Analysis of the Fading Factor of an Adaptive Fading Kalman Filter under Ramp GNSS Fault Conditions

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A GNSS fault detection method using an adaptive fading Kalman filter is proposed for detecting GNSS faults such as step- and ramp-type bias error in pseudorange measurements. The fading factor of the filter is used as a detection parameter. In order to detect the GNSS fault signals regardless of the GNSS fault type, the proposed method is based on a single base station that has a fixed location and is already known. In the simulations, the different fault signal types are represented by the ramp bias error and the step bias error of the pseudorange. The change in the fading factor according to the bias error is quantitatively analyzed, and a detection threshold is established to detect the GNSS fault signal by analyzing the change in the error covariance. In addition, the value of the fading factor is applied to adjust the Kalman gain and the effect of the fault signal is mitigated by controlling the Kalman gain of the filter. The performance of the proposed fault detection method is evaluated by simulations, and the results thereof confirm that this method can detect each channel affected by fault signals when GNSS faults occur.

Key Words: Adaptive Fading Kalman Filter, Fading Factor, Fault Detection, GNSS Fault

Nomenclature

B: receiver clock bias
B': clock drift error
C: covariance
F: system dynamic matrix
G: deterministic input matrix
H: measurement matrix
K: Kalman gain
M: window size
N: satellite number (channel number)
P: error covariance
Q: process noise covariance
R: measurement noise covariance
T: elapsed time
T: threshold (diagonal matrix)
V: velocity
X: x-axis position
Y: y-axis position
Z: z-axis position
b: ramp-type bias error
c: velocity of the light
e: error components without bias error
n: element of measurement noise
u: control input vector
v: measurement noise
w: process noise
x: state vector
z: measurement vector
Δt: clock error of the receiver
α: fading factor
ρ: pseudorange

Subscripts
0: initial
N: satellite number
U: user
X: x-axis coordinate
Y: y-axis coordinate
Z: z-axis coordinate
j: discrete time step
k: discrete time step

1. Introduction

Recently, the number of applications that rely on GNSS for various uses has been increasing, and the quality of the navigation solutions is threatened by intentional interference, unintentional interference or GNSS failure. Cases in which intentional interference has caused damage have been constantly reported,1) and so it is necessary to prepare countermeasures for such activity because they can cause damage, or even the loss of human life in the worst case. Various types of intentional interference signals have been observed, and these can be typically classified as jamming, meaconing, and spoofing.2,3) Jamming signals have a much stronger signal power than the received GNSS signal, making receivers useless. Meaconing signals transmit the received signal after having been received from GNSS satellites. Spoofing signals

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attempt to deceive the GNSS receiver, and this signal is structured to resemble a set of normal GNSS signals. The spoofing signal is a greater threat than the other forms of intentional interference because it can result in large errors in the navigational solution, thereby deceiving users. Unintentional interference can be expected at low levels for a GNSS receiver operating practically anywhere in the world.\(^{4)}\) There are a number of systems in daily life that rely on the transmission of RF signals within the L-band. Frequencies near those used by GPS signals can cause the degradation of GPS signal quality. In the case of GPS failure, there are a few types of errors that affect the quality of the system.\(^{5)}\) The representative errors are GPS clock error, GPS ephemeris error, GPS code and carrier incoherence, and GPS signal distortion.\(^{6,7)}\)

These threats can corrupt the pseudorange measurements of a GPS directly or indirectly. Thus, various integrity monitoring methods\(^{8)}\) have been studied in order to reduce the effects of errors. The vulnerability of GPS signals has been investigated in Volpe\(^{9)}\) and Ochieng et al.\(^{10)}\) There are various methods to monitor the quality of GPS signals, but we are focusing on autonomous integrity monitoring by extrapolation (AIME).\(^{11,12)}\) AIME is a sequential algorithm, and its test statistics are based on innovation of the Kalman filter. The main objective of this research is to propose a fault detection method for a GNSS fault signal that affects the pseudorange accuracy in order to actively monitor the quality of the given navigation solution. In previous works, the representative errors of GPS are modeled as single-step or noise-type errors in the received pseudorange measurement. The ramp-type error, which is represented as GPS clock error or the effect of GPS spoofing signal on the pseudorange, is rarely analyzed and its effect on multiple channels has not been analyzed well in previous works. Thus, we have been focusing on the specific types of GPS faults, such as ramp and step, which are used to reflect the effect of spoofing signals on the pseudorange. The proposed algorithm is based on a detection method for a fault signal using a fault detection method with an adaptive fading Kalman filter that is applied for a static user whose position is already known, which is based on our previous work.\(^{13)}\) In our previous work, the types of fault signal were defined as the ramp-type and random noise error of pseudorange, and a single fault was only considered. However, this paper considers faults in multiple channels, and covers a step-type bias error as well as ramp-type bias error in the pseudorange. Furthermore, an analysis of the filter parameters is performed to confirm the effect of the fault signal on the fading factor and Kalman gain.

