ANALYSIS AND PROCESSING OF SHAFT ANGULAR VELOCITY SIGNALS IN ROTATING MACHINERY FOR DIAGNOSTIC APPLICATIONS

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ABSTRACT

This paper presents the application of some modern signal processing methods to the analysis of angular velocity signals in a rotating machine for diagnostic purposes. The signal processing techniques considered in this paper include: classical non-parametric spectral analysis; principal component analysis; joint time-frequency analysis; the discrete wavelet transform; and change detection algorithm based on residual generation. These algorithms are employed to process shaft angular velocity data measured from an internal combustion engine, with the intent of detecting engine misfire. The results of these analyses show that these algorithms have potential for on-board diagnostic application in passenger and commercial vehicles, and more generally for failure detection of other classes of rotating machines.

1. INTRODUCTION

Angular velocity measurements have the potential of assisting in diagnosis of many abnormal operating conditions in a large class of rotating machinery. This potential stems from the fact that many faults in rotating machinery will cause changes in the torsional vibration characteristics in the machine. Therefore, careful processing and analysis of torsional vibration signals will give an early warning of abnormal conditions.

Diagnosis of internal combustion engine faults using measured shaft angular velocity signals is not a novel concept; for example [4], [5], [6] discuss various approaches to extracting diagnostic information regarding individual cylinder combustion performance using a measurement of crankshaft angular velocity. The problem of diagnosing abnormal combustion has received even greater attention in recent years as the California Air Resources Board (CARB) and the United State Environmental Protection Agency (EPA) have ruled that production vehicles must be equipped with devices capable of monitoring the presence of engine misfire on line. This paper proposes the use of various signal processing techniques to accomplish this end.

To briefly review the IC engine dynamics, a general engine model is depicted in Figure 1. The cylinder indicated pressure will generate the indicated torque $T_i(\theta) = P_i(\theta)g(\theta)$, by virtue of the crank-slider mechanism, described by the geometry function $g(\theta)$. The net torque accelerating the crankshaft, and therefore causing the shaft speed to fluctuate around a short-term mean value, is equal to:

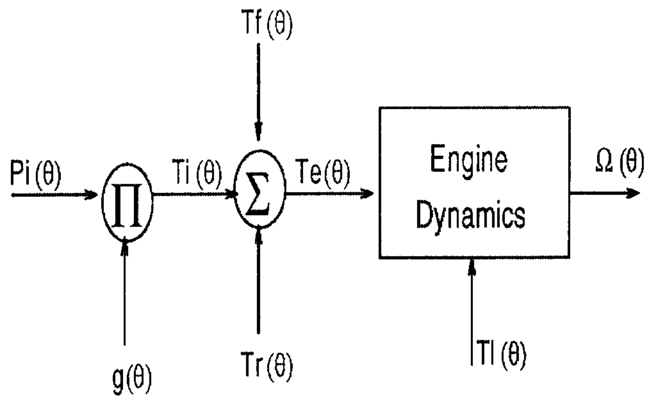

Figure 1. Dynamic models of IC engines

$$T_e(\theta) = T_i(\theta) + T_f(\theta) + T_r(\theta) + T_L(\theta) \tag{1}$$

where $T_r(\theta)$ is the inertia torque caused by the reciprocating motion of the piston-connecting rod assembly, , $T_f(\theta)$ is the friction and pumping loss torque, and T_L is the load torque. This net engine torque causes the crankshaft to rotate at an angular speed $\omega(\theta)$. The relationship between $T_e(\theta)$ and $\omega(\theta)$ depends on the number of cylinders and on the specific characteristics of a given engine; an example is given in [6]. For the purpose of this study, it is sufficient to remark that the fluctuations in engine angular speed that are the object of this study are related to the torque produced by each cylinder, and are also affected by un-measurable disturbances (e.g., friction and pumping torque), deterministic disturbances (e.g., reciprocating inertia torque), and noise. In this study we shall be solely concerned with analysis of the angular speed signal. The use of linear and nonlinear estimators of engine torque has also been proposed, but is beyond the scope of this paper.

2. DIAGNOSTIC ALGORITHMS

It is important to make some remarks about the nature of the signals of interest prior to delving into the description of the various algorithms. In all rotating machines, the variables of interest are very nearly periodic when observed with the angle of shaft rotation as the independent variable. In the present paper this angle shall be denoted by *theta*, and shall invariably be equal to the angle of rotation of the crankshaft. The relationship between *theta* and t is in general nonlinear (see e.g., [6]). However, one need not be concerned with this relationship in the analysis of data that is directly sampled in the angle of rotation domain; this will invariably be the case in the work presented here. Finally, we denote the transform domain variable corresponding to *theta* by *lambda*.

