DESIGN OF TRAINING DATA-BASED QUADRATIC DETECTORS WITH APPLICATION TO MECHANICAL SYSTEMS

Bahman Samimy[1] *Giorgio Rizzoni*[1] *Akbar M. Sayeed*[2] *Douglas L. Jones*[2]

[1]The Ohio State University, Columbus, OH 43210*

[2]University of Illinois, Urbana, IL 61801†

ABSTRACT

Reliable detection of engine knock is an important issue in the design and maintenance of high performance internal combustion engines. Cost considerations dictate the use of vibration signals, measured at the engine block, for knock detection. Conventional techniques use the energy in a bandpass filtered version of the vibration signal as a measure. However, the low signal-to-noise ratio (SNR) in the vibration measurements significantly degrades the performance of such bandpass energy detectors. In this paper, we explore the design and application of more general quadratic detection procedures, including time-frequency methods, to this challenging problem. We use statistics estimated from labeled training data to design the detectors. Application of our techniques to real data shows that such detectors, by virtue of their flexible structure, improve the effective SNR, thereby substantially improving the detection performance relative to conventional methods.

1. INTRODUCTION

For more than 60 years, knock has been recognized as a major problem limiting the development of fuel efficient, high compression ratio, spark ignition engines [1]. During these years, a considerable amount of work has been done in order to understand the complex knock phenomenon with the aim of increasing efficiency, reducing noise and pollution, and increasing engine life. The paper by Leppard [2] is probably one of the best introductions to the fundamental issues involved in knock detection in internal combustion engines.

A large number of today's passenger automobiles are equipped with knock control systems which depend on accurate knock detection. Most knock detection schemes employ one or more accelerometers, often tuned to the nominal first knock resonance mode of the engine, mounted on the engine block. The measured vibration signal is usually filtered, rectified and integrated, and the resulting measure of the energy of the knock vibration is compared to a threshold dependent on the operating state of the engine (especially engine speed) to make a decision as to whether knock is present or not. Mathematically, the detection statistic of the bandpass filter energy detector is equivalent to

$$L_{\mathrm{BPF}}(r) = \int_{f_1}^{f_2} \mid F_r(f) \mid^2 df \qquad (1)$$

where $F_r(f)$ is the Fourier transform of the observed signal $r(t)$. The main shortcoming of this scheme is that the spectrum of the noise overlaps with the frequency band in which the knock signal energy is contained. Unfortunately, the vibration signal measured by the accelerometers suffers from poor signal-to-noise ratio (SNR) at high engine speeds due to the high level of background noise and extraneous vibrations signals. The poor SNR can significantly degrade the detection performance of the bandpass filter energy detector. A more sensitive measurement can be obtained if the combustion pressure is directly measured in each cylinder. However, the cost and complexity of an individual-cylinder pressure sensing scheme makes this option infeasible in production vehicles at this time. Nevertheless, the ability to measure combustion pressure in a laboratory setting is very important in assessing the performance of different detection methods.

As mentioned above, the bandpass filtered vibration signal suffers from low SNR (especially at high engine speeds), and thus new detection methods that exploit other characteristics of the knock signal are needed for reliable knock detection based on the vibration measurements. Knock signals exhibit transient, nonstationary characteristics that could potentially be exploited using time-frequency-based methods [3]. Recently, a time-frequency-based quadratic detection theory has been developed [4] which seems promising for applying to the knock detection problem. However, the techniques developed in [4] require knowledge of certain statistics that need to be estimated. Fortunately, in the knock detection problem, labeled training data is usually available from which the required statistics can be estimated and used to design optimal quadratic detectors.

In this paper, we discuss the design of such training data-based quadratic detectors and assess their performance relative to the conventional bandpass filter energy detector. As we will see, such training data-based quadratic detectors, by virtue of their more general structure, can yield a substantial improvement in detection performance, especially in low SNR situations. In the next section, we briefly describe relevant quadratic detection theory and discuss the

*This work was supported by the Chrysler Corporation and the NSF under Grant. No. DDM-9157211.

†This work was supported by the Office of Naval Research under Grant No. N00014-95-1-0674, and the Schlumberger Foundation.

issue of designing the optimal detectors from training data. The experimental set up is described in Section 3, and the results of applying the proposed detectors are presented in Section 4. Section 5 concludes the paper with a summary of the paper and implications of the results presented.

