The Backlash Gap size Estimation for Electromechanical Actuator in an Operational Behavior

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ABSTRACT

More electric aircraft are lighter and more energy efficient than conventional aircraft. Hence, the design of electromechanical devices and its preventive maintenance strategies are in increasing need and challenge for flight control systems. One of the most significant mechanical parameter for aging is the backlash gap size. Hence, it presents a good indicator for failure detection, diagnosis and prognostic. In this work, an estimation method of this parameter is proposed for any electromechanical actuator (EMA); rotary or linear with roller screw or ball screw, used to actuate any flight control surface of the aircraft; flaps, ailerons…etc. This method presents a simple and easy technique for implementation in real time based on a Linear Kalman Filtering (LKF).

1. INTRODUCTION

Couplings mechanical components, such as gearbox, ball screw and roller screw…etc., introduce backlash phenomenon. Therefore its estimation is fundamental for its compensation and implementation in control, for fault detection, diagnosis, or prognostic. Unfortunately, there are only few contributions in the literature in this way.

In modeling viewpoint, most popular model of backlash is considered as a dead zone (Tustin, 1947), (Liversidge, 1952), (Cosgriff, 1958), (Freeman, 1957). De-Marchi (1998) presents a backlash model with 'Compliance' that means an intrinsic property allowing an object to be elastic. Nordin, Galic and Gutman (1997) and, Lagerberg and Egardt (2007) consider the backlash model as flexible shaft, this model is physically more accurate than the traditionally used dead-zone. Vörös (2010) proposes a mathematical model for backlash with hard dynamic nonlinearity, which uses appropriate switching functions and their complements. The so called inertia driven model (Nordin & Per-Olof, 2002) is applied to describe the backlash phenomenon.

In the way of backlash estimation, some identifications schemes are proposed but still remain open. In (Egardt & Lagerberg, 2007) a nonlinear estimators for backlash size and state are developed, using Kalman filtering theory, this estimation schemes considers that the state model is a system switching between two linear modes, called 'contact mode' and 'backlash mode' in absolute reference of state. Hence, this presents a complex model with a significant cost computing. In (Vörös, 2010) an identification method based on a mathematical model for backlash with hard dynamic nonlinearity, which uses appropriate switching functions and their complements, therefore, the knowledge of the model structure is required and any industrial application is given in this approach. Too many papers treat of the control for mechanical system with backlash compensation (Lorinc & Béla, 2009), (Lagerberg & Egardt, 2007), (Nordin & Per-Olof, 2002), (Kalantari & Saadat, 2009) and (Kolnik & Agranovich, 2012). Indeed, Nordin and Per-Olof (2002) summarize the introduced backlash models and compensation within controller. Lorinc and Béla (2009) take into account backlash compensation and nonlinear friction in the same time where the mechanical system is treated in a hybrid system approach. In (Kalantari & Saadat, 2009) an adaptive algorithm is designed, based on different regions of the system angular position error. Since for backlash compensation, this one is estimated by a learning unit in the adaptive controller. Therefore, learning method is not very accurate and requires a known backlash structure. In (Kolnik & Agranovich, 2012) a backlash compensation control method is proposed, it's based on two-mass system model where the backlash is treated as torque disturbance, then a disturbance observer (DOB) is constructed in order to estimate and compensate the disturbance. So, the aim of this method is to reduce torsional vibrations, but not to give a precise value of the backlash gap size. As well, one can find an estimation method based on signal processing, in this way Jaber and Bicker (2016) propose a backlash diagnosis

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Notice that this method is patented.

in the gearbox of industrial robot joints, it's based on time-frequency signal analysis scheme, as wavelet transform applied on a specific signal profile. Adding to significant cost computing, the studied displacement profile is neither operational nor random behavior.

In this paper we propose a dynamic model backlash with dead zone and a flexible shaft. This model is similar to (Lagerberg & Egardt, 2007) and (Nordin & Galic, 1997), but, it's presented on the relative reference. The aim is to identify the backlash gap size related to the dead zone by assuming that the stiffness and damping are known, and upstream and downstream actuator positions are measured. So, the advantage of this estimation approach is that it's based on linear Kalman filtering with three variables state only by considering the backlash gap as white noise. Thus, this makes the implementation very easy in real time with a very low computing cost.

