AUTOMATIC FAULT MONITORING USING ACOUSTIC EMISSIONS *

Gopal T. Venkatesan, Dennis West, Kevin M. Buckley, Ahmed H. Tewfik, Mostafa Kaveh

Department of Electrical Engineering
University of Minnesota
Minneapolis, MN 55455

ABSTRACT

Techniques for automatic monitoring of faults in machinery are being considered as a means to safely simplify or dispense with expensive periodic fault inspection procedures. This paper presents results from an ongoing investigation into the feasibility of using Acoustic Emissions (AEs) for automatic detection of microcrack formation/growth in machine components.

1. INTRODUCTION

Periodic inspection and/or preventive maintenance of machines are time-consuming, expensive and require substantial down time. Hence, automatic fault monitoring techniques have received considerable attention as an economical alternative, their feasibility being largely governed by the technique's ability to detect the fault with reasonable certainty.

Acoustic Emissions (AEs) are stress waves emitted by stressed material undergoing deformation processes such as plastic deformation or crack growth. Diagnostics based on AEs is a passive, nondestructive evaluation (NDE) method and is hence, an attractive option for automatic monitoring of faults in machines. These stress waves can be detected by piezoelectric transducers (PZT) placed strategically on the material specimen. The characteristics of AE signals from crack growth have been extensively studied (e.g., [1]). Most of these studies were done for isolated material specimens in controlled laboratory conditions at very high SNRs. In a practical case, however, when the AE signal has to be detected while the machine is in operation, the AE is buried at very low SNRs under strong interference/noise caused by mechanical motion in the machine. This noise is quite complex and highly nonstationary, and arises due to a number of factors that, other than vibration, may include fretting, hydraulic noise and electromagnetic interference [2]. Most of these noise events are transient and not quite unlike AE signals. Hence, the task of detection is not merely limited to the detection of transient signals in white noise [4]. It also becomes important to classify these detected transient events as AE signatures or otherwise. In consequence, the detection of crack growth signatures from the measured data is not a trivial problem. The problem is further compounded by the fact that in the case of complex material geometries the characteristics of the AE might not be known *a priori* to a large extent. Also, the noise is highly machine and load dependent and it is not possible to fully characterize it under all possible permutations of the working environment. In consequence, the question is whether, given a knowledge of the structure of a machine and the characteristics of the noise under certain load conditions, the partial *a priori* knowledge can be effectively used to detect AE signals at very low SNRs with a very high probability of detection with low false alarm rates. In this paper, we present an approach for detecting AEs in helicopter rotor components [3][4]. This approach can be possibly adopted, with suitable changes, for other machinery, rotating or otherwise.

*THIS WORK WAS SUPPORTED BY THE OFFICE OF NAVAL RESEARCH UNDER MURI CONTRACT N00014-95-1-0539. MANY THANKS TO HONEYWELL INC., MINNEAPOLIS, FOR KIND PERMISSION TO USE THEIR DATA.

2. THE NOISE/SIGNAL MODEL

Vibration data recorded from a rotor component in a helicopter is quite likely to exhibit some periodicity in its characteristics. A major proportion of the energy of this data is concentrated at the lower end of the spectrum, usually less than 50 KHz [4]. AEs, on the other hand, are transient in nature, with dominant spectral content over 100 KHz (and possibly extending to 2-3 MHz). Therefore, a high-pass filter with a cutoff of 50 KHz should be used at the preamplification stage before A/D conversion. Even after this preprocessing is done, AEs are still buried under higher frequency interference at low SNRs.

Figure 1 and 2 show typical data observed over two time periods or cycles(one cycle corresponds to one full rotation of the rotor). Note that the data provided by Honeywell contained only the background noise and the first dominant transient. The other periodic and random transients, which are fretting and electromagnetic noise respectively, were measured separately in our lab and added to the above data at expected SNRs. Note also that several AEs measured during microcrack growth in Tantalum Nitride specimens [3] have been added to the data shown in Figure 2 at low SNRs. The efficacy of our approach at detecting these weak AEs is presented in this paper.

