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CLUSTERING OF TRIBOLOGICAL FAULTS USING THE WARD METHOD

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ABSTRACT

This work aims to use the Ward Method to treat signals from the tribological parameter monitoring through the use of a test bench to simulate contact failures in an air compressor to create a system of detection and classification of failures, without supervision, with the use of Kohonen Self organizing maps, applied to reliability centered maintenance on the of electromechanical processes.

Keywords: tribology, reliability centered maintenance, signal analysis.

INTRODUCTION

Reliability-centric maintenance is one of the key methodologies applied to the concept Industries 4.0 to maintain cost savings and product reliability in production. There are large interest and effort in researching systems on board that integrates sensing, fault diagnosis, and control into a single microchip (Sun, *et al*., 2004). This technology would be the future of industries 4.0 with the advancement of microelectromechanical systems and uses automatic data processing and decision making without human intervention. The use of artificial neural networks (ANNs) has been a powerful tool in automated detection and diagnosis of machine conditions, machining operations and industrial processes (Howard, 1994).

The use of vibration signals is common for status monitoring and diagnostics of rotating machines. By comparing the vibration signals of a machine that works with and without defective conditions, faults such as mass unbalance, shaft misalignment, rotor friction, gear failure and rolling defects can be detected (Azovtsev, *et al*., 1996 and McCormick and Nandi, 1997). With the use of online monitoring systems, the signals can also be used to detect incipient failures of machine components, minimizing the possibility of catastrophic risk. An approach for identification and quantification of the characteristic features, relevant to the bearing conditions, becomes an issue according to Shiroishi, *et al*. (1997). The procedures request vibration signal multi-stage processing, high-pass or band-pass filtering, demodulation, low-pass filtering of the demodulated signal and, at the end, processing to extract the desired characteristic features.

The need for a reliable, fast and automated procedure of diagnostics is mandatory, although often the visual inspection of the frequency-domain features of the vibration signals is suitable for the identification of the faults. According to Howard (1994), artificial neural networks (ANNs) are powerful tools in automated detection and diagnosis of machine conditions, machining operations (Sun, *et al*., 2004) and industrial processes (Tarassenko, 1998). Several RNAs use the pre-processed frequency domain resources of the measured vibration signals to monitor the condition of the machine.

The self-organizing architectures, defined by Kohonem (1982), generate mappings of a space of high dimension in structures whose topological dimension is inferior to the original one. These mappings are capable of preserving the neighbor relationships of the input data. This makes them interesting for applications in various areas of engineering, exploratory data analysis and combinatorial optimization and signal processing.

The use of a distributed representation of prototypes (or reference vectors) in clustering issues makes it easier to find out the intrinsic structure of the data, and it is necessary to obtain a set of representatives and group them (or label them, after segmentation), according to some criterion. Map post-processing methods, post-training, have been proposed, allowing the identification of complex groupings on the map (Vesanto, 2000).

METHODOLOGY

The experimental research was based on a qualitative approach, developed in a single step. It consists of collecting the generated signals, vibration, from a 350 Ω strain gauge and a condenser microphone installed on the electromechanical system - an air compressor, shown in Figure 1, performed through a data collector in a test bench.

Fig. 1 - Test bench with transducers. (a) Shows the test bench; (b) coupled microphone; (c) the strain gauges on oil plate.

The test bench was built to accommodate the electromechanical system used in this experiment (air compressor), the equipment for data collection, the computer to store the data collected in specific software, the sensors used in the experiment and other measurement devices, safety and control equipment that were necessary to carry out laboratory tests.

Four strain gauges, two 120 Ω extensometers and two 350 Ω extensometers were used to verify, previously, the behavior, sensitivity, of the two different impedances of the transducers, duly installed, according to the manufacturer's recommendation and technical literature. The strain gauges were installed in a ¼ bridge configuration, i.e., three fixed resistors and the strain gauge as a variable resistor on the Wheatstone bridge.

The data collection equipment chosen was the Instrunet I-555, because it is ready for direct use of several types of sensors common to signal analysis systems, such as load cells, strain gauges, potentiometers, accelerometers, thermocouples, RTD (resistance temperature detectors), and current and voltage measurements. It also comes with the software and all accessories required for installation and use.

Each Instrunet network is controlled by an Instrunet i240 DSP (Digital Signal Processing) card that connects to Windows 32bits or 64bit, Vista, 7, 8 or 10 through a high-speed USB 2.0 port at 480 mbits/s. Every i240 controller is a self-contained computer that uses a powerful 32-bit DSP processor and has on-board RAM to control all the details of data acquisition on its own network.

