SIGNAL ANALYSIS TECHNIQUES FOR INCIPIENT FAILURE DETECTION IN TURBOMACHINERY

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Abstract

This paper reviews the status of an investigation to develop, implement, and evaluate signal analysis techniques for the detection and classification of incipient mechanical failures in turbomachinery. Signal analysis techniques available to describe dynamic measurement characteristics are reviewed. Time domain and spectral methods are described, and statistical classification in terms of moments is discussed. Several of these waveform analysis techniques have been implemented on a computer and applied to dynamic signals. A laboratory evaluation of the methods with respect to signal detection capability is described. Plans for further technique evaluation and data base development to characterize turbopump incipient failure modes from Space Shuttle main engine (SSME) hot firing measurements are outlined.

Introduction

Although little can be done to anticipate mechanical failures which exhibit very short periods of growth, most failures are preceded by growing tolerances, imbalance, bearing element wear, and the like, which may manifest themselves through subtle modifications in the waveform observed by dynamic measurements. Incipient failure detection is based on observing and recognizing measurable phenomena that occur as a result of nominal system operation and those associated with component degradation. The techniques are analytical, but their application is necessarily empirical, based on correlation between derived signature characteristics and observed mechanical condition.

Turbomachinery malfunction may result from a number of distinct failure modes such as turbine blade wear or bearing element fatigue. Each of these mechanisms may be expected to influence the waveform or spectral content measured by a transducer in a somewhat different fashion. Thus, it is clear that a single best signal analysis technique or indicator is not to be expected for system condition monitoring. A series of tests, each designed to detect a given failure mode, is therefore desirable.

The Space Shuttle main engines have and are presently undergoing extensive hot firing tests at which time vibration measurements on the high pressure fuel and oxidizer turbopumps are acquired. Thus, a wealth of vibration data is available from these components under widely varying operational conditions. Under contract with NASA/MSFC, Wyle is investigating techniques of analyzing these data to indicate SSME component condition.

Techniques and Applications

Review of the literature on machinery condition diagnostic methodologies indicate approaches employing thermal, chemical, metallographic, and vibration analysis techniques.[1,2] This discussion is limited to the assessment of motion detected by a transducer fixed to the machine during operation. (Appropriate sensor selection and location is not a trivial consideration with respect to component fault detection.) Historically, the most common diagnostic approach has been to detect and track the root-mean-square vibration level (displacement, velocity, or acceleration) as an indication of machinery condition. Performing the same analysis in separate frequency bands provides some improvement in fault identification since gross failure modes, such as imbalance, may show up at well-defined frequencies with respect to the synchronous speed. Signature analysis techniques thus fall naturally into two categories, time domain methods and characterization in the frequency domain. Several of these techniques presently under evaluation are next described.

Time Domain Methods

Time Domain Averaging. This method is a well-known technique for extracting periodic signals from noisy or complex waveforms.[3,4] The procedure can be explained by assuming a given signal x(t) is the sum of a periodic component p(t), and additive noise, n(t):

$$x(t) = p(t) + n(t).$$

By summing one time slice of x(t) with another but delayed one period later than the previous, the periodic component will add coherently, and the noise component, if uncorrelated, will not. After N additions of the signal with itself, the time domain average signature, D(t), may be expressed as

$$D(t) = \frac{1}{N} \sum_{n=0}^{N-1} x(t+nt).$$

This process is equivalent to a comb filter[4] in the frequency domain as illustrated in figure 1. As the number of replications increases, so does the sharpness of the main lobes and attenuation of nonharmonic frequencies. The TDA method has been effectively applied to large rotating machinery evaluations, and implementation on a small computer is quite direct. It is noted that the process is coherent, requiring that the period of the signal to be extracted be known or assumed.