2. MODELING OF EMA

In the goal to estimate the mechanical backlash with an operational profile displacement, one has to build a generic dynamical model equivalent to the EMA. So any electromechanical actuators; rotary or linear can be viewed as a transmission between two masses; the first one is a permanent magnet synchronous motor (PMSM), the second inertia is a transformation into the motor axis of screw mass according to the screw thread and/or reduction ratio, i.e. if θ is the angular position, and r is reduction ratio, then, PMSM position in translational absolute reference is given by $X_1 = \theta.r/2.\pi$. Thus, one considers a dynamic system with two masses and spring damper as explained bellow (Figure 1).

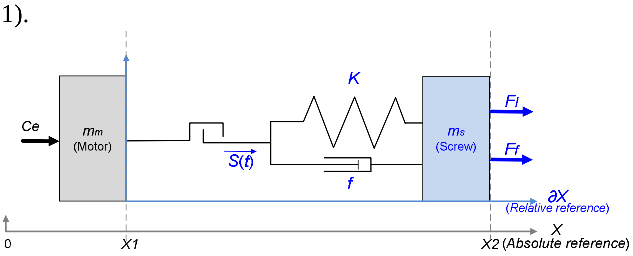

Figure 1. Backlash model of EMA.

where:

X	Position in the absolute reference (m)
f	Damping coefficient ($N/(m/s)$)
K	Stiffness (N/m)
$S(t)$	Backlash (m)
m_m	Motor inertia (in translational) (Kg)
m_s	Roll screw mass (Kg)
F_l	Aerodynamic load (N)
F_f	Frictions force (N)
δX_0	Initial displacement (m)

Remark: Motor inertia in translational is given by the transformation: $m_m = J_m.(r/2.\pi)^2$ where J_m is the rotary inertia ($Kg.m^2$).

2.1. Frictions Model

Prior to give backlash model, it is important to highlight the friction assumptions considered in this study, because these hypotheses have an impact on the aerodynamic load measurement, we will see in the simulation example. For simplification, let us consider that the coupling between the screw and the PMSM is infinitely rigid. Thus, the whole frictions considered in this study are given by (Karam, 2007):

$$F_f = F_v \dot{X} + signe(\dot{X})\left[F_{dry} + \eta\left|F_l\right|\right] \tag{1}$$

where:

X	Position in the absolute reference (m)
$\dot{X}$	Speed in the absolute reference (m/s)
F_f	Global frictions (N)
F_v	Viscous friction parameter ($N/(m/s)$)
F_{dry}	Dry frictions (N)
η	Efficiency (%)

Notice that these frictions can be distributed among two masses. Emphasize also that the force sensor measures only the aerodynamic loads F_l . Thus, sum of external forces applied to the screw is given by:

$$F_{ext} = F_l + F_f \tag{2}$$

2.2. Backlash State Model

By considering us within the relative reference fixed at the motor inertia i.e. $\delta X = X_2 - X_1$, the fundamental principle of dynamics related to the position variation applied on the screw inertia gives:

$$m_s.\delta\ddot{X} = -(K + \Delta K)(\delta X - \delta X_0 - S) - (f + \Delta f).\delta\dot{X} + F_{ext} \tag{3}$$

Terms ΔK and Δf are respectively the uncertainties of stiffness K and structural damping f.

The backlash identification scheme is based on Kalman filtering by using the relative dynamic model (3). Thus, the goal is to estimate the backlash variation $S(t)$ that is considered as an exogenous input perturbation. The main hypothesis here, is to consider that the dynamic variable $S(t)$ is an integral type added to a random white noise with a known spectral power density. That means:

$$\dot{S} = 0 + b(t) \tag{4}$$

Where $b(t)$ is a white noise without bias and with a known spectral power density.

