HIGHER-ORDER STATISTICS AND SUPPORT VECTOR MACHINES APPLIED TO FAULT DETECTION IN A CANTILEVER BEAM

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Abstract: In this paper, it is proposed a method to detect structural faults or damages using Higher-Order Statistics (HOS). For this, vibration signals were taken from cantilever beams. Such vibrations were generated by a DC motor with varying rotation, generating vibrations at various frequencies. Vibration signals and engine speed control were performed by an Arduino board. After the signal acquisition, parameters are extracted by means of second-, third- and fourth-order cumulants and then the most relevant ones were selected by the Fisher's Discriminant Ratio (FDR). To fault detection, a Support Vector Machine (SVM) classifier has been designed in its One-Class version, where only one-class knowledge is required. The results showed a good ability to represent vibration signals via HOS along with a large reduction in dimensionality given using FDR and a good generalization by means of the SVM classifier. Failure detection results showed 100% success rates.

Index terms: Vibration Analysis, Structural Health Monitoring, One-Class Learning.

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INTRODUCTION

Innovation and technological development experienced in the last decades allowed industrial operations to be carried out almost exclusively by machines with a reduced level of human intervention. Thus, the factory floor was characterized as an environment with a high degree of automation and intense use of information technology.

According to Thoben et al. (2017), discussions about the new era of technological development translated into the concept of intelligent industry or industry 4.0 which intensifies automation processes and characterizes a manufacturing environment increasingly dominated by interconnected and autonomous machines. However, machines continue susceptible to failure or damage and this can lead to serious risks to the health and safety of people interacting with them, as well as financial and environmental problems.

In order to avoid or minimize such problems, preventive and predictive maintenance practices should be applied (Liao and Wang, 2013) and one of the preventive maintenance practices is the Structural Health Monitoring (SHM). Some scientific works involving advanced techniques of signal processing and pattern recognition have been implemented, such in Farrar and Worden (2012), which presented detailed reviews of fault detection techniques focused on vibration analysis. In Avendano-Valencia and Fassois (2014), it was applied SHM to detect faults in wind turbines. Mustapha et al. (2015) proposed a methodology for monitoring the conditions of a bridge based on vibration analysis and pattern recognition. SHM can also be applied to detect sensor failures as demonstrated in Hernandez-Garcia and Masri (2014) where the authors used statistical monitoring (such as PCA – Principal Component Analysis) with the same purpose. Jassim et al. (2013) performed a study using finite element method and vibration analysis for detecting failures in a cantilever beam.

In the present paper, a SHM practice methodology based on vibration analysis is proposed. The goal of the paper is to develop a fault detector for cantilever beams based on higher-order statistics and Support Vector Machine (SVM). To do this, we make innovative use of the one-class version of the SVM classifier as fault detector. This method is commonly referred as One-Class Support Vector Machine (OC-SVM) (Schölkopf et al., 2001; Theodoridis and Koutroumbas, 2009) and benefits from using data of only one class of a classification problem in comparison with the conventional SVM. In the case of fault detection, such a benefit makes the designing of the detector simpler, since it is not necessary the knowledge of the fault events to design the method. In addition, we exploited well known cumulant-based features to build a compact vector signature to represent the structural health of the cantilever beam. Such cumulants take advantage of being less sensible to Gaussian noise.

MATERIAL AND METHODS

The proposed methodology was performed on an aluminum alloy cantilever beam. The method contains 4 steps: Data Acquisition, Feature Extraction, Feature Selection and Detector Design. For vibration data acquisition, it was used an accelerometer in conjugation with an anti-aliasing filter. The accelerometer was controlled by an ARDUINO® board. First, data collection was performed considering the cantilever beam without failure. In the second test, a failure was introduced in the cantilever beam, which was characterized by a transverse cross-sectional cut of 1mm long by 10mm wide (Figure 1). After data acquisition, tests with the fault detector were performed. Higher-Order Statistics (HOS) technique was used for the extraction of characteristics and the Fisher's Discriminant Ratio (FDR) was used for the selection of the most relevant features for fault detection. The combination of HOS and FDR for the extraction and selection of features has already been successfully used by Barbosa et al. (2016) and it has been proved that they lead to compact signatures (feature vectors) of fault in cantilever beams. Finally, for the classification of the vibration signals, the one-class support vector machines (OC-SVM) was used.