The concept of an adaptive fading Kalman filter is to apply a fading factor to the Kalman gain in order to adjust the tracking performance of the filter. The fading factor is calculated using the relation between the estimated innovation covariance that is obtained by the filter in each channel and the calculated innovation covariance. A fault signal is detected using the fading factor of an adaptive fading Kalman filter as the detection parameter, which is used to directly adjust the Kalman gain according to the quality of measurement. The use of the fading factor makes it possible to detect a fault signal, and the Kalman gain can be adjusted to reduce the influence of the fault signal. Thus, the proposed method can be applied to monitor integrity in the case of a fixed user because it can detect an abnormal pseudorange of multiple channels.

Section 2 introduces an adaptive fading Kalman filter. Section 3 discusses the fault detection method that uses the adaptive fading Kalman filter to detect the fault signal, where the fading factor of the filter is used as a detection parameter. The state variables and filter model are also explained. In Section 4, Parameter Analysis, the change in the fading factor according to the bias error is quantitatively analyzed, and the detection threshold is established to detect the fault signal by analyzing the change in the error covariance. Section 5 reports on the simple simulations performed to evaluate the performance of the proposed fault detection method. In these simulations, the fault signal types are represented by the ramp bias error and step bias error of the pseudorange. Finally, conclusions are given in Section 6.

### 2. Adaptive Fading Kalman Filter

An adaptive fading Kalman filter\(^{14)}\) is implemented to reduce the effect of faults in the measurement by using the fading factor of the Kalman filter. The fading factor is referred to as a memory factor, and it is defined as the comparison between the residual of the calculated covariance using past measurements and the residual of the estimated covariance at present. A threshold, which is set according to a reference value with a fading factor, is used to assess whether or not to trust past measurements or the present estimation. As a result, the Kalman gain can be adjusted to make an estimate by using the model with a robust disturbance. This structure is thus used to improve estimation performance of the filter in the case where there is an unexpected disturbance in the environment. The basic system and measurement model equations for the adaptive fading Kalman filter are as follows:\(^{14)}\):

\[
\begin{align*}
\dot{x}_k &= F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + w_{k-1}, \\
\zeta_k &= H_kx_k + v_k,
\end{align*}
\]

where \(w_k\) is the process noise, which is white Gaussian noise \(w_k \approx N(0, Q_k)\), and \(v_k\) is the measurement noise, whose distribution is also white Gaussian \(v_k \approx N(0, R_k)\). \(Q_k\) and \(R_k\) are the covariance matrices, and the correlations between the process noise and measurement noise are expressed using

\[
E\left( w_kw_j^T \right) = Q_k \delta_{k-j}, \quad E\left( v_kv_j^T \right) = R_k \delta_{k-j}, \quad E\left( w_kv_j^T \right) = 0.
\]

The Kalman filter is initialized as follows:

\[
\dot{x}_0^+ = E(x_0), \quad \hat{P}_0^+ = E\left[ (x_0 - x_0^-)(x_0 - x_0^-)^T \right].
\]

Based on how much the user wants the filter to forget past measurements, a memory factor (or fading factor) \(\alpha\) is set to be larger than one. If \(\alpha\) is equal to one, the fading Kalman filter is equivalent to a standard Kalman filter. In most applications, \(\alpha\) is set to be only slightly greater than one (for ex-
ample, \( \alpha \approx 1.01 \).\(^{14}\)

