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CONDITION MONITORING OF GEARS UNDER MEDIUM ROTATIONAL SPEED

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This paper presents a pre-processing technique to select the optimal filtering frequency band identifying gear fault signature and use the filtered signal to calculate statistical features. The selected technique the cyclic spectral correlation, as proposed by Antoni [11]. It allows the visualization of excitations of the signal on a map. According to the literature, this technique appears to be more powerful than the time-frequency methods as it exploits the cyclostationary nature of signals, emitted by rotating machinery. This work analyses the benefits of filtering the signal before proceeding to feature extraction. The last step of this analysis is related to dimensionality reduction using the Principal Component Analysis method. In order to understand the influence of different gear fault conditions, healthy, chipped-tooth and missing-tooth measurements have been performed in a Machine Fault Simulator from SpectraQuest under different speed regimes. The central goal of this paper is to obtain key features that allow the identification of the condition of the gear at different speeds.
Keywords: Missing Tooth, Chipped Tooth, Condition Monitoring, Feature Extraction, Feature Dimension Reduction

1. Introduction

Condition Monitoring aims at detecting faults to minimize production costs and optimize predictive maintenance. Such process is often cumbersome since the detectability of faults depends on the geometry of the components under analysis, the type and severity of the fault, the speed regime, location of the sensors and signal processing applied. Gears are an important component of rotating machines, and often the faults in these components are the cause of catastrophic breakdown of industrial applications. For this reason a great effort has been put into research of this subject.

Every machine inclunding rotating components has a specific sound and vibration signature related to its construction and structural health state. Thus, changes in the vibration signature can be used to detect incipient defects before they become critical.

Accordingly, gearbox faults can be diagnosed through the changes that occur at particular frequencies. Gearbox frequencies of interest are the shaft rotation frequency, gear mesh frequency and its correspondent harmonics and sidebands [5].

The signals are commonly seen to have signatures from other components, plus the transmission path and added noise submerge the signature of the component, that is the focus of the analysis. As this happens, some signal processing methods are commonly applied to enhance the signature of the analyzed mechanical component. Tandon and Choudhury [1] give a review of acoustic bearing signals, noting that resonant modes of the structure carry the impulses due to the signal originating from the gear fault. Ghasemloonia and Khadem [2] apply various methods, and conclude that applying envelope analysis allows one to obtain the faulty frequencies of bearings, and predict the evolution of the fault. They defend that filtering of the these carrier waves and demodulation, envelope analysis, provides satisfactory results in detecting the faulty signatures.

It is thus necessary to apply band-pass filters to the measured signals in order to enhance the fault signatures, which are carried by the resonant properties of the structure. The correct band-pass filter parameters must then be selected in order to obtain the signal that allows the identification of the fault. However, the detection of the band of frequencies on the spectrum and on time-signal is not trivial. In past years the filter selection was based on educated guesses and on trial-and-error iteration [1]. The appearance of Kurtogram [9] promised to solve this problem, as it allowed an automatic filter selection based on the maximization of the Spectral Kurtosis, however this method does not always return the correct band for the filter. The Kurtogram is often seen to be unable to select the bearing fault frequencies, whilst the CSC provides the correct filter selection [8]. The Kurtogram provides, however, a method to automate the process, and it is commonly seen that the solution given by Kurtogram is frequently derived as a first step [9]. Another process is the Scalogram [3] obtained by using the Wavelet Transform, yielding a time-frequency domain representation. This however does not represent the impulses having less magnitude, and fails to show the hidden periodicites of the signal when these derive from random frequency components [10].

Due to the large variations, direct comparison of signatures is difficult, and thus statistical features provide a reduced data set for the application of pattern recognition and tracking technique. Ideally, these features are more stable and better behaved than the raw signature data itself [6]. With a great number of features, the information is difficult to decompose, and thus methods that allow the dimension reduction allow a visual examination of the full set of features at once. One possiblity is the principal component analysis (PCA) [7] , which is an unsupervised feature reduction method, and another is the linear discrimant analysis (LDA), where both allow one to decrease the number of features. In [7], the authors used PCA to reduce 18 features to six efficient features, and obtained the same accuracy in classifying the faulty states after training and testing the data. These methods also allow to diagnose the faults, if the cluster of points for each state is well separated. The signal processing and features should be well defined and determined for new cases, and the the new axis rotation matrix from the PCA or LDA would locate the new data point to the correspondent condition.

2. Methodology

2.1 Proposed Method

The method presented in this paper is the application of Envelope Analysis by selecting the correct band-pass filter taken from the maximum coefficients at the shaft speed determined by the cyclic spectral correlation (CSC).

