Diagnosis methodology for identifying gearbox wear based on statistical-time feature reduction

Juan Jose Saucedo-Dorantes [a], Miguel Delgado-Prieto [c], Roque Alfredo Osornio-Rios [a] and Rene de Jesus Romero-Troncoso [b†].

[a]*CA Mecatronica, Facultad de Ingenieria, Campus San Juan del Rio, Universidad Autonoma de Queretaro, Rio Moctezuma 249, Col. San Cayetano, 76807 San Juan del Rio, Queretaro, Mexico.*

[b]*CA Procesamiento Digital de Señales, CA Telematica, Division de Ingenierias, Campus Irapuato-Salamanca, Universidad de Guanajuato, Carretera Salamanca-Valle km 3.5+1.8, Comunidad de Palo Blanco, 36700 Salamanca, Guanajuato, Mexico.*

[c]*Technical University of Catalonia (UPC), Department of Electronic Engineering, MCIA Research Center, Rbla. San Nebridi n° 22, Gaia Research Building, 08222 Terrassa Spain.*

jsaucedo@hspdigital.org, miguel.delgado@mcia.upc.edu, raosornio@hspdigital.org

† Corresponding author: troncoso@hspdigital.org

Abstract

Strategies for condition monitoring are relevant to improve the operation safety and to ensure the efficiency of all the equipment used in industrial applications. The feature selection and feature extraction are suitable processing stages considered in many condition monitoring schemes to obtain high performance. Aiming to address this issue, this work proposes a new diagnosis methodology based on a multi-stage feature reduction approach for identifying different levels of uniform wear in a gearbox. The proposed multi-stage feature reduction approach involves a feature selection and a feature extraction ensuring the proper application of a high-performance signal processing over a set of acquired measurements of vibration. The methodology is performed successively; first, the acquired vibration signals are characterized by calculating a set of statistical time-based features. Second, a feature selection is done by performing an analysis of the Fisher score. Third, a feature extraction is realized by means of the Linear Discriminant Analysis technique. Finally, fourth, the diagnosis of the considered faults is done by means of a Fuzzy-based classifier. The effectiveness and performance of the proposed diagnosis methodology is evaluated by considering a complete dataset of experimental test, making the proposed methodology suitable to be applied in industrial applications with power transmission systems.

Keywords: *Gearbox, Condition monitoring, Fault Diagnosis, Feature Reduction, Vibrations.*

1 Introduction

Gears are extensively used in most of the mechanical power transmission systems due to their robustness, competitive cost and reliability [1]-[3]. Despite their reliability, the appearance of unexpected faults in gearboxes may occur at any time, causing unscheduled breakdowns in the elements of the associated kinematic chain. It has been reported that the appearance of gear faults account for 80% of the breakdowns in transmission machinery systems and 10% of the faults in rotating machinery [4]-[5]. Therefore, strategies of condition monitoring and fault detection related to gearbox transmission systems play a key role to ensure the effectivity and safety of multiple industrial processes [6]-[8].

Considering real situations from industrial applications, the appearance of faults in gearboxes can be generated by different sources such as fluctuating load, poor lubrication, deficient cooling, gearing and coupling inaccuracies, among others [9]. Most of the faults in gearboxes usually start from incipient faults such as wear and tear in gears which are known as superficial faults; consequently, an overheating generated by the friction increases between gears causing a reduction of its mechanical properties, which tends to accelerate the degradation of the gearbox [10]. Although incipient faults such as wear in gears are those which originate crucial failures in gearboxes transmission systems, this kind of fault has not been totally detected until the appearance of a critical breakdown. In this sense, the most critical faults are related to the appearance of gear teeth irregularities; such faults are: tooth breakage, chipped tooth, root crack, spalling, pitting and tooth surface damage, and due to their typical appearance, these faults have been widely addressed [11]-[13]. Hence, the appearance of faults in a gearbox transmission system affects its proper operation causing mainly the occurrence of vibrations, the increasing of noise besides that the temperature in the mechanical system is affected [14]-[15].

Condition monitoring schemes that are used to perform the assessment of gearbox transmission systems involve the measurement and analysis of different physical magnitudes such as stator currents, acoustic emissions, temperatures and vibrations [8], [16]-[17]. However, due to most of the mechanical power transmissions systems are composed of rotating parts, the occurrence of vibrations in these systems is inevitable; in fact, vibrations are one of the main characteristics in rotating machines and under the incidence or appearance of mechanical faults their vibrational signatures tend to be modified [18]-[19]. Indeed, with regard to the appearance and identification of mechanical faults, advantageous results may be performed through the measurement of physical magnitudes which nature is purely mechanic like vibrations [20]. Thus, vibration-based schemes remain as one of the most accepted, reliable and suitable approaches used for condition monitoring and fault identification of mechanical faults in industrial applications. Classically, the Root Mean Square (RMS), numerical indicator is estimated from vibration measurements in order to assess the general condition of the machine [21]. The vibration signals can be characterized extending their analysis into frequency and time-frequency domains [16],[22]-[23]. Even though the most well-known frequency and time-frequency domain techniques such as fast Fourier transform, Wavelet analysis or Hilbert-Huang transform among others, have been satisfactory applied to condition monitoring schemes, the simplicity and low computational cost of statistical time-domain features represents a suitable characterization solution, mainly, for considering its capability to estimate general trends from signals [24].

