

Fault Detection and Isolation for Electro-Mechanical Actuators Using a Data-Driven Bayesian Classification

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ABSTRACT

This research investigates a novel data-driven approach to condition monitoring of Electrical-Mechanical Actuators (EMAs) consisting of feature extraction and fault classification. The approach is designed to accommodate varying loads and speeds since EMAs typically operate under non-steady conditions. Since many common faults in rotating machinery produce unique frequency components, the approach is based on signal analysis in the frequency domain of both inherent EMA signals and accelerometers.

The feature extraction process exposes fault frequencies in the signal data that are synchronous with motor position through a series of signal processing techniques consisting of digital re-sampling to the position domain, Power Spectral Density (PSD) computation to the frequency domain, and feature reduction. The reduced dimension feature is then used to determine the condition of the EMA with a trained Bayesian Classifier. Signal data collected from EMAs in known health configurations is used to train the algorithms so that the condition of EMAs with unknown health may be predicted.

A passive, linear load test fixture is used to provide a known load (2,400-lbf) on a MOOG industrial MaxForce EMA used for the testing. A seeded fault testing methodology is used to induce known faults in the ball screw and then used as training and validation data for the proposed work. Various desired driving commands are utilized to simulate "real-world" conditions. Laboratory results show that EMA condition can be determined over multiple operating conditions. Although the process was developed for EMAs, it can be used generically on other rotating machine applications as a Health and Usage Management System (HUMS) tool.

CITATION: Chirico, A. and Kolodziej, J., "Fault Detection and Isolation for Electro-Mechanical Actuators Using a Data-Driven Bayesian Classification," *SAE Int. J. Aerosp.* 5(2):2012, doi:10.4271/2012-01-2215.

INTRODUCTION

Electro-Mechanical Actuators (EMAs) are the next progression in flight control actuation as the industry continues to move towards the goal of All Electric Aircraft [1]. Currently, these types of actuators are used mainly on secondary flight control surfaces, such as spoilers and horizontal tail stabilizers, but not on primary surfaces. This is mainly due to the failure modes of the EMA's which can not be mitigated in flight as easily as its hydraulic actuator counterparts. Specifically, the risk of jamming can cause a flight control surface to lock in place, compromising the safe operation of the flight control system. However, there are many benefits for more electric aircraft such as overall weight reduction, increased reliability, better maintainability, reduced operating costs and increased safety [2].

Integrated Health Management (IHM) offers an advantage to make the adaptation of EMAs in critical applications more practical by indicating the need for service prior to catastrophic EMA failure and disruption of service. IHM is also a viable progression from Statistical Based Maintenance to Condition Based Maintenance (CBM) for flight control actuation systems. In CBM, the condition of the equipment is monitored and maintenance is based on the assessed condition. As such, IHM systems must be capable of monitoring degradation and detecting faults at the early stages of its development, in advance of full functional failure.

Review of EMA Health Monitoring Techniques

Within the field of actuator fault detection and isolation, data driven techniques have included Wavelet Analysis, Statistical analysis, Neural Network analysis, and Frequency domain analysis. For instance, Balaban et. al. [3] used several statistical features including accelerometer sensor standard deviation, thermocouple temperature deviation from nominal, and thermocouple drift. In Bodden et. al. [4] vibration sensors were used to detect fault frequencies that would appear as components started to wear. In Baybutt et. al. [5] one of the methods employed was to measure the degree of overlap of signal probability densities between a baseline "Healthy" EMA set and EMA's with artificially aged capacitors during steady state operating conditions.

These works focused primarily on feature extraction, but several other works also included health classification and prognostics, such as by Byington et. al. [6] which used FFT based feature techniques in addition to a neural network error tracking method. Automated Health Classification was accomplished by a Fuzzy Logic Classifier with Data fusion and a prognostics model was developed using a Kalman filter feature based state space tracking routine. Another approach taken by Brown et. al. [7] used the Hilbert Transformation as the feature extraction technique for identifying turn-to-turn winding faults for a Brushless DC motor in an EMA and a particle filter for anomaly detection and prognostics.

