Use of a Spatially Adaptive Thresholding Method for the Condition Monitoring of a Wind Turbine Gearbox

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ABSTRACT

Condition monitoring of wind turbine gearboxes is an important practice in order to determine the state of the wind turbine drivetrain. In this way reparative actions could be taken whenever needed, resulting in reduction of maintenance costs. In this paper, time-frequency analysis is performed on real wind turbine gearbox datasets using the empirical mode decomposition method. Then, the outlier analysis method is applied to the power of certain intrinsic mode functions of the decomposed - using the empirical mode decomposition method - gearbox experimental datasets. These intrinsic mode functions are chosen according to their frequency content. They are related to the harmonics of the meshing frequency of the damaged stage of the gearbox examined. The outlier analysis method is a well- established method in the structural health monitoring field that computes discordancy measures for data and compares them with a threshold. Here, it is used as a standard approach whose results can be used for comparison. Finally, a novel thresholding method is proposed for feature discrimination - the phase space thresholding method. It is shown that for the particular case of gear tooth damage, because of the way it manifests in the vibration signals, the phase space thresholding method proves to be a very satisfactory method that can be used for an enhanced condition monitoring strategy.

KEYWORDS : *condition monitoring, empirical mode decomposition, outlier analysis, phase space thresholding method, adaptive threshold*

INTRODUCTION

The condition monitoring field aims at the health assessment of rotating machinery examined through the monitoring of parameters indicative of their condition. In order to perform condition monitoring based on the collection of vibration signals most of the times advanced signal processing and machine learning algorithms are needed for the feature extraction and feature discrimination steps of this process.

Feature discrimination can be achieved by two different approaches, the *supervised* and the *unsupervised learning* approaches. *Unsupervised learning* methods for damage detection do not require all the class labels of the acquired data. This is an advantage over the *supervised learning* methods, since it is the most common case that data describing all damage classes of a structure, cannot be provided. A good tutorial overview of such techniques can be found in reference [1]. Some of the *supervised learning approaches* used in the structural health monitoring and condition monitoring field include: Bayesian classification methods, nearest-neighbour algorithms, artificial neural network classifiers [2, 3] and more recently support vector machines [4]. *Unsupervised learning approaches* have received less attention [5]; it is not easy however to apply in practice supervised learning techniques due to the lack of training data required for the models corresponding to damaged systems. For this reason, in the current study the authors propose an unsupervised learning approach.

Novelty detection belongs to the unsupervised learning approaches and in statistics is also known as *outlier detection* and it can be achieved by assuming that selected features defining a normal condition follow the Gaussian distribution [6]. In [6] the Mahalanobis squared-distance measure is used as a discordancy measure and the threshold value is estimated through the employment of a Monte Carlo method.

Here, a different outlier detection method will be proposed. It is based on the idea of *spatial adaptation*, a term that exists in the statistical literature and describes methods that can be used for regression and classification and operate without an initially pre-defined fixed basis, but rather create this basis during their application, according to the data being analysed.

The method proposed in this paper was developed originally in reference [7] where it was used for acoustic-Doppler velocimetry data analysis. Spike detection in this case was achieved by exploiting the three following concepts [7, 8]: a) that differentiation enhances the high frequency portion of the signal, b) that the expected maximum of a random series is given by the *universal threshold*, and c) the idea of a "good" data cluster in a dense cloud in phase space or Poincaré maps. In this paper, it will be shown that the method can be successfully applied for the purposes of condition monitoring when one follows the steps described here.

1. BACKGROUND THEORY

1.1 Outlier analysis

Outlier analysis is already known in the structural health monitoring field since the publication of reference [6]. For his reason the authors will just summarise the basic theory of the method in this section.

In general, the *outlier analysis* method computes discordancy measures for data and compares them with a threshold. In the case of multivariate data, the discordancy measure is the *Mahalanobis squared-distance*:

$$D_\zeta^2 = (\{x\}_\zeta - \{\bar{x}\})^T [\Sigma]^{-1} (\{x\}_\zeta - \{\bar{x}\}) \tag{1}$$

where $\{x\}_\zeta$ is the feature vector corresponding to the candidate outlier, $\{\bar{x}\}$ is the sample mean of the normal condition features and $[\Sigma]$ is the normal condition feature sample covariance matrix.