Commonly, the calculation of a high-dimensional set of features is considered in order to obtain large sets of information. Thus, the consideration of redundant and non-significant information into the numerical feature set proposed to characterize the physical magnitude is inevitable. In this regard, dimensionality reduction procedures have been included in condition monitoring methodologies aiming to remove non-useful information which can lead to a posterior low diagnosis performance [22]. The purpose of such dimensionality reduction is to obtain a significant representation of the original set of features. The most commonly applied techniques used to reduce the dimensionality of data sets are Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA). Yet, each one of these feature reduction techniques lies with a specific objective function, that is, the main objective of PCA is the identification of those orthogonal components that are aligned to those directions where maximum data dispersion is retained, while, the objective of LDA is to maximize the separation between data sets of different classes [26]-[27]. The main difference between PCA and LDA techniques is that LDA retains information of the different classes, supervised approach, whereas PCA does not, unsupervised approach; thus, a specific dimensionality reduction technique is selected depending of the criteria of application and also depends of the proposed focus for being used.

Although several methodologies related to the condition monitoring and fault detection in gearbox transmission systems have been presented in the last years, most of these are focused on the diagnosis and detection of critical faults. In this regard, in [28], a multi-criterion fusion framework for feature selection is proposed, where the effectiveness, correlation and performance of classification are taken into account during the diagnosis of different failure modes in a planetary gearbox. Although this scheme allows identifying different failure modes, the proposed strategy only involves the identification of critical gear faults such as root crack and missing tooth. In [13], a multi-stage feature selection based on genetic algorithms is proposed for carrying out the selection of the best set of condition parameters extracted from vibration signals through time, frequency and time-frequency domains. The selected set of features is then used in a neural network to classify different fault conditions of a gearbox. Although this approach is evaluated with a large number of features, the proposed strategy is also focused on critical gear faults. Indeed, despite the large number of proposed methodologies for assessing the condition of gearbox transmission systems, most of these have been focused on critical faults, which exhibit significant affectation patterns that facilitate their detection.

The main contribution of this work lies on the proposal and validation of a diagnosis methodology based on a dimensionality feature reduction approach for the identification and classification of different levels of uniform wear as an incipient fault in a gearbox transmission system. The fault patterns of the different levels of wear considered are characterized by calculating a statistical-time set of features from the acquired vibration signals. Then, the resulting sets of features are analyzed by means of the proposed multi-stage feature reduction approach. First, a Fisher score based feature selection stage is proposed to determine the most representative subset of features; then, the resulting set of features is subjected to a compression procedure through a linear discriminant analysis approach. This last feature reduction stage allows obtaining a 2-dimensional visualization of the measurements. Finally, due to the resulting 2-dimensional set of features, a simple neuro fuzzy based classification algorithm is used to obtain the gearbox condition and fault classification. The validation of the proposed methodology is performed through experimental tests, where four different treated conditions at different operating frequencies are considered. The obtained results show the effectivity of detection and classification of wear in a gearbox linked to a kinematic chain, making the proposed methodology suitable for industrial machinery diagnosis.

2 Feature reduction approaches

Dealing with mechanical power transmission systems, the feature set plays a key role that compromises the performance of the fault identification schemes. Thus, the use of an inappropriate set of features cannot be representative enough to describe the different condition in a rotating electromechanical system, thus the use of a large number of features may increase the capability of discrimination. However, such increase of features does not ensure the addition of relevant information related to the malfunctions in the working condition of mechanical power transmission systems. For that reason, different strategies or procedures related to feature reduction have been considered in condition monitoring schemes. In this regard, independently of whether condition monitoring schemes are used to assess electrical or mechanical machines, the main included feature reduction strategies are feature selection and feature extraction [24]-[26].

The feature selection is considered a strategy with filtering purposes, where all the elements of a set of features are individually evaluated in order to rank them according to their individual discriminative capabilities; and despite a specific feature does not provide meaningful information by itself; it can provide relevant information by its combination with other different features. Generally, most of the strategies with filtering purposes do not necessitate a specific learning algorithm and are very effective as well as being easy and fast to compute. Most of the filtering techniques are based in general properties or characteristics of the datasets, such as dependences, distances and consistencies among others [8], [26]. In general, the objective of considering feature selection strategies for being applied to condition monitoring schemes is to retain those features with the best discriminative capabilities among conditions [13], [28].

The feature extraction is considered a strategy with transformation purposes, where the elements of a set of features are combined in order to enhance a specific characteristic. PCA is the most well-known unsupervised technique used to reduce the dimensionality of datasets by extracting a new set of features [22]. This technique has been widely included in classic feature reduction approaches to project a high-dimensional dataset into a new and non-redundant set of features. In these extracted features, known as principal components, most of the dataset variance is represented. Although PCA technique is based on statistical analysis, it is not considered the separation of different classes. In this regard, LDA is the most well-known supervised feature extraction technique used for linear dimensionality reduction in problems where multiple classes are addressed. The main objective of the LDA technique lies on finding a new lower-dimensional projection where the most discriminative information among data points belonging to different classes is maximized [26]. Because the LDA is a supervised technique, it is an appropriate technique to maximize the condition monitoring performance dealing with the identification of an available set of fault conditions.

Indeed, LDA deals with multi-class problems, thus, considering a multi-class problem with C classes composed by N samples, the LDA computes the between-class scatter matrix as follows [29]:

$$S_b = \sum_{j=1}^{C} N_j(\boldsymbol{m_j} - \overline{\boldsymbol{m}})(\boldsymbol{m_j} - \overline{\boldsymbol{m}})^T \tag{1}$$

where N_j corresponds to the total number of samples in the *j-th* class C_j, taking into account all the classes $\overline{\boldsymbol{m}}$ is the mean of all the samples and $\boldsymbol{m_j}$ is the mean of the class C_j. Also the LDA considers the computation of the within-class scatter matrix as:

$$S_w = \sum_{j=1}^{C} \sum_{i=1}^{N_j} \left(\boldsymbol{x_i^j} - \boldsymbol{m_j}\right)\left(\boldsymbol{x_i^j} - \boldsymbol{m_j}\right)^T = \sum_{j=1}^{C} S_{w_j} \tag{2}$$

where x_i^j is the *i-th* sample which belongs to the class C_j, resulting in S_{wj} the corresponding covariance matrix of the class C_j.

