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Unknown-Parameter Identification for Accurate Control of 2-Link Manipulator using Dual Extended Kalman Filter

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2링크 매니퓰레이터 제어를 위한 듀얼 확장 칼만 필터 기반의 미지 변수 추정 기법

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Abstract In this paper, we described the unknown parameter identification using Dual Extended Kalman Filter for precise control of 2-link manipulator. 2-link manipulator has highly non-linear characteristic with changed parameter thought tasks. The parameter kinds of mass and inertia of system is important to handle with the manipulator robustly. To solve the control problem by estimating the state and unknown parameters of the system through the proposed method. In order to verify the performance of proposed method, we simulate the implementation using Matlab and compare with results of RLS algorithm. At the results, proposed method has a better performance than those of RLS and verify the estimation performance in the parameter estimation.

Key Words : manipulator, dual extended kalman filter, nonlinear dynamic system, ordinary differential equation, Lagrangian.

요 약 본 논문은 듀얼 확장 칼만 필터를 기반으로 2링크 매니퓰레이터의 정밀한 제어를 위한 미지 변수 추정법을 제안한다. 2링크 매니퓰레이터 시스템은 기구학 및 동역학 방정식에 비선형성을 가지며 내부 파라미터의 변화에 민감한 특성을 보인다. 이러한 시스템의 경우 내부 미지 파라미터의 추정이 매우 중요하다. 특히 거친 환경에서 작업을 수행함에 있어서 중량과 관성행렬의 변화는 시스템을 불안정하게 만드는 요소이다. 따라서 본 논문에서 제안한 방법을 기반으로 시스템의 상태 및 미지 변수를 동시에 추정하여 앞서 소개한 문제점들을 해결하고자 한다. 제안한 방법은 Mathwork에서 제공하는 Matlab 기반으로 시뮬레이션을 수행했고, 그 결과는 RLS 알고리즘과 비교하여 성능을 분석하였다. 제안된 방법은 상태 및 미지 변수 추정에 RLS 방법보다 뛰어난 추정 성능을 보임을 확인 하였다.

주제어 : 매니퓰레이터, 듀얼 확장 칼만 필터, 비선형 동역학 시스템, 상미분방정식, 라그랑지안

1. Introduction

Industrial robots which do various tasks are used in the manufacturing industry. Many industrial robots are consisted of manipulators instead of human arms and hands. Recently, the recognized robots based on a motion, gesture, temperature and infrared sensor are researched from a function of the repeated working [1].

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Manipulator has to be precisely controlled for a manufacturing accuracy and a safety of workers. However, in case of the manipulators taken the complex structures, deriving the mathematical model is very difficult. Inaccurate modelling for the control leads to the factor of decreasing the performance in system. Therefore, design of robust control is required for increasing the performance in a situation of the uncertain system model [2,3].

Proportional Derivative (PD) and Proportional Integral Derivative (PID) controllers are used in most of industries of the traditional control methods[4-7]. PD and PID controller can apply the low processing system and get a satisfying performance. On the other hands, the performance of the system required to the fast response and processing is decreased in applying PD and PID controller[8-13]. In order to prohibit the decrease of control performance, many researchers studied control methods of multi value control, passive control and sliding mode control[14-17]. However, the parameter identification is also needed to apply kinds of its control methods. Specifically, we are not sure for accuracy of parameter identification when the system has a nonlinearity and disturbance from external input.

In this paper, we present the parameter identification method using Dual Extended Kalman Filter(DEKF) including a measurement noise for a precise control. In order to verify the performance of parameter estimation, we employ the 2-Link Manipulator to do a simulation. The results of parameter estimation show that the accuracy is more improvement than estimation results of Recursive Least Sqaure(RLS) method.

2. Two-Link Manipulator System

In this section, we present an introduction to the dynamics of two-link manipulator and derive the equations of motion. The mechanical system is described in Fig. 1. It is consisting of the coupled Links and the operating motors. In order to derive dynamic model, we handle with a set of nonlinear, second-order, ordinary differential equations which depend on the kinematic and inertial properties of the system. Lagrange's equation is as follows:

$$\frac{d}{dt}\frac{\partial L}{\partial \dot{q}_i}-\frac{\partial L}{\partial q_i}=\tau_i \quad \text{for } i=1,2,\cdots,n \qquad (1)$$

where Lagrangian L defines $L(q,\dot{q})=T(q,\dot{q})-V(q)$, difference between the kinetic energy $T(q,\dot{q})$ and the potential energy $V(q)$ of the system. τ_i is the external force acting on the $i-th$ generalized coordinate. $q=[q_1,q_2,\cdots q_n]^T$ is position vector of manipulator, $\dot{q}=[\dot{q}_1,\dot{q}_2,\cdots \dot{q}_n]^T$ is velocity vector.