2. REVIEW OF QUADRATIC DETECTORS

Engine knock detection can be cast as a binary hypothesis testing problem in which, based on a measured signal, $r(t)$, it has to be decided whether the hypothesis H_1 is true (knock present) or H_0 is true (knock absent). A decision is made by comparing a real-valued "test statistic" of the data, $L(r)$, to a threshold. We are interested in detectors of the form

$$L_{\mathbf{Q}}(r) = \langle \mathbf{Q}r, r\rangle \equiv \int\int Q(t,u)r(u)r^*(t)dtdu \ , \qquad (2)$$

where $\mathbf{Q}$ is a linear operator, and hence $L_{\mathbf{Q}}(r)$ is quadratic in the data. The detector $L_{\mathbf{Q}}$ is a generalization of the bandpass energy detector L_{BPF} since it is a weighted sum of the magnitude-squared outputs of a bank of linear (time-varying) filters determined by the eigenfunctions of $\mathbf{Q}$:

$$L_{\mathbf{Q}}(r) = \sum_k \lambda_k \left|\langle u_k, r\rangle\right|^2 \qquad (3)$$

where the λ_k's are the eigenvalues and the u_k's are the eigenfunctions of $\mathbf{Q}$.

The motivation for using quadratic detectors stems from the fact that if the measured signal is Gaussian under both hypotheses, the optimal test statistic $L(x)$ is quadratic. In particular, if[1]

$$\begin{aligned} H_0 : r(t) &\sim N(0, R_1) \\ H_1 : r(t) &\sim N(0, R_0) \end{aligned} \qquad (4)$$

then the optimal test statistic based on the likelihood ratio (LR) is given by

$$L_{\text{LR}}(r) = \langle \mathbf{Q}_{\text{LR}} r, r\rangle = \left\langle \left(\mathbf{R}_0^{-1} - \mathbf{R}_1^{-1}\right) r, r\right\rangle \qquad (5)$$

where $\mathbf{R}_0^{-1}$ is the inverse of the linear operator $\mathbf{R}_0$ whose kernel is the correlation function R_0

$$(\mathbf{R}_0 s)(t) = \int R_0(t,u)s(u)du \qquad (6)$$

and similarly for $\mathbf{R}_1^{-1}$. An important special case is the "signal plus noise" scenario in which $H_0 : R_0 = R_n$ (noise only) and $H_1 : R_1 = R_s + R_n$ (signal plus noise). In this case, an alternative to the LR-based detector is the quadratic detector that maximizes "deflection" defined as [5, 4]

$$H(\mathbf{Q}) \equiv \frac{(E_1[L(r)] - E_0[L(r)])^2}{\text{Var}_0[L(r)]} \qquad (7)$$

where $L(r)$ is of the form (2), E_i denotes expectation operator under hypothesis i, and Var_0 denotes variance under H_0. The deflection-optimal detector is given by

$$\begin{aligned} L_{\text{D}}(r) &= \langle \mathbf{Q}_{\text{D}} r, r\rangle = \left\langle \mathbf{R}_n^{-1}\mathbf{R}_s\mathbf{R}_n^{-1} r, r\right\rangle \\ &= \left\langle (\mathbf{R}_1 - \mathbf{R}_0)\,\mathbf{R}_0^{-1} r, \mathbf{R}_0^{-1} r\right\rangle \ . \end{aligned} \qquad (8)$$

The effect of the operator $\mathbf{R}_n^{-1}$ can be interpreted in terms of a time-varying *prewhitening* filter that decorrelates the noise. One attractive feature of L_{D} is that it is optimal (with respect to the deflection criterion[2]) for detecting an arbitrary second-order signal (not just Gaussian) in Gaussian noise.

In this paper, we explore the performance of L_{D}, relative to that of the bandpass filter detector L_{BPF}, for engine knock detection. As mentioned in the Introduction, the knock signals have a dominant harmonic structure. Depending on the conditions, the frequencies of the different harmonics can vary to some extent. Moreover, the onset of knock within each cycle can occur at slightly different times from cycle to cycle. The time-frequency-based quadratic detection framework developed in [4] is ideally suited for such unknown or random time/frequency shifts in the signal. Thus, we also explore the application of such time-frequency detectors which can be described as [4]