Equations (1) and (2), and the time update and measurement update for each time step \( k \) are used to obtain estimation results as follows:

\[
\begin{align*}
\hat{P}_k^+ &= \alpha^2 F_{k-1} \hat{P}_k^- F_{k-1}^T + Q_{k-1}, \\
K_k &= \hat{P}_k^- H_{k}^T (H_{k} \hat{P}_k^- H_{k}^T + R_{k})^{-1}, \\
\hat{x}_k^+ &= \hat{x}_k^- + G_{k-1} u_{k-1}, \\
\hat{x}_k^+ &= \hat{x}_k^- + K_k (z_k - H_k \hat{x}_k^-), \\
\hat{P}_k^- &= (1 - K_k H_k) \hat{P}_k^- ,
\end{align*}
\]

where \( \hat{P} \) is not equal to the covariance of the estimation error. The fading Kalman filter is more robust against modeling errors than a standard Kalman filter.\(^{14}\) In general, an adaptive fading Kalman filter can be designed to trust the model rather than the measurement in the case where a fault is detected, and the estimates are given by adjusting the fading factor. Thus, the adaptive fading Kalman filter is used to detect and remedy a spoofing signal. The filter model that is applied in the fault detection method is explained in further detail in the next section.

### 3. Fault Detection Method

The faults caused by GPS failures are defined as step error and ramp error (drift error) in the pseudorange measurements of each channel of GPS signals. The fault models are not meant to be rigorous, but rather to capture the behavior of the GPS faults.\(^{6,7}\)

Step errors in pseudoranges can be easily detected by snapshot receiver autonomous integrity monitoring (RAIM) methods based on current measurements. However, in the case of ramp error, it is the most difficult to easily detect when the change rate of the error is small. Thus, in this paper, an analysis on change of fading factor is performed in order to set the proper detection thresholds when ramp-type error occurs in the measurement.

The pseudorange and Doppler of the specific time and area are determined by the characteristics of the GNSS signal. Therefore, the change in the pseudorange of each channel increases when the spoofing signal is received and affected. For this reason, the change in pseudorange is used as an important parameter to detect a GNSS fault signal, including a spoofing signal.

The proposed fault detection method is based on an adaptive extended Kalman filter (EKF) structure. The state model for the adaptive fading Kalman filter is the constant velocity model shown below\(^{13,15}\):

\[
x_{k+1} = F x_k + w_k, \tag{10}
\]

where \([ X \ Y \ Z \ V_X \ V_Y \ V_Z \ B \ \dot{B} ]^T_k \) are the state variables of the filter and denote the three-axis receiver position, velocity, receiver clock bias, and clock drift error, respectively. \( w_k \) indicates the process noise.

The measurement model uses the equation of the linearized pseudorange, and the pseudorange equation for one channel is expressed as

\[
\rho_N = \sqrt{(X_U - X_N)^2 + (Y_U - Y_N)^2 + (Z_U - Z_N)^2} + c \Delta t
\]

where \( \rho_N \) is the pseudorange of the \( N \)-th channel, \([ X_U \ Y_U \ Z_U ]^T \) is the user position, \([ X_N \ Y_N \ Z_N ]^T \) is the satellite position of the \( N \)-th channel, \( c \) is the speed of light, and \( \Delta t \) is the clock error of the receiver. The pseudorange of Eq. (12) is linearized at the nominal point, \( x = [ X_U \ Y_U \ Z_U ]^T \), and can be expressed using

\[
\rho_N = \rho_X + h_{X,N} X_U + h_{Y,N} Y_U + h_{Z,N} Z_U + c \Delta t
\]

where \( x \) is the position of the estimated user, \( \rho_X \) is the estimated pseudorange at the nominal point, \( h_{X,N} = \partial \rho_N / \partial X_U \), \( h_{Y,N} = \partial \rho_N / \partial Y_U \), and \( h_{Z,N} = \partial \rho_N / \partial Z_U \). The linearized pseudorange can be expanded as follows\(^{13,16}\):

\[
\begin{bmatrix}
\rho_1 \\
\vdots \\
\rho_N \\
\end{bmatrix}_k = \begin{bmatrix}
X \\
Y \\
Z \\
V_X \\
V_Y \\
V_Z \\
B \\
\end{bmatrix}_k + \begin{bmatrix}
n_{\rho 1} \\
\vdots \\
n_{\rho N} \\
\end{bmatrix}_k, \tag{15}
\]