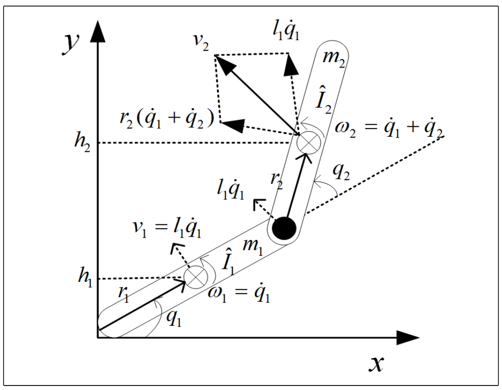

Fig. 1. Two-link manipulator

In case of manipulator system, the kinetic energy is derived with quadratic from.

$$T(q,\dot{q})=\frac{1}{2}\dot{q}^TM(q)\dot{q} \qquad (2)$$

where $M(q)$ is inertia matrix and generally inertia matrix has the characteristic of the symmetric and the positive definite.

The vector form of the equation (1) is as follows:

$$\frac{d}{dt}\frac{\partial L}{\partial \dot{q}}-\frac{\partial L}{\partial q}=\tau \qquad (3)$$

The Lagrangian L is substituted in equation (3):

$$\frac{d}{dt}\left(\frac{\partial T(q,\dot{q})}{\partial \dot{q}}\right)-\frac{\partial T(q,\dot{q})}{\partial \dot{q}}+\frac{\partial V(q)}{\partial q}=\tau \qquad (4)$$

The general manipulator dynamic equation using equation (2) and (4) can be derived as follows:

$$M(q)\ddot{q}+C(q,\dot{q})\dot{q}+g(q)+d=\tau \qquad (5)$$

where $g(q)$ in n-order gravity vector and defines $g(q)=\dfrac{\partial V(q)}{\partial q}$. $C(q,\dot{q})$ is n-order Coriolis and centrifugal vector. d is the disturbance vector.

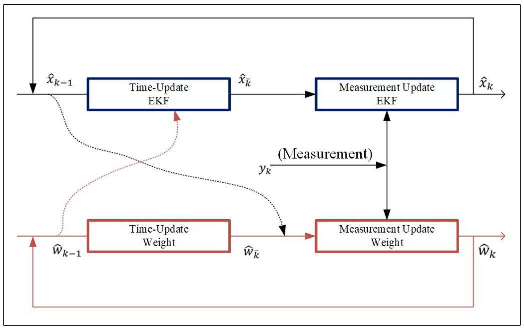

Fig. 2. Diagram of dual extended kalman filter

From Fig. 1, we can derive the velocity vector v_2.

$$v_2=\sqrt{\begin{aligned}&(l_1\dot{q}_1)^2+(r_2(\dot{q}_1+\dot{q}_2))^2\\&+2(l_1r_2\dot{q}_1)((\dot{q}_1+\dot{q}_2))c_2\end{aligned}} \qquad (6)$$

The kinetic energy of two-link manipulator system is as follows:

$$\begin{aligned}T(q,\dot{q})&=\frac{1}{2}m_1v_1^2+\frac{1}{2}\hat{I}_1w_1^2+\frac{1}{2}m_2v_2^2+\frac{1}{2}\hat{I}_2w_2^2 \quad (7)\\&=\frac{1}{2}m_1r_1^2\dot{q}_1^2+\frac{1}{2}\hat{I}_1\dot{q}_1^2+\frac{1}{2}m_2[l_2^2\dot{q}_1^2\\&\quad+r_2^2(\dot{q}_1+\dot{q}_2)^2+2l_1r_2\dot{q}_1(\dot{q}_1+\dot{q}_2)c_2]\\&\quad+\frac{1}{2}\hat{I}_2(\dot{q}_1+\dot{q}_2)^2\end{aligned}$$

where $c_1=\cos q_1$, $c_2=\cos q_2$, $c_{12}=\cos(q_1+q_2)$, $s_1=\sin q_1$, $s_2=\sin q_2$, and $s_{12}=\sin(q_1+q_2)$.