$$L_{\text{TF}}(r) = \max_{(t,f)\in S_{\text{TF}}} (Pr)(t,f;\Phi) \qquad (9)$$

where S_{TF} is a region representing possible time-frequency offsets in the signal, and $P(\Phi)$ is a quadratic time-frequency representation from Cohen's class defined as [3]

$$\begin{aligned} (Pr)(t,f;\Phi) = &\int\int\int r\left(u+\frac{\tau}{2}\right) r^*\left(u-\frac{\tau}{2}\right) \\ &e^{-j2\pi\tau v}\Phi(u-t, v-f)d\tau du dv \end{aligned} \qquad (10)$$

where the kernel Φ is related to the kernel Q_{D} of the operator $\mathbf{Q}_{\text{D}}$ by

$$\Phi(t,f) = \int Q_{\text{D}}\left(t+\frac{\tau}{2}, t-\frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \ . \qquad (11)$$

Since the quadratic detectors require the knowledge of R_1 and R_0 (or R_s and R_n), labeled training data is used to estimate these correlations. In particular, if N_1 knocking training vectors, $\{x_{k,1} : 1 \le k \le N_1\}$, and N_0 non-knocking training vectors, $\{x_{k,0} : 1 \le k \le N_0\}$, are available, we estimate the correlation functions as[3]

$$\hat{\mathbf{R}}_1 = \frac{1}{N_1}\sum_{k=1}^{N_1} x_{k,1}x_{k,1}^H \qquad (12)$$

$$\hat{\mathbf{R}}_0 = \frac{1}{N_0}\sum_{k=1}^{N_0} x_{k,0}x_{k,0}^H \qquad (13)$$

[1] The notation $r(t) \sim N(0,R)$ means that $r(t)$ is a zero-mean Gaussian signal with correlation function R; $R(t_1,t_2) = E[r(t_1)r^*(t_2)]$.

[2] Deflection is also interpreted as a measure of SNR.

[3] For Gaussian data, the estimates in (12) and (13) are maximum likelihood estimates [5].

where x^H denotes Hermitian transpose of x. These estimates can then be used to design the detectors. The performance of the resulting training-data based detectors is assessed by applying them to new test data and computing the receiver operating characteristic (ROC) curves.

3. EXPERIMENTAL SET UP

To validate the concepts outlined in the preceding sections, an experimental study was conducted in collaboration with Chrysler Corporation. A 3.5 ℓ V-6 engine coupled to a water brake dynamometer was used in all of the experiments. The engine was tested at different speeds under normal operating conditions and under increasing knock conditions. Knock was induced by varying the spark advance with the engine running at wide open throttle (see [6, 7] for details).

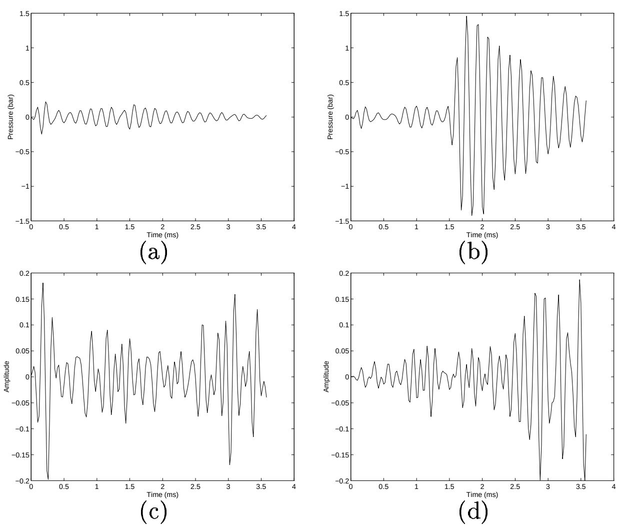

Figure 1. Typical bandpass filtered signals. (a) Non-knocking pressure signal. (b) Knocking pressure signal. (c) Non-knocking vibration signal. (d) Knocking vibration signal.

Figure 1(a) depicts a typical bandpass filtered pressure signal corresponding to a normal combustion. Figure 1(b) depicts a typical signal acquired during a knocking combustion. The increase in the amplitude of the oscillation is very evident, suggesting that if a direct measurement of pressure were available, the very high SNR would make the detection problem nearly trivial. As we mentioned earlier, it is standard practice to use an accelerometer mounted on the engine block to detect the occurrence of knock in production engines. Figures 1(c) and 1(d) depict the accelerometer signals corresponding to the pressure signals of Figures 1(a) and 1(b). It is virtually impossible to detect by the naked eye which of the two vibration signal traces corresponds to a knocking cycle, even with a priori knowledge. Moreover, we note that the engine operating conditions were relatively favorable in this case (background noise increases at higher engine speeds).

