ENVELOPE ANALYSIS AND DATA-DRIVEN APPROACHES TO ACOUSTIC FEATURE EXTRACTION FOR PREDICTING THE REMAINING USEFUL LIFE OF ROTATING MACHINERY

Darren F. Kavanagh‡, Patricia Scanlon† and Frank Boland‡*

†Alcatel Lucent - Bell Laboratories Ireland, Dublin, Ireland
email:scanlon@alcatel-lucent.com
‡Dept. of Electronic and Electrical Engineering, Trinity College Dublin, University of Dublin, Ireland
email:kavanadf,fboland@tcd.ie

ABSTRACT

The ability to predict the Remaining Useful Life (RUL) of Rotating Machines is a highly desirable function of Automated Condition Monitoring (ACM) systems. Typically, vibration signals are acquired through contact with the machine and used for monitoring. In this paper, a novel implementation of the ubiquitous feature extraction approach Envelope Analysis (EA) is applied to acoustic noise signals ($< 25kHz$) to predict the RUL of a rotating machine. A well known drawback of the EA approach is that the frequency band of interest must be known or pre-estimated. Therefore, this approach is compared to a Data-Driven approach to feature extraction which utilizes an Information Theoretic approach to feature selection that does not require any a-priori information regarding the frequency band of interest. It is shown that the Data-Driven approach, with an accuracy of 97.7%, significantly outperforms the EA approach, with an accuracy of 93.7%. This study also shows that the improved performance of the Data-Driven approach is due to new information being uncovered in spectral locations across the entire spectrum from 0 to 25kHz, and not just within one frequency band typically used by the EA approach.

Index Terms— Acoustic Signals, Signal processing, Information Theory, Pattern classification, Mechanical Bearings.

1. INTRODUCTION

Automated Condition Monitoring (ACM) of rotating machinery typically involves the detection and diagnosis of defects in bearings, this approach is widely reported on in the literature [1, 2, 3]. While the detection and diagnosis of defects is useful for ACM, there is an increasing demand for ACM systems to also predict the Remaining Useful Life (RUL) of machinery. Predicting the RUL allows for improved reliability of machinery, scheduling of maintenance prior to failure to prevent machine downtime and the removal of the cost of unscheduled maintenance. Predicting the RUL of a machine has been explored to a much lesser extent in the literature [4, 5, 7].

ACM systems reported in the literature typically acquire and monitor the vibrational signal, both low frequency vibrations and acoustic emissions (high frequency vibrational signal) [1, 2, 3, 4]. The acquisition of such vibrational signals requires physical contact with the machine being monitored. However, in real world conditions, it is not always desirable or possible to acquire good quality vibration signals. In this paper, the acoustic noise signal ($< 25kHz$) is monitored in order to determine the RUL. This approach is advantageous as it allows for remote, non-contact monitoring of machines. As an aside, while acoustic signals are obviously susceptible to ambient noise, vibrational signals are also susceptible to vibrational noise from nearby sources (e.g. machinery, etc).

Envelope Analysis (EA) feature extraction technique is widely reported on in the literature for detection and diagnostics of bearing defects using the machines vibration signal [1, 2, 3]. This approach to feature extraction is ubiquitous in the Condition Monitoring industry. To the best of our knowledge, no application of the EA approach to acoustic noise signals ($< 25kHz$) or to the task of predicting the RUL of machines, has been reported in the literature. The work presented in this paper describes a novel implementation of the traditional EA feature extraction technique applied to acoustic noise signals to determine the RUL of a rotating machine.

However, one major drawback of the EA approach to feature extraction, often discussed in the literature [1, 6], is that the frequency band of interest, the cut-off frequencies, must be determined a-priori. A Data-Driven approach to feature extraction is therefore proposed to addresses this weakness in the EA implementation. This Data-Driven approach utilizes Information Theory for Feature Subset Selection to se-

Manuscript received Sept. 5th, 2007. *This work was carried out while the first author was on internship at Bell Laboratories Ireland. This work was supported by IDA Ireland and the Irish Research Council for Science Engineering and Technology.

lect only these salient spectral features across the entire spectrum and hence move noisy features from the feature vector [5, 7]. This approach does not require any a-priori information regarding the frequency range of potential defects.