From Figures 1 and 2 it can be noted that the signal contains a number of strong transient signals whose durations are much less than one cycle. We will refer to these as transient noise. In addition to the above, "steady" lower level noise which we will refer to as background noise, is also present. On the basis of the time of occurence of these transient noise events with respect to the start of the cycle (henceforth, in this paper, time of occurence will implicitly mean the time of occurence with respect to, or referenced to, the start of the cycle under scrutiny), we have two categories 1) quasi-periodic transient events, (labeled as p in Figure 1), that occur at approximately the same time in every cycle, and, 2) aperiodic or random transient events. Quasi-periodic transient events may arise due to frictional rubbing (or fretting) of surfaces. Random transient events may be caused, for example, due to electromagnetic interference or due to roller joints.

Based on the above data, a suitable model for the noise

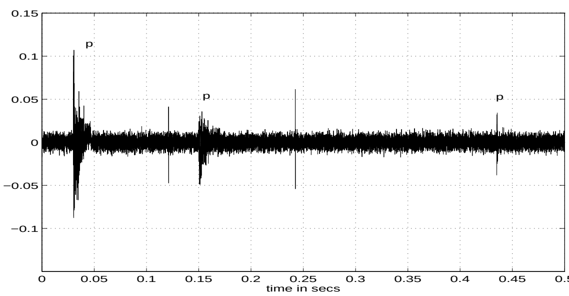

Figure 1. Data recorded over one cycle

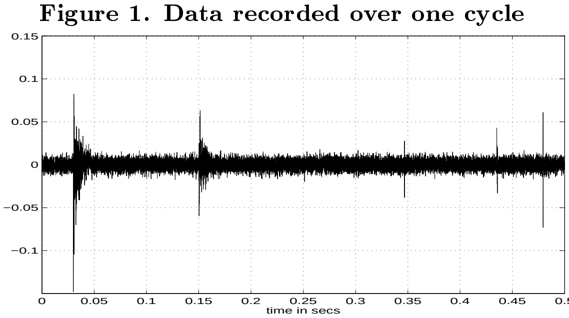

Figure 2. Data recorded over the next cycle

during the i^{th} cycle would be,

$$y^i(n) = x^i(n) + \sum_{k=1}^{P^i} a_k^i p_k^i(n - u_k^i - \Delta u_k^i) + \sum_{l=1}^{R^i} b_l^i r_l^i(n - v_l^i) + w^i(n) \quad (1)$$

Note that the time index n is referenced from the start of the cycle. $x^i(n)$ is the background noise and $w^i(n)$ is zero mean white noise. $p_k^i(n)$ is the k^{th} periodic transient noise event with amplitude a_k^i and $r_l^i(n)$ is the l^{th} random transient noise event with amplitude b_l^i. The amplitudes of $p_k^i(n)$ and $r_l^i(n)$ have been normalised to unity. The u_k^i's and v_l^i's are the times of occurence of the periodic and random transient events referenced from the start of the i^{th} cycle. Typically, $P^i = P^{i-1}$ and $p_k^i(n)$ is highly correlated with $p_k^{i-1}(n)$. Also, $u_k^i = u_k^{i-1}$, and Δu_k^i models the "jitter" about the mean value due to transient imbalances.

AE signals related to crack growth are typically transient in nature and tend to occur in "bursts" i.e. a temporal sequence of multiple, possibly highly correlated events [5].

$$s^i(n) = \sum_{j=1}^{S^i} c_j^i g_j^i(n - t_j^i) \quad (2)$$

Here, S^i is the number of AE events in the i^{th} cycle. The constant c_j^i is the amplitude of the j^{th} AE event g_j^i whose amplitude has been normalised to unity.