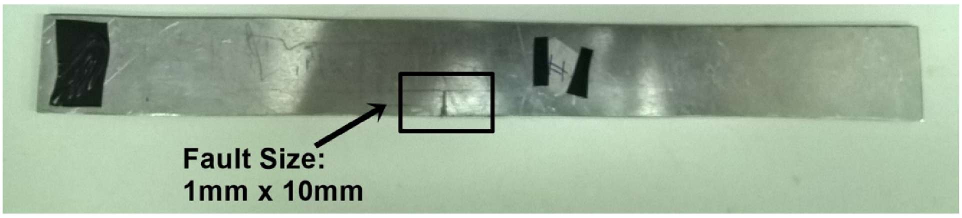

Figure 1: Beam used in experiment with fault.

Acquisition of Signals

The bench tests were performed by using an aluminum alloy beam, with dimensions of 330 mm in length, 35 mm in width and 2 mm in thickness. For the generation of vibrations in the beam, a DC motor of 24 mm in diameter by 12 mm in length was used, coupled to an axis of 2 mm in diameter by 10 mm in length. The total length of Motor + Shaft was 22 mm. Mass of 21.0g and a maximum frequency range up to 90Hz were also considered.

A three-axis accelerometer model MMA7361, with dimensions of 27.9 mm x 18.6 mm, was used to capture the vibrations of the beam. Some of its operating characteristics are: average bandwidth frequency on the X and Y axis of 400Hz and on the Z axis of 300Hz, mass of 2.5g and Power Spectral Density RMS of 0.1 Hz - 1 kHz.

To control both accelerometer and motor, the microcontroller ARDUINO® model MEGA2560 was used. A low-pass filter with a cutoff frequency of 100Hz (anti-aliasing) was also used. An ATX type power supply was used to power the filter and motor circuits.

For the acquisition of signals, the microcontroller was connected to a computer via USB port and the data was stored in a spreadsheet for later analysis in MatLab® software.

In order to carry out the tests, the beam had one end clamped by a support and the other beam end was kept free. The motor was fixed with a double-sided adhesive tape, close to the beam clamping and the accelerometer was attached at the free end, also with the tape, as shown in Figure 2. A motor with adjustable speed was used to excite the beam over a wide range of frequencies. For this, an automatic rule was programmed inside ARDUINO®, in which the engine speed was varied from zero to maximum value (around 90 Hz), returning from maximum speed to zero in a gradual and continuous way.

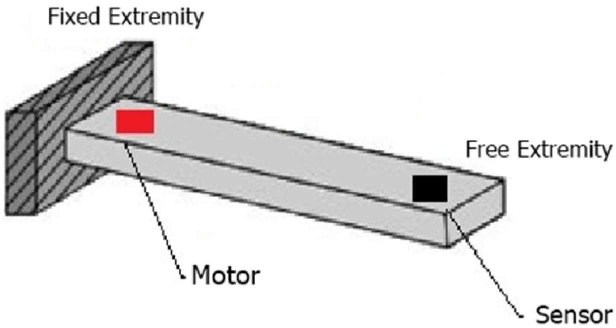

Figure 2: Collection scheme.

After the assembly of experiments, 10 acquisitions of signals were made in a flawless beam. Each acquisition lasted 2 minutes and the signals were collected with a sampling time around 0.005 seconds, or 200Hz. This generated a total of 24,000 samples in each signal. This data acquisition rate was chosen due to the maximum frequency of the motor (90Hz). Thus, the sampling rate would meet the Nyquist's Theorem for sampling.

Then, 10 signal acquisitions were performed, considering the beam excited by the DC motor under the same experiments' conditions, considered for the beam without failure. Such failure was induced with the objective of simulating a real intermediate level fault with the purpose of detecting it using the proposed method. The experimental setup is presented in Figure 3. It is important to note that at each signal acquisition, the setting up of the experiment was disassembled and reassembled to guarantee its repeatability.

