CONDITION MONITORING FOR DRY FRICTION BUILDUP IN AN INDUSTRIAL HYDRAULIC SYSTEM USING UNSCENTED KALMAN FILTER

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ABSTRACT

This paper presents a method for on-line fault monitoring and diagnosis, which is implemented in the hydraulic control system in the cutter module of an industrial fish processing machine. Raw data from the pressure sensors and displacement sensors of the machine are analyzed on line, and residual values are generated using an Unscented Kalman Filter (UKF). By comparing these values against a set thresholds and estimated state of the system, the specific faults are detected when they occur, and are properly diagnosed. In particular, faults related to dry friction in the moving components are detected using residual moving average errors (MAE). This fault is manually introduced to the supporting tables of the sliding cutter. The effectiveness of the method is evaluated experimentally, for the induced faults.

Keywords: Machine health monitoring, hydraulic control system, fault detection and diagnosis, unscented Kalman filter.

INTRODUCTION

There are pros and cons of hydraulic systems compared to other power sources. In particular, hydraulic systems are more compact and can supply high levels of power, which can greatly improves the performance of a machine [1-2]. The detection and isolation of faults in engineering systems is of great practical significance. An experimental evaluation of a leakage fault detector in hydraulic actuator based on Extended Kalman Filtering (EKF) was developed in [4-5]. Identification of external leakage at either side of the actuator as well as the internal leakage between the two chambers was examined. The lack of an effective method for handling temporal data is seen as one of the key problem in real-time fault detection and diagnosis [3]. Addressing this challenge, the main objective of the present paper is to develop, implement, and study a suitable model-based approach for on-line detection and diagnosis of possible faults in a complex hydraulic system in real time using Unscented Kalman Filter (UKF) methodology. With this technique, system linearization may be avoided. An automated industrial fish processing machine is chosen as the application platform for the present work. Specifically, the effect of dry friction on the cutter table is investigated in the context of fault diagnosis.

EXPERIMENTAL SET-UP

The traditional "Iron Butcher" which is commonly used in the fish-processing industry, has been redesigned and developed in our Industrial Automation laboratory at UBC to automate the fish cutting process and to reduce the meat wastage by guiding the cutter to the optimum location for cutting. The challenges include, accurate positioning of cutter blades and smooth cutting of fish. As shown in Fig. 1, to control the X motion, a position transducer is mounted at the head of the hydraulic cylinder. Two gage-pressure transducers are installed on the head and rod sides of the cylinder to measure the fluid pressures $P_1$ and $P_2$ in the corresponding chambers. Under normal operating conditions, the hydraulic flows $q_1$ and $q_2$ entering chambers 1 and 2 and the flow can be regulated by adjusting the input current to the servo-valve.

Fig. 1: The hydraulic actuation system in one axis.

DYNAMIC MODELING

Dynamic modeling will take into account the nonlinear nature of the actuator dynamics [1]. The displacement of the
Valve spool will change the single-rod hydraulic actuator. This creates a force that is applied to the external load by the actuator and may be expressed in the form:

\[ F = P_1 A_1 - P_2 A_2 = M \ddot{x} + f_f \]  

(1)

where \( P_1, P_2 \) are the pressures in chamber 1 and chamber 2, \( A_1 \) and \( A_2 \) are effective piston areas of chamber 1 and chamber 2, \( M \) is the equivalent moving mass in \( Y \) direction, \( f_f \) is the opposing frictional force of the actuator and \( \ddot{x} \) is the piston displacement in \( Y \) direction.

Applying a linear orifice area gradient, the flow equations of the servo-valve are obtained as:

\[
\begin{align*}
Q_1 &= -C_d A_{orifice} x \sqrt{\frac{2}{\rho} (p_1 - P)} \text{sign}(p_1 - P) & x_1 \geq 0 \\
Q_2 &= C_d A_{orifice} x \sqrt{\frac{2}{\rho} (P_2 - p_2)} \text{sign}(P_2 - p_2) \\
Q_1 &= -C_d A_{orifice} x \sqrt{\frac{2}{\rho} (p_1 - P)} \text{sign}(p_1 - P) & x_1 < 0 \\
Q_2 &= C_d A_{orifice} x \sqrt{\frac{2}{\rho} (P_2 - p_2)} \text{sign}(P_2 - p_2)
\end{align*}
\]

