WAVELET ANALYSIS TO DETECT THE KNOCK ON INTERNAL COMBUSTION ENGINES

ANAMARIA RĂDOI , VASILE LĂZĂRESCU ADRIANA FLORESCU

Keywords: Knock detection, Wavelet analysis, Time-frequency methods, Vibration signals, Pressure signals, Prototype.

The paper presents an effective method of detecting the state of knock, using the wavelet analysis. This, as a time-frequency method, is applied to non-stationary signals as those provided by the pressure sensors in the combustion chamber and engine vibration block. The advantages of wavelet analysis can be materialized by local detailing, meaning that it can be taken only a part of the signal, in our case, that part which contains essential characteristic of knock. The method is based on pattern recognition using a neural network type called wavelet network. The experimental results confirm theoretical assumptions of work regarding this type of knock's detection and create premises for further deepening of the research field.

1. **INTRODUCTION**

The support of modern diagnosis is based on measurement tests and on the characteristic parameters which are determined in different conditions of work. This activity involves acquisition, processing and interpretation of obtained data, but also the presentation of the attached results.

Furthermore, the way an injection engine works must meet air pollution requirements, while being efficient too. The last affirmation can be translated in lower fuel consumption and more efficiency. As for the level of gas emission, the engine has a number of sensors which detect the signals sent by several systems (which activity is supervised by a board computer) in order to submit to the current legislation's requirements. All these requirements imply a permanent supervising of the engine and this will increase the engine's life.

University "Politehnica" of Bucharest, Spl. Independentei 313, 060042, rdi_ana@yahoo.com

Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **54**, *3,* p. 301– 310, Bucarest, 2009

Due to fast modern evolution, assuring the quality of a product represents an essential target to achieve. Current control systems of an engine are designed to reduce the emission of exhaust gas while increasing the power and saving the fuel. This is obtained by optimizing the period of spark for a given rate of fuel/air, which is limited by the appearance of the detonation. Since 1920, most of the engines' manufacturers have concentrated their attention upon the characteristics of the detonation.

2. **WAVELET ANALYSIS AND ENGINE KNOCK**

The detonation occurs when the mixture fuel/air in the combustion chamber meets a critical point and the unused mixture self-ignites, before the front of ignition reaches him. The waves appeared after this shock determine dramatic increase of the pressure in the combustion chamber, making, in most of the cases, a specific noise, which gives the name of this phenomenon.

Better the knock is detected, more effective the supervising of the engine is. The detonation is almost always detected using sensors, such as:

– *pressure sensors* which measure the pressure inside the cylinder;

– *accelerometers* which measure directly the vibrations of the engine block determined by the detonation;

– *sensors for detecting the ionization current*;

– *optical devices* which analyze the mixture fuel/air in the combustion chamber.

The methods of extracting the information given by knock divide themselves in three big groups: methods of analysis in time domain, in frequency domain, and time-frequency methods. The resonant frequencies in case of detonation can be found between 3 and 10 kHz, depending on the cylinder's geometry and the propagation speed. There are certain shortcomings related to the way the signal is filtered because of the noise that cannot be easily removed. This is the reason why time-frequency methods, as the wavelet analysis, prove to be efficient.

A useful method of detecting the knock is the wavelet analysis, which is a time-frequency method that can be applied to non-stationary signals like the signals appeared because of the detonation. The analysis is based on the recognition of shapes, using a neural network type called wavelet network. A shape is, in fact, a vector containing relevant information about a system, extracted in our case from the signal processing. The signal is determined either by the vibration of the engine block, either by the pressure existing in the combustion chamber. The recognition of shapes is meant to classify the object in three groups ω_j (objects from the same group have similar proprieties):

– *absence of knock*, ω_A (class *A*);

– *increasing knock*, ω_I (class *I*);

– *heavy knock*, ω_H (class *H*).

3. **THE DIAGNOSIS**

The method of diagnosis, illustrated in Fig. 1, is done in five steps:

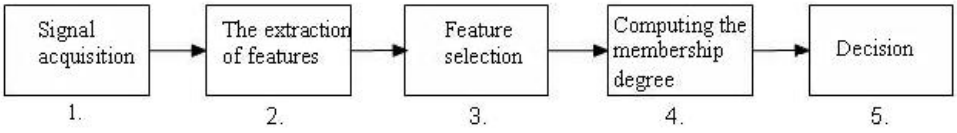


Fig. 1 – The steps of the diagnosis method.

