MODELLING AND CLASSIFICATION OF ACOUSTIC PULSE SIGNALS BY WAVELET NETWORKS

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ABSTRACT

This article presents two modelling methods using wavelet networks. Both methods are intended to be used for an acoustic pulse signal classifier. We present a few results obtained with signals coming from a recording of the percussive response of metal parts. The object of this application is the non-destructive testing of these parts, as defects perturb the acoustic signature. The first modelling method uses wavelet networks to perform a non-linear regression on the signal to be classified. The second consists of non-linear auto-recursive modelling of the signal by means of the networks. The use of wavelet networks enables us to combine the generalizing capacities of neural networks with the efficiency of wavelet analysis of pulse signals.

\[ O(t_i) = \sum_{j=1}^{M} \Psi(w_j t_i - b_j), 1 < i < N \] (1)

Learning takes place by adjusting the parameters \( w_j, b_j \) and \( a_j \) so as to make the quadratic error function

\[ E = \sum_{i=1}^{N} (s(t_k) - O(t_k))^2 \] (2)

a minimum. When adjustment is finished, the classification is performed on the final values for the weights \( w_j, b_j \) and \( a_j \). The second method we developed consists of non-linear auto-recursive modelling of the signal to be processed.

\[ \hat{x}_n = F(x_{n-1}, \ldots, x_{n-d}) \] (3)

d being the order of the model. For each class \( C_k \) of the signal, a network \( R_k \) is trained to perform auto-recursive prediction, from a learning base of signals of known classes. Classification is then carried out according to the prediction error obtained with each network on an unknown signal.

1. INTRODUCTION

The aim of this study is to classify acoustic pulse signals. Recognition of such signals is particularly interesting in the field of non-destructive testing in an industrial environment. The classification we perform is based on the use of wavelet networks [2, 4]. Such networks are in fact neural networks of the Perceptron type[7] for which the activation functions are wavelets[1]. We hope to combine this ease of learning and generalization of formal neural networks with the high performance of wavelet analysis for very transient signals. We consider two modelling methods for making our classification. The first consists of performing a non-linear regression on the temporal acoustic signal \( s(t) \). To do this, we used a wavelet network with one hidden layer. This is the approach used by the I.R.I.S.A. team [5, 6]. Modelling is done by using formal neural network learning algorithm of the gradient descent type [3] in order to iteratively achieve a breakdown of the signal \( s(t) \) into \( M \) time-frequency atoms.

2. MODELLING BY NON-LINEAR REGRESSION

For this modelling, we use a wavelet network with one hidden layer. The activation function for the neurons of the hidden layer are wavelets, whereas the single neuron of the output layer is linear (see fig. 1). The output \( y_j \) of the \( j^{th} \) neuron is

\[ y_j(t) = \Psi(w_j t - b_j) \] (4)

\( \Psi \) being a wavelet function. We chose to use a 'Mexican hat' wavelet in our application, which has for equation

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\[ \Psi(x) = (1 - x^2)e^{-\frac{x^2}{2}} \] (5)

Figure 1. Wavelet network for non-linear time regression modelling with M hidden wavelons.

After having tried out networks on various types of wavelets without being able to bring out any general rule for making our choice. We see that the form of expression (4) corresponds to the equation of wavelet \( \Psi \) contracted by a factor \( w_j \) and translated by a value \( b_j \).

The output from the linear neuron is then

\[ O(t) = \sum a_j \Psi(w_j t - b_j) - b_0 \] (6)

When we adjust the weights \( w_j \), \( b_j \) and \( a_j \) of the network to minimize the difference \( (O(t_i) - s(t_i)) \) for each instant \( t_i \) at which the signal \( s \) is sampled, we are in fact taking an approximation by decomposing into \( M \) wavelets, each neuron representing the contribution of one wavelet.

2.1. Initialization - Learning

The weights of the network are adjusted by minimizing the expression

\[ E = \sum_{i=1}^{N} (O(t_i) - S(t_i))^2 \] (7)

by a gradient descent method.

The disadvantage of these gradient descent learning methods is that they are relatively slow and, above all, very sensitive to the initial values of the weights, particularly because of the existence of local minima of \( E \). We decided to take an advantage of the signification of the weights in the networks as wavelet coefficients to optimize their initialization.

Figure 2. Initialization of the wavelet network. a) Signal to model. b) Wavelet chosen with FFT. c) Cross correlation Signal-Wavelet. d) Translated wavelet. e) Remainder signal.

1. We use a Fast Fourier Transform to determine at which scale the signal is the most energetic. Thus we fix the parameter \( w_1 \) of the first neuron.

2. The time bias parameter \( b_1 \) is fixed by cross-correlation of the signal and the wavelet at scale \( w_1 \).

3. Finally, the amplitude \( a_1 \) is determined by minimizing the energy of the remainder \( \sum_{i=1}^{N} (s_i - a_1 \Psi(w_1 t_i - b_1))^2 \). We obtain

\[ a_1 = \frac{\langle s|O \rangle}{||O||^2} \] (8)

Once the first neuron has been initialized in this way (see fig. 2), the second is initialized by reiterating operations 1 to 3 on the residual signal [10]. This way of initializing the network weights greatly reduces the network convergence time. The use of wavelets and the 'physical sense' they give to the network parameters enables us to reduce the computing load for learning while obtaining a more robust and reproducible breakdown.
than would be the case for random initialization.

Figure 3. Modelling of an acoustic pulse signature with a 20-wavelon wavelet network. After 500 iterations, we obtain a relative error of 7%.

2.2. Results

We used our wavelet network to model the percussion acoustic response of mechanical parts. We show (see fig. 3) the result