International Journal of Control, Automation and Systems 16(3) (2018) 1226-1238
http://dx.doi.org/10.1007/s12555-017-0087-1
ISSN:1598-6446 eISSN:2005-4092
http://www.springer.com/12555

Inertial Parameter Estimation of an Excavator with Adaptive Updating Rule Using Performance Analysis of Kalman Filter

Kwang-seok Oh* **and Ja-ho Seo**

Abstract: This paper presents a rotational inertia estimation algorithm for excavators based on recursive least-squares with forgetting and an adaptive updating rule that uses the performance analysis of the Kalman filter. Generally, excavators execute a swing motion with various materials, and the rotational inertia of the excavator is changed greatly due to the excavator's working posture. The large variation in the rotational inertia of the excavator has an influence on the dynamic behaviors of the excavator, and an estimation of the excavator's rotational inertia is essential to developing a safety system based on prediction of dynamic behavior. Therefore, a real-time rotational inertia estimation algorithm has been proposed in this study using a swing dynamic model. The proposed estimation algorithm has been designed using only swing velocity, utilizing the recursive least squares method with multiple forgetting for practical application to actual excavators. Two updating rules have been applied to the estimation algorithm in order to enhance the estimation performance. The first proposed rule is the damping coefficient updating rule. The second rule is the forgetting factor updating rule based on real-time analysis of linear Kalman filter estimation performance. The performance evaluation of the estimation algorithm proposed in this paper has been conducted based on the excavator's typical dumping scenario. The performance evaluation results show that the developed inertia estimation algorithm can estimate actual rotational inertia with the two designed updating rules using only excavator swing velocity.

Keywords: Dumping scenario, forgetting factor, Kalman filter, recursive least squares (RLS), rotating inertia, updating rule.

1. INTRODUCTION

The excavator is one of the most important pieces of heavy equipment in construction sites. Excavators perform various functions, such as digging and ground-leveling. Furthermore, an excavator carries various materials using its operational elements, consisting of a boom, arm, and bucket that move with a swing motion. While performing the swing motion, the working posture of the excavator changes greatly. In addition, blindspots exist around the excavator because the operator must continuously look forward to monitor its dynamically changing position. Since the excavator often operates with workers nearby, life-threating accidents, such as collisions with nearby workers, can occur due to blindspots and operator carelessness. Most fatal accidents in construction are caused by workers being struck by objects, such as heavy equipment, in construction sites; this accounts for 87% of all construction-related fatalities [1]. Therefore, much research has been conducted to reduce fatal accidents at construction sites by using various environmental sensors.

Lee *et al*. [2] suggested a safety monitoring system to decrease fatal accidents for workers at construction sites. Seward *et al*. [3] proposed a hazard factor analytic report to define safety requisites for an autonomous robotic excavator based on a design of an excavator and a safety management system. Feng *et al*. [4] developed a robot system and algorithm which can establish an assembly plan automatically using a computer-based architectural design. Giretti *et al*. [5] performed analytic research on the development and application of a next-generation real-time automatic health and safety management system at construction sites. In their study, ultra-wideband (UWB) technology was used for real-time location tracking between workers and equipment at construction sites where surroundings change dynamically. Riaz *et al*. [6] proposed a conceptual model that uses a next-generation information and communication technology (ICT) solution to make an innovative, leading health and safety management system using a global positioning system (GPS) with smart sensors and wireless networks called SightSafety. The system also provides reports on dangerous events that

Manuscript received February 18, 2017; revised June 27, 2017 and September 27, 2017; accepted November 21, 2017. Recommended by Associate Editor Young Soo Suh under the direction of Editor Duk-Sun Shim.

Kwang-seok Oh is with the Department of Mechanical Engineering, Hankyong National University, 327, Jungang-ro, Anseong-si, Gyeonggi-do, Korea (e-mail: oks@hknu.ac.kr). Ja-ho Seo is with the Department of Automotive, Mechanical and Manufacturing Engineering, University of Ontario Institute of Technology, 2000 Simcoe St N, Oshawa, ON L1H 7K4, Canada (e-mail: seojaho@gmail.com).
* Corresponding author.

have occurred, thereby enabling managers to learn from their experiences during the construction of a project. Park *et al*. [7] developed a Bluetooth-based proximity detection and alert system that can be used in roadway work zones, and evaluated its reliability and utility. Cho *et al*. [8] developed a hybrid LIDAR system and a projection-recognition-projection (PRP) framework to enhance the safety and productivity of construction sites by permitting heavy equipment operators to perceive three-dimensional work environments in real-time at dynamic construction sites, and evaluated its performance. Wang *et al*. [9] established an automatic object perception system using a fast surface modeling technique for rapid perception of three-dimensional work environments when operating heavy equipment at construction sites. Teizer *et al*. [10] developed a technical system for real-time location tracking by collecting and analyzing data to automatically classify static and dynamic hazard factors at construction sites. The suggested technical system automatically gathers and analyzes spatial-temporal conflicts between workers-on-foot and the identified hazards. Ray *et al*. [11] proposed a new technology that dynamically detects equipment blind spots using the head posture of the operator, based on the random forests algorithm. Wenzel *et al*. [12] proposed a model-based vehicle estimator, which can be utilized for a combined estimation of vehicle states and parameters using the dual extended Kalman filter (DEKF) technique.

After careful review of previous research, existing studies focus on hazard warning systems based on sensor system development to perceive surrounding objects, and the status and position of equipment. However, because these studies do not take into consideration active safety systems, such as collision avoidance, additional investigations are needed to ensure safety at construction sites. Therefore, this study proposes a rotational inertia estimation algorithm for an excavator as an active safety system. Because an excavator dynamically changes its working posture, and works with various materials, its rotational inertia varies greatly. This relatively massive change in rotational inertia affects the dynamic rotational behavior of an excavator. Therefore, estimating the rotational inertia of an excavator by predicting its rotational behavior is critical for avoiding collisions with nearby objects, including workers. Rotational speed was assumed to be measured to estimate the rotational inertia of an excavator, and the linear Kalman filter (LKF) was used to estimate rotational acceleration. The study estimated rotational inertia based on recursive least squares (RLS) with a multiple forgetting factor method using estimated angular acceleration and rotational speed. In addition, a swing dynamic model of an excavator was used to design an estimation algorithm. Updating rules were used to enhance rotational inertia estimation performance. The first rule is the updating rule, which updates estimated values based on a damping coefficient. The second rule is a rule that updates the forgetting factor by analyzing the estimated error of the LKF, which is used to predict rotational acceleration. The performance of the proposed algorithm has been evaluated by analysis and by comparison with analytically-derived rotational inertia. The derived inertia is based on a dumping scenario, which is a typical working pattern of an excavator. Performance evaluation of the rotational inertia estimating algorithm was designed and conducted in the Matlab/Simulink environment. The result of the performance evaluation showed rotational inertia estimation efficiency in real time, despite various changes in material and working postures. The remainder of this paper is organized as follows.

Section 2 explains the rotational inertia estimation algorithm. Section 3 describes the updating rules for estimation performance enhancement. Section 4 analyzes the results of the performance evaluation based on an actual working scenario. Finally, Section 5 discusses the results and offers suggestions for future work.

2. ROTATIONAL INERTIA ESTIMATION ALGORITHM

The RLS method using multiple forgetting factors has been used to estimate the rotational inertia of an excavator, and the mathematical model used is the swing dynamic model. Fig. 1 illustrates the model schematics for the inertia estimation algorithm.

In Fig. 1, an LKF block estimates the rotational speed and rotational acceleration of an excavator, and transmits them to a block that executes RLS analysis with multiple forgetting. Analyzed error information is then transmitted to the error analysis block to analyze errors in real time. The recursive least squares with multiple forgetting block estimates required values other than rotational inertia, and transmits them to the updating block. The updating block transmits renewed estimated values based on the updating rule defined by analyzed errors and estimated values to RLS with the multiple forgetting block. For practical use of the algorithm, this study assumes that only the rotational velocity of an excavator is measurable, and the rotational damping coefficient of working equipment can

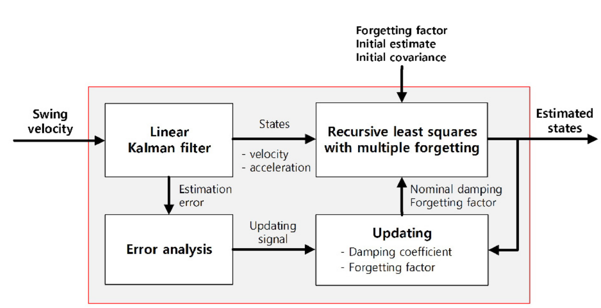


Fig. 1. Model schematics for the estimation algorithm.

be deduced with experiments. The formula below indicates the swing dynamic model of an excavator used in the proposed estimation algorithm:

$$J_t\ddot{\theta}_{sw} = -b\dot{\theta}_{sw} - T_f + T_{sw}, \tag{1}$$

where J_t and b are the total rotational inertia and damping coefficients, respectively; $\ddot{\theta}_{sw}$ and $\dot{\theta}_{sw}$ are the rotational acceleration and rotational speed, respectively; and T_f and T_{sw} are the static friction torque and swing torque, respectively. Rotational inertia J_t is the sum of the rotational inertia of an excavator and that of materials in the bucket. The next section explains the estimation algorithm of rotational speed and rotational acceleration based on the LKF in order to estimate the rotational inertia of an excavator.

