Fingerprint analysis concept for gearbox health monitoring on speed transitory conditions using motor current signature analysis

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ABSTRACT

Preventing downtimes in machinery operation is becoming fundamental in industrial standards. The most common strategy to avoid costly production stoppages is the preventive maintenance, combining it with reactive maintenance in detected malfunctions. Preventive maintenance can reduce costs, increase uptime and help maintaining the quality of the produced goods. But it can generate added costs to maintenance. Broadly, the most efficient maintenance strategy is condition-based maintenance. To apply it condition monitoring (CM) must be put in place.

CM is more easily implemented relaying in a technique such as the fingerprint analysis concept (Ferreiro, 2016). The asset in a good health state is monitored as a set of pre-defined operating conditions. The monitorization can be triggered during the whole asset's life-time in the same pre-defined operating conditions. As a result, a reference value is taken which accounts for normality. This value will be compared with measurements made throughout the life. The goal is to be able to detect and determine the appearance of abnormalities.

Similarly, the fixed cycle features test assesses the machine performance degradation in a fixed cycle (Liao, 2009). In this case the concept is focused on machinery that works in close loops with comparable conditions. The machines parameters are measured during the working cycle, setting the baseline, and compared between them in the search of abnormalities that may point out any potential faults.

Both concepts, fingerprint and fixed cycle feature test concept can be applied to gearboxes. They are crucial elements in industrial machinery, conventionally monitored using accelerometers. Which have a significative cost and can be hard to install in place to provide useful information.

Motor current signature analysis overcomes the inconveniences of accelerometers. This analysis technique provides a non-intrusive method, and it is based in readily available signals. Changes in the current signal are related with variations of the speed and/or external load of the electric motor. Thus, the health state of the gearbox connected to the motor can be examined through an exhaustive analysis of the input currents (Arellano-Padilla, 2009).

In the present work motor current signature analysis is used for the determination of the health of gearbox. A specially designed test bench is used in which gears in different health status are tested. The measured signals are analyzed using discrete wavelet decomposition, in different decomposition levels and with different mother wavelets. Additionally, a dual-level time synchronous averaging analysis is performed on the same signal to compare the performance of the two methods. From both analyses, the relevant features of the signals are extracted, cataloged and classified using diverse methods.

The results obtained allow to differentiate the different type of defects on the gears. Allowing to detect the different fault conditions and enabling the assessment of the health state of the gearbox using only the motor current signal.

1. INTRODUCTION

Formerly the most common maintenance strategy was run to failure. Slowly preventive maintenance has gained importance. But it may cause unnecessary maintenance actions. CM prevents this inefficiency, at the same time it also prevent catastrophic failure. CM is defined as the continuous or periodic measurement and interpretation of data to indicate the condition of an item to determine the need for maintenance (BS 3811:1984).

Thus, CM is used to schedule maintenance activities according to the health condition of the asset., CM has been identified as a valuable tool to ensure the in service maximum utilization of assets. Therefore the benefits of CM include, among others, increase in equipment availability, reduce lifecycle cost, reduce risk, reduce wastage and rework.

Often continuous data acquisition, combined with analysis and pre-established warning/alarm levels is needed for CM. CM tools have greatly improved with time, making them more reliable and less costly. This has allowed CM to be introduced in manufacturing processes were it wasn´t present before.

An implementation of a CM program must be integrated by three key steps:

1. Data acquisition: To obtain data, relevant to the health state of the system.

2. Signal pre-processing: Improve data to noise ratio from the data collected in step 1.

3. Signal processing: To handle the data collected in step 1.

4. Feature selection: It gives the means to interpret the data. It must be able to detect the fault, locate it in the system, and identify the typology of the fault.

The above steps will provide the needed information so that the operators/maintenance engineers to take the best decision. The degradation of a system is monitored providing the means to act before the system has a failure.