Feature Extraction

The HOS Parameter Extraction is performed by calculating the second, third, and fourth order cumulants of the vibration signal. The mathematical expressions for the second, third and fourth orders of a stationary random process composed of real random variables with zero mean, are respectively (Mendel, 1991):

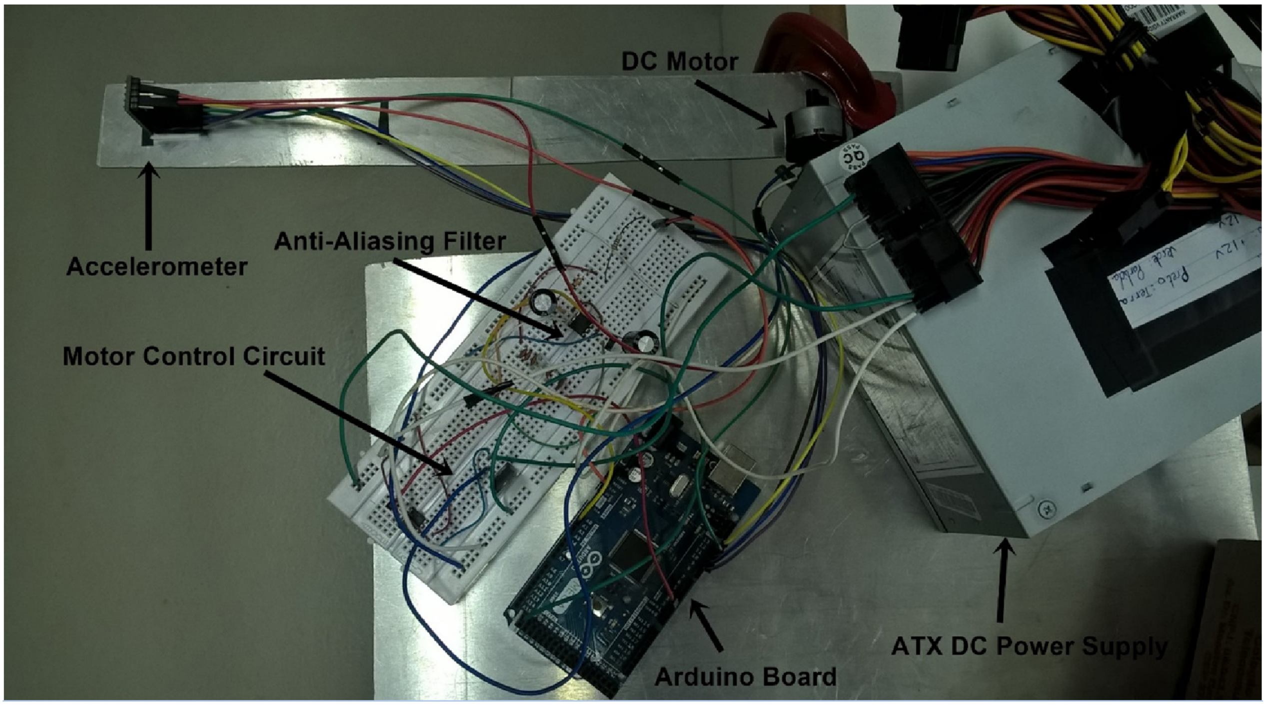

Figure 3: Experimental setup for signal acquisition.

$$C_{2,x}[i] = E\{x[n]x[n+i]\}, \quad (1)$$

$$C_{3,x}[i] = E\{x[n]x^2[n+i]\}, \quad (2)$$

$$C_{4,x}[i] = E\{x[n]x^3[n+i]\} - 3C_{2,x}[i]C_{2,x}[0], \quad (3)$$

with i = 0, 1,…, N/2 – 1, are lags in time for a vector with finite length (N), and *"E"* is the expected value operator. The stochastic approximations of Equations (1), (2) and (3) can be written, respectively, as:

$$C_{2,x}[i] = \frac{2}{N}\sum\nolimits_{n=0}^{N}\{x[n]x[n+i]\}, \quad (4)$$

$$C_{3,x}[i] = \frac{2}{N}\sum\nolimits_{n=0}^{N}\{x[n]x^2[n+i]\}, \quad (5)$$

$$C_{4,x}[i] = \frac{2}{N}\sum\nolimits_{n=0}^{N}\{x[n]x^3[n+i]\} - \\ -\frac{2}{N^2}\sum\nolimits_{n=0}^{N}\{x[n]x[n+i]\}\sum\nolimits_{n=0}^{N}\{x^2[n]\}, \quad (6)$$

Feature Selection

The HOS-based features can be chosen aiming a better compromise between low computational cost and performance. The low computational cost is due to the reduction of the dimensionality of the problem while the good performance is obtained because the HOS can extract relevant parameters from the vibration signals. In order to select the most representative cumulants for the beam fault detection problem, Fisher's Discriminant Ratio (FDR) was used in Duda et al. (2000). Its cost function is described by Equation 7.

$$J_c = (\mu_i - \mu_j)^2 \circ \left(\frac{1}{\sigma_i^2\sigma_j^2}\right), \quad (7)$$

where μ_i, μ_j, σ_i and σ_j are the mean and variance vectors of the traits extracted from classes *i* and *j*, respectively. The symbol ∘ is the product of Hadamard. Thus, the larger vector values J_c will indicate the most relevant characteristics for the separation between classes *i* and *j*, since they present the largest distances between classes and the smallest intra-class measurements. This presents the most relevant parameters for the classification, presenting the largest distance between the classes of the beam with and without failure and the shortest distance from one event to the other belonging to the same class.

