RUL Prediction of Reaction Wheel Motor in Satellites

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ABSTRACT

For advanced agile attitude control of the satellite, reaction wheels are used actuated by motor. In order to ensure reliable operation, fault detection and prediction of remaining useful life (RUL) of the motor is of great importance. In this study, multi-scale Extended Kalman Filter (EKF) is employed for this purpose using the data of input current and output velocity measured in the life test of the motor. The motor dynamic behavior is modeled by the ordinary differential equations (ODEs). Characteristic behavior of the reaction wheel that degrades as the motor is used over repeated cycles is taken as the health indicator. The degradation value is defined by damping coefficient by solving the micro EKF problem using the input and output measurements at each cycle. Then, the RUL is predicted by solving the macro EKF problem based on the regression model of damping coefficient, which enables proactive action before the motor failure is encountered.

1. INTRODUCTION

Methods of attitude controlling of satellites include passive control using torque generated by the cosmic environment and active control using a satellite mounted actuator. The reaction wheel is to use active control and a driver that controls the attitude of the satellite with the reaction torque generated when the wheel is attached to the motor shaft with a certain moment of inertia and the speed of the wheel is changed. The motor used to control reaction wheel is given in Figure 1. In order to ensure the reliable operation and prevent unwanted failure of the reaction wheel, the fault detection and life prediction of the actuating motor is of great importance. The motor is brushless direct current (BLDC) type, and torque is generated by Lorentz's force law (Boldea, 1999).

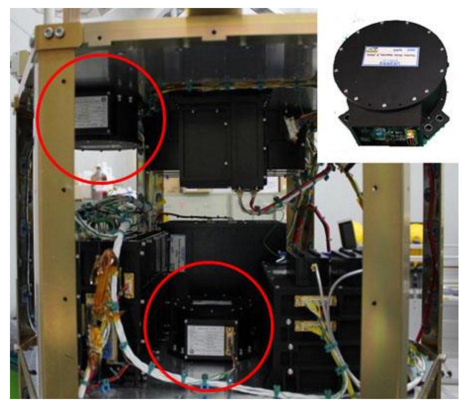

Figure 1**.** A motor from Korea Space Launch Vehicle-I

The motor usually degrades its function due to the repeated use, which appears as the damping increase over time. In this study, the prognosis of the motor is carried out in order to predict its life by employing the Extended Kalman Filter method. The motor dynamics are used for this, which is given by the ordinary differential equations (ODEs). Damping is employed as the parameter for motor health indicator (Skormin, 1994). The damping parameter is estimated at each cycle using the micro EKF, from which the life against the threshold is predicted using the macro EKF (Xiong, 2014). The data are obtained from the life test of the actuating motor during the wheel speed control mode. It consists of time, current, and angular velocity, where the input and output data are the current and velocity respectively.

2. MULTI-SCALE EKF

The overall framework is given in Figure 2, in which the steps are summarized as follows. In Figure 2, multi-scale EKF consists of two steps; On-line damping estimation algorithm and Off-line trend monitoring algorithm. In damping estimation, parameters are updated every moment of time, while parameter estimation is performed only macro time step in trend monitoring algorithm.

