Covariance Analysis Study for KOMPSAT Attitude Determination System

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Abstract

The attitude knowledge error model is formulated for specifically KOMPSAT attitude determination system using the Lefferts/Markley/Shuster method, and the attitude determination(AD) error analysis is performed so as to investgate the on-board attitude determination capability of KOrea Multi-Purpose SATellite(KOMPSAT) using the covariance analysis method. Analysis results show there is almost no initial value effect on Attitude Determination(AD) error and the sensor noise effects on AD error are drastically decreased as is predicted because of the inherent characteristic of Kalman filter structure. However, it shows that the earth radiance effect of IR-sensor(earth sensor) and the bias effects of both IR-sensor and fine sun sensor are the dominant factors degrading AD error and gyro rate bias estimate error in AD system. Analysis results show that the attitude determination errors of roll, pitch and yaw axes are 0.056, 0.092 and 0.093 degrees, respectively. These numbers are smaller than the required values for the normal mission of KOMPSAT. Also, the selected on-orbit data of KOMPSAT is presented to demonstrate the designed AD system.

Key Word : Covariance Analysis, Attitude Determination System, Kalman Filter, KOMPSAT

Introduction

Generally, there are two methods to determine a spacecraft attitude while it flies: one is the direct attitude determination method using the measurement information of earth sensor, sun sensor or star tracker, etc., the other is the indirect attitude determination method using an estimation method with the measurement information from various sensors. While the former has several disadvantages such as a noise currupted sensor measurement problem, missing attitude information when the sensor field of view is temporarily blocked with some objects, the implementation algorithm is much simpler than the latter. The latter is much more complex than the former in the on-board implementation sturcture, but this method is more effective than the former when a spacecraft need depend on a gyro only for controlling attitude with the blockage of sensor field of view temporarily because of its inherent sensor noise rejection function and gyro bias estimation, and so on.

Over the last several decades, there are many researchers who have studied attitude determination algorithm which can be implemented on the on-board processor of low earth orbit spacecraft. As a result, many fruitful results have been developed and applied to solve a specific attitude determination problem and also, employed for spacecraft flown already. Even though there are several attitude

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estimators used for on-board processing, it is believed that pseudo-inverse estimator and Kalman filter algorithm are the most popular methods. Among these methods, the pseudo-inverse estimator[1] does not provide any filtering process of measurement noise while it has the advantage of being relatively simple and computationally fast. In this algorithm, the gain matrix depends on the measurement matrix so that the estimate states always corresponds to an exact fit to the most current sensor data. Usually the pseudo-inverse estimator was used because of its simplicity and computationally fast when the calculation capability of on-board processor was limited. The most popular state estimator for on-board processing is the Kalman filter which has been used for many satellite programs such as SPOT, AXAF, SSTI, ROCSAT and KOREASAT 3, and many unknown military satellite programs since it was first applied to Apollo program. Recently, many research results come out for precise attitude estimation using the Kalman filter method incorporated with gyro set and star sensor or sun sensor and earth sensor[2-3].

KOMPSAT is the first low earth orbit satellite for the remote sensing and scientific data gathering purposes in Korea. It was already launched from Vandenburg, U.S. Airforce base, CA. on December 21, 1999 and now is conducting its required mission successfully.

The primary Attitude & Orbit Control Subsystem(AOCS) of KOMPSAT consists of three sets of Kearfott's two-axis rate integrating gyros, two sets of Ithaco's Conical Earth Sensors providing two-axis attitude errors from the chord length error and the phase angle shift, and Daewoo Heavy Industry(DHI)'s two sets of analog fine sun sensors whose field of view is sun aspect angle of +/-29 degrees and the sun cross axis angle of +/-2 degrees. The Kalman filter technique is utilized by incorporating these sensor measurements for attitude determination in KOMPSAT. The pointing knowledge of the earth sensor and the fine sun sensor are both 0.075 degree(2σ), and the scale factor of gyro is 0.5 arc-second per pulse with the noise equivalent angle of 2 arc-second(2σ) over 0.737 second. The required pointing accuracy for the cartographic mission is 0.1deg(2σ) for roll and pitch axes. The estimated elements of the Kalman filter for KOMPSAT attitude determination system consist of 6 elements: roll, pitch, yaw errors and rate biases of gyroes. Estimated roll and pitch errors are updated by the conical earth sensor measurement at every 16 seconds. Estimated yaw error is updated by fine sun sensor measurement two times per orbit over 65 seconds each whenever KOMPSAT is flying over the North Pole and South Pole areas. The functional block diagram of KOMPSAT attitude determination is depicted in Fig. 1.

