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Engine Knock Detection from Vibration Signals using Pattern Recognition

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Abstract. The paper deals with a diagnostic method that allows to detect engine knock. The developed algorithm differentiates three kinds of engine cycles: absence of knock, increasing knock and heavy knock. The decision is taken from a block vibration signal. The diagnostic method is based on pattern recognition. Three models of different data shapes provided from the accelerometer are elaborated. This is done using a time-scale analysis tool called a wavelet network. It allows to extract relevant features from the signal. The aim of the method is then to partition the feature space into classes representing the knock states. Experimental results are reported.

Sommario. Viene presentato un metodo diagnostico che consente di individuare la detonazione in un motore alternativo ad accensione comandata. L'algoritmo proposto permette di distinguere tra tre differenti situazioni: assenza di detonazione, detonazione incipiente e detonazione marcata. La scelta tra tali condizioni viene effettuata a partire dal segnale relativo alle vibrazioni del blocco motore (fornito da un accelerometro) attraverso una procedura di riconoscimento. Il metodo si basa sulla definizione di tre diverse forme d'onda di riferimento che vengono elaborate utilizzando uno strumento di analisi denominato "wavelet network": esso permette di evidenziare i principali aspetti che caratterizzano il segnale. Scopo del metodo è quindi quello di suddividere lo spazio delle diverse condizioni di detonazione in classi differenti e di riconoscere le condizioni in cui si trova ad operare il motore. Nell'articolo vengono riportati alcuni risultati sperimentali ottenuti tramite la procedura descritta.

Key words: Wavelet network, Pattern recognition, Spark ignition, Internal combustion engines, Automotive applications

1. Introduction

Knock is an important phenomenon for spark-ignition engines. Since the twenties, many engine manufacturers have devoted their whole attention to study knock characteristics. Papers about it abound in literature [2,3], and the problem today is still of interest. Indeed, both the continuous need in increasing engine efficiency and present requirements with regard to control of exhaust emissions make engine manufacturers work close to knocking conditions. Nevertheless, knock can lead to engine damages. Most people agree that knock results from an abnormal combustion of the mixture. When some conditions into the combustion chamber reach a critical state, the still unburned mixture autoignites. It causes the propagation of a shock wave into the chamber and a specific noise, often audible, which gives the event the name. Of course in order not to deteriorate engines, it is necessary to avoid this phenomenon.

The better knock is identified, the more efficient the engine monitoring is. In most cases, knock is detected from signals recorded in engines. These signals are especially acquired from a cylinder pressure or a block vibration sensor. From the data, some researchers decide to differentiate knocking cycles from not knocking cycles [2,6]. Others try to quantify the knock intensity and to define several magnitude degrees of knocking conditions [8]. To do so, several signal processing methods are then applied to the data. The method that seems to be the most often used is based on a frequency-domain manipulation [3]. For instance, data are band-pass filtered (within range of 5–10 kHz), and then integrated during knocking, while a proper threshold is set to detect knock.

Other approaches are sometimes used. Parameters can be calculated from a signal time analysis or more rarely from a time-frequency one, while some methods use signal derivative [8]. The pattern recognition approach is rarely used for knock detection: few works belong to this field [1,7]. Our paper also deals with a method based on pattern recognition applied to knock detection. As for Bartz [1], our purpose consists in recognizing several knock intensities when most people only detect two states: knock presence and absence. At each cycle, the aim of the method is to detect knock occurrences and in these cases to express the phenomenon severity.

Section 2 introduces the diagnosis with a pattern recognition approach. Section 3 gives an overview of the diagnostic method. Particular neural networks called wavelet networks are defined in Section 4. Section 5 presents the originality of our method, that is based on the use of wavelet networks to provide a block vibration signal representation. The experimental set-up and the full process leading to the final decision is also described. This work, supported by PSA Peugeot Citroën, has led to results with real data which are reported.

2. Pattern Recognition for Diagnosis

Performing the diagnosis of a system leads to determine its operating state. For instance, if we consider the engine as our system, “absence of knock”, “increasing knock” and “heavy knock” can constitute three different operating modes of the system.