2.1. On-line damping estimation

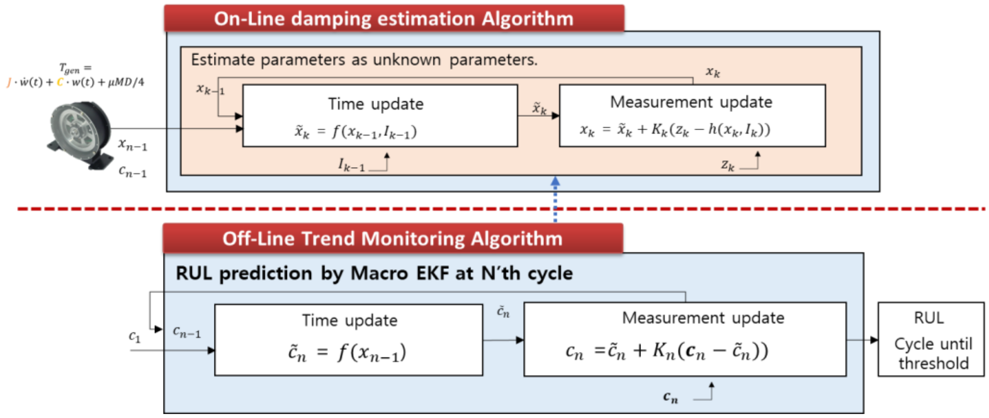

Fig. 2. Motor application algorithm

The governing equation of the motor dynamics is given as follows as Eq. (1)

$$T_{gen} = \mathrm{J} \cdot \dot{w} + \mathrm{c} \cdot \mathrm{w} + \mu \mathrm{MD}/4 \tag{1}$$

where T_{gen}= KI is the input torque given by the input current I , K is torque efficiency, J is the motor inertia, $\dot{w}$ is an acceleration of the motor, c is the bearing friction coefficient, w is the velocity, μ is constant, M is weight and D is diameter respectively.

Using this equation in the KF framework(Hu,2012), the state and measurement model for the motor are given respectively as follows, Eq. (2). These equations are in recursive form as below.

$$x_k = f(x_{k-1}, I_{k-1}) + q_{k-1}$$
$$z_k = \mathrm{h}(x_k) + v_k$$

or

$$\begin{bmatrix} \tilde{w}_k \\ \tilde{c}_k \end{bmatrix} = \begin{bmatrix} w_{k-1} + \left(-c_{k-1} w_{k-1} + \frac{\mu MD}{4} - K I_{k-1}\right) dt/J \\ c_{k-1} \end{bmatrix} + q_{k-1} \tag{2}$$
$$\begin{bmatrix} w_k \\ \dot{w}_k \end{bmatrix} = \begin{bmatrix} \tilde{w}_k \\ \left(-c_k \tilde{w}_k + \frac{\mu MD}{4} - K I_{k-1}\right)/J \end{bmatrix} + v_k$$

where the state variable vector x includes w and c, and the measurement variable z includes w and its acceleration w. Here, c are the health. And q and v denote the noise for the system and measurement respectively.

k is current time index. The symbol ~ means the time update at the next step k from the previous $k-1$. The equation can be further linearized into the form: Eq. (3), (4)

$$\tilde{x}_k \cong F x_{k-1} + B I_{k-1} + q_{k-1} \tag{3}$$
$$z_k \cong \mathrm{H} \tilde{x}_k + v_k$$

$$F = \frac{\partial f}{\partial x} = \begin{bmatrix} 1 - c \cdot dt/J & -w \cdot dt/J \\ 0 & 1 \end{bmatrix}$$
$$B = \frac{\partial f}{\partial u} = \begin{bmatrix} dt/J \\ 0 \end{bmatrix} \tag{4}$$
$$H = \frac{\partial h}{\partial x} = \begin{bmatrix} 1 & 0 \\ -c/J & -w/J \end{bmatrix}$$

As the measurement data are continually given one at a time over the time sampling period during a single cycle, the state is estimated based on the KF formula, in which the mean and the covariance of the state variable for the time update and measurement update are given as follows respectively, Eq (5) and Eq. (6):

Time update:

$$\tilde{x}_k = F_k x_{k-1}$$
$$\tilde{P}_k = Q_{k-1} + F_k P_{k-1} F_k' \tag{5}$$

Measurement update:

$$x_k = \tilde{x}_k + K_k \left(z_k - H_k \tilde{x}_k \right)$$
$$P_{k|k} = \tilde{P}_k - K_k H_k \tilde{P}_k \tag{6}$$

where $K_k = \tilde{P}_k H_k' S_k^{-1}$, $S_k = H_k \tilde{P}_k H_k' + R_k$, and Q, R are noise covariances of state and measurement models, respectively.