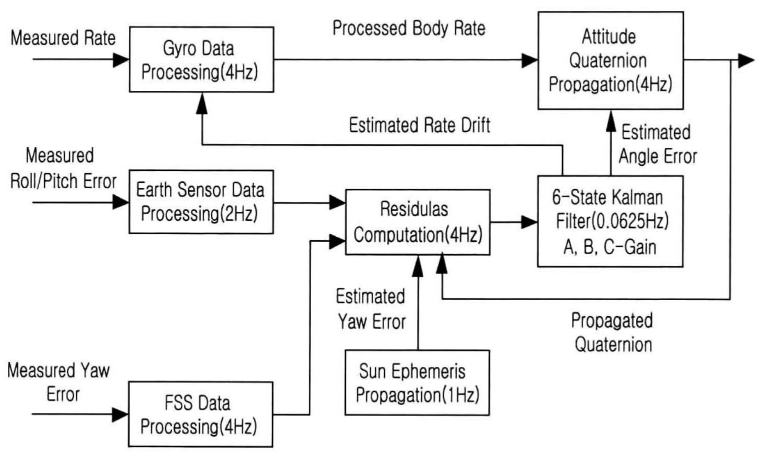

Fig.1. Functional Block Diagram of KOMPSAT Attitude Determination

The estimated sun line of sight vector computed by the Solar Ephemeris propagator of the flight software is transformed from ECI(Earth Centered Inertial) frame to the fine sun sensor coordinate frame, and the difference between the estimated and measured line of sight vectors forms the residual as an input to the Kalman filter algorithm. Another idea of attitude determination of KOMPSAT is Kalman filter with gyro-compassing, for the roll gyro rate bias estimation which is in-distinguishable from the yaw error of spacecraft. In flight software, three kinds of Kalman filter gains, so called, A-gain, B-gain, C-gain, are employed, so-called gain scheduling method. A-gain is selected to expedite its convergence whenever attitude determination is initiated, which consists of large approximated filter gains, the B-gain after attitude updating with the A-gain until initial attitude update with the fine sun sensor. The C-gain after initial attitude updating with the fine sun sensor is kept through the science mission for steady state condition. Six state-variables including gyro rate biases and attitude errors for each axis is estimated with the filter gains and attitude residuals.

As shown in Fig. 2, the earth sensor measurement is not used above the latitude of 45 degree and below than the latitude of -45 degree for the attitude estimation so as to avoid the earth radiance problem.

Fine sun sensor is operating only at the North and South Pole area for attitude update. In flight software, +/-2 degree of active angle of fine sun sensors is defined to eliminate its measurement uncertainty. Thus, the attitude update for yaw axis is performed while the sun vector stays in the active angle range. Attitude propagation using the rate information from gyro set is executed in order to get attitude information while attitude updates with 16 second interval.

The primary objective of the current study is to investigate thoroughly KOMPSAT attitude determination performance using a covariance analysis method.

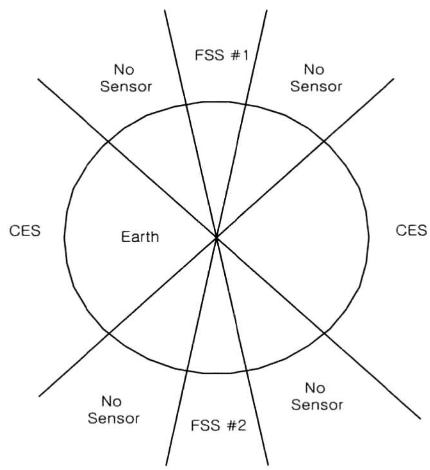

Fig. 2. Sensor Activation Region

Measurement Model

The gyro model developed by Farrenkopf is depicted as[1]

$$\vec{\omega}_g = \vec{\omega} + \vec{b}_g + \vec{\eta}_{g1} \tag{1}$$

$$\dot{\vec{b}}_g = \vec{\eta}_{g2} \tag{2}$$

where $\vec{\omega}_g$, $\vec{\omega}$ denote the measurement output vector of gyro set and true rate, respectively. The three component vector $\vec{b}_g$ is the gyro rate bias which can assume to be a very slow varying component, $\vec{\eta}_{g1}$, $\vec{\eta}_{g2}$ are the zero mean Gaussian gyro rate noise and rate random walk vector components, respectively.