As for pattern recognition purpose, it consists in classifying an object into a class ω_j [4], which is part of a set of M known classes. Indeed each class is composed of similar objects: therefore, when an object is affected to class ω_j, it means this object and those of class ω_j are very much alike. For our study, each class corresponds to a knock state. Then three classes are possible:

- Absence of knock (ω_A).
- Increasing knock (ω_I).
- Heavy knock (ω_H).

The object mentioned above is called a pattern. A pattern is a vector that contains relevant information about the system: it is supposed to carry enough information in order to characterize the system operating mode. The features composing the pattern are extracted at a time t from the observed system. In our case, they are extracted from the block vibration signal. Then they define a feature space whose dimension d is the number of relevant parameters. Of course, the choice of these parameters is particularly important: the more pertinent the features are, the more reliable the final diagnosis is.

3. General View of the Diagnostic Method

The whole diagnostic method represented on Figure 1 indicates that five modules are required to provide a partition of the feature space in classes.

- The first step consists of using a block vibration signal sensor. The provided signal is the starting point of our work: all the following phases depend on this signal.

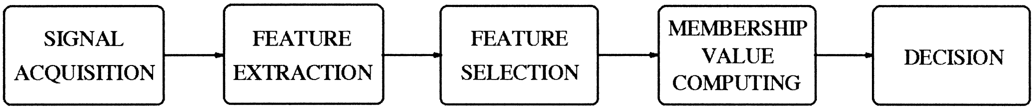

Figure 1. Diagnostic line architecture.

– The vibration signal is not used in its primitive form: it must be processed to allow the extraction of relevant parameters to compose efficient patterns. That is, the purpose of the feature extraction stage developed in the next section.
– The aim of feature selection phase is to choose d' parameters among the d possible parameters constituting the patterns ($d' < d$). It allows to reduce the complexity of the diagnostic algorithm without breaking its efficiency. Indeed, the d' parameters are discriminated. They are supposed to be different if they are extracted from an engine cycle showing a heavy knock or from another cycle indicating an increasing knock.
– The goal of the next module is to provide any pattern with a membership degree to the three existing classes. The performed classification of patterns is not exclusive. Every class ω_i with $i \in \{A, I, H\}$ has a membership function Φ_i taking values in [0,1]. The function Φ_i takes its maximum value for patterns that belong strongly to the class ω_i. The further the patterns move away from the class ω_i, the smaller is the value of Φ_i.
– The last stage concerns the elaboration of a decision rule that allows to associate a pattern to its nearest class.

The originality of our paper especially concerns the constitution of patterns. It is based on the use of a time-scale analysis tool called wavelet network.

4. Wavelet Networks

These particular neural networks were introduced by Zhang and Benveniste [9]. They propose to perform any continuous function by a specific architecture of a multi-layer neural network: the neurons activation functions of the hidden layer are wavelets (see Figure 2). Such a network calculates the weighted summation of N wavelets. So any one-dimensional signal $x(t)$ can be represented by:

$$\hat{x}(t) = \sum_{k=1}^{N} w_k \Psi_k(t), \tag{1}$$

with

$$\Psi_k(t) = \Psi\left(\frac{t - b_k}{a_k}\right), \tag{2}$$

where
– t: time,
– $\Psi(t)$: mother wavelet,
– w_k: kth wavelet coefficient,
– b_k: kth wavelet translation parameter,
– a_k: kth wavelet dilation parameter.