As shown in Figure 2 and above equations, in the time update, the state variables are updated from the previous time step by the input torque T or input current I. Then they are corrected by the measured data z in the measurement update. In the Fig. 4, the trend curve shows w using in the measured data z.

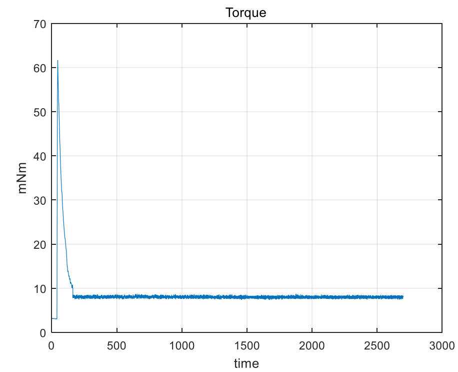

Figure 2. Reaction Wheel input Torque in Transient State

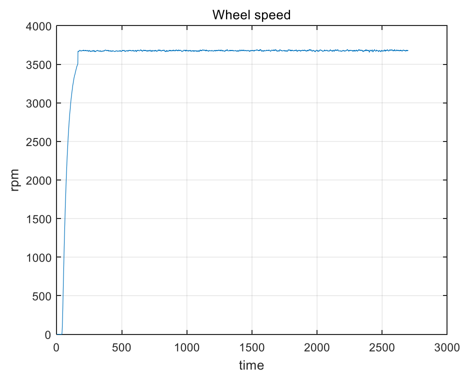

Figure 3. Reaction Wheel Angular Velocity in Transient State

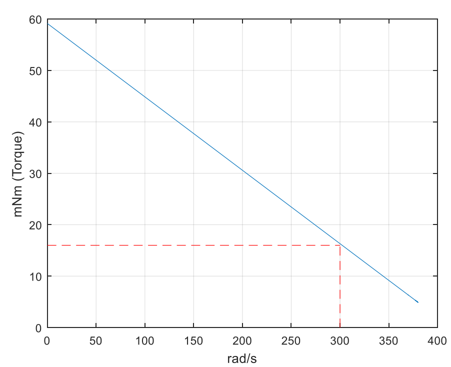

Figure 4. Characteristic Curve of Reaction Wheel

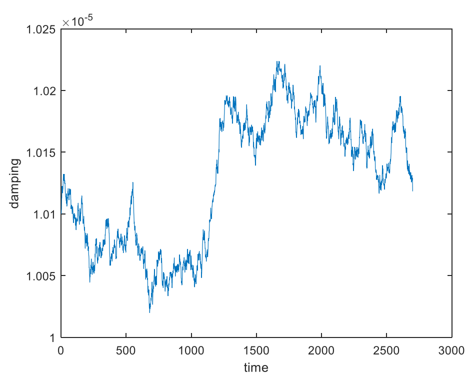

Figure 5. Short-term damping friction coef

Using the input torque as given by Figure 3 over a cycle with duration of 2500 seconds, the KF calculation results in the output velocity as shown in Figure 4. Once the velocity is obtained, characteristic curve of the motor is also made by using the output torque as given by $\boldsymbol{T_{output}} = \boldsymbol{J} \cdot \dot{\boldsymbol{w}}$ and angular velocity $\boldsymbol{w}$ as the y and x axis respectively. The result is given in Figure 5. It is known that the characteristic curve is used to evaluate the motor performance degradation in the satellite research community.

2.2. Setting the threshold

Figure 6 is a torque/speed curve graph of typical DC motor, which can be used to set the threshold. This shows how much motor transfer torque and how fast the output speed is. As shown in the Figure 6, the output speed is decreasing even though the motor transmits the same torque. When the motor was first designed as a design condition, the minimum requirement is over 300rad/s on 16mNm. So, it was deemed to be a failure if the minimum requirement is not fulfilled. We use this as a basis for threshold to estimate the remaining useful life.

