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Characterization of mechanical vibrations in a metal structure using the transform Cepstrum

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ABSTRACT

This work adequately characterizes and correlates the effects generated by inducing mechanical vibrations on a metallic structure as a means of determining or predicting potential alterations or failures in bodies used in civil and industrial works of a static nature. Vibration sensors (piezoelectric), experimental information capture software (Labview) and the application of signal processing and classification tools were used for this. Various previous works have used signal processing techniques such as Fourier and Wavelet. These show indications about the relationship between the processed signals and the structural alterations of the different tests. On this occasion, through the use of Cepstrum analysis as an alternative tool for the processing of mechanical vibrations and complementary to the use of a dissimilarity technique (Euclidean distance) for the assessment of the ability to differentiate between classes grouped according to the anomaly studied and The use of statistical indicators to evaluate the homogeneity of the data has made it possible to show deviations that can be linked to structural defects (perforation, welding, denting and shear) of a metallic armor at the laboratory level. Finally, it was evidenced that the use of Cepstrum coefficients as characteristic information of the anomaly, at an experimental level, broadens the knowledge base and undoubtedly allows the implementation of the bases to encourage the academic and commercial development of tools or techniques for remote inspection of static equipment that is of great use to society.

Keywords: Detection of structural alterations; Cepstral coefficients; Mechanical vibrations

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1. Introduction

Mechanical vibration analysis has been used in different contexts. In some as a predictive maintenance tool on rotating equipment [1] [2] [3] [4] [5] [6]. Studies range from the use of multi-sensors and multidimensional time series analysis [7] [8], up to multiple regression models focused on monitoring the condition in rotating machines [9]. Various transformations of the time series have been used (Fourier,Cepstrum,Wavelet) to characterize the behavior of the machines in different modes of operation [10] [11], where the objective is to extract relevant information that allows classifying each mode of operation [12]. In other contexts, mechanical vibrations have focused on making non-destructive evaluations of structures in different materials [13] [14] [15] [16]. Advances focus both on the use of various sensors to obtain vibration signals [17] [18], the management of remote structural health monitoring systems [19] [20], and the use of transformations to the data obtained and artificial vision methods [21] [22] that allow contrasting. On the subject of vibration analysis and its correlation with structural failures of equipment or systems, the bases have been established for the investigation and development of experimental tests that allow to deepen and guarantee successful results in the determination of structural alterations or defects in metallic components [23] from the measurement and correlation of mechanical vibration signals induced by the excitation of the structures by an adapted device (coil) to generate them [24]. The main problem is that according to the bibliography consulted, to date, Fourier and wavelet analysis [23] [24] [23-24], the results have not been satisfactory concerning the specific identification of patterns that can be linked or directly associated with possible conditions of damage or alteration of the studied structure, [25]. For this reason, our study evidences The tests are carried out on a metallic structure (1.7 meters) in carbon steel, as shown in Figure1.a, in which three piezoelectric sensors (see Figure 1.c) are randomly located to detect the signals produced by the excitation mechanical with a coil located in the upper section Figure 1.b. The structural defects analyzed are welding, shear cutting, perforations, and an additional specimen without anomalies. These can be seen in Figure. 2.transformation) [26]. This allows that evaluation for the behavior of vibrational signals in such a way that they allow to generate confidence in the alternative use of this technique in determining static type structural damage.

2. Materials and methods

2.1 Materials

The tests are carried out on a metallic structure (1.7 meters) in carbon steel, as shown in Figure1.a, in which three piezoelectric sensors (see Figure 1.c) are randomly located to detect the signals produced by the excitation mechanical with a coil located in the upper section Figure 1.b. The structural defects analyzed are welding, shear cutting, perforations, and an additional specimen without anomalies. These can be seen in Figure. 2.

Figure 1. a. Test structure. b. Vibration generating coil. c. Piezoelectric sensors

Figure 2. 1. Welding. 2. Shears.3. dubbed 4. Perforated.

The signals are captured by an electronic card (National Instruments USB 6008 and PCB electronic card, to operation of vibrator coil- see Figure 3). An interface elaborated in Labview (Figure 4) with which the data is obtained in editable files type TXT. These data are then imported into MATLAB for the corresponding information processing and correlation.