1. Firstly, it is used a sensor in order to acquire the vibration signal of the engine.

2. The vibration signal is not used in its primitive form, it is processed to allow the extraction of specific parameters which characterises a certain shape, the best way possible.

3. The feature selection consists in choosing the best d' parameters from a number of d possible parameters $d' < d$). This fact reduces the complexity of the diagnosis method without reducing its efficiency.

4. The next step identifies, for each shape, the membership degree of that shape at a certain class. Each class ω_j, $j \in \{A, I, H\}$ has a membership function ϕ_j, which values can be found in [0, 1].

In this paper, we used the gaussian membership function because the set of data is big enough to consider this type of function:

$$\phi_j(x) = \exp\left(-\frac{(m_j - x)^2}{2\sigma_j^2}\right),$$

m_j and σ_j^2 are the center and the width of j^{th} set and are defined by the next equations:

$$m_j = \frac{1}{n_j}\sum_{i=1}^{n_j} x_{ij},$$

$$\sigma_j^2 = \frac{1}{n_j}\sum_{i=1}^{n_j}(x_{ij} - m_j)^2,$$

where x_{ij} is the i^{th} pattern of the j^{th} class.

The function ϕ_j takes its maximum values for those shapes (called patterns) that strongly belong to class ω_j. On the opposite, when the shape doesn't belong to class ω_j, the value of function ϕ_j is smaller.

5. The last step finds the basic rule upon which the decision is taken. The decision allows the association of each pattern with the closest class.

4. USING THE WAVELET NETWORK FOR DIAGNOSIS

Introduced by Zhang and Benveniste [3], the wavelet network is, in fact, a particular neural network. They propose the decomposition of every continuous function using neural networks. Such a network contains the coefficients which appear by adding a number of N wavelet functions specified before, each one with its own coefficient. In this way, every one-dimensional signal $x(t)$ can be represented as it follows:

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

where

$$\psi_k(t) = \psi\left(\frac{t - b_k}{a_k}\right).$$

In the last equation, the following notations were used: t – time, $\psi(t)$ – mother wavelet function, w_k – wavelet coefficient (rank k), b_k – wavelet parameter of translation (rank k), a_k – wavelet parameter of dilatation (rank k).

Wavelet coefficients, dilatation and translation parameters are adapted so that the signal acquired from the output of the network estimates, with a small error, the input signal.

The first difficulty which arises in the diagnosis is the next: is there a posibility to extract the information from the observed signal and to recognise the state of the system starting from this information? Well, the answer is yes. Using the wavelet network, the signal can be decomposed in elementary signals. In order to obtain a better approximation of the signal, all the wavelet coefficients, time and scale parameters are observed.

In this way, the studied model is the following :

– a number of wavelet functions for the decomposition of the signal;

– time and scale parameters for each wavelet function.

The wavelet coefficients are not model parameters; they only quantify the similarities between the observed signal and the model proposed for the system's states.

The *prototype* is a form which strongly belongs to a certain class, being representative for that class. So, the function ϕ_j takes maximum values for the prototypes of the *j*-th class. From the n_j patterns of the learning set, p_j prototypes are selected. The scope of this algorithm is to divide the learning set into groups of patterns. If the algorithm is repeated several times, certain stable patterns can be distinguished.

The knock's detection is based on a very important step in our analysis, the decision. This can be taken, considering as a pattern the wavelet coefficients that result by decomposing each signal.

Considering a pattern, for example *x*, we want to introduce it in one of the classes ω_m. The function $\phi_m^k(x)$ takes its maximum for *x* belonging to class ω_m, where *k* is the model of study, chose by us.

$$x \to \omega_m \quad \phi_m^k(x) = \max_{i=1,M} \phi_i^k(x).$$

The final decision will be taken based on the model which proves to be the best.

It is defined:

$$R_k(x) = \frac{\phi_p^k(x)}{\phi_m^k(x)},$$

where

$$\phi_m^k(x) = \max_{i=1,M} \phi_i^k(x)$$

$$\phi_p^k(x) = \max_{i=1,M,i\neq m} \phi_i^k(x).$$

Therefore, if

$$R_k \approx 0,$$

then

$$\phi_m^k(x) >> \phi_p^k(x).$$

This implies that

$$\phi_m^k(x) >> \phi_i^k(x), \quad \forall i = \overline{1,M},\ i \neq m.$$

It results that *x* belongs to class *m*.