2.3. Off-line trend monitoring

In the health assessment, the degradation of health parameter c is modeled by the linear equation over cycles as follows as Eq. (7).

$$\mathrm{y} = \mathrm{a} \cdot t \tag{7}$$

where t represent cycle, then the coefficients a is determined using the EKF by the estimated health parameters over cycles. The state and measurement model are then given respectively as follows, Eq (8).

$$\begin{aligned} x_n &= f(x_{n-1}) + q_n \\ z_n &= \mathrm{h}(x_n) + v_n \end{aligned} \quad \text{or} \quad \begin{aligned} \begin{bmatrix} \tilde{c}_n \\ \tilde{a}_n \end{bmatrix} &= \begin{bmatrix} c_{n-1} + a_{n-1} \cdot dt \\ a_{n-1} \end{bmatrix} + q_{k-1} \\ z_n &= \tilde{c}_k + v_n \end{aligned} \tag{8}$$

where the state variable x includes the bearing friction coef c. and its degradation parameters, a. The measurement z is the updated damping friction coefficient. In this case, the KF matrices are given by Eq (9).

$$\begin{aligned} F &= \frac{\partial f}{\partial x} = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix} \\ H &= \frac{\partial h}{\partial x} = [1\ 0] \end{aligned} \tag{9}$$

As the measurement data are continually given one at a cycle up to the current cycle, the state and unknown parameters are estimated based on the KF formula using the same formula as above.

3. PARAMETER ESTIMATION USING MICRO EKF

3.1. Estimating damping coefficient

It is well known that the damping friction coefficient of the bearing increases over cycles, which means that the bearing friction can be a good health parameter in the motor health management. In this section, the damping parameter is estimated at each cycle using the micro EKF as a short-term diagnosis. Then RUL is estimated for the purpose of the long-term prognosis using the macro EKF, taking the parameter as the performance degradation indicator of the motor. The results are given in Figure 6 & Figure 7. Short-term estimation is obtained in the cycle as shown in Fig .6, short-term can be define 1 cycle. However, in the test, the duration of one cycle varies from cycle to cycle, ranging between the minimum of 170 up to the maximum of 100,000 seconds. After progressing over the cycles, the long-term damping friction parameter is estimated using the macro EKF as shown in Figure 7.

3.2. Setting the threshold

The gradient of the points from Fig. 6 from 0 rad/s and 300 rad/s is gradually increasing as shown in the direction of the arrow of the Fig. 8. The increase is checked if the gradient is less than the minimum re-quirement as the red dot line in the Fig. 8. As shown in Fig. 8, it was confirmed that the slope of the charac-teristic curve was represented as a point and was gradually increasing as the cycle was increased. The slope of the characteristic curve assumed to have reached the design conditions, which is the red line as a threshold. The gradient of characteristic curve of Fig 8 is shown in the Fig. 9. The failure value of the char-acteristic curve slope is 0.1428 in Fig. 9 and can be used to estimate the remaining useful life into damp-ing coefficient as shown as Fig. 10.

In the Fig. 10, the threshold is set from the gradient of characteristic curve is applied to damping coeffi-cient. The axes are damping friction coefficient and gradient of the characteristic curve using Fig. 5. The failure value of damping coefficient is defined 0.147*10-5 using the threshold of the gradient of the characteristic curve in Fig. 10.

4. HEALTH ASSESSMENT AND RUL PREDICTION OVER LONG-TERM DEGRADATION

In this step, the friction coefficient is treated as the state variable. The state equation is the degradation model in this case, which varies linearly over the cycle. Measurement data are provided by estimating the coef. and averaging over the cycle. Then the data are given one at a cycle. RUL estimation has progressed as Kalman filter. During estimation, the parameter is estimated with RUL to get accurate results.

4.1. Parameter estimation of motor using Extended Kalman filter

The slope is set at constant but unknown in this study. Then the state variables are the damping friction coef. and its slope in the KF process. Figures 11, 12, 13 are the results of the estimation and RUL prediction. The Figure 11, Figure 12 and Figure 13 represent the estimation of the damping friction coef. using the data up to the 20th, 40th and 58th cycle and prediction based on that in the future. The two green curves are their predictive intervals. As can be found, the more measurement data are used, the more accurate prediction with narrower interval is achieved.