This paper compares a novel implementation of the EA technique to a Data-Driven approach to acoustic feature extraction for predicting the RUL of a rotating machine. This Data-Driven approach also highlights some shortcomings of the EA approach by illustrating that the relevant information is spread over several locations across the frequency spectrum from 0 to 25kHz. The paper is organized as follows. Section 2 describes Acoustic Machine Noise and both the EA and Data-Driven feature extraction techniques. Section 3 describes the experimental implementation. The results of experiments are provided in section 4. Finally, section 5 concludes.

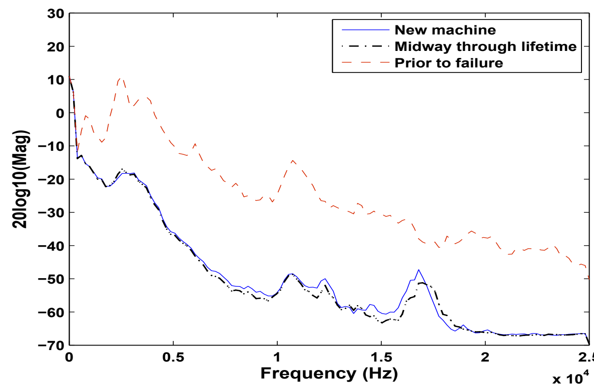

Fig. 1. Standard log energy spectrum of the acoustic data sampled at different points over the lifetime of the machine.

2. ACOUSTIC SIGNAL PROCESSING

2.1. Acoustic Machine Noise

The rotating machine used in the experiments presented in this paper was comprised of several moving parts, including two rolling element bearings (REB). Eventual failure of the machine was attributed to complete bearing seizure. As the machine degrades over time, defects in the REBs such as cracks or spalls occur generating vibrations in the spectrum. The frequency at which these vibrations occur is termed the Characteristic Defect Frequency (CDF). Furthermore, these impulses in turn excite higher order resonances within the bearing structure and neighbouring parts [3].

Figure 1 shows the standard log energy spectrum of data sampled at different points in time over the lifetime of the machine e.g. new machine, machine midway through it's lifetime machine and immediately prior to failure (bearing seizure). This figure illustrates that there is obvious differences in the acoustic spectrum once a defect has fully developed and failure is imminent. However, there is much more subtle differences between a new machine and a machine midway through it's lifetime.

2.2. Envelope Analysis Feature Extraction

The EA technique for ACM typically bandpass-filters the signal around one of the resonant frequencies, thus eliminating most of the unwanted noise signals from other sources. This bandpass-filtered signal is then demodulated by rectification and smoothed by low-pass filtering. The spectrum of the envelope signal in the low-frequency range is obtained to get the CDF of the machine bearing. One of the problems with this technique is that the frequency range of interest must be known or pre-estimated. This frequency range of interest can be determined by manually inspecting the data before and after failure to determine the frequency range with the highest Signal to Noise ratio, or by using an automated approach that examines the statistical kurtosis of the spectral components to determine the cut off frequencies of the band [1]. Another approach uses fixed frequency bands across the spectrum and the passband of interest is determined by empirical testing which does not require the defect frequencies or resonances to be pinpointed [2]. Empirical tests are performed in order to select one frequency band of interest to use for ACM.

Rectification (de-modulation) was achieved using three different techniques as follows: (a) taking the Absolute value, (b) squaring the signal and (c) obtaining the Analytic signal using the discrete Hilbert transform. Absolute value, $A_a[n]$ takes the absolute value of the discrete-time domain samples, essentially mimicking the full wave rectifier in the traditional analogue based approach. Squaring, $A_b[n]$involves taking the square of the discrete-time domain samples, this and higher order powers have been explored in studies by Ho et al. [1]. The Analytic signal approach is the most complex of the three, in terms of computation. An analytical signal is defined in (1) as a complex signal created by taking the original and then adding in quadrature its Hilbert transform, which is sometimes termed the 'pre-envelope' of the real signal.

$$z[n] = x_r[n] + jx_i[n], \tag{1}$$

where $x_i[n]$ is the Hilbert transform of $x_r[n]$,

$$A_c[n] = (x_r^2[n] + x_i^2[n])^{1/2} \tag{2}$$

The absolute value $A_c[n]$ of the complex analytic signal forms the signal envelope. The Short-Time Fourier Transform (STFT) of $A_{all}[n]$ is computed to obtain the spectral envelope features. Using the resulting spectral components pattern recognition algorithms can then be then be applied to determine the RUL of the machine.