By taking expected value of above Eq. (1), (2), the estimated rate can be expressed as

$$\hat{\vec{\omega}} = \vec{\omega}_g - \hat{\vec{b}}_g \tag{3}$$

$$\dot{\hat{\vec{b}}}_g = 0 \tag{4}$$

Incorporated with gyro measurement data, fine sun sensor measurement for yaw error and earth sensor measurement for roll and pitch errors are used for attitude update. In this study, the sensor models are simply taken as the linear combination of mean measurement, sensor bias and measurement noise

Attitude Knowledge Error Formulation

According to [3], several formulation methods of the attitude knowledge error have been suggested. Among these methods, The Lefferts/Markley/Shuster(LMS) method[4] used for a filter design is utilized in this study for the attitude knowledge error formulation. Suppose the current true attitude denoted by quaternion, $\bar{q}$ is defined by first rotating the body by an amount of the current attitude estimated quaternion, $\hat{\bar{q}}$ and then rotating the body by $\bar{q}_e$, the attitude error quaternion that can be assumed as a small angle. Then, the current true attitude expressed in quaternion notation has the form of

$$\bar{q} = \hat{\bar{q}} \otimes \bar{q}_e \tag{5}$$

where $\bar{q}$ is the current true attitude quaternion, $\otimes$ denotes quaternion multiplication operator. Suppose a quaternion is expressed as the combination of a vector and a scalar components: $\bar{q} = \{\vec{q},\ q_4\}$, the quaternion multiplication can be defined as $\bar{p} \otimes \bar{q} = \{\vec{p} \times \vec{q} + p_4\vec{q} + q_4\vec{p},\ \ p_4 q_4 - \vec{p} \bullet \vec{q}\}$.

After differentiating Eq. (5) and using the quaternion estimated kinematic relation $\dot{\hat{q}} = \frac{1}{2}\hat{q} \otimes \{\hat{\vec{\omega}},0\}$, also post-multiplying the conjugate estimated quaternion, $\hat{\bar{q}}^*$, a simple algebraic manipulation produces

$$\dot{\bar{q}}_e = \{-\hat{\vec{\omega}} \times \vec{q}_e, 0\} + \frac{1}{2}\bar{q}_e \otimes \{\vec{\omega} - \hat{\vec{\omega}}, 0\} \tag{6}$$

where $\vec{q}_e$ is the vector component of error quaternion.
Using Eq. (1) through Eq. (4), Eq. (6) can be rewritten as

$$\dot{\bar{q}}_e = \{-\hat{\vec{\omega}} \times \vec{q}_e, 0\} + \frac{1}{2}\bar{q}_e \otimes \{-\Delta\vec{b} - \vec{\eta}_{g1}, 0\} \tag{7}$$

$$\Delta\dot{\vec{b}} = \vec{\eta}_{g2} \tag{8}$$

where the gyro rate bias difference is $\Delta\vec{b} = \vec{b}_g - \hat{\vec{b}}_g$, $\vec{\eta}_{g1}$ denotes the zero mean Gaussian gyro drift rate noise, and $\vec{\eta}_{g2}$, the zero mean Gaussian gyro drift rate random walk same as specified in Eq. (1) and (2).

If $\bar{q}_e$ is the attitude small angle quaternion as assumed above, using small angle approximation relationship: $q_e \cong \frac{\varphi_e}{2}$ and neglecting higher than the first order term $\vartheta(2)$, Eq. (7) becomes

$$\dot{\vec{\varphi}}_e = -\hat{\vec{\omega}} \times \vec{\varphi}_e - \Delta\vec{b} - \vec{\eta}_{g1} \tag{9a}$$

where $\vec{\varphi}_e$ is the estimation angle error vector(1x3) and the cross product, $\hat{\vec{\omega}}\times$, can be expressed as a skew symmetric matrix form of

$$\hat{\vec{\omega}}\times = \begin{bmatrix} 0 & -\hat{\omega}_z & \hat{\omega}_y \\ \hat{\omega}_z & 0 & -\hat{\omega}_x \\ -\hat{\omega}_y & \hat{\omega}_x & 0 \end{bmatrix}. \tag{9b}$$