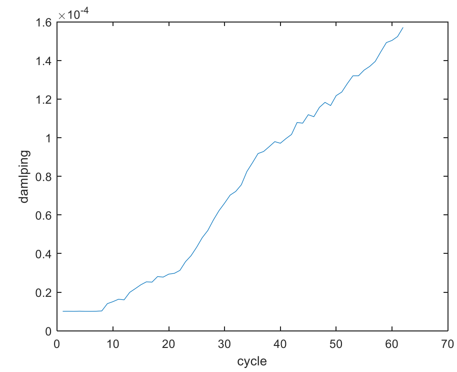

Figure 6. Long-term friction coef

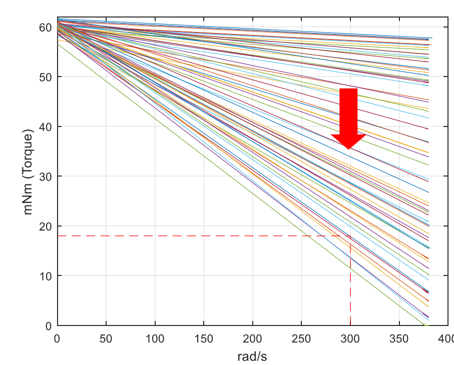

Figure 8. changes of characteristic curve

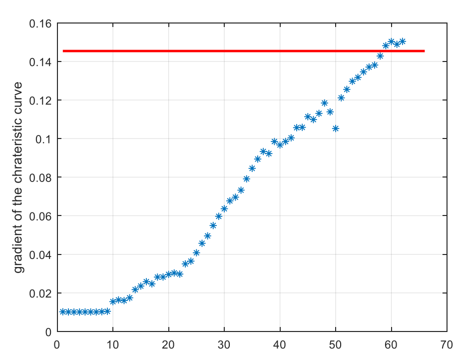

Figure 9. changes of characteristic curve gradient

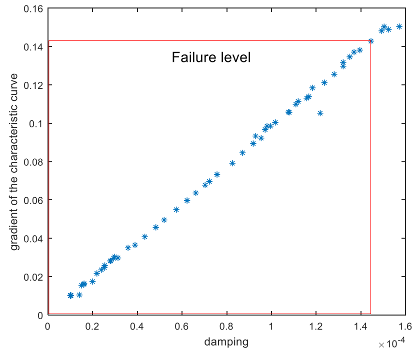

Figure 10. characteristic curve vs damping coefficient

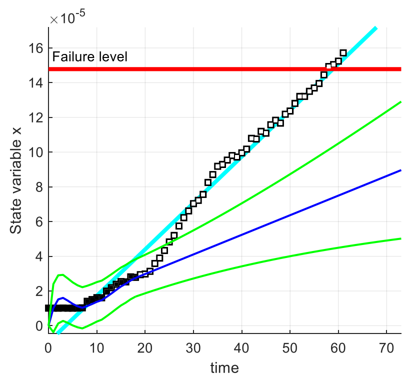

Figure 11. estimating result by KF at 20th cycle

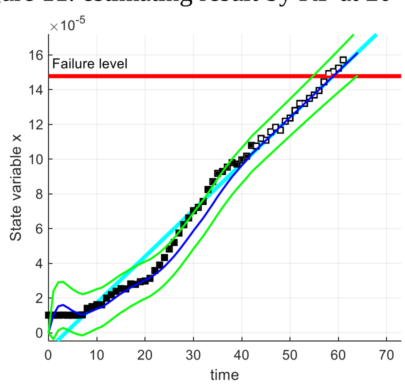

Figure 12. estimating result by KF at 40th cycle

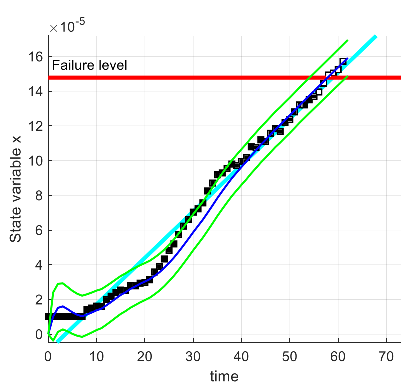

Figure 13. estimating result by KF at 58th cycle

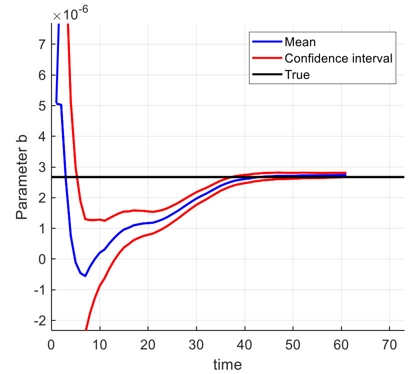

Figure 14. parameter estimating

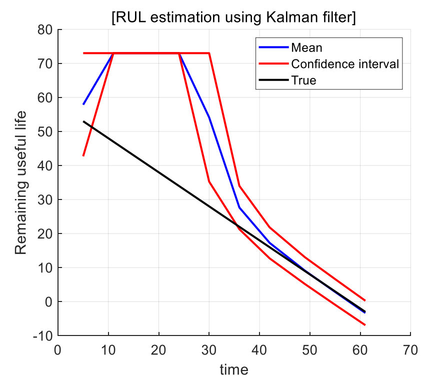

Figure 15. RUL estimation

After progressing over the cycles, the long-term gradient change is estimated as shown from Figure 11 to Figure 13, in which the long-term deterioration of gradient over the cycles is clearly observed. In order to predict the RUL based on this degradation data, the coefficient is modeled by 1st order polynomial as mentioned in the previous section. The macro EKF is used to estimate the model parameters. Then the RUL is predicted based on the estimated linear model. The results are given in Figure 14.

4.2. RUL prediction

After progressing over the cycles, the long-term damping friction parameter is estimated as shown in Figure 14, in which the long-term deterioration of the friction coefficient over the cycles is clearly observed. The Figure 14 represents the converged result of the slope of the degradation model, where the true value of 2.6715e-06. In order to predict the RUL based on this degradation data, the coefficient is modeled by a linear equation as mentioned in the previous section. The macro EKF is used to estimate the model parameters. The predictive bounds quickly narrow down as more data are introduced. Then the RUL is predicted based on the estimated a linear equation model. The Figure 15 represents the RUL as a function of cycle, where the black line is the true value, and the red curves are the predictive bounds of RUL.