Classifier Design

The SVM is a machine learning technique based on the statistical learning theory developed by Vapnik (1998). The objective of the SVM is to find a hyperplane that divides the two classes studied in this work (class of the beam with and without fault). All points with the same characteristics are on the same side of the hyperplane, maximizing the distance between the two classes of the hyperplane (Theodoridis and Koutroumbas, 2009).

One SVM advantage is the use of the kernel function, which allows a high efficiency in obtaining the limits of the region to be separated. The principle of this function is the treatment of non-linearly separable data, causing the SVM to promote a transformation of the input space to a space of higher dimension, that is called parameter space. As function kernel, it was, considered a Gaussian type one. In this work, it was used the one-class learning version of SVM, developed by Schölkopf et al. (2001). The Equation 8 demonstrates the dual problem, whose objective is to minimize it.

$$\min 0.5\sum_{j,k} \alpha_j \alpha_k G\left(x_j x_k\right), \tag{8}$$

where a_j, a_k represent the Lagrange's multipliers and $G(x_j, x_k)$ represents the Gram Matrix (values obtained by kernel function) with the terms x_j, x_k.

RESULTS AND DISCUSSION

Figures 4 and 5 show, respectively, the vibration signals of a faulty beam and a non-faulty one. The acceleration and deceleration characteristics of the DC motor were reflected in the vibration signals. In addition, the peaks indicate the excitation of the low-frequency modes of the beam.

Each collected vibration signal, containing a total of 24,000 samples, was partitioned into two of 12,000 copies, resulting in a total of 20 events for each class (beam with and without fault). Data related to the beam was divided into training (12 events) and test (8 events). All beam-related data were used for testing.

After the analysis, the best parameters were selected using FDR. Figure 6 shows the FDR obtained for each parameter. The first 12,000 are calculated for the second order cumulant, the subsequent 12,000 are for the second order, and the last 12,000 for the fourth order. It is noted that third-order cumulants are more representative, with more expressive J_c values.

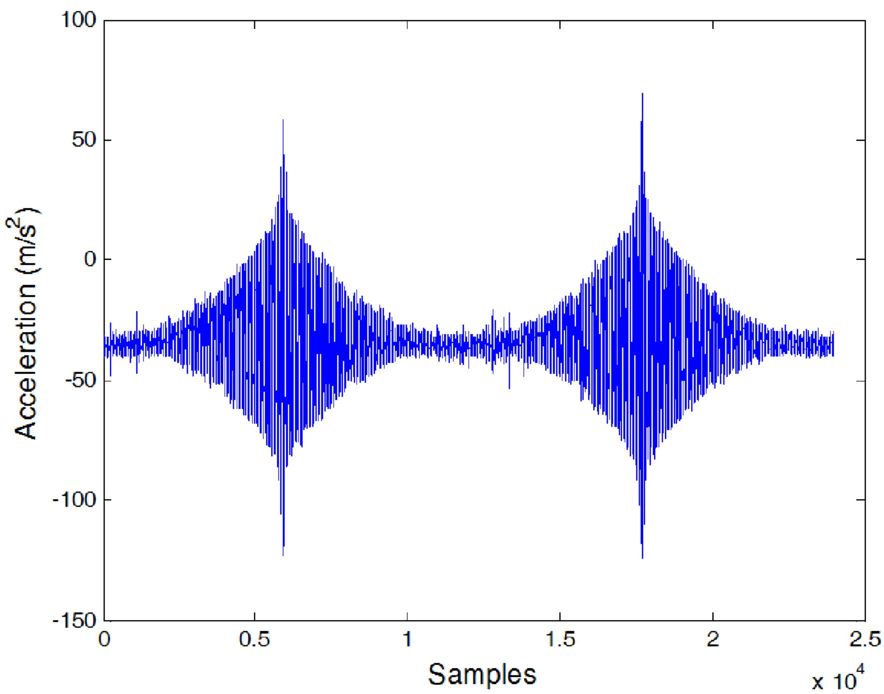

Figura 4: Vibration signals from the beam without failure.

