Tightly Coupled INS/GPS Navigation System using the Multi-Filter Fusion Technique

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Abstract

For robust INS/GPS navigation system, an efficient multi-filter fusion technique is proposed. In the filtering for nonlinear systems, the representative filter - EKF, and the alternative filters - RHKF filter, SPKF, etc. have individual advantages and weak points. The key concept of the multi-filter fusion is the mergence of the strong points of the filters. This paper fuses the IIR type filter – EKF and the FIR type filter – RHKF filter using the adaptive strategy. The result of the fusion has several advantages over the EKF, and the RHKF filter. The advantages include the robustness to the system uncertainty, temporary unknown bias, and so on. The multi-filter fusion technique is applied to the tightly coupled INS/GPS navigation system and the performance is verified by simulation.

Keywords: Multi-filter fusion, EKF, RHKF filter, tightly coupled INS/GPS.

1. Introduction

INS/GPS integrated system is the general navigation system for seamless navigation. The research on the performance enhancement of INS/GPS system has been carried out actively. Especially, the integration filter is one of the important research themes. Extended Kalman filter (EKF) is the representative filter for nonlinear system such as INS and is a widely used filter in many areas of filtering, estimation, prediction, control, tracking, and many others. However, despite its superior practical usefulness, this filter has several weak points. The estimation error of the EKF is bounded in mean square under certain conditions. These conditions include the requirements that the initial estimation errors as well as the disturbing noise terms are small enough, and there must not be modeling uncertainties in the filter model [1]. The EKF may yield large error due to the modeling uncertainties. The reason is that the EKF is an IIR (Infinite Impulse Response) filter [2,3].

The weak points of the EKF can be overcome partially by alternate filters such as RHKF (Receding Horizon Kalman FIR) filter that has FIR (Finite Impulse Response) characteristics, SPKF (Sigma Point Kalman Filter) that utilizes UT (Unscented Transformation) concept, and so on [2~5]. Especially, the RHKF filter has robustness to the modeling uncertainties and temporally disturbing noise terms due to the FIR construction. However, the convergence characteristics of the FIR filter are inferior to the IIR filter. Therefore, tuning is somewhat difficult in the real environment.

In this paper, an adaptive filter concept is used for fusion of the advantages of these filters. In adaptive filter areas, there are process noise covariance estimation methods by minimizing the Frobenius norm using the filter residuals and by using MMAE (Multiple Model Adaptive Estimation) [6], multiple model fusion method using IMM (Interacting Multiple Model) technique [7], and so on.

This paper proposes a multi-filter fusion technique. This fusion technique has an important significance: IIR filter(EKF) and FIR filter(RHKF filter) are fused for nonlinear systems. The fusion probability is calculated using the residuals of the two filters. Based on the probability, the outputs of the nonlinear systems and the error covariance matrix of the filters are fused. The nonlinear systems and the filters are updated using the fused values. The final solution is calculated by combining the outputs of the updated nonlinear systems using the fusion probability. This fusion technique has the advantages of the IIR filter as well as FIR filter.

The proposed fusion technique is applied to the tightly coupled INS/GPS integrated system. When MEMS based INS is utilized, the INS/GPS designed using the fusion technique has robust characteristics to the un-modeled sensor error drift. The performance of the fusion technique is verified by simulation results.

2. Multi-Filter Fusion Technique

In order to use the optimal linear filter (Kalman filter) in a nonlinear system, the nonlinear system/measurement models are linearized and the error states are estimated. EKF updates the nonlinear system using the estimated error sates. Because of the linearization process, the certain condition must be satisfied to stabilize the EKF [1]. In low-cost systems, however, modeling uncertainties may be occurred during filter design due to the low-quality sensors/system. This may cause the EKF to diverge. RHKF filter has been investigated to overcome this weak point. Supposing full observability is satisfied at all times, the RHKF filter can provide the robust solution against the modeling uncertainties, temporally time-varying disturbances, etc. [2]. However, the primary condition, full observability, for the RHKF filter may not be satisfied partially according to the application models. This may cause instability of the system as well as filter. On the other hand, the stability of the EKF can be remains for a while even in the time period of unobservable due to the IIR construction. In this paper, the IIR type filter and the FIR type filter are fused to combine the advantages of the two filters.

