Combustion diagnosis for internal combustion engines with real-time acquisition and processing

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Abstract

The use of vibration signals for internal combustion engines diagnosis is now well established for several applications such as knock detection or valve mechanics behaviour assessment. If standard knock detection can be performed in real time, diagnoses are generally carried out off-line due to algorithm complexity. Our aim was to get some insights on the time-frequency properties of the vibration signal in order to improve off-line techniques and propose adapted real time algorithms for combustion diagnosis. This paper addresses the problem of the identification of combustion related vibrations among others noise sources. In order to help this identification, pressure traces from in-cylinder sensors are also recorded and processed. Thus, pressure forces that generate the "thermal noise" in the vibration signal can be analyzed separately. The "thermal noise" associated events can be more easily isolated from the mechanical noise in the vibration signal mixture.

1 Introduction

The development of new technologies in internal combustion (IC) engines for emissions and fuel consumption reduction constitutes a very acute challenge in engine research. One could refer to the increasing use of alternative energy from biomass, and the growing development of Flexfuel vehicles, which can use mixtures of ethanol or gasoline in any proportion, as examples of those cutting edge research fields. Flexfuel engines, in particular, represent a great challenge for IC engine improvement, as optimal efficiency for any fuel composition is desired.

These new generations of spark ignition engines require a correct ignition adjustment for each fuel, to guarantee optimal performance. A recent trend towards ignition adjustment exploits the detection of knocking combustion phenomena [1]. Engine knock is an unwanted phenomenon that may cause engine damage. However, optimal performance is often obtained when the spark advance remains close to the knocking condition. A proposed strategy consists in controlling spark advance by using close-loop control algorithms with knocking condition detection, and in adapting the advance regulation optimally with respect to the detected knocking limit.

Knock detection for efficient combustion control of spark ignition engine can be performed through the use of in-cylinder pressure sensors. Nevertheless, their cost and the environment hostility limit their practical use outside test beds. A more cost effective approach consists in using accelerometer sensors located on the engine surface and [2] showed its potential for knock detection. Gasoline series vehicles are already equipped with knock sensors but the existing detection techniques require further improvements such as improved noise and speed robustness, adaptability to combustion conditions and, above all, a better characterization than standard binary classification in "knocking" or "not-knocking" conditions.

This paper addresses the challenge of knock detection improvements with time-frequency analysis. The later technique is better suited than standard Fourier transforms to the non-stationary features of the vibration signals recorded from accelerometers. Time-frequency representations yield more insights to the properties of the vibration signal associated with the knock phenomenon, and are generally more noise resilient. Information provided by time-frequency techniques is essential to provide a real time methodology suitable for close-loop control.

After a presentation of the knocking phenomenon background, we will describe the experimental setup, as well as the dedicated acquisition system that was developed to address real-time data recording and processing.

Time-frequency analysis of both pressure traces and vibration data is performed and results provide useful insights on the knock related vibration signals. We then take advantage of this improved understanding to develop a real time knock detection approach.

The paper is organized as follows: we present in Section 2 the acquisition platform which also implements real time combustion analysis algorithms. Section 3 is dedicated to the background of the knock phenomenon. Time-frequency analysis, which provides appropriate tools for the study of non stationary signals such as knock related vibrations, is reviewed in Section 4. Finally, Section 5 details the proposed real time knock analysis and its application on real engine experiments with varying conditions.

2 Real-time combustion analysis platform

IFP has developed an acquisition and processing platform dedicated to the analysis and monitoring of combustion-related processes for test bed engines. It allows triggered acquisition for off-line data analysis (as well as for algorithm design), real-time signal processing and communication with other monitoring or control and diagnosis units.

The platform is based on a Host-Target architecture. The Host PC is dedicated to software development and communications with the Target. The Target is an industrial PC working on Mathworks™ xPC Target® real-time kernel. Its hardware architecture contains an IFP Timer Board coupled with a windowed acquisition module designed for high-resolution (16-bit) multi-channel analogue data acquisition. Analogue acquisitions are triggered independently on each channel on the base of a 0.1° crank angle (CA) resolution angular coder or the 6°-CA resolution flywheel, depending on the engine speed. The windowing of the data on a reduced angle range (around each cylinder Top Dead Centre, TDC) allows the recording of useful parts in the considered signals. High-frequency signal sampling in the acquisition window is performed with two modes: time-based or angle-based. Depending on the mode, data sampling is performed up to 200 kHz (time-base) or 0.1°-CA (angle-base). Eight channels are usually recorded, including, for instance, signals from in-cylinder and rail pressure, accelerometer, knock or ionization current sensors. Figure **1** displays the system description and architecture.