Due to space limitations, the reader who is interested in details of the instrumentation used in this study is referred to [6].

2.1. Spectral Analysis

Discrete Fourier Transform

Since the signal of interest is quasi-periodic, with period equal to one engine cycle (two revolutions for a four-stroke engine), a simple DFT based approach is a sensible solution. Define the basic data window (period) to be *4pi* radians, and let the engine firing frequency, $lambda_f$ be defined as the event that occurs N times per period, where N is the number of cylinders. If the torque produced by each of the N cylinders is identical, the spectral content of the signal will be at the firing frequency and its harmonics. Any maldistribution in engine torque production results in an increase in the spectral content below the firing frequency. An simple metric [4] based on a small number of spectral components can therefore be used to detect the presence of abnormal combustion, including misfire.

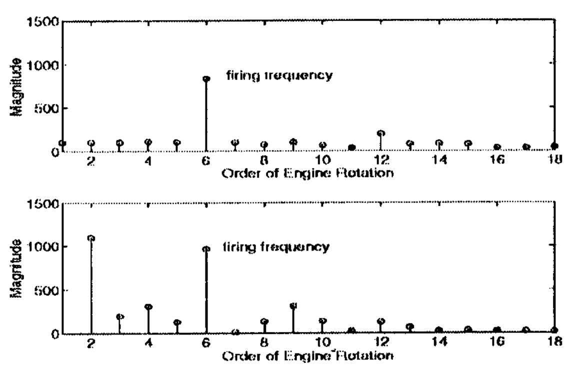

Figure 2. Angular velocity spectra. Top: normal. Bottom: misfiring

Principal component analysis

Principal component analysis(PCA) is an effective way to reduce the size of a data set and to extract data features [3], based on which, pattern recognition can be done in a particularly efficient manner. To identify individual misfiring cylinders, PCA is applied to the computed spectrum of the crankshaft speed, consisting of N complex numbers.

Let $y_i(t)$ be the ith cycle of the crankshaft speed signal, $Y_i(\omega) = FFT(y_i(t))$, then form a matrix

$$X_i = [Y_i(\omega_1), Y_i(\omega_2), ..., Y_i(\omega_N)]^T.$$

Note that X_i is a vector with complex elements. The covariance of X can be obtained as

$$\Sigma = \sum_{i=1}^{M} X_i X_i^T. \tag{2}$$

With singular value decomposition,

$$\Phi^T \Sigma \Phi = diag(\sigma_{ii})$$

where

$$\Phi = [\phi_1, \phi_2, ..., \phi_N]$$

is the normalized eigenvector matrix, and σ_{ii}, $i = 1, 2, .., N$, is arranged as a descending order. For our particular application to engine speed spectrum, we have found that, the first two principle components represent 90% of the total spectrum energy, i.e.

$$\sum_{i=1}^{2} \sigma_{ii} > 0.9 \sum_{i=1}^{N} \sigma_{ii}. \tag{3}$$

According to these two principal components, the truncated transform is defined by the subspace

$$\hat{\Phi} = [\phi_1, \phi_2]. \tag{4}$$

Finally, each cycle of the signal that needs to be classified can be transformed into a point in this two-dimensional subspace in terms of

$$\begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \hat{\Phi}^T X_i$$

. As an example, classification of misfire in cylinder 1 from the normal firing for a six cylinder engine is shown in Figure 3.

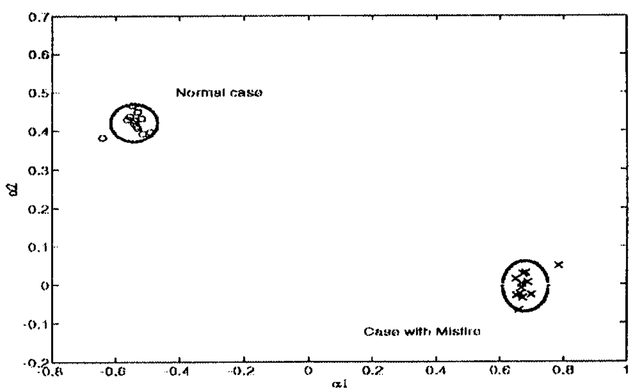

Figure 3. Classification of misfire using PCA

2.2. Engine Misfire Analysis Using Time-Frequency Representation

In recent years, a considerable amount of work has been done in the area of time-frequency representations (TFRs). the tutorial papers by Cohen [7] and Hlawatsch [8] provide excellent reviews of the subject. A special class of TFRs which has received a considerable amount of attention in the area of signal processing is the class of representations which satisfy the basic property of ***time-frequency shift invariance*** [8]: if the signal is delayed in time and/or modulated in frequency, then its TFR will be shifted by the same time delay and/or modulation frequency.