Fig. 1 represents the procedure proposed in the present paper. The filter parameters are determined from knowledge of the carrier frequencies that are modulated by the frequencies of interest, such as the gear mesh frequency. Then Features are calculated on the demodulated signal and selected based on their performance. Finally the PCA and LDA are applied to provide a solid method to reduce the high dimensional space of the full features into clusters of different fault cases.

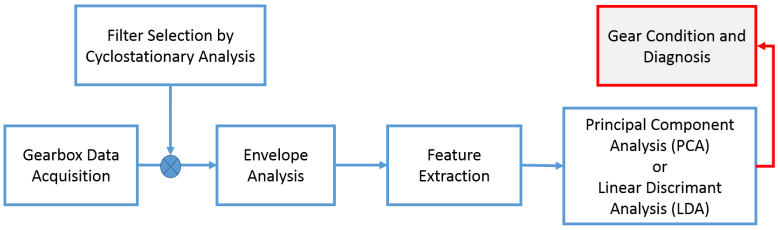


Figure 1: Proposed method for gearbox faults diagnosis.

2.2 Pre-Processing Methods

Two main methods are adopted to obtain clearer gearbox signals. One is cyclic spectral correlation (CSC), which is used as the identification of the structure resonant modes, the carriers, and as selection criterion for the band-pass filter, thus providing an alternative to the Kurtogram. The other is the Envelope Analysis, where only the impulsive frequencies that carry the shaft frequencies are band-pass filtered around said carrier frequencies.

Cyclic Spectral Correlation (CSC)

Cyclic spectral correlation (CSC), allows for the definition of appropriate filter bands by identifying the cyclo-stationary aspects of the signal. This is made possible by a statistical descriptor which measures the level of periodicity of a signal. The cyclo-stationarity of a signal x is defined as the level of T-periodicity of its autocorrelation R_{xx}.

$$R_{xx}(t,\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x\,(t-\frac{\tau}{2})\;(t+\frac{\tau}{2})dt \tag{1}$$

The definition allows one to obtain the cyclo-stationarity of second order, which models well the bearing signals, as well as the first order, which models well the gear signals. In fact, it efficiently differentiates between these two [11].

The CSC determines the spectrum of the signal at each different periodic lag. In other words, it shows the correlation levels at each carrier frequency f when modulated by the cyclic frequencies α. The examination of these coefficients is where the CSC reveals the cyclo-stationary signals carriers at their modulation (cyclic) frequency.

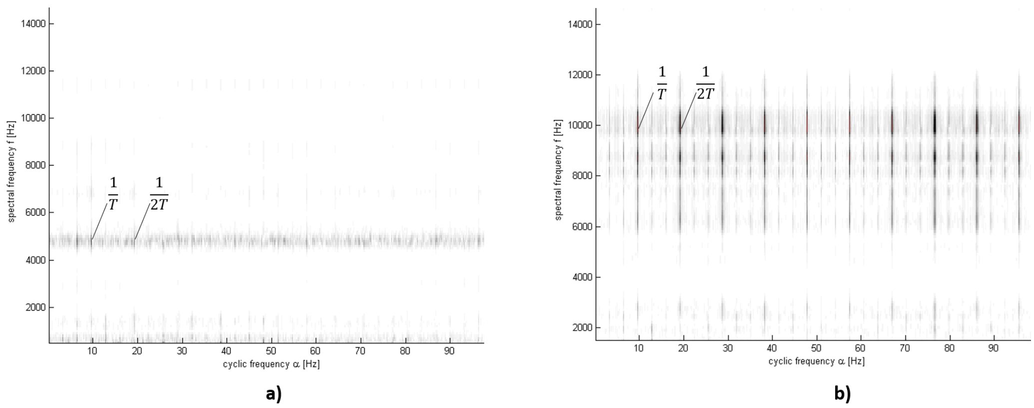


Figure 2: Cyclostationary analysis of two faulty gearbox: a) chipped tooth ; b) missing tooth.

The analysis, besides the ability to reveal both hidden and deterministic signals, also allows automation of the process of the Envelope Analysis. Assuming the speed of the gearbox shaft is known, the corresponding cyclic frequency coefficients are selected, and the maximum values are extracted. Applying this method to an example given in fig.2, it is seen that the maximum value of the chipped tooth for the shaft frequency of $\frac{1}{T}$ results in a spectral frequency equal to 4.5 kHz. The resonant modes due to the missing tooth impulses are shown to be different when compared to the chipped tooth impulses, and at a cyclic correlation of $\frac{1}{T}$ results in a wide band of frequencies centered around 8.5 kHz. This is indeed the filter selection that occurred on fig.3 that enhanced the missing tooth impulses.

