New Signal Processing Techniques for Enhanced Knock Detection in SI Engines

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Abstract

Standard knock sensor signal processing typically consists of band-pass filtering followed by integration over a specified time/angular window. The resulting knock intensity serves as input to knock detection & correction part of an engine management system (ECU). While this treatment was initially performed by dedicated ICs, it has recently been implemented by ECU software, leading to a digital signal processing approach. In spite of some evident advantages of this approach, the processing method itself had not changed significantly. In this paper, the possibilities of taking better advantage of digital signal processing techniques are discussed and investigations on some possibilities for improving the overall knock detection performance by means of enhancing the signal processing techniques are presented.

1. Introduction

The significant number of gasoline car engines produced and used in the world makes even a small improvement in engine efficiency and fuel consumption a considerable step towards a more sustainable future. One field where there should still be space left for a such improvement is engine knock control. It is well known that optimal engine performance is achieved close to the limit of knock appearance. This stimulates the research of more efficient knock detection techniques allowing to approach this limit more closely.

Knock information is normally supplied by an accelerometric sensor mounted on engine surface. Several signal processing research approaches can be found in the literature on knock detection. The non-stationary nature of the knocking signal gave rise to time-frequency analysis and detectors based on these methods, e.g. [1,2,3,4]. Given that in-cylinder pressure signal is more suitable but less accessible for knock detection than usual accelerometric signal, there have been investigations on its reconstruction from structure-borne sound based on an engine transfer function model [5,6,7]. On the other hand, black box approach using neural networks has been used for classification of engine cycles with respect to knocking tendency, e.g. [8].

The present paper is concerned with knock detection based on a parametric knock signal model. Similar models can be found in the literature and are used basically to describe the knock frequency variation [9] and for the aforementioned in-cylinder pressure reconstruction [10]. Our goal is to construct a knock detector associated to the adopted signal model and analyse its performance.

The structure of the paper is as follows. In section 2 we introduce the knock signal model, formulate the detection problem and discuss the detection performance. Section 3 considers practical implementation of the detection test where some simplifications are made. Finally, the described algorithm is applied to real engine signals in section 4, before the paper is concluded in section 5.

2. Knock signal model and detection problem

Time-frequency analysis of real engine knock signals and a physical insight into the combustion and knocking process taking place in the combustion chamber stimulate writing the knock sensor signal as a multiresonance process with time-variant frequencies [11]. We choose the real number formulation and write

$$x(t) = s(t) + n(t) = \sum_{p=1}^{P} a_p w_p(t) \cos(2\pi(\alpha_p t^2 + \beta_p t) + \varphi_p) + n(t) \tag{1}$$

where

a_p – *amplitude of resonance* p

$w_p(t)$ – *envelope of resonance* p

$\alpha_p, \beta_p, \varphi_p$ – *phase function coefficients of resonance* p

$n(t)$ – *additive noise*

Quadratic phase functions correspond to a linear frequency modulation. The envelope functions $w_p(t)$ have two parameters, instance of resonance begin $t_{0,p}$ and time scale τ_p. The chosen envelope function is

$$w_p(t) = \frac{t - t_{0,p}}{\tau_p} \exp(-\frac{t - t_{0,p}}{\tau_p} + 1)\Theta(t - t_{0,p}) \tag{2}$$

with $\Theta(t)$ being the Heaviside unit step function. An example of this function is represented in Fig. 1. For each of the P resonances, we thus have a six-element parameter vector $\boldsymbol{\theta}_p = [a_p, \alpha_p, \beta_p, \varphi_p, t_{0,p}, \tau_p]^{\mathrm{T}}$. Finally, we suppose for further analysis that $n(t)$ is a white Gaussian noise.

The knock detection problem can be seen as deciding between two hypothesis:

H0:	$x(t) = n(t)$	no knock (noise only)
H1:	$x(t) = s(t) + n(t)$	knock is present

A knock detector performance is given by its receiver operating characteristic (ROC) which tells the probability of detection P_d (deciding H1 when knock is present) for a given probability of false alarm P_{fa} (deciding H1 when knock is absent).