Experiment Description

All experiments are performed on a time basis of 180 seconds. Twenty-eight experiments were performed. Each experiment had 1,363,637 samples (Sample Rate x Experiment Time). The experiments were performed with the equipment in standard operation, varying its mode of operation (pressure variation) and introducing failure modes. The experiments were performed twice to obtain a larger amount of data, maintaining the same time pattern for all experiments, as listed in Table 1.

Table 1 - Description of the Experiments

Experiment	Condition / Failure Mode
01 and 02	Moto compressor Off
03 and 04	Without fan and pressure 0,0 bar
05 and 06	Without fan and pressure 2,5 bar
07	Without fan and pressure 4,5 bar
08 and 09	Normal and pressure 0.0 bar
10 and 11	Normal and pressure 2.5 bar
12 and 13	Normal and pressure 4,5 bar
14 and 15	Corrosion and pressure 0,0 bar
16 and 17	Corrosion and pressure 2.5 bar
18 and 19	Corrosion and pressure 4.5 bar
20 and 21	Internal Bearing and Bearing Fault 0.0 bar
22 and 23	Internal Bearing and Bearing Fault 2.5 bar
24 and 25	Internal Bearing and Bearing Fault 4.5 bar
26	Debris and pressure 0.0 bar
27	Debris and pressure 2,5 bar
28	Debris and pressure 5.5 bar

The tribological failure modes were introduced by exchanging the original 6202 bearing, from the back of the electric motor (worst case - farthest from the sensors), presenting the failure modes specified in Table1, experiments number fourteen to twenty eight. Two of these bearing failure modes can be observed in Figure 2.

Fig. 2 - Tribological failures in 6202 bearing. (a) Corrosion and (b) debris.

Each Experiment has 90 points. Some experiments have the same nature. The lines relate the experiments, while the columns relate the groups that were found. Nevertheless, most of the failures were well differentiated from the other failure modes.

Feature Extraction Method

The analysis of the signals is done through neural networks, which input vector of the network is provided through energy profiles of harmonic and non-harmonic frequency bandwidths obtained from the fast fourier transform (FFT) of the signal in frequency domain.

The FFT is calculated at each two-second interval, sufficient time for the engine shaft to perform 115 rpm. At this stage, several experiments were carried out where variations were made in the mode of operation of the equipment and known modes of failure were introduced in the compressor to verify the effectiveness of the recognition of these faults by the chosen monitoring method, using the system energy variation, obtained from the data generated by the FFT, self-organizing maps and image segmentation.

The frequency spectrum chosen was 3.686 Hz (approximately half of the sampling rate - 7.575,75 Hz - Nyquist-Shannon Sampling Theorem). This spectrum bandwidth covers all tribological failures introduced into the experiment and represents 64 fundamental harmonic frequencies of the motor shaft, whose nominal velocity is 3,450 rpm (57.5 Hz). For the fundamental frequency and its harmonics, a frequency band range of ± 10% was defined to specify the bandwidth that would be used to quantify the variation of the energy per band, relative to the fundamental frequency and their harmonics.

The other bandwidths are the intervals between the fundamental frequency bands and their harmonics. 128 frequency bandwidth energy profiles were used per transducer, sweeping the entire spectrum mentioned. The energy of each frequency band was obtained using the Parseval theorem and its unit is Joule (J).

The Parseval Theorem is usually written according to Eq. 1:

$$\int_{-\infty}^{\infty} |x(t)|^2 dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X(\omega)|^2 d\omega = \int_{-\infty}^{\infty} |X(2\pi f)|^2 df \qquad (1)$$

Where $X\,(\omega) = F_{\omega}\{x(t)\}$ represents the normalized continuous Fourier transform and $\omega = 2\pi f$ is the angular speed in rad/s.

The interpretation of this form of the theorem is that the total energy of the signal can be calculated by summing the power per sample in time or frequency domain, Eq. (2).

$$\sum_{n=0}^{N-1} |x[n]|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X[k]|^2 \qquad (2)$$

where X[k] is the DFT (Discrete Fourier Transform) of x[n], both with the length of **N**.

In Figure 3, it is presented a general summary of the frequency spectra where it can be observed a better resolution of the strain gauges for low frequencies.