One of the main problems cited in many of these works was the masking of defects due to differing and non-constant operating conditions. For instance as motor speed and load vary the amount of vibration changes and fault frequencies are spread throughout the frequency spectrum, making fault identification difficult. This problem was also cited by Romeral et. al. [8] who proposed the use of the Discrete Wavelet Transform (DWT) to show how frequency content varies with time with non-stationary conditions. Another approach to deal with non-steady motor velocities was proposed by Huh et. al. [9] who used a digital re-sampling method to map signals from the time domain to the spatial domain since many faults in rotating machinery are synchronous with motor position.

Another issue that arises in EMA health monitoring is the permissibility of using specialized sensors, so emphasis has been placed on the ability to use only available EMA signals. A technique known as Motor Current Signature Analysis (MCSA) has been shown to be successful for identifying faults in components that are part of motor controlled systems, such as motor, bearing and gear faults by Zhou et. al. [10]. Another challenge is due to the potentially large number of feature variables that result from using multiple feature extraction methods. Principal Components Analysis (PCA) is a way of identifying patterns in data and reducing the dimensionality of the data. For instance Malhi and Gao [11] uses PCA as a feature selection scheme for contending features for bearing defect classification.

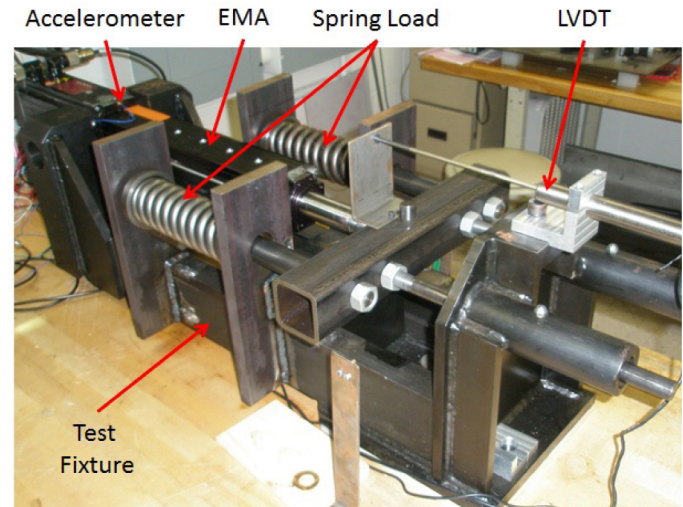


Figure 1. MOOG MaxForce EMA in Test Fixture

Outline and Objectives

This research focuses on the feature extraction and fault diagnosis portions of the IHM process for condition monitoring of Electromechanical Actuators. The goal is to improve upon previous research in EMA health monitoring by creating a data-driven approach that is able to handle non-steady motor speeds and varying loading conditions, is able to use standard and non-standard EMA sensors, and can handle multiple contending features.

This paper is organized as follows. The proposed approach to feature extraction and fault classification is presented and demonstrated via simulation using generated data. The approach is then tested with actual lab generated data from a MOOG MaxForce EMA (Fig. 1) over four different operating conditions using a healthy EMA and an EMA with a ball screw fault. The performance of the approach is demonstrated by the percentage of false positives and false negatives. Finally, plans for improvement and future work is given.

EMA FAULT DETECTION APPROACH

The fault detection scheme after data acquisition is comprised of feature extraction, and fault classification as shown in Fig. 2. The objective is to assign a class that relates to the condition of the EMA based on the sensor measurement x . Ideally the predicted condition matches the true condition of the EMA. The system from which measurements are obtained include the EMA to be monitored and the associated environment. The system is excited with inputs r , and results in the measurement output, x . The measurement data is transformed after data acquisition by the feature extraction process in order to give insight into the condition of the EMA. It also serves to reduce the size of the data prior to classification. A feature vector z is then input to

a classifier which uses this data to predict the condition of the EMA $\omega(z)$ from a possible set of conditions $\omega \in \{\omega_1, \omega_2, \omega_3, \dots\}$.