The optimal projecting vector $\boldsymbol{W_{LDA}}$ chosen during the LDA allows to obtain well-separated classes since the computed matrix contains orthonormal columns which maximize the ratio of the determinant of the between-class matrix of the projected samples to the determinant of the within-class scatter matrix of the projected samples:

$$\boldsymbol{W_{LDA}} = \arg\max \frac{|W^T S_b W|}{|W^T S_w W|} = [\boldsymbol{w_1} \quad \boldsymbol{w_2} \quad \cdots \quad \boldsymbol{w_m}] \tag{3}$$

where $\{\boldsymbol{w}_i | i = 1,2,\cdots,m\}$ belongs to the set of generalized eigenvectors also known as discriminant vectors of the S_b and S_w that correspond to the *C-1* largest generalized eigenvalues $\{\boldsymbol{\lambda}_i | i = 1,2,\cdots,m\}$.

Thus, the feature extraction resulting in $\boldsymbol{V}$ is performed through the projection of the original data set of features $\boldsymbol{X}$ into the low dimensional $\boldsymbol{W_{LDA}}$ as follows:

$$\boldsymbol{V} = \boldsymbol{W_{LDA}}^{\boldsymbol{T}} \boldsymbol{X} \tag{4}$$

3 Diagnosis methodology

The proposed methodology for identifying gearbox wear is composed by five stages as the flow chart of Figure 1 depicts. First, in the data acquisition stage, the occurrence of vibrations in the perpendicular plane of the gearbox rotating axis is acquired.

Second, in the feature estimation stage, a characterization of each acquired vibration signal is performed by estimating a set of 15 statistical-time features. The proposed set of statistical-time features comprises: mean, maximum value, RMS, square root mean, standard deviation, variance, RMS shape factor, square root mean shape factor, crest factor, latitude factor, impulse factor, skewness, kurtosis, and normalized fifth and sixth moments. These proposed statistical-time features and their corresponding equations are listed in Table 1. Moreover, due to the potentiality to analyze trends of signals and the high-performance source of information, advantageous and accurate results have been successfully obtained by including the proposed set of statistical-time features in condition monitoring schemes for fault identification in electromechanical systems [7], [21], [24].

The third stage is the feature selection; in this reduction stage the discriminative capabilities of the estimated statistical features, which belong to all of the healthy-faulty pairs of classes, are separately analyzed with the aim to preserve and filter those discriminant features that better describe the gearbox working condition. The feature selection process is proposed to be performed by means of computing the Fisher score; which can be considered as brute-force based Fisher analysis, in which the ratio between the within-class scatter estimation and the between-classes scatter estimation is obtained. Specifically, this computed value may be interpreted as a relative measurement which represents the distance between different classes and dispersion among data points belonging to each class. Then, a set of features which produces a small Fisher score implies poor discriminative capabilities, while a large Fisher score implies better discriminative capabilities. The ranking of the features is proposed to be performed according to their relevancy; in this sense, those features that are better ranked in terms of the Fisher score are considered the features with high faults discriminative capabilities, while those features that are worst ranked are considered as non-discriminative features without poor information related to the fault condition. The feature selection is proposed to be carried out under a combinatorial approach; therefore, Fisher scores are obtained by carrying out combinations between all the available statistical features. Thus, the discriminative capabilities are evaluated by considering different subsets composed by one, two and three features. In order to discard the useless and non-discriminative features, in the feature selection procedure the discriminative capabilities of the statistical-time subsets of features considering all of the healthy-faulty pairs of classes is analyzed. Then, after evaluating the Fisher score of each statistical feature, the first ranked subset of statistical features is considered as the most relevant and discriminative subset of features that provides a better description to distinguish between the corresponding pair of fault condition and healthy condition of the gearbox.

In the fourth stage, feature extraction, all the subsets of features identified as most discriminative for each healthy-faulty pair of classes are then subjected to a base transformation and a compression process by means of the LDA technique. As a result of this process, a new set of features is extracted composed by a weight combination of the previously selected statistical features. Accordingly, due to the accomplished base transformation, it is possible to project the new set of extracted features into a 2-dimensional space allowing obtaining a visual interpretation of the different considered conditions. Furthermore, the resulting representation of the extracted features into a 2-dimensional space makes easier the classification task. Thus, the most discriminative statistical features selected in the previous stage are projected into a new base with a reduced dimensional space where their discriminative capabilities between the considered conditions are maintained.

Finally, the classification and fault diagnosis are done in the fifth stage, and the set of extracted features are evaluated in order to obtain the diagnose and classification of the different considered conditions. In this sense, it must be highlighted that, in the proposed diagnosis methodology, a successive processing of features (feature selection and feature reduction) is considered; and through its implementation, those features that are not significantly capable to represent the characteristic patters related to the gearbox working condition are removed. Thus, since the number of features is reduced to two, and the faults patterns has been emphasized, the use of simple classification structure is possible. In this case, a Fuzzy-based classifier for carrying out the diagnose and classification of the considered conditions is proposed. In fact, in a classic Fuzzy-based inference system there is an antecedent that is the input, such input is evaluated by means of a membership functions with the purpose to determine its degree of association to a specific fuzzy-event. In the proposed classifier, the extracted set of features are the inputs to be evaluated in the membership functions. Then, a conclusion is performed by computing the consequent or output of the fuzzy-based inference system through a series of logical operations that are also known as fuzzy rules. The proposed classifier has four outputs that represent every one of the considered conditions, the consequent of each membership function in the fuzzy-based inference system is determined by a Sugeno-style membership.