Random Decrement Analysis. The response of a structural dynamic system is a function of both the applied loading and system properties. Changes in system characteristics such as modal frequencies or damping may be indicative of component degradation. The so-called random decrement signature has been applied extensively to the extraction of structural system characteristics in the presence of complex loading.[5,6] The procedure is similar to the TDA method described above in that the measured signal is repetitively shifted and added to itself:

$$\delta(\tau) = (1/N) \sum_{n=1}^{N} x(t_n+\tau).$$

However, in the present case, the time delay between successive segments, t_n, is no longer a fixed period but is determined by the amplitude and/or slope of the signal attaining specified values. The most popular choice in defining a trigger level for acquiring successive samples is to simply specify an amplitude threshold, x_s (such as the rms value of the signal), at which time each segment is initiated, giving

$$t_n = t \text{ when } x(t) = x_s.$$

Figure 2 illustrates the evolution of a random decrement signature from a complex response measurement.[5] An advantage of the randomdec method is that system characteristics need not be known a priori. As structural flaws or cracks develop in a component, the altered structural characteristics will modify the randomdec signature, providing an indication of possible incipient failure.

Characterization by Moments. If our measurement, x(t), be assumed a representative sample function drawn from a stationary process, statistical moments can be estimated in terms of time averages:

$$m_n = (1/T) \int_0^T \left[x(t) - m_1\right]^n dt$$

$$m_1 = (1/T) \int_0^T x(t)dt.$$

The first two moments are the familiar mean and variance, respectively. Note that if the signal is symmetric about the mean, all odd order moments are zero.

Of special interest is the normalized fourth moment, or kurtosis coefficient:

$$K = m_4/m_2^2.$$

Similar to the peak/rms ratio, the kurtosis provides an indication of the spread of the distribution, i.e. the proportion of extreme values with respect to the rms level. For example,

$K = 1$, square wave
$K = 1.5$, sine wave
$K = 3$, random signal with Gaussian amplitude distribution

Bearing faults or seal rubs often cause intermittent contact over a fraction of a revolution of the machine. The onset of such behavior therefore imparts an impulsive nature to a measurable signal, which may be detected as an increase in the kurtosis coefficient. Since the kurtosis coefficient is normalized by the signal variance, this parameter should be relatively insensitive to machinery loading conditions.

Adaptive Noise Cancellation. Measurements obtained on the SSME turbopump housing during engine operation are corrupted with a high level of undesired noise from a multitude of sources. The concept of adaptive noise cancellation is a means by which signals corrupted by additive noise or interference can be estimated. An adaptive filter is a recursive numerical algorithm which, for stationary stochastic inputs, closely approximates the performance of a fixed Wiener estimation filter. The method uses a "primary" input containing both the desired signal and noise along with a "reference" signal correlated in some unknown way with the primary input noise. The reference input is weighted based on its past values and subtracted from the primary input to yield an estimate of the desired signal. The general concept of adaptive noise cancellation is discussed in detail in reference 7, and use of the process as applied to machine monitoring is presented in reference 8. Reference 8 also describes the application of statistical moment and cepstrum analysis techniques to turbine bearing fault detection subsequent to adaptive filtering. Application of the adaptive filtering technique to SSME turbopump measurements is illustrated in the next section.

Envelope Detection. Bearing element and transmission gear mesh frequencies have been observed as an amplitude modulation superimposed on a measured complex vibration time history. Envelope detection has therefore been applied to the identification of related defects. The general approach is to detect the envelope of the measured signal followed by spectrum analysis to extract predominant frequency contributions in the envelope time history. These frequencies have been associated with flaws, which may not be detectable in the spectrum of the original wideband signal. In 1958, Dugundji introduced the concept of a pre-envelope function defined as

$$z(t) = x(t) + i\,\hat{x}(t)$$

where $x(t)$ is the original time signal, and $\hat{x}(t)$ is Hilbert transform of $x(t)$.