If we express Eq. (8) and (9) into a state-space form

$$\begin{Bmatrix} \dot{\vec{\varphi}}_e \\ \Delta\dot{\vec{b}} \end{Bmatrix} = \begin{bmatrix} -\hat{\vec{\omega}}\times & -I_{3x3} \\ 0_{3x3} & 0_{3x3} \end{bmatrix} \begin{Bmatrix} \vec{\varphi}_e \\ \Delta\vec{b} \end{Bmatrix} + \begin{Bmatrix} -\vec{\eta}_{g1} \\ \vec{\eta}_{g2} \end{Bmatrix} \tag{10a}$$

Thus, the system matrix is assumed to be 6x6 dimension, the number of states is 6 for this study and $[\vec{\eta}_{g1} \;\; \vec{\eta}_{g2}]^T$ is assumed to be uncorrelated Gaussian white noise processes with the properties of

$$E[\vec{\eta}_{g1} \;\; \vec{\eta}_{g2}]^T = 0,$$
$$E\{[\vec{\eta}_{g1} \;\; \vec{\eta}_{g2}]\,[\vec{\eta}_{g1} \;\; \vec{\eta}_{g2}]^T\} = Q_F(t)\delta(t-\tau), \quad Q_F(t) = \begin{bmatrix} \sigma_{g1}^2 I_{3x3} & 0_{3x3} \\ 0_{3x3} & \sigma_{g2}^2 I_{3x3} \end{bmatrix} \tag{10b}$$

where $Q_F(t)$ is the power spectral density matrix of system noise and σ_{g1}^2, σ_{g2}^2 denote the power spectral densities for gyro drift rate noise and gyro drift rate random walk, respectively. Note that it is assumed the gyro noise characteristics of all three axes are same without loss of generality. For the attitude measurement data, an earth sensor for roll and pitch error measurements and a fine sun sensor for yaw error measurement are utilized. After assuming sensor geometry are aligned with spacecraft control axes exactly, the measurement output can be simply expressed in a combination of control axis measurement error and its noise as a following form for the filter design purpose,

$$\vec{z}_F(t) = H_F\vec{x}_F(t) + \vec{v}(t) \tag{11a}$$

where $\vec{z}_F$ is a noise corrupted output, state variable is defined as $\vec{x}_F = [\vec{\varphi}_e \;\; \Delta\vec{b}]^T$, the measurement noise vector, $\vec{v}(t)$ is a zero mean Gaussian measurement noise with

$$E[\vec{v}] = 0,$$
$$E[\vec{v}\vec{v}^T] = R(t)\delta(t-\tau) = \sigma_s^2 I_{3x3} \tag{11b}$$

where σ_s denotes the noise standard deviation of an earth sensor and a fine sun sensor. Usually, the higher dimension of true model is considered incorporated with Eq. (10) for covariance analysis depending on how many states are considered in the true model: gyro scale factor error, sensor misalignment, and sensor bias can be augmented with a system model used for a filter design. Taking the expection of Eq. (10), (11) give the general form of estimation model

$$\dot{\hat{\vec{x}}}_F = A_F\hat{\vec{x}}_F \tag{12a}$$

$$\hat{\vec{z}}_F = H_F\hat{\vec{x}}_F \tag{12b}$$

Suppose a general form of true model may be expressed as

$$\dot{\vec{x}}_T = A_T\vec{x}_T + B_T\vec{w}_T \tag{13a}$$

$$\vec{z}_T = H_T\vec{x}_T + v \tag{13b}$$

and from Eq.(12), (13), the estimate is given by

$$\dot{\hat{\vec{x}}}_F = A_F\hat{\vec{x}}_F + K[\vec{z}_T - \hat{\vec{z}}_F] \tag{14}$$

The subscripts in Eq. (13) and (14) illustrates the fact that the matrices of true model and measurement output in Eq. (13) are not same as Eq. (12). For this study, the earth sensor and sun sensor biases, the earth radiance effect are augmented with a filter design model, Eq. (10). Thus, the state variable of the true model becomes

$$\vec{x}_T = [\vec{\varphi}_e \quad \Delta\vec{b} \quad \vec{\varphi}_b \quad \vec{\varphi}_r]^T \tag{15}$$

where $\vec{\varphi}_e$ is the estimation angle error vector(1x3), $\Delta\vec{b}$ is the gyro rate bias difference vector, $\vec{\varphi}_b$, $\vec{\varphi}_r$ denote the earth sensor and sun sensor biases, the error due to the earth radiance effect, respectively.