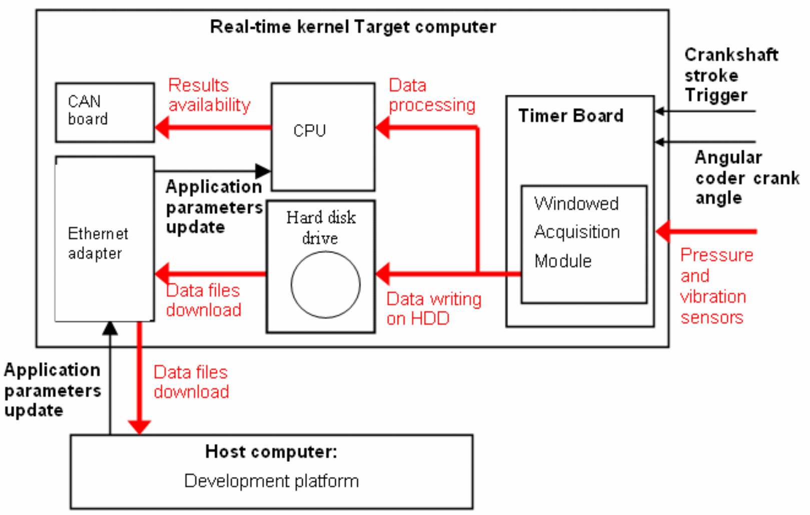

Figure 1: Combustion Analysis Platform hardware architecture diagram.

Designed after extensive off-line analysis of recorded data, the fast prototyping stage of signal processing algorithms' implementation is performed within Simulink® and the Signal Processing Blockset®. The combination of xPC Target® and Real-Time Workshop® allows to generate code and to download it onto the target running in real-time. Executable application building can be divided into two main steps: C code generation with Real Time Workshop, compilation and linking with Visual C/C++ .net®. The design stages are represented in Figure **2**.

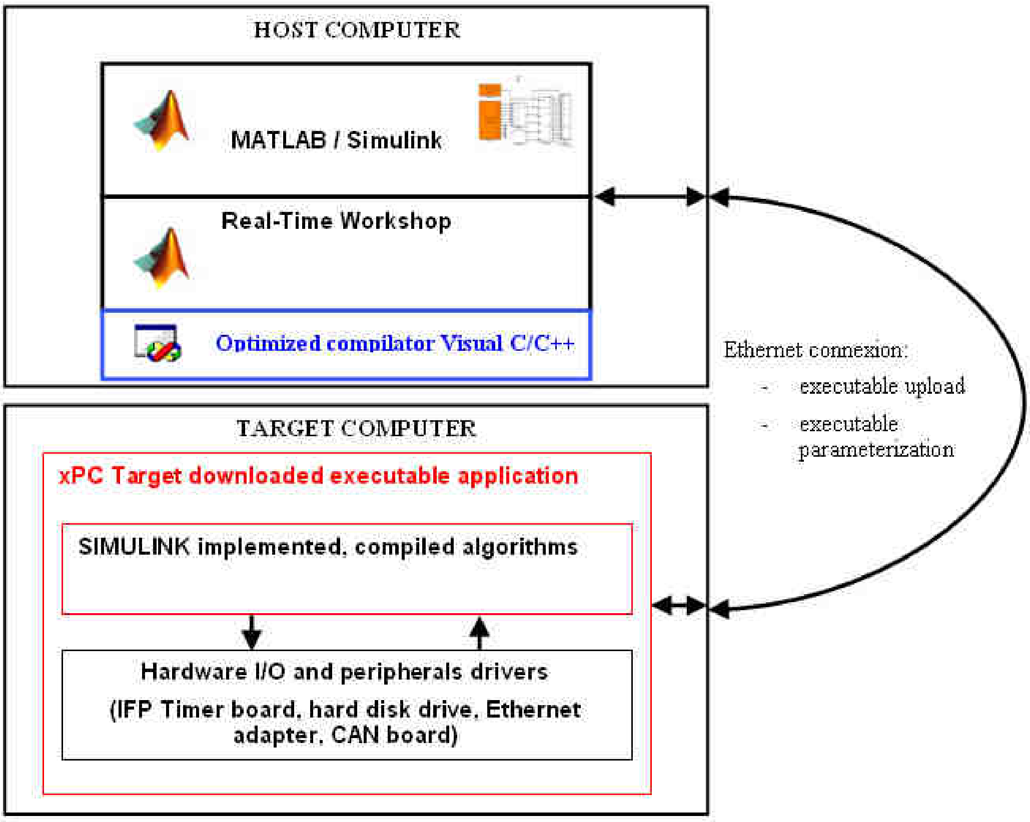

Figure 2: Fast prototyping software architecture diagram.