2.1. Rotational state estimation using the LKF

Information about the rotational speed and rotational acceleration of an excavator is required to develop the rotational inertia estimation algorithm. Therefore, the study utilizes the LKF, which uses rotational acceleration as a measurement to estimate rotational speed and rotational acceleration. It also assumes that only the swing velocity of an excavator is measurable, and it can be measured by sensors to develop a practical estimation algorithm. A double integrator model was used to estimate rotational acceleration, and the discrete-time invariant linear system used in this study is as follows:

$$\begin{aligned} x_k &= F_{k-1}x_{k-1} + w_{k-1}, \\ y_k &= H_k x_k + v_k, \end{aligned} \tag{2}$$

where $x_k = \begin{bmatrix} \dot{\theta}_{sw,k} & \ddot{\theta}_{sw,k} \end{bmatrix}^T$; y represents the output vector; and w_k and v_k mean process noise and measurement noise, respectively. w_k and v_k are both assumed to be a white Gaussian distribution of which each mean is 0. F and H are the state transition and observation matrices, respectively, and are defined by the following formula:

$$F = \begin{bmatrix} 1 & \Delta T \\ 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 \end{bmatrix}, \tag{3}$$

where ΔT is sampling time used in the LKF, defined as 0.1 in the study. Since the defined process noise and measurement noise are assumed as uncorrelated zero-mean white Gaussian distributions, each covariance Q_k and R_k can be expressed as the formula below:

$$w_k = N(0, Q_k), \ \ v_k = N(0, R_k), \tag{4}$$

$$E\left[w_k v_k^T\right] = 0. \tag{5}$$

Covariance matrix Q_k (process noise) can be expressed as $diag[0, a]$. Here, a means noise variance of rotational acceleration of an excavator, and it cannot be determined properly by a stationary random process. Thus, the study defines the mean value of rotational acceleration which an excavator generally uses during work in an actual working scenario. It is also assumed that the estimated initial values for estimates and error covariance are given with uncertainty. LKF estimates of the state vector are applied with the following two steps: (step-1] prediction, and (step-2] update. In step-1, a priori estimates of the state vector and error covariance are calculated as follows:

$$\hat{x}_{k|k-1} = F_{k-1}\hat{x}_{k-1}, \tag{6}$$

$$P_{k|k-1} = F_{k-1}P_{k-1}F_{k-1}^T + Q_{k-1}. \tag{7}$$

In step-2, a priori values are updated by using the Kalman gain and a priori estimates. The optimal Kalman gain, K, can be computed from the following performance index that is the sum of the expectation of estimation errors.

$$J_k = E\left[(x_1 - \hat{x}_1)^2\right] + \cdots + E\left[(x_n - \hat{x}_n)^2\right]. \tag{8}$$

The optimal Kalman gain that minimizes the performance index J_k and a priori estimates are described as follows:

$$K_k = P_{k|k-1}H_k^T\left(H_k P_{k|k-1} H_k^T + R_k\right)^{-1}, \tag{9}$$

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k\left(y_k - H_k\hat{x}_{k|k-1}\right), \tag{10}$$

$$P_k = (I - K_k H_k) P_{k|k-1}, \tag{11}$$

where I means a unit matrix. The next section explains the rotational inertia estimation algorithm based on RLS estimation with the multiple forgetting method by using estimated rotational speed and acceleration.

2.2. RLS estimation with multiple forgetting

In this study, the RLS estimation method, which is a multivariable state estimation method, is used to estimate the rotational inertia of an excavator, J_t. As explained in the previous section, the rotational inertia of an excavator varies with working posture and materials. In order to estimate rotational inertia, the estimation of variables other than rotational inertia defined in swing dynamics is required. Furthermore, better estimation performance can be obtained by considering the rate of change of each variable using multiple forgetting factors [13]. To apply the RLS estimation with multiple forgetting method, the swing dynamic model used for LKF can be rewritten into a kind of linear regression model as follows:

$$y = \phi^T\theta, \tag{12}$$

$$\phi^T = \begin{bmatrix} \phi_1 & \phi_2 & \phi_3 \end{bmatrix} = \begin{bmatrix} \hat{\ddot{\theta}}_{sw} & \hat{\dot{\theta}}_{sw} & -1 \end{bmatrix}, \tag{13}$$

$$\theta = \begin{bmatrix} \theta_1 & \theta_2 & \theta_3 \end{bmatrix} = \begin{bmatrix} J_t & b & (T_{sw} - T_f) \end{bmatrix}, \tag{14}$$

where y has a constant value of 0 by the mathematical definition; and θ_1, θ_2, θ_3 are the values that need to be estimated, and which can be defined as the estimated rotational inertia, damping coefficient, and difference value between swing torque and frictional torque, respectively.

Because the defined estimates vary by working condition with different rates of change, reasonable estimation is possible by applying multiple forgetting factors individually. To apply forgetting factors (λ_1, λ_2, λ_3) individually, a decoupled cost function related to each estimate is defined as follows:

$$\begin{aligned} &J\left(\hat{\theta}_1(k), \hat{\theta}_2(k), \hat{\theta}_3(k), k\right) \\ &= \frac{1}{2}\sum_{i=1}^{k}\lambda_1^{k-i}\left(y(i)-\phi_1(i)\hat{\theta}_1(k)-\phi_1(i)\theta_2(i)\right. \\ &\quad \left.-\phi_1(i)\theta_3(i)\right)^2 \\ &\quad +\frac{1}{2}\sum_{i=1}^{k}\lambda_2^{k-i}\left(y(i)-\phi_1(i)\theta_1(i)-\phi_1(i)\hat{\theta}_2(k)\right. \\ &\quad \left.-\phi_1(i)\theta_3(i)\right)^2 \\ &\quad +\frac{1}{2}\sum_{i=1}^{k}\lambda_3^{k-i}\left(y(i)-\phi_1(i)\theta_1(i)-\phi_1(i)\theta_2(i)\right. \\ &\quad \left.-\phi_1(i)\hat{\theta}_3(k)\right)^2. \end{aligned} \tag{15}$$

The right term of the cost function defined above represents the estimated error at the k-step. To calculate an optimal estimate while minimizing the cost function, a partial differentiation equation about each estimate can be deduced as follows:

$$\frac{\partial J}{\partial \hat{\theta}_1(k)}=0,\ \frac{\partial J}{\partial \hat{\theta}_2(k)}=0,\ \frac{\partial J}{\partial \hat{\theta}_3(k)}=0. \tag{16}$$

By solving the partial differentiation equation above for θ_1, θ_2, θ_3, the value is obtained as follows:

$$\begin{aligned} \hat{\theta}_1(k) &= \left(\sum_{i=1}^{k}\lambda_1^{k-i}\phi_1(i)^2\right)^{-1} \\ &\quad \times\left(\sum_{i=1}^{k}\lambda_1^{k-i}\left(y(i)-\phi_2(i)\theta_2(i)-\phi_3(i)\theta_3(i)\right)\right), \end{aligned} \tag{17}$$

$$\begin{aligned} \hat{\theta}_2(k) &= \left(\sum_{i=1}^{k}\lambda_2^{k-i}\phi_2(i)^2\right)^{-1} \\ &\quad \times\left(\sum_{i=1}^{k}\lambda_2^{k-i}\left(y(i)-\phi_1(i)\theta_1(i)-\phi_3(i)\theta_3(i)\right)\right), \end{aligned} \tag{18}$$

$$\begin{aligned} \hat{\theta}_3(k) &= \left(\sum_{i=1}^{k}\lambda_3^{k-i}\phi_3(i)^2\right)^{-1} \\ &\quad \times\left(\sum_{i=1}^{k}\lambda_3^{k-i}\left(y(i)-\phi_1(i)\theta_1(i)-\phi_2(i)\theta_2(i)\right)\right). \end{aligned} \tag{19}$$