where \( n_{\rho 1} \) is the measurement noise.
where \([ \rho_1 \rho_2 \cdots \rho_N ]^T \) are the measurements and denote the pseudorange of the \( N \)-th channel satellite, \([ \hat{\rho}_1 \hat{\rho}_2 \cdots \hat{\rho}_N ]^T \) are the pseudorange at the estimated user position, and \([ n_1 n_2 \cdots n_N ]^T \) indicate the noise in the measurement. \([ h_{X,N} \ h_{Y,N} \ h_{Z,N} ] \) are the line-of-sight vectors between each satellite and the base station, and these can be expressed as follows:\(^{13,15,17}\):

\[
\begin{align*}
H_k &= \begin{bmatrix} h_{X,1} & h_{Y,1} & h_{Z,1} & 0 & 0 & 0 & 1 & 0 \\
: & : & : & : & : & : & : & : \\
h_{X,N} & h_{Y,N} & h_{Z,N} & 0 & 0 & 0 & 1 & 0 
\end{bmatrix}, \\
\end{align*}
\]  
(16)

The fading factor is used to monitor the change in the pseudorange for each channel to reduce the change in the pseudorange error has occurred. Therefore, the fading factors for the channels affected by the fault signal are larger than \( T \), and those of the rest of the channels become \( T \). Applying this characteristic, it is possible to detect the fault signal and the satellite channel affected by the fault signal. After determining which satellite channels are being affected by the fault signal, the Kalman gain is adjusted by the fading factor as follows, in terms of features of the filter, to prevent the fault signal from affecting the entire system:\(^{17}\):

\[
K_k = \begin{bmatrix} 1 / \alpha_k(1) & K_{11} & \cdots & 1 / \alpha_k(N) & K_{1N} \\
: & : & \cdots & : & : \\
1 / \alpha_k(1) & K_{81} & \cdots & 1 / \alpha_k(N) & K_{8N} 
\end{bmatrix}
\]  
(23)

where \( K_k \) is the adjusted Kalman gain with the dimension of \( 8 \times N \) by the fading factor and \( 1 / \alpha_k(N) \) indicates the inverse of the fading factor for each channel. \( K_{ij} \) is the Kalman gain before the adjustment, and it is updated using the following equation in the Kalman filter\(^{13}\):

\[
K_k = P_k H_k^T [ H_k P_k H_k^T + R_k ]^{-1}
\]  
(24)

where \( K_k \) is the Kalman gain matrix with a dimension of \( 8 \times N \) and is composed of the value of \( K_{ij} \). The fading factor, which is a detection parameter \( \alpha_k \), and the setting of the threshold \( T \) are explained in further detail in the next section.

The overall structure of the proposed algorithm is shown in Fig. 1. This algorithm consists of two parts, general Kalman filter\(^{14}\) and fault decision, and fading factor calculation based on adaptive fading logic. The operation principle of the second part is shown in Fig. 2.

During normal operation, the value of the estimated innovation covariance \( \hat{C}_k \) is less than the calculated innovation covariance \( C_k \), and all components of the fading factor \( \alpha_k \) are set to the critical value of one. Therefore, the Kalman
gain will be updated by a regular Kalman filter update expression. If a large measurement error occurs, \( \alpha_k \) will exceed one. In this case, the Kalman gain is reduced by the product of the reciprocal of the measurement information to make it less reliable. Therefore, the effect of a failed channel can be reduced using this filter structure.

4. Parameter Analysis

One channel of the GPS signal is considered in order to quantitatively analyze the effect of the fault signal on the fading factor and Kalman gain. The fault signal for parameter analysis is defined as a spoofing signal that can be modeled using the ramp-type bias error of the pseudorange. Thus, it is assumed that the ramp-type bias error is added on the \( k \)-th step, as shown in Fig. 3.\(^{20}\)