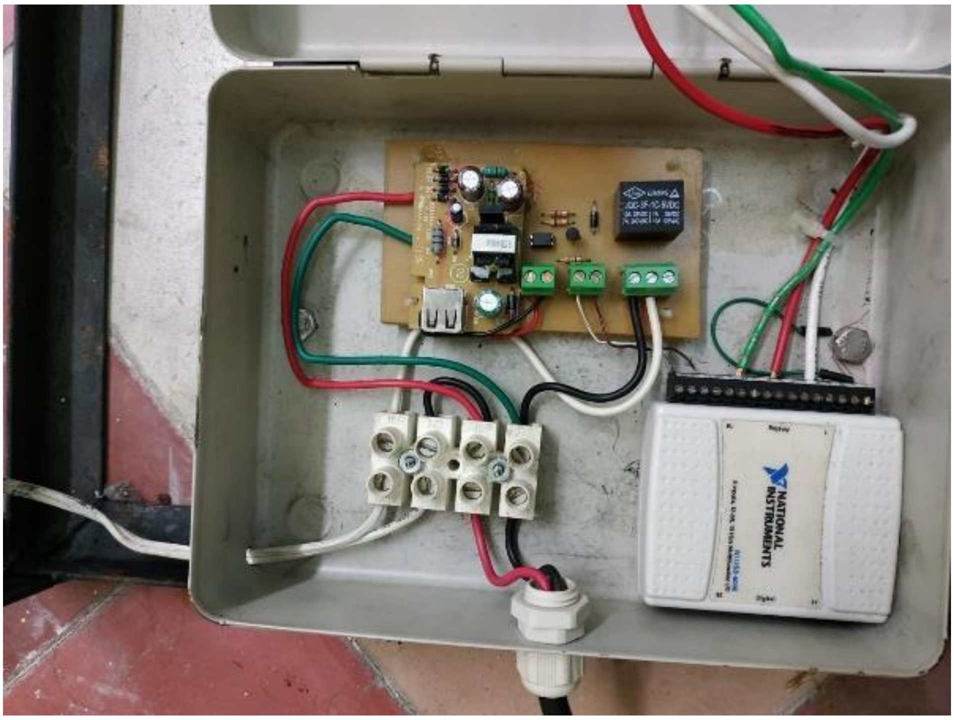

Figure 3. Electronic card for the management of power and control circuits and data acquisition system

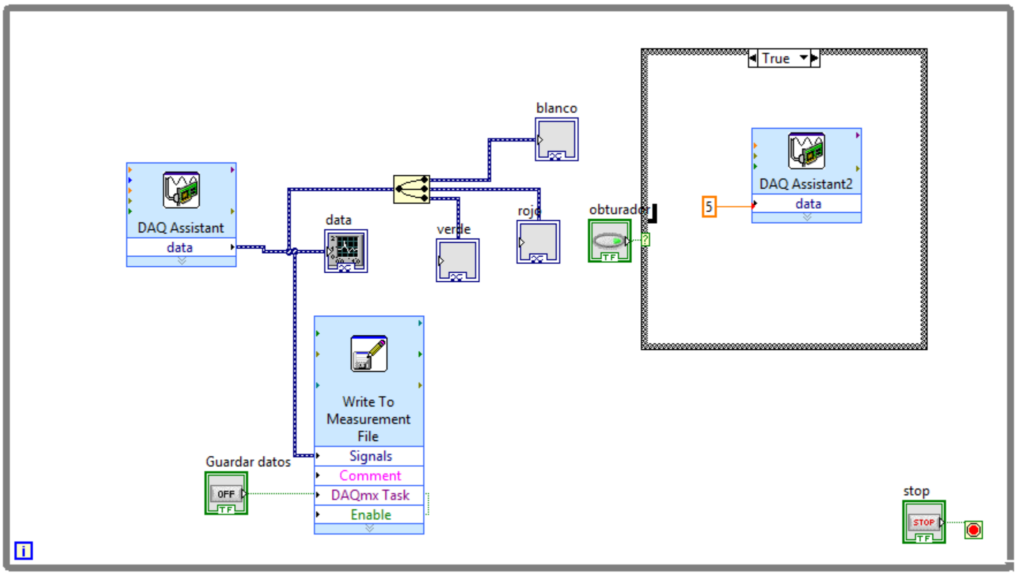

Figure 4. Data acquisition algorithm developed in Labview

2.2 Methods

The structure information capture procedure uses three sensors that have been labeled (white, red, and green) and were located in the following components of the structure:

- A white sensor on a long diagonal bar
- A red sensor on horizontal short bar

- A green sensor on a long diagonal bar

For the development of the experimentation, the following steps were carried out:
Step 1. Baseline evaluation (no defects): The shutter (coil) on the Labview display is actuated for approximately 5 seconds. The information (from the three sensors) is captured and stored in a text file recording 1,000 samples per second for a total of 5,000 samples. In total there are 25,000 samples based on the fact that each test is repeated five times.
Step 2. Evaluation for each defect The activity carried out in Step 1 is performed in the same way for each of the four types of defects defined and located at randomly chosen sites.