The optimal ROC curve with the highest possible P_d for a given P_{fa} is obtained by the *Neyman-Pearson likelihood ratio test* [12]. In our case, this test turns out to be

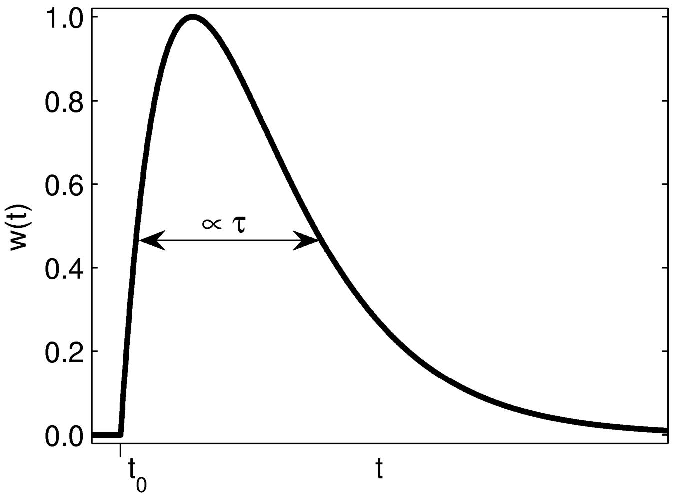

Fig. 1: Resonance envelope function form as given by equation (2)

equivalent to computing the correlation between the measured signal $x(t)$ and the knock signal $s(t)$ given by the model, followed by applying a threshold on this value. Thus it decides H1 if

$$\sum_k x(t_k)s(t_k) > \gamma \tag{3}$$

This test can only be applied if all the model parameters are known, otherwise $s(t)$ is not accessible. This is never the case in practice and the Neyman-Pearson (NP) test is of theoretical use only, giving the upper bound of performance of any real world detector.

We first compare the NP bound to the performance of the standard knock detection scheme. The latter is represented in Fig. 2. Knock sensor signal is band-pass filtered, rectified and integrated in a predefined time window to get a knock intensity measure. The ROC curve of such detector is derived in [13].

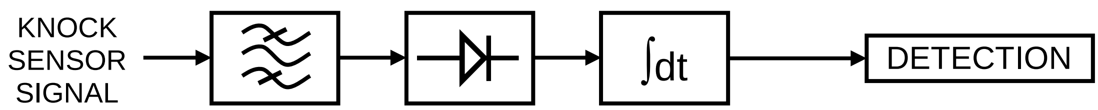

Fig. 2: Standard signal processing for knock detection

A numerical example is given in Fig. 3, together with the NP bound. The parameter values are chosen to have the same orders of magnitude as in a real knock signal. We took three resonances with the following parameter vectors:

$\boldsymbol{\theta}_1 = [1, -2.3 \cdot 10^5 \text{Hz/s}, 7\text{kHz}, 3.9, 0.61\text{ms}, 0.60\text{ms}]^T$

$\boldsymbol{\theta}_2 = [0.8, -2.8 \cdot 10^5 \text{Hz/s}, 12\text{kHz}, 1.1, 0.64\text{ms}, 0.56\text{ms}]^T$

$\boldsymbol{\theta}_3 = [0.5, -3.2 \cdot 10^5 \text{Hz/s}, 17\text{kHz}, 5.7, 0.67\text{ms}, 0.57\text{ms}]^T$

The signal duration was 2.21ms, sampled at 75kHz. A 2nd order infinite response band-pass filter with quality factor 2.3, centered on the strongest resonance was used. Signal-to-noise ratio was fixed at -5dB.

We can notice that there is a significant performance gap between the ROC curve corresponding to the standard knock treatment and the optimum bound. This indicates that there is space left for a potential improvement of this knock detection method. We focus on this item in the following section.