In the figure 1, $f_i(\cdot)$ means nonlinear system functions. The initialization for the multi-filter fusion is as follow:

$$M = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix} \qquad (1)$$

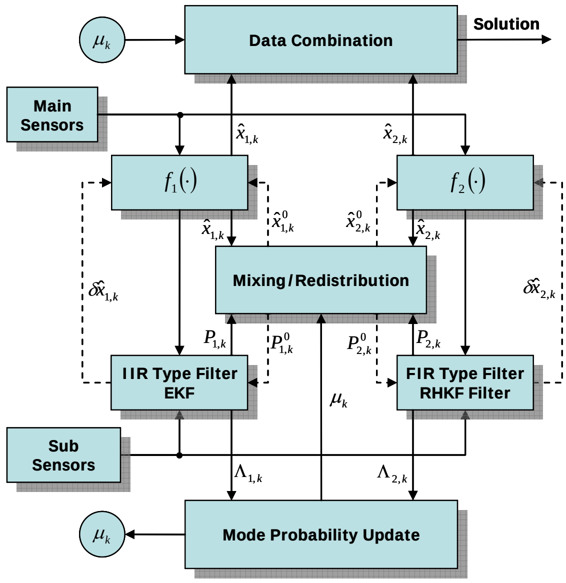


Figure 1. Structure of multi-filter fusion technique.

$$\mu = \begin{bmatrix} n_1 \\ n_2 \end{bmatrix} \tag{2}$$

$$\bar{c}_j = \sum_{i=1}^{2} M_{ij}\mu_i \tag{3}$$

where M is Markov transition matrix, $m_{i1} + m_{i2} = 1$, μ is mixing probability, $n_1 + n_2 = 1$, and $\bar{c}$ is normalization factor.

The nonlinear systems are propagated at output periods of the main sensors and the filters are updated after acquiring the outputs of the sub sensors. The nonlinear systems are compensated using the filter outputs. Then, the states of the nonlinear systems and the error covariance matrices are fused and redistributed. In order to do this process, the *mode probability* is updated. The mode probability means the adaptive fusion gain and is updated using the filter residuals. First, the *likelihood ratio* is calculated.

$$\Lambda_{j,k} = \frac{1}{\sqrt{2\pi \|S_{j,k}\|}} \exp\left\{ -\frac{1}{2k} \sum_{i=1}^{k} r_{j,i}^T S_{j,i}^{-1} r_{j,i} \right\} \tag{4}$$

where $r_{j,i}$ is the residual of j filter at time i, and $S_{j,i}$ is the residual covariance as follows:

$$r_{j,i} = z_i - \hat{z}_{j,i} \tag{5}$$

$$S_{j,i} = H_{j,i} P_{j,i}^{-} H_{j,i}^T + R_j \tag{6}$$

Then, the mode probability is updated using the calculated likelihood ratio.

$$\mu_{j,k} = \frac{1}{c} \Lambda_{j,k} \bar{c}_j \tag{7}$$

where $c = \sum_{i=1}^{2} \Lambda_{j,i} \bar{c}_i$.

In the mixing/redistribution part, the states of the nonlinear systems, and the error covariance matrices are recalculated.

$$\hat{x}_{j,k}^0 = \sum_{i=1}^{2} \hat{x}_{i,k} \mu_{i|j,k} \tag{8}$$

$$P_{j,k}^0 = \sum_{i=1}^{2} \left\{ P_{i,k} + \left[\hat{x}_{i,k} - \hat{x}_{j,k}^0\right]\left[\hat{x}_{i,k} - \hat{x}_{j,k}^0\right]^T \right\} \mu_{i|j,k} \tag{9}$$

where the *mixing probability* is calculated as follows:

$$\mu_{i|j,k} = \frac{1}{\bar{c}_j} M_{ij} \mu_{i,k} \tag{10}$$

where $\bar{c}_j = \sum_{i=1}^{2} M_{ij} \mu_{i,k}$.

The redistributed states are feedback to the nonlinear systems and the error covariance matrices are feedback to the each filter. The equations (4) ~ (10) are iterated as filter process.