The combination of both hardware and software features of the platform allows the design of signal processing algorithms from data offline post-processing (with time-frequency transforms) to low complexity real time algorithms.

3 Knock phenomenon

3.1 Introduction and challenges

Spark ignition engines are subject to an abnormal combustion process called “knock”. It is associated with fast pressure increases which turn into engine vibrations causing the familiar knocking sound. Knock is a potential damage source for the piston crown or the cylinder walls. It furthermore limits engine efficiency. Fine knock detection strategies increase engine performance, combustion stability, reduce transient noises and, to some extent, pollution (CO_2 for instance). Traditional detection methods rely on amplitude/energy detection for one or several frequency bands, computed using a Fourier transform or a band-pass filtered signal obtained from instrumental devices. Knock amplitude or energy is then detected using fixed or updated discriminating thresholds [3]. Though effective at low speeds, these traditional methods seem to reach their limits at high engine speed or when other noise sources interfere (background noise, injection power unit disturbances, etc.)

Several authors [4] have pointed out that the knock signal is unsteady since chamber volume and sound speed vary through a combustion cycle. They therefore investigated ``time-frequency" analysis methods such as Wigner-Ville or wavelet transforms [5]. These methods are able to discriminate knock characteristics and are generally robust to background noises.

3.2 Basics on knock properties

Several knock definitions exists, and we will follow a generic one, from [6]:

"Knock is an undesirable mode of combustion that originates spontaneously and sporadically in the engine, producing sharp pressure pulses associated with a vibratory movement of the charge and the characteristic sound from which the phenomenon derives its name."

The knock phenomenon is classically viewed as an abnormal combustion process. In normal combustion, a spark plug ignites a gaseous mixture of air, fuel and residual gases toward the end of the compression stroke. The mixture burns and the front flame propagate from the point of ignition to the cylinder walls and the piston crown [7].

The major theory for knock onset is auto-ignition. In this theory, unburned gases ahead from the front flame ("end gases") are compressed. The elevation of temperature and pressure may lead to a point where precombustion reactions have time to develop to a self-ignition of the unburned gases. We refer to [8] for a comparison between knock models. Auto-ignition may also start from "hot spots" in the end gases melange. The resulting impulsive pressure increase excites the cylinder cavity resonances, which are transmitted to the engine structure. It results in engine vibrations to the audible level.

In the case of cylindrical combustion chamber, the resonant frequency can be expressed as

$$f_{m,n,p} = \frac{c}{2}\sqrt{\left(\frac{x_{m,n}}{B}\right)^2 + \left(\frac{p}{L}\right)^2}\,, \tag{1}$$

where c denotes the speed of sound in gas, B the radius of the cylinder bore and L the axial length of the cylinder cavity which changes as the piston moves. The indices m, n and p are integers denoting respectively circumferential, radial and axial mode numbers. The $x_{m,n}$ terms are determined by solving

$$\frac{d\,J_m(\pi z)}{dz} = 0\,, \tag{2}$$

with J_m the Bessel function of the first kind of order m and the n^{th} zero for a specific order m. Usually, the axial mode is neglected because knock generation occurs when the piston is close to the TDC position. Equation (1) then becomes:

$$f_{m,n,p} \approx \frac{c x_{m,n}}{2B}\,. \tag{3}$$

According to a thermodynamic relation, the velocity of sound can be approximated as:

$$c^2 = \gamma R T\,, \tag{4}$$

where γ is the isentropic coefficient, R the gas constant and T the in-cylinder temperature.

The frequency is thus a function of the chamber geometry, the temperature and the isentropic constant. Consequently, different fuel compositions with different thermal properties may cause changes in the resonant frequency values.