Assuming the constant transition matrix over the every sampling time interval, the discrete form of the estimate model Eq. (12) is

$$\hat{\vec{x}}_F(k) = \Phi_F\hat{\vec{x}}_F(k-1) \tag{16a}$$

$$\hat{\vec{z}}_F(k) = H_F\hat{\vec{x}}_F(k) \tag{16b}$$

where the transition matrix, $\Phi_F = e^{A_F \cdot \Delta T}$, ΔT denotes the attitude update interval and assuming only orbital rate $\hat{\omega}_0$ exists and other rate components are zero without loss of generality, Φ_F can be simplified as

$$\Phi_F = \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ 0_{3x3} & I_{3x3} \end{bmatrix} \tag{16c}$$

$$\Phi_{11} = \begin{bmatrix} \cos\hat{\omega}_0\Delta T & 0 & \sin\hat{\omega}_0\Delta T \\ 0 & 1 & 0 \\ -\sin\hat{\omega}_0\Delta T & 0 & \cos\hat{\omega}_0\Delta T \end{bmatrix} \tag{16d}$$

$$\Phi_{12} = \begin{bmatrix} \frac{-1}{\hat{\omega}_0}\sin\hat{\omega}_0\Delta T & 0 & \frac{-1}{\hat{\omega}_0}(1-\cos\hat{\omega}_0\Delta T) \\ 0 & -\Delta T & 0 \\ \frac{1}{\hat{\omega}_0}(1-\cos\hat{\omega}_0\Delta T) & 0 & \frac{-1}{\hat{\omega}_0}\sin\hat{\omega}_0\Delta T \end{bmatrix} \tag{16e}$$

$H_F = [I_{3x3} \quad 0_{3x3}]$, I_{3x3} is the identity matrix, and 0_{3x3} is a null matrix.

Also, the discrete form of the true model with a zero mean random noise sequence is described by

$$\vec{x}_T(k) = \Phi_T\vec{x}_T(k-1) + \Gamma\vec{w}_T(k-1) \tag{17a}$$

$$\vec{z}_T(k) = H_T\vec{x}(k) + \vec{v}(k) \tag{17b}$$

where $\Phi_T = e^{A_T \cdot \Delta T}$, $\Gamma = \int_0^{\Delta T} e^{A_T \cdot S} ds \cdot B_T$

Introducing that the best estimate is the conditional mean given all previous data, the a priori estimate at time k can be found from the a posteriori estimate at time (k-1) by propagation using the deterministic system model of Eq. (16). The discrete form of the a priori estimate model which means that propagating model without a measurement update, is expressed as

$$\hat{\bar{x}}_F^-(k) = \Phi_F \hat{\bar{x}}_F^+(k-1) \tag{18a}$$

$$\hat{\bar{z}}_F(k) = H_F \hat{\bar{x}}_F^-(k) \tag{18b}$$

where Φ_F is defined in Eq. (16).

A posteriori estimate at time k by adding multiplication of the error between measurement and estimated output by Kalman filter to a priori estimate, is given by

$$\hat{\bar{x}}_F^+(k) = \hat{\bar{x}}_F^-(k) + K[\bar{z}_T(k) - H_F \hat{\bar{x}}_F^-(k)] \tag{19}$$

Usually, the true model of Eq. (17) tries to describe a real world, and the estimate model of Eq. (16) is not identical to the true model. Suppose the number of an estimated state is subset of the number of a true model state. Now, we can start the formulation of covariance analysis by introducing a matrix to account for the dimensional incompatibility between two models with the similar method of [5]. A priori estimate error can be defined as

$$\tilde{x}^-(k) = W^T \hat{\bar{x}}_F^-(k) - \bar{x}_T(k) \tag{20}$$

where the matrix W =[I 0], I is an identity matrix and 0 is a null matrix and W has the property of $WW^T = I$.