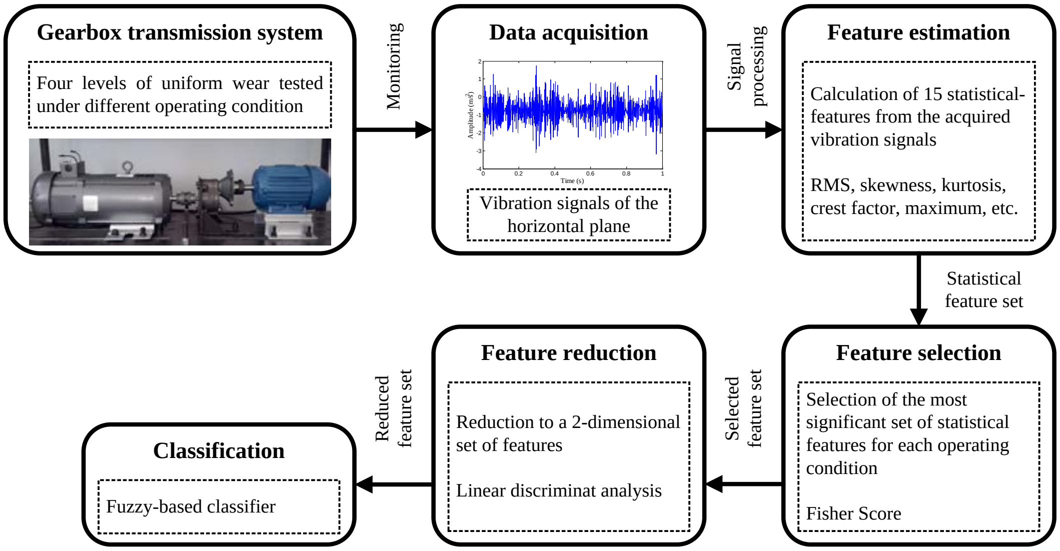


Figure 1: Flow chart of the proposed methodology used for identifying gearbox wear.

Table 1. Set of proposed statistical-time features

Mean	$\bar{x} = \frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert$	(1)
Maximum value	$\hat{x} = max(x)$	(2)
Root mean square	$RMS = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k)^2}$	(3)
Square root mean	$SRM = \left(\frac{1}{n} \cdot \sum_{k=1}^{n} \sqrt{\lvert x_k \rvert}\right)^2$	(4)
Standard deviation	$\sigma = \sqrt{\frac{1}{n} \cdot \sum_{k=1}^{n} (x_k - \bar{x})^2}$	(5)
Variance	$\sigma^2 = \frac{1}{n} \cdot \sum_{k=1}^{n} (x_k - \bar{x})^2$	(6)
RMS Shape factor	$SF_{RMS} = \frac{RMS}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(7)
SRM Shape factor	$SF_{SRM} = \frac{SRM}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(8)
Crest factor	$CF = \frac{\hat{x}}{RMS}$	(9)
Latitude factor	$LF = \frac{\hat{x}}{SRM}$	(10)
Impulse factor	$IF = \frac{\hat{x}}{\frac{1}{n} \cdot \sum_{k=1}^{n} \lvert x_k \rvert}$	(11)
Skewness	$S_k = \frac{E[(x_k - \bar{x})^3]}{\sigma^3}$	(12)

Kurtosis	$k = \frac{E[(x_k - \bar{x})^4]}{\sigma^4}$	(13)
Fifth moment	$5thM = \frac{E[(x_k - \bar{x})^5]}{\sigma^5}$	(14)
Sixth moment	$6thM = \frac{E[(x_k - \bar{x})^6]}{\sigma^6}$	(15)

4 Experimental setup

The experimental setup used for testing the different considered conditions and the data acquisition system (DAS), used to acquire the experimental vibration signals are shown in Figure 2. The test bench is based on a kinematic chain, it has a variable frequency drive (VFD) (WEGCFW08) to feed and control the rotational speed of a 1492-W three-phase induction motor (WEG00236ET3E145T-W22). The induction motor is coupled to a 4:1 ratio gearbox (BALDOR GCF4X01AA) driving its input shaft, this gearbox is used to test the different levels of uniform wear studied in this work. Besides, the gearbox in turn couples the induction motor to a DC generator (BALDOR CDP3604), such generator is used as a non-controlled mechanical producing around 20% of the nominal load in the induction motor under working conditions. The occurrence of vibrations in the perpendicular plane of the gearbox rotating axis are measured and acquired using a triaxial accelerometer (LIS3L02AS4), this accelerometer is mounted on a board with its proper signal conditioning and its anti-alias filtering. A 12-bit 4-channel serial-output sampling analog-to-digital converters (ADS7841) is used on board of the DAS to acquire the vibration signals, the sampling frequency is set to 3 kHz and the DAS is configured to acquired 270 kS during 90 seconds of continuous sampling in the induction motor from the startup to the steady-state. Such DAS is a proprietary, low-cost design, based on field programmable gate array technology (FPGA). In order to automatize the test run, a relay controlled by the DAS provides control over the induction motor startup. All the acquired vibration signals are stored in a personal computer (PC) for offline analysis. Ninety axial vibration measurements for each considered condition, where each one of the acquired measurement belongs to one second of the gearbox working condition, are acquired. Due to each acquired vibration signal consists of ninety consecutive samples, for each considered condition it is estimated a characteristic vibrational pattern with 15 numerical statistical features and ninety consecutive samples.