The defects implemented in the structure are: Defect 1 (DF1) corresponds to replacing and evaluating a long diagonal bar with one with weld filler. Defect 2 (DF2) corresponds to replacing and evaluating a long diagonal bar with one with a shear cut of 1 mm wide by 2 centimeters long. Defect 3 (DF3) corresponds to replacing a short horizontal bar in the state of deformation. Defect 4 (DF4) corresponds to replacing and evaluating the system with a horizontal bar drilled in the center (3 holes).

For the data analysis, the variation coefficient (CV- see table 1) was used, taking the cepstral coefficients as class characteristics, to evaluate the repeatability of the test in the five repetitions. (see the results in Figure. 3). The Cepstrum coefficients are extracted from information represented in the frequency domain (equation 1) and transformed to a time-domain (Qfrecuency), filtered to finally apply the inverse Fourier transform in the entire sampling range. This procedure seeks to appreciate a greater degree of definition of relevant points (coefficients) that can be classified and associated with the different types of defects in the structure.

Table 1. Statistical calculus

Statistical	Calculation method
Average value	$x' = \frac{\sum_{n=1}^{N} x(n)}{N}$
Standard Deviation	$\sigma = \sqrt{\frac{\sum_{n=1}^{N}(x(n) - x')^2}{N-1}}$
CV: Coefficient of variation	$CV = \frac{x'}{\sigma} * 100\%$

$$C_c(\tau) = \mathcal{F}^{-1}\{\log(F(f))\} = \mathcal{F}^{-1}\{\ln(A(f)) + j\phi(f)\} \quad (1)$$

Cc is the Cepstrum coefficients that allow the reconstruction of the signal. On the other hand, to estimate the differentiation capacity of the cepstrum coefficients applied to each defect, the Euclidean distance was implemented, as shown in equation 2.

$$d_{ij} = \sqrt{\sum_{K=1}^{P}(X_{iK} - X_{jK})^2} \qquad (2)$$

X_{ik} represents the reference observation and X_{jk} represents the vector to which it is being compared. In this way, the greater the distance values, the greater the separation capacity is evidenced.

3. Results and discussion

The statistical analysis of variability (CV) for the three sensors shows a percentage below 10% Figure. 5 for the blank test (reference) and in general for the evaluation of each of the defects, therefore, there is repeatability in the experimental test.