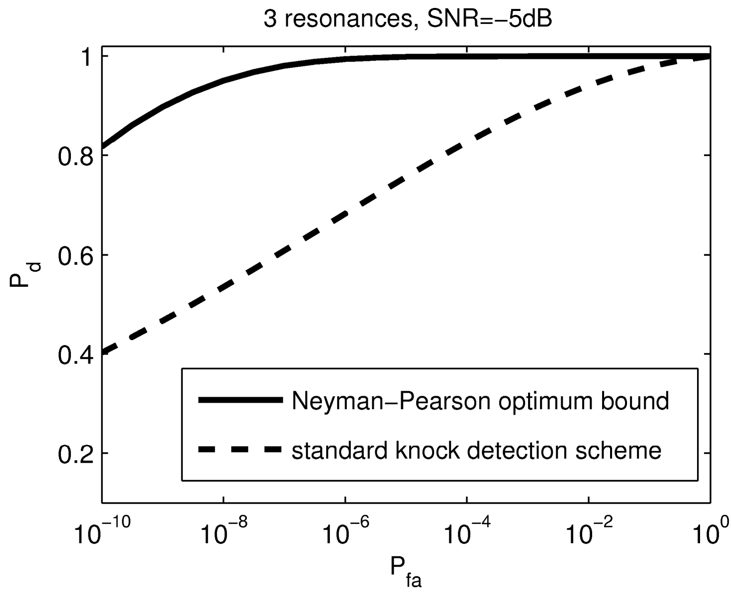

Fig. 3: ROC curves for the Neyman-Pearson test and the standard knock detector

3. Generalised likelihood ratio test and its derivation

We have seen in the previous section that the NP likelihood ratio test requires all model parameters $\boldsymbol{\theta}_1,...,\boldsymbol{\theta}_P$ to be known. What we can do in practice is to replace those parameters by their estimates $\hat{\boldsymbol{\theta}}_1,...,\hat{\boldsymbol{\theta}}_P$ and apply the test using the resulting estimated signal $s(t;\hat{\boldsymbol{\theta}}_1,...,\hat{\boldsymbol{\theta}}_P)$. This is known as the *generalised likelihood ratio test*.

In order to estimate the unknown parameters, we could think of the maximum likelihood estimator, the case which is treated in [14] for this type of signal. This approach can hardly be used in practice due to a high dimensional function minimisation we are brought to. A feasible alternative is proposed in [15], yet for monocomponent signals. We decided to analyse if a model complexity reduction could be acceptable in order to simplify the estimation. For this purpose, we considered the case where amplitude variations of each resonance are discarded, since the exact signal amplitude form is not necessarily needed to perform the detection. In other words, $s(t)$ from Eq. (1) is replaced by a constant amplitude signal:

$$s(t)=\sum_{p=1}^{P}\cos(2\pi(\alpha_p t^2+\beta_p t)+\varphi_p) \tag{4}$$

While ignoring the amplitude time dependence, we still sum up the samples coherently when calculating the detection test correlation Eq. (3). The evident benefit is the fact that now only phase parameters are to be estimated. The loss in detection performance is given in Fig. 4 for the previous numerical example. We can state that the degradation is noticeable at low false alarm rates but is still leaving a considerable space above the standard detection scheme.

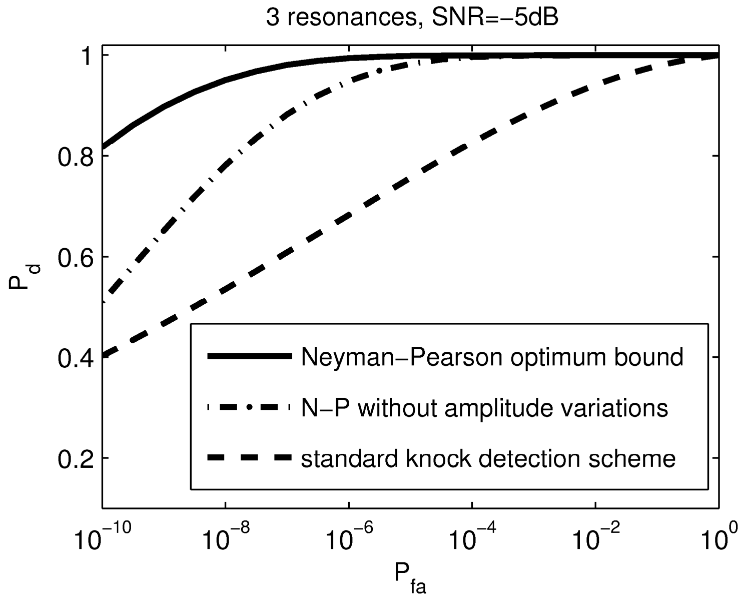

Fig. 4: Performance degradation when amplitude variations are discarded

In order to estimate the remaining phase parameters $\alpha_p, \beta_p, \varphi_p$, the High Order Ambiguity Function (HAF) could be used, whether on separated signal resonances or potentially on the entire signal [16]. However, we consider a further simplification here. The instantaneous frequency of a given signal resonance from Eq. (1) or Eq. (4) is

$$f_p(t)=2\alpha_p t+\beta_p \tag{5}$$

The relative frequency shift due to α_p that occurs during the signal observation time window depends obviously on the window length. If the window is short enough, we can neglect the linear term from Eq. (5) and the samples $x(t_k)s(t_k)$ from Eq. (3) will still be summed approximately in phase. Note that each β_p should now be the average frequency of a given resonance, contrary to the previous case where this was the instantaneous frequency value at $t=0$.