5. CONCLUSION

In this paper, process is developed and implemented to apply to real motor data for reaction wheel in satellite for off-board long term RUL prediction in a single KF framework. Thus, by solving the macro EKF problem based on the regression model of damping coefficient, it enables proactive action and estimates remaining useful life before the motor failure is encountered.

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BIOGRAPHIES

Yuri Yun received the B.S degree of mechanical engineering from Korea Aerospace University in 2017. She is now M.S student at Korea Aerospace University. Her current research is focused on the prognostics and health management for rotary machines.

Junyong Lee received his B.E. and M.E. degrees in Aerospace Engineering from Korea Aerospace University, Korea, in 2014 and 2016, respectively. He is currently a Ph.D. candidate at the same University. His research interest is developing attitude hardware such as reaction wheel, CMG etc.

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Joo-Ho Choi received the B.S degree of mechanical engineering from Hanyang University in 1981, the M.S. degree and Ph.D. degree of mechanical engineering from Korea Advanced Institute of Science and Technology (KAIST) in 1983 and 1987, respectively. During the year 1988, he worked as a Postdoctoral Fellow at the University of Iowa. He joined the School of Aerospace and Mechanical Engineering at Korea Aerospace University, Korea, in 1997 and is now Professor. His current research is focused on the reliability analysis, design for life-time reliability, and prognostics and health management.