Envelope Analysis

The fundamental basis to envelope analysis is to band-pass filter vibrations that occur at high frequencies, thus removing the undesired mechanical component signatures, and enhancing the signal-to-noise ratio.

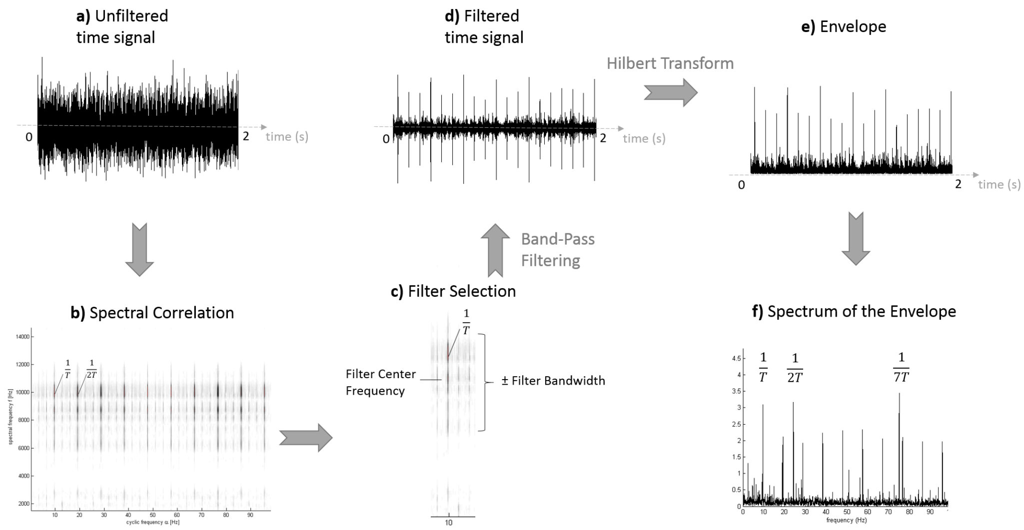


Figure 3: The process of Envelope Analysis for a faulty gearbox with acoustical signal.

The CSC determines the filter parameters from the speed reference. Afterwards the signal is filtered with these parameters and the envelope is applied, so as to obtain the low frequencies of interest.

3. Feature Extraction

3.1 Time Domain Features

Features are measured properties that provide information on an observed phenomenon, such as the state of a gear in this case. The selected features are usually applied to obtain the amplitude levels of the vibration signal after envelope analysis. The amplitudes in the time domain are theoretically affected by the fault in that band of frequencies. Well-selected features will thus contain information about possible faults in the structure. Selected features known to perform well for the studied type of faults [4, 5] are:

- 75^{th} Percentile (P_{75})
- Shannon Entropy ($Ent_{Shannon}$)
- Logarithmic Entropy Energy (Ent_{log})
- Standard Deviation (σ)
- Peak to Peak (PP)
- ENA4

- Crest Factor (CF)
- Speed

3.2 Principal Component Analysis (PCA)

As it is difficult to visualize 8 features and to obtain more definitive conclusions towards developing a diagnostic tool, these features are transformed into a lower dimensional space. This dimensionality reduction can be established through the use principal component analysis (PCA).

PCA is a technique that transforms the m features of a measurement into a set of m uncorrelated variables, referred to as principal components (PCs). The transformation is determined by the eigenvectors of the covariance matrix between the feature values (vectors of dimension m) and defined such that the first PCs contribute the most to the variance. In short, this process selects a vector that maximizes the variance of the dataset, and the following orthogonal vectors to it that maximize the remaining variance.

When it is assumed that a greater variability captures more information about the state of the gears, and low variability is caused by noise, keeping only the first $n < m$ PCs will still allow to differentiate healthy and faulty gears while making visualization more practical.

While PCA can be used for dimensionality reduction, since it only takes the selected features into account and does not use the information about gear states. This type of methods, that do not incorporate information about the class (i.e. gear states in this application) where a measurement belongs to are said to be unsupervised. In contrast supervised methods do utilize class information to find the optimal transformation of the features.

3.3 Linear Discriminant Analysis(LDA)

Linear Discriminant Analysis (LDA) is a supervised method that can be used to perform dimensionality reduction. Unlike PCA, the transformation generated by the LDA will group measurements of the same class as close as possible with minimizing the variability in the class, while maximizing variability between the classes.

By the nature of the method, LDA reduces the *m* features of the measurement to *k - 1* variables, with *k* being the number of different classes. In this application with *k = 3* gear states, the transformation with LDA will thus results in *2* variables.

