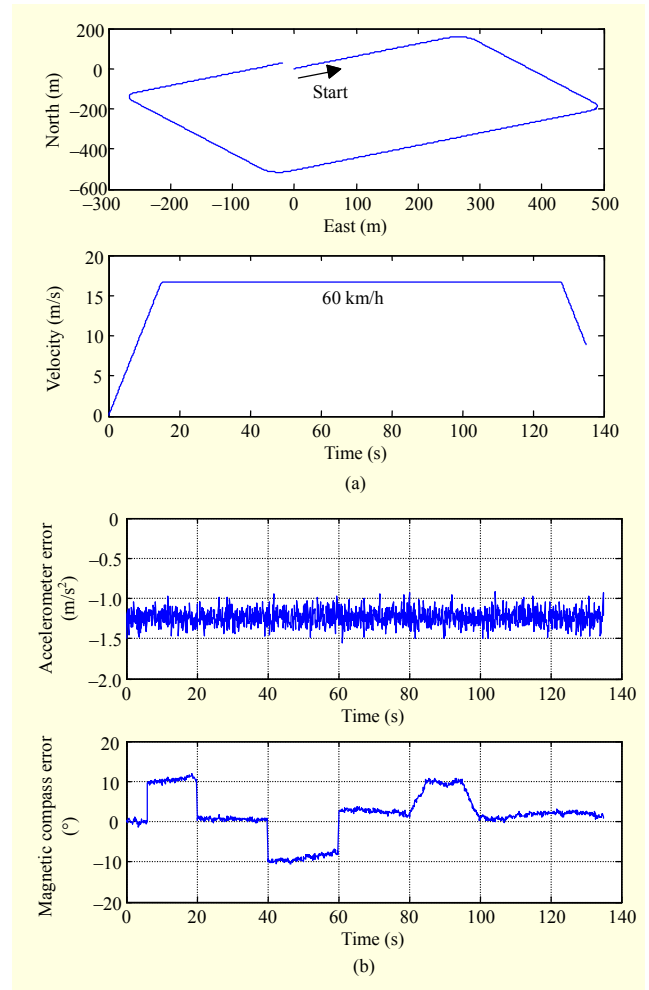


Fig. 3. Simulation environment: (a) trajectory and (b) sensor errors.

Figure 4(b) denotes estimated magnetic compass bias. It can be seen that the EKF cannot estimate the varying magnetic compass bias exactly within a short time due to the IIR structure and the model uncertainty. On the other hand, the MRHKF filter can estimate the varying magnetic compass bias comparatively well due to the FIR structure and fast estimation property even when there is model uncertainty. Figure 4(c) denotes the estimated position. It can be seen that the position estimation error in the DR/GPS using the MRHKF filter is converged into the GPS error range. However, in the DR/GPS using the EKF, there is a strong possibility of error regarding the estimated position, despite the good GPS measurement. This phenomenon is caused by the erroneous estimation result of the magnetic compass bias. In this simulation, it can be confirmed that the estimation performance of the MRHKF filter is better than the EKF when there is model uncertainty.

Figure 5 shows the simulation results when the GPS signal is blocked at 30/45 and 90/105.

