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# Knock Detection based on Neural Networks

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**Abstract – The paper presents a new method for knock detection based on two neural networks. First a discrete Hopfield network extracts features from the structural vibration signal. Then the first and the forth coefficients of the autoregressive model and the maximal and minimal value of the signal are applied to a feedforward neural network in order to detect the knock. Once a cycle has been detected as a knock containing one, for the next cycle the engine can be protected in order to avoid further appearances of knock. For the feedforward neural network it was experimentally determined that four neurons in the hidden layer is the best solution for the knock detection.**

**Keywords: Neural network, Feature extraction, Hopfield algorithm, Knock detection**

## I. INTRODUCTION

In essence, engine knock is caused by spontaneous ignition of a portion of end gas during the combustion cycle. The extremely rapid release of the chemical energy in the end gas that accompanies spontaneous ignition results in high local pressure and produces a shock wave.

This shock wave excites combustion chamber acoustic resonance, producing the familiar knocking sound [1].

Knock results in rapid rise in temperature and pressure. The velocity of the flame front may exceed 2000 m/s and high-frequency pressure fluctuations may reach 90 Bar at extreme knock.

Knock has to be avoided because of its damaging effect on the engine, especially when it occurs at high speed. At lower speed, knock is unwanted because of the annoyance to passengers.

Knock also reduces efficiency due to heat loss resulting from the turbulence in the combustion chamber. Corresponding power loss can reach up to 10% at heavy knock [2].

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 [3].

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.

That is why a considerable amount of oscillation exists in the pressure signal due to excitation of acoustic resonance modes in a knocking combustion.

Because the measurement of the combustion pressure is difficult, usually the structural vibration signal is collected.

The study proposes a new method for knock detection, using the structural vibration signal processing.

This signal has a non-stationary spectral content and can be described only using methods that characterize the signal both in time and in frequency.

Engine cycles affected by knock can be identified based on features extracted from the "global" structural vibration signal. The identification of different features could be used to protect the engine.

## II. FEATURE EXTRACTING USING SEQUENTIAL LEAST SQUARES ALGORITHM

The Hopfield algorithm is used in this study to extract the features from the structural vibration signal. It will be find that this algorithm is faster than the standard least squares algorithm (SLS) and it is able to extract the parameter, based on a time series of structural vibration signal.

Let us to consider a moving average time-series model:

$$\hat{x}_k = \sum_{i=1}^{n} a_i x_{i-k} \tag{1}$$

where $\hat{x}_k$ is the estimated sample, at $k$-th sample instant and $x_k$ is the actual signal value at sample time $k$; $a_i$ is the feature we want to extract.

The SLS algorithm finds the parameters $a_i$ based on the following set of two recursive equations:

$$\begin{cases} \hat{\mathbf{a}}_r = \hat{\mathbf{a}}_{r-1} + \mathbf{P}_r \mathbf{X}_r \left(x_r - \mathbf{X}_r^T \hat{\mathbf{a}}_{r-1}\right) \\ \mathbf{P}_r = \mathbf{P}_{r-1} - \dfrac{\mathbf{P}_{r-1}\mathbf{X}_r\mathbf{X}_r^T\mathbf{P}_{r-1}}{1 + \mathbf{X}_r^T\mathbf{P}_{r-1}\mathbf{X}_r} \end{cases} \tag{2}$$

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with initial values $\hat{\mathbf{a}}_0 = \mathbf{0}_{m\times 1}$ and $\mathbf{P}_0 = \mathbf{0}_{m\times n}$.