There are many technologies that can be used for condition monitoring, including:

- Oil analysis (Randall, 2011)
- Thermography (Randall, 2011)
- Acoustic emission (Caesarendra, 2016)
- Vibration analysis (Randall, 2011)
- Motor current analysis (Benbouzid, 2000)

In the work that is presented an analysis of the health state of a gearbox is done. Three health states are included in this investigation (Severe damage, Medium damage and little damage. The current is analyzed extracting features form the signal, and by previously using a wavelet decomposition and dual level time synchronous averaging, showing the suitability of the pre-processing techniques for the health estimation of gears.

This paper is structured as follows: section 2 shows the fingerprint and the fixed cycle features test concepts for CM. In section 3 the equipment used for the experimental work; the motor current analysis performed in this work are presented in section 4 and section 5, respectively; and, finally, some conclusions are explained in section 6.

2. STRATEGIES TO APPLY CONDITION MONITORING

The most common strategy to implement CM so far, has been periodic inspection by an expert, but this is slow and may not be cost effective. In other cases, sensors for continuous monitoring have been added, but it is not widespread mainly for two reasons, the cost and the complexity of the installation.

It is important, for the application of continuous condition monitoring in a successful way, that the boundary conditions of the asset (i.e. speed, charge…) when measuring are comparable. That is why the fingerprint concept and the fixed cycle feature test have been developed.

2.1. Fingerprint concept

The fingerprint concept is based on the uniqueness of the signals generated at each asset, in an analogue way to our fingerprints (FERREIRO, 2016). The asset in a good health state is monitored as a set of pre-defined operating conditions. The monitorization can be triggered during the whole asset's life-time in the same pre-defined operating conditions. As a result, a reference value is taken which accounts for normality. This value will be compared with measurements made throughout the life. The goal is to be able to detect and determine the appearance of abnormalities.

The concept is applied following 4 steps (Bravo - Imaz, 2018). First, a failure mode analysis is made to select the fault objectives to be monitored. Second, the boundary conditions of the asset for the measurements are selected (speed, charge…). Third, an experimental campaign is performed, especially focusing on modeling normality to stablish the baseline of the health indicators. Finally, a prototype is designed and diploid.

2.2. Fixed cycle feature test

Fixed Cycle Feature Test (FCFT) is and strategy for monitoring and predictive maintenance of machines. FCFT, first introduced in (Liao, 2009), defines a fixed operational cycle consisting of both stationary and transient operational regimes to capture the signature of the machine in a variety of working regimes. Based on the possible spectrum of working loads and speeds, a working cycle is designed to collect data during a combination of different loads and speeds. Signature of the machine during this standard cycle is collected and analyzed to provide the health condition of the machine and provide predictions by comparing the current status of the machine to its previous cycles.

3. EXPERIMENTAL

The test rig, test procedure and the gears used in this paper are described in this section.

3.1. Test rig

The different gears were tested in the gearbox prognostic simulator (GPS) test rig, manufactured by Spectra Quest Inc, shown in figure 1. The test rig is that it allows the testing of faults that otherwise would be difficult to test in real machinery.

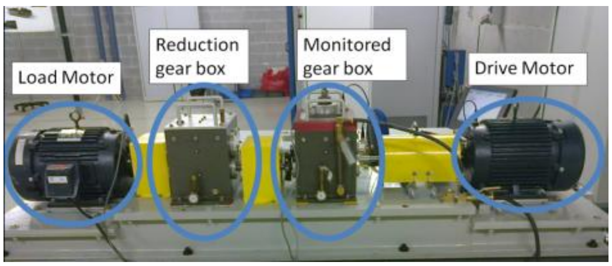

Figure 1. GPS test rig.

The GPS test rig is formed by two confronted motors; one is the diving motor (whose current is being measured) while the other motor provides the load. In addition, two gearboxes are used, the monitored and a reductor for the load motor. Both motors are identical; three-phases, two pair of poles and asynchronous.

The gearbox under test is the first one located after the driving motor. The monitored gearbox is a two stage gearbox, composed by three shafts, as shown in Figure 2. The test gear is the first one outside the driving motor, located in the input shaft.

The hall sensor is installed in the electric cabinet to monitor the current of the driving motor, more precisely a Lem HTA 100.