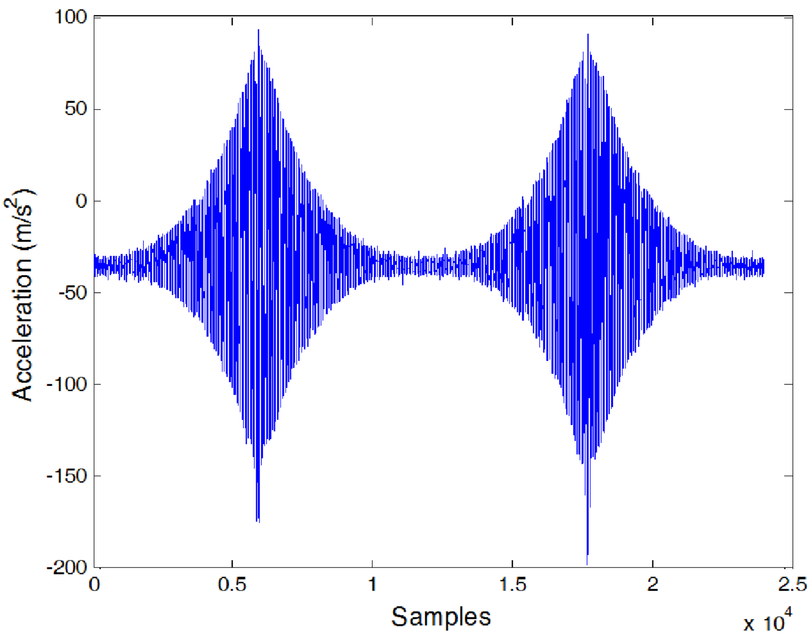

Figure 5: Vibration signals from failed beam.

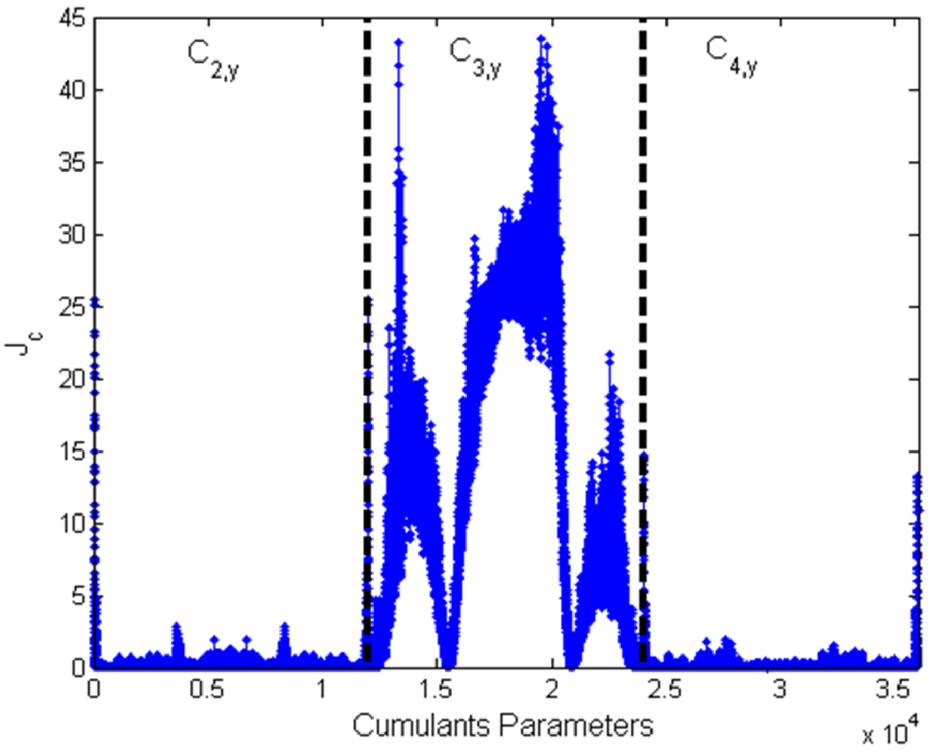

Figure 6: FDR obtained for the parameter vector during tests.