4 Time-frequency analysis of knock phenomenon

4.1 VIBRATION SIGNAL NATURE

The vibration signal exhibits non-stationary features due to different kind of sources such as valve openings and closures, piston slaps and additive noises. Transient waves generated by these sources overlap each other and the challenge is to detect the parts of the vibration signal associated to the knock phenomenon. To help the identification of the knock contribution, pressure traces acquired from in-cylinder pressure sensors are also used as a reference signal.

Figure 3 presents typical pressure and vibration signals associated with a spark injection engine. The difference between non-knocking and knocking conditions can be easily identified by the apparition of a high amplitude transient event with limited bandwidth frequency content. These non-stationary features of vibration signal and knock related contributions have to be analyzed by appropriate techniques using time-frequency representations.

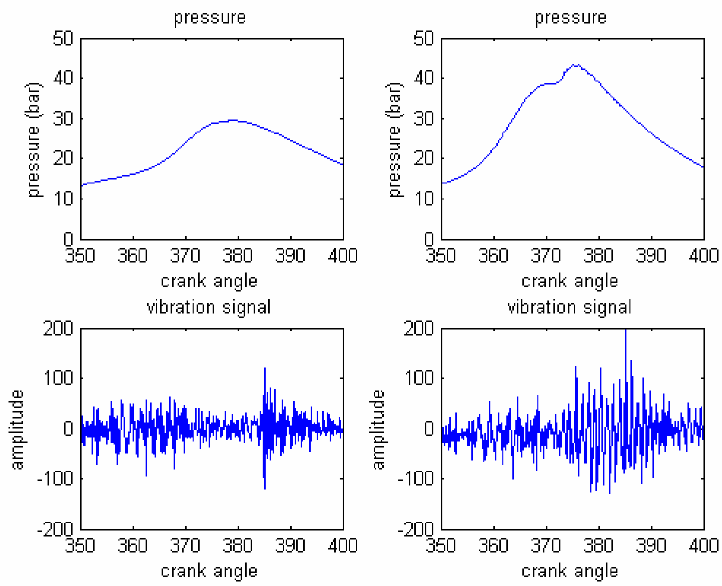

Figure 3 : Pressure and vibration signals in non-knocking and knocking condition.

4.2 Short-time Fourier transform and the spectrogram

The Fourier transform is not well suited tool to the analysis of a non-stationary signal since it projects the signal onto infinite waves which are completely delocalized in time. Vibration signal components could not be discriminated with the frequency information alone, as these components may possess similar frequency content. A time dimension has to be added to the standard frequency analysis and bidimensional functions of time and frequency variables have to be considered. A first and simple technique introducing time-dependency in the Fourier transform is to perform Fourier transform in a sliding window *h*. The obtained transform is the short-time Fourier transform (STFT), with mathematical expression given by:

$$STFT(t,\upsilon;h) = \int_{-\infty}^{+\infty} x(u)h^*(u-t)\,e^{-j2\pi\upsilon u}\,du\,. \tag{5}$$

This time-frequency representation is very intuitive and provides a friendly tool to address the properties of a non-stationary signal. The time resolution of the STFT is proportional to the duration of the analysis window and the frequency resolution is proportional to the analysis window bandwidth. Due to the Heisenberg-Gabor inequality, an optimal resolution in both domains can not be reached, resulting in a trade-off between time and frequency resolutions. A consequence of the choice of a particular window is the signal's stationary assumption inside this window and the signal analysis with a fixed time-frequency resolution. Usually, the time-frequency analysis based on the STFT is visualized through its squared modulus. This energy distribution defines the spectrogram as a quadratic representation. The main drawback of this type of representation is the introduction of interference structures with respect to the quadratic superposition principle.

4.3 Wigner-Ville Transform

If the STFT and the spectrogram provide a first diagnosis of a non-stationary signal, their limitations are rapidly reached and more sophisticated techniques have to be considered. Among these time-frequency techniques, the Wigner-Ville distribution is of particular interest. This transform is very similar to the STFT. The main difference resides in the analysis window which is not a standard fixed window but the signal itself, temporally inverted:

$$W_x(t,\upsilon) = \int_{-\infty}^{+\infty} x(t+\tau/2)x^*(t-\tau/2)\,e^{-j2\pi\upsilon u}\,d\tau \,. \tag{6}$$

The main advantage of this representation is to avoid the choice of an arbitrary analysis window. Here the window is always well adapted to the signal. A description of the Wigner-Ville distribution properties can be found in [9].