4. APPLICATION OF QUADRATIC DETECTORS

To evaluate the performance of various detectors, we used vibration data collected at 2000 rev/min and sampled at 50 kHz. Each combustion cycle corresponded to 250 samples which were used to determine the presence or absence of knock in that cycle. That is, for the bandpass energy detector, the magnitude-squared output of the filter was summed over 250 samples, and for the quadratic detectors the operator $\mathbf{Q}_{\mathrm{D}}$ corresponded to a 250 $\times$ 250 matrix. Since only about N=100 cycles each of knocking and non-knocking cycles were available to us, there was not enough data to use different samples to design the detectors and to evaluate their performance. Thus, we used cross-validation to assess the performance of the designed quadratic detectors: for each pair of knocking/non-knocking cycles, we used the remaining data to design the detector and then used it to detect the presence of knock on the chosen pair (that was not used in the design). ROCs were generated by averaging the performance over the N corresponding pairs of training vectors.

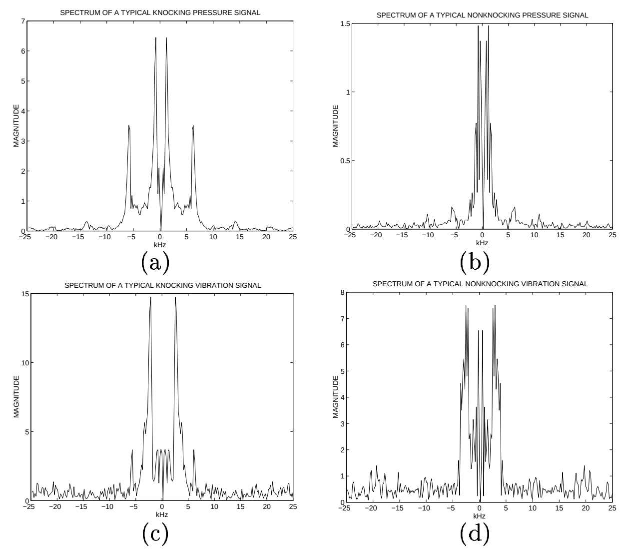

Figure 2. Spectrum of typical pressure and (corresponding) vibration signals. (a) Pressure: knocking. (b) Pressure: non-knocking. (c) Vibration: knocking. (d) Vibration: non-knocking.

Figure 2 shows the spectrum of typical pressure and corresponding vibration signals. The strong harmonic component at around 6kHz carries much information about the knocking behavior.[4] The bandpass filter used for L_{BPF} had a passband between from 5kHz to 8kHz to capture most of the information in this harmonic while suppressing broadband noise. A highpass filtered version of the signal, with a cutoff frequency at about 5kHz, was used for the design and performance evaluation of the quadratic detectors. How-

[4]The amplitudes of the knocking and nonknocking signals are typically not as disparate as in Figure 2; the figures only illustrate the spectral structure of the various signals.

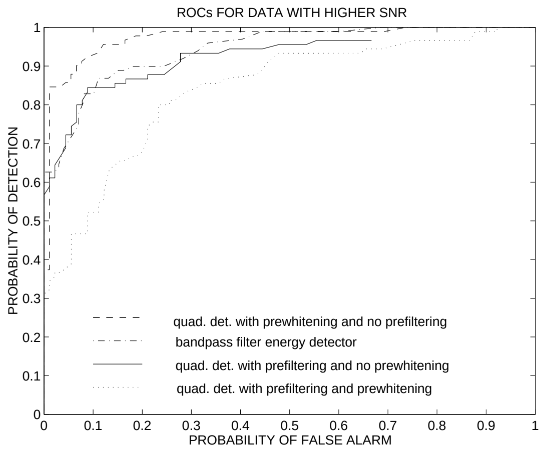

Figure 3. Data with higher SNR: Comparison of the ROCs of the quadratic detector, with and without prefiltering/prewhitening, and a conventional bandpass energy detector.