2.3. Data-Driven Feature Extraction

Conventional spectral features are first extracted from the acoustic data. The acoustic data signal is split into windowed (hamming) non-overlapping time frames, and the STFT is applied which results in an estimate of the short-term, time-localized frequency content of the acoustic signal. This spectral feature extraction approach results in irrelevant, noisy parts of the spectrum being included in the feature vector.

The EA approach attempts to isolate the frequency band of interest and attenuate noise outside of this band. However, it is proposed that the salient information for determining the RUL may exist in several different locations across the entire spectrum from 0 to 25kHz. Therefore, an Information Theoretic approach to feature subset selection (FSS) is employed to remove noisy data from the feature vector by only selecting features relevant to the task of predicting the RUL. Specifically, Mutual Information (MI) is used as a measure of usefulness of each spectral component and therefore the MI criterion forms a basis for FSS of spectral components, MI-FSS, to optimize the choice of features used as inputs to the classifier to predict the RUL of the machine. This approach does not require a-priori information regarding the spectral location of potential defects and their resonances and determines the relevant spectral features for monitoring using information obtained from the data acquired over the lifetime of the machine only. This feature extraction technique is described in more detail in [7].

Figure 2 illustrates which spectral components are selected using the MI-FSS criterion for given subset sizes of 0, 16, 64 and 128 features. The frequency bands used for EA feature extraction approach, detailed in section 3, are also illustrated for comparison on figure 2. The figure shows that the most important 16 features exist primarily (10-15), (15-20) kHz frequency bands. Further increasing the number of features, it can be seen that relevant information for predicting RUL is spread out over all the different frequency bands proposed in the previous section. Thus, a subset of the spectral components is selected via MI-FSS and used as input to the pattern recognition algorithms to determine the RUL of the machine.

3. EXPERIMENTAL IMPLEMENTATION

Acoustic data was captured using a microphone in close proximity to a rotating machine over its entire lifetime. The rotating machine was maintained at a constant load and shaft speed (approx. 80 Hz), in high heat conditions to accelerate failure over a period of approximately 6 months. Ultimate machine failure was due to complete bearing seizure. Acoustic data was acquired at a sampling rate of 50,000 samples/second.

For the EA feature extraction implementation, the fixed frequency bands used for selecting the pass-bands were as follows: F1(1-2.5), F2(2.5-5), F3(5-10), F4(10-15), F5(15-20), F6(20-25) and F7(15-25) kHz; achieved using high order FIR (window) bandpass filters. A similar approach was taken in [2]. Rectification was performed using the three techniques as described in Section 2.2. The Short-time Fourier Transform[1] (STFT) was computed to obtain the Envelope Spectrum.

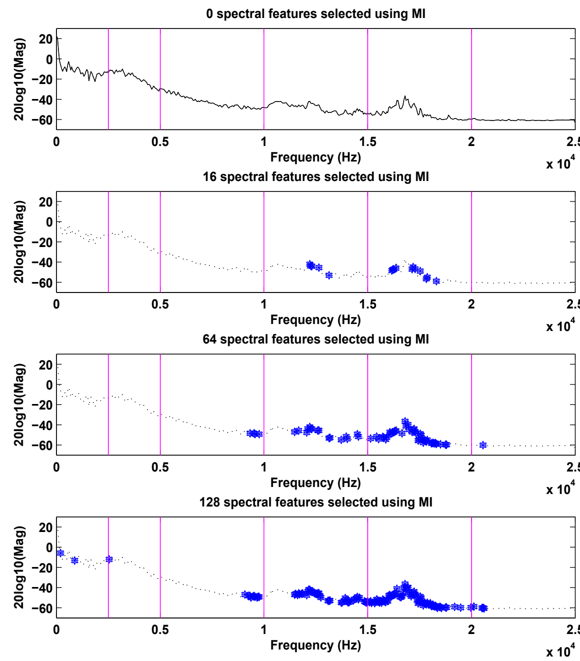

Fig. 2. Selecting spectral components using the data driven Mutual Information Feature Subset Selection approach.

The Data-Driven approach to feature extraction involves first extracting 512 log-spectral features via a straight-forward (STFT[1]) of the acoustic data. The resultant spectral feature vector spans the entire spectrum from 0-25kHz. The MI-FSS approach is then employed to select the top 128 features according to the MI criterion described in section 2. These 128 features were retained in the feature vector for classification.