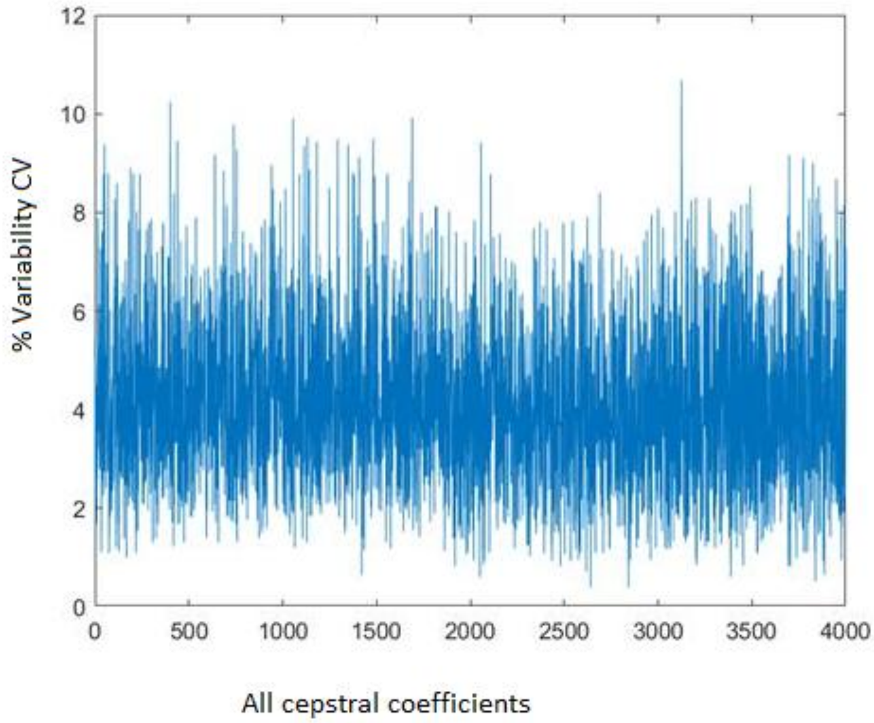

Figure 5. Comparison of the coefficient of variation for the tests taking all the cepstral coefficients.

A preliminary analysis with the Fourier spectra shows small differences in each of the spectra. Some examples are shown in Figure 6-8.