$$\tilde{x}(t) = x(t - t_0)e^{j2\pi f_0 t} \Rightarrow T_{\tilde{x}}(t, f) = T_x(t - t_0, f - f_0) \quad (5)$$

Many of these representations have been derived in different fields using different approaches with the aim of understanding what a time-varying spectrum is. Cohen [7] pointed out that there is an underlying structure among all these representations, and formulated a unified approach to study their properties. Each member of the class shares the general form of

$$T_x(t, f; \Phi) = \frac{1}{4\pi^2} \iiint \Phi(\mu, \tau) x(\mu + \frac{\tau}{2}) x^*(\mu - \frac{\tau}{2}) e^{-j\xi t - j2\pi f t + j\xi\mu} d\mu d\tau d\xi \quad (6)$$

where $x(\mu)$ is the time-domain signal, $x^*(\mu)$ is its complex conjugate and $\Phi(\xi, \tau)$ is a so-called kernel function which characterizes the particular representation. More recently, there has been an increasing interest in the use of TFRs for the analysis of mechanical systems [10, 11].

In our study we chose data acquired from a V-12 Lamborghini engine as a candidate for time-frequency analysis. The data sets acquired include normal and misfiring operation. In Figures 4 and 5, we plot the ***theta-lambda*** representation of the engine speed fluctuation under these two conditions. In this representation, an exponential Kernel [9] is used in order to suppress cross-terms. From these two figures, one can see that under misfiring condition, the energy is transferred to sub-harmonics. Also, under normal operating condition, the energy is distributed uniformly over the cycle , however, under misfiring condition, the energy distribution is not uniform.

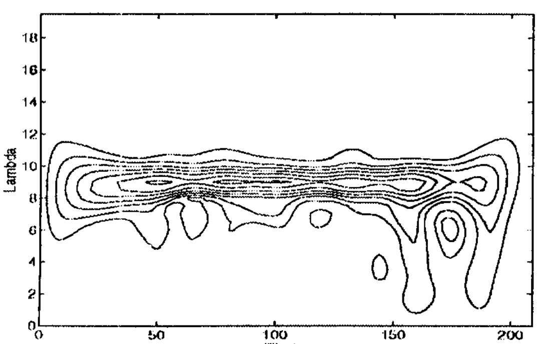

Figure 4. Theta-Lambda representation of one cycle under normal operating conditions.

2.3. Discrete Wavelet Transform

The Discrete Wavelet Transform allows a general function of time to be decomposed into a series of orthogonal basis functions, called wavelets. The aim of this study was to determine whether the same type of classification that was

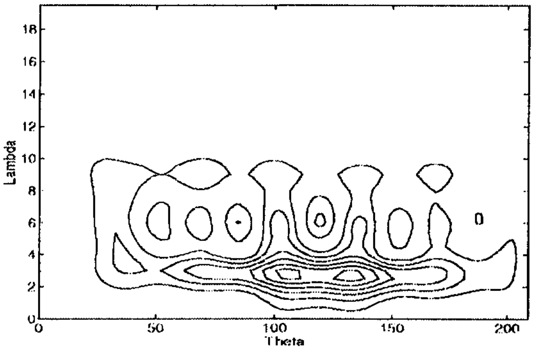

Figure 5. Theta-Lambda representation of one cycle with the engine misfiring.

shown to be possible using the DFT can also be accomplished with the DWT.

Feature extraction by DWT

The wavelet expansion of a signal $f(t)$ can be expressed as follows [2]:

$$f(t) = a_0\phi(t) + a_1 W(t) + \ldots + a_{2^j+k} W(2^j t - k) + \ldots, \quad (7)$$

where $\phi(t)$ is the scaling function, a_i the wavelet coefficients, $W(t)$'s are wavelets.