The threshold value that labels the inlier and outlier observations can be estimated through the employment of a *Monte Carlo* method. Briefly, a $p \times n$ matrix (p-observations, n-dimensions, in order that the matrix dimensions match the dimensions of the extracted features) is generated and populated with elements randomly drawn from a zero-mean, unit standard deviation Gaussian distribution. Then the Mahalanobis squared-distance is calculated for all elements and the largest value stored. This is repeated a large number of times, each time storing the largest Mahalanobis squared-distance, which are then sorted in order of magnitude. The threshold is assigned as a percentile of the resulting array of Mahalanobis squared-distances.

1.2 Phase-space thresholding method

The alternative method proposed in this paper is known as the *phase-space thresholding* method. This method constructs an ellipsoid in three- dimensional phase space and points lying outside the ellipsoid are designated as spikes. In [7], a three-dimensional Poincaré map or a phase space map is a plot in which a variable and its derivatives are plotted against each other. The threshold used in this case is defined by the Universal criterion and an ellipsoid is formed in this way in the three-dimensional space that separates inliers from outliers. The *universal threshold* arises from a theoretical result from normal probability distribution theory that was introduced in the landmark paper given in reference [10]. For n independent, identically distributed, standard, normal random variables ξ_i the expected absolute maximum is:

$$E(|\xi_i|_{max}) = \sqrt{2\log n} = \lambda_U \tag{2}$$

where λ_U is termed the *universal threshold*. For a normal, random variable sample, that consists of n data points and whose standard deviation is estimated by σ and the mean is zero, the expected absolute maximum is:

$$\lambda_U \sigma = \sqrt{2\log n}\sigma \tag{3}$$

The algorithm consists of a number of sequential iterations that stop when the number of good data becomes constant (or, equivalently the number of new points identified as outliers, peaks in the power diagrams in this case, falls to zero). If u_i is the dataset being analysed, then each iteration has the following steps:

- Calculate Δu_i and $\Delta^2 u_i$ for the first and second derivatives from:

$$\Delta u_i = (u_{i+1} - u_{i-1})/2 \tag{4}$$

$$\Delta^2 u_i = (\Delta u_{i+1} - \Delta u_{i-1})/2 \tag{5}$$

- Calculate the standard deviations of all three variables σ_u, $\sigma_{\Delta u}$ and $\sigma_{\Delta^2 u}$, and then the expected maxima using the *universal criterion*.
- Calculate the rotation angle of the principal axis of the $\Delta^2 u_i$ versus u_i using the cross correlation:

$$\theta = tan^{-1}(\frac{\sum u_i \Delta^2 u_i}{\sum u_i^2}) \tag{6}$$

- Each set of variables $\{u_i, \Delta u_i, \Delta^2 u_i\}$, determines a point in spherical coordinates. For each pair of these variables, an ellipse can be calculated. Therefore, for Δu_i versus u_i the major axis is $\lambda_U \sigma_u$ and the minor axis is $\lambda_U \sigma_{\Delta u}$; for $\Delta^2 u_i$ versus Δu_i the major axis is $\lambda_U \sigma_{\Delta u}$ and the minor axis is $\lambda_U \sigma_{\Delta^2 u}$; and for $\Delta^2 u_i$ versus u_i the major and minor axes a and b respectively, can be shown by geometry to be the solution of:

$$(\lambda_U \sigma_u)^2 = a^2 cos^2\theta + b^2 sin^2\theta \tag{7}$$

$$(\lambda_U \sigma_{\Delta^2 u})^2 = a^2 sin^2\theta + b^2 cos^2\theta \tag{8}$$

- For each projection in space the points that lie outside of the ellipse are identified and replaced with a smoothed estimate in order to perform the next iteration.

At each iteration, replacement of the outliers reduces the standard deviations calculated in two and thus the size of the ellipsoid reduces until further outlier replacement has no effect.