(2)

where \( P_1 \) and \( P_2 \) are the return pressure and supply pressure, \( Q_1 \) and \( Q_2 \) are fluid volume flow rates to chamber 1 and chamber 2, \( x \) is the valve spool displacement, \( \rho \) is the hydraulic oil density, and \( C_d \) and \( A_{orifice} \) are the orifice coefficient of discharge and area gradient, respectively. Using continuity equations and assuming compressibility of the hydraulic fluid, a relationship between chamber pressure, \( V_h \) is volume of the fluid inside a hose that connects the servo-valve to the actuator, and \( \beta \) is effective bulk modulus of the fluid. Combining equations (2) and (3) to eliminate flow parameters, one gets:

\[
\begin{align*}
\dot{P}_1 &= \frac{\beta}{A_1 x + V_h} \left[ C_d A_{orifice} x \sqrt{\frac{2}{\rho} (p_1 - P_1)} \right] A_{x} \ddot{x} & x_1 \geq 0 \\
\dot{P}_1 &= \frac{\beta}{A_1 x + V_h} \left[ C_d A_{orifice} x \sqrt{\frac{2}{\rho} (P_2 - p_2)} \right] A_{x} \ddot{x} & x_1 < 0 \\
\dot{P}_2 &= \frac{\beta}{A_2 (L-x) + V_h} \left[ C_d A_{orifice} x \sqrt{\frac{2}{\rho} (P_2 - p_2)} \right] A_{x} \ddot{x} & x_1 \geq 0 \\
\dot{P}_2 &= \frac{\beta}{A_2 (L-x) + V_h} \left[ C_d A_{orifice} x \sqrt{\frac{2}{\rho} (p_1 - P_1)} \right] A_{x} \ddot{x} & x_1 < 0
\end{align*}
\]

(4)

Due to the complexity of nonlinear friction and difficulty in its modeling, researchers have come up with approximated expressions to represent friction in dynamic modeling [2]. Friction is usually modeled as a function of velocity, and opposes the motion. Due to the significance of friction in a dynamic system, in 1985 Karnopp [6] proposed a stick-slip friction model, which provides a straightforward method for representing and simulating friction effects. Later in 1996, Laval [7] proposed a similar method which improved Karnopp’s model for friction in a hydraulic cylinder, as:

\[
f_f = \left\{ \begin{array}{ll}
(1 - e^{-C_b})|\text{sign}(\ddot{x}) + d \dot{x} & \ddot{x} \neq 0 \\
0 & \ddot{x} = 0
\end{array} \right.
\]

(6)

where \( f_f \) is static friction, \( f_d \) is slip friction, \( C_b \) is friction coefficient, and \( d \) is effective damping ratio. To express the position of the flow controlling valve as a function of the drawn current, the following quadratic equation can be written:

\[
K_{sp} u = \ddot{x}_v + 2 \omega_d d \dot{x}_v + \omega_d^2 x_v
\]

(7)

where \( K_{sp} \) is spool valve position variable, \( \omega_d \) is natural frequency of the valve, \( u \) is valve input current, and \( d \) is damping ratio.

**UKF ALGORITHM**

Unscented Kalman Filter (UKF) uses the unscented transformation to pick sigma points around the data mean. These sigma points are then propagated through nonlinear functions, from which the mean and covariance of the estimate are then recovered. The result is a filter which more accurately captures the true mean and covariance. In addition, this technique removes the requirement to explicitly and precisely calculate Jacobians, which is complicated. Julier and Uhlmann [8-10] introduced unscented transformation (UT) which uses sampled data to calculate the mean and the covariance. The following equations explain the algorithm used in the UKF, which is an extension to UT:

1) Consider an \( n \)-state discrete-time nonlinear system at step \( k \), with \( f \) and \( h \) representing the nonlinear state function and the measurement function, respectively, given by

\[
x_{k+1} = f(x_k, u_k, t_k) + w_k; \quad y_k = h(x_k, t_k) + v_k
\]

(8)

\[
w_k = (0, Q_d); \quad v_k = (0, R_d)
\]

2) Initialize the filter using the following equations:

\[
\hat{x}_0 = E(x_0) \\
P_0 = E[(\hat{x}_0 - x_0)(\hat{x}_0 - x_0)^T]
\]

(9)

The next step uses the “Time Update” equations which propagate the state estimate and covariance from one measurement time to the next.