Finally, the output solution is calculated in the *Data Combination* part using the error compensated solutions of the nonlinear systems as follows:

$$\hat{x}_k = \sum_{i=1}^{2} \hat{x}_{i,k} \mu_{i,k} \tag{11}$$

3. Application to Tightly Coupled INS/GPS

3.1 INS Mechanization Equations

INS mechanization equations are

$$\dot{q} = \frac{1}{2} q * \left\{ \omega_{ib}^b - C_b^n \left(\omega_{ie}^n - \omega_{en}^n \right) \right\} \tag{12}$$

$$\dot{V}^n = C_b^n f^b - \left(2\omega_{ie}^n + \omega_{en}^n\right) \times V^n + g^n \tag{13}$$

$$\dot{L} = \frac{V_N}{R_m + h}, \quad \dot{l} = \frac{V_E}{(R_t + h)\cos L}, \quad \dot{h} = -V_D \tag{14}$$

where q is a quaternion, the direction cosine matrix C_b^n from body frame to navigation frame can be calculated using the quaternion. $V^n = \begin{bmatrix} V_N & V_E & V_T \end{bmatrix}^T$ is a velocity vector in the navigation frame, $\begin{bmatrix} L & l & h \end{bmatrix}^T$ is a position vector in the ECEF frame. f^b and ω_{ib}^b are accelerometer assembly output and gyro assembly output, respectively. ω_{ie}^n and ω_{en}^n are calculated as follows:

$$\begin{aligned} \omega_{ie}^n &= \begin{bmatrix} \Omega_N & 0 & \Omega_D \end{bmatrix}^T \\ &= \begin{bmatrix} \Omega_{ie}\cos L & 0 & -\Omega_{ie}\sin L \end{bmatrix}^T \end{aligned} \tag{15}$$

$$\begin{aligned} \omega_{en}^n &= \begin{bmatrix} \rho_N & \rho_E & \rho_D \end{bmatrix}^T \\ &= \begin{bmatrix} \frac{V_E}{R_t + h} & -\frac{V_N}{R_m + h} & \rho_N \tan L \end{bmatrix}^T \end{aligned} \tag{16}$$

where R_m and R_t are meridian and traverse radii of curvature in the earth ellipsoid.

$$R_m = \frac{R_0\left(1 - e^2\right)}{\left(1 - e^2 \sin^2 L\right)^{3/2}} \quad , \quad R_t = \frac{R_0}{\sqrt{1 - e^2 \sin^2 L}} \tag{17}$$

where $R_0 = 6{,}378{,}137$ is equator radius of the earth ellipsoid and $e = 0.0818191908426$ is eccentricity.

The $g^n = \begin{bmatrix} 0 & 0 & g_e \end{bmatrix}^T$ is the earth gravity vector in the navigation frame.

$$g_e = \begin{cases} \dfrac{g_0}{\left(1 + h/\sqrt{R_m R_t}\right)^2} & , h \geq 0 \\ g_0\left(1 + h/\sqrt{R_m R_t}\right) & , h < 0 \end{cases} \tag{18}$$

where $g_0 = 9.780318 \begin{pmatrix} 1 + 0.0053024\sin^2 L \\ -0.0000059\sin^2 2L \end{pmatrix}$.

3.2 Tightly Coupled INS/GPS

For tightly coupled INS/GPS, the error model is derived using the linear perturbation method.

$$
\begin{aligned}
\delta\dot{x}_k &= F_k \delta x_k + G_k w_k \\
&= \begin{bmatrix} F_{pp} & F_{pv} & 0_{3\times3} & 0_{3\times3} & 0_{3\times3} & 0_{3\times1} \\ F_{vp} & F_{vv} & F_{va} & C_b^n & 0_{3\times3} & 0_{3\times1} \\ F_{ap} & F_{av} & F_{aa} & 0_{3\times3} & -C_b^n & 0_{3\times1} \\ & & & 0_{7\times16} & & \end{bmatrix} \delta x_k \\
&\quad + \begin{bmatrix} 0_{3\times3} & 0_{3\times3} & 0_{3\times1} \\ C_b^n & 0_{3\times3} & 0_{3\times1} \\ 0_{3\times3} & C_b^n & 0_{3\times1} \\ 0_{6\times3} & 0_{6\times3} & 0_{3\times1} \\ 0_{1\times3} & 0_{1\times3} & 1 \end{bmatrix} w_k \\
z_k &= \begin{bmatrix} \frac{\partial\rho_1}{\partial L} & \frac{\partial\rho_1}{\partial l} & \frac{\partial\rho_1}{\partial h} & 0_{1\times12} & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial\rho_n}{\partial L} & \frac{\partial\rho_n}{\partial l} & \frac{\partial\rho_n}{\partial h} & 0_{1\times12} & 1 \end{bmatrix} \delta x_k + v_k \qquad (19) \\
&= \begin{bmatrix} \hat{\rho}_1 \\ \vdots \\ \hat{\rho}_n \end{bmatrix} - \begin{bmatrix} \rho_1 \\ \vdots \\ \rho_n \end{bmatrix} \\
\delta x &= [\delta L \quad \delta l \quad \delta h \quad \delta V_N \quad \delta V_E \quad \delta V_D \quad \phi_N \quad \phi_E \quad \phi_D \\
&\qquad \nabla_x \quad \nabla_y \quad \nabla_z \quad \varepsilon_x \quad \varepsilon_y \quad \varepsilon_z \quad C_{bias}]^T
\end{aligned}
$$