A posteriori estimate error can be defined as

$$\tilde{x}^+(k) = W^T \hat{\bar{x}}_F^+(k) - \bar{x}_T(k) \tag{21}$$

Substituting Eq. (18) and (21) into Eq. (20) produces Eq. (22)

$$\tilde{x}^-(k) = W^T \Phi_F W[\tilde{x}^+(k-1) + \bar{x}_T(k-1)] - \Phi_T \bar{x}_T(k-1) - \Gamma \bar{\omega}_T(k-1) \tag{22}$$

Defining $\Delta\Phi = W^T \Phi_F W - \Phi_T$ and rearranging Eq. (22) gives Eq. (23)

$$\tilde{x}^-(k) = W^T \Phi_F W \tilde{x}^+(k-1) + \Delta\Phi \bar{x}_T(k-1) - \Gamma \bar{\omega}_T(k-1) \tag{23}$$

Now, let's define $X^- = [\tilde{x}^-(k) \;\; \bar{x}_T(k)]^T$ and $X^+ = [\tilde{x}^+(k) \;\; \bar{x}_T(k)]^T$ for covariance equations. Then, a priori error covariance is

$$X^- X^{-T} = \begin{bmatrix} P^-(k) & V^{-T}(k) \\ V^-(k) & U^-(k) \end{bmatrix} \tag{24}$$

and a posteriori error covariance is

$$X^+ X^{+T} = \begin{bmatrix} P^+(k) & V^{+T}(k) \\ V^+(k) & U^+(k) \end{bmatrix} \tag{25}$$

Using Eq. (24) and (25), the priori error covariance extrapolation equation incoperated with Eq. (17) can obtained as

$$\begin{bmatrix} P^-(k) & V^{-T}(k) \\ V^-(k) & U^-(k) \end{bmatrix} = \begin{bmatrix} W^T \Phi_F W & \Delta\Phi \\ 0 & \Phi_T \end{bmatrix} \cdot \begin{bmatrix} P^+(k-1) & V^{+T}(k-1) \\ V^+(k-1) & U^+(k-1) \end{bmatrix} \begin{bmatrix} W^T \Phi_F W & \Delta\Phi \\ 0 & \Phi_T \end{bmatrix}^T + \begin{bmatrix} Q(k-1) & -Q(k-1) \\ -Q(k-1) & Q(k-1) \end{bmatrix} \tag{26}$$

where $Q(k-1)=\int_{t_{k-1}}^{t_k}\Phi(t_k,s)\bar{\omega}\bar{\omega}^T\Phi^T(t_k,s)ds$ Similarly, when a measurement is made for update, the error covariance update equation using Eq. (19), (21), (24) and (25), is derived as

$$\begin{bmatrix} P^+(k) & V^{+T}(k) \\ V^+(k) & U^+(k) \end{bmatrix} = \begin{bmatrix} I-W^TKH_FW & -W^TK\Delta H \\ 0 & I \end{bmatrix}\begin{bmatrix} P^-(k) & V^{-T}(k) \\ V^-(k) & U^-(k) \end{bmatrix}\begin{bmatrix} I-W^TKH_FW & -W^TK\Delta H \\ 0 & I \end{bmatrix}^T + \begin{bmatrix} W^TKRK^TW & 0 \\ 0 & 0 \end{bmatrix} \quad (27)$$

where $\Delta H = H_FW - H_T$ and R is the power spectrum sequence of measurement noise. Now, covariance analysis can be performed by iterating Eq. (26) and (27).

Analysis Results of KOMPSAT Case

The covariance error analysis is performed using KOMPSAT data. The attitude determination system of KOMPSAT utilizes sets of gyro, earth sensor and fine sun sensor as is mentioned already. For the simulation purpose, initial attitude errors used for analysis are 1.0 deg(3σ) for roll, pitch, yaw axes, respectively and 0.25 deg/hour(3σ) for initial roll, pitch, yaw gyro bias drift error, respectively. Table 1 shows the sensor error sources in 3σ used for covariance analysis input. The 35 hour run is performed so as to get the steady state results, and as depicted in Fig. 2, yaw axis error is updated only at the South and North Pole areas over about 65 seconds each. KOMPSAT