4. Experimental Setup

The experiments were conducted in a machine fault simulator (MFS) from SpectraQuest, built specifically for the study of mechanical damage, shown in fig.4.

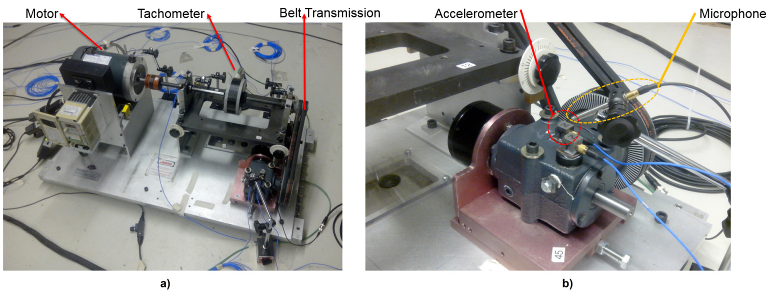


Figure 4: SpectraQuest's Machine Fault Simulator (MFS) test rig from Siemens.

The Gearbox faults are divided into three levels of damage imposed on the pinion **:** Healthy, Chipped Tooth, and Missing Tooth. Figure 5 shows the pinions, for the healthy and faulty specimens.

In this paper, only accelerometer signals in the z-direction (vertical) were considered.

Each measurment is 90 seconds long and is divided into 3-seconds observations. Signals are acquired at 8 speeds, with a minimun of 16 revolutions each, resulting in a dataset with 720 observations in total.

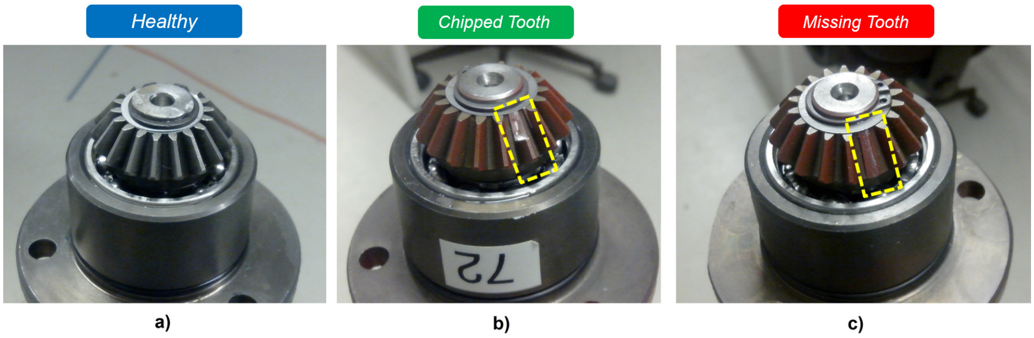


Figure 5: Three pinions for the experimental test: a) healthy ; b) chipped tooth ; c) missing tooth.

The applied features for the fault diagnosis show a correlation with the speed of the shaft. In order to discriminate them from the analysis, the various frequencies of interest are presented in Table 1.

Table 1: **Frequencies of Interest for Different Speeds**

Motor Speed	780	1020	1260	1500	1740	1980	2220	2460
Input shaft frequency (f_r)	5.2	6.8	8.4	10	11.6	13.2	14.8	16.4
Gear Mesh Frequency (GMF)	86	115	144	172	201	229	265	293

5. Analysis

The same filter is applied to all three cases in order to compare them under the same conditions. The signals are first compared without any pre-processing and then filtered around 4.5 kHz and 8.5 kHz.

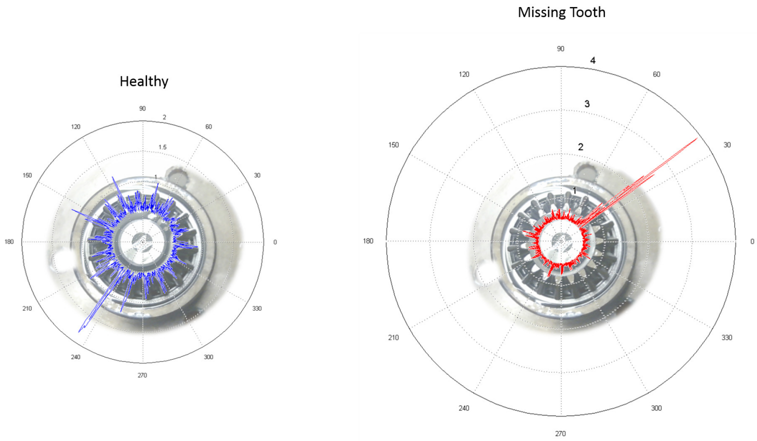
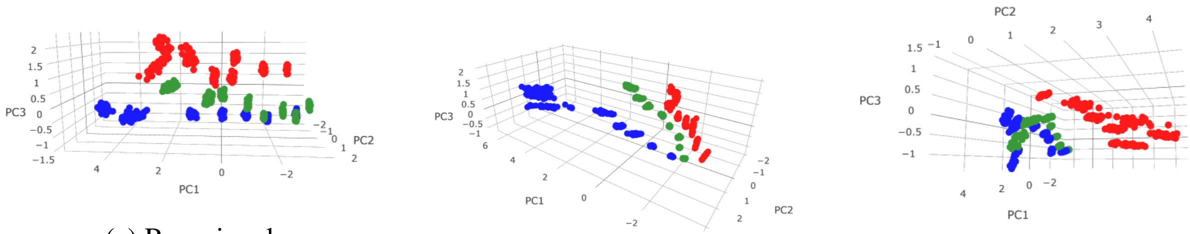