where

$$
F_{pp} = \begin{bmatrix} \frac{\rho_E R_{mm}}{R_m + h} & 0 & \frac{\rho_E}{R_m + h} \\ \frac{\rho_N}{\cos L}\left(\tan L - \frac{R_{tt}}{R_t + h}\right) & 0 & \frac{\rho_N \sec L}{R_t + h} \\ 0 & 0 & 0 \end{bmatrix}
$$

$$
F_{pv} = \begin{bmatrix} \frac{1}{R_m + h} & 0 & 0 \\ 0 & \frac{\sec L}{R_t + h} & 0 \\ 0 & 0 & -1 \end{bmatrix}
$$

$$
F_{vp} = \begin{bmatrix} V_E\left(-2\Omega_N + \rho_N \sec^2 L\right) + \frac{\rho_E R_{mm}}{R_m + h} - \rho_N \rho_D R_{tt} & 0 & \frac{V_D \rho_E}{R_m + h} - \rho_D \rho_N \\ V_N\left(2\Omega_N - \rho_N \sec^2 L + \frac{\rho_D R_{tt}}{R_t + h}\right) - V_D\left(-2\Omega_D + \frac{\rho_N R_{tt}}{R_t + h}\right) & 0 & \frac{V_N \rho_D - V_D \rho_N}{R_t + h} \\ -2\Omega_D V_E + \rho_N^2 R_{tt} + \rho_E^2 R_{mm} & 0 & \rho_N^2 + \rho_E^2 \end{bmatrix}
$$

$$
F_{vv} = \begin{bmatrix} \frac{V_D}{R_m + h} & 2\Omega_D + 2\rho_D & -\rho_E \\ -2\Omega_D - \rho_D & \frac{V_D - V_N \tan L}{R_t + h} & 2\Omega_N + \rho_N \\ 2\rho_E & -2\Omega_N - 2\rho_N & 0 \end{bmatrix}
$$

$$
F_{va} = \begin{bmatrix} 0 & -f_D & f_E \\ f_D & 0 & -f_N \\ -f_E & f_N & 0 \end{bmatrix}, \quad \begin{bmatrix} f_N \\ f_E \\ f_D \end{bmatrix} = C_b^n f^b
$$

$$
F_{ap} = \begin{bmatrix} \Omega_D - \frac{\rho_N R_{tt}}{R_t + h} & 0 & -\frac{\rho_N}{R_t + h} \\ -\frac{\rho_E R_{mm}}{R_m + h} & 0 & -\frac{\rho_E}{R_m + h} \\ -\Omega_N + \rho_N \sec^2 L - \frac{\rho_D R_{tt}}{R_t + h} & 0 & -\frac{\rho_D}{R_t + h} \end{bmatrix}
$$

$$
F_{av} = \begin{bmatrix} 0 & \frac{1}{R_t + h} & 0 \\ -\frac{1}{R_m + h} & 0 & 0 \\ 0 & \frac{\tan L}{R_t + h} & 0 \end{bmatrix}
$$

$$
F_{aa} = \begin{bmatrix} 0 & \Omega_D + \rho_D & -\rho_E \\ -\Omega_D - \rho_D & 0 & \Omega_N + \rho_N \\ \rho_E & -\Omega_N - \rho_N & 0 \end{bmatrix}
$$

$$
R_{mm} = \frac{\partial R_m}{\partial L} = \frac{3R_0\left(1 - e^2\right)e^2 \sin L \cos L}{\left(1 - e^2 \sin^2 L\right)^{6/2}}
$$

$$
R_{tt} = \frac{\partial R_t}{\partial L} = \frac{R_0 e^2 \sin L \cos L}{\left(1 - e^2 \sin^2 L\right)^{3/2}}
$$