Nevertheless, as a quadratic representation, the Wigner-Ville spectrum includes interference structures which may lead to pitfalls in its interpretation. To limit these interferences, several techniques have been implemented such as the use of analytic signal to avoid interference between components located near the frequency symmetry axis. Smoothing techniques allow the attenuation of interferences patterns. In the later case, the obtained distributions are smooth pseudo Wigner-Ville transforms.

4.4 Reassignment method

The reassignment was introduced to improve the spectrogram resolution, but may also be applied to the Wigner-Ville spectrum. The original idea of the reassignment technique [10] consists in assigning each value of the spectrogram at the centre of gravity of this domain instead of at a geometrical center of the time–frequency domain. This is done by using the phase information of the STFT.

4.5 Wigner-Ville Distribution and cyclostationarity

The use of the Wigner-Ville distribution is on the one hand justified by the good time-frequency resolution. On the other hand, [11] showed that most engine vibrations may be regarded as cyclostationary. Components of these vibrations are mutually not correlated and the cross-terms in the Wigner-Ville distribution can be cancelled by averaging different combustion cycles. Theoretically, the resulting mean Wigner-Ville distribution converges to the Wigner-Ville spectrum containing the auto-terms only.

4.6 Time-frequency analysis of the vibration signal

Figure 4 represents spectrograms of a pressure trace and a vibration signal. The STFT used a 129 point Hamming window. The resonance frequency, generated by the knock phenomenon, can easily be observed in the gradient pressure spectrogram. The vibration signal spectrogram shows a more complex content with several transient events but the first resonant frequency can be detected between 380° and 400° CA indexes and below 10 kHz. Our purpose is to precisely determine the frequency content of the knock.

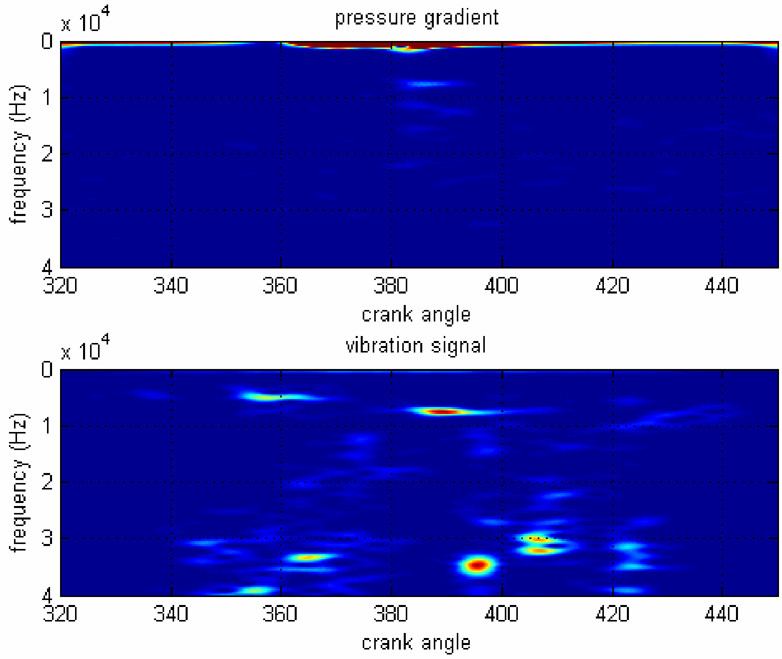

Figure 4: Pressure gradient and vibration signal spectrograms.

Figure 5 shows the resolution gain obtained with the Wigner-Ville distribution and the reassignment technique. In some cases, the resolution obtained with the reassigned spectrogram may even compare to that of the pseudo Wigner-Ville distribution. Thus we recommend the use of this technique in addition to the reassigned pseudo Wigner-Ville representation.