In an urban area, the GPS signal can be blocked due to a

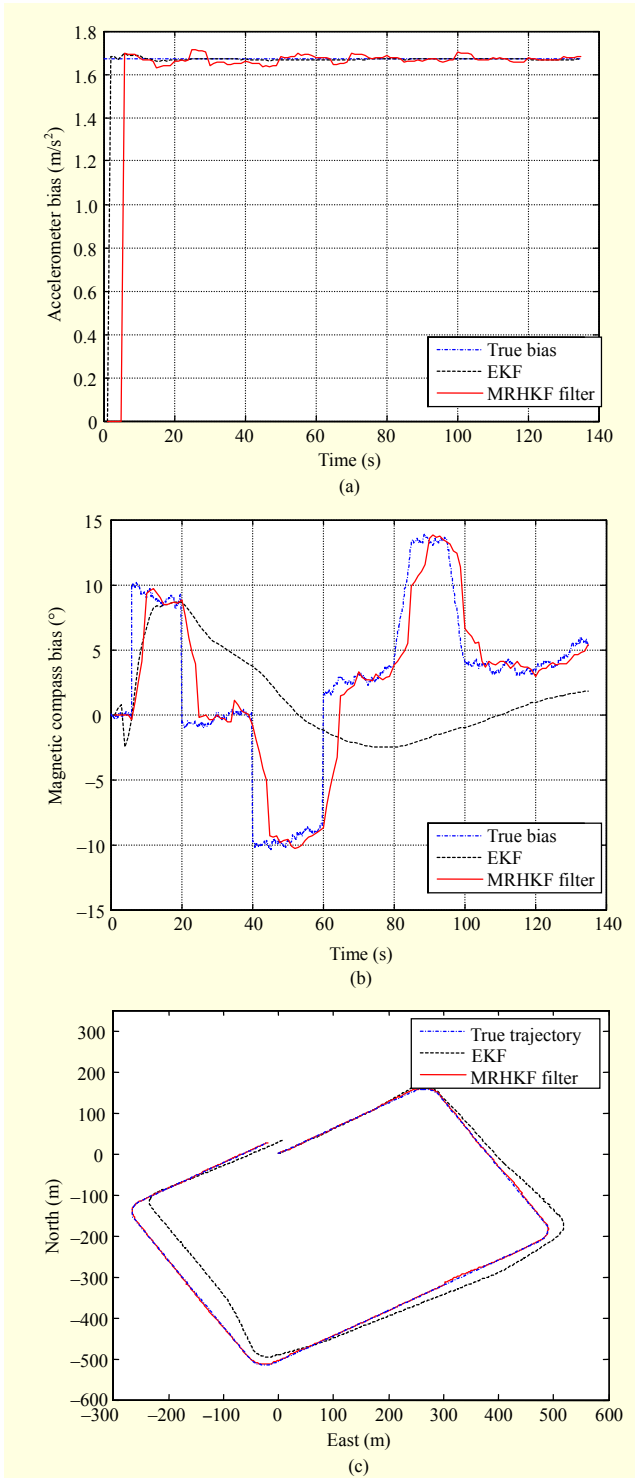


Fig. 4. Simulation results: (a) estimated accelerometer bias, (b) estimated magnetic compass bias, and (c) estimated position.

tunnel, building, and so on. If the GPS signal is blocked, the measurement update cannot be processed in the filters. In this case, the hidden horizon of the MRHKF filter cannot be changed into the active horizon because the inverse matrix of