In order to make the measurement matrix, the chain rule is used as follows:

$$
\frac{\partial\rho_i}{\partial L} = \frac{\partial\rho_i}{\partial x_u}\frac{\partial x_u}{\partial L} + \frac{\partial\rho_i}{\partial y_u}\frac{\partial y_u}{\partial L} + \frac{\partial\rho_i}{\partial z_u}\frac{\partial z_u}{\partial L} \qquad (20a)
$$

$$
\frac{\partial\rho_i}{\partial l} = \frac{\partial\rho_i}{\partial x_u}\frac{\partial x_u}{\partial l} + \frac{\partial\rho_i}{\partial y_u}\frac{\partial y_u}{\partial l} + \frac{\partial\rho_i}{\partial z_u}\frac{\partial z_u}{\partial l} \qquad (20b)
$$

$$
\frac{\partial\rho_i}{\partial h} = \frac{\partial\rho_i}{\partial x_u}\frac{\partial x_u}{\partial h} + \frac{\partial\rho_i}{\partial y_u}\frac{\partial y_u}{\partial h} + \frac{\partial\rho_i}{\partial z_u}\frac{\partial z_u}{\partial h} \qquad (20c)
$$

where

$$
\begin{aligned}
h_i &= \begin{bmatrix} \frac{\partial\rho_i}{\partial x_u} & \frac{\partial\rho_i}{\partial y_u} & \frac{\partial\rho_i}{\partial z_u} \end{bmatrix}^T = \begin{bmatrix} -\frac{x_i - x_u}{r_i} & -\frac{y_i - y_u}{r_i} & -\frac{z_i - z_u}{r_i} \end{bmatrix}^T \\
r_i &= \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2 + (z_i - z_u)^2} \\
x_u &= (R_t + h)\cos L \cos l \\
y_u &= (R_t + h)\cos L \sin l \\
z_u &= \left(R_t(1 - e^2) + h\right)\sin L
\end{aligned}
$$

$$
\frac{\partial x_u}{\partial L} = R_{tt} \cos L \cos l - (R_t + h)\sin L \cos l
$$

$$
\frac{\partial x_u}{\partial l} = -(R_t + h)\cos L \sin l
$$

$$
\frac{\partial x_u}{\partial h} = \cos L \cos l
$$

$$
\frac{\partial y_u}{\partial L} = R_{tt} \cos L \sin l - (R_t + h)\sin L \sin l
$$

$$
\frac{\partial y_u}{\partial l} = (R_t + h)\cos L \cos l
$$

$$\frac{\partial y_u}{\partial h} = \cos L \sin l$$

$$\frac{\partial z_u}{\partial L} = R_{tt}(1-e^2)\sin L + \left(R_t(1-e^2)+h\right)\cos L$$

$$\frac{\partial z_u}{\partial l} = 0$$

$$\frac{\partial z_u}{\partial h} = \sin L$$

And measurement is calculated as

$$\hat{\rho}_i = \sqrt{(x_i-\hat{x}_u)^2 + (y_i-\hat{y}_u)^2 + (z_i-\hat{z}_u)^2} + \hat{C}_{bias} \qquad (21)$$

Using (19) ~ (21), the EKF and the RHKF filter for the tightly coupled INS/GPS can be implemented. In order to apply the multi-filter fusion technique to the tightly coupled INS/GPS, the construction of the figure 1 is modified as figure 2. The sub INS/GPS module 1 using the EKF and the sub INS/GPS module 2 using the RHKF filter are processed separately. Then mode probability update and mixing/redistribution parts are carried out to fuse the two sub modules. Finally, data combination part is processed to generate the error compensated and fused navigation solution.

4. Simulation and Results

In order to verify the performance of the proposed tightly coupled INS/GPS integrated system using the multi-filter fusion technique, simulation is carried out. GPS data used in this simulation is generated using MATLAB Toolbox. It is assumed that GPS errors except for thermal noise are compensated. The horizon size of the RHKF filter is set by 10 seconds.

4.1 Case 1: Normal Case

The sensor error is modeled as random constant and the sensor error model in the filters is set as random constant. The simulation result is shown in figure 3.