For real-time parameter estimation, the equation above could be rearranged to a recursive form as follows:

$$\begin{aligned} \hat{\theta}_1(k) &= \hat{\theta}_1(k-1)+L_1(k)\left(y(k)-\phi_1(k)\hat{\theta}_1(k-1)\right. \\ &\quad \left.-\phi_2(k)\theta_2(k)-\phi_3(k)\theta_3(k)\right), \\ \hat{\theta}_2(k) &= \hat{\theta}_2(k-1)+L_2(k)\left(y(k)-\phi_1(k)\theta_1(k)\right. \\ &\quad \left.-\phi_2(k)\hat{\theta}_2(k-1)-\phi_3(k)\theta_3(k)\right), \\ \hat{\theta}_3(k) &= \hat{\theta}_3(k-1)+L_3(k)\left(y(k)-\phi_1(k)\theta_1(k)\right. \\ &\quad \left.-\phi_2(k)\theta_2(k)-\phi_3(k)\hat{\theta}_3(k-1)\right). \end{aligned} \tag{20}$$

Here, L_i (i = 1, 2, 3) is the optimal estimation gain calculated for parameter estimation. The optimal estimation gain is calculated in each step based on the parameters, forgetting factors, and covariance of the estimate. Assuming that the true value ($\theta(k)$) and the estimate ($\hat{\theta}(k)$) of parameters have an error sufficiently small to ignore in the calculation of an individual estimate, such an estimate can be arranged as follows:

$$\begin{aligned} &\begin{bmatrix} \hat{\theta}_1(k) \\ \hat{\theta}_2(k) \\ \hat{\theta}_3(k) \end{bmatrix} \\ &= \begin{bmatrix} 1 & L_1(k)\phi_2(k) & L_1(k)\phi_3(k) \\ L_2(k)\phi_1(k) & 1 & L_2(k)\phi_3(k) \\ L_3(k)\phi_1(k) & L_3(k)\phi_2(k) & 1 \end{bmatrix}^{-1} \\ &\quad \times \begin{bmatrix} \hat{\theta}_1(k-1)+L_1(k)\left(y(k)-\phi_1(k)\hat{\theta}_1(k-1)\right) \\ \hat{\theta}_2(k-1)+L_2(k)\left(y(k)-\phi_2(k)\hat{\theta}_2(k-1)\right) \\ \hat{\theta}_3(k-1)+L_3(k)\left(y(k)-\phi_3(k)\hat{\theta}_3(k-1)\right) \end{bmatrix}. \end{aligned} \tag{21}$$

Because the elements that compose the inverse matrix of the equation above have values that are never zero, an inverse matrix value of (21) always exists. In order to derive a proof for the convergence properties of the designed adaptive inertia estimation algorithm, the following generalization of the recursive equations must be considered [14].

$$\hat{\theta}(k) = \hat{\theta}(k-1)+a(k)L(k)e(k), \tag{22}$$

$$\begin{aligned} &P(k) \\ &= \frac{1}{\lambda(k)} \\ &\quad \times\left[P(k-1)-a(k)\frac{P(k-1)\phi(k)\phi(k)^T P(k-1)}{1+r(k)}\right]. \end{aligned} \tag{23}$$

Here, $a(k)$ is a time-varying scalar function to be determined in a class which will be specified in terms of the inverse of (23).

$$\begin{aligned} P(k)^{-1} &= \lambda(k)P(k-1)^{-1} \\ &\quad +\beta(k)\lambda(k)\phi(k)\phi(k)^T, \end{aligned} \tag{24}$$

$$\beta(k) = \frac{a(k)}{1+r(k)-a(k)r(k)}, \tag{25}$$

$$r(k) = \phi(k)^T P(k-1)\phi(k). \tag{26}$$

Equation (24) can be considered as a discrete-time system with the state $P(k)^{-1}$ and input $\beta(k)\lambda(k)\phi(k)\phi(k)^T$. If the value of $a(k)$ is one, $\beta(k)$ has the value of one, and the $P^{-1}=0$ will be the globally attractive equilibrium point for the free motion of the system (24). The input term $\beta(k)\lambda(k)\phi(k)\phi(k)^T$ tends to prevent the convergence of $P^{-1}(k)$ to the equilibrium point $P^{-1}=0$, and $\beta(k)$ is bounded by Assumption 1 described as follows:

Assumption 1: There exists $c>0$ such that $a(k)/(1+r(k)-a(k)r(k))\geq c, \forall t$.

With the additional Assumption 2 described as below, the convergence analysis has been carried out.

Assumption 2: The data generation mechanism is described by $y(k)=\phi(k)^T\theta(k)$.

The analysis is conducted without taking any persistent excitation assumption on $\phi(k)^T$ for granted. Based on the aforementioned assumptions, the unexcitation subspace $\bar{S}$ and excitation subspace S are defined as follows:

$$\bar{S}=\left\{x\in R^n \,|\, \ni L<\infty : x^T\sum_{1}^{N}{}_t\phi(k)\phi(k)^T x<L, \forall N\right\}, \tag{27}$$

$$S=\bar{S}^{\perp}. \tag{28}$$

Equation (29) describes the defined Lyapunov-like function for the convergence proof of the estimation.

$$V(k)=\tilde{\theta}(k)^T P(k)^{-1}\tilde{\theta}(k). \tag{29}$$

Here, $\tilde{\theta}(k)$ is the error between estimated state and actual state $\hat{\theta}(k)-\theta(k)$. The state estimation error $\tilde{\theta}(k)$ can then be projected on subspaces S and $\bar{S}$, denoted by $\tilde{\theta}_E(k)$ and $\tilde{\theta}_U(k)$, respectively. In order to obtain the convergence results described in the following theorem, behavior analysis was conducted based on the defined Lyapunov-like function in (29).

Theorem 1: Based on the data generation mechanism described by Assumption 1 and estimation equation (22), the following statements are satisfied for any given $\tilde{\theta}(0)$ and $P(0)>0$.

1) $\left\|\tilde{\theta}(k)\right\|\leq h$ for all k, h is a proper constant.

2) $\lim_{k\to\infty}\tilde{\theta}_E(k)=0$.

Based on (22), (23), and (29), and the defined error state, the dynamics of the Lyapunov-like function can be derived as follows:

$$V(k)=\lambda(k)V(k-1)-a(k)\lambda(k)\frac{e(k)^2}{1+r(k)}. \tag{30}$$

The following inequality can be entailed since the value of $a(k)$ is always larger than zero.

$$V(k)\leq\lambda(k)V(k-1). \tag{31}$$

The decrease rate of $V(k)$ is controlled by the forgetting factor. The following inequality condition can be obtained by repeatedly using (24) and (31) with $P(0)^{-1}$ and $V(0)=\tilde{\theta}(0)^T P(0)^{-1}\tilde{\theta}(0)$.

$$\prod_{i=1}^{k}\lambda(i)V(0)\geq\tilde{\theta}(k)^T\left[P(0)^{-1}+cM(k)\right]\tilde{\theta}(k)\prod_{i=1}^{k}\lambda(i), \tag{32}$$

Here, $M(k)=\sum_{i=1}^{k}\phi(k)\phi(k)^T$. Equation (32) then implies the following equations:

$$V(0)\geq\lambda_{\min}\left[P(0)^{-1}\right]\left\|\tilde{\theta}(k)\right\|^2, \tag{33}$$

$$V(0)/c\geq\tilde{\theta}(k)^T M(k)\tilde{\theta}(k). \tag{34}$$

It can be shown that the inequality condition in (34) is sufficient to ensure that the estimation error tends to zero along the defined excitation subspace. Based on the aforementioned proof, it can be shown that the adaptive parameter estimation algorithm proposed in this study is in a steady state condition with updating rules. The next section explains the real-time updating rules that the study suggests using to improve the estimation performance of the RLS estimation.