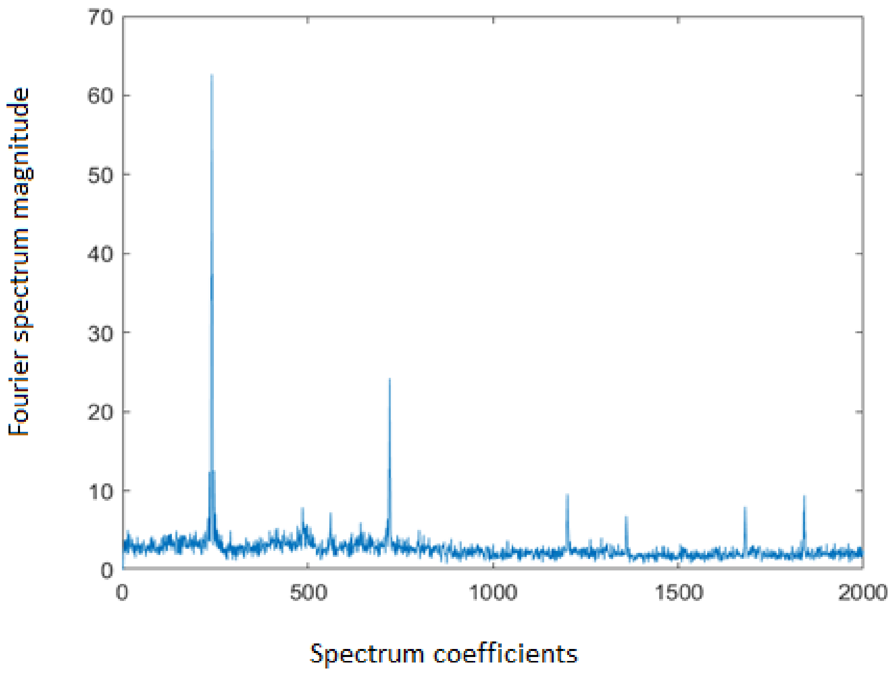

Figure 6. FFT representation of the reference sensor

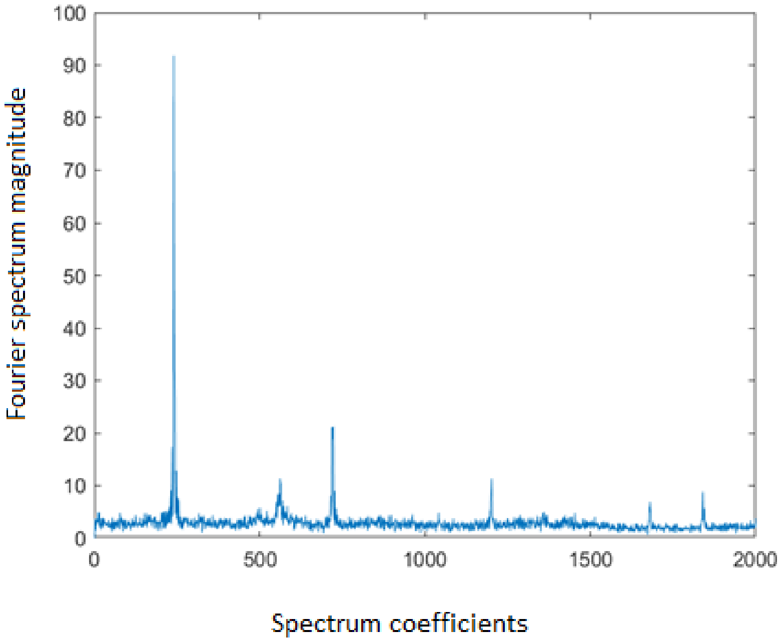

Figure 7. FFT DF1 default behavior

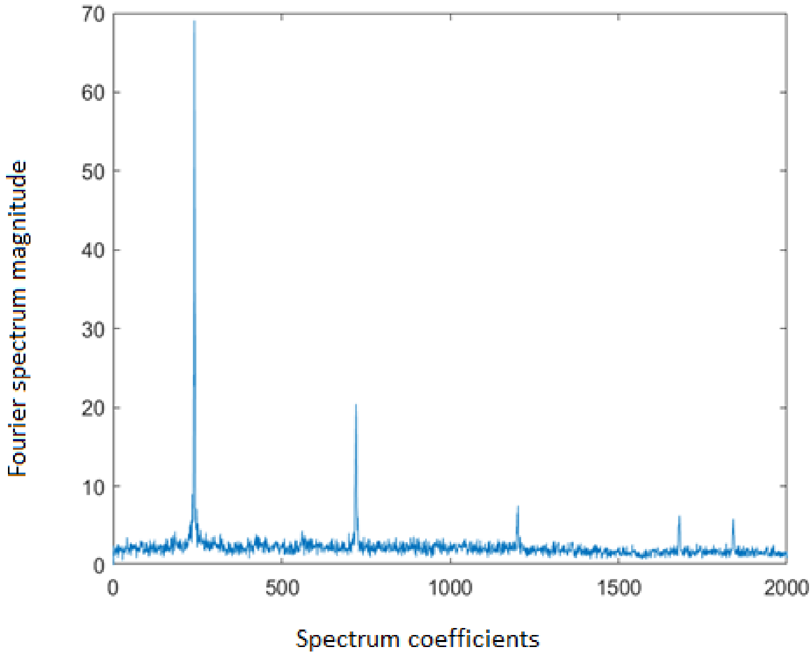

Figure 8. FFT DF3 default behavior

The application of the FFT allows showing as the principal deviations (signal) those associated with the defects represented as DF1 and DF3 for low-frequency values at deviation levels of 48% and 8% respectively compared to the reference data, the other defects (DF2DF4) did not show appreciable differences in the frequency domain.

The analysis with cepstrum coefficients allows us to see variations for the DF2 and DF4 defects, which were not possible to identify with the application of the FFT, this can be seen in Figure 9-11 at low frequencies (close to the origin) with variations between 2 and 4 units.