Table 1. Sensor Error Source

Error Source	Units	Value(3σ)
Earth sensor roll bias	Deg	0.0336
Earth sensor pitch bias	Deg	0.0310
Fine sun sensor yaw bias	Deg	0.087
Roll radiance	Deg	0.097
Pitch radiance	Deg	0.091
Earth sensor roll noise	Deg	0.0216
Earth sensor pitch noise	Deg	0.0188
Fine sun sensor yaw noise	Deg	0.010
Gyro angle random noise	$\text{Deg/sec}^{1/2}$	7.631e-5
Gyro rate random noise	$\text{Deg/sec}^{3/2}$	8.417e-8

attitude determination system utilizes, so called, a gain scheduling method(A-Gain, B-Gain, C-Gain) depending on the pre-set cases. Whenever spacecraft is flying over the area greater than the latitude of +/-45 deg, earth sensors are not used for attitude update except while the A and B-gains are in use. After first sun sensor update is executed, a steady state(C-gain) is used for attitude update. As shown in Table 2, the A and B-gains in KOMPSAT are used in order to expedite its convergency of attitude error estimate without the estimation of gyro bias drift error: The A-gain is for direct usage of measurement data without an estimation process and the B-gain is for attitude updating with a gyro compassing. The C-gain is used for the attitude error estimate and the gyro bias drift error estimate. The C-gain is listed in Table 3.

Fig. 3 and 4 show the error covariance analysis results for roll, pitch and yaw axes. As seen in Fig. 3, the attitude determination errors of roll, pitch, yaw axes are 0.056 deg., 0.092 deg., 0.093 deg. in 3σ, respectively. It also shows that about 15 hours (about 9 orbits) are taken to reach the steady state of the roll axis error estimate while about 5 hours (about 3 orbits) are required for the steady state for pitch axis. Also, it shows that yaw axis error estimate requires about 10 hours (about 6 orbits). The reason why pitch axis convergency time is shorter than other axes, is due to the orbital rate which is the nominal value of pitch axis rate while zero rate for roll and yaw axis nominal rate. According to Fig. 4, the estimated gyro bias drift errors are 0.33 deg/hr., 0.06 deg/hr., 0.18 deg/hr., respectively. The results of Fig. 4 is summarized in Table 5. Fig. 4 shows the gyro bias error covariance analysis results for roll, pitch and yaw axes. Analysis results show there is almost no initial value effect on the attitude determination error and the sensor noise effects on the attitude determination error.

Table 2. A and B-Gain Values

	A-Gain			B-Gain		
Estimated Items	Ki1	Ki2	Ki3	Ki1	Ki2	Ki3
Roll Angle	1.0	0	0	0.2	0	0
Pitch Angle	0	1.0	0	0	0.2	0
Yaw Angle	0	0	1.0	0.5	0	0.1
Roll Gyro Bias	0	0	0	0	0	0
Pitch Gyro Bias	0	0	0	0	0	0
Yaw Gyro Bias	0	0	0	0	0	0

Table 3. C-Gain Values

Estimated Items	Ki1	Ki2	Ki3
Roll Angle	0.0089	0	0.021
Pitch Angle	0	0.0176	0
Yaw Angle	-4.6e-5	0	0.27
Roll Gyro Bias	-1.67e-6	0	1.22e-4
Pitch Gyro Bias	0	-4.5e-6	0
Yaw Gyro Bias	-4.308e-6	0	-4.78e-5

Based on the covariance analysis results incorporated with the on-orbit estimated gyro drift data, we can predict the maximum of current gyro drift. Fig. 5, 6, 7 show the estimated steady state gyro drift of on-orbit data when the steady state gain is using for the gyro drift estimation. These drift estimated values are subtracted from the rate measurement for rate correction through the gyro data processing algorithm. According to these Figures, the averge estimated gyro drift of roll, pitch, yaw axis are about 1.0 deg/hr., -0.39 deg/hr., -0.02 deg/hr., respectively. Also, figures show that the maixmum gyro rate drifts of roll, pitch, yaw axes are currently about 1.33 deg/hr., -0.46 deg/hr., 0.2 deg/hr., respectively, which are reasonable except the roll gyro drift. It is believed that the larger rate bias in roll axis than another axis is due to its misalignment caused by launch environment or the roll rate bias may be under-estimated from the ground test results. However, this kind of rate bias can be easily corrected by removing it from the measured rate at the on-board. Also, we can notice the abrupt change of estimated drift in figures, which is mainly due to the temperature change caused by the eclipse and the sun light.