3. UPDATING RULES FOR ESTIMATION PERFORMANCE ENHANCEMENT

Since the rotational inertia estimation algorithm suggested in the study should estimate three variables at the same time, reasonable initial estimates and an appropriate forgetting factor that can closely follow the changes in the estimates are essential. Therefore, two updating rules have been applied in the study to address the limitation of the estimation algorithm. The first updating rule is as follows: If it is assumed that a damping coefficient of an excavator can be deduced by experiment, estimates can be updated by a deduced nominal damping coefficient when the estimated damping coefficient is outside of a certain error range. The second updating rule is a rule designed to estimate the rotational speed and rotational acceleration of an excavator, considering the estimation performance of the LKF. An excavator generates rapid changes in rotational acceleration when it accelerates or decelerates during work, and they converge to the true value due to a decrease in estimation performance of the applied LKF after a certain time. While the value estimated by the LKF converges to the true value, the estimation performance of rotational inertia also declines by estimated errors. Therefore, to enhance estimation performance, the updating rules have been designed in the study not to diverge, but to converge by monitoring estimated errors of the LKF in real time and by updating the forgetting factor defined for each estimate when estimation performance decreases. In order to determine the point at which estimation performance starts to decline, the study used the error dynamics of the LKF. The next section describes detailed updating rules.

3.1. Damping coefficient updating rule

The damping coefficient updating rule applied in the study is illustrated in Fig. 2. The nominal damping coefficient ($\bar{\theta}_2$) in Fig. 2 is the rotational damping coefficient (b) of a real excavator, which is assumed to be given by experiments. To enhance the estimation performance of the RLS-based estimation algorithm, the algorithm has been composed as follows: When the absolute value of error between the estimated damping coefficient and the defined nominal damping coefficient is calculated to be greater than a certain value, (ε), the estimate is placed in the updating region, and it can be renewed into a nominal damping coefficient. However, if the estimate exists in the no updating region in Fig. 2, updating does not occur because it is considered to be a reasonable estimation. The value of ε, which classifies the updating region, should be defined experimentally considering the LKF and the performance of the rotational inertia estimating algorithm. This study defined defines the value of (ε) as 5. The following equations explain the proposed updating rule for the damping coefficient applied to the estimation algorithm.

$$\begin{aligned}
&\text{If } \left|\bar{\theta}_2-\hat{\theta}_2\right| \le \varepsilon: \text{ No updating}\\
&\quad \hat{\theta}_2(k)=\hat{\theta}_2(k-1)+L_2(k)\big(y(k)-\phi_1(k)\theta_1(k)\\
&\qquad\qquad -\phi_2(k)\hat{\theta}_2(k-1)-\phi_3(k)\theta_3(k)\big)\\
&\text{else: updating}\\
&\quad \hat{\theta}_2(k)=\bar{\theta}_2+L_2(k)\big(y(k)-\phi_1(k)\theta_1(k)\\
&\qquad\qquad -\phi_2(k)\hat{\theta}_2(k-1)-\phi_3(k)\theta_3(k)\big)\\
&\text{end}
\end{aligned} \tag{35}$$

The next section explains the updating rule for the forgetting factor, i.e., the second rule that updates the forgetting factor in real time based on the LKF.

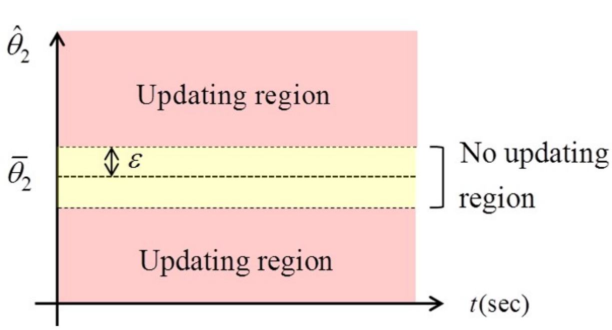


Fig. 2. Updating rule for damping coefficient.

3.2. Forgetting factor updating rule

The forgetting factor updating rule is an updating rule that considers estimating the performance of the LKF as mentioned previously. Since it is the rule that updates the forgetting factor when there is a relatively large decline in the estimation performance of the LKF, a quantitative analysis of the estimation performance of the LKF is needed. In addition, because the estimation performance of the Kalman filter can be quantitatively analyzed based on the error dynamics of the Kalman filter, a mathematical analysis of the error dynamics is conducted in this study based on estimation algorithm equations of the LKF [15, 16]. To derive the error dynamics, the existing LKF equations are arranged as follows, using the definition $\tilde{x}_k = x_k - \hat{x}_k$ of state estimation error.

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k\left(y_k - H_k\hat{x}_{k|k-1}\right), \tag{36}$$

$$\tilde{x}_k = x_k - F_{k-1}\hat{x}_{k-1} - K_k\left(y_k - H_kF_{k-1}\hat{x}_{k-1}\right). \tag{37}$$

By substituting output vector y in equation (37), an equation is deduced as follows:

$$\tilde{x}_k = x_k - F_{k-1}\hat{x}_{k-1} - K_k\left(H_kx_k + v_k - H_kF_{k-1}\hat{x}_{k-1}\right). \tag{38}$$

Collecting terms reduces the LKF error dynamics to:

$$\tilde{x}_k = (I-K_kH_k)\left(x_k - F_{k-1}\hat{x}_{k-1}\right) - K_kv_k. \tag{39}$$

By substituting the definition of state vector in formula (2) for formula (39), the result is as follows:

$$\tilde{x}_k = (I-K_kH_k)\left(F_{k-1}x_{k-1} + w_{k-1} - F_{k-1}\hat{x}_{k-1}\right) - K_kv_k. \tag{40}$$

Using the definition or error state in the k-1 step, the estimation error dynamics for the LKF are finally derived as follows:

$$\tilde{x}_k = (I-K_kH_k)\left(F_{k-1}\tilde{x}_{k-1} + w_{k-1}\right) - K_kv_k. \tag{41}$$

The Kalman gain K used in the above equation is an applied steady state gain. To identify a point at which the estimation performance largely declines, a rotational acceleration term among disturbance terms in error dynamics is needed. Therefore, formula (41) can be rearranged to a state space equation form as follows:

$$\tilde{x}_k = (I-K_kH_k)F_{k-1}\tilde{x}_{k-1} + (I-K_kH_k)w_{k-1} - K_kv_k. \tag{42}$$

A disturbance term defined by equation $(I-K_kH_k)w_{k-1} - K_kv_k$ can be calculated by steady state Kalman gain, process noise, and measurement noise (43) in each step. A probabilistic analysis has been conducted. Since the analysis of estimation performance of the rotational acceleration of an excavator is required to estimate the rotational

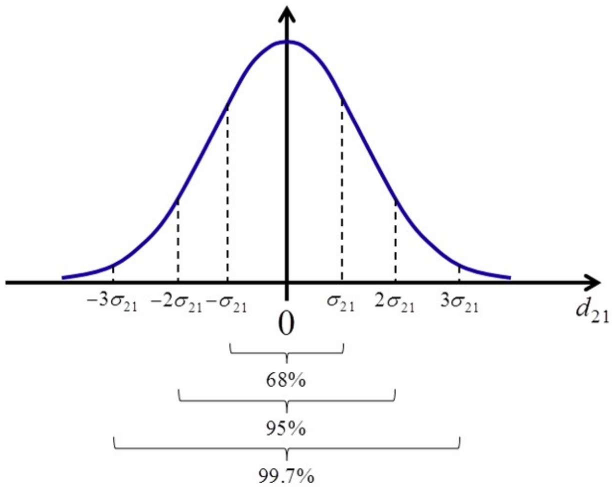


Fig. 3. Disturbance distribution.

inertia efficiently, disturbance (element (2,1)) of the rotational acceleration estimation in disturbance term (d) of the formula (42) is described as follows:

$$d_{21} = -K_{ss,(2,1)}w_{(1,1)} + w_{(2,1)} - K_{ss,(2,1)}v_{(1,1)}. \quad (43)$$

Since it is assumed that the defined process noise and measurement noise are Gaussian distributions of which each mean is 0, the disturbance of rotational acceleration, d_{21}, which is a Gaussian distribution, has been described as follows:

$$d_{21} \sim N\left(0, K_{ss,(2,1)}^2 Q_{(1,1)}^2 + Q_{(2,1)}^2 + K_{ss,(2,1)}^2 R_{(1,1)}^2\right). \quad (44)$$

By using standard deviation

$$\sqrt{K_{ss,(2,1)}^2 Q_{(1,1)}^2 + Q_{(2,1)}^2 + K_{ss,(2,1)}^2 R_{(1,1)}^2}$$

of the disturbance, a point at which the estimation performance rapidly declines compared to the real-time standard deviation of the residual value of the LKF has been derived. In a case in which the estimation performance of LKF rapidly declines when an excavator accelerates or decelerates during rotation, the rotational acceleration estimation performance is decreased. This situation is the point at which the forgetting factor must be updated. To determine this, the study compared the standard deviation of the LKF residual with the derived disturbance based on error dynamics. Fig. 3 illustrates the disturbance distribution of the LKF.