It has been shown that these relations minimized the cost function defined as:

$$F = \frac{1}{2}\sum_{i=1}^{M}(x_i - \hat{x}_i)^2 \tag{3}$$

But we can manipulate (3) into a new form:

$$F = \frac{1}{2}\sum_{i=1}^{M}\left(x_i - \sum_{j=1}^{n} a_j x_{i-j}\right)\left(x_i - \sum_{l=1}^{n} a_l x_{i-l}\right) \tag{4}$$

The above relation can be written as:

$$F = -\frac{1}{2}\sum_{j,l=1}^{n}\left(-\sum_{i=\max(l+1,j+1)}^{M} x_{i-j}x_{i-l}\right)a_j a_l -$$

$$-\sum_{j=1}^{n}\left(\sum_{i=j+1}^{M} x_{i-j}x_i\right)a_j + \frac{1}{2}\sum_{i=1}^{M} x_i^2 \tag{5}$$

## III. FEATURE EXTRACTION USING NEURAL SYSTEM

A discrete Hopfield system enables patterns to be stored or remembered by the network, having the ability to retrieve the complete pattern when presented with an incomplete or corrupted one.

The situation is even more difficult in the case of spike trains in that the occurrence of spikes must, in general be considered as a discrete sampling of some governing probability distribution. The determination o˜ even t˙e average properties of t˙e distribution requires many more samples than for a continuous wavefı rm. Due to the short duration of the spike, simple averaging is extremely sensitive to the number of samples unless the number of samples is large. The time required to obtain a large number of samples from a physiological system subject the data to long-term nonstationarities which may further obscure significant features. Hence the major constrains on the processing of spike train data are short duration of each spike event and long-term nonstationarity may require that a limited number of samples be used.

The used Hopfield network structure consists of a set of *n* units, each having a current output at time *t*.

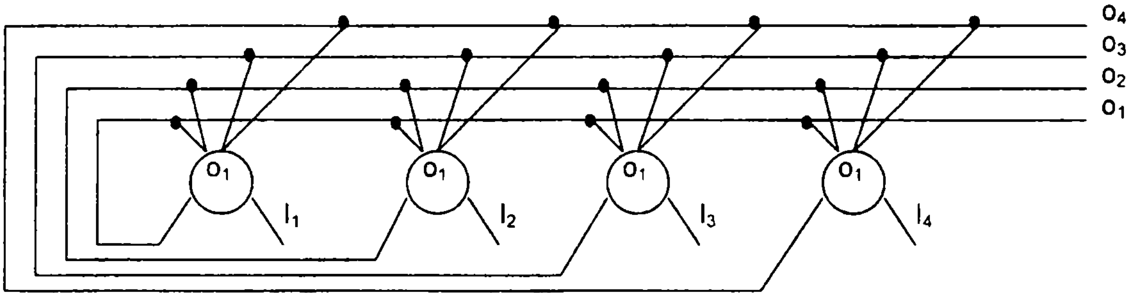



Fig. 1. Hopfield network structure

It is known a Hopfield network minimized a cost function *F*, defined by the relation above, when the connection weight are symmetric, if we use the Hopfield update rule [8].

$$F = -\frac{1}{2}\sum_{j,l=1}^{n} w_{ij} o_j o_l - \sum_{j=1}^{n} I_j o_j \tag{6}$$

The update equation for the cell outputs is:

$$\Delta o_{ir} = \lambda_i \left(\sum_{j=1}^{n} w_{ij} o_{jr} + I_i\right)$$
$$o_{ir} = o_{i(r-1)} + \Delta o_{ir} \tag{7}$$

$\lambda_i$ represent the gain term which establish the convergence rate of the algorithm. The convergence is achieved when $\Delta o_{ir}$ becomes close to zero. In practice, this convergence is assumed when $\Delta o_{ir}$ is less than a small-predetermined threshold value *e*.

The cost function defined in the case of moving average time-series model is likely the cost function used for Hopfield network, if we make this notation:

$$w_{ij} = -\sum_{i=\max(l+1,j+1)}^{M} x_{i-j}x_{i-l}$$
$$I_j = \sum_{i=j+1}^{M} x_{i-j}x_i \tag{8}$$

## IV. RESULTS AND DISCUSSIONS

The used Hopfield network structure used for extracting the parameters of the autoregressive model consists of a set of 4 units, each having a current output at time $t$. It is known a Hopfield network minimized a cost function F, defined by the relation above, when the connection weight are symmetric, if we use the Hopfield update rule [4].