The pre-envelope is a (mathematically) complex time signal, the modulus of which is the signal envelope.

$$|z(t)| = \left\{x^2(t) + \hat{x}^2(t)\right\}^{\frac{1}{2}}.$$

The availability of microprocessors and the fast Fourier transform (FFT) algorithm has made it possible to implement envelope detection software on Fourier-based analyzers due to the duality between Fourier/Hilbert transforms. Thus, the pre-envelope function may be extracted by Fourier transforming the original vibration signal, discarding all negative frequencies, doubling the positive frequency values, and taking the inverse transform of this one-sided spectrum. The modulus of the resulting complex valued time history yields the desired signal envelope. An obvious computational advantage of the above approach is that the envelope function can be directly extracted using a standard FFT analyzer and calculator. Subsequent spectrum analysis of the envelope time history is then a simple additional step in the computation. It might be noted that the resulting envelope signal may also be analyzed by the above time averaging techniques to investigate signal characteristic/fault correlations.

Frequency Decomposition

Turbomachinery components exhibit distinct characteristic frequencies associated with machine operation such as shaft speed, impeller blade passage, bearing element rotation, etc. Spectral representation of measurements, either by band-pass filtering or frequency transformation, is therefore the most popular approach in practice for machine condition trending and fault identification.

Power Spectral Density (PSD). If a measurement time history is viewed as a representative sample function from a stationary random process, the mean-square density spectrum (or PSD) describes the frequency distribution of the process mean-square. The PSD may be estimated in several ways but is now most commonly extracted by applying the discrete Fourier transform on a digital spectrum analyzer and defined by

$$S_x(f) = (1/T) \left\langle x^*(f)\ x(f) \right\rangle$$

where $S_x(f)$ is the PSD at frequency f, x(f) is the discrete Fourier transform of a segment of the time history of length T, and the asterisk denotes the conjugate complex; the brackets indicate an ensemble average. Due in part to the availability and efficiency of digital analyzers, the PSD and cross PSD have become the standard format for complex signal description and system parameter identification. Another reason for its popularity is the straightforward interpretation of linear excitation/response relations and system characteristics in the frequency domain.

Bispectrum Analysis. As the PSD is the spectrum of the process second moment, the bispectrum represents the (two-dimensional) spectrum of the third joint moment and can be estimated by

$$B(f_1,f_2) = 1/T \left\langle x(f_1)x(f_2)x^*(f_3) \right\rangle, \; f_1 + f_2 = f_3.$$

The PSD and bispectrum may be seen to be the first two of a heirarchy of higher order statistical descriptions as the mean and variance are to higher order moments. Higher order spectra have been applied for some time to define joint correlations in statistical data[9] and more recently to dynamic system parameter identification.[10,11] As a diagnostic tool, the normalized bispectrum may be applied to detect the onset of nonlinear system behavior and possible associated component degradation. The bispectrum analysis technique can be implemented on contemporary FFT analyzers since only one-dimensional transforms are required. Symmetry of the function permits evaluation over only a portion of the two-dimensional frequency plane.

Cepstrum Analysis. The power cepstrum[12] was first defined as the power spectrum of the logarithm[13] of the ordinary PSD and may be written as

$$C_x(\tau) = \left| \mathscr{F}\left\{\log S_x(f)\right\} \right|^2$$

where $\mathscr{F}$ denotes the Fourier transform and the variable τ in the cepstrum is called the quefrency. Alternative expressions for the power cepstrum include the absolute value of the above, without squaring, and the indicated transform, which is real, as opposed to its squared modulus. In any event, the power cepstrum serves to indicate periodicities in the PSD. Thus, an increase in the harmonic content or uniform sidebands in the signal will be indicated by peaks in the power cepstrum. The quefrency at which a given peak occurs defines the period (or frequency difference) between a series of harmonic components. It may be noted that the power cepstrum is, in truth, a time domain characterization of the measured signal since the quefrency has units of time. The cepstrum technique has been applied successfully to remove echoes (periodic reflections) in acoustic and sonar applications as well as to enhance the harmonic content in bearing element vibration spectra.