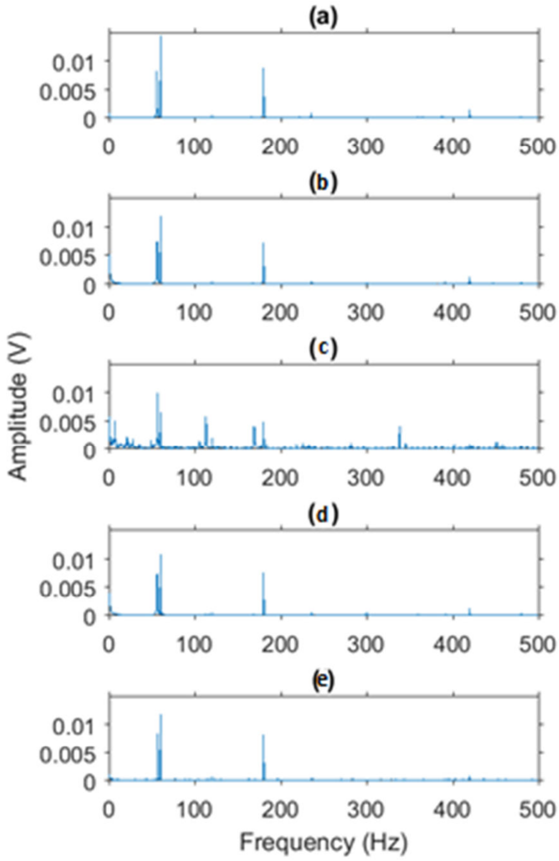

Fig. 3 - Strain gauge frequency domain response. (a) Without motor fan; (b) regular operation; (c) corrosion; (d) ball pass inner race failure; (e) debris.

According to the results obtained in the graphs presented in the frequency domain, it is observed that there is difficulty in solving the failures with the types of analysis used. Much more difficult is the classification of fault modes based on the previous observation.

Using the energy of the frequency bandwidth, as per Parseval Theorem, represented by Eq. 2, for the frequency spectra obtained from the FFT, it can be seen in Figure 4 that all experiments have been identified in a better way than the method used for the frequency domain. The graphs show the curves indicating the energy in each frequency band. (X = 8 is the energy of the 8th frequency band). This feature is of great relevance because it enables the vector formed by the frequency bandwidth energy profiles to be a good starting data input for the Kohonen map that will be used for the automated, unsupervised fault detection and classification system.

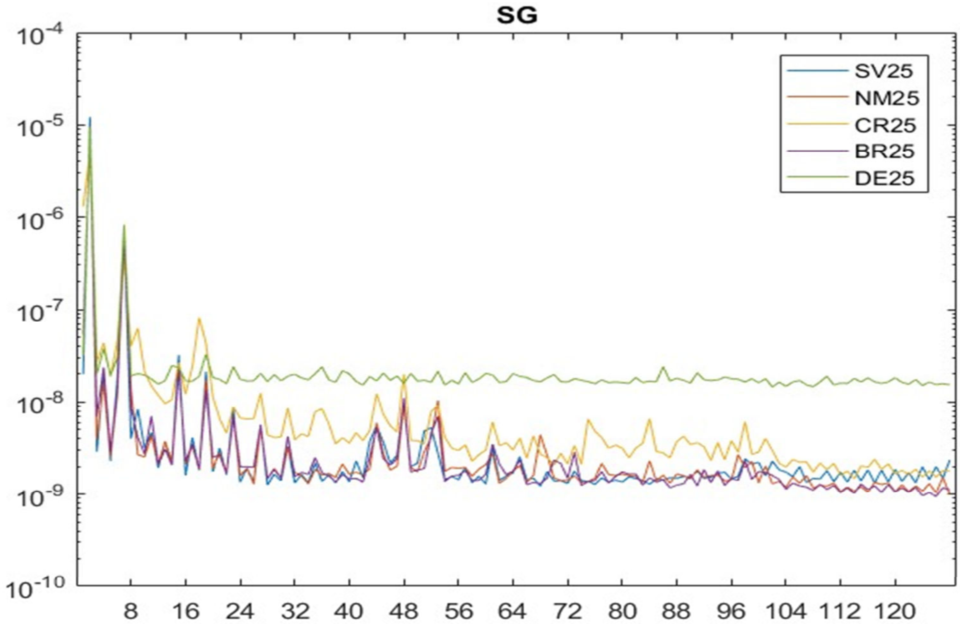

Fig. 4 - Strain gauge frequency bandwidth energy. SV25 = Without Fan 2.5 bar; NM25 = Normal operation at 2.5 bar; CR25 = Corrosion at 2.5 bar; BR25 = Rolling failure at 2.5 bar; DE25 = Debris at 2.5 bar.