The data (signal plus noise) measured during the i^{th} cycle is then given by,

$$z^i(n) = y^i(n) + s^i(n) \quad (3)$$

Note that thus far we have made no assumptions about the spectral content of the noise and AE signals. However, in the filtering and processing of $z^i(n)$ we will make the following assumptions :

1) The spectral content of the AE signals are concentrated in a few spectral coefficients. The energy of the background noise $x(n)$ in these coefficients is insignificant compared to the total energy of $x(n)$. It is assumed that $x(n)$ is stationary over time durations much longer than that of the transient events.

2) Periodic noise transients, i.e., $p_k^i(n)$, occur at approximately the same time index (referenced from start of the cycle) at every cyle. As mentioned before, we will assume that $p_k^i(n)$ is highly correlated with $p_k^{i-1}(n)$.

3) AE signals are assumed to exhibit no periodicity. It is important to note that this assumption does not imply that AE signals cannot occur over two consecutive periods. We merely assume that the time of occurence of the AE signals over consecutive periods are not correlated even though there might exist a high degree of correlation between the actual AE events over both periods. Also the characteristic decay rates of AE signals, though widely varying depending on the characteristic of the crack and its location with respect to the sensor, are in general, lower than that of electromagnetic transients and much higher than that of fretting transients. We will, therefore, exploit this *a priori* knowledge of the range of decay rates exhibited by AE signals at the eigenfiltering/denoising stage [2].

4) Random transient noise events in the same cycle or over consecutive cycles may or may not be highly correlated, depending on the actual sources of these events.

3. THE PROPOSED APPROACH

We will now consider the processing of the data measured during the current cycle shown in Figure 2. For the processing, we take into account the knowledge of the characteristics of the data gathered in the previous cycle (shown in Figure 1). Figure 3 shows the block diagram of the proposed approach for the above signal/noise models and assumptions. The basic methodology is to reduce the given data to a collection of transient events in white noise by filtering out the background noise. This is done in the prefiltering stage by fitting an AR model to $x(n)$ with blocks of data chosen from the previous cycle, corresponding to time intervals that do not contain any transient events. Then a denoising of the time series is done to effectively pick out the transients, some of which might be buried in the white noise at low SNRs. The quasi-periodic transient events are discarded, following which a simple preliminary detection is done based on a history of the number of random transient events observed in every cycle. If AE signals are detected at the preliminary detector, then additional signal processing is done to localize/characterize the source of the AE signals. This would not only confirm the decision made in the previous stage, but also give some reasonable estimate of the criticality of the crack.

3.1. Eigenfiltering/Denoising

The output of the prefilter is a collection of transient events in additive white noise. If the exact decay rate were known then optimal data tapers that have minimal spectral leakage outside the frequency range (or frequency bin) of interest can be found in closed form [6]. However, as mentioned in Section 2, we have no exact *a priori* knowledge of the decay rate of the AE signals. However, a range of decay rates that they might exhibit is known. Though, a closed form solution for the optimal tapers does not exist in this case, the tapers can still be computed numerically as a generalized eigenvector problem. The set of eigenvectors computed for each frequency bin are then used as the filter coefficients (with time index reversed) for the bank of filters corresponding to that frequency bin. The output of these eigenfilters are then combined as a weighted sum using the corresponding eigenvalues. As shown in Figure 3,

