Linear Bearing Fault Detection Using an Artificial Neural Network Based on a PI Servo System with the Observer for High-speed Automation Machine

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Abstract. This research presents the novel approach for linear bearing fault detection by using Artificial Neural Network (ANN) based on observable information for high-speed automation machine. The dynamics modelling of feed drives and servo system design using pole placement technique were established to support the propose method. Three conditions of linear bearings which included healthy, 50 % of lubrication oil and starved lubrication were set up. Feature extraction of the data was analyzed by statistical approach. The results explains clearly that the control system design has a performance for tracking response and the ANN model can achieved 99.7 % accuracy by using the Levenberg Marquardt algorithm.

1. Introduction

Recently, Hard Disk Drive (HDD) has been the important data storage device. The Head Gimbal Assembly (HGA) is the major part in HDD. It’s consist of two main components which are the slider and the suspension. The HGA uses for reading and writing the data. The process to produce HGA, the Auto Core Adhesion Mounting machine (ACAM) was used for dispensing a glue and attaching the slider onto the suspension by utilizing the feed drive actuator for moving fixture clamp to the desired position. In order to facilitate the fluent motion and eliminate the effect of friction the linear bearing is an important supporting component in feed drive actuator, however, when the machine operating in continuous time and high speed condition the linear bearing easier to occur fault that affect to miss position of adhesive dispensing and slider attaching misalignment. In addition also decrease performance of the control system. The reviews on modern control design technique for feed drive actuator and linear bearing fault detection will be provided as follows. The comparison of PI-servo with Ogata method was studied by Saengsri. S. The experiments validate by robustness on external disturbance [1]. In addition, the electromagnetic levitation was applied the servo system using pole placement with state observer for controller design [2]. Xie D. Presented control system of feed drive in CNC machine by integrating the fuzzy logic with PID architecture for adjusting controller gain [3]. Friction model has extended to XY feed drive for improving the performance tracking with using the PID and state feedback control [4]. The ball bearing fault is considered as a critical element. Neural network classification using the vibration signal based on Hilbert footprint analysis was discussed. The results show propose method is given accuracy 87.3-100 % [5]. In addition, bearing fault detection employed the deep convolution neural network was presented by Zhao D. The method automatically recognizes in the time-frequency image and generate 98.3% accuracy [6]. In other hand, Chen Z. Studied on a rolling bearing fault diagnosis by providing deep neural network for classifying. Four feature applying into vibration signal in both time and frequency domain [7]. To study on fault detection and isolation of linear bearing in ACAM by using Artificial Neural Network (ANN). The data of motor current, FFT and crest factor was measured for the training data set. The experiments show that the model which training by use three parameters have a high accuracy at 93% [8]. Looking more closely though many fault detection techniques, most vibration signal was widely proposed,
however, several machines are limitation area for installation and cost of sensor is one important to consider.
This paper presents an approach to modelling the dynamics of feed drives in high-speed automation machine such as ACAM and linear bearing fault detection based on observer information to replace the sensor measurement data. The mathematical model in the state space of servo motors with a lead screw is used to analyze in the modern control design technique. The design of PI servo system control using a pole placement method with state observer was established to support fault detection by using machine learning architecture. The experiment investigates the use of motor current, angular velocity and table velocity for feature extraction with statistical parameters to training ANN model. The proposed method has been tested with neural network toolbox in MATLAB software and the result was discussed with the highest accuracy of fault detection and diagnostics.

2. Dynamics modelling of feed drive with DC servo motor
The most common direct current (DC) servo motor is an actuator in feed drives because it can be used a wide range operating speed and driving with high torque for the machine tool. The feed drive system analyze in this paper consist of a lead screw driven by a DC servo motor through the coupling. The clamping unit mounts on the worktable and supported by four linear bearing block and the linear guild to move axially. In ACAM, constrained of two XY stage and in each axis consist of the same component, therefor, design only one feed drive will be applied to others. The physical modelling of the single-axis is shown in Figure 1.