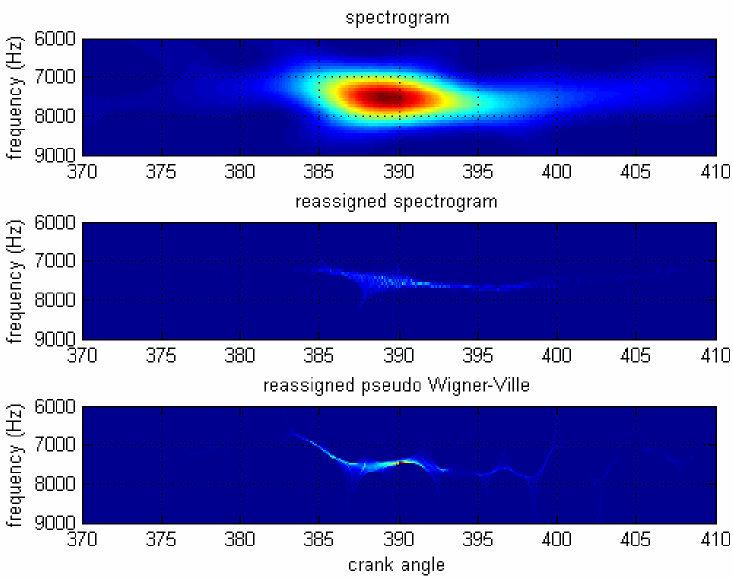

Figure 5: Spectrogram (top), reassigned spectrogram (middle), reassigned pseudo Wigner-Ville distribution (bottom).

The reassigned pseudo Wigner-Ville spectrum provides good resolution which allows the observation of differences in the frequency content of knock vibration related to load or composition variations. Figure 6 depicts the variation of the energy and frequency content for three different setting points for which the load increases (indicated by the IMEP, Indicated Mean Effective Pressure index). Here, as the temperature reached in the combustion chamber becomes higher, the resonant frequency increases. This frequency variation may be observed both on pressure and vibration signals, which confirms the relevance of this indirect measurement.

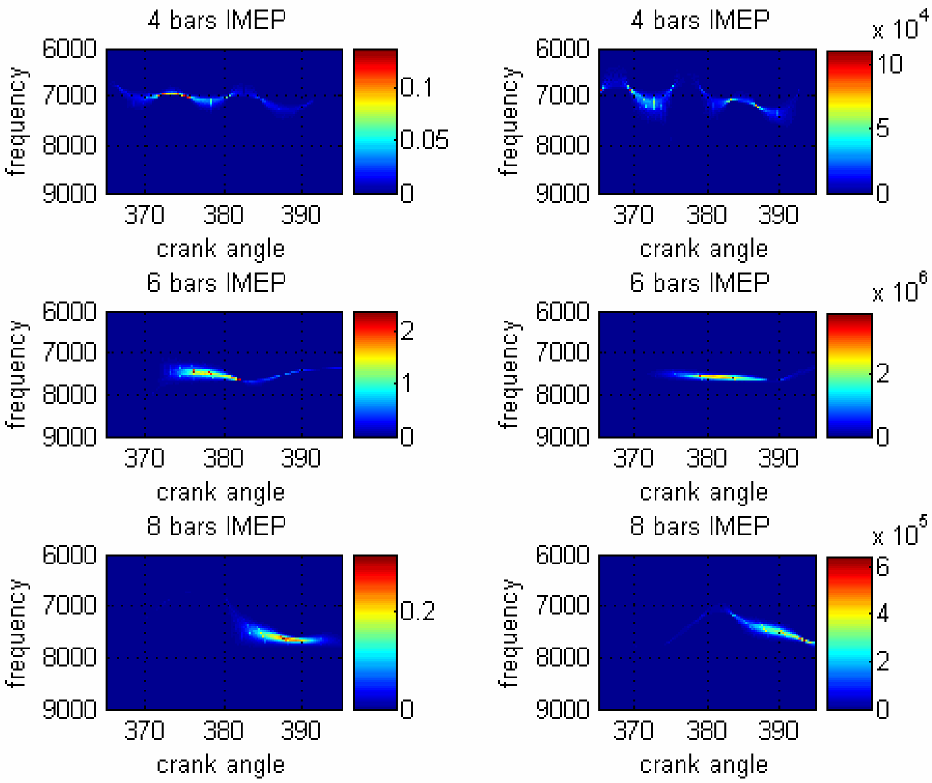

Figure 6: Knock frequency variation due to load increase (pressure on the left and vibration signal on the right).

5 Real time knock analysis

5.1 Real time issues

The time-frequency representations presented in the previous part are well suited to signal analysis for off-line diagnosis. Nonetheless, the computation time and the large number of operations needed to perform a Wigner-Ville distribution often exceed on-board processor capabilities. The objective is to find a signal processing strategy which can be implemented in real time in order to identify the occurrences of the knock phenomenon. The proposed methodology should take into account several issues:

- real time implementation,
- noise robustness,
- adaptation to the knock frequency variations,
- improvement of the binary knock-no knock response given by state-of-the-art techniques as well as providing a finer quantification of the knock phenomenon.