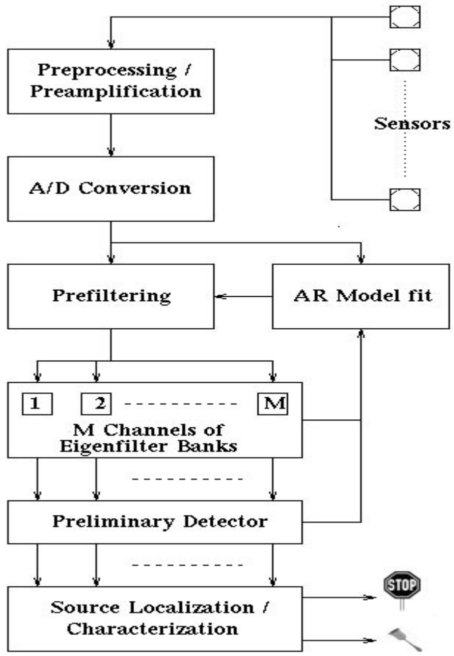

Figure 3. Block Diagram of Proposed Approach

each of these eigenfilter banks correspond to one channel. Using a set of these eigenfilter banks, each corresponding to a given frequency bin of interest, decomposes the original time series into several components.

We need to maximize the functional,

$$f = \frac{\int_{\omega_1}^{\omega_2} \int_{\tau_{min}}^{\tau_{max}} |E(\tau,\omega)|^2 d\tau d\omega}{\int_{-\pi}^{\pi} \int_{\tau_{min}}^{\tau_{max}} |E(\tau,\omega)|^2 d\tau d\omega} \quad (4)$$

where $E(\tau, \omega)$ is the DFT of the tapered data. Closed form expressions for the optimal tapers from the above equation is not possible. But optimal tapers for different frequency bins can be obtained numerically as the solution to generalized eigenvalue problems by discretizing the above integral, i.e.,

$$\max_{\mathbf{w}} \frac{\mathbf{w^H A w}}{\mathbf{w^H B w}} \quad (5)$$

where $\mathbf{A}$ is given by

$$\sum_{\tau=\tau_{min}}^{\tau_{max}} \sum_{\omega=\omega_1}^{\omega_2} e^{-\tau n} sin(\omega n) \quad (6)$$

n is the discrete time index. Note that for $\mathbf{B}$ the limits of the inner summation changes to $\omega = 0$ to $\omega = \pi$.

Using a partial knowledge of the range of expected decay rates for AE signals we numerically estimated the optimal tapers for frequency bins of 100 KHz width at low SNRs. Figure 4 shows a typical taper obtained for the frequency bin 50 to 150 KHz - the frequency bin containing the AE signals. Figure 5 shows the generalized eigenvalues that give a measure of the spectral compactness (the energy concentrated in the required frequency band) of the tapers. It can be seen that the spectral compactness drops off rapidly beyond a certain number of dominant tapers, corresponding to the number of Rayleigh frequency spacings present within the given frequency band of interest [6].

Figure 6 shows the output of the channel containing the AE signals. The collection of time series' of all the channels

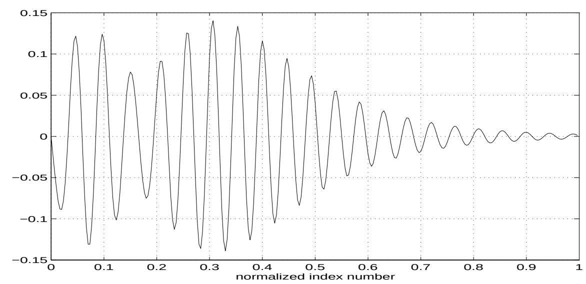

Figure 4. An Optimal Taper

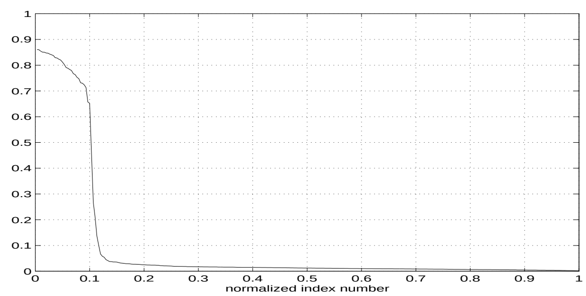

Figure 5. Spectral Compactness of Tapers

can be thought of as a decomposition of the original time series on a highly redundant frame. Several techniques have been proposed for denoising of a time series using thresholding of the frame coefficients. We will use the soft thresholding technique proposed in [7]. The threshold obtained using the above method is depicted in Figure 6 with a dashed line. Figure 7 shows the denoised time series of the above channel. Figure 8 is a "zoomed-in" look at the denoising of a single AE event.