σ_{21} in Fig. 3 is the standard deviation

$$\sqrt{K_{ss,(2,1)}^2 Q_{(1,1)}^2 + Q_{(2,1)}^2 + K_{ss,(2,1)}^2 R_{(1,1)}^2}$$

of the disturbance of rotational acceleration. To classify the time when the estimation performance declines relatively largely, $3\sigma_{21}$, which is the largest value, occurring with a 99.7% probability, is defined as a boundary value and is compared with the standard deviation of the LKF residual calculated in real time. The mathematical definition of the LKF residual and standard deviation calculated in real time is as follows:

$$\tilde{x}_{k,residual} = K_k\left(y_k - H_k\hat{x}_{k|k-1}\right), \quad (45)$$

$$s_{k,residual}^2 = \frac{1}{v_k}\left[(\lambda v_{k-1})\, s_{k-1,residual}^2 + \frac{w_k - 1}{w_k}\left(\tilde{x}_k - \tilde{x}_{k-1}\right)^2\right], \quad (46)$$

$$w_k = \sum_{i=1}^{k} \lambda^{k-i}, \quad v_k = \frac{2\lambda_r\left(1-\lambda_r^{k-1}\right)}{(1-\lambda_r)(1+\lambda_r)}. \quad (47)$$

To calculate the standard deviation ($s_{residual}$) of the LKF residual, recursive variance with the forgetting method has been used. λ_r represents the forgetting factor used to calculate the real-time standard deviation, and it is defined as 0.9 in this study to reasonably apply the degree of change of the standard deviation. The value should be defined with consideration for the rate of change of the rotational acceleration, which is generally used while an excavator works. The updating rule is designed to perform updating of the forgetting factor if the calculated standard deviation(s) in real time are larger than the maximum value, $3\sigma_{21}$, which covers 99.7% of occurrences under the error dynamic disturbance distribution, and not to perform updating otherwise. This is the rule that determines the time when the estimation performance of the LKF decreases. Moreover, the forgetting factors have been updated in real time based on the analyzed result of the disturbance term of the LKF error dynamics. The proposed updating rule of the real-time forgetting factor can be arranged as follows:

if $s \geq 3\sigma_{21}$: Forgetting factor updating
  $\lambda_1^{updating}, \ \lambda_2, \ \lambda_3^{updating}$
else: No updating
  $\lambda_1, \ \lambda_2, \ \lambda_3$
end (48)

λ_1 in Table 1 is designed so that the forgetting factor should be renewed to a value that is close to 1, and not to diverge unless there occurs a considerable change in the estimate of rotational inertia under the condition of low estimation performance of the LKF. However, λ_3 is designed to be renewed to a value close to 0 when a relatively large change occurs under the updating condition, as the forgetting factor is related to the torque of the equipment. λ_2 is designed to maintain a certain value without being updated because it is the forgetting factor related to the damping coefficient, which remains constant. However, since the changes in the value of the forgetting factor (very close to 0) can cause poor estimation performance, the convergence performance has been checked by updating the third forgetting factor, λ_3, to 0 in this study. The

Table 1. Defined forgetting factors for updating.

Forgetting factor	No updating	Updating
λ_1	0.5	0.99
λ_2	1	1
λ_3	0.99	0.1

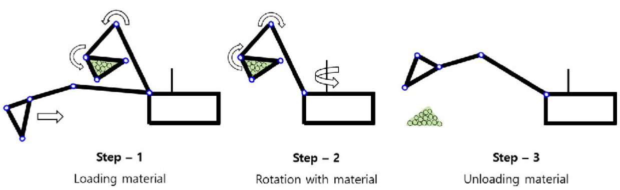


Fig. 4. Typical working scenario: dumping.

next section explains the performance evaluation of the algorithm based on an actual working scenario.

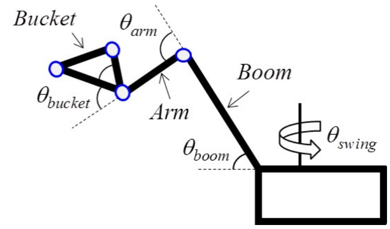
4. ACTUAL WORKING SCENARIO BASED PERFORMANCE EVALUATION

In this study, for realistic validation of the estimation algorithm, a performance evaluation was conducted using actual data based on dumping, which is a typical working scenario of an excavator. The true value of rotational inertia as a comparison value can be obtained using the analytical rotational value derived using common software. It is also assumed that only the rotational speed of an excavator is measurable.

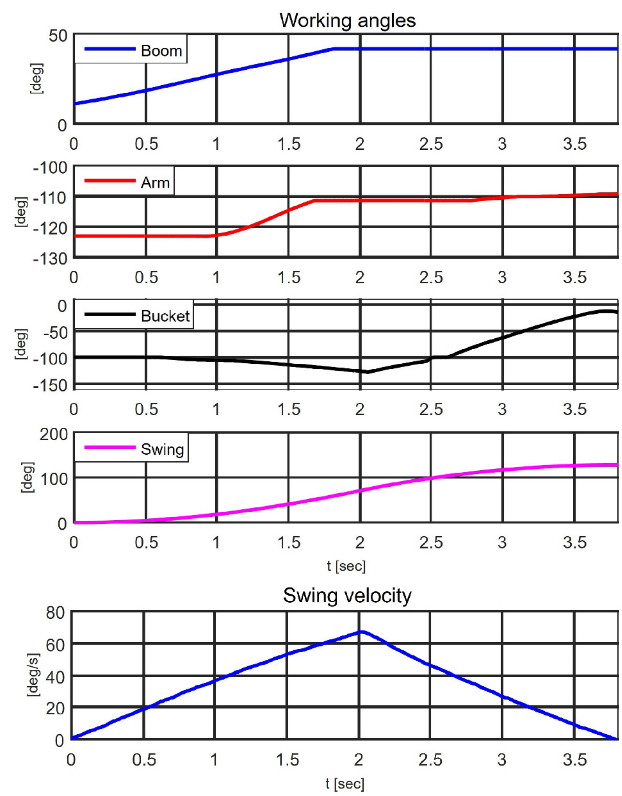
Step-1 is the stage of placing materials in the bucket to translocate them, and step-2 is the stage of moving to translocate materials to the goal position with a rotational motion. A performance evaluation of the estimation algorithm is conducted in step-2, since the proposed estimation algorithm uses the rotational speed of an excavator to estimate the rotational inertia. Finally, step-3 is the stage of dumping the materials in the bucket. Fig. 5 below illustrates the dynamic behavior of an excavator regarding the working scenario defined in Fig. 4.

For a realistic performance evaluation, the study applies noise that has a zero mean and 0.01 standard deviation Gaussian distribution to swing velocity. The performance evaluation was conducted in step-2, at which point the collision risk is relatively high and the rotational inertia changes largely due to the change in working posture among the defined working steps. A simulation was performed using a swing dynamic model of an excavator under the Matlab/Simulink environment in the performance evaluation, and properties of an actual five-ton excavator were applied to the swing dynamic model. A quantitative performance evaluation of error analysis in the time domain was conducted by comparing the analytical rotational inertia with the estimated rotational inertia. In addition, the analytical rotational inertia was computed by using commercial software, which is capable of dynamic body modeling and analysis. Figs. 6 and 7 illustrate the estimated result of rotational inertia using the proposed algorithm.

Table 2 shows a summary of the average change rate and estimated errors of rotational inertia according to the working conditions.



(a) Working parts' angles: boom, arm, bucket, and body.

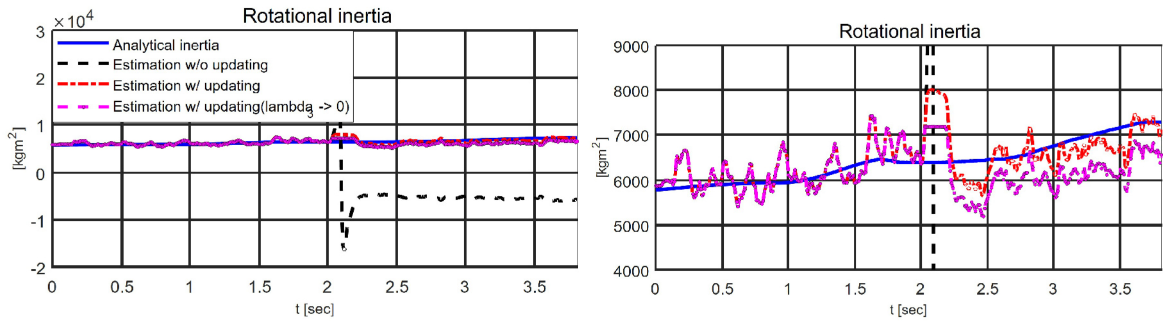


(b) Working angles and swing velocity.