Implementation and Simulation

Five of the above techniques have been implemented on a computer and applied to the extraction of known signals from noise and to SSME turbopump vibration measurements. Software development and results are documented in references 1 and 2. We here illustrate several results indicative of technique performance.

The TDA method was implemented on a Hewlett Packard 5451-C computer system and applied to the extraction of a sinusoid with additive noise. The results of this exercise are illustrated in figure 3. The spectrum of the sinusoid is shown in figure 3(a). The spectrum of the same sine plus noise is shown in figure 3(b). Improvement in the discrimination of the spectral component is illustrated in figure 3(c), representing 50 TDAs and figure 3(d), after 150 TDAs. As noted previously, the TDA method requires a priori knowledge of periodicities sought. However, based on ordered sampling corresponding to tachometer or synchronous speed measurements, improved resolution of significant spectral components by this method has been obtained.

Performance of the randomdec method on a sine wave plus noise process is illustrated in figure 4. The input signal is shown in the top illustration. The associated randomdec signature is shown in the center. Increased periodicity in this signature is evident though the signature is still quite complex. As a matter of interest, a second randomdec was extracted using the first as input and is shown in the lower time history. The imbedded sine wave is here seen to be well identified. As noted in the above discussion, the randomdec algorithm has the advantage of not requiring prior knowledge of periodicities in the signal. The establishment of optimum threshold conditions for signature extraction requires further investigation.

The adapative filter concept was implemented using an available hard-wired digital filter (DAC 1025I). A schematic of the data analysis setup is shown in figure 5. Typical pre- and post-filtered PSDs from a high pressure oxidizer turbopump measurement are shown in figure 6. The first spectrum represents the ordinary PSD of the signal obtained with a 12.5-Hz resolution. The second illustrates the same spectral decomposition obtained after processing of the signal with the adaptive filter. A marked improvement in resolution of turbopump periodic components is clear. Identification of synchronous and blade passage harmonics has been enhanced significantly. Work remains in the engineering interpretation of spectral values obtained from adaptive filtered measurements.

As a final illustration, figure 7 shows some results from a bearing life investigation where the statistical moment technique was applied.[14] This figure illustrates the time history of rms acceleration and kurtosis coefficient measured on the bearing housing of a roller bearing during endurance test on a Timken test machine. Note the distinct increase in kurtosis coefficient at approximately 457 hours, which is not reflected in the acceleration time history. Inspection at this time revealed a small fatigue crack on the inner race though the test continued for 657 hours, at which time extensive bearing damage was observed.

The above results are quite promising. Implementation of moment spectra, envelope spectra, and bispectral methods is presently in progress. Generation of a data base of adaptive filtered spectra for SSME hot firing measurements is also being performed. Recent additional SSME measurements obtained internal to the turbopump casing will be most useful to detection technique evaluation. Upon completion of this evaluation, the most promising techniques will be optimized computationally and integrated into the MSFC diagnostic data evaluation system.

Acknowledgments

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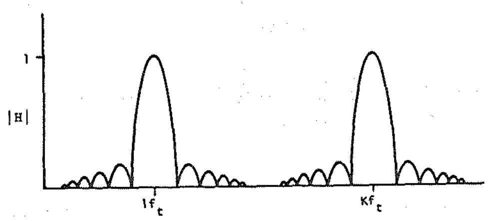

Figure 1. Time domain average comb filter

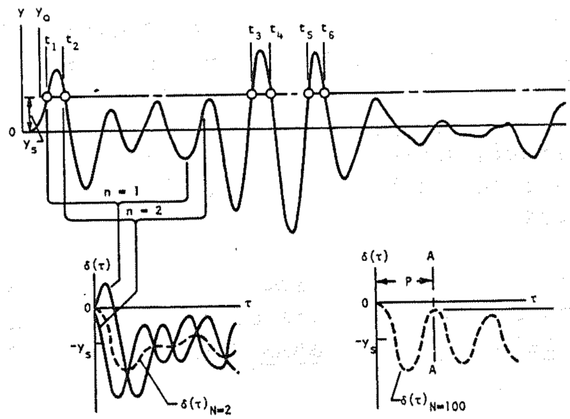

Figure 2. Evolution of a random decrement signature[5]