Figure 6: Order Tracked of the healthy pinion and missing tooth pinion

The results show that both the healthy case and the chipped tooth case present the same resonant modes around the 4.5 kHz band, and that their variation is negligible for different speeds, where the same resonant modes are all around this band of frequencies. The missing tooth shows a different band of resonant modes around the 8.5 kHz band, and similarly to the other two cases, these resonant modes do not vary with the speed.

This selection provided with the correct carrier frequencies for the impulses as expected. Figure 6 represents an angular re-sampled representation of the signals after performing the envelope analysis of the healthy case at 4.5 kHz and the missing tooth case at 8.5 kHz. These show clearly one missing tooth impulse per revolution, and the healthy case shows 18 impulses per revolution, one impulse for each of the 18 teeth on the gear.

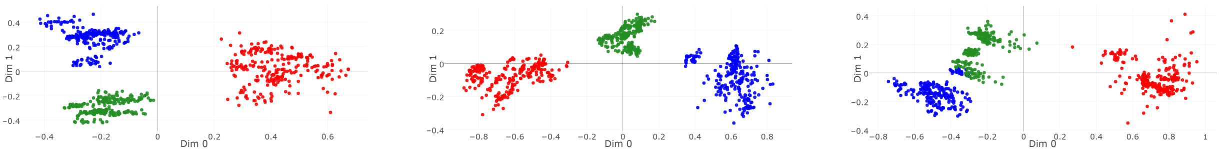


(a) Raw signal (b) Filtered around 4500Hz (c) Filtered around 8500Hz

Figure 7: 3D PCA plot of the Vibration Signals

Applying the PCA directly to the raw signals already allows to differentiate the three different faults. Filter 1 provides the best results to distinguish the three fault levels, as all of them are separated from each other for every measured speed in the PCA plot (fig.7a). This agrees with the analysis so far, as for this filter parameters the envelope signals were seen to have a decreasing level of amplitudes, from the healthy, through the chipped and until the missing. This trend is also represented in Fig.7b. As Fig. 7c shows, Filter 2 selected the frequencies of interest for the missing tooth signal, allowing to distinguish the missing tooth even better. The samples corresponding to this gear fault are completely separated from the other two gears, making visual identification of this fault becomes evident for all speeds with better results than for the raw case.

Unlike PCA, which solely represents the data in an efficient manner, the focus of LDA is to discriminate the classes efficiently. Due to this nature, dimensionality reduction applied with LDA results in a better differentiation in a low dimensinal space compared to PCA.



(a) Raw signal (b) Filtered around 4500Hz (c) Filtered around 8500Hz

Figure 8: 2D LDA plot of the Vibration Signals

For the raw signals and with filter 1 applied, all faults can be diagnosed. Filter 2 is only able to clearly distinguish missing tooth. The performance for the healthy and chipped tooth cases is clearly lower compared to the analysis of the raw signal and Filter 1, as seen in fig. 8.

5.1 Conclusions

In the present paper, gearbox faults were analysed using different signal processing techniques. Envelope analysis enhances the fault signature, but its application depends on the filter selection. Spectral Correlation proves to be a strong filter selection for the all vibration signals analyzed, resulting in clear signals for each fault case. With the pre-processed signals, the features extracted relevant information that allows differentiation between faulty signals. The analysis concludes that spectral correlation is a strong tool for filter selection, and the methodology correctly diagnoses faults.

LDA shows good results separating the cases without any filter, but being a classification method, a label needs to be assigned. Filtering around the chipped tooth resonant modes shows clear separation of the three cases, using PCA, making the application of the remaining filter redundant, as the missing tooth fault is already diagnosed with the former filter.

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