Given the two simplifications that we introduced, we are brought to estimating a fixed frequency of the signal $s(t)$ and then computing the correlation from Eq. (3). This is done at the same time by computing the Fast Fourier Transform (FFT) of the measured signal $x(t)$. Frequency estimation is done by searching for the FFT peak location and the correlation from Eq. (3) is equal to the FFT peak value. The fact that there are several resonances in the signal involves the FFT peak search to be carried out on suitable frequency subbands. Finally, a linear combination of peak values is taken as the detection quantity that is to be compared to a threshold. In this way, we have the possibility to integrate some a priori knowledge by properly ponderating a particular resonance.

4. Real signal application

We now consider an application of the described detection algorithm to a real knock signal data. We use a database of 400+400 engine cycles where in-cylinder pressure and knock sensor signals were recorded. One half of the database corresponds to a knock-free engine operation ("knock off") while in the other half knock occurs frequently ("knock on"). The test engine was operating at 2200rpm. In what follows, in-cylinder pressure refers to the oscillating part of the signal only, i.e. high-pass filtered pressure signal.

First we identify the frequency subbands in which resonances are to be detected. This is done by calculating the mean spectrum of the "knock on" signal database. The resonances are determined as those peaks that appear both in knock sensor

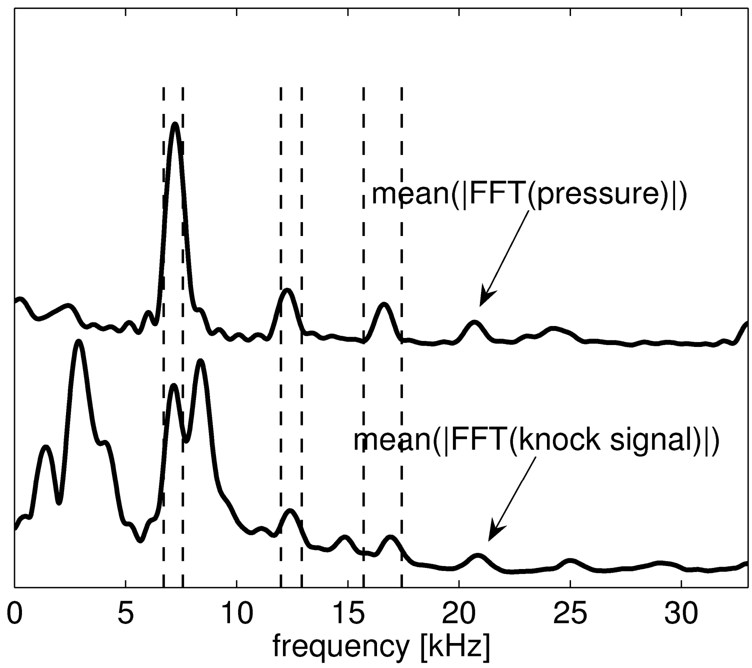

Fig. 5: Mean spectra of in-cylinder pressure and knock sensor signals together with frequency subband limits

signal as well as in in-cylinder pressure signal. The two spectra are shown in Fig. 5. We consider the lowest three resonances and determine the frequency borders in order to avoid the vibration noise that is characteristic for the knock sensor signal.

The reference for knock detection performance comparison is the maximum in-cylinder pressure value. On one side, we observe the correlation between this reference value and the knock intensity to which a detection threshold is applied. We compare the proposed FFT-based test and the standard treatment from Fig. 2. In the first case, the knock intensity is a linear combination of the three FFT peak values and in the second case, it is the output of the time integrator block. These results are represented in Fig. 6 for all the 800 engine cycles. In the same figure, the reference detection line which is used later on is also indicated, chosen at 0.3bar. As before, the filter for the standard treatment was a 2^{nd} order infinite response band-pass filter with quality factor 2.3. It was centered on the resonance that gave the best correlation.