Using the backlash model of EMA (3) and the hypothesis (4) the process model can be written in state space form:

$$\dot{x}(t) = Ax(t) + Bu(t) + Mw(t) \tag{5}$$

$$y(t) = Cx(t) + v(t) \tag{6}$$

Where:

$$x = [\delta X \quad \delta\dot{X} \quad S]^T \tag{7}$$

$$y = [\delta X]^T \tag{8}$$

are the state and measurement vectors, $v(t)$ is measurement noise, $w(t)$ includes uncertainties and global disturbances input process:

$$w(t) = [0 \quad \Delta p(t) \quad b(t)] \tag{9}$$

with

$$\Delta p(t) = -\Delta K.\delta X - \Delta f.\delta\dot{X} + \Delta K.S(t) \tag{10}$$

Therefore we assume that the covariance matrices of $v(t)$ and $w(t)$ are known. And:

$$A = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{K}{m_S} & \frac{-f}{m_S} & \frac{K}{m_S} \\ 0 & 0 & 0 \end{bmatrix} \tag{11}$$

$$B = \begin{bmatrix} 0 & \frac{1}{m_s} & 0 \end{bmatrix}^T \tag{12}$$

$$M = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{1}{m_s} & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{13}$$

$$C = [1 \quad 0 \quad 0]^T \tag{14}$$

$$D = 0 \tag{15}$$

are respectively, state matrix, input control matrix, exogenous input matrix and measurement matrix. Finally, the input control is given by

$$u = F_{ext} \tag{16}$$

Therefore, notice that speed and frictions are unknown, so the external forces as given by (2) are unknown. Thus, by considering $|F_f| << |F_l|$, the input control can be written as:

$$u \cong F_l \tag{17}$$

Well, loads are measured by forces sensor. This hypothesis has a little impact on result that will be discussed in the illustration example.

3. ESTIMATION OF BACKLASH WITH KALMAN FILTER

3.1. Model Discretization

To implement Kalman Filter, we assume that the output of the continuous system (5) and (6) is sampled within a period time Ts in discrete observation. We assume that the control input *u* is a piecewise constant over the sampling period Ts by using Zero-order hold. One notices that $x(kT_s) = x(k)$. Hence, the discrete state equation is given by:

$$\dot{x}(k+1) = A_d x(k) + B_d u(k) + M_d w(k) \tag{18}$$

$$y(k) = C_d x(k) + v(k) \tag{19}$$

Where these matrices are approximate starting from the general solution of continuous system (5) and by integration between instants $t_0 = kT_s$ and $t = (k+1)T_s$. Thus, we find (Franklin, Powell, and Workman, 1997):

$$A_d = e^{AT_s} \tag{20}$$

$$B_d = \int_0^{T_s} e^{A\upsilon} B d\upsilon \tag{21}$$

$$M_d = I_n \tag{22}$$

$$C_d = C \tag{23}$$

Hence, we can use a numerical approximation, or using *The Control Toolbox* of MATLAB® to obtain discreet matrices.

3.2. Kalman Algorithm

The LKF is an optimal estimator which searches the cost function $J = \sum_{k=1}^{m} E\{\tilde{x}^2(k)\}$ at the least square sense. The $\tilde{x}(k)$ is defined by $\tilde{x}(k) = \hat{x}(k) - x(k)$ which is the difference of estimation state $\tilde{x}(k)$, and system state $x(k)$. The LKF algorithm is described by the following two step recursive equations by using the discreet state model (18) and (19) (Maybeck, 1982):

Step 1 (prediction step)

$$\hat{x}(k+1/k) = A_d \hat{x}(k/k) + B_d u(k) \tag{24}$$

$$P(k+1/k) = A_d P(k/k) A_d{}^T + M_d W_d M_d{}^T \tag{25}$$

Step 2 (prediction step)

$$K_f(k+1) = P(k+1/k).C_d{}^T \left(C_d P(k+1/k) C_d{}^T + V_d\right)^{-1} \tag{26}$$

$$\begin{aligned} \hat{x}(k+1/k+1) &= \hat{x}(k+1/k) \\ &+ K_f(k+1).\left(y(k+1) - C_d \hat{x}(k+1/k) - D_d u_d(k+1)\right) \end{aligned} \tag{27}$$

$$P(k+1/k+1) = \left(I_n - K_f(k+1) C_d\right) P(k+1/k) \tag{28}$$

Where W_d and V_d are the process noise and measurement noise covariance respectively with known power spectral densities. $\hat{x}(k+1/k)$ and $\hat{x}(k+1/k+1)$ are the prediction and the estimation state covariance respectively. $P(k+1/k+1)$ and $P(k+1/k)$ are the prediction error and the estimation error covariance respectively (Maybeck, 1982).