Viewing and Analyzing Data Clusters Using Auto-Organized Networks and Image Segmentation

Self-organizing maps (SOM) are algorithm trained to classify input vectors according to how they are grouped in the input space. With the application of these algorithms in the self-organized map, the result is connected areas of neurons that identify complex (non-parametric) geometry in the input space.

The main purpose of Kohonen's self-organizing maps is to group incoming data that are similar to each other by forming classes or clusters called clusters. In a classifier network there is an input unit for each component of the input vector. During training the network determines the output unit that best responds to the input vector; the weight vector for the winning unit is adjusted according to the training algorithm. During the self-organizing process of the map, the cluster unit whose vector of weights closest to the vector of input patterns is chosen to be the "winner". The winning unit and its neighboring units have their weights updated according to a rule. (Haykin, 1999).

To obtain the neurons of the Kohonem maps the input data are energy vectors, calculated by the Parceval method starting from the strain gauge signals. The algorithm used is based on the Python Software Foundations methodology in the toolbox "kohonen.kohonen.Map(params)".

Ward's Agglomerative Hierarchical Clustering Method

The algorithm used to apply the Ward method to the data cluster is based on the Scipc.org methodology in the scipy.cluster module. The input vector for the algorithm is formed by the weights of the neurons obtained on the Kohonen map.

Performs hierarchical/agglomerative clustering on the condensed distance matrix Z. y must be a $\binom{n}{2}$ sized vector where n is the number of original observations paired in the distance matrix. A matrix Z is returned by $(n-1)$. At the $i-th$ iteration, clusters with indices $Z[i,\ 0]$ and $Z[i,\ 1]$ are combined to form cluster $n + i$. A cluster with an index less than n corresponds to one of the n original observations. The distance between clusters $Z[i,\ 0]$ and $Z[i,\ 1]$ is given by $Z[i, 2]$. The fourth value $Z[i,\ 3]$ represents the number of original observations in the newly formed cluster. The following linkage methods are used to compute the distance $d(s,t)$ between two clusters s and t. The algorithm begins with a forest of clusters that have yet to be used in the hierarchy being formed. When two clusters s and t from this forest are combined into a single cluster u, s and t are removed from the forest, and u is added to the forest. When only one cluster remains in the forest, the algorithm stops, and this cluster becomes the root. A distance matrix is maintained at each iteration. The $d[i,j]$ entry corresponds to the distance between cluster i and j in the original forest. At each iteration the algorithm must update the distance matrix to reflect the distance of the newly formed cluster u with the remaining clusters in the forest.

Suppose there are $[u]$ original observations $u[0],\dots,u[|u|-1]$ in cluster u and $|v|$ original objects $v[0],\dots,v[|v|-1]$ in cluster v. Recall s and t are combined to form cluster u. Let v be any remaining cluster in the forest that is not u. method='ward' uses the Ward variance minimization algorithm. The new entry $d(u,v)$ is computed as follows,

$$d(u,v) = \sqrt{\frac{|v|+|s|}{T}d(v,s)^2 + \frac{|v|+|t|}{T}d(v,t)^2 + \frac{|v|}{T}d(s,t)^2} \qquad (3)$$

where u is the newly joined cluster consisting of clusters s and t, v is an unused cluster in the forest, $T = |v| + |s| + |t|$, and $|*|$ is the cardinality of its argument. This is also known as the incremental algorithm.

RESULTS

The results from self organizing maps (Kohonen, 1996) are shown in Figure 5 and summarized in Table 2. The number of segments (or clusters) is inferred by heuristic rules and using datas of the energies vectors, calculated by the Parceval method. Segmented maps allow sorting new samples. The method does not use class information at any point in training or analysis (group definitions).

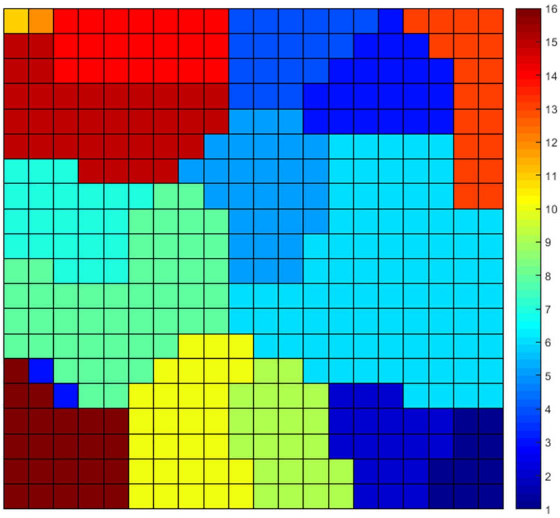

Fig. 5 - Results of Kohonen self-organizing maps.