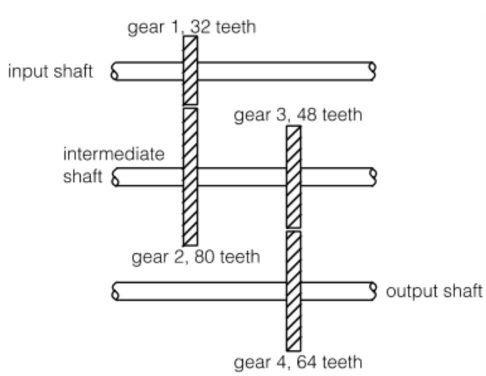

Figure 2. Schema of the monitored gearbox.

3.2. Tested gears

During the experiments the whole set-up is maintained in the same configuration except for the different gears under test inserted in the position of the gear 1 of the first gearbox (the 32 teeth gear in Figure 2).

Three gears are used in this study: one in a healthy state, which is used as reference; one with pitting in the teeth; and one with eccentricity in the shaft hole. Figure 3 displays photographs of these gears highlighting their representative health features. The pitting of the second gear was generated from intensive use in the gearbox. The eccentricity was intentionally produced by machining the gear.

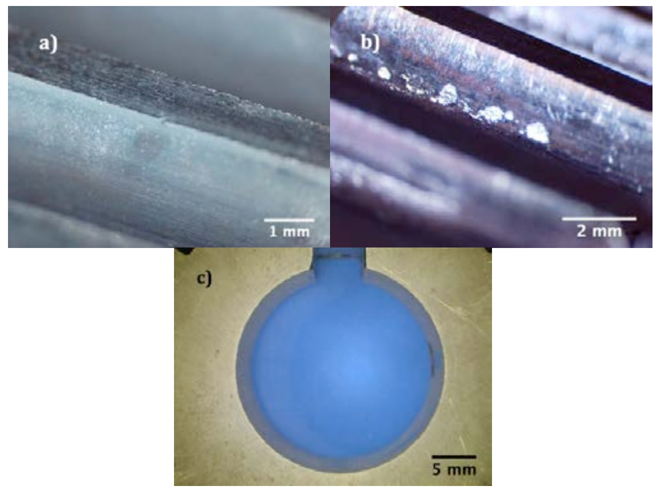

Figure 3. Images of the representative characteristics of the gears tested in this work. (a) healthy gear. (b) gear with pitting. (c) gear with eccentricity.

3.3. Test procedure

The current feeding the motor during the transient regime caused by speed changes from 1000 r.p.m to 1500 r.p.m, in a 30 s time interval is recorded. For each one of the tested gears, an experiment was conducted following the same structure: starting from cero speed, the motor was accelerated to the starting velocity target (1000 r.p.m.). Then the speed ramp to the final speed (1500 r.p.m.) was executed at constant acceleration, with a fixed duration of 30 s. After this the drive is commanded to stop and the cycle is repeated. A total number of 15 of such cycles are performed in each experiment, resulting in 15 data sets for each of the gears.

The sampling speed used for the measurements is 50000 Hz.

4. MOTOR CURRENT SIGNATURE ANALYSIS

The techniques used to pre-process the data, to compute features from the processed data and to select the most relevant features are explained in this section, as well as the algorithm used for classifying the features.

Motor current signature analysis has the potential to be used to determine the health state of the gears down-stream of the motor. But an extensive signal pre-processing and processing must be performed. In this section tow techniques for signal pre-processing and the features obtained are presented here.

4.1.Theoretical background

Motor current signature analysis has been used typically for the diagnosis of electric motor condition (Benbouzid, 2000). This technique can assess the condition of the winding, rotor bars and the internal bearings. For such purpose signal analysis is mandatory. The most common techniques used for motor current signal analysis are time domain analysis (using characteristic values), spectrum analysis, as well as Cepstrum analysis.

For the case of studying mechanical elements out of the motor some papers have been found. In particular, in the present paper motor current signature analysis has been proposed for monitoring bearings out of the motor (Singh, 2014). The signal analysis techniques used in this previous work also include time-frequency domain analysis. No commercially available product analyzing mechanical components out of the motor is known to the authors.