The estimation result can be expressed in terms of the ramp-type bias error and the measurement input in the \( k \)-th step\(^{31}\) as follows:

\[
\hat{x}_k^+ = \hat{x}_k + K_k (z_k - H_k \hat{x}_k) \\
= \hat{x}_k + K_k (z_k + b_k - H_k \hat{x}_k) 
\]

where \( \hat{x}_k \) represents the measurement with a bias error and \( b_k \) indicates the ramp-type bias error. To analyze the estimation performance of the filter, the error components can be expressed in terms of the residual as follows:

\[
\tilde{e}_k = (z_k - H_k \hat{x}_k) + b_k = e_k + b_k 
\]

where \( \tilde{e}_k \) refers to the error components that include the bias error and \( e_k \) represents the error components without the bias error. As shown in the equations above, the effects on it appear in the error components in the \( k \)-th step because the ramp-type bias \( b_k \) is added. The window size is set to three to obtain the estimated error covariance and the error in steps \( k-1 \) and \( k-2 \) that are respectively expressed as follows:

\[
\tilde{e}_{k-1} = e_{k-1}, \\
\tilde{e}_{k-2} = e_{k-2}. 
\]

From the above equation, there is no effect on the previous interval bias error because the bias error exists after the \( k \)-th step. The estimated error covariance is obtained using the error in the three intervals and can be expressed as follows:

\[
\tilde{C}_k = \frac{1}{2} \sum_{i=k-2}^k \tilde{e}_i^2 = \frac{1}{2} \left( (e_k + b_k)^2 + e_{k-1}^2 + e_{k-2}^2 \right) \\
= \frac{1}{2} \left( e_k^2 + e_{k-1}^2 + e_{k-2}^2 \right) + e_k b_k + \frac{1}{2} b_k^2 
\]

(28)

\[
= \hat{C}_k + e_k b_k + \frac{1}{2} b_k^2.
\]

Regardless of the bias error, the calculated error covariance can

\[
C_k = H_k P_k H_k^T + R_k. 
\]

(29)

The fading factor \( \tilde{a}_k \) is defined as the proportion of the estimated error covariance obtained in Eq. (28) to the calculated error covariance when the bias error is added. It can be expressed as:

\[
\tilde{a}_k = \frac{\tilde{C}_k}{C_k} = \frac{\hat{C}_k + e_k b_k + \frac{1}{2} b_k^2}{C_k} \\
= \alpha_k + \frac{e_k b_k + \frac{1}{2} b_k^2}{C_k} 
\]

(30)

where

\[
\beta_k = \left( e_k b_k + \frac{1}{2} b_k^2 \right) / C_k
\]

is defined, and the fading factor can be expressed as follows with a value that is larger than one.

\[
\tilde{a}_k = \alpha_k + \beta_k > 1.
\]

(31)

From the equation above, the fading factor has an affect on \( \beta_k \) of the ramp-type bias error. Here, the fading factor without a bias error \( \alpha_k \) can be expressed by the proportion of the estimated error covariance \( \hat{C}_k \) to the calculated error covariance \( C_k \); that is, \( \hat{C}_k/C_k \). In general, the fading factor \( \alpha_k \) is always smaller than one because \( \hat{C}_k \) is smaller than \( C_k \) since the measurement does not include the error components affected by bias. This can be expressed as follows:

\[
\min\{\alpha_k\} < \alpha_k < \max\{\alpha_k\}, \\
\min\{\alpha_k\} \geq 0, \ max\{\alpha_k\} \leq 1.
\]

(32)

However, the range of the fading factor \( \tilde{a}_k \) is changed by \( \beta_k \) when bias error components are added to the measurements.

\[
\min\{\alpha_k\} + \beta_k < \alpha_k + \beta_k < \max\{\alpha_k\} + \beta_k, \\
\tilde{a}_k = \alpha_k + \beta_k > \min\{\alpha_k\} + \beta_k > 1.
\]

(33)

From Eq. (30) and Eq. (33), the upper equation can be rearranged as:

\[
\beta_k = \frac{e_k b_k + \frac{1}{2} b_k^2}{C_k} > 1 - \min\{\alpha_k\}.
\]

(34)
By applying the conditions of $e_k > 0$, $b_k > 0$, $C_k > 0$ to Eq. (34), the detectable condition of the bias magnitude can be expressed as:

$$b_k > -e_k + \sqrt{e_k^2 + 2C_k - 2C_k \min(\alpha_k)}.$$  (35)

Equation (31) is established when the bias condition is satisfied by the upper equation. If $e_k$ (about 1 m on the base station) and $C_k$ are decided, the bias $b_k$, which is greater than those values, can be detected.