2. EXPERIMENTAL DATASETS

The experimental gearbox vibration data analysed in this study comes from an NEG Micon NM 1000/60 wind turbine in Germany. The measurements of the experimental data have been taken by members of the company EC Grupa, a Polish engineering company that maintains the wind turbine system from which the gearbox vibration datasets were obtained. The gearbox consists of three gear stages: one planetary gear stage and two spur gear stages. The measurements come from a single accelerometer chosen by EC Grupa to be carrying more information concerning the damage of the gearbox. The sampling frequency of the measurements was 25000 Hz.

Acceleration signals from this gearbox were obtained at three different dates: $31/10/2009$, $11/2/2010$ and $4/4/2010$. The first dataset was described as the one to be used as a reference. This is sensible because one expects damage to increase. If it transpired that the system was undamaged at the first test, then one would see clear signatures of damage in the later data. If it transpired that damage was already present during the first test, one can still use it as a reference and look for increased signatures of damage. The second dataset was considered to be one describing an early tooth damage of the gearbox and the third one was the dataset of the vibration signal with progressed tooth damage in the gearbox.

Generally, it is known that it is in the harmonics of the meshing frequency of the damaged gear pair that damage features occur.

The frequency components of the signal are the following:

- 15.07, 30.14 Hz: relative meshing frequency and second harmonic of the planetary gear,
- 89.535, 179.07 Hz: relative meshing frequency and second harmonic of the 1^{st} parallel gear stage,
- 352, 705, 1056, 1410, 2115, 2820 Hz: relative meshing frequency and harmonics of the 2^{nd} parallel gear stage.

In order to perform time-frequency analysis, the signals were decomposed using the *empirical mode decomposition method* (EMD) into a set of signal components (oscillatory functions) in the time-domain called *intrinsic mode functions* (IMFs). The EMD is now relatively known in the signal processing field. The procedure for extracting the IMFs from the signal analysed is known as the *sifting process* and is an empirical algorithm (not mathematically proven), as suggested by the name of the method, that is described thoroughly in [11]. Each extracted IMF (decomposed signal component in the time-domain) represents a frequency region in the frequency domain with the first IMF representing the highest frequencies of the signal and the sequential IMFs representing corresponding sequential lower frequency regions of the signal. Figure 1 shows the EMD results of only the first four out of thirteen IMFS produced for each case.

In this example the second IMF produced by the decomposition proved to be the one most sensitive to damage since it described in the frequency domain a harmonic of the meshing frequency of the damaged gear stage, making the impulses known to be related in the condition monitoring field to such damages as gear tooth faults [12] more visible (Figure 1). Envelope analysis can then be performed in order to enhance the impulsive nature of the damage features. Envelope analysis is most commonly performed using the *Hilbert Transform* (HT), in this study though an alternative approach is used exploiting the use of the Teager Kaiser energy operator and an energy separation algorithm, which for certain signals and under the appropriate circumstances is known to improve the results [13]. This approach has only been used very few times in the condition monitoring field [14, 15]. The power of the envelope of the second IMF is finally the signal chosen in order to perform outlier analysis (Figure 2).