In order to predict the RUL of the machine, a classification approach is proposed that determines what state of degradation, or 'wear states', the machine is currently in. In this paper, 10 wear states are used to predict the RUL. The degradation of the machine progresses through several stages of physical wear. As the exact location in time where such degradation events occur is difficult to ascertain the data is divided into 10 equal segments for labeling. Each segment or wear state represents a different time interval over the lifetime of the machine from 1 to 10, where 1 is new and 10 is approaching failure. The Nearest Neighbour (NN) classification algorithm is used to determine the RUL of the machine. In the NN algorithm the training samples are mapped into multidimensional feature space which is partitioned into regions based on the class labels. The class is predicted to be the class of the closest training sample using the Euclidean distance metric.

[1]Note: For both the EA and the DD approach the frame duration was 20msec with a 1024-pt FFT and then averaged over 100 consecutive frames.

The data used in the classification training step is sampled over the lifetime of the machine. For testing, separate data is sampled over the same lifetime. Once the features are extracted for every sample in the training set, the mean and standard deviation is computed for normalization. Each feature dimension in the training set is separately scaled and shifted to have zero mean and unit variance. These normalization parameters are then applied to the test set.

4. RESULTS AND DISCUSSION

Both the EA and Data-Driven feature extraction approaches have been applied to the acoustic data signals. A detailed set of results is presented in Table 1 using the EA feature extraction approach and the passbands indicated in section 3. That is, for the three different rectification techniques: Absolute Value (EnAbs), Square Value (EnSqr) and the Analytic Signal (EnAn). The results indicate that F4 and F5 perform considerably better than the other bands. Figure 2 also illustrates that these bands contain the majority of relevant information for predicting RUL. From the results we can observe that all approaches perform best in the band F5 [15-20]kHz. While the EnAbs and EnAn approaches are comparable, the EnAbs performs marginally better with an accuracy of 93.7%.

Table 2 compares the results from each of the EA approaches with and without using a low pass filter (LPF) effect of selecting a subset of the spectral components i.e. the first 128 spectral components. It is shown that using the LPF does not improve the accuracy for the task of predicting the RUL. The results of the Data Driven approach to feature extraction is also presented in Table 2. Using all 512 features implies that no FSS is performed on the spectral components, whereas using 128 features implies that the MI-FSS criterion was employed to select the top 128 MI features for processing. It is shown that the MI-FSS Data-Driven approach to feature extraction greatly improves accuracy in predicting the RUL of the machine with an accuracy of 97.7%.

5. CONCLUSION

The results in this paper indicate that there exists sufficient information in the acoustic signal emitted from a machine to determine the RUL using both the novel implementation of the traditional EA feature extraction approach, providing an accuracy of 93.7% and a Data-Driven approach to feature extraction was also employed providing a significantly higher accuracy of 97.7%. It is proposed that the success of this approach is due to: noisy irrelevant features being removed from the feature vector; the inclusion of relevant information in the feature vector that is spread throughout the spectrum from 0 to 25 kHz; and the absence of a-priori assumptions in the feature extraction process.

While some automated approaches to selecting the cut-off frequencies for the frequency band of interest exist for EA, this approach is still impaired due to the fact that information is spread over different locations across the entire spectrum as illustrated in Figure 2. Therefore, simply widening the band to incorporate all such information will only result in noisy data also being included in the resulting feature vector. This is verified by the results of the wider passband of F7 (15-25 kHz) in Table 1 which performs poorer than the narrower passband of F5 (15-20 kHz). In addition, it is proposed that the Data-Driven approach is a more suitable candidate for use in ACM as it removes the empirical analysis required to determine the frequency range of interest when applying traditional EA approach to different machines/environments.

Table 1. Classification performances accuracies for the different Envelope Analysis implementations

	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**
EnAbs	32.7	31.1	38.1	84.2	**93.7**	36.3	93.3
EnSqr	29.5	26.7	35.0	80.8	**81.4**	31.1	76.8
EnAn	31.4	31.1	33.7	79.2	**93.2**	28.7	92.5

Table 2. Classification accuracies comparing Envelope Analysis to Data-driven Approach

No. Features	128	512
EnAbs (with/without LPF)	92.7	93.7
EnSqr (with/without LPF)	79.2	81.4
EnAn (with/without LPF)	92.7	93.2
Spectral (with/without MI-FSS)	**97.7**	94.8

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