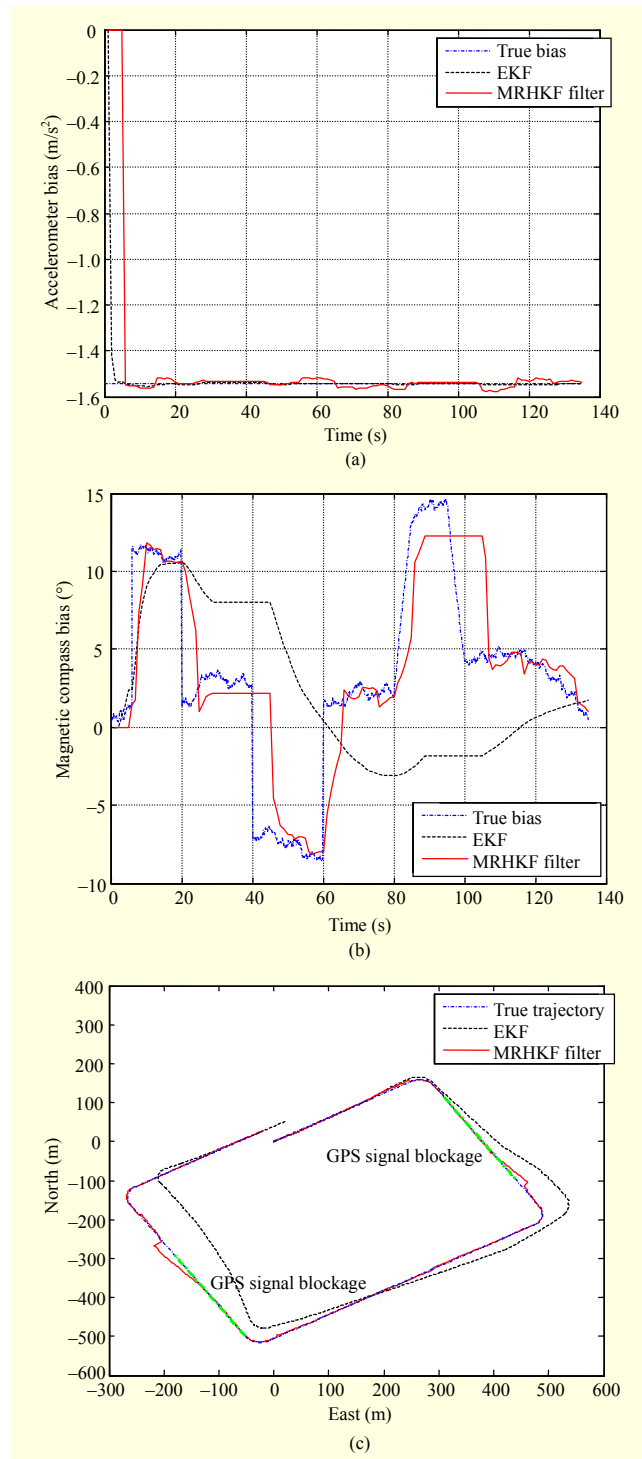


Fig. 5. Simulation results when GPS signal blockages exist: (a) estimated accelerometer bias, (b) estimated magnetic compass bias, and (c) estimated position.

the inverse covariance matrix cannot be calculated in (13). As shown in Fig. 6, the current hidden/active horizon is extended as long as the GPS signal is blocked.

When the GPS signal is blocked, the sensor bias estimates

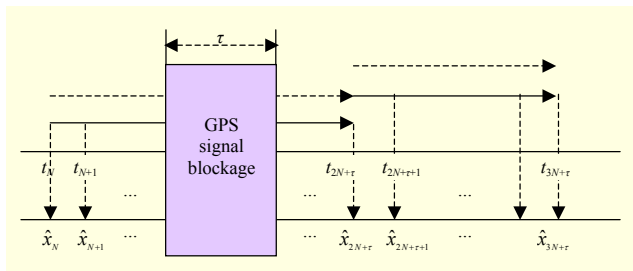


Fig. 6. Horizon extension when GPS signal is blocked.

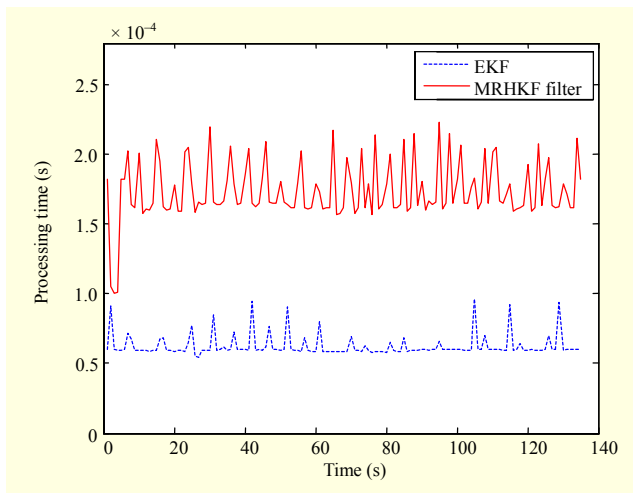


Fig. 7. Processing times of EKF and MRHKF filter.

are maintained, as can be seen in Fig. 5(a) and (b). In this section, the position error increases with time because the measurement update cannot be processed as denoted in Fig. 5(c). After the GPS signal is restored, the MRHKF filter effectively estimates the varying magnetic compass exactly within a short time. In these simulation results, the good estimation performance of the MRHKF filter can be reconfirmed even when there is a GPS signal blockage.

Moreover, the computational burden of the MRHKF filter is about twice that of the EKF because the MRHKF filter processes two filters, the RHKF filter in the hidden horizon and the EKF in the active horizon, in parallel. This is evident in Fig. 7, which shows the processing times computed using the “tic/toc” command in MATLAB.

V. Concluding Remarks

In this paper, a modified RHKF filter and a DR/GPS integrated system using it were proposed. The RHKF filter is robust to model uncertainty, temporary disturbance, and so on, due to the FIR structure. However, the convergence characteristics of the RHKF filter are poor and the computational burden is heavy, due to the receding horizon

FIR structure. Moreover, the conventional RHKF filter can be used in linear systems. In this paper, the inverse covariance form of the linearized Kalman filter was combined with the receding horizon FIR strategy for application in nonlinear systems. It was then combined with the EKF to enhance the convergence characteristics. Finally, the receding interval was extended to reduce the computational burden. Therefore, the modified RHKF filter has the merits of an FIR filter and enhanced performance. This filter was applied to a magnetic compass module-based DR/GPS integrated system. It was shown that the modified RHKF filter can estimate the varying bias of the magnetic compass efficiently even when there is model uncertainty and the GPS signal is blocked temporarily.

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