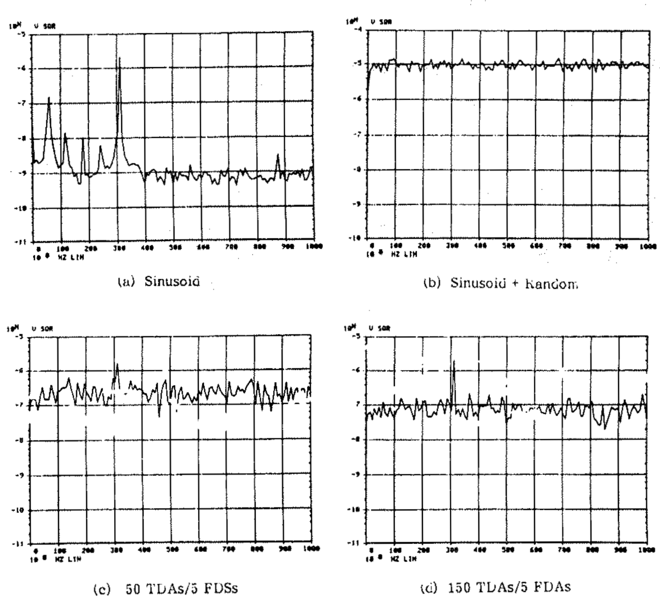

Figure 3. Spectrum of time domain averaged signal of sinusoid with additive random noise