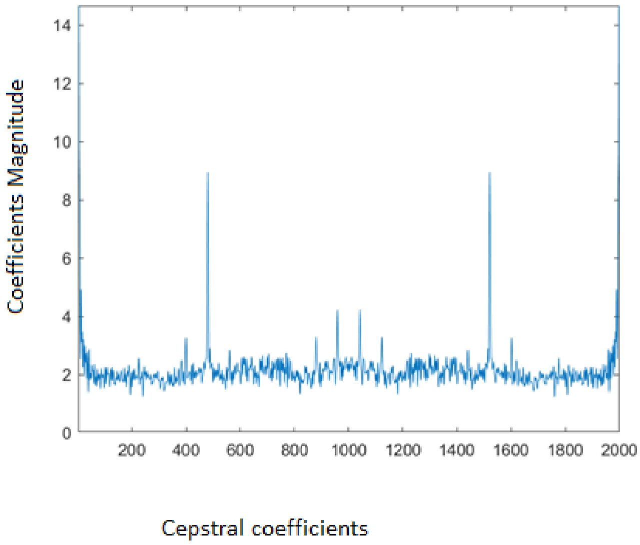

Figure 9. Cepstrum reference sensor

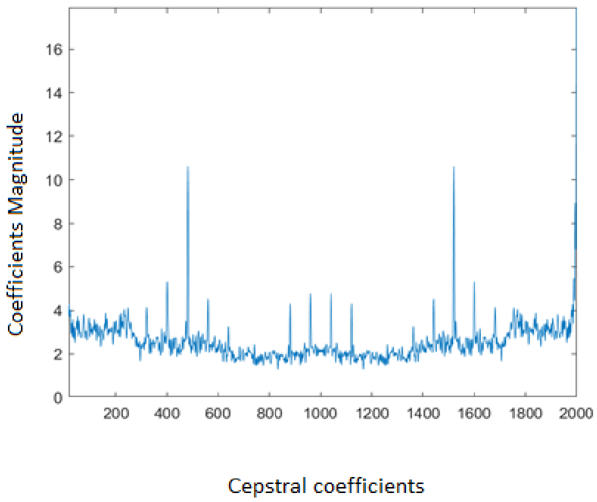

Figure 10. Cepstrum defect DF2

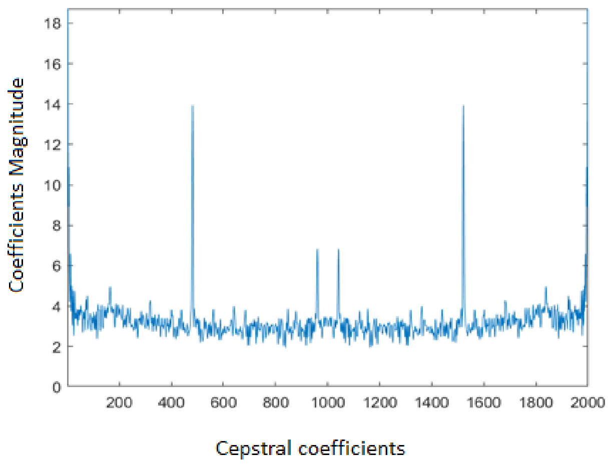

Figure 11. Cepstrum defect DF4

Separation capacity was quantified by evaluating the Euclidean distance between each class and the reference (reference specimen). In this way, it was possible to evaluate the similarity of data in an experiment using the clustering technique where it is possible to infer that small distances between elements represent similarity and large distances dissimilarity. In this sense, it is expected that large differences between signals versus the reference values, allow us to determine how possible it is to identify each defect. In Table 2 and Figure. 12-14, the summarized results can be seen.

Table 2. Distances between the reference element (normal) and each defect, taken for each of the sensors

DEFECTS	DISTANCES (WHITE SENSOR)	DISTANCES (RED SENSOR)	DISTANCES (GREEN SENSOR)
DF1	38.4	37.3	20,39
DF2	25.4	18.4	15.6
DF3	31.1	49.6	15.9
DF4	39.7	46.2	22.4

Figure. 12. Represents the Euclidean distances of four defects concerning normal element in the provided information from the white sensor. Also, Figure 13. represents the Euclidean distances of four defects concerning normal element in the provided information from the red sensor, and Figure 14 represents the same, but for the green sensor.

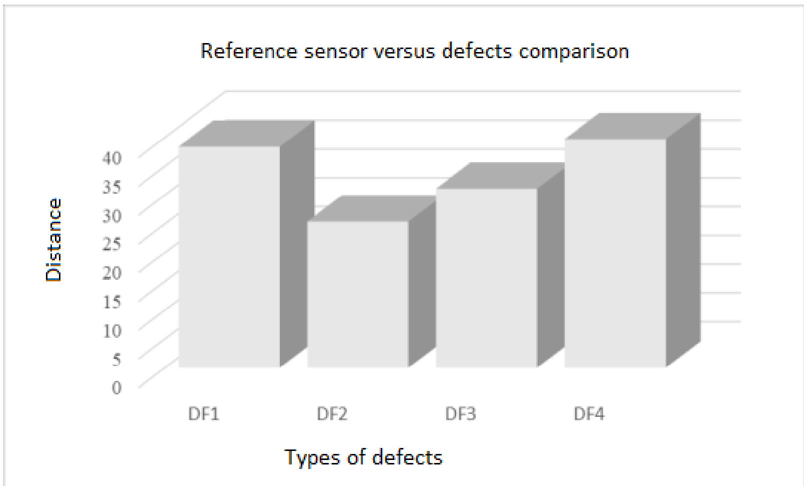

Figure 12. Distance of each defect in relation to the reference value (white sensor)