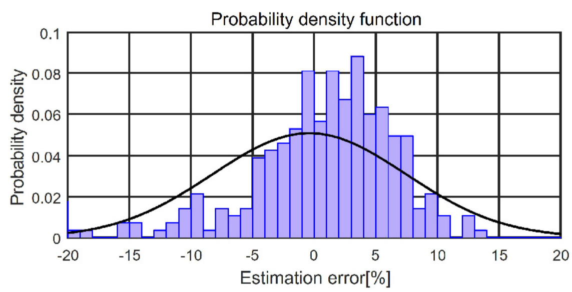
Fig. 5. Typical working scenario: dumping.

Table 2. Change rate and estimation error.

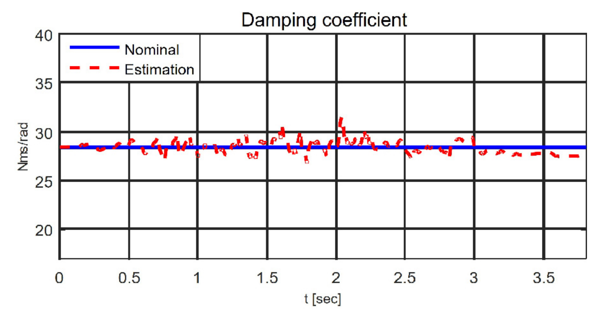
Division	Rotational inertia average change rate (kgm^2/sec)	Estimation error (%)	
		Average	Standard deviation
Without material	396.46	-0.41	7.84
With material	1,563.88	-1.53	5.18



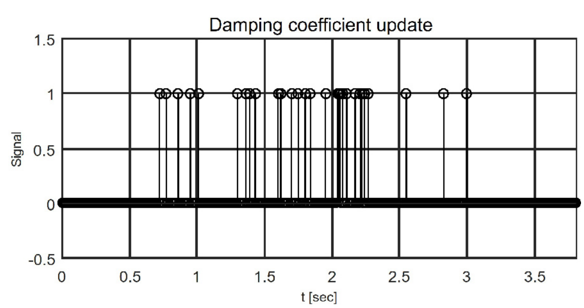
(a) Estimation result: rotational inertia.



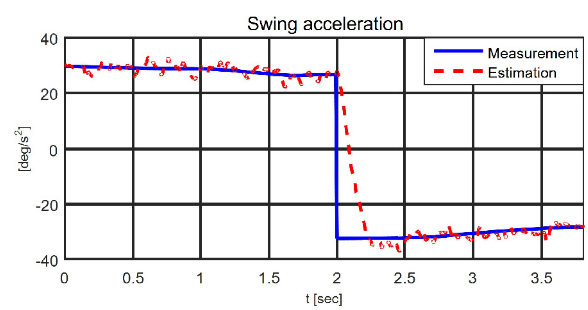
(b) Rotational inertia estimation error distribution: with updating.



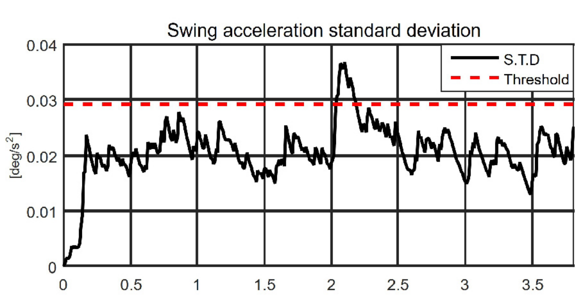
(c) Estimation result: damping coefficient.



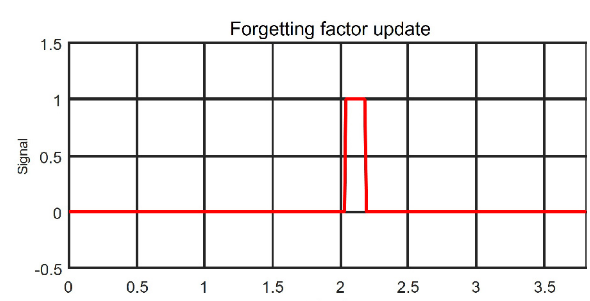
(d) Updating result: damping coefficient.



(e) Swing acceleration estimation.



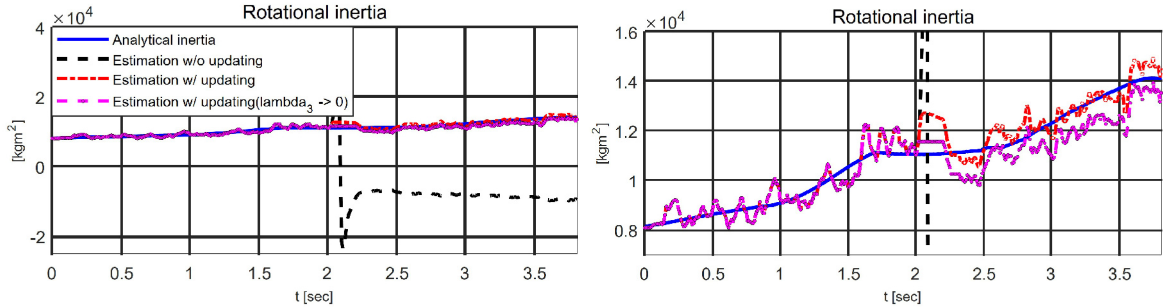
(f) Standard deviation: LKF residual.



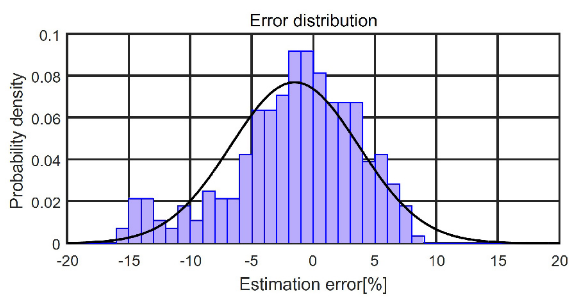
(g) Updating result: forgetting factors.

Fig. 6. Results: without material.

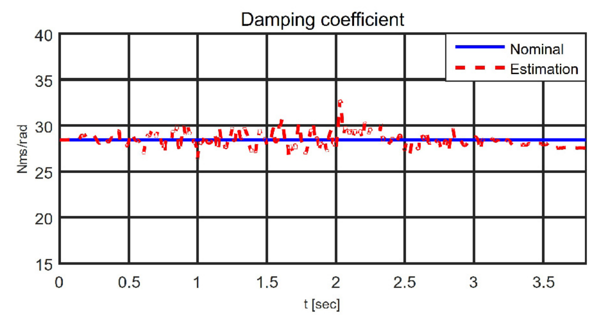
As illustrated in Figs. 6 and 7, even under the with-material condition (sand stone, 425 kg) in which rotational inertia largely changes, the proposed rotational inertia estimation algorithm showed a reasonable estimation result, with an average 0% estimation error and 5% standard deviation. Moreover, although rotational inertia changes due to the working posture of working parts, it has been validated that good estimation performance is achieved by ap-



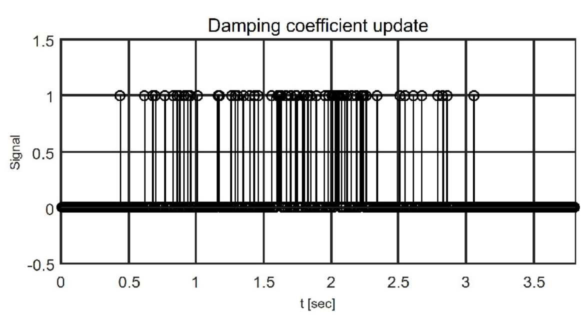
(a) Estimation result: rotational inertia.



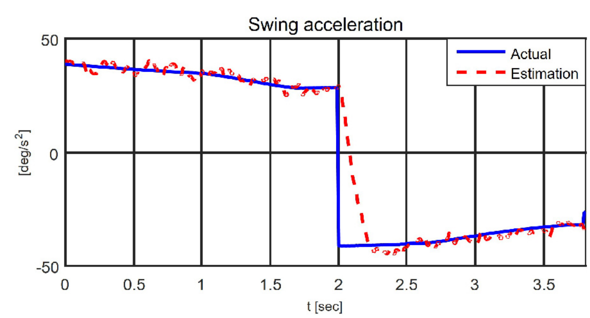
(b) Rotational inertia estimation error distribution: with updating.