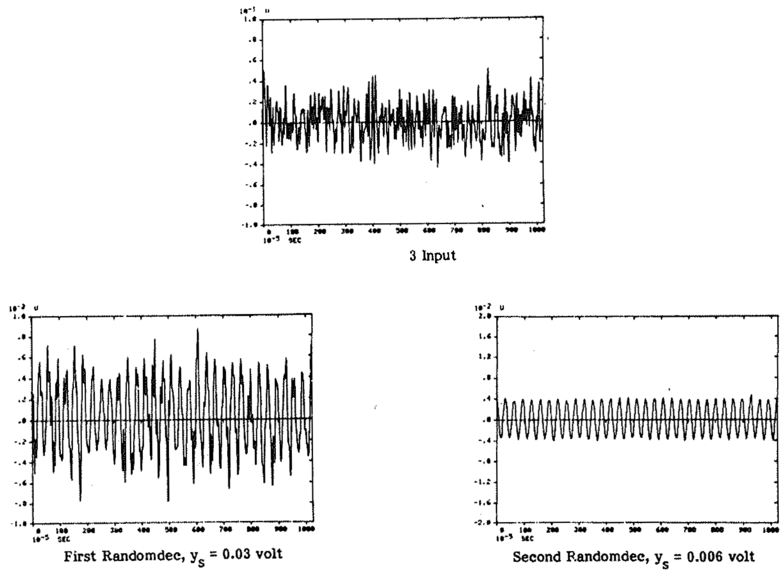

Figure 4. Random decrement signature of sinusoid plus noise

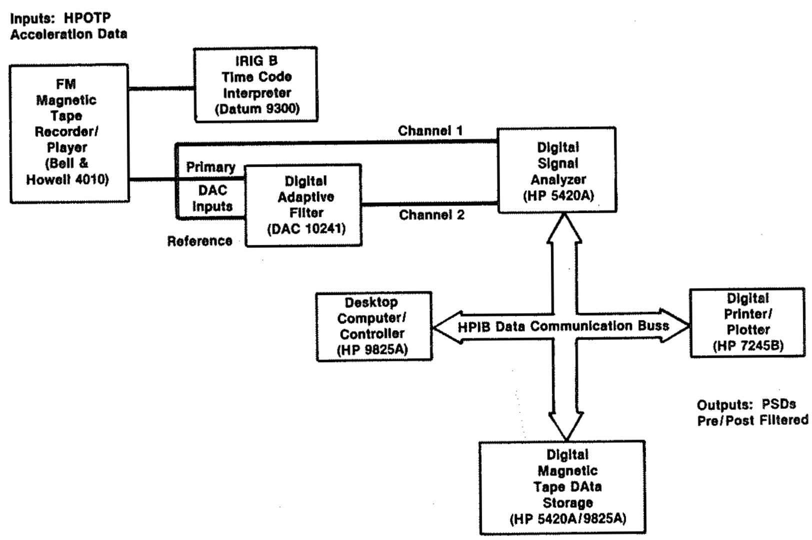

Figure 5. Data reduction flowchart for implementing adaptive noise cancellation

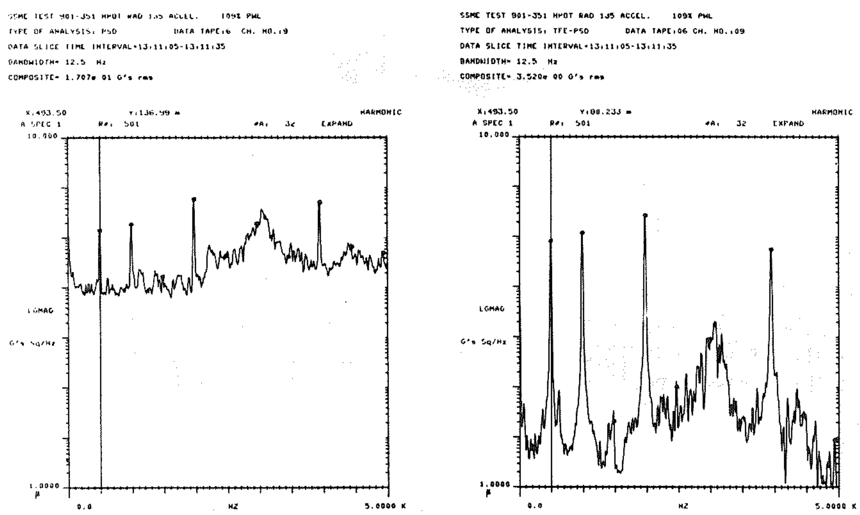

Figure 6. Spectrum of SSME turbopump measurement before and after adaptive filtering

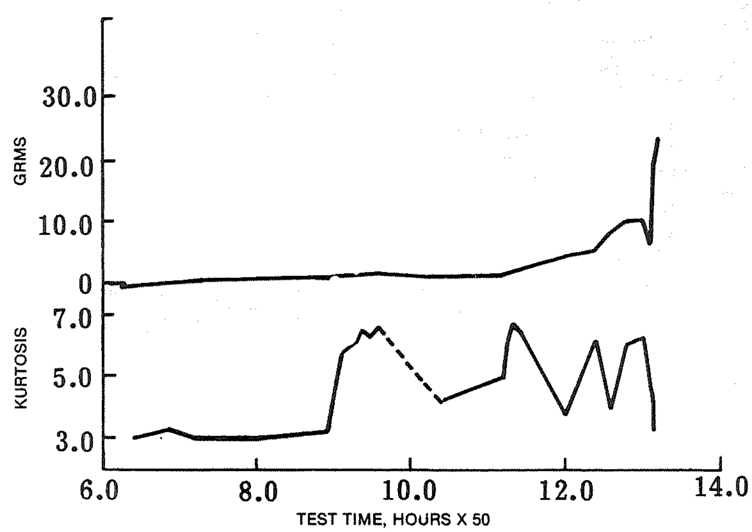

Figure 7. Variation of acceleration[14] and kurtosis coefficient with test time