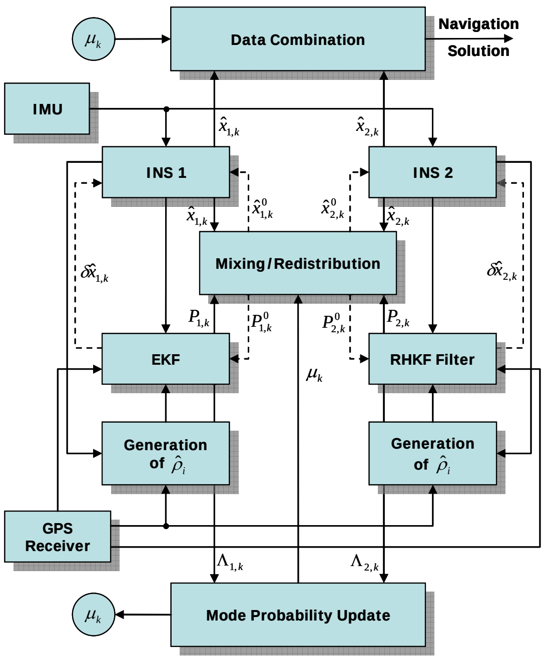
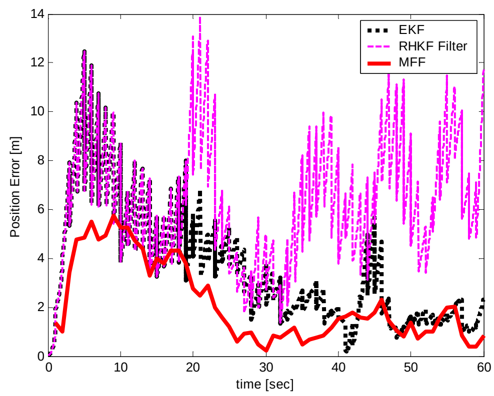
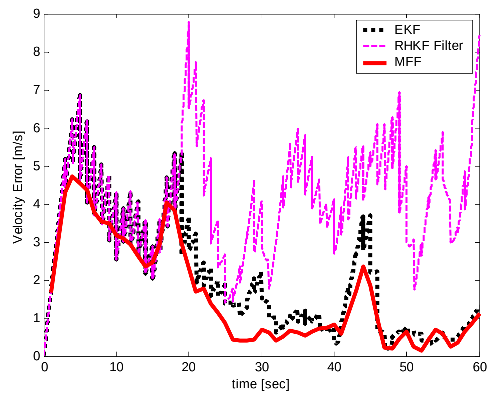


Figure 2. Structure of tightly coupled INS/GPS using the multi-filter fusion technique.

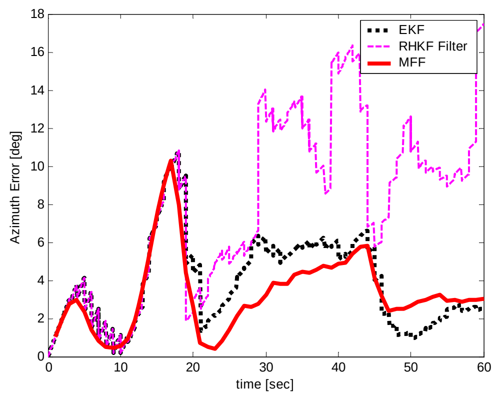
It can be shown that the proposed technique has smoothing effect. The position error (a) and velocity error (b) of RHKF filter are larger than that of EKF because the convergences of RHKF filter is restricted in the horizon. The position and velocity errors of the multi-filter fusion are smaller than EKF and RHKF filter. The azimuth error (c), sensor bias estimation errors (d), (e), and clock bias estimation (f) of EKF decrease with time. On the other hand, that of RHKF filter is bounded but is not converged. The result of the multi-filter fusion converged with time because the multi-filter fusion takes the strong points of the filters. The mode probabilities (g) of the two filters converge to 0.5 in the time section of twice horizon size of the RHKF filter. Then, the mode probability of EKF is slightly larger than that of RHKF filter because the error of EKF is smaller than that of RHKF filter in this case. In the normal case, therefore, the performance of EKF is better than that of RHKF filter, and the filter using the multi-filter fusion technique provides a good solution because of the reflection of the merits of EKF.