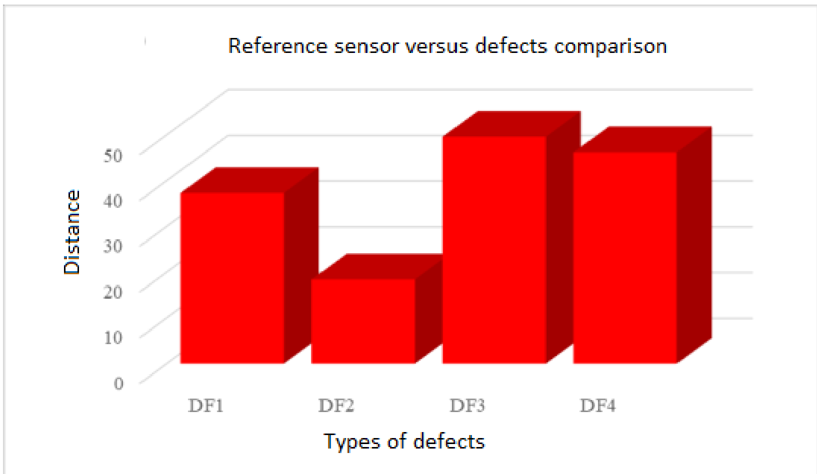

Figure 13. Distance of each defect in relation to the reference value (red sensor)

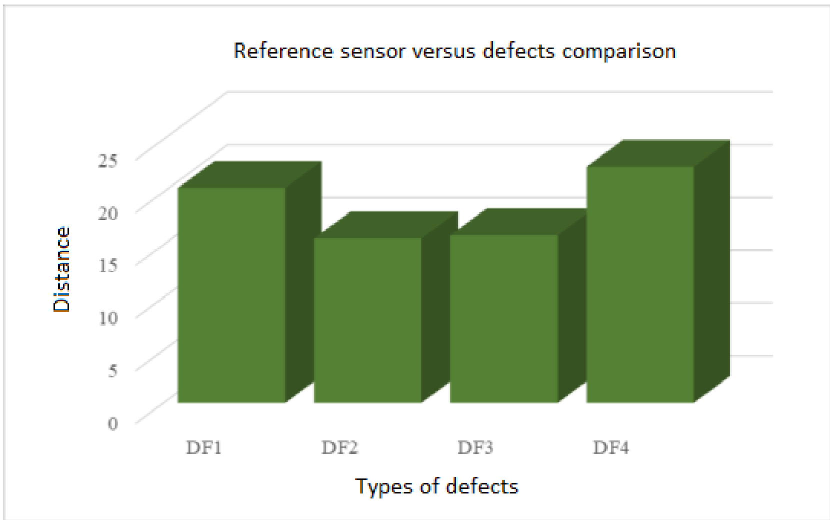

Figure 14. Distance of each defect in relation to reference value (green sensor)

In the figures it can be seen how the greatest degree of magnitude corresponds to the defect (DF4) of the horizontal bar with three holes (1.5 centimeters in diameter), followed by the defect (DF1) of the bar with 360 ° welding, followed by the defect (DF3) deformation of the bar and finally the DF2 small partial cut of 2 mm of the bar. The red sensor shows the Euclidean distance for the DF3 defect (greater than others), which may be associated with the sensitivity of the acquisition device (sensor) or influenced by the physical closeness between the sensor and the strain. The tests did not include comparisons of the distances between the cepstral coefficients for each defect. For this reason, there is no objective evidence of the differentiation of the alteration from each other. Therefore, it's interesting to study the effects of differences between the distance of the sensor, the relationship of alteration's dimension to found correlations for these structures.

In the present work, the problem of detecting structural alterations in metallic bodies based on the use of the Cepstrum transform has been addressed. It is interesting to highlight that the consulted literature reports analyze fiber metal laminates [23] but not metal structures that may be bearing to vibrations such as those exist in the construction industry. However, a previous study reported the use of PCA and FFT principal component analysis [24], but there were short distances between classes (less than unity). In this work, we have found great values of de distances, based on the Euclidean distance, between the cepstral coefficients (applied to non-stationary signals, as recommended by [26]), of each class, with values much higher than those reported in the background. In this way, the characteristics found are widely differentiable. The above facilitates the expert systems and artificial intelligence use like recommended in [25] to automatically detect the alteration and have a rapid diagnosis that can industrially employ.

4. Conclusions

With the work carried out, it has been shown that it is possible to adequately differentiate each alteration of the metallic structure using the cepstral coefficients as characteristics of each class in the structure response to vibratory excitation. The Euclidean distance made it possible to quantify these differences observed visually. The resulting values are between 16 and 50. Although these values are dimensionless, they represent a quantitative indicator of the differentiation capacity associated with the cepstrum characteristics. It is a result to use in an automatic classifier.

However, a later stage of the study should incorporate tests with additional defects simultaneously, in such a way that with the information (distances) obtained in the present, the number of defects that a metallic structure can have at a given moment can be correlated and with this expand the potential uses of the technique.

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