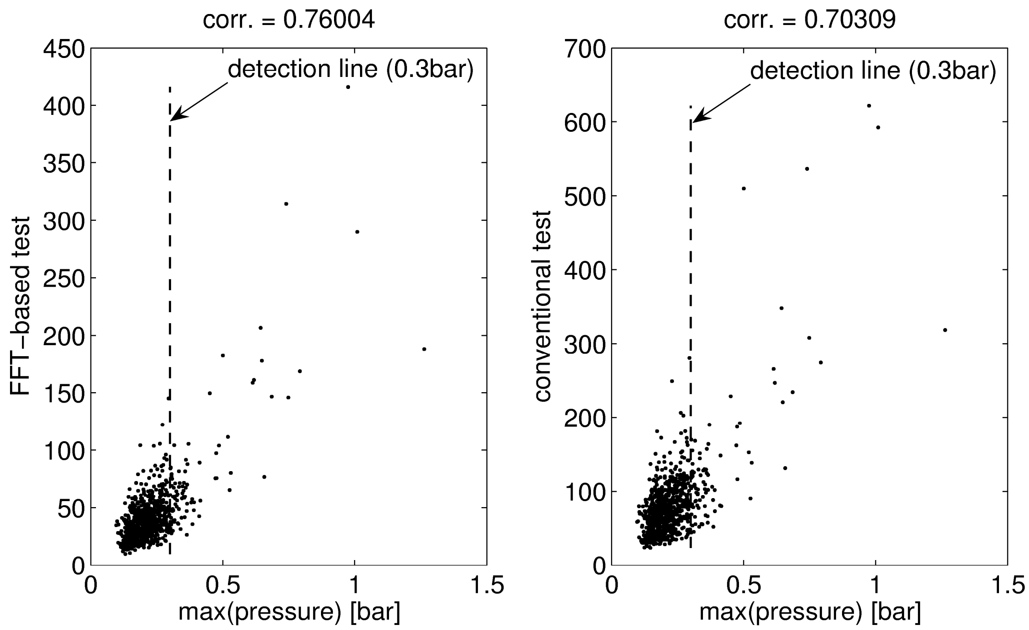

Fig. 6: Correlation between the reference maximum pressure value and the two knock intensities

The proposed FFT based test results in a higher correlation coefficient. However, this correlation may not be the best measure of performance since it depends highly on a few points of strongest knock. As mentioned before, the detector performance is given by the ROC curve. That is why on the other side we also make this comparison. We use the indicated detection line from Fig. 6 to decide whether knock is present or not. Sweeping the threshold value, false alarms and correct detections are counted to give an empirical ROC curve. It is shown in Fig. 7 for the two detection algorithms discussed as well as for the case where quadratic phase (i.e. linear frequency modulation) is not neglected. For the latter, HAF is used to estimate the phase coefficients $\alpha_p, \beta_p, \varphi_p$. There is nevertheless a practical restriction on false

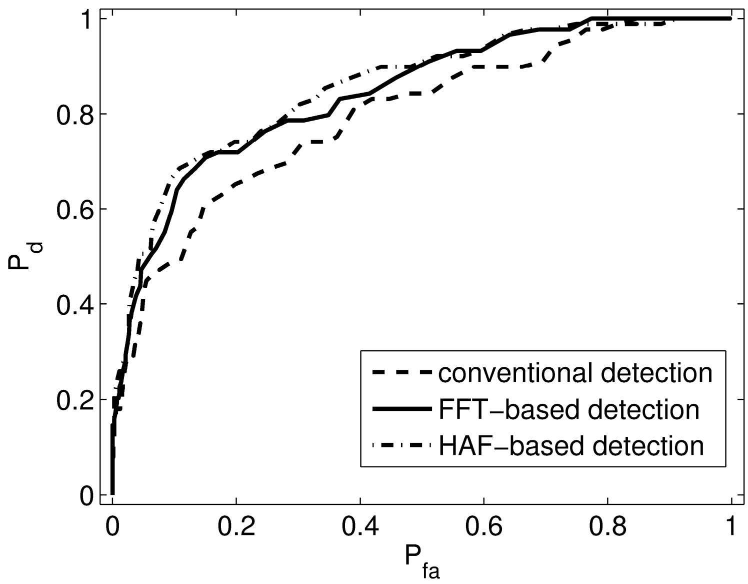

Fig. 7: Empirical ROC curves for the two compared detection algorithms and for the HAF-based method that supposes quadratic phase functions

alarm rates we can achieve, which is limited by the database size. We can note that the FFT-based detection outperforms the standard one, while HAF-based detection gives a slight further improvement, however with a higher computational cost, when considering the number of basic microprocessor operations needed to implement the algorithms.

5. Conclusions

This paper presented a knock detection algorithm based on a mathematical model of knock sensor signal. The research of an improved detector is stimulated by the detection theory which states that the actual signal processing based on the band-pass filtering is far below the optimal Neyman-Pearson ROC characteristic. We first presented the optimal test for the hypothetic case of all parameters being known. Since we have to estimate those parameters in practice, we introduced a two-step simplification where amplitude variations and quadratic phase functions were omitted. With some restrictions on signal length, we can thus perform the detection by computing a Fast Fourier Transform of the knock signal which is not expensive in terms of required computational power. Finally, we showed some results of application of the presented algorithm to real engine data.

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