4.2.Discrete wavelet technique

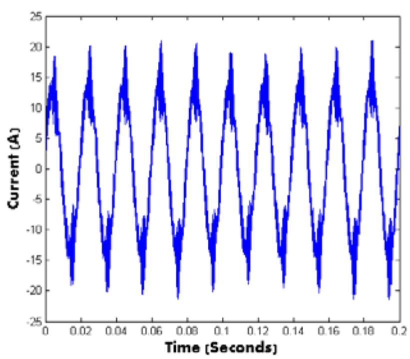

Figure 4. Image of the crude current information from the U channel of the driving motor.

In the wavelet pre-processing (Cusidó et al., 2008) (Peng et al., 2004), a wide range of mother wavelets was used from Haar, Daubechies, Symlets, Coiflets, BiorSplines, ReverseBior and DMeyer families summing a total of 106 different mother wavelets. In each case, 16 decomposition levels were obtained, and for each decomposition level 14 parameters were calculated: rms, average, peak value, crest factor, skewness, kurtosis, median, minimum, maximum, deviation, variance, clearance factor, impulse factor, and shape factor (Chandan et al, 2012) (Subasi, 2007). In total, 23744 descriptors were calculated for each one of the data sets.

4.3.Dual-level Time Synchronous Averaging

Time Synchronous Averaging (TSA) is a well-established technique for improving the signal-to-noise ratio and strengthening the periodic waveforms generated by the rotating components. For current signals, however, TSA is not effective due to two main reasons: 1) the motor slip slightly changes with the changes in speed and load, and hence the ergodicity and stochasticity of the noise components do not apply. 2) The supply line component, which is the most dominant peak in the current spectrum, oscillates at a slightly higher frequency than the actual speed of the motor due to slip phenomenon. Since this component is not cyclo-stationary and its wavelength is slightly longer than a full shaft rotation, it is neither fully retained nor completely eliminated using TSA method. Removing the supply line frequency using a bandpass filter is also a major challenge as it is very close to the shaft speed peak.

First introduced in (Ardakani, 2015), Dual-level Time Synchronous Averaging (DLTSA) is designed to overcome these challenges and effectively remove the supply line frequency component while retaining the cycle-stationary components of the current signal. These cyclo-stationary components can then be used to extract features that represent the health condition of the mechanical components within the motor itself or the downstream equipment such as shaft, bearing or gear systems. Figure 5 shows a flowchart of the DLSTA approach. Detailed explanation of the method is provided in (Ardakani, 2015), (Ardakani, 2016).

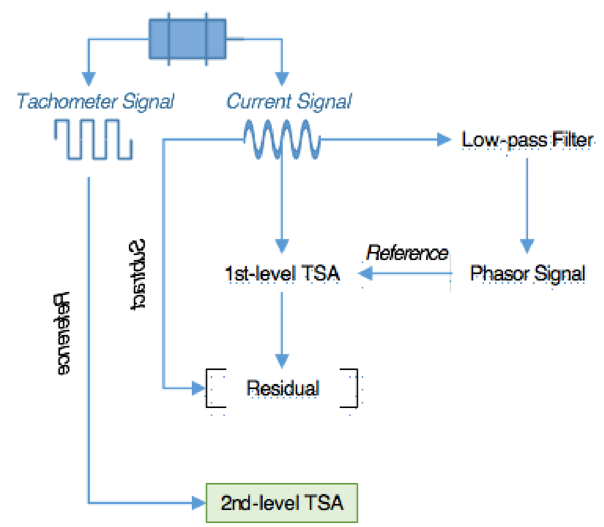

Figure 5. Flowchart of the suggested DLTSA approach (Ardakani, 2016).

The DLTSA approach was applied to the same data sets. After, features in both angle and order domains were extracted from signal data. The extracted features included standard deviation, kurtosis, peak-to-peak and crest factor in the angle domain, and magnitude of the signal at different orders in order domain. The same features were also extracted from classical residual and difference signals. The selection of the most relevant features was performed by four different techniques: analysis of variance, correlation feature selection, information gain and relief.