The fading factor is multiplied by the Kalman gain in the form of a reciprocal number, and this can be expressed as:

$$\tilde{K}_k = \frac{1}{\alpha_k} K_k = \frac{1}{\alpha_k + \beta_k} K_k.$$  (36)

The above equation is used to express the difference between the Kalman gain without bias error $K_k$ and Kalman gain with ramp-type bias error $\tilde{K}_k$ as follows:

$$K_k - \tilde{K}_k = K_k - \frac{1}{\alpha_k} K_k = K_k - \frac{1}{\alpha_k + \beta_k} K_k = \left(1 - \frac{1}{\alpha_k + \beta_k}\right) K_k.$$  (37)

As shown in the above result, the Kalman gain with bias error is smaller than that without bias error. This result makes it possible to estimate performance against disturbance because the estimated value is more reliable than the measurement.

While the fading factor without a bias does not exceed $T$, the fading factor with a bias is greater than one by $\beta_k$. Therefore, detection is easy if the threshold $T$ for detection is set to one. The results of the simulation are presented in the next section.

5. Simulations

The proposed method is distinct from previous methods\textsuperscript{22} in that detection is simply carried out using analysis on a stationary receiver, the position of which is already known. This method is designed to comprehensively detect fault signals, and three simulations are conducted to evaluate it. The conditions of the simulations are as follows. First, the faults that are represented as spoofing signals are modeled by the ramp-type bias and step-type bias of the pseudorange. Second, a minimum of four satellites are needed to estimate the position, as shown in Fig. 4. In this figure, the number for each satellite, including 1, 2, 8, and 10, are expressed as Ch1, Ch2, Ch3, and Ch4 in the simulations, respectively. When DOP is calculated using these four satellites, PDOP is an average of 6.4506 and GDOP is an average of 8.1499. The change in the fading factor is presented by monitoring the change in the pseudorange for each channel. The pseudorange measurement noise for the filter model is set to a standard deviation of about 5.5 m. For all simulations, the total simulation time is set to 1800 sec, and a fault signal is added after 700 sec. In addition, the performance of the proposed method is compared to that of a least squares method that uses EKF without adaptive logic.

First, a simulation is performed to analyze the detection performance of the proposed method when a fault signal is added as a step-type bias with 200 m on the pseudorange of Ch4. The fault detection based on the adaptive fading Kalman filter is used to obtain the fault detection results shown in Figs. 5 to 9. Figure 5 shows the difference between the true and measured values in the first simulation. As shown in Fig. 5, the pseudorange difference is compared to the true value changes as the step-type bias is received. Figure 6 shows the change in fading factor according to the change in the pseudorange of the GNSS signal. As shown in this figure, the fading factor for Ch4 increases when a bias is present. This property thus makes fault detection possible when the fading factor is above a certain threshold, and the detection results can be obtained as shown in Fig. 7. By setting the detection threshold, the fault signal is neglected and the detection results can be expressed as zero when the fading factor is smaller than one. If the fading factor is greater than one, a fault signal is considered to exist and the detection result can be expressed as one. As shown in this figure, the fault signal is de-
ected in Ch4 after 700 sec because the fault signal has been added to Ch4.

Figure 8 presents the position error for a static user when Ch4 is affected by the spoofing signal. The position of the user is estimated using the pseudorange of four channels. If an adaptive fading filter is not used, there is a large change in the position error estimated based on the step-type bias error (star points in Fig. 8). However, if an adaptive fading filter is used, the estimated position error does not change. Figure 9 shows the estimated position for the user applying each method when the spoofing signal is present. The effect of fault signal is minimized by multiplying the fading factor with the Kalman gain. As mentioned in the previous section, the Kalman gain is adjusted by the fading factor in the adaptive fading Kalman filter. As a result, the effect of the fault signal is reduced when the proposed algorithm is used. Therefore, the navigation solution calculated using the algorithm is more accurate than the one calculated using the conventional algorithm, as shown in Figs. 8 and 9. In Fig. 8, the position error is expressed in ENU coordinates and the position estimation results for the ECEF coordinate are shown in Fig. 9. The position estimation RMSE of the proposed algorithm is 1.5795 m, and that of the least squares method is 85.3368 m.