For a specified wavelet, the transformation defines a one to one correspondence between the signal and the coefficients a_i. If we name another vector

$$\Omega = [a_0, a_1, a_2, \ldots,]$$

, then we simplify the notation of the transformation:

$$\Omega = DWT(f(t)) \quad (8)$$

Now consider one cycle of the engine crankshaft speed, $y_a(t)$, with normal firing, and another cycle of the crankshaft speed, $y_b(t)$, with misfiring, Then we can transform $y_a(t)$ and $y_b(t)$, using DWT to get wavelet coefficients. Assume that we are only interested in the first eight coefficients (this number was determined experimentally), then we get two vectors, the elements of which are wavelet coefficients:

$$\vec{a} = [a_0, a_1, \ldots, a_8]^T,$$
$$\vec{b} = [b_0, b_1, \ldots, b_8]^T.$$

One should expect any differences in the signals $y_a(t)$ and $y_b(t)$ will be reflected through the wavelet coefficients a_i and b_i.

Geometric Classifier

The change in the speed waveform caused by engine misfire can be detected by judging the Euclidean distance from the vector $\vec{b}$ to the $\vec{a}$, and the angle spanned by the two vectors:

$$d = ||\vec{a} - \vec{b}||$$
$$\theta = cos^{-1}(\frac{\vec{a}^T \vec{b}}{||\vec{a}|| ||\vec{b}||}.$$

Figure 6 is an example of detecting misfire in different cylinders for the six cylinder engine, using this geometric classifier based on the DWT.

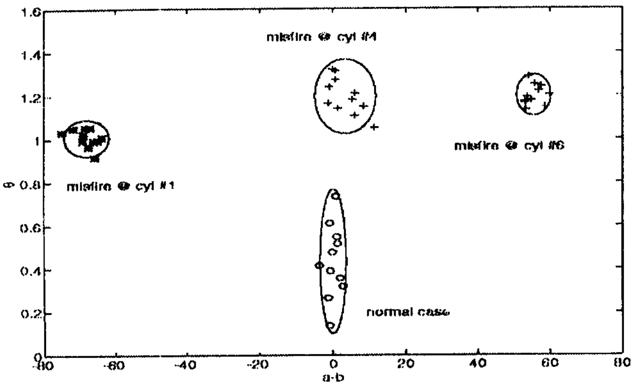

Figure 6. Classification of misfire using DWT

2.4. Change detection

Change detection is another signal processing technique that can be used to detect abrupt changes in a signal. Note that when an engine runs at steady state, the shaft speed signal is quasi-periodic, as stated earlier. To detect abrupt changes in the speed which are caused by misfire, a residual is generated in terms of

$$r(t) = \bar{y}(t) - y_i(t), i = 1, 2, \ldots, \tag{9}$$

where $\bar{y}(t)$ is the moving average of the healthy cycles without misfire, $y_i(t)$ is the current cycle to be examined. Plotting the histogram of the residual shows that r(t) is sufficiently close to having a zero-mean Gaussian distribution; we assume it is also independent. Any of a number of detection algorithms can be applied to detect changes in the residual, so as to detect cylinder misfire. These range from the simplest Schwart control chart, to geometric average cumulative sum, to the sequential probability ratio test (SPRT), to the generalized likelihood ratio test (GLRT) [1]. In the following example, the Schwart control chart is applied to 100 cycles of speed data from the six cylinder engine, in which eight cycles have misfire. The detection thresholds are set to

$$T = \mu \pm k \frac{\sigma}{\sqrt{(N)}},$$

where

- μ: the mean of r(t)
- σ: the standard deviation of r(t)
- N: number of samples in each testing

The results are demonstrated in Figure 7, where it is apparent that eight cycles have been detected as being characterized by misfire.

3. CONCLUSIONS

This paper has illustrated that a range of signal processing techniques are available for the analysis of data from rotating machinery; although the results presented here are obviously limited, we believe that each of the methods presented has significant potential for on-line application

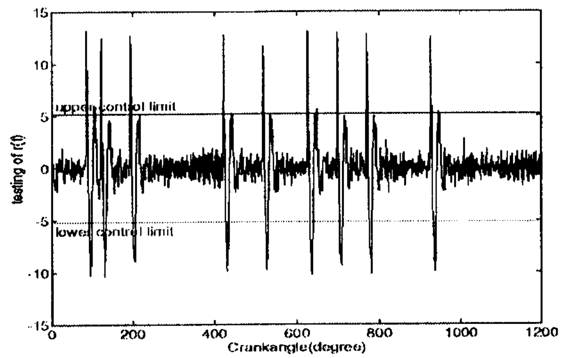

Figure 7. Detection of misfire by Schwart Control algorithm

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