The potential energy equation is as follows:

$$\begin{aligned}U(q)&=m_1gh_1+m_2gh_2 \qquad (8)\\&=m_1gr_1s_1+m_2g(l_1s_1+r_2s_{12})\end{aligned}$$

The Lagrangian equation can be calculated by using the equation (7) and (8).

$$\begin{aligned}L(q,\dot{q})&=T(q,\dot{q})-U(q) \qquad (9)\\&=\frac{1}{2}m_1r_1^2\dot{q}_1^2+\frac{1}{2}\hat{I}_1\dot{q}_1^2+\frac{1}{2}m_2[l_2^2\dot{q}_1^2\\&\quad+r_2^2(\dot{q}_1+\dot{q}_2)^2+2l_1r_2\dot{q}_1(\dot{q}_1+\dot{q}_2)c_2]\\&\quad+\frac{1}{2}\hat{I}_2(\dot{q}_1+\dot{q}_2)^2-m_1gr_1s_1+m_2g(l_1s_1+r_2s_{12})\end{aligned}$$

The dynamic equation of system referred by equation (5) is as follows:

$$\begin{aligned}&M(q)= \qquad (10)\\&\begin{bmatrix}I_1+I_2+m_2l_1^2+2m_2l_1r_2c_2+I_1 & I_2+m_2l_1r_2c_2\\ I_2+m_2l_1r_2c_2 & I_2+I_{m2}\end{bmatrix}\\&C(q,\dot{q})\dot{q}=\\&\begin{bmatrix}-m_2l_1r_2s_2\dot{q}_2 & -m_2r_2l_1s_2(\dot{q}_1+\dot{q}_2)\\ m_2l_1r_2s_2\dot{q}_1 & 0\end{bmatrix}\begin{bmatrix}\dot{q}_1\\ \dot{q}_2\end{bmatrix}\\&g(q)=\\&\begin{bmatrix}-m_1r_1gc_1-m_2l_1gc_1-m_2r_2gc_{12}\\ -m_2gr_2c_{12}\end{bmatrix}\\&d=\\&[\end{aligned}$$

where F_{si}, F_{vi} are the i-th stop and kinetic friction force .

3. Estimation Algorithm

The Extended Kalman Filter(EKF) provided an efficient method for generating approximate maximum likelihood estimates of the state of a discrete-time nonlinear dynamical system[18,19]. The filter involves a recursive procedure to optimally combine noisy observations with predictions from the known dynamic model[8,9]. A second use of the EKF involves estimating the parameters of a model in Fig. 2. In this paper, we consider the dual estimation problem, in which both the states of the dynamical system and its parameters are estimated simultaneously, given only noisy observations. To be more specific, we consider a discrete-time nonlinear dynamical system.

$$\begin{aligned} x_{k+1} &= f(x_k, u_k, w_k) + v_k \\ y_k &= H(x_k, u_k, w_k) + n_k \end{aligned} \tag{11}$$

where the state states x_k and the set of model parameters w for the dynamical system mush be simultaneously estimated from only the observed noisy signal y_k.v_k and n_k are the process and measurement noise.

The algorithm of dual extended kalman filter(DEKF) is consisting of extended kalman filter and weight filter in Table 1.

The dynamic equation for weight filter is defined.

$$\begin{aligned} w_{k+1} &= w_k + r_k \\ D_k &= G(x_k, w_k) + e_k \end{aligned} \tag{12}$$

where the parameter w_k correspond to a stationary process with identity state transition matrix, driven by process noise r_k. The output D_k corresponds to a nonlinear observation on w_k.

The algorithm of weight filter is given by Table 2.

4. Parameter Identification

In this section, we describe the parameter identification from the dynamic equation. the parameters can be divided with a dynamic regressor. The parameters vector w is as follows:

$$w = \begin{bmatrix} I_{1,zz} + m_2 l_1^2 + I_{m1} \\ I_{2,zz} \\ m_2 r_2 l_1 \\ m_1 r_1 + m_2 l_1 \\ m_2 r_2 \\ I_{m2} \\ F_{s1} \\ F_{s2} \\ F_{v1} \\ F_{v2} \end{bmatrix} \tag{13}$$

Linear dynamic equation based on the equation (13) is derived.