![Figure 1. The physical modelling of feed drive](image)

According to Figure 2 the state space model with state vector is arranged in matrix form show in equations (1) - (2).

\[
\begin{align*}
\frac{d}{dt} & \begin{bmatrix}
i_a \\
\theta_m \\
x_t \\
\dot{x}_t
\end{bmatrix} = \\
& \begin{bmatrix}
R_a & 0 & -K_b & 0 & 0 \\
0 & L_a & 0 & 0 & 0 \\
K_t & J_m & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
i_a \\
\theta_m \\
x_t \\
\dot{x}_t
\end{bmatrix} + \\
& \begin{bmatrix}
1 \\
0 \\
0 \\
0
\end{bmatrix} u
\end{align*}
\]

\[
y(t) = [0 \ 0 \ 0 \ 1 \ 0] [i_a \ \theta_m \ \dot{x}_m \ x_t \ \dot{x}_t]^T
\]

Where \(i_a\) is the motor armature current (A), \(\theta_m\) is the motor rotation angle (rad) and \(x_t\) is the worktable position (m), \(J_m\) is the moment of inertia (kg\(\cdot m^2\)) and \(B_m\) is the coefficient of viscous friction (N\(\cdot m/s\)/rad), \(R_a\) is the armature resistance (Ω), \(V_a\) is the armature voltage (V), \(L_a\) is armature inductance (H), \(K_t\) is the torque coefficient (N\(\cdot m/A\)), \(K_b\) is the back electromotive force coefficient (V\(\cdot s/rad\)), \(M_t\) regarded as total of worktable mass (kg) and \(C_t\) is the damping coefficient of the lead screw (N\(\cdot s/m\)), \(K_s\) represents total equivalent stiffness coefficient of the lead screw (N/m) and \(R\) used as convert factor coefficient of motor rotation to lead screw position (mm/rad) its calculate by \(l/2\pi\) which \(l\) is lead screw pith (mm). In this work the system identification approach has made practical use for estimating the system parameters of the feed drive system through experimental data.
3. Fault detection architecture using artificial neural network with PI servo system

The design of the PI servo system is presented in this paper illustrated in Figure 2. In order to signify in transient and tracking response signal along with supporting the fault detection architecture.

![Figure 2. Fault detection scheme](image)

3.1. PI servo system design with observer

The stability criteria are early precious to analyze, therefore, the pole placement method was applied to determine the state feedback gain and PI servo controller gain. The designing requires state variable feedback through gain $K$, in practices, the measuring of all state variables is difficult. The observer technique was used for estimating the state variable of the process under measurement output signal and measurable input. The first step of the control system design should be checking the controllability and the observability of the system. It was found that the matrix ranks equal to system order, which confirms the system is observable and controllable. The next step of the state feedback gain must be placing desire close loop pole because the location of the poles corresponds directly to the eigenvalues of the system, which control the characteristics of the response of the system. The design with position control of the worktable by providing over damp response. Based on state space equation as equation (3) all state vector was estimated by using observer that could be written as equation (4) - (5).

\[
\dot{x} = Ax + Bu, \quad x(t_0) = x_0
\]
\[
y = Cx
\]
\[
\dot{x} = A\dot{x} + Bu + L[y - C\dot{x}]
\]
\[
\dot{e} = [A - LC]e
\]

From the equation (5) that is the dynamic behaviour of error between plant and observer. The matrices observer gain is determined from eigenvalue of matrix $(A-LC)$ that meaning the observer pole which is should be faster than 10 times of close loop pole.

3.2. Data pre-processing and feature extraction

The process of data pre-processing is important for cleaning the measurement information before extraction the feature and model training. The state observer information includes current, table velocity and the estimation error was investigated on three bearing condition. The data collected to help of MATLAB/Simulink software in one operating speed and under control loop situation. Four statistical feature established on state vector data there are given as input to artificial neural network. To analyzed, difference number of hidden layer and three learning algorithm are used. The data separation is divided into training 70%, validation 15% and testing 15%. The discussion on feature extraction by implementing the four statistical parameters consist of standard deviation, kurtosis, crest factor and root mean square (RMS) are expressed below.
\[
\sigma = \sqrt{n \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}
\]  

(6)

Where \( \sigma \) is the standard deviation, \( n \) is the number of samples, \( x_i \) is amplitude of individual samples and \( \bar{x} \) is an average of samples.

\[
Kurtosis = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{x_i - \bar{x}}{\sigma} \right)^4
\]  

(7)

The kurtosis is indicated the peak of wave form, basically, if the signal has a random with an impulsive the kurtosis coefficient is more than 3. The periodic waveform can be used crest factor to explain in equation (8).

\[
Crest \ factor = \frac{\text{peak value}}{\text{rms value}}
\]  

(8)

Root Mean Square (RMS) is the power of the average value of the signal. As the amplitude increase the RMS value is mounted.

\[
RMS = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}
\]  

(9)

3.3. Artificial Neural Network (ANN)

An artificial neural network arranged in a common tool of machine learning, which is spread in data science and engineering filed because now day computational calculation has become efficient for solving the numerical and mathematical problem. The ANN is a simulation architecture of the human biological nervous system as shown in Figure 3. The working process first accepts and weigh multiple inputs, then linear summation and sent to the mathematical activation function to make decisions.