4. SIMULATION AND DISCUSSION

4.1. Simulation Result with Real Data Loads

To improve the result of this estimation scheme, one uses a complete dynamic model that includes frictions which are distributed among screw and PMSM independently according to (1). Therefore, frictions are considered unknown in this study. Hence, all values parameters used in backlash state model (18) and (19) are not provided for confidentiality reasons, as well, all data used for illustration are normalized.

To make an operational scenario we use the real data profile, especially PMSM and screw positions in translational (Figure 2) and aerodynamic loads (Figure 3).

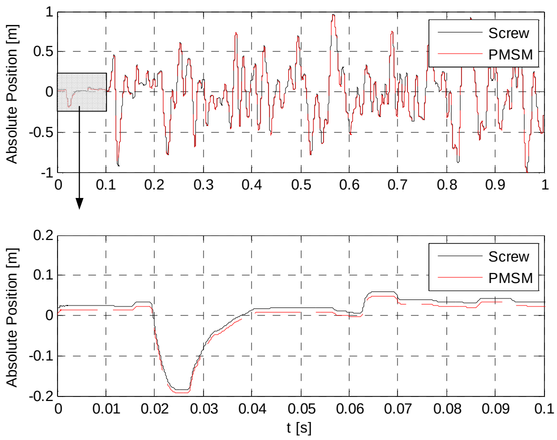

Figure 2. Screw and motor position in translational. Notice that a zoom in a small interval also is given for more visibility.

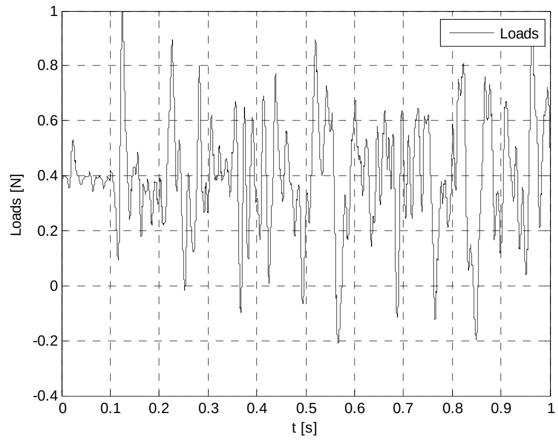

Figure 3. Aerodynamic loads.

The measured state considered in this study is the relative position between screw and PMSM in translational. Thus, Figure 4 shows the convergence of estimated relative position to the real one by using LKF.

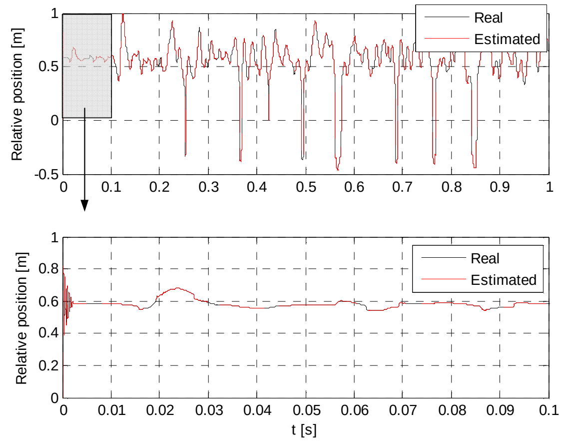

Figure 4. Relative position (Screw – PMSM) in translational.

Hence, by considering the backlash as a dynamic variable, it fluctuates between two values corresponding respectively to the upper and lower bound of real gap backlash as shown in Figure 5. We also note a small variation around both upper and lower backlash bound. This phenomenon is due to the measured loads that not include frictions as defined by (2). Indeed, aerodynamic loads are often supporting moving (positive load) who push the backlash to the upper bound, and the dry frictions are either added or subtracted into real aerodynamic loads, according to speed sign as defined in (1) and shown in Figure 6 and Figure 7. The same problem occurs around the lower backlash bound, when the loads are in the opposite (negative) way of the screw displacement as shown in Figure 7.