For our application, the Morlet wavelet is selected as the mother wavelet $\Psi(t)$:

$$\Psi(t) = \mathrm{e}^{\mathrm{i}ct}\, \mathrm{e}^{-\alpha^2 t^2/2} \qquad \text{with } \alpha = 1 \text{ and } c = 5. \tag{3}$$

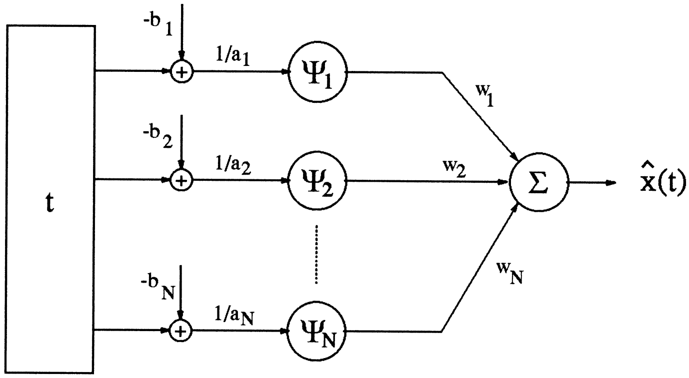

Figure 2. Architecture of a wavelet network.

Note that the shape of the N wavelets with regard to the oscillation number remains unchanged. On the other hand, both their time location and their dilation/contraction parameter differ from each other. To learn the signal $x(t)$, the network optimizes the criterion J_1:

$$J_1 = \frac{1}{2}(x(t) - \hat{x}(t))^2. \tag{4}$$

Wavelets weights, dilation, and translation parameters vary adaptively, according to the back-propagation algorithm, in order to make the network output fit the input signal.

As knock appearance leads to alterations of some parts of a vibration block signal, we propose to elaborate a model for these variations.

5. Experimental Set-up

5.1. Database

The first step in order to elaborate the diagnostic method consists of making a database. It is composed of several block vibration signals acquired from the same engine at a constant speed. In order to tune the parameters of the method, these data need to be labelled. Indeed, the combustion state in the chamber must be known for each engine cycle. For this reason, cylinder pressure is recorded at the same time as cylinder block vibration. It is true that knock is easily distinguishable by rapid and large oscillations of cylinder pressure (see Figure 3). The data are generated over a range of operating conditions with spark advance variations: three different spark advance are tuned. They are assumed to lead to three different knock states: absence of knock, increasing knock, and heavy knock. However, the ultimate label is given to each engine cycle by an expert who carefully looks at each cylinder pressure signal.

Unfortunately at this time we are provided a small data set composed of only 58 cycles identified as:

- 21 non-knocking cycles,
- 19 increasing knocking cycles,
- 18 heavy knocking cycles.

In order to lead a rigorous analysis, the database must be divided into two groups:

- a training set,
- a validation set.

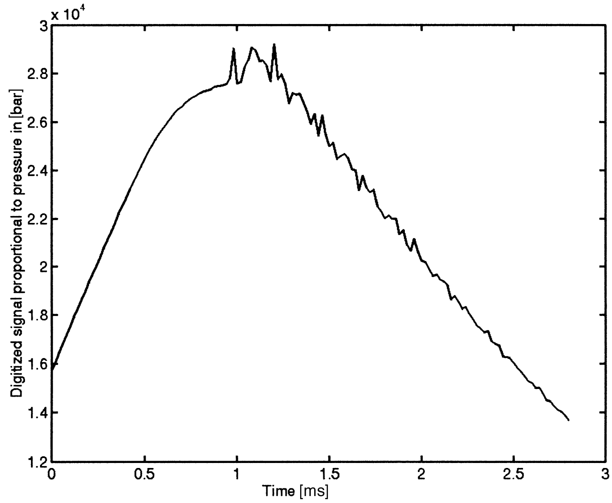

Figure 3. Pressure signal vs. time for heavy knock. The window is about 35 degrees large, ending 20 degrees after the crank angle of peak pressure.

Table 1. Engine cycles breakdown

Engine cycles	Absence (ω_A)	Increasing (ω_I)	Heavy (ω_H)
Learning set	16	14	13
Test set	5	5	5

The training set allows to adjust the diagnostic method parameters while the second set purpose is to validate the algorithm. Then, the training set is composed of 43 cycles since the validation set includes 15 cycles. The breakdown of the cycles according to the three knock states is shown in Table 1.