5.2 Real time time-frequency analysis

Time-frequency representations are able to provide information on the frequency content variation of the knock phenomenon. The main idea of our processing strategy is to analyze signals in a narrow bandwidth where the knock phenomenon appears. This strategy requires the observation of only a small number of frequency components. Consequently, techniques based on sliding Discrete Fourier Transform (DFT) have been assessed and especially those which can be implemented in a recursive way.

The Goertzel algorithm [12], used in dual-tone multi-frequency decoding, was considered. This algorithm computes a single DFT. The algorithm is implemented in the form of a second-order infinite impulse response filter (IIR). The *z*-domain transfer function of the Goertzel algorithm is:

$$H(z) = \frac{1 - e^{-j2\pi k/N} z^{-1}}{1 - 2\cos(2\pi k/N) z^{-1} + z^{-2}}, \tag{7}$$

where N is the number of samples of the considered angular sequence and k is the frequency-domain index in the range $0 \le k \le N-1$. The advantage of the Goertzel algorithm is its iterative implementation that requires fewer operations than a traditional DFT. A limited bandwidth spectrogram can thus be obtained with a sliding Goertzel algorithm version in the same way as in the STFT, for a single frequency bin only.

Another algorithm is even more interesting in real time applications, the sliding discrete Fourier transform (SDFT) described in [13]. This algorithm uses the circular property of the DFT which states that if $X(k)$ is the DFT of a sequence, the DFT of the sequence shifted by one sample is $X(k)e^{j2\pi k/N}$. This property can be expressed with the following difference equation:

$$S_k(n) = S_k(n-1)e^{j2\pi k/N} - x(n-N) + x(n), \tag{8}$$

where S_k is the spectral component determined at each angular sample n for the frequency-domain index k. Once the first spectral component is computed, only a very limited number of operations is needed, in contrary to the Goertzel algorithm. This process is valuable in computing real time spectra. The SDFT thus requires two real adds and one complex multiply per output sample. Nevertheless, a particular attention has to be taken in order to check the SDFT stability; applying this algorithm to a narrow bandwidth, which generally increases its robustness. Figure 7 shows the summation of two discrete spectral components computed in the knock bandwidth between 7 and 9 kHz determined by the Goertzel and the SDFT algorithms, one can observe the good agreement in the variation of the spectral component summation versus angle.

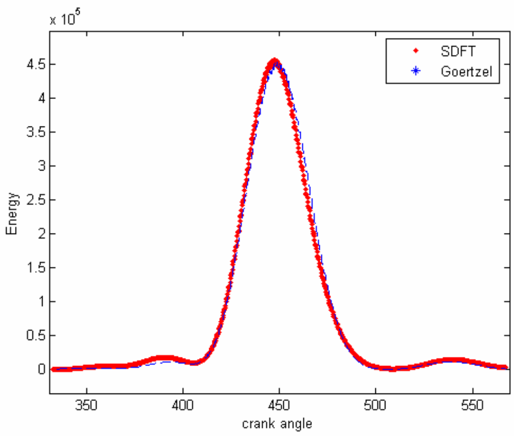

Figure 7: Comparison of the spectral component energy versus angle determined with Goertzel and SDFT algorithms.

The proposed methodology can be summarized in three steps:

- angular acquisition,
- band-pass filtering of the vibration data,
- spectral components determination of a few number of frequencies in order to identify the presence of knock related vibrations and summation of the energy of these spectral components.

5.3 Real time knock detection

For the application of the proposed methodology, several tests on a four-cylinder direct injection engine with different speeds and loads have been performed with a variation of the spark advance.

A first test consisted in increasing the spark advance in order to meet the knock condition and perform our real time detection strategy. The engine speed was 1500 rpm and the indicated mean effective pressure (IMEP) was 6 bars, with 120 recorded cycles. The spark advance varies from -13° to -18° (Figure 8, bottom). As one can observe on Figure 8, where the energy of the spectral components versus angle are displayed, the non-knocking and knocking occurrences are well determined as well as the intensity of the phenomenon.