In this work four different conditions are considered to be evaluated alternatively in the gearbox: healthy (HLT), 25%, 50% and 75% of uniform wear, respectively. Regarding the considered faults, in order to produce the wear fault condition in gears, it was artificially made by a gear factory. Thus, considering a set of gears in a healthy condition, these are subjected to a machining process where all of its teeth are worn by a tungsten cutter; then, such gears are also subjected to a lapping process aiming to make as real as possible the induced wear in gears. The gearbox used in this work consists of only two gears, one of them is the driver gear and the other one is the driven gear, and each one of these gears have 5 and 72 teeth, respectively. Therefore, in this work are addressed three different levels of uniform wear and a healthy condition in order to prove the effectiveness of the proposed diagnosis methodology. From Figure 3a to Figure 3d the studied gears are shown: HLT, 25%, 50% and 75% of uniform wear, respectively.

The experimentation for the considered conditions is carried out by replacing each one of the faulty gears (worn gears), with the healthy one, alternatively. Three different operating frequencies for driving the induction motor have been considered, and the frequencies of 5Hz, 15 Hz and 50 Hz are set in the VFD causing an averaged rotating speed of 294 rpm, 890 rpm and 2985 rpm in the induction motor, respectively.

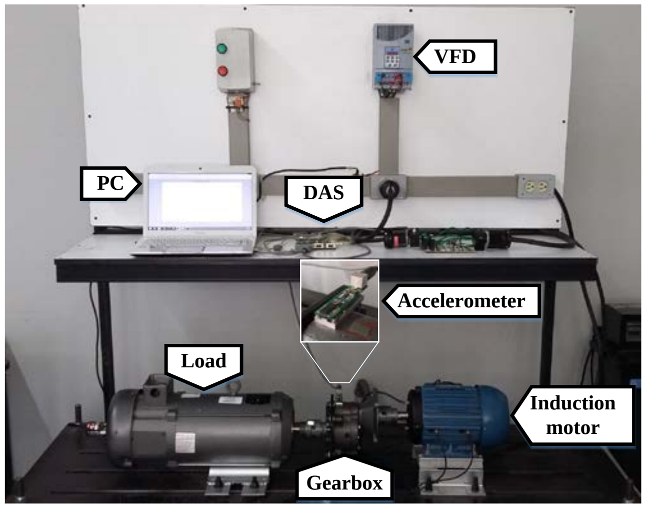
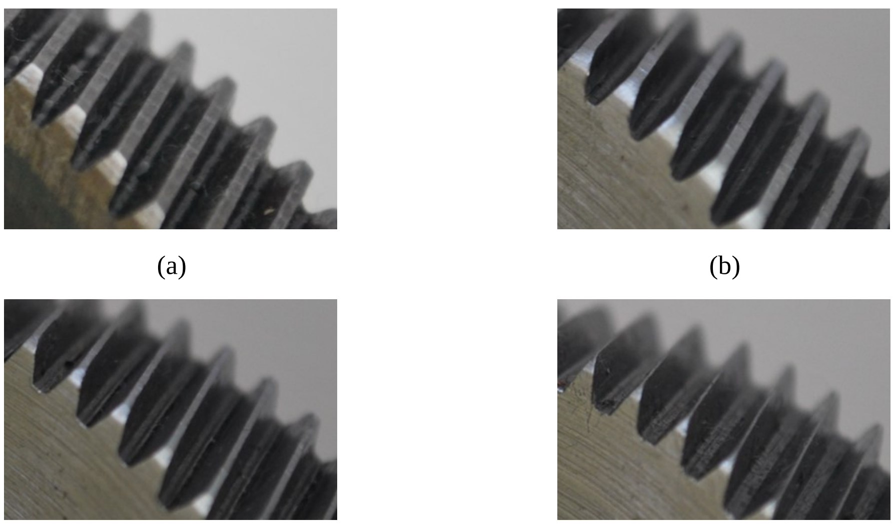


Figure 2: Experimental test bench used to experiment and to identify gearbox wear.



(a) (b)

(c) (d)

Figure 3: Set of gears evaluated in the gearbox: (a) Healthy, (b) 25 %, (c) 50% and (d) 75 % of wear.

5 Validation of the method

The proposed gearbox wear diagnosis methodology is implemented in Matlab, that is used to process the acquired vibration signals and to provide the diagnosis of the condition. As aforementioned, in the proposed work, the acquired vibrations signals belong to those vibrations in the perpendicular plane of the gearbox rotating axis since some studies has reported that the occurrence of perpendicular vibrations on the rotating axis is related to the inappropriate working conditions of rotational machines [5], [13], [24]. Regarding the proposed methodology, the data acquisition is performed by carrying out different experiments at different operating frequencies for driving the induction motor: 5 Hz, 15 Hz and 50 Hz. Thereby, the stored vibration signals consist of ninety seconds which correspond to the continuous monitoring of the gearbox working under the three different considered conditions, then, each acquired vibration signal is segmented in equal parts of one second in order to generate a consecutive set of samples and to facilitate the processing of the signals.

Afterwards, the feature estimation is carried out through the estimation of 15 statistical-time features from each acquired vibration signal; that is, the statistical features are estimated from each segmented part. As a result, a characteristic vibrational pattern is estimated from each vibration signal; thus, each considered condition is now represented by a set of 15 statistical-time features with 90 consecutive samples. Despite the high characterization provided by the statistical features, not all of them exhibit the same representative information related to the gearbox condition. In this regard, aiming to retain the best discriminative statistical features, the estimated sets of statistical-time features are then analyzed through a multi-stage feature reduction approach, where procedures for feature selection and feature extraction are included.