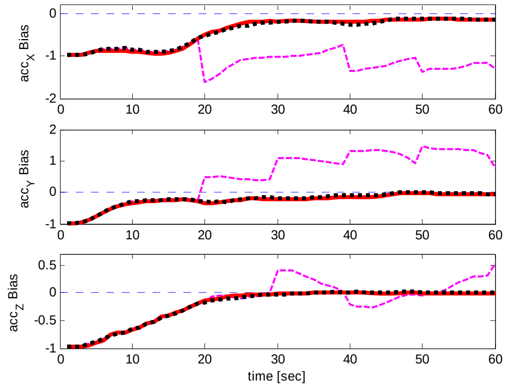
(a) position error



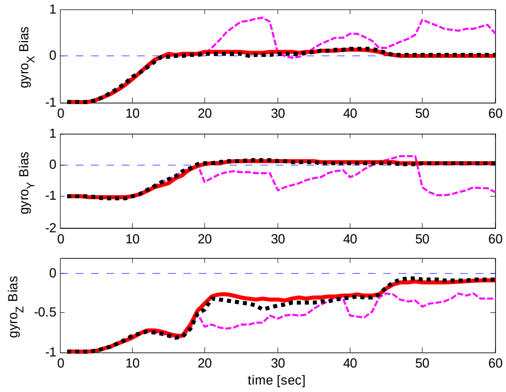
(b) velocity error



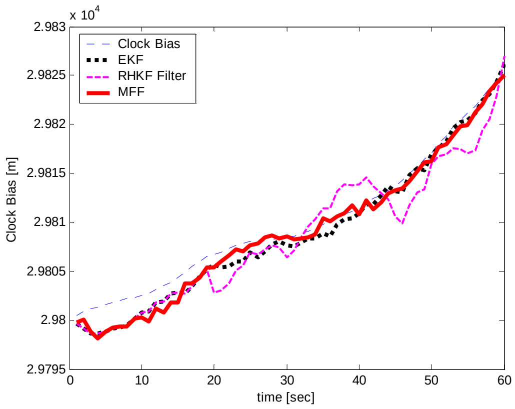
(c) azimuth error



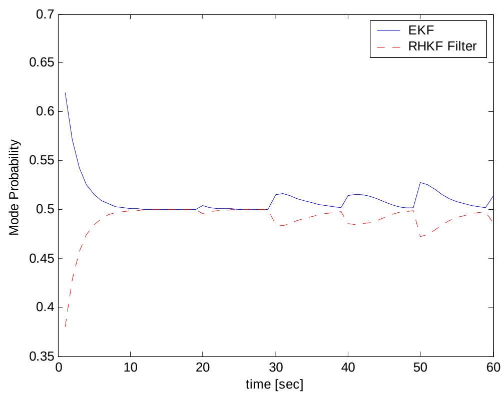
(d) accelerometer bias estimation error



(e) gyro bias estimation error



(f) clock bias estimation



(g) mode probability

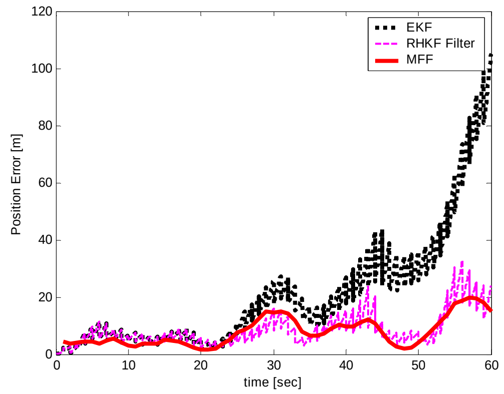
Figure 3. Simulation result of case 1.

4.2 Case 2: Model Uncertainty

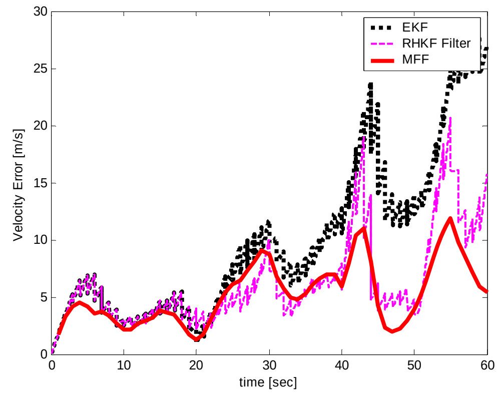
The sensor error is modeled as random walk as follows:

$$\begin{aligned} \nabla_{i\_k} &= \nabla_{i\_k-1} + w_{\nabla i\_k}, \;\; w_{\nabla i} \sim N(0,(500ug)^2) \\ \varepsilon_{i\_k} &= \varepsilon_{i\_k-1} + w_{\varepsilon i\_k}, \;\; w_{\varepsilon i} \sim N(0,(0.05^{\circ}/s)^2) \end{aligned} \qquad (22)$$