On the other hand, if $R_k \approx 1,$ we cannot tell anything about pattern *x*, whether it belongs to class *m* or *p*.

In this case, a threshold of ambiguity, T_a, can be marked.

There is also another threshold, T_d, called distance threshold and it appears only when the forme is too far from any class.

5. **THE EXPERIMENT**

In order to detect the knock in a real case, one-dimensional discrete wavelet analysis is applied on a set of real data. The purpose of this study is to recognize the detonation phenomenon, starting from two different signals, namely the signal acquired by the accelerometer and pressure in the combustion chamber, measured with a special sensor of pressure. Wavelet analysis involves dividing the signal band in sub-bands, taking into account that the sampling frequency of the signal is about 50 kHz. In this case, the useful band of the signal is between 0 – 25 kHz. As it was said earlier, we must take in consideration that the resonant frequencies in case of knock can be found between 3 and 10 kHz.

Therefore, we used the Discrete 1-D Wavelet Transform which can be applied for non-stationary processes such as vibration and pressure signals. The decomposition tree on three levels is given below, in Fig. 2.

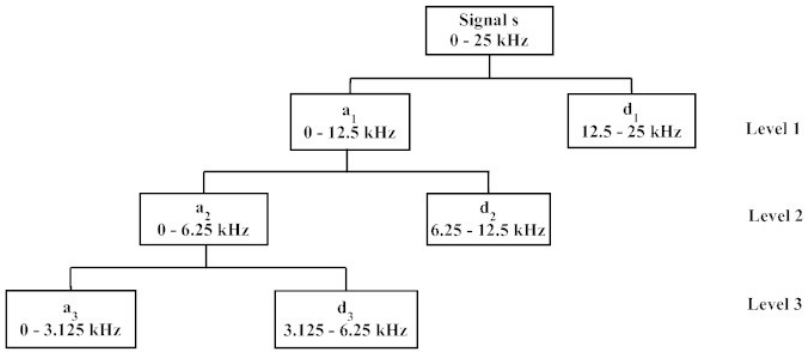


Fig. 2 – Wavelet decomposition tree on three levels.

The analysis was made using the Wavelet Toolbox, provided by Matlab 7.0.1, and the mother wavelet function used, for simplicity, is the Harr function.

The Wavelet Toolbox provided by Matlab 7.0.1 avoids the effective computation of parameters a_k and b_k, because the process makes the signal's decomposition fast and easy. This Toolbox doesn't need to find these parameters because we need only the coefficients given by this procedure.

The previously mentioned set of data was created for an engine working at 2000 rpm. For this state, the cylinders' pressure and the vibration of the engine block were acquired and about 230 samples per cycle were extracted for a set of

9000 cycles. In this analysis, the last level chosen for detail is level number three, but there are given also the next three levels in order to underline the fact that as the level increases, the information about the knock decreases because the frequency band is smaller and smaller. Therefore, it can be considered that the third level is optimal, fact that can be seen also in the next figures.

For each detail level, and for the original signal, the rate of detecting the knock and the error made are computed. As it was said earlier, two types of signals are used: vibration signal, acquired from the engine's vibration (Table 1), and pressure signal, acquired from the combustion chamber (Table 2).

The behaviour of the engine's vibration signal and the wavelet coefficients are represented in Fig. 3, in case of knock, and in Fig. 4, in case of non-knock. The notations are: s – the original signal, d1 – d5, a5 are wavelet coefficients.

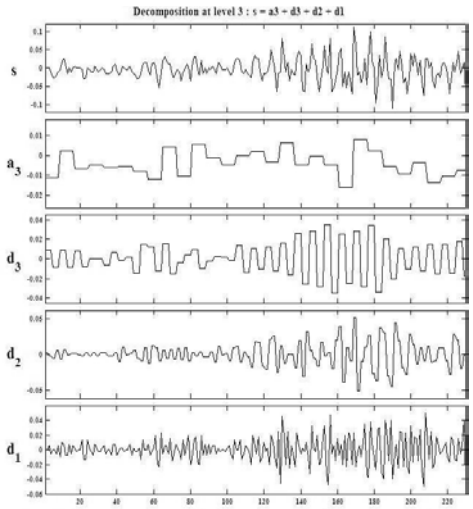


Fig. 3 – Vibration signal, with knock.