3) Initially choose a set of sigma points to propagate from time step \((k-1)\) to \(k\) :
\[ \bar{x}^{(i)} = \left\{ nP_{x_{i-1}}^{(i)} \right\} \quad i = 1, \ldots, n \]
\[ \bar{x}^{(i+n)} = -\left\{ nP_{x_{i-1}}^{(i)} \right\} \quad i = 1, \ldots, n \]
\[ \bar{x}^{(i+1)} = \hat{x}_{k-1}^{(i)} + \bar{x}^{(i)} \quad i = 1, \ldots, 2n \]

4) Transform the sigma points into the \( \hat{x}^{-} \) vector and combine to obtain \( a \) priori state estimate \( x_{k}^{-} \) and its predicted error covariance (by taking process noise into account) \( P_{k}^{-} \), at time \( k \):
\[ \hat{x}_{k}^{(i)} = f\left( \hat{x}_{k-1}^{(i)}, u_{k}, w_{k} \right) \quad i = 1, \ldots, n \]
\[ \hat{x}_{k}^{(i+1)} = \frac{1}{2n} \sum_{i=1}^{2n} \left[ \bar{x}^{(i)} - \hat{x}_{k}^{(i)} \right] \quad i = 1, \ldots, n \]
\[ P_{k}^{(i)} = \frac{1}{2n} \sum_{i=1}^{2n} \left( \hat{x}_{k}^{(i)} - \hat{x}_{k} \right) \left( \hat{x}_{k}^{(i)} - \hat{x}_{k} \right)^{T} + Q_{k} \]

Now the “Measurement Update” has to be implemented since the “Time Update” step has been completed. However, to save the computational effort, instead of generating a new set of sigma points, the same sigma points generated in the “Time Update” step are used. Accordingly, as before, the predicted observation vector \( \hat{y}_{k} \) and its predicted covariance \( P_{y} \) are obtained using the following equations:
\[ \hat{y}_{k}^{(i)} = h\left( \hat{x}_{k}^{(i)}, t_{k} \right) \quad i = 1, \ldots, n \]
\[ \hat{y}_{k} = \frac{1}{2n} \sum_{i=1}^{2n} \hat{y}_{k}^{(i)} \quad i = 1, \ldots, n \]
\[ P_{y} = \frac{1}{2n} \sum_{i=1}^{2n} \left( \hat{y}_{k}^{(i)} - \hat{y}_{k} \right) \left( \hat{y}_{k}^{(i)} - \hat{y}_{k} \right)^{T} + R_{k} \]

5) To estimate the similarities between \( \hat{x}^{-} \) and \( \hat{y}_{k} \), the cross-covariance matrix is calculated using the following expression:
\[ P_{xy} = \frac{1}{2n} \sum_{i=1}^{2n} \left( \hat{x}^{-} - \hat{x}_{k} \right) \left( \hat{y}_{k}^{(i)} - \hat{y}_{k} \right)^{T} \]

6) In the concluding step of the algorithm, the filter gain \( K_{k} \), the final updated state estimate \( \hat{x}_{k}^{+} \), and the covariance \( P_{k}^{+} \) are computed. The equations are as follows:
\[ K_{k} = P_{xy} \left( P_{y} \right)^{-1} \]
\[ \hat{x}_{k}^{+} = \hat{x}_{k}^{-} + K_{k} \left( y_{k} - \hat{y}_{k} \right) \]
\[ P_{k}^{+} = P_{k}^{-} - K_{k} P_{y} K_{k}^{T} \]