Subsequently, in the feature selection stage, there are analyzed the discriminative capabilities of the estimated statistical-time features by calculating their Fisher score. Hence, in order to discard those features with non-discriminative capabilities, the feature selection is applied over all possible combinations in sets of features composed by one, two, and three features, for each healthy-faulty pair of classes. Also, it should be noted that by performing separately the analysis to the three healthy-faulty pairs of classes, the features with better discriminative capabilities are filtered. The three healthy-faulty pair of classes considered are: healthy-25% gear wear, healthy-50% gear wear and healthy-75% gear wear. As the proposed Fisher score analysis represents a combinatorial problem among features, it could be unaffordable the required computational burden. In this sense, the Fisher analysis is limited to sets of features composed by a maximum of three features, since the computational burden respond as an unfeasible factorial function to the increase of analyzed features. Therefore, in order to carry out the selection process during the experimental validation, only subsets composed by combinations of one, two and three statistical features are considered to be evaluated for computing their corresponding Fisher score. After the assessment of all the possible combinations of sets of features composed by one, two and three features, the sets are ranked according to their relevancies in terms of Fisher score; that is, sets of features with better discriminative capabilities produce largest values of Fisher score. Then, aiming to filter the best statistical features, the first ranked subset is considered as the best set of features to distinguish between the corresponding pair of fault condition and healthy condition.

Therefore, the statistical features that better describe the gearbox working conditions are obtained through the proposed feature selection approach, and the selected subsets are considered the best with capabilities of class separation. In Table 2 are summarized the details of the selected subsets of statistical-time features for the three considered faulty conditions under the different operating frequencies. It should be clarified that the selected subsets of features summarized in Table 2 correspond to the first ranked subset of features in terms of Fisher score; furthermore, these selected subsets of features are computed by analyzing combinations of three statistical features. Hence, the computed values of Fisher score correspond to the Fisher score generated by those statistical features that compose the selected sets of features. It should be considered that values of Fisher score equal to 1 mean that the within-class scatter estimation is equal to the between-classes scatter estimation. Therefore, the statistical features with better discriminant capabilities are those that trend to generate a value of Fisher score higher than 1. Consequently, according to the obtained values of Fisher score listed in Table 2, advantageous discriminative capabilities are obtained between classes of the healthy condition and faulty condition. Also, it is noticed that a statistical feature can appear repeated in different subsets of selected features for the same gearbox working condition. Although a statistical feature appears repeated more than one time, it must be considered only one time for the final set of features selected. For example, considering the selected subsets of features obtained when the operating frequency is 5 Hz, the final subset of selected statistical features is composed by the SRM, the standard deviation, RMS, mean and the variance.

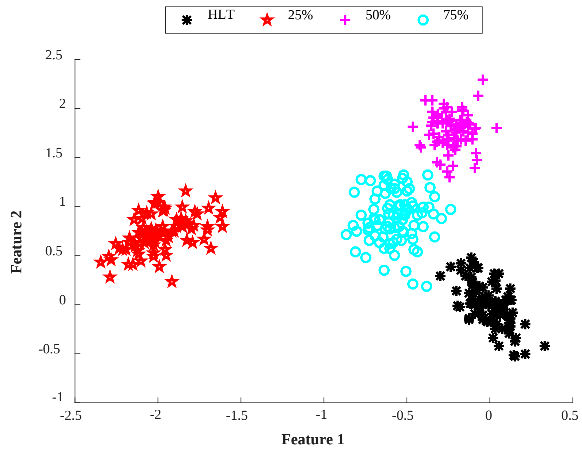
In regard with the use of combinations of one, two and three features, the results do not show significant differences and, when it was considered combinations of one and two features the resulting subsets were composed by, in general, the same statistical features but with a different value of Fisher score. Even though combinations of one, two and three features were used to perform the Fisher score analysis, the selected subsets resulted to be composed of three features. The Fisher score analysis by considering one and two features was useful to ensure that some specific statistical features prevail in the characterization of the gearbox working condition. Moreover, the Fisher score analysis allows to understand that, as well as a feature may produce a higher value of Fisher score by itself, this feature may take part also of a low value of Fisher in a set of features due to its combination with other features, and the same can occur in the opposite way. In this sense, the importance of such analysis is emphasized.

Table 2. Detail of the selected subsets composed by considering combinations of three statistical time features in the Fisher score analysis.

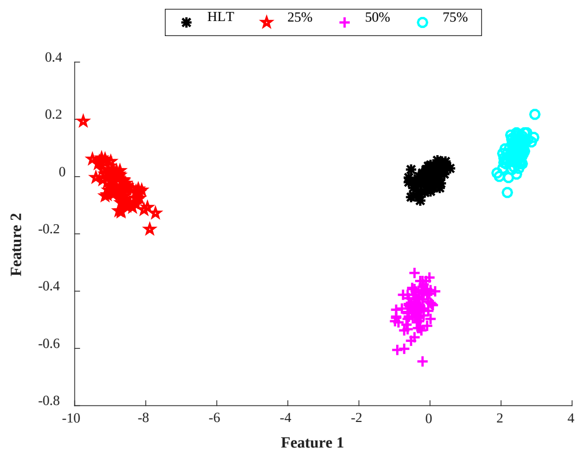
	Operating frequency					
	5 Hz		15 HZ		50 Hz	
Gear condition	Selected subset of features	Computed Fisher score	Selected subset of features	Computed Fisher score	Selected subset of features	Computed Fisher score
25 %	SRM-Std. deviation-RMS	1693.43	Std. deviation-RMS-SMR	34946.22	Std. deviation-RMS-Variance	366.91
50 %	Mean-Variance-Std. deviation	419.58	Mean-Std. deviation-Variance	877.73	Mean-S. factor RMS-S. factor SMR	408.61
75 %	Std. deviation-Variance-RMS	74.92	SRM-RMS-Std. deviation	684.15	RMS-Std. deviation-Variance	1620.95

In the feature extraction, the selected subsets of statistical features are subjected to a compression procedure and a base transformation through the LDA technique. Thus, through this strategy of feature extraction, it is obtained a new subset of features, and such new extracted features are composed by a weighted combination of the previously selected statistical features. As a result of the base transformation, it is possible to obtain a visual representation of the considered conditions into a 2-dimentional space. In this proposal three different operating frequencies to drive the induction motor are considered, then, the feature extraction process is individually applied to the selected subsets of features for each of the different operating frequencies.