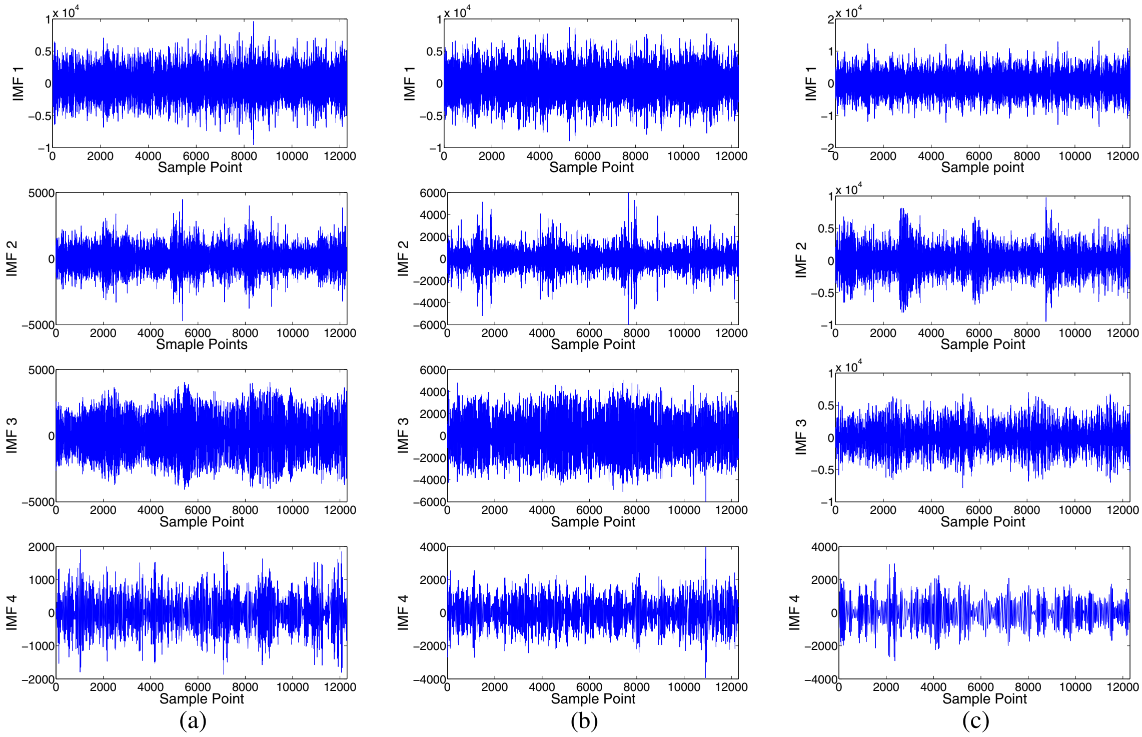

Figure 1 : First four IMFs of the wind turbine gearbox data: (a) 31/10/2009, (b) 11/2/2010, and (c) 4/4/2010.

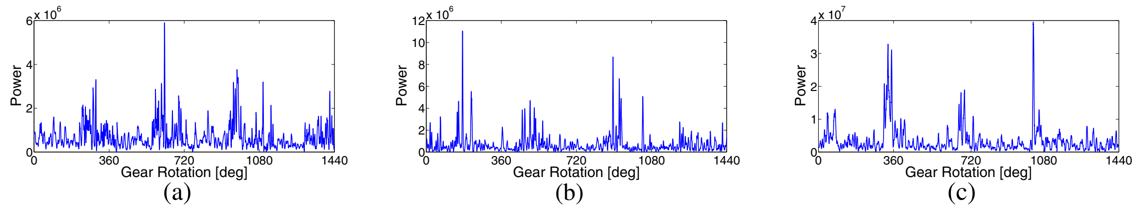

Figure 2 : Power (TKEO/ Desa-1) of the 2^{nd} IMF: (a) 31/10/2009 (b) 11/02/2010 and (c) 4/04/2010.

3. Results and discussion

Concerning the outlier analysis results and the way the features were selected in the power diagrams, a 10-dimensional feature was defined as a 10-point time window. One series of 200 features was defined as reference and used for the training data. The training data were chosen carefully in order that no peaks (of the power measure) would be included in them. Whenever a fault appears, the outlier statistics diagram should show a peak that is distinct from the normal condition data.

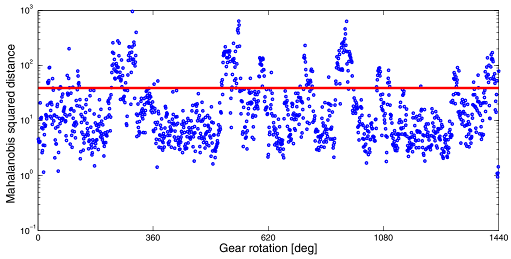

Figure 3 : Outlier statistics for the power of the 2^{nd} IMF for the 31/10/2009 dataset (training data 280-480).

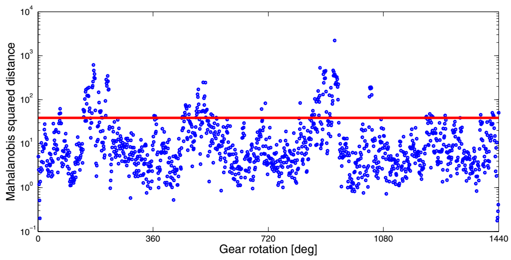

Figure 4 : Outlier statistics for the power of the 2^{nd} IMF for the 11/2/2010 dataset (training data 200-400).