**STATE SPACE MODEL**

Converting the expressed dynamic equations into the state space form, the six state variables of the state vector are:
\[ \ddot{x} = [x_{1}, x_{2}, x_{3}, x_{4}, x_{5}, x_{6}]^{T} = [x, \dot{x}, P, P_{y}, x_{1}, \dot{x}_{1}]^{T} \]
Discretising the state space model of UKF algorithm with respect to time using the sampling time \( T \) and the process time step \( k \) one has:
\[ x_{1}(k+1) = T x_{2}(k) + x_{1}(k) \]
\[ x_{2}(k+1) = \frac{T}{M_{v}} \left( A_{x_{1}}(k) - A_{x_{2}}(k) - f_{r}(k) \right) + x_{2}(k) \]

where:
\[ f_{r} = \begin{cases} T \beta & \text{if } x_{1}(k) > x_{2}(k) \\ 0 & \text{otherwise} \end{cases} \]
\[ x_{1}(k) > x_{2}(k) \]
\[ x_{1}(k) \leq x_{2}(k) \]
\[ x_{1}(k+1) = T x_{2}(k) + x_{1}(k) \]
\[ x_{2}(k+1) = T \left[ K_{y} \nu(k+1) - 2 \alpha_{d} \rho d_{m} x_{1}(k) - \alpha_{d}^{2} x_{1}(k) \right] + x_{2}(k) \]

Table 1 shows the identified parameters of the dynamic model.

**Table 1: Dynamic parameters of the hydraulic system.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( A_{p} )</td>
<td>1.144 x 10^{-3} m²</td>
</tr>
<tr>
<td>( f_{c} )</td>
<td>3769 N</td>
</tr>
<tr>
<td>( V_{p} )</td>
<td>8.50 x 10^{-2} m³</td>
</tr>
<tr>
<td>( A_{d} )</td>
<td>0.323 x 10^{-3} m²</td>
</tr>
<tr>
<td>( f_{d} )</td>
<td>278 N</td>
</tr>
<tr>
<td>( A_{friction} )</td>
<td>0.04 m²/m</td>
</tr>
<tr>
<td>( L )</td>
<td>0.056 m</td>
</tr>
<tr>
<td>( C_{b} )</td>
<td>58 m/s</td>
</tr>
<tr>
<td>( d_{friction} )</td>
<td>8.9 x 10^{-3} Pa</td>
</tr>
<tr>
<td>( d )</td>
<td>127 N/s/m</td>
</tr>
<tr>
<td>( K_{d} )</td>
<td>3.8 x 10^{-3} m/s</td>
</tr>
<tr>
<td>( \rho )</td>
<td>857 kg/m³</td>
</tr>
<tr>
<td>( M_{v} )</td>
<td>55.7 kg</td>
</tr>
<tr>
<td>( \omega_{d} )</td>
<td>126 rad/s</td>
</tr>
<tr>
<td>( P_{v} )</td>
<td>20.7 MPa</td>
</tr>
<tr>
<td>( v_{1} )</td>
<td>0.001</td>
</tr>
</tbody>
</table>

**FAULT MONITORING RESULTS**

Sometimes the cutter table may not reach the correct position due to insufficient lubrication at the cutter carriage. Therefore, the actuator movement will be restricted and the actuator will fall short of reaching the designated location (Fig. 2).

Fig. 2: Actuator displacement with dry friction buildup.

Fig. 3 shows the residual error signals due to the dynamic friction load. It is observed that the residual error of
the actuator position increases much more than those of the pressures in chambers 1 and 2.

![Graphs showing residual errors](image)

Fig. 3: Residual error for: (a) actuator displacement, (b) pressure in chamber 1, (c) pressure in chamber 2.

Table 2 presents the variation of the residual MAEs. It can be seen that both pressure residual errors have increased and are within the same order of magnitude. Also the increase in actuator displacement MAE is the largest among the three.

<table>
<thead>
<tr>
<th>Fault</th>
<th>Pressure in chamber 1 (MPa)</th>
<th>Pressure in chamber 2 (MPa)</th>
<th>Actuator position (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry friction</td>
<td>0.092</td>
<td>0.085</td>
<td>1.98</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

In this paper, a model-based on-line condition monitoring scheme using Unscented Kalman Filter (UKF) was developed and implemented in the hydraulic system of an automated industrial fish processing machine. The work involved an important contribution of Kalman filtering in fault monitoring and diagnosis. In this study, the UKF scheme correctly identified the state of the system and generated a residual error given by the difference between the measured and the predicted outputs. A nonlinear state-space model was developed for the hydraulic positioning system, and was validated through experimentation. The UKF scheme was able to accurately detect dry friction buildup on the sliding table of the cutter.

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