5.2. Learning Phase

5.2.1. *Model elaboration*

The method developed must classify the whole learning set into three classes. To do so, several wavelet networks as described above are used. Our approach consists of elaborating three models for absence of knock, increasing knock and heavy knock. So three block vibration signals are selected according to the expert's advice. Each of them is decomposed using a wavelet network. A base of 40 wavelets is considered. Their connection weights, their scale and time parameters are adapted in order to make the best signal approximation. At this stage, three models are provided. Each of them is characterized by:

– 40 wavelet time parameters,
– 40 wavelet scale parameters,
– 40 wavelet connection weights.

In fact, a model is composed of 40 wavelets whose time locations and scales are fixed. Only the connection weights of each wavelet are going to change in the following step. Figure 5 shows the 40-wavelet base that constitutes the model of the increasing knock class. It is elaborated from the vibration signal in Figure 4.

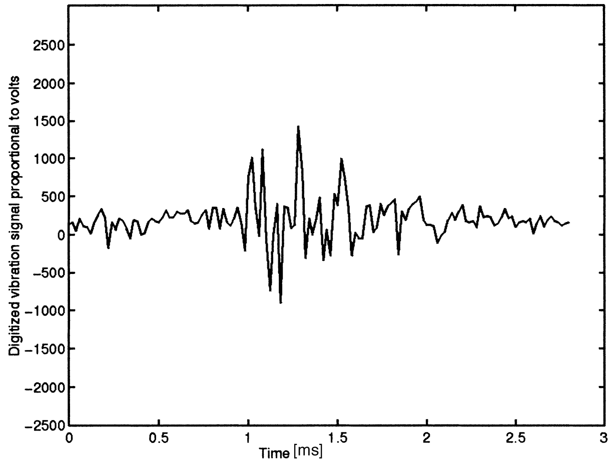

Figure 4. Vibration signal vs time for increasing knock.

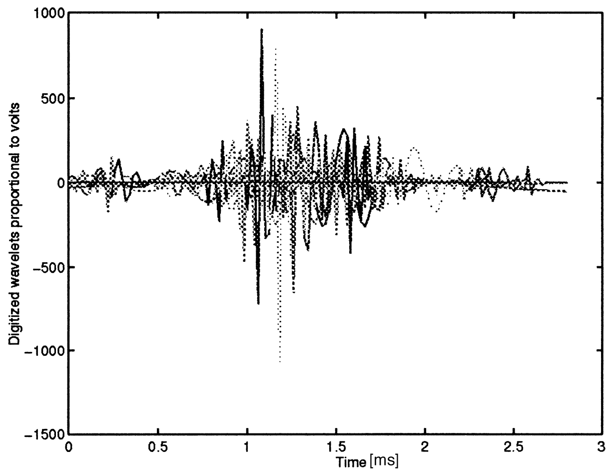

Figure 5. Model for increasing knock.

5.2.2. *Feature extraction*

Each signal from the training set is presented to the three models. The models try then to make the best approximation of the input signals. This is done by adapting the wavelet weights. Suppose the input signal presented to the model shown in Figure 5 is the signal displayed in Figure 6. Then the network adapts its connection weights to fit the signal. The final decomposition using the 40 wavelets of the model (see Figure 5) is illustrated in Figure 7. The resulted approximation is indicated on Figure 8. Note that the input signal is not exactly reconstituted. The approximation must contain the main signal features.

These weights are supposed to be representative of the knock state. Indeed, if the studied signal and the model have similar oscillations, the adapted weights may be very close to those of the model. The connection weights can be considered as indicators of similarities between a model and the observed signal. For this reason, a pattern, in this method, is composed of these connections weights.

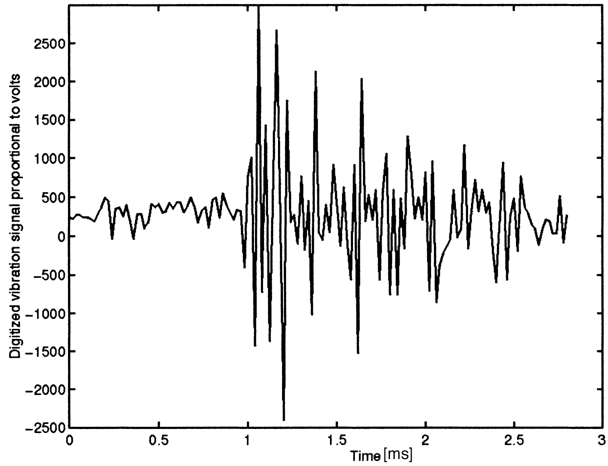

Figure 6. Vibration signal vs. time for heavy knock.