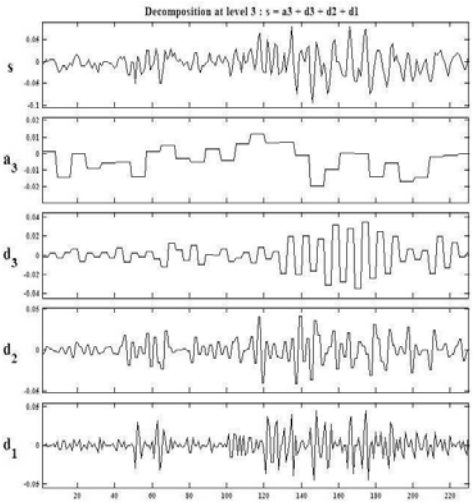


Fig. 4 – Vibration signal, without knock.

The detection rate and the error rate can be defined as probabilities which can be computed as it is shown below:

$$P(\text{"detection"}) = P(x \in K'/x \in K) + P(x \in F'/x \in F),$$

$$P(\text{"error"}) = P(x \in F'/x \in K) + P(x \in K'/x \in F),$$

where: *K(F)* is the set of signals with knock (without knock), included in each class from the start; *K'(F')* is the set of signals on which we apply the algorithm mentioned before in order to include it in a class or another.

Using the definition of dependent events, we can express the two probabilities in a simple form:

$$P(\text{"detection"}) = \frac{P(x \in K' \cap K)}{P(x \in K)} + \frac{P(x \in F' \cap F)}{P(x \in F)},$$

$$P(\text{"error"}) = \frac{P(x \in F' \cap K)}{P(x \in K)} + \frac{P(x \in K' \cap F)}{P(x \in F)}.$$

We used as a knock indicator (KI in the domain literature) the mean of the coefficients' values because it is a tool provided by the Wavelet Toolbox.

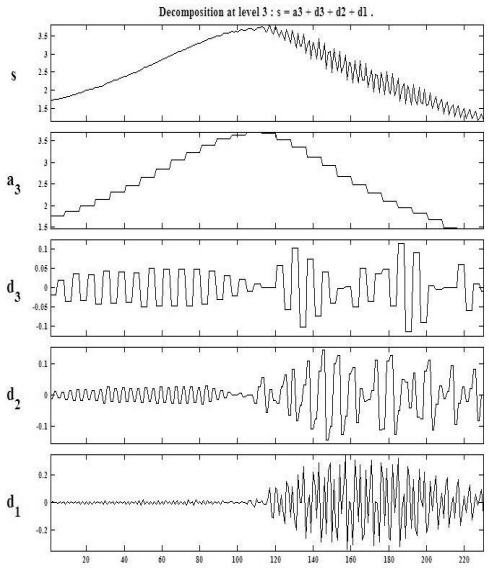


Fig. 5 – Pressure signal, with knock.

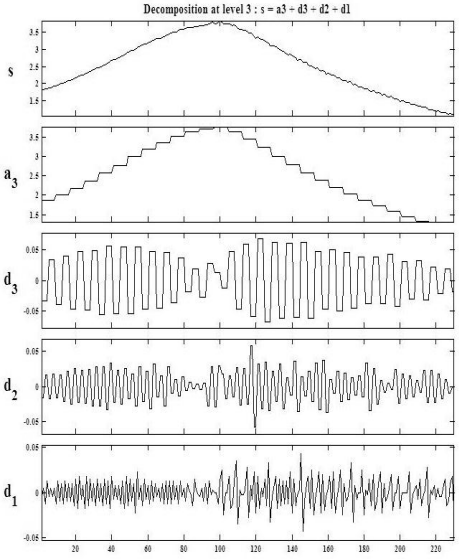


Fig. 6 – Pressure signal, without knock.