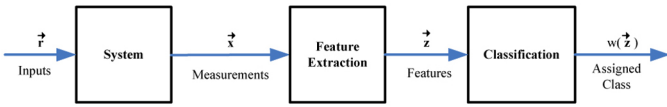


Figure 2. EMA Fault Detection Architecture

Feature Extraction

In feature extraction, the measurement data is transformed in order to expose patterns and signatures within the data that give insight into the condition of the EMA. The feature extraction method proposed in this paper is aimed at exposing faults that produce fault signatures in the frequency domain that are synchronous with motor position. Frequency analysis of vibration and motor current signals has been shown to be effective in exposing fault signatures in rotating machine equipment to isolate various faults and failures at the incipient stage, including: bearing and gear faults, screw defects, stator and armature faults, broken rotor bar and end ring faults, and eccentricity faults, among others [12, 13, 14, 15].

In this research, the feature extraction architecture, shown in Fig. 3, is used to extract the frequency information. Signal data that is originally sampled according to a fixed sampling interval, T_s is re-sampled to the position domain. The signal is then transformed to the frequency domain by computing the power spectral density. A binning process groups the frequency content of the filtered PSD signal into energy bins and then the data is reduced by a Feature Space Transformation process. The transformation matrix is optimized using training samples so that the most important information in the data is retained - much like in image compression.

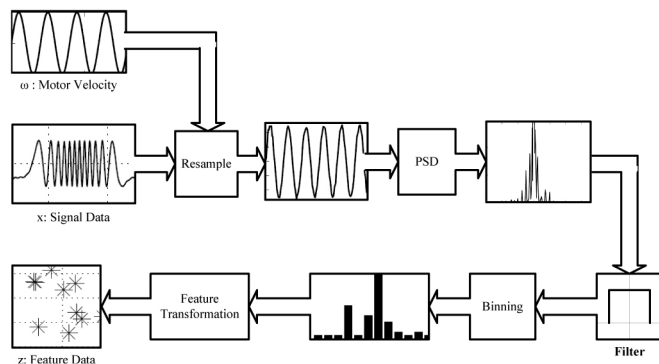


Figure 3. Feature Extraction Method

Re-Sampling Technique

Due to the operation of the motor, many electrical and mechanical fault signatures in rotating equipment are synchronized with the angular motor position. Since normal

operation of an EMA for many applications involves varying motor velocities, fault signatures will be periodic with motor position, but not in time. If signals are acquired according to the sampling period, T_s , a post processing method must exist to re-sample the signal according to the spatial sampling period, θ_s , to expose the periodic nature of the fault. Various interpolation and filtering techniques may be used, for instance Eq. (1):

$$x(n) = x(k) + \frac{x(k) - x(k-1)}{\theta_c(k) - \theta_c(k-1)} (n\theta_s - \theta_c(k-1)) \quad (1)$$

Where θ_c is the time sampled cumulative motor angle. The equation maps the time sampled signal $x(k) = x(kT_s)$ to the spatially sampled signal $x(n) = x(n\theta_s)$.

Power Spectral Density

The two sided power spectrum of a discrete signal is:

$$S_{xx}(k) = \frac{2}{w_f L^2} X_w(k) X_w^*(k) \quad -L/2 < k \leq L/2 \quad (2)$$

Where L is the number of samples, and $X_w(k)$ is the Discrete Fourier Transform (DFT) of the windowed signal $x_w(n)$:

$$x_w(n) = w(n)x(n) \quad (3)$$

For instance, a rectangular window results when $w(n) = 1$, or a Hanning Window of length L may be used to reduce the effect of leakage in out of band frequencies, Eq. (4). The window factor w_f in Eq. (2) is needed to scale the power spectrum to account for the loss of amplitude when using a non-rectangular window.

$$w(n) = \frac{1}{2} \left(1 - \cos \left(2\pi \frac{n}{L} \right) \right) \quad (4)$$

Since a single FFT has some uncertainty, several FFTs of length L are computed for a given signal and the resulting two sided power spectrums are averaged together to get a more accurate estimate:

$$\bar{S}_{xx}(k) = \frac{1}{M} \sum_{m=1}^M S_{xx}^m(k) \quad (5)$$

Where M is the total number of computed two sided power spectrums, and S_{xx}^m denotes the m^{th} power spectrum. Finally, the continuous power spectral density is computed from the averaged two sided power spectrum:

$$\tilde{G}_{xx}(k) = 2T_p \bar{S}_{xx}(k) \quad k = 1, \dots, L/2$$