$$\tau = Y(q, \dot{q}, \ddot{q}) w \tag{14}$$

$$\Downarrow$$

$$\begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} =$$

$$\begin{bmatrix} \ddot{q}_1 & Y_{12} & Y_{13} - gc_1 & -gc_{12} & 0 & sign(\dot{q}_1) & 0 & \dot{q}_1 & 0 \\ 0 & Y_{22} & Y_{23} & 0 & -gc_{12} & \ddot{q}_2 & 0 & sign(\dot{q}_2) & 0 & \dot{q}_2 \end{bmatrix} w$$

$$\begin{aligned} \therefore Y_{12} &= \ddot{q}_1 + \ddot{q}_2 \\ Y_{13} &= 2c_2 \ddot{q}_1 + c_2 \ddot{q}_2 - s_2 \dot{q}_2 (2\dot{q}_1 + \dot{q}_2) \\ Y_{22} &= \ddot{q}_1 + \ddot{q}_2 \\ Y_{23} &= c_2 \ddot{q}_1 + s_2 \dot{q}_1^2 \end{aligned}$$

Table 1. Extended state kalman filter

Initialize with:

$$\hat{x}_0 = E[x_0]$$

$$P_{x_0} = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T]$$

for $k \in 1, \cdots, \infty$, the time-update equations of the extended kalman filter are

$$\hat{x}_{k+1}^- = f(\hat{x}_k, u_k)$$

$$P_k^- = A_{k-1} P_{k-1} A_{k-1}^T + Q_{xk}$$

and the measurement-update equations are

$$K_k = P_k^- C_k^T (C_k P_k^- C_k^T + R_k)^{-1}$$

$$\hat{x}_k = \hat{x}_k^- + K_k (y_k - H(\hat{x}_k^-))$$

$$P_k = (I - K_k C_k) P_k^-$$

where

$$A_k \approx \frac{\partial F(x,u)}{\partial x}\Big|_{\hat{x}_k}, \qquad C_k \approx \frac{\partial H(x,u)}{\partial x}\Big|_{\hat{x}_k}$$

and where Q_k, R_k are covariance of v_k, n_k, respectively.

Table 2. Extended weight kalman filter

Initialize with: $\hat{w}_0 = E[w_0]$ $P_{w_0} = E[(w_0 - \hat{w}_0)(w_0 - \hat{w}_0)^T]$ for $k \in 1, \cdots, \infty$, the time-update equations of kalman filter are $\hat{w}_{k+1}^- = \hat{w}_k$ $P_{w k}^- = P_{w k-1} + Q_{w k}^r$ and the measurement-update equations are $K_k^w = P_{w k}^- (C_k^w)^T (C_k^w P_{w k}^- (C_k^w)^T + R_{x k}^e)^{-1}$ $\hat{w}_k = \hat{w}_k^- + K_k^w (D_k - G(\hat{w}_k^-, x_{k-1}))$ $P_{w k} = (I - K_k^w C_k^w) P_{w k}^-$ where $C_k^w \approx \frac{\partial G(x_{x-1}, w)^T}{\partial w}\Big\vert_w$

In order to identify the parameters (13), the equation of state-space matrix form is considered. Here, the previous equation (5) is adopted to equation (10).

$$p = M(q)\dot{q} = W_2(q,\dot{q})w \tag{15}$$

$$= \begin{bmatrix} \dot{q}_1 & \dot{q}_1 + \dot{q}_2 & (2\dot{q}_1 + \dot{q}_2)\cos q_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \dot{q}_1 + \dot{q}_2 & \dot{q}_1 \cos q_2 & 0 & 0 & \dot{q}_2 & 0 & 0 & 0 & 0 \end{bmatrix} w$$

The equation (5) is transformed as follows:

$$\dot{p} - W_1(q,\dot{q})w = \tau \tag{16}$$

where, $W_1(q,\dot{q})w = C^T(q,\dot{q})\dot{q} - g(q) - d.$

The regressor of system based on the momentum is derived.

$$Y(q,\dot{q},t)w = u \tag{17}$$

where, $Y(q,\dot{q},t) = W_2(q,\dot{q}) - \int W_1(q,\dot{q})dt.$

$$u = \int \tau dt$$

The state variable is defined for applying to proposed method.