Our approach was also applied to a second test. Data were acquired with a different speed (3000 rpm) but with the same IMEP (6 bars). The spark advance decreases from -31° to -35°. Figure 9 confirms the validity of our approach and it can be observed that sporadic knocking conditions are present for this test, and so, for every value of the spark advance. For several cycles, the energy of the spectral components is quite high and reveals strong knocking conditions.

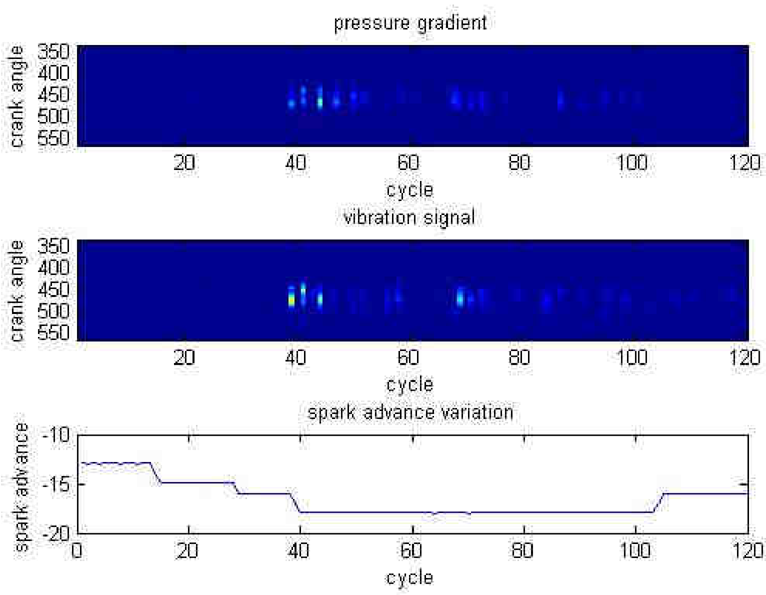

Figure 8: Real time knock analysis of the first test at 1500 rpm and 6 bars IMEP (top: results from the application of the proposed methodology applied to the pressure signal, middle: results from the same methodology applied to the vibration signal, bottom: spark advance).

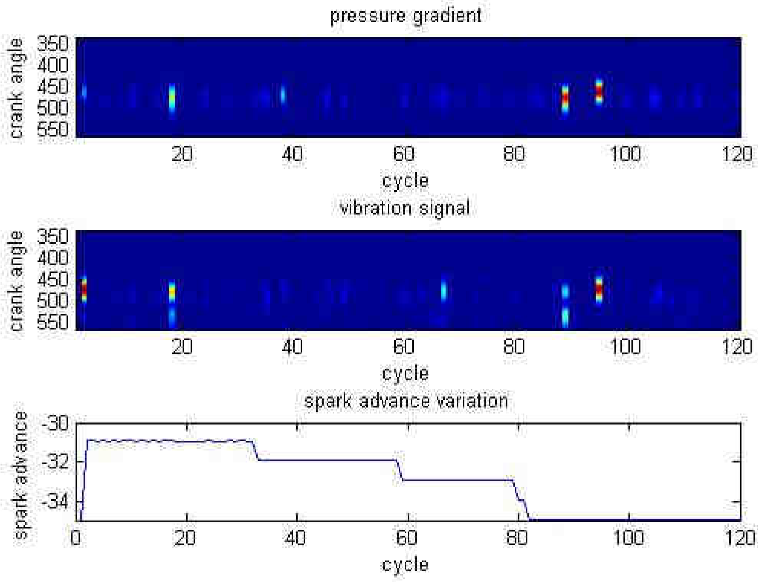

Figure 9: Real time knock analysis of the second test at 3000 rpm and 6 bars IMEP (top: results from the application of the proposed methodology applied to the pressure signal, middle: results from the same methodology applied to the vibration signal, bottom: spark advance).

6 Conclusion

Engine performance optimization can be performed with spark advance control with a strategy based on knocking detection. An economical approach for the knocking detection consists in using accelerometer sensors located on the engine and to extract information on the occurrence of the knocking phenomenon from vibration signals. Time-frequency analysis techniques such as the Wigner-Ville distribution or the reassigned spectrogram are used to characterize precisely the frequency content of the knocking related signal components, which may vary in function of fuel composition in the particular case of Flexfuel engine. A real time methodology for spark adjustment close-loop control is proposed, which is able to provide information on the presence of knock. Tests show that it is possible to provide also information on knock intensity.

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