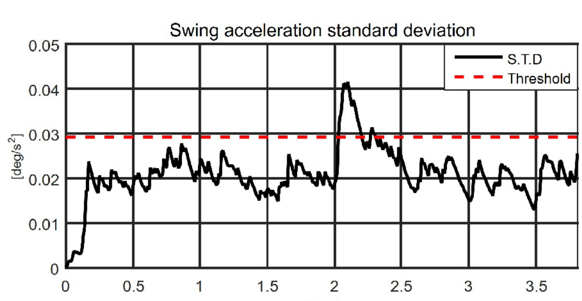
(c) Estimation result: damping coefficient.



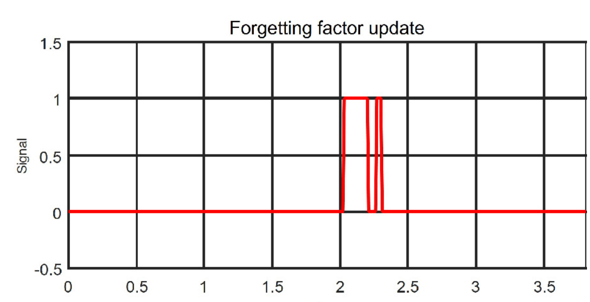
(d) Updating result: damping coefficient.



(e) Swing acceleration estimation.



(f) Standard deviation: LKF residual.



(g) Updating result: forgetting factors.

Fig. 7. Results: with material (sand stone, 425 kg).

plying a reasonable forgetting factor independently. Fig. 6 presents a situation in which rotational inertia increases by approximately 1,500 kgm^2, in general, through position change without having materials in the bucket. It has been confirmed that the estimation performance of the LKF decreases due to the rapid change in rotational acceleration when an excavator decelerates during rotation. However, by the damping coefficient and forgetting factor updating rules suggested in the study, it is confirmed that the estimate does not diverge from the nominal value and the actual rotational inertia is reasonably estimated. Fig. 7 illustrates the condition in which a five-ton excavator, the object excavator, works containing the maximum amount of materials based on the data. It is a working condition under which the excavator rotates with a rotational inertia changing by approximately 7,000 kgm^2due to the working posture change of the equipment. As illustrated in Table 2, the rate of change of rotational inertia under the with-material condition is approximately four times that under the without-materials condition. This shows a relatively large change in rotational inertia. However, it is confirmed that rotational inertia is reasonably estimated by the estimation algorithm based on the updating rule. As shown in Figs. 6 and 7, the updating rule of the suggested forgetting factor calculates the standard deviation of the LKF residual in real time. In addition, parameter estimation was possible by reasonably considering the change characteristics possessed by each estimate, and comparing this to the disturbance which is analyzed based on error dynamics. If the damping coefficient, which is estimated not to diverge by the defined damping coefficient updating rule, is outside of a certain range, it was confirmed that the value is updated and becomes convergent.

4.1. Comparison with another estimation algorithm

The performance of the inertia estimation algorithm proposed in this paper was analyzed by comparing it with another estimation algorithm. In order to conduct the performance analysis, the Sliding Mode Observer (SMO) based estimation algorithm was used [17]. The observer equation was defined based on the swing dynamics in (1) to estimate rotational inertia. The defined observer equation formed as a state space equation is shown as

$$\begin{bmatrix} \dot{\hat{x}}_{s,1} \\ \dot{\hat{x}}_{s,2} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \hat{x}_{s,1} \\ \hat{x}_{s,2} \end{bmatrix} + \begin{bmatrix} 0 \\ -bx_{s,2} - T_f + T_{sw} \end{bmatrix} v, \tag{49}$$

where $\hat{x}_{s,1}$ and $\hat{x}_{s,2}$ represent estimated states of θ_{sw} and $\dot{\theta}_{sw}$, respectively; and v is a discontinuous injection term. In order to secure the stability of the SMO, the observer and linear coordinate transformation matrices have been defined as follows:

$$C = \begin{bmatrix} 1 & 1 \end{bmatrix}^T, \tag{50}$$

$$T_C = \begin{bmatrix} nullspace(C)^T & C \end{bmatrix}^T. \tag{51}$$

Without a loss of generality of the transformed swing dynamic equation and observer equation, the error dynamics can be divided into two parts, state and output. The separate equations are as follows:

$$\dot{e}_1 = A_{11}e_1 + A_{12}e_y + F_1 v, \tag{52}$$

$$\dot{e}_y = A_{21}e_1 + A_{22}e_y + F_2 v. \tag{53}$$

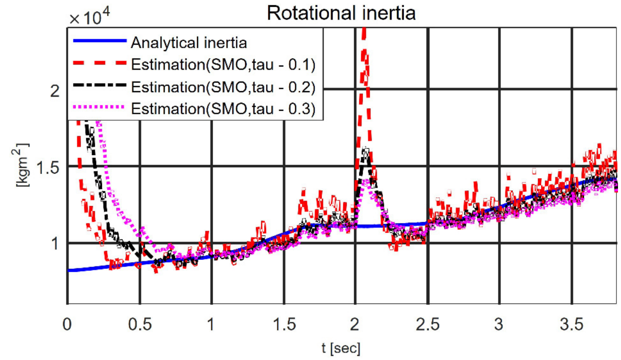


Fig. 8. Estimation results using SMO.

A_{ij} (i & $j = 1, 2$) and F_i ($i = 1, 2$) are the transformed system and disturbance matrices, respectively, from (49); and e_1 and e_y represent error terms for state and output, respectively. Based on the eta-reachability condition in SMO, e_y can converge to zero in finite time using the injection term in (54).

$$v = \rho sign(e_y), \tag{54}$$

where ρ is the magnitude of the injection term that should be determined to meet the eta-reachability condition for stability. The equivalent injection term v_{eq} can then be derived based on (53) as follows:

$$v_{eq} = -F_2^{-1}A_{21}e_1. \tag{55}$$

By substituting the equivalent injection term into (52), the error dynamics for states can be derived as follows:

$$\dot{e}_1 = \left(A_{11} - F_1F_2^{-1}A_{21}\right)e_1. \tag{56}$$

It can be found that the pole of the error dynamics for states in (56) always has a value of -1. Therefore, stability can always be secured. Based on the comparison between the observer equation and the swing dynamic equation, it can be found that the derived equivalent injection term represents the inverse of rotational inertia. The rotational inertia can be estimated based on the following equation:

$$J_t \approx 1/v_{eq}. \tag{57}$$

The equivalent injection term has been derived using a first-order filter. Fig. 8 presents the estimation results using SMO, and Fig. 9 shows the comparison results of the proposed algorithm and the SMO-based algorithm.

The tau in Fig. 8 is the time constant of the first-order filter used to generate the equivalent injection. As can be seen in Fig. 8, the variation of the estimated value decreases as the value of tau increases. However, it can be seen that the estimation delay increases as the value of tau increases. In Fig. 9, the estimation results are shown using

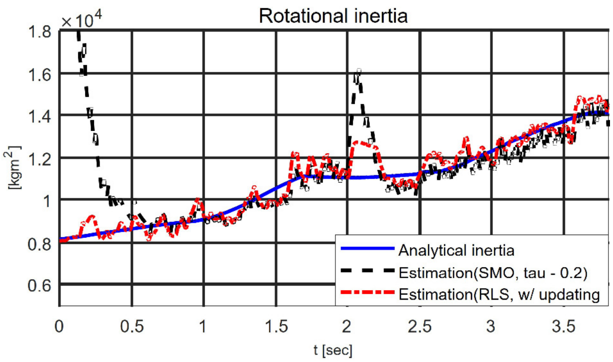


Fig. 9. Comparison results: the proposed algorithm (with material) and SMO-based algorithm.

Table 3. Comparison of the two estimation algorithms.

Division	RLS-based algorithm	SMO-based algorithm
Disadvantage	Relatively exact initial conditions are required (rotational inertia and velocity)	All parameters are required; proper tau value is required
Advantage	All parameters are not required (only swing velocity and damping coefficient are required)	Initial conditions are not required (convergence property)

two algorithms, the RLS-based algorithm and the SMO-based algorithm. All of the results in Fig. 9 show reasonable estimation performance. However, some differences exist between the proposed algorithm and the SMO-based algorithm. Table 3 presents a comparison of the two estimation algorithms.