The failure monitoring system presented was far beyond the initial expectation, not only classifying known tribological failure modes, but also modes of failure of the compressor itself, such as the breaking of a fan and the classification of modes of operation at different working pressures.

Table 2 - Description of the results

Region	Experiment	Condition / Failure Mode
1	01 and 02	Moto compressor Off
12	03 and 04	Without fan and pressure 0,0 bar
9	05 and 06	Without fan and pressure 2,5 bar
2	07	Without fan and pressure 4,5 bar
6	08 and 09	Normal and pressure 0.0 bar
6	10 and 11	Normal and pressure 2.5 bar
10	12 and 13	Normal and pressure 4,5 bar
7 and 8	14 and 15	Corrosion and pressure 0,0 bar
8	16 and 17	Corrosion and pressure 2.5 bar
3 and 4	18 and 19	Corrosion and pressure 4.5 bar
16	20 and 21	Internal Bearing and Bearing Fault 0.0 bar
5	22 and 23	Internal Bearing and Bearing Fault 2.5 bar
6	24 and 25	Internal Bearing and Bearing Fault 4.5 bar
13	26	Debris and pressure 0.0 bar
15	27	Debris and pressure 2,5 bar
11 and 15	28	Debris and pressure 5.5 bar

The groups formed are shown in Figure 6, which shows the formation of sixteen clusters, based on the cut in the longest distance between groups. Within each cluster we have different defects with similar characteristics and between the groups we verified different characteristics for the tribological faults what are represented by the weights of the neurons.

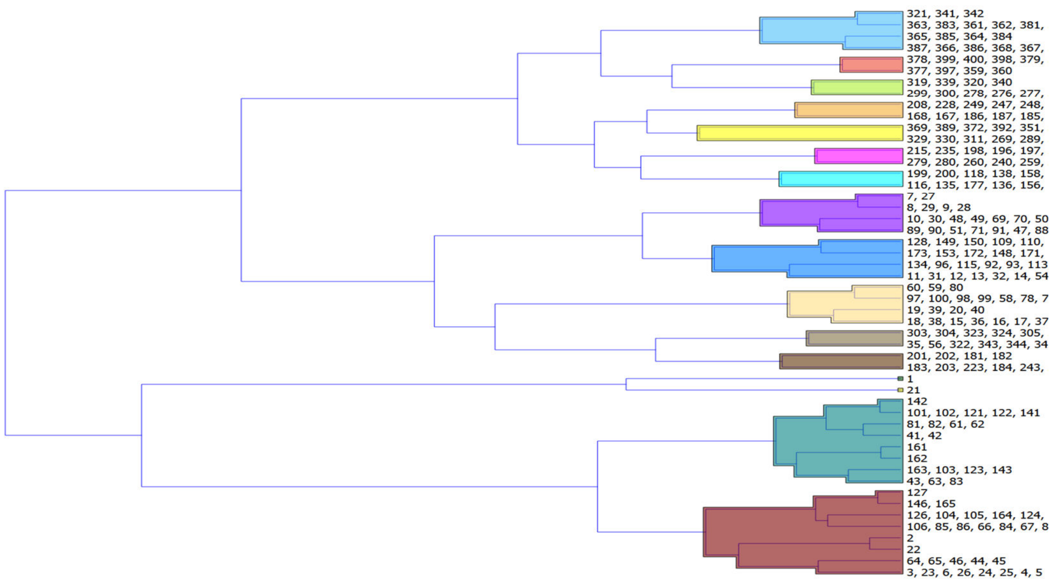

Fig. 6 - Dendrogram from the weights of the neurons obtained on the Kohonen map.

CONCLUSIONS

This paper shows the efficiencies the Ward Method approach in the detection and classification of tribological faults through the use of artificial intelligence tools in the treatment of signals using Kohonen self organizing maps techniques. Also, the choice of using the energy profiles from the system frequency bandwidths to calculate the total energy of the system, by the Parseval theorem, and thus permit analysis of the vibration phenomena in the whole frequency spectrum was one the main contribution of this research.

The failure monitoring system presented was far beyond the initial expectation, not only classifying known tribological failure modes, but also modes of failure of the compressor itself, such as the breaking of a fan and the classification of modes of operation at different working pressures.

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