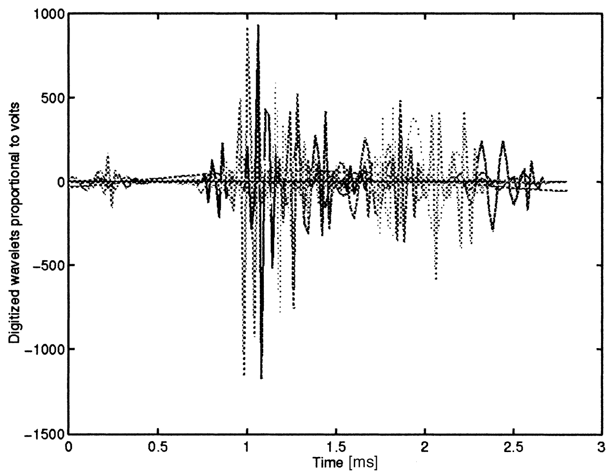

Figure 7. Wavelet decomposition.

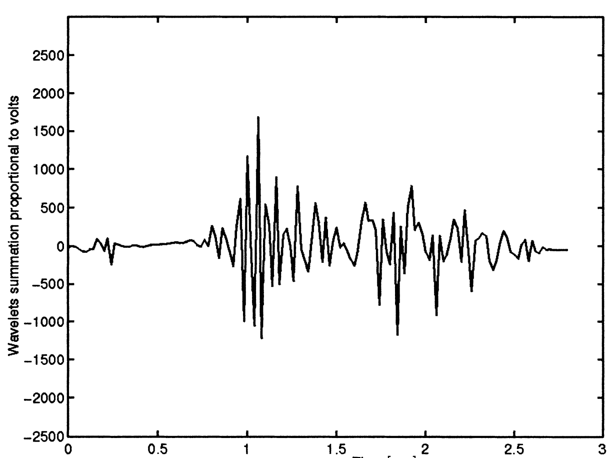

Figure 8. Approximation of a heavy knock signal.

Table 2. Learning set results (95 % confidence interval)

Magnitudes	ϵ_A	ϵ_I	ϵ_H	ϵ	δ
Mean	18.10 %	34.80 %	5.98 %	19.80 %	79.59 %
σ	7.21 %	17.32 %	5.13 %	7.93 %	8.04%
Low boundary	13.39 %	23.48 %	2.63 %	14.62 %	74.34 %
High boundary	22.81 %	46.12 %	9.34 %	24.99 %	84.84 %

5.2.3. *Decision making*

However, every connection weights (40) are not kept. Four of them are selected during the feature selection phase. They are assumed to discriminate, as well as possible between three classes, the patterns from the training set.

For each model k, three membership functions Φ_i^k with $i \in \{A, I, H\}$ are calculated. A pattern x is then affected to the class ω_m whose membership function $\Phi_m^k(x)$ takes its maximum value for x. So each model is able to lead to a decision. But two models can propose different decisions for the same pattern. For this reason, the decision rule operates the integration of the three possible diagnostics. It is based on a certitude notion expressed by a membership ratio [5]: a diagnosis is considered as certain if the difference between the two maximum membership values of the two prevalent classes is big enough. The ultimate decision is given by the model whose diagnostic is the most certain. During this perfecting phase, the relevant wavelets of the decomposition are chosen, the membership functions are created and the decision rule is elaborated.

5.3. Perfecting Step

The perfecting step consists in presenting each cycle from the validation set to the diagnostic process in order to classify it into one of the three known classes: absence of knock, increasing knock and heavy knock. This stage is of course faster than the previous one. Indeed only the feature extraction is calculated. Every input vibration signals are decomposed on the wavelet bases defined from the model elaboration phase. Then the decision is straightforward.