A second simulation is performed to analyze the detection performance of the proposed detection method when a ramp-type bias, such as a time error, exists. In this simulation, the fault signal is added as a ramp-type bias with a slope of 10 m/s on the pseudorange of Ch4. Using fault detection based on the adaptive fading Kalman filter, the fault detection results are shown in Figs. 10 to 14.

Figure 10 shows the difference between the true and estimated pseudoranges in each channel. As shown in Fig. 10, there is a drastic difference in pseudorange compared to the true value when the ramp-type bias is received. Figure 11 shows the change in fading factor according to the change in pseudorange of the GNSS signal. As shown in this figure, the
fading factor for Ch4 increases when a bias exists. This property is used to make fault detection possible when the fading factor is above a certain threshold, and detection results can be obtained as shown in Fig. 12. As this figure shows, the spoofing signal is detected in Ch4 after 700 sec because the spoofing signal is added. Figure 13 shows the position error for the static user when Ch4 is affected by the spoofing signal. While there is a large change in the position error estimated due to the ramp-type bias error (star points in Fig. 13) when the adaptive fading filter is not used, the estimated position error does not change when the adaptive fading filter is used. Figure 14 shows the estimated position for the user applying each of the methods when a spoofing signal is present. The effect of the fault signal is minimized by multiplying the fading factor with the Kalman gain.

Therefore, the navigation solution that is calculated using the proposed algorithm is more accurate than that calculated using the conventional algorithm, as shown in Figs. 13 and 14. The position estimation RMSE of the proposed algorithm is 0.8922 m and that of the least squares method is 2.1973 km.

A third simulation is performed to analyze the multiple detection performance of the proposed detection method. In this simulation, fault signals are defined as spoofing signals and are added as ramp-type biases with a slope of $-10 \text{ m/s}$ on the pseudorange of Ch4 is added. Using fault detection based on the adaptive fading Kalman filter, the fault detection results are shown in Figs. 15 to 19. Figure 15 shows the difference between the true and estimated pseudoranges for each channel. As shown in Fig. 15, there is a drastic difference in pseudoranges compared to the true value while ramp-type biases are being received in multiple channels. The ramp-type bias errors are generated by the bias input derived from
the simulation case. Figure 16 shows the change in fading factor according to the change in pseudorange of the GNSS signal. As shown in this figure, the fading factors for Ch1, Ch2 and Ch4 increase when biases exist (Ch3 is normal). This property can thus be used to make fault detection possible when the fading factors are above a certain threshold, and the results of the detection can be obtained as shown in Fig. 17. As shown in this figure, the fault signals are detected for Ch1, Ch2 and Ch4 after 700 sec because fault signals have been added in the channels.

Figure 18 shows the error in the position of a static user, and Fig. 19 shows the estimated position for the user using each method. The solution for the navigation calculated by the proposed algorithm is more accurate than that calculated using the conventional algorithm because the effect of the fault signals is minimized by multiplying the fading factor with the Kalman gain. The position estimation RMSE for the proposed algorithm is 1.4497 m and that of the least squares method is 10.4570 km. In the third simulation, we confirmed that the proposed method can detect multiple fault signals. The proposed algorithm is based on a single receiver, of which the location is already known and fixed. Therefore, it is possible to detect each channel affected by fault signals by monitoring only the change in fading factor for each channel because the fading factor of a channel affected by a fault signal increases.

6. Conclusions

This research proposes a fault detection method that uses an adaptive fading Kalman filter to detect and mitigate GNSS fault signals such as step- and ramp-type bias error. The fading factor for the filter is used as the detection parameter. Simulations and a quantitative analysis of the filter parameters are conducted by modeling the fault signal according to the ramp-type and step-type biases of the pseudorange. Simulations were performed to evaluate the performance of the proposed fault detection method, and if the bias error existed, the fading factor was greater than the detection threshold due to the increase in fading factor. Thus, fault signals can be detected by monitoring the change in fading factor. In addition, the fault detection method was confirmed to work well using simulations where multi-channel errors exist. Thus, the proposed fault detection method can be applied as an algorithm to monitor integrity in the case of a fixed user because it can detect abnormal pseudoranges for each channel.
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