After a careful comparison of the two estimation algorithms, it is found that the estimation algorithm proposed in this study uses only rotational velocity and a nominal damping coefficient. Relatively exact initial conditions of rotational inertia and velocity are required to secure the property of convergence. It was confirmed that rotational inertia can be reasonably estimated using the proposed estimation algorithm when it largely changes in the dumping scenario. However, there exists a limitation in which the estimation algorithm should have access to certain characteristics of the system, such as process noise and measurement noise, used in the linear LKF. Therefore, we are planning to develop a real-time rotational inertia estimation algorithm by using an unscented Kalman filter without noise information about the system in future studies. The next section presents the conclusions of the study.

5. CONCLUSION

This study proposed an algorithm is based on RLS with a multiple forgetting factor to estimate the rotational inertia of an excavator in real time. An excavator normally operates with rotational motion. Fatal accidents, such as those involving collisions with surrounding objects, often occur due to the carelessness of equipment operators and blind spots. Applying safety control systems such as emergency braking systems is critical to prevent typical accidents at construction sites, such as collisions. However, the rotational inertia of the equipment, which affects the dynamic behavior of excavators, varies with the materials and working posture. Therefore, a rotational inertia estimation is required to implement a safety control system for collision avoidance. In this paper, two updating rules were applied to enhance the estimation performance of the suggested rotational inertia estimation algorithm. The first rule updates the damping coefficient, which can be derived by experiment and can maintain a relatively certain value. The second rule updates the forgetting factor by considering the estimation performance of the applied LKF. To update the forgetting factor, the study analyzed the disturbance of the error dynamics of the LKF based on probabilistic analysis. A performance evaluation of the estimation algorithm was conducted using rotational inertia, which was analytically deduced based on an actual working scenario. In addition, the SMO-based estimation algorithm was compared with the RLS-based estimation algorithm proposed in this study [17, 18]. Results of the performance evaluation demonstrated a reasonable estimation in a working scenario. In addition, it was shown that materials largely affect the change in rotational inertia. Overall, it was confirmed that the updating rules can enhance estimation performance. Furthermore, the proposed estimation algorithm achieves reasonable estimation performance, despite using only rotational velocity and a nominal damping coefficient. It was also found that a limitation exists in which the estimation performance of the proposed algorithm is affected by the estimated initial value, as well as whether or not the noise statistics information used for the LKF is known. The difficulties involved in using the proposed algorithm can be summarized as follows:

1) Initial conditions, such as rotational inertia, speed, and covariance should be known.
2) The damping coefficient should be known.
3) Forgetting factors are not optimized for estimation.

Therefore, we plan to improve the estimation performance of rotational inertia estimation by developing and applying a change detection algorithm for errors that have probabilistic traits, along with applying an unscented LKF. We also plan to develop a realistic performance evaluation by applying field tests. The proposed estimation algorithm and performance evaluation have been designed and conducted in a Matlab/Simulink environment. It is expected that the results of this study can be practically applied to the safety control systems of actual excavators in the future.

REFERENCES

[1] J. Hinze and J. Teizer, "Visibility-related fatalities related to construction equipment," *Safety Science*, vol. 49, pp. 709-718, 2011. [click]

[2] U. Lee, J. Kim, H. Cho, and K. Kang, "Development of a mobile safety monitoring system for construction sites," *Automation in Construction*, vol. 18, pp. 258-264, 2009. [click]

[3] D. Seward, C. Pace, R. Morrey, and I. Commerville, "Safety analysis of autonomous excavator functionality," *Reliability Engineering and System Safety*, vol. 70, pp. 29-39, 2000.

[4] C. Feng, Y. Xiao, A. Willette, W. McGee, and V. Kamat, "Vision guided autonomous robotic assembly and as-built scanning on unconstructed sites," *Automation in Construction*, vol. 59, pp. 128-138, 2015. [click]

[5] A. Giretti, A. Carbonari, B. Naticchia, and M. Grassi, "Design and first development of an automated real-time safety management system for construction sites," *Journal of Civil Engineering and Management*, vol. 15, pp. 325-336, 2009.

[6] Z. Riaz, D. Edwards, and A. Thorpe, "SightSafety: a hybrid information and communication technology system for reducing vehicle/pedestrian collisions," *Automation in Construction*, vol. 15, pp. 719-728, 2006. [click]

[7] J. Park, E. Marks, Y. Cho, and W. Suryanto, "Performance test of wireless technologies for personnel and equipment proximity sensing in work zones," *Journal of Construction Engineering and Management*, vol. 142, no. 1, 2016. [click]

[8] Y. Cho and M. Gai, "Projection-Recognition-Projection method for automatic object recognition and registration for dynamic heavy equipment operations," *Journal of Computing in Civil Engineering*, vol. 28, no. 5, 2014. [click]

[9] C. Wang and Y. Cho, "Smart scanning and near real-time 3D surface modeling of dynamic construction equipment from a point cloud," *Automation in Construction*, vol. 49, pp. 239-249, 2015. [click]

[10] J. Teizer and T. Cheng, "Proximity hazard indicator for workers-on-foot near miss interactions with construction equipment and geo-referenced hazard areas," *Automation in Construction*, vol. 60, pp. 58-73, 2015. [click]

[11] S. Ray and J. Teizer, "Dynamic blindspots measurement for construction equipment operators," *Safety Science*, vol. 85, pp. 139-151, 2016.

[12] T. Wenzel, K. Burnham, M. Blundell, and R. Willams, "Dual extended Kalman filter for vehicle state and parameter estimation," *Vehicle System Dynamics*, vol. 44, no. 2, pp. 153-171, 2006. [click]

[13] A. Vahidi, A. Stefanopoulou, and H. Peng, "Recursive least squares with forgetting for online estimation of vehicle mass and road grade: theory and experiments," *Vehicle System Dynamics*, vol. 43, no. 1, pp. 31-55, 2005. [click]

[14] S. Bittanti, P. Bolzern, and M. Campi, "Recursive least-squares identification algorithms with incomplete excitation: convergence analysis and application to adaptive control," *IEEE Transactions on Automatic Control*, vol. 35, no. 12, pp. 1371-1373, 1990.

[15] R. Reza, "Kalman-consensus filter: Optimality, stability, and performance," *Proceedings of the 48th IEEE Conference on Decision and Control held jointly with the 28th Chinese Control Conference, CDC/CCC 2009*, IEEE, 2009.

[16] A. Corigliano and S. Mariani, "Parameter identification in explicit structural dynamics: performance of the extended Kalman filter," *Computer Methods in Applied Mechanics and Engineering*, vol. 193, no. 36, pp. 3807-3835, 2004.

[17] M. Mahyuddin, J. Na, G. Herrmann, X. Ren, and P. Barber, "An adaptive observer-based parameter estimation algorithm with application to road gradient and vehicle's mass estimation," *UKACC International Conference on Control*, Cardiff, UK, pp. 3-5, September 2012.

[18] X. Zhang and Z. Li, "Sliding-mode observer-based mechanical parameter estimation for permanent magnet synchronous motor," *IEEE Transactions on Power Electronics*, vol. 31, no. 8, pp. 5732-5745, 2016. [click]

Kwang-seok Oh received his B.S. degree in mechanical engineering from Hanyang University in 2009 and his M.S. degree in mechanical and aerospace engineering from Seoul National University, Korea in 2013. He is a Professor in the Department of Mechanical Engineering at Hankyong National University, Korea. His research interests include autonomous vehicle, fault-tolerant control, safey control, and driver modeling.

Ja-ho Seo received his B.S degree in agricultural machinery and process engineering from Seoul National University, Seoul, Korea in 1999, his M.E degree in mechanical engineering from the University of Quebec (Ecole de Technologie Superieure), Montreal, Canada in 2006, and is Ph.D. in mechanical engineering from the University of Waterloo, Waterloo, Canada in 2011. He was with the Department of Mechanical and Mechatronics Engineering of the University of Waterloo as a postdoctoral fellow in 2011, the Department of System Reliability of the Korea Institute of Machinery & Materials (KIMM) as a senior researcher for 2012-2016, and the Department of Biosystems Machinery Engineering of Chungnam National University, Korea as an assistant professor for 2016-2017. Since 2017, he has been an assistant professor at the Department of Automotive, Mechanical and Manufacturing Engineering, University of Ontario Institute of Technology where he has been involved in research on the development of autonomous control systems for intelligent mobile machines.