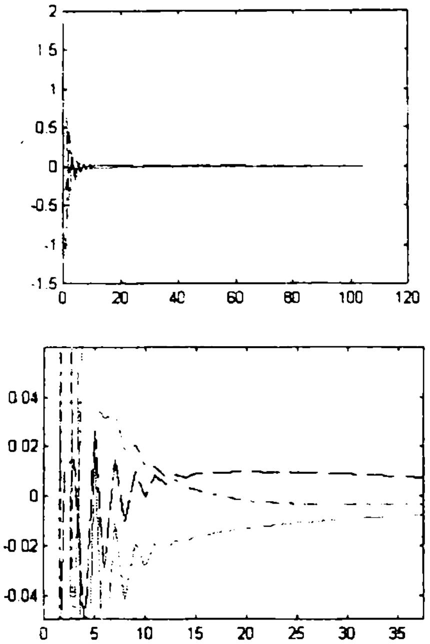


Fig. 1 The error in feature extraction using Hopfield algorithm

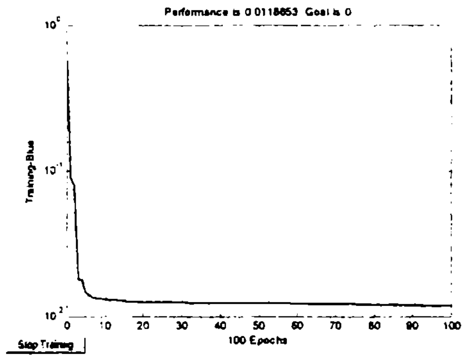
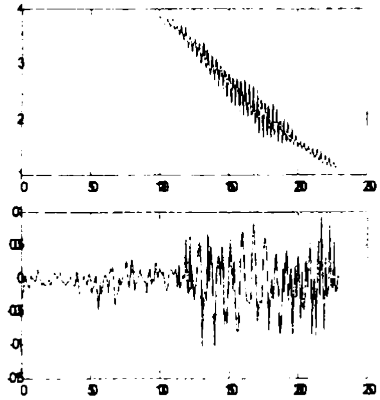


Fig. 2. The global error during learning

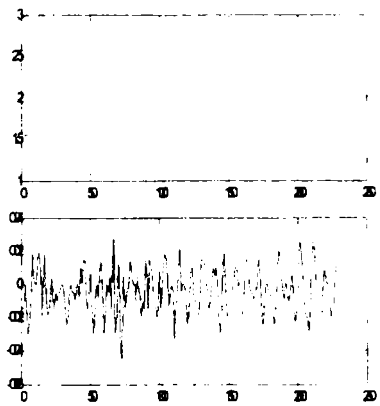
For the knock detection part of the study a two-layer perceptron (a hidden layer and an output layer) is used to find out the segments affected by knock. It was found experimentally that four units are enough for the hidden layer. The output layer has a single unit and that's due to the classification problem: two classes of signals must be identified - first, the "segments without knock " class, and second, the "segments with knock" class. In the case of "segments with knock" the output unit $o_1$ has a positive, closed to +1 value, and in the case of "segments without knock" it has a value closed to 0. For both the hidden layer and the output layer a sigmoid activation function was chosen. For the units in the hidden layer the sigmoid activation function is unipolar and for the output unit the sigmoid activation function is bipolar.

The neural network needs less than 500 steps to learn if the global error threshold is set at the 0.01. The success rate of the classification is 95% for the learning data and 92% for the testing data.

The data used in the study are acquired at a 50 kHz sampling rate, using a CAD with 12 bits. Two data sets are available: one for a rotation speed of 2000 rpm, containing 9996 combustion cycles and the other for a rotation speed of 4000 rpm, containing 8423 rotation cycles. The analyzed engine has 4 cylinders, a power of 16 kW and was full load during the study. The combustion pressure was recorded using a Kisler sensor. In fig. 3 is depicted an example of a combustion cycle with, and without knock.



(a) cycle with knock



(b) cycle without knock

Fig. 3 Combustion cycle – left side: the combustion pressure and right side: the structural vibration signal

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