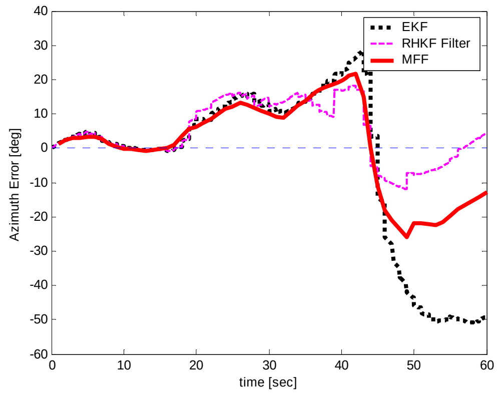
However, the sensor error model in the filters is set as random constant. Namely there is model uncertainty. The simulation result is shown in figure 4. In this case, the estimation errors in EKF diverge with time due to the IIR feature. However, the estimation errors of RHKF filter are bounded. This is the strong point of the FIR filter. The filter using the proposed multi-filter fusion technique merges the merits of the filters. Therefore, the estimation errors of the multi-filter fusion are not diverged. Moreover, it has smoothing effect. After time section of twice horizon size of RHKF filter, it can be seen that the mode probabilities are calculated favorable to RHKF filter.



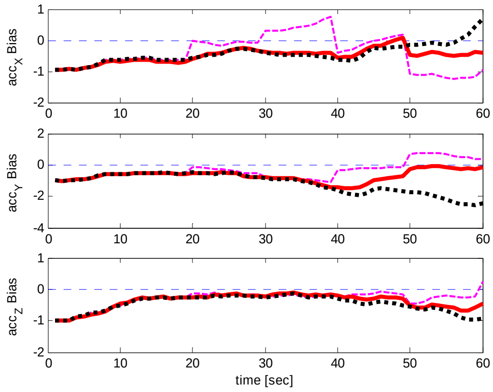
(a) position error



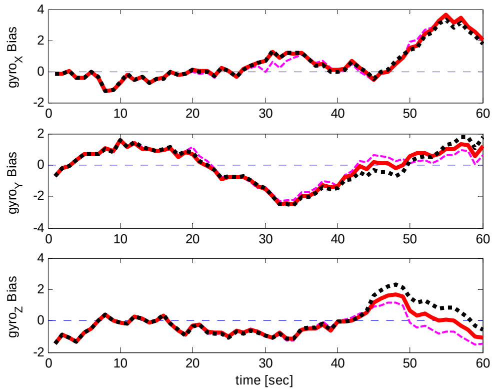
(b) velocity error



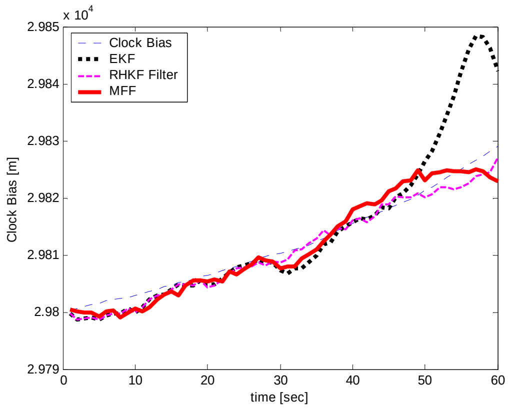
(c) azimuth error



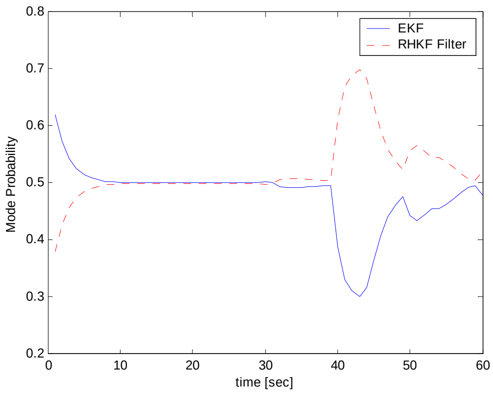
(d) accelerometer bias estimation error



(e) gyro bias estimation error



(f) clock bias estimation



(g) mode probability

Figure 4. Simulation result of case 2.

The two simulation results show that the filter using the proposed multi-filter fusion technique provides a better solution over EKF and RHKF filter irrespective of the model uncertainty.

5. Conclusion

A multi-filter fusion technique for merging of EKF and RHKF filter was introduced and an application filter for tightly coupled INS/GPS integrated system was proposed. The proposed multi-filter fusion technique has two meanings: fusion of nonlinear filters and fusion of IIR filter and FIR filter. The adaptive fusion probability is calculated using filter residuals and then the filter outputs are merged based on the probability. The filter designed by the multi-filter fusion technique provides a better solution over the conventional stand-alone filter. The performance of the filter was verified by simulation.

It can be expected that the proposed tightly coupled INS/GPS integrated system can provide a good navigation solution even in the case that the sensor error model can not be estimated exactly in the MEMS-INS/GPS system.

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