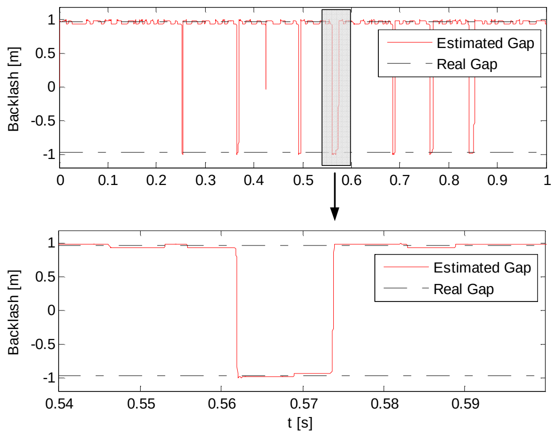

Figure 5. Backlash gap estimation.

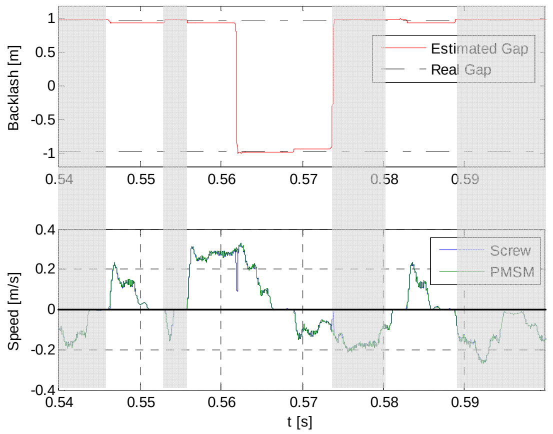

Figure 6. Backlash vs Speed.

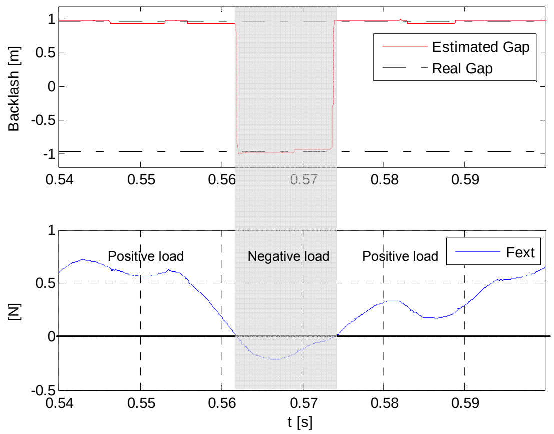

Figure 7. Backlash vs loads.

Thus, the backlash fluctuations around the upper or lower bound is considered negligible by assuming that aerodynamic loads are more important than dry frictions. Hence, based on this assumption, to estimate the gap size of backlash that we note ΔS , we propose a statistical method using upper average and lower average of the estimated backlash signal:

$$\Delta S \cong \sum_{k=1}^{p} \frac{S_p(k)}{p} - \sum_{k=1}^{n} \frac{S_n(k)}{n} \tag{29}$$

Where:

$$S_p(k) = \left\{ S(k) \quad / \quad S(k) \geq \frac{\max(S(k)) + \min(S(k))}{2} \right\} \tag{30}$$

$$S_n(k) = \left\{ S(k) \quad / \quad S(k) < \frac{\max(S(k)) + \min(S(k))}{2} \right\} \tag{31}$$

Are respectively; upper average and lower average of the estimated backlash

5. CONCLUSION

In this paper, a new method of identification is proposed; it's about the backlash gap size estimation for electromechanical actuator in an operational behavior. The estimation scheme is based on LKF by considering that the backlash variable as an integral type added to a random white noise with a known spectral power density. This method has the advantage to estimate any backlash form that can be considered as a random signal. In the end, an example of simulation using real loads and displacement profile is illustrated to show the relevance of this method. In perspective works, more complex model of backlash will be studied with the same philosophy.

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