In order to reduce the size of the data and hence the computational complexity, only two parameters were chosen, those with higher J_c. These parameters were presented to the classifier. After the design and execution of the classifier, an accuracy of 100% of the method was observed, Figure 7, which is a representation of the parameter space performed by the two most relevant third-order cumulants.

The gray region in Figure 7 represents the closed region performed by the SVM. Events within gray region are classified as without failure and the events outside it are classified as fault. It is noted (Figure 7) a clear linear separation between faulty and non-faulty events. It is also noted that the events without failure in the test set were correctly classified, showing the generalization of the method and also the repeatability of the assembled experiment.

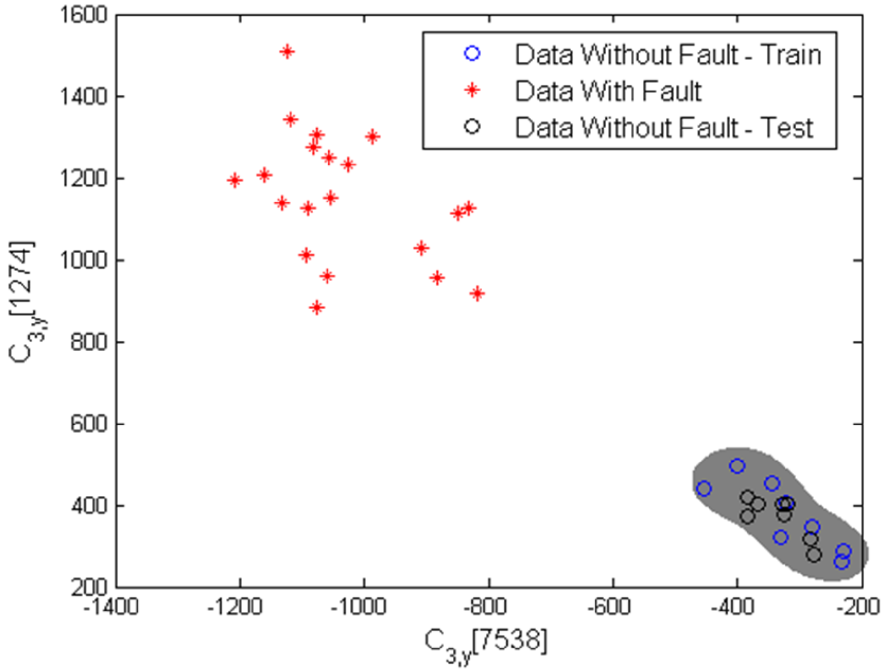

Figure 7: The obtained features space and the decision boundary of the classifier (the gray region).

The use of FDR makes the distance between the classes maximized in a very simple way, both in the mathematical sense (FDR equations are simpler, when compared to other equations that have the same function), and computationally (algorithm performed only in the training phase). Moreover, the use of the unsupervised SVM does not require any specific knowledge about the faults, since, obtaining the detector model requires only data relating to the beam without failure, which greatly facilitates the design of the method. In comparison with Barbosa (2016), this method shows an increase of detection rate using small training sets. To obtain 100% of detection rate in this type of fault, the authors used a training set with 750 events. Small training sets imply in low computational cost to implement the method. Which presents good efficiency of detection allied with low computational cost what is desirable, for example, in real-time applications.

In terms of computational costs, the proposed procedure requires low processing, since the training of the detector is performed only once and only two parameters were used for the detection. In quantitative terms, is required on average 0,5 seconds to project the SVM and test the detector.

Another point to be highlighted is that the method used no preprocessing to remove or reduce noise from the signals. This shows potentiality of HOS to extract relevant information from vibration signals. Compared with the current literature methods, the proposed method takes advantage of using only data from the health cantilever beam to be designed, i. e., no information about the fault condition is required.

CONCLUSIONS

The proposed method was able to detect, in experimental tests, the structural failure in a vibratory structure of a cantilever beam type. The use of HOS and parameter selection with the FDR allowed the reduction of the number of dimensions to be classified for only two parameters extracted from the HOS, generating a linear separation between the classes with and without failure. Results showed consistence since an efficient and low installation cost method was proposed. In addition, it can be used to aid in better decision making about an exchange of machine components, thus optimizing the structural life of parts which reduces costs in the production process and safety increasing. Failure detection results showed 100% success rates.

Highlights were mainly in the efficiency of the method and low operating and computational costs. For future projects, it is expected to propose an approach that measures the level of failure, classifying its severity and indicating the fault location.

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