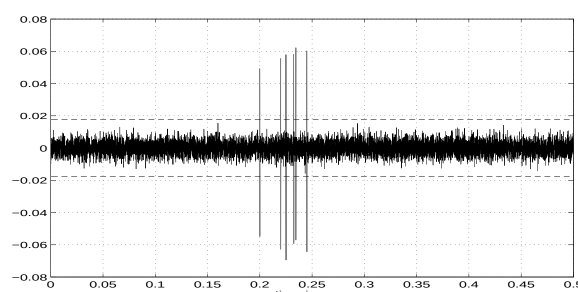

Figure 6. Output of channel that contains the AE signals

3.2. Preliminary Detection using Count Statistics

The input to this section is a collection of denoised transients. The first step is to separate the random transients from the quasi-periodic transient events that occured over both cycles. The starting time indices of the transients are estimated from the denoised data using simple thresholding. A similar estimate is already available for the previous cycle. Due to inherent "jitter", caused due to load imbalances and thresholding variances, the time index of quasi-periodic events in the two cycles will not be identical. As mentioned in Section 2, if a stochastic model for this jitter is available then events corresponding to the same quasi-periodic process can be identified using a maximum likelihood criterion. To distinguish between quasi-periodic/random events, we form the likelihood matrix given by $L = [l_{ij}]$, where l_{ij}

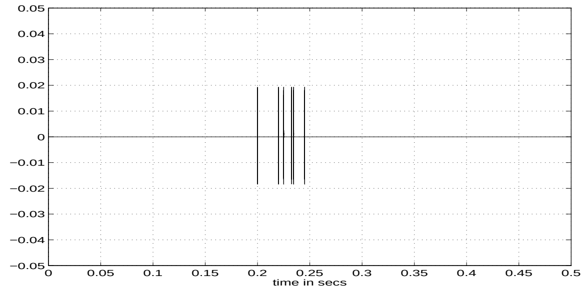

Figure 7. Denoised Time Series of one channel

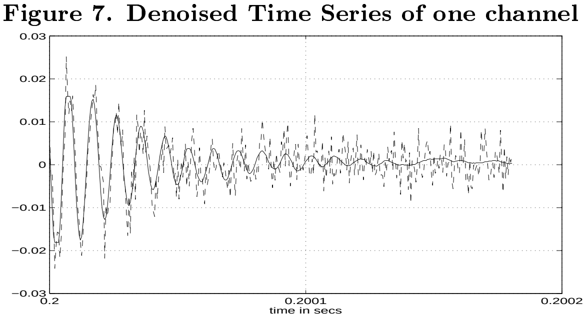

Figure 8. Denoising of single AE event

is the likelihood that the i^{th} transient from the current cycle and the j^{th} transient from the previous cycle belong to the same periodic process. For a given transient of index i from the current cycle, $\max_j l_{ij}, l_{ij} > \delta$ gives the maximum likelihood of the index of the transient in the previous cycle that corresponds to the same periodic process, i.e., the column that contains the maximum value along each row gives the maximum likelihood estimate of the index. Note that this maximum value in each row should be above a certain threshold. If a maximum value in a row cannot be found above the given threshold the event corresponding to that row index is assumed to be a random occurence.

At this stage of the project, the spectral characteristics of these random transient events are not known. Hence, we propose a simple detection scheme using count statistics once the quasi-periodic transient events have been separated out. A count of the random transient events in every cycle is done. A history of these counts over a number of cycles is used to detect the occurence of AE signals. Here we assume a simplistic case, wherein in the absence of the AE signals, randomly occuring transient events can be modeled as Poisson occurences governed by a rate λ. The presence of a train of AE events in a cycle can hence be detected as nonstationarities of the underlying Poisson model [8].