Conclusions

The attitude knowledge error model is formulated for specifically KOMPSAT attitude determination system using LMS method, and the attitude determination error analysis is performed so as to evaluate the on-board attitude determination filter using the covariance analysis method instead of Monte Carlo method which requires extrodinary time consumption. The KOMPSAT requirements of attitude determination error are 0.12 deg(3σ) for roll and pitch axes, and 0.15 deg(3σ) for yaw axis, respectivly. Therefore, the analysis results demonstrate that all requirements are fully satisfied as seen in Table 4. Also, the on-orbit data of estimated gyro rate drift is presented to demonstrate the filter stability and to estimate the maximum current gyro rate drift. Following this study, a preliminary study of attitude determination is now undertaking for a future spacecraft which will have more enhanced pointing capability.

Table 4. Covariance Analysis Results (3σ)

	Attitude Determination Error (deg)	Gyro Drift Bias Error (deg/hr)
Roll	0.056	0.33
Pitch	0.092	0.06
Yaw	0.093	0.18

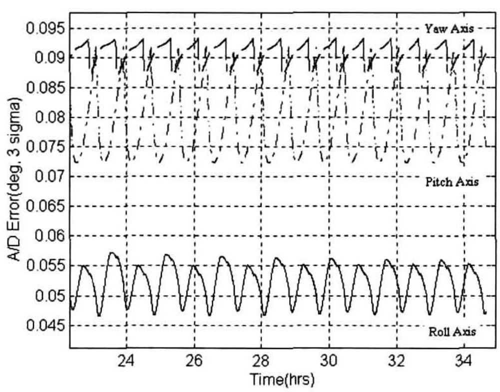

Fig. 3. Attitude Determination Error with all Noises and Biases

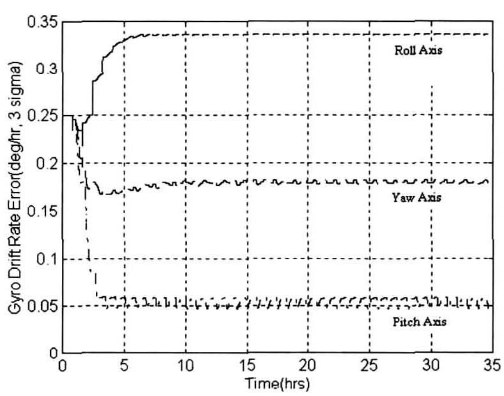

Fig. 4. Gyro Drift Rate Error with all Noises and Biases

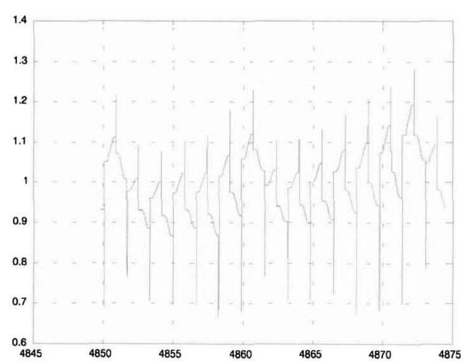

Fig. 5. On-Orbit Estimated Gyro Drift Rate in Roll Axis

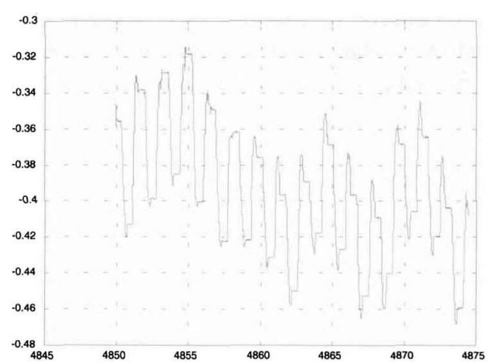

Fig. 6. On-Orbit Estimated Gyro Drift Rate in Pitch Axis

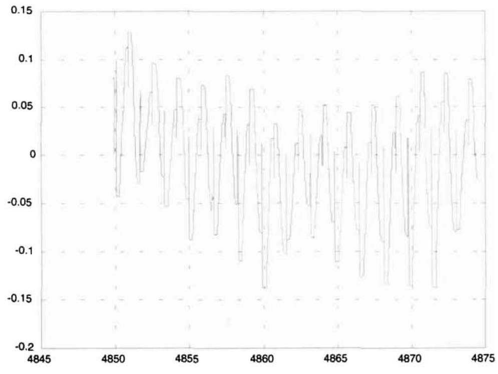

Fig. 7. On-Orbit Estimated Gyro Drift Rate in Yaw Axis

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