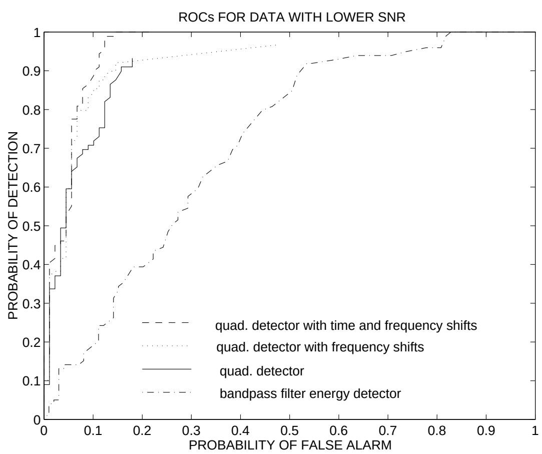

Figure 4. Data with lower SNR: Comparison of the ROCs of the quadratic detector, time-frequency detectors, and a conventional bandpass energy detector.

ever, in some cases, using raw (unfiltered) data yielded better performance.

Figure 3 shows the results for one data set. The SNR in this case is relatively high, and the performance of the prefiltered, nonprewhitened quadratic detector, ($\mathbf{Q}_{\mathrm{D}} = \mathbf{R}_s$), is comparable to that of L_{BPF}. Applying prewhitening ($\mathbf{Q}_{\mathrm{D}} = \mathbf{R}_n^{-1}\mathbf{R}_s\mathbf{R}_n^{-1}$) to the prefiltered data results in a degradation in performance. However, using prewhitening on *unfiltered* (raw) data results in substantial improvement in performance compared to the bandpass filter detector. These results indicate that the lower frequencies do contain some discriminating information. However, we found that using a lowpass filter energy detector, as opposed to a bandpass one (L_{BPF}), hurts performance. Thus, the richer structure of the general quadratic detector has the capacity to exploit both the low and high frequency information.

Figure 4 shows the ROCs for a different data set with lower SNR. We note that the performance of L_{D} is substantially better than that of L_{BPF}. Moreover, additional improvements in performance are obtained by incorporating time and frequency shifts in L_{D} as suggested by the time-frequency detection framework of [4]. The improved performance yielded by time-frequency quadratic detectors also demonstrates that the underlying data does indeed have different time and frequency offsets for different cycles. Note that such time-frequency offsets were not taken into account in the *design* of the quadratic detector kernel $\mathbf{Q}_{\mathrm{D}}$; they were used only in the application of the quadratic detector. Further improvements could result from incorporating time-frequency shifts in the design of $\mathbf{Q}_{\mathrm{D}}$.

5. CONCLUSIONS

The results presented here have shown that general quadratic detectors, designed from labeled training data, can yield substantially better detection performance compared to the conventional bandpass energy detector used for knock detection. Time-frequency-based quadratic detection schemes, which can account for unknown or random time-frequency shifts, also yield a significant improvement in performance.

Owing to their rich structure, such training data-based quadratic detectors have the ability to capture discriminating features without the aid of any *a priori* information or preprocessing. However, with limited and noisy training data, judicious preprocessing can result in an improvement in performance.

In addition to reliable knock detection from low-cost vibration data, such training data-based detectors, owing to their flexible structure, are applicable in a wide variety of applications where labeled training data is available.

REFERENCES

[1] T. Boyd, *Gasoline: What Everyone Should Know About It*, Frederick A. Stoker Company, 1925.

[2] W. Leppard, "Individual-cylinder knock occurence and intensity in multicylinder engines", *SAE Technical Paper No. 820074*, 1982.

[3] L. Cohen, *Time-Frequency Analysis*, Prentice Hall, 1995.

[4] A. Sayeed and D. Jones, "Optimal quadratic detection using bilinear time-frequency and time-scale representations", *IEEE Trans. Signal Processing*, December 1995.

[5] H. Poor, *An Introduction to Signal Detection and Estimation*, Springer-Verlag, 1988.

[6] B. Samimy and G. Rizzoni, "Mechanical signal analysis using time-frequency signal analysis", *Proc. IEEE, Special Issue on Time-Frequency Analysis (preprint)*, 1996.

[7] B. Samimy, G. Rizzoni, and K. Leisenring, "Improved knock detection by advanced signal processing", in *SAE 1995 International Congress and Exposition, SAE Technical Paper No. 950845, Also in Special Publication, SP-1086, Engine Management and Driveline Controls*, March 1995, pp. 178–181.