Monte-Carlo simulations were done with synthetic data generated similar to the two cycles of data discussed above. Figure 9 shows the ROC curves obtained for various values of k (5 to 15), where k is the number of AEs synthetically introduced into one cycle. Note that the false-alarm rates (FAR) in the figure are rates/cycle, and hence, for a cycle of 1 second duration a FAR of 10^{-5} would be equal to about 28 hours. These ROC curves can be improved by incorporating *a priori* knowledge of the spectrum of the the AE signals or the interference transient events. This preliminary detection can operate at higher than acceptable FARs, as the source characterization/localization stage succeeding the above will provide a further reduction in FARs.

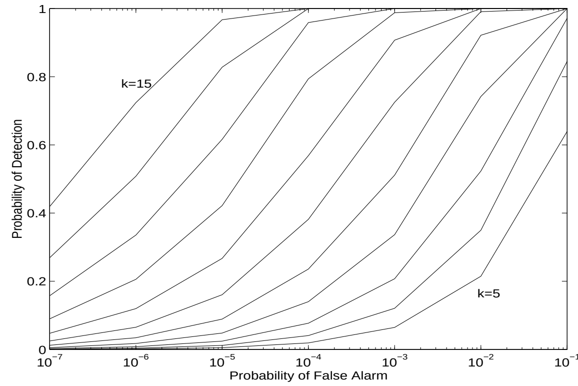

Figure 9. ROC curves for k=5 to 15

4. CONCLUSIONS

An approach for detecting AEs in helicopter rotor components for automatic fault monitoring has been presented. A suitable noise/signal model has been proposed. In these models, care has been taken to assume minimal *a priori* knowledge of the characteristics, as might well be the case for complex component geometry and machine structure. A simple preliminary detector using count statistics, based on random and "burst" properties of AE events has been proposed. Additional signal processing after this front end detection is required to localize and characterize the source of the AE signal. This could provide a confirmation of the actual occurence of a crack growth/formation and also provide an estimate of the severity of the occurence.

REFERENCES

[1] T. F. Drouillard, "A History of Acoustic Emission," J. of Acoustic Emission, vol. 14, no. 1, pp. 1-34, 1996.

[2] C. M. Scala, J. F. McCardle and S. J. Bowles, "Acoustic Emission Monitoring of a Fatigue Test of an F/A-18 Bulkhead," Journal of Acoustic Emission, vol.10, no. 3/4, pp. 49-60, 1992.

[3] K. Buckley, G. Venkatesan, D. West and M. Kaveh, "Detection and Characterization of Cracks for Failure Monitoring and Diagnostics," ICASSP 96, Atlanta, May 1996.

[4] D. West, G. Venkatesan, A. Tewfik, K. Buckley and M. Kaveh, "Detection and Modeling of Acoustic Emissions for Fault Diagnostics," IEEE SSAP Workshop, Corfu, Greece, 1996.

[5] D. Mitrakovic, I. Grabec and S. Sedmak, "Simulation of AE signals and signal analysis systems," Ultrasonics, Sept 1985, pp. 227-232.

[6] J. Park, C. R. Lindberg and D. J. Thomson, "Multiple-taper Spectral Analysis of Terrestrial Free Oscillations," Geophys. J. R. astr. Soc., vol. 91, pp. 755-794, 1987.

[7] D. L. Donoho, "Denoising by Soft Thresholding," IEEE Trans. on Information Theory, vol. 41, no.3, May 1995, pp. 613-627.

[8] D. R. Cox and P. A. W. Lewis, *The Statistical Analysis of Series of Events*, John Wiley and Sons Inc., New York, 1966.

[9] M. R. Leadbetter, G. Lindgren and H. Rootzen, *Extremes and Related Properties of Random Sequences and Processes*, New York: Springer-Verlag, 1983.