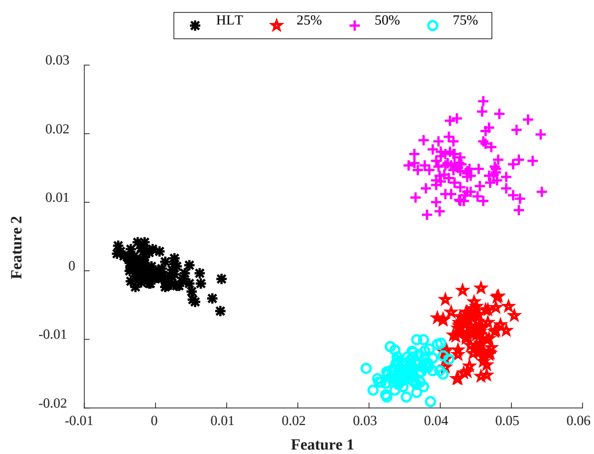
Consequently, three different projections into a 2-dimensional space are obtained by carrying out the feature extraction process through LDA technique; Figure 4 shows the resulting projections of the extracted sets of features by driving the induction motor at three different frequencies, 5 Hz, 15 Hz and 50 Hz. As it is expected, in the three resulting projections corresponding to the different operating frequencies, it is obtained a clear separation between the considered faulty conditions and the healthy one. Yet, although in some data points of different classes tend to appear close to each other, the centers of the clustered data are separated. Moreover, in order to ensure the effectivity and applicability of the diagnosis, it is important to notice that no overlapping between the HLT and any of the faulty conditions appear.


HLT
25%
50%
75%
Feature 2
Feature 1

(a)


HLT
25%
50%
75%
Feature 2
Feature 1

(b)


HLT
25%
50%
75%
Feature 2
Feature 1

(c)

Figure 4: Resultant projection of the extracted set of features obtained by the application of the proposed multi-stage feature reduction strategy to the original set of features. (a) When the induction motor is driven at 5 Hz, (b) 15 Hz and (c) 50 Hz.

Even though there are others techniques that can be used in feature extraction stages, for this proposed diagnosis methodology LDA is the most appropriate technique considering that LDA deals with multi-class problems from a supervised approach. In this sense, in order to highlight the effectiveness of the proposed multi-stage feature reduction approach with respect to the results computed by a classical one-stage feature reduction approach, the feature reduction procedure is also carried out by the other well-known technique, the PCA. Thus, the feature reduction by means of PCA over the original data set of 15 statistical features that characterize the gearbox condition at, for example, the operating frequency of 5 Hz, has been performed. As aforementioned, PCA preserves as much as possible the variance of the data distribution along its principal components. In Figure 5 the extracted features resulting by considering the PCA as a feature extraction technique are shown. These extracted features represent into a 2-dimensional space the considered conditions of the gearbox when the induction motor is driven at 5 Hz. From Figure 5 it is possible to notice that the data points of the different classes are grouped in elongated areas as scattered data, besides data points of the condition of HLT, 50% and 75% of gear wear are overlapped between themselves. Although PCA has been included in classic feature reduction approaches used as a unique feature reduction stage, in this proposed diagnosis methodology PCA as a unique feature reduction stage shows disadvantages in the separation of the considered conditions, since PCA seeks for global distribution of data and makes no consideration with different classes that are non-connected in the feature space.

Moreover, aiming to highlight the effectiveness that the application of the proposed feature selection offers before performing the feature extraction and in order to demonstrate that the selected sets of features contain the most discriminative fault-related information, the feature extraction is also carried out by means of PCA using the selected set of features obtained when the induction motor is drive at 5 Hz. Thus, Figure 6 shows the projection of the extracted features performed by the PCA from the selected sets of features for the gearbox conditions when the induction motor is driven to 5 Hz. It is possible to notice from Figure 6, that in this work the proposed feature selection process leads to improve the performance of the PCA in the feature extraction. Yet, although PCA is an unsupervised approach, the overlapping problems disappear by means of considering a previous feature selection process since the non-discriminative features are removed.

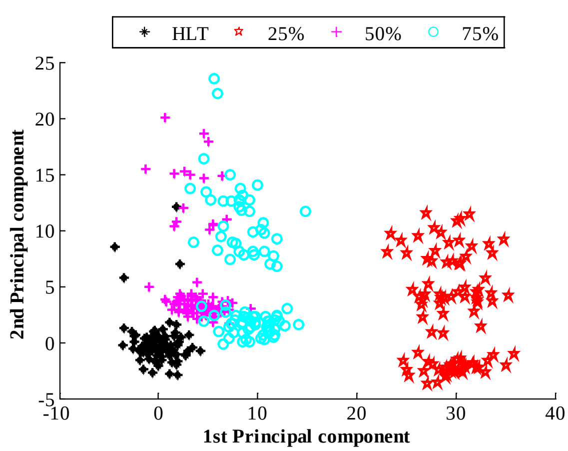


Figure 5: Projection of the extracted set of features computed thought the application of the PCA as a unique feature reduction stage over the original dataset of features that characterize the gearbox conditions at the operating frequency of 5 Hz.