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} q_1 \\ q_2 \\ \dot{q}_1 \\ \dot{q}_2 \end{bmatrix} \tag{18}$$

The state-space matrix form is as follows:

$$\frac{dx}{dt} = \begin{bmatrix} x_3 \\ x_4 \\ M^{-1}(x_1,x_2)[\tau - C(x_1,x_2,x_3,x_4) \\ (x_3,x_4) - g(x_1,x_2) - d(x_3,x_4)] \end{bmatrix} \tag{19}$$

4. Simulation Results

In order to verify the performance of unknown estimation simulation using RLS and proposed method in Matlab(2016a) environments. We set all of the parameters of dynamical system as the unknown parameters. The initial parameters (initial value and error covariance) of state and weight estimator are set as follows:

$$x_0 = zeros(1,2) \qquad w_0 = zeros(1,10) \qquad P_x = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, P_w = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix}_{10 \times 10} \tag{20}$$

Table 3. Analysis of parameter estimation results

Unknown Parameters	RLS algorithm (RMSE)	Proposed method (RMSE)
w[1]	0.0228	0.0222
w[2]	0.0025	0.0025
w[3]	0.0034	0.0033
w[4]	0.0184	0.0191
w[5]	0.0069	0.0053
w[6]	0.0034	0.0027
w[7]	0.0154	0.0081
w[8]	0.0290	0.0073
w[9]	0.0187	0.0170
w[10]	0.0176	0.0123

For the estimators, initial process noise covariances of each estimator are given as

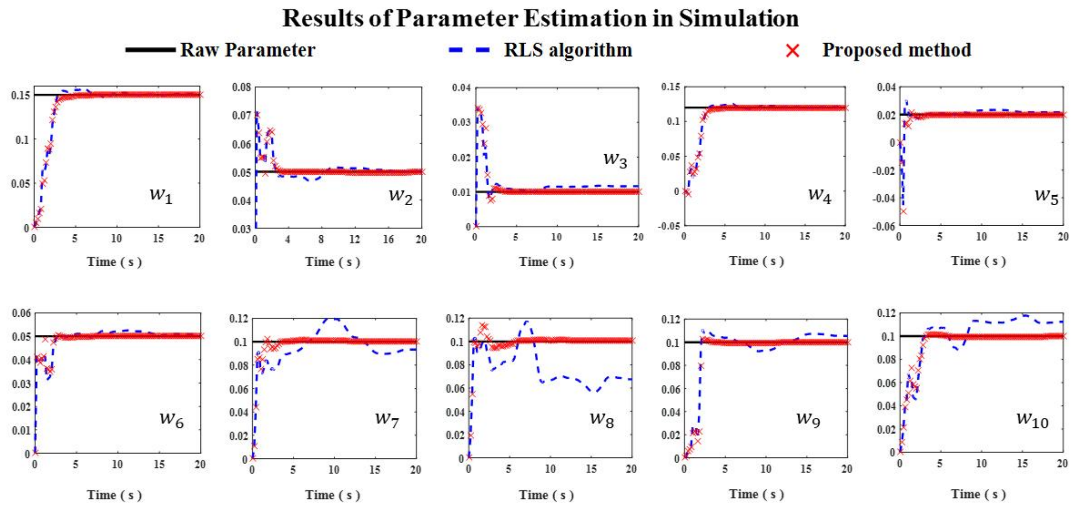

Fig. 3. Results of parameter estimation performance

$$Q_{xk} = diag[10^{-4}, 10^{-5}] \quad (21)$$
$$Q_{wk} = 0.5\, I_{10\times 10}$$

In Fig. 3, the black line means the raw parameter, the dot-blue line and the shape of x are estimation results of RLS algorithm and proposed method, respectively. Fig. 3 shows the performance of proposed method and RLS algorithm. Specifically, estimation results of parameter value *w[7]* and *w[8]* have a large estimation error in RLS results. On the other hands, the proposed method shows the constants performance of all parameter estimation. All estimated parameter is converged to raw parameter values. The computational results based on root mean square error are summarized and given in Table 3.

In Table 3, the proposed method can estimate unknown parameters well without the parameter *w[4]* in view of performance based on the numerical result.

5. Conclusion

In this paper, we present the unknown parameter estimation using Dual Extended Kalman Filter for precise control. In order to estimate unknown parameter of dynamic system, we derive state equation and state-space matrix form including the inertial characteristic of system. The results of parameter estimation in Fig. 3 shows that the proposed method have good performance to estimate unknown parameter despite the measurement noise. In particular, numerical analysis result also show the proposed method have better performance compared to RLS algorithm.

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