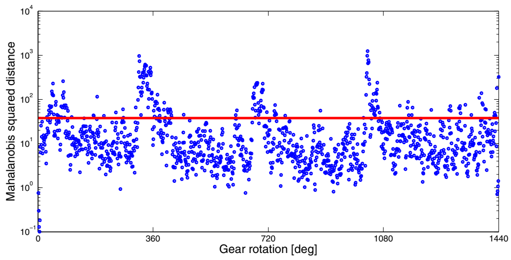

Figure 5 : Outlier statistics for the power of the 2^{nd} IMF for the 4/4/2009 dataset (training data 350-550).

The results of the outlier analysis using the Mahalanobis squared-distance measure, presented here in Figures 3, 4 and 5 show that the method manages to detect the peaks in the power. The results are presented in a log scale in the figure. A significant amount of outliers at areas where the damaged gear rotation degrees don't coincide with the expected period of damage.

In order to eliminate the additional alarms detected and continue in an adaptive signal processing framework, the spatially adaptive thresholding method proposed will be used and its results on the same dataset will be presented at this point.

Finally Figures 6,7 and 8 show the final estimation of outliers using the phase space method. The diagrams are very satisfying, since all of the power peaks have been detected and it is shown that in this particular case the method indeed manages to detect particularly the points where there is an increase of power known to be related to tooth damage while at the same time labels the points that do not have such a dramatic power increase as inliers. Therefore it seems that in this case the results are indeed improved and that the application of the phase-space thresholding technique is a very promising and straightforward strategy for condition monitoring, especially when the faults observed are gear tooth faults or bearing faults, known to produce impulses in the vibration signals.

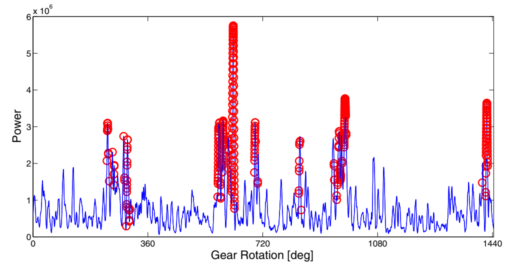

Figure 6 : Estimated outliers using the spatially adaptive threshold for the power of the 2^{nd} IMF for the 31/10/2009 dataset.

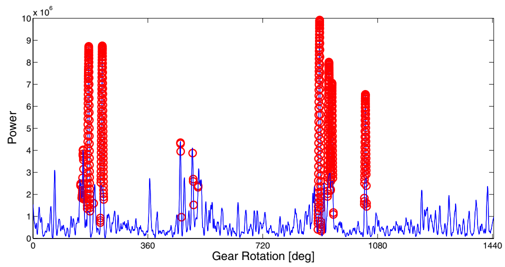

Figure 7 : Estimated outliers using the spatially adaptive threshold for the power of the 2^{nd} IMF for the 11/2/2010 dataset.

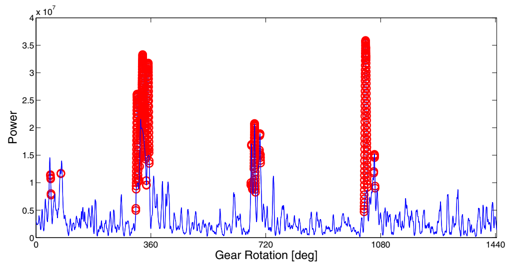

Figure 8 : Estimated outliers using the spatially adaptive threshold for the power of the 2^{nd} IMF for the4/4/2009 dataset.

CONCLUSION

In this study, two different novelty detection methods are applied to the features obtained from a time-frequency analysis of real wind turbine gearbox data, based on the empirical mode decomposition method. The first one has been used many times for damage detection and therefore, here, is treated as a standard approach. The use the Mahalanobis squared-distance for outlier analysis produced satisfying results that suggest that the method could be a simple choice for the specific application.

The second method presented is an adaptive thresholding method (*phase space thresholding*) that has not been used before in the condition monitoring field. Since the kind of features examined here are peaks in the power diagrams of the Hilbert or Teager spectra (and generally any kind of time-frequency analysis spectra), the method proved quite effective, identifying all the points in the diagrams related to damage.

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