Table 1

The vibration signal

Entries	Original signal	First level detail	Second level detail	Third level detail
Detection rate	4.5 %	45.45 %	63.63 %	45.45 %
Error rate	96.4 %	3.5 %	14.2 %	21.4 %

Taking into consideration the pressure signal, we obtain:

Table 2

The pressure signal

Entries	Original signal	First level detail	Second level detail	Third level detail
Detection rate	47.7 %	50 %	54.54 %	68.18 %
Error rate	46.42 %	17.85 %	25 %	39.28 %

If we use FFT (Signal Processing Toolbox, a toolbox provided by Matlab), for the same signals (Table 3), the results are as it follows :

Table 3

FFT analysis

Entries	Vibration signal	Pressure signal
Detection rate	52.7 %	28.1 %
Error rate	73.5 %	71.9 %

6. **CONCLUSIONS**

This method of diagnosis is indicated for non-stationary signals, studied in time-frequency domain, as the signals of pressure and vibration are. The method is based on pattern recognition, using a neural network named wavelet network. Wavelet analysis gives good results for the second and the third level of detail. As the level increases, it cannot be decided whether the knock exists or not because few samples are taken into account.

All the experiment is based on a vast set of data, almost 9000 cycles for each type of signal, vibration and pressure signal. The detection of knock was done using the Wavelet Toolbox provided by Matlab 7.0.1 and we used function Harr as mother wavelet. In order to compute the rate of detection and the rate of error, we used statistical methods based on dependent events.

The pressure signal gives a better rate of detection than the other one, especially for the third level (almost 70%) and this happens because the resonant frequencies in case of knock can be found between 3 and 10 kHz, as it was said earlier, in a previous paragraph. The third detail level contains the primary information in case of knock. Due to the particular aspect of the pressure signal, the knock is easily identified because this signal has some discontinuities near its maximum level in case of knock.

Moreover, one of the major advantages of the wavelet analysis is that of making local analysis – just a part of the signal can be observed, namely that part that contains knock, and, so, the detection is optimized.

Knock phenomenon can appear and dissapear in a very short time, producing a small discontinuity. In this case Fourier analysis is not of any interest because it can't detect that discontinuity, fact that can be observed also in the tables presented. In order to improve the sensitivity of the analysis, the wavelet transform brings the advantage of catching a momentary state change. Wavelet coefficients offer information that cannot be provided by other analysis methods. Furthermore, this analysis can be used for compression, but also for removing the noise in a signal without modifying it.

The results of the analysis made using a set of real data confirmed the initial suppositions. The rate of detection can still be optimized using more complex methods of pattern recognition.

ACKNOWLEDGEMENT

This work was supported by The Research Grant CNSIS – UPB PN – II – ID – PCE – 2008 – 2, code ID_1693.

Received on November 6, 2008

REFERENCES

1. J. H. Thomas, B. Dubuisson, *A Diagnostic Method Using Wavelets Networks*, IEEE International Conference on Systems, Man and Cybernetics, **1**, *1*, pp. 244–249, 1996.
2. J. H. Thomas, B. Dubuisson, M. A. Dillies-Peltier, *Engine Knock Detection from Vibration Signals Using Pattern Recognition*, Meccanica, **32**, *5*, pp. 431–439, 1997.
3. Zhang Q. and Benveniste A., *Wavelet networks*, IEEE Trans. Neural Networks, **3**, pp. 889 – 898, 1992.
4. Amara Graps, *An Introduction to Wavelets*, IEEE Computational Science and Engineering, **2**, *2*, pp. 50–61, 1995.
5. J. M. Borg, Ka C. Cheok, G. Saikalis, S. Oho, *Wavelet-based Knock Detection with Fuzzy Logic*, Proceedings of CIMSA 2005, 20-22 July 2005, pp. 26-31.
6. J. Chang, M. Kim, K. Min, *Detection of misfire and knock in spark ignition engines by wavelet transform of engine block vibration signals*, Measurement Science and Technology, **13**, pp. 1108-1114, 2002.
7. Adelaida Mateescu, N. Dumitriu, L., Stanciu, *Semnale şi sisteme*, Edit. Teora, Bucharest, 2001, pp. 786–806.
8. D. Stanomir, *Introducere în analiza wavelet*, "Politehnica" Univ. Press, Bucharest, 2000.
9. D. Stanomir, O. Stănăşilă, *Metode matematice în teoria semnalelor*, Edit. Tehnică, Bucharest, 1980.