5.4. Results

As our provided data are not numerous enough to lead to a very significant result, we propose to run the diagnostic algorithm several times. Nine training sets are randomly selected among the whole data set composed of 58 engine cycles. The proportion of training cycles and validation cycles is kept as mentioned in Table 1. The final results are presented in Tables 2 and 3. Error probabilities and recognition rates estimator are computed for the Gaussian approximation with an interval of confidence of 95%. ϵ_A, ϵ_I and ϵ_H estimate the recognition error probabilities of classes ω_A, ω_I and ω_H. ϵ and δ estimate respectively the global recognition error probability and the recognition rate. The mean and the standard deviation (σ) of these magnitudes evaluated for nine experiments are presented.

Note that heavy knock cycles are the best recognized. The worst recognition error is obtained for the increasing knock class. It could be explained by the fact that this class is located between the two others. Moreover, the limit that separates different knock states is gradual.

Table 3. Test set results (95 % confidence interval)

Magnitudes	ϵ_A	ϵ_I	ϵ_H	ϵ	δ
Mean	26.67 %	49.44 %	11.11 %	30.04 %	65.93 %
σ	20.00 %	25.79 %	14.53 %	6.56 %	8.46 %
Low boundary	13.60 %	32.59 %	1.62 %	25.75 %	60.40 %
High boundary	39.73 %	66.30 %	20.60 %	34.33 %	71.45 %

6. Conclusions and Prospects

The diagnostic method seems to be encouraging insofar as two classes representing different knock intensities (increasing and heavy) are found.

However, it seems quite obvious that much more engine cycles need to be tested. The training phase would allow then to elaborate a decision rule that would take more knowledge into account. In the same way, a larger validation set would be useful in order to validate entirely the diagnostic method.

Additional research could also be done on feature selection. Indeed, our selection is not optimal but adapted to the size of the learning set, so we are not sure to select the right number of features to operate the best discrimination between classes. It is obvious that this number must be increased.

The use of wavelet networks looks particularly attractive, and block vibration signals which are non-stationary are well adapted to time-scale or time-frequency analyses. In fact, pattern recognition using time-scale analysis could even probably lead to recognize more knock states. This approach is worth applying on other automotive problems referring to transient signals.

References

1. Bartz, R., Schmitz, G. and Bohnke, P., ‘New methods for knock detection in a gasoline engine’, *MTZ*, **51**(6) (1992), 286–293.
2. Chun, K.N. and Heywood, J. B. *Characterization of Knock in a Spark-Ignition Engine*, SAE, No. 890156, 1989, pp. 1–14.
3. Chun, K. M. and Kim, K. W., *Measurement and Analysis of Knock in a SI Engine Using the Cylinder Pressure and Block Vibration Signals*, SAE, No. 940146, 1994, pp. 286–293.
4. Dubuisson, B., *Diagnostic et Reconnaissance des Formes (Diagnosis and Pattern Recognition)*, HERMES, 1990.
5. Frelicot, C., Masson, M. H. and Dubuisson, B., ‘Reject options in fuzzy pattern classification rules’, in: *Proc. EUFIT’95*, Aachen, **3**, 1995, pp. 1495–1464.
6. Harle, N. and Bohme, J. F., ‘Analysis and detection of knocking signals from spark ignition engines’, in: I.T. Young (ed.), *Signal Processing III: Theories and Applications*, 1986, pp. 1029–1032.
7. Molinaro, F. and Castanie, F., ‘Signal processing pattern classification techniques to improve knock detection in spark ignition engines’, *Mech. Systems Signal Process.* **9**(1), (1995), 51–62.
8. Puzinauskas, P. V., *Examination of Methods Used to Characterize Engine Knock*, SAE, No. 920808, 1992, pp. 1–13.
9. Zhang, Q. and Benveniste, A., ‘Wavelet networks’, *IEEE Trans. Neural Networks* **3**(6) (1992), 889–898.