5. RESULTS

The results obtained were very promising, proving that motor current signature analysis is a valid technique for the analysis of gears, in gearboxes moved by electrical motors.

In the next section both preprocessing techniques will be compared. For that porpoise different classifiers and variable selection techniques are benchmarked. To be able to compare the results properly a t-student analysis is performed. Finally, the features from both methods are added up, and the same classifiers and selection methods are used, to determine if both feature sets are complementary.

Due to the intrinsic characteristics of our dataset (in which there were three different classes with equal number of instances per class) it was decided to use accuracy to measure the performance of the models. Other performance measures were also considered but, as the classes were balanced, they were discarded in favor of accuracy due to its simplicity and ease of understanding, as the use of more metrics would not provide much more information in this case scenario, and it would add complexity to the analysis.

The features that are used in this work are explained in section 4.2 y 4.3, as the wavelet and DLTSA pre-processing methods have produced too different sets.

5.1. Results from the classifiers

The data processed is the data from the U line of the drive motor of the GPS test rig.

To classify and allow an easy evaluation and interpretation of the parameters extracted from both types of analysis (wavelet and DLTSA), different classification algorithms (classifiers) were used; Bayesian network, J48 tree, intense based learning and sequential minimal optimization. Weka data mining software (Weka 3, 2018) was used for this purpose. The best features obtained from wavelet and DLTSA analysis have been previously selected using the analysis of variance, correlation feature selection, information gain and the relief algorithms. The features selected by each one of these methods constitute the feature vectors that will be given as input to the classifiers. For the wavelet method, these vectors contain: 23 features from the analysis of variance, 62 features from the correlation feature selection, 62 features from information gain and 62 from relief. For the DLTSA method, the feature vectors consisted of 7 features from the analysis of variance, 23 from the correlation feature selection, 23 from the information gain method, and 23 from the relief methods.

Each feature vector represents one stream of experimental signals collected from the test-stand. Remind that there are 15 repetitions, or labels, from each class of fault, i.e. 15 labels from the healthy state, 15 labels from the eccentricity fault and 15 labels from the pitting fault. The classifiers were tested using the cross-validation method. It divides the data set in 10 parts and uses one of them for testing and the rest for training. Each of the parts contains an approximately equal number of labels from each class. It does it 10 times, and the result is the mean and deviation of the testing.

In a future application, a big enough is key for the implementation of this method. The bigger the number of classified the better the results. A first set of data should be recorded and classified and used for training porpoise. After the best set of features, selection methods and classifiers will be selected and used. Based on the selection done future classifications can be performed.

We cannot say which analysis method (wavelet or DLTSA) is better based on the results complied in Tables 1 and 2. To determine if the differences in the results from each method are statistically relevant, a Student's *t*-test was performed. The results are shown in table 3.

Finally, the cross-validation method was applied to the classifiers using the combined set of features obtained from wavelet and DLTSA analysis. This analysis will allow us to determine if both data sets (wavelet and DLTSA) are complementary. The same feature selection methods and classifiers as the above cases were used. The results obtained showed that the lowest mean is 87.75 % and the highest is 100 % for this case. If compared directly, the results are improved (the lowest mean of classification is improved). These results are better than the ones obtained from each of the data sets separately.

6. CONCLUSION

Experiments have been performed, obtaining data from real machinery, testing different health states of gears. An analysis of the signal and a classification of the descriptors obtained were performed. The current signal signature analysis has proved to be a valuable technique for the health classification of gears moved by an electric motor.

Comparing the results from discrete wavelet decomposition and DLTSA, using the results of the Student's t-test, some of the results appear to be better for the Wavelet technique and others for the DLTSA, but both are strongly dependent on the feature selection and classification methods selected. Strong variations in the percentage of accuracy and its deviations can be seen. Therefore, with the present data set, no clear differences exist in the performance of both techniques (although the wavelet analysis provides a 100% accuracy in one of the instances). The combination from both pre-processing techniques, wavelet and DLTSA, provides an improvement of the results, as the worst results in the tables are improved if compared with both methods.