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Figure 3. The single model of a perceptron unit
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Within the model of ANN, amount of neural ordinarily impose into one or more layer perceptron. In definition the ANN consist of one input layer, one or multi of hidden layer and one output layer. The selecting of hidden layer number is huge impact to model performance, therefor in design phase many works should find the optimal number of hidden layers. The activation function usually implements relate in each type of problem. In our work sigmoid function was assigned to solve. It’s have values from 0 to 1 in nonlinear profile function as given by equation (10).

\[
sig(x) = \frac{1}{1+e^{-x}}
\]  

(10)
Three learning functions comprise the Scale conjugate method, Levenberg Marquardt algorithm and Resilient back propagation was comparable to selecting the highest accuracy of neural network model.

4. Experimental setup
The experimental setup is X-Y state actuator of ACAM machine as shown in Figure 4 for testing and simulation control system with the fault detection scheme. The major component consisting of lead screw with 5 mm pitch diameter driven by DC servo motor 200 watt with incremental encoder 2500 PPR resolution and 24 Volts power supply. The linear encoder used as a feedback sensor to measure the position of the worktable.

![Feed driver system in ACAM](image)

On each axis have supporting by four linear bearings. The motor driver amplifier will be received control signal from control unit before sent to the motor. In part of controller interface, RAPCON platform was applied with MATLAB/Simulink 2017a for design the propose method and used for collecting the data. In this paper, we have two encoders for validate the observer estimation result. For the linear bearing fault condition demonstrate on removing the lubricant left only 50% and starved lubricant condition compare with healthy bearing which are recommended for 2 ml to appropriate lubrication.

5. Results

5.1. Tracking response and observer performance
The controller, which designed as a PI servo system with state estimation using observer was examined by tracking response. For the position control of the worktable the design, test input has a reference at 50 mm, 58 mm and 66 mm, respectively that refer to the actual machine in the HGA process. The signal decomposition of ramp input 50 mm desire position and the other is step response. It was found that the system has an error in ramp input test, however, it reminds with an efficiency of position control which can be tracking reference input which can be compensated and eliminate error for the desire step response. On the other hand, the state observer is the ability for plant output estimation. Figure 5 is observation error and the state variable of the current signal, angular velocity, table velocity, angular position, and table position.
5.2. Fault indication result on lubricant level

From the data manipulating and feature extraction into four statistical parameters the healthy condition, lubrication level 50% and starved lubricant of linear bearing were investigated in this research to perform the effect of linear bearing in the abnormal operating condition.

| Algorithm          | Epoch | Hidden layer No. | %Accuracy |
|--------------------|-------|------------------|-----------|
| Scale Conjugate    | 7     | 10               | 99.2      |
|                    | 7     | 15               | 99.2      |
|                    | 16    | 20               | 99.4      |
| Levenberg Marquardt| 20    | 10               | 99.4      |
|                    | 8     | 15               | 99.4      |
|                    | 6     | 20               | 99.7      |
| Resilient Backprop | 9     | 10               | 99.2      |
|                    | 11    | 15               | 99.2      |
|                    | 10    | 20               | 99.2      |

The training process was compared to three learning algorithms with a varying hidden layer number that implement in MATLAB software. The results discussed in Table 1. The best performance of the ANN classifier can be measured on the model accuracy that is the error between the target and output must be the smallest. According to Table 1. Show clearly the ANN model which training by using the Levenberg Marquardt method offers the highest accuracy of 99.7% with a lower epoch. The confusion matrix illustrates the detail of class accuracy and correcting the prediction for the best ANN fault classification model as shown in Figure 6.
6. Conclusion
This paper presents linear bearing fault detection for high-speed automation machine by integrating the intelligence method as an ANN with modern control system as PI servo system with an observer. The state variable includes current, angular velocity and table velocity was extracted to four statistical parameters for training input. The experimental results of position control system with an observer shows fast transient response, zero steady-state error and the state variable information from an observer. The ANN model using 20 hidden layers and Levenberg Marquardt algorithm can be identified three faults on the linear bearing which consisted of healthy condition, lubricant 50%, and starved lubricant with 99.7% accuracy.

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