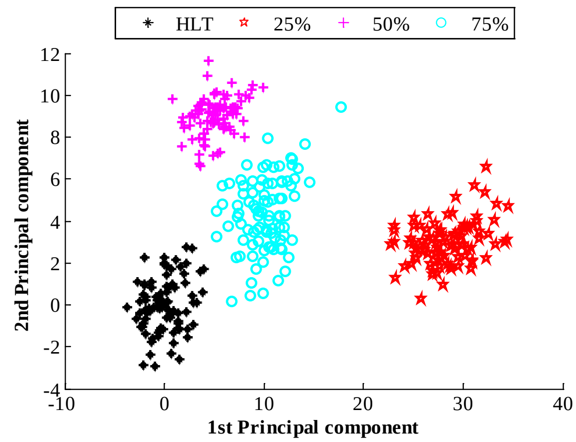


Figure 6: Projection of the extracted set of features performed by means of PCA to reduce the dimensionality of the selected sets of features that characterize the gearbox conditions at the operating frequency of 5 Hz.

With regard to the classification, a fuzzy-based classifier is used to carry out the fault diagnosis and to generate the output classes. Indeed, a high-performance characterization of the considered conditions is performed by the successive application of the proposed multi-stage feature reduction method (feature selection and feature reduction). Consequently, the consideration of a simple structure in the classifier allows to obtain accurate results without an excessive computational burden. Thereby, a classic fuzzy-based inference system is proposed to carry out the final diagnose and the classification of the considered conditions. Thus, in the proposed Fuzzy-based classifier the extracted sets of features are evaluated by means of membership functions in order to determine its degree of association to a specific fuzzy-event. Afterwards, the diagnosis is performed by computing the consequent of the fuzzy-based inference system through the evaluation of the series of logical operations, and the consequent of each membership function in the fuzzy-based inference system is determined by a Sugeno-style membership. The training of the proposed Fuzzy-based classifier is done by considering 50 epochs.

Aiming to demonstrate the effectiveness of the proposed diagnosis methodology and to obtain statistically significant results, the training and test of the proposed fuzzy classifier has been carried out following a 5-fold cross-validation scheme. In this sense, the extracted sets of features composed by 360 samples (90 samples per condition) are considered as the original database. Then, these database is divided in two different datasets. The first dataset composed by 288 samples (72 samples per condition), is used for training the classifier, and the second one that comprises 72 samples (18 samples per condition), is used for testing the classifier.

Thereby, with respect to the performance of classification, all the variance data available in the original databases are used, and through the consideration of the 5-fold cross-validation scheme, five classification ratios are obtained. Then, it is computed the average of these five classification ratios, and in Table 3 are summarizes the average of the classification ratios achieved during the training and the test of the proposed fuzzy-classifier of the extracted subsets of features. It is noticed that the classification ratios obtained under the 5-fold cross-validation scheme exhibit a stable behavior, which considers the different operating frequencies within the rage of 94.3% to 99.8% in the training stage, and within 92.2% to 99.1% for the test stage. Moreover, in order to prove the effectiveness of the proposed multi-stage feature reduction, the same structure of the fuzzy-based classifier is also trained and tested using the extracted features obtained by considering PCA as a unique feature reduction stage. Thus, the resulting classification ratios achieved by applying PCA over the original data sets when the induction motor is driven to 5 Hz are 88.9% during the training and 87.4% for the test. These classification ratios represent a poor performance for a condition monitoring methodology. In this regard, considering the results generated through the application of the proposed diagnosis methodology, the global ratio of classification is improved by around 11% in comparison with the results by using PCA as the unique feature reduction stage. On the other hand, due to the proposed feature selection stage is applied previously to the feature reduction, the performance of the of the PCA is improved when is performed the dimensionality reduction of the selected sets of features that characterize the gearbox condition operating at 5 Hz. In this regard, the classification ratios achieved by applying PCA over the selected sets of features are 98.3% during the training and 97.1% during the test; in this work, this improvement is generated by the fact of being carried out the proposed feature selection process.

These results reflect the high performance of the proposed multi-stage feature reduction approach and its application in the development of diagnosis schemes for assessing gearbox transmission systems.

Table 3. Performance of the achieved classification during the training and test of the Fuzzy inference system under the considered conditions at different operating frequencies.

Operating frequency	Train	Test
5 Hz	99.32%	98.88%
15 Hz	99.82%	99.1%
50 Hz	94.3%	92.2%

6 Conclusions

This work presents a new diagnosis methodology for assessing the condition of a gearbox under different incipient fault conditions of uniform wear. There are three important characteristics that must be to highlighted in this new proposed methodology. The first one is related to the use of vibration signals that remain as the most reliable for industrial applications, and the proposed set of statistical-time features which allows obtaining a better characterization of the acquired vibration signals providing relevant information that is correlated to the gearbox working condition. The second one lies with the application of the proposed multi-stage feature reduction approach for processing the estimated set of statistical features. The application of a consecutive feature reduction over the statistical-time features, allows obtaining the approximation to an optimum set of features by different considerations, from the removal of the less discriminative features to the compression of the most significant subsets of statistical features. The third one is the use of a simple classifier based on a fuzzy inference system capable to perform the recognition of the considered conditions.

Four different experimental conditions have been evaluated in the gearbox, including the healthy and faulty conditions. Under the considered experimental conditions carried out at different operating frequencies, the proposed diagnosis methodology shows reliability in the obtained fault diagnosis results, and 92% of total classification ratio is achieved in the worst-case classification. Besides, in this work, it is also showed the possibility to detect incipient faults through the evaluation and the diagnosis of the three different levels of uniform wear. Note that this is the first time that the appearance of uniform wear has been addressed in condition monitoring schemes applied to gearboxes transmission systems. The obtained results make the proposed methodology suitable for the diagnosis of gearbox transmission systems in industrial applications. Future work will be focused on the implementation of the proposed gearbox wear diagnosis methodology for online identification, besides the analysis of the appearance of uniform wear in gearboxes combined with other faults.

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