Table 1. Results from the cross validation of the features selected for the Wavelet analysis.

Wavelet analysis								
	Classifier							
	Bayesian Network		**Sequential minimal optimization**		**Intense based learning**		**J48 tree**	
	μ (%)	**σ**	**μ(%)**	**σ**	**μ (%)**	**σ**	**μ (%)**	**σ**
Anova	85.05	14.49	88.65	15.60	90.85	13.01	72.95	19.68
CFS	100.00	0.00	97.25	8.05	86.90	13.78	90.30	12.98
Gain	88.00	16.13	90.20	14.30	90.05	12.72	90.80	13.35
Relief	87.80	16.10	92.35	13.38	95.50	10.58	89.30	14.32

Table 2. Results from the cross validation of the features selected for the DLTSA analysis.

DLTSA analysis								
	Classifier							
	Bayesian Network		**Sequential minimal optimization**		**Intense based learning**		**J48 tree**	
	μ (%)	**σ**	**μ(%)**	**σ**	**μ (%)**	**σ**	**μ (%)**	**σ**
Anova	92.05	10.76	74.55	16.56	94.75	9.88	91.05	12.54
CFS	94.70	9.56	63.75	17.87	84.90	15.36	91.60	11.26
Gain	59.60	9.58	61.55	14.83	58.35	18.18	64.20	14.66
Relief	94.45	9.74	69.20	19.88	94.00	10.00	92.50	10.98

Table 3. Results from the Student's *t*-test analysis.

Student's *t*-test analysis				
	Classifier			
	Bayesian Network	**Sequential minimal optimization**	**Intense based learning**	**J48 tree**
	***t* value**	***t* value**	***t* value**	***t* value**
Anova	1.226490	-1.959858	0.754938	2.452777
CFS	1.753145	5.405058	0.306491	-0.239240
Gain	5.107274	4.607240	2.651491	2.918252
Relief	-0.530402	2.544566	-2.367907	-1.078985

Table 4. Results from the cross validation of the features selected for the sum of Wavelet and DLTSA analysis.

Wavelet +DLTSA analysis								
	Classifier							
	Bayesian Network		**Sequential minimal optimization**		**Intense based learning**		**J48 tree**	
	μ (%)	**σ**	**μ(%)**	**σ**	**μ (%)**	**σ**	**μ (%)**	**σ**
Anova	96.05	8.54	92.50	12.34	85.25	14.27	81.80	15.71
CFS	100.00	0.00	98.25	6.64	95.70	8.99	87.15	13.62
Gain	95.35	9.14	92.30	12.58	90.25	12.72	87.15	12.84
Relief	87.80	16.10	93.70	11.21	98.40	5.90	88.00	11.98

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Dr. Alfredo García-Arribas got his Ph.D. degree at the Universidad del País Vasco (Spain) in 1996. He is currently with the Departamento de Electricidad y Electrónica in the same University. He is mainly interested in soft magnetic properties of materials and their application to magnetic sensors and actuators.

Dr. Jay Lee is Ohio Eminent Scholar, L.W. Scott Alter Chair Professor, and Distinguished Univ. Professor at the University of Cincinnati and is founding director of National Science Foundation (NSF) Industry/University Cooperative Research Center (I/UCRC) on Intelligent Maintenance Systems (IMS), which is a multi-campus NSF Industry/University Cooperative Research Center which consists of the University of Cincinnati (lead institution), the University of Michigan, Missouri University of S&T, and the University of Texas-Austin. Since its inception in 2001, the Center has been supported by over 100 global companies.

His current research focuses on intelligent prognostics and predictive analytics. He has authored/co-authored numerous highly influential articles and technical papers in the areas of machinery monitoring and prognostics, E-manufacturing, and intelligent maintenance systems.

Prof. Lee has over 20 patents and trademarks. He is a Fellow of ASME, SME, as well as a founding fellow of the International Society of Engineering Asset Management (ISEAM) and has received a number of awards including the most recent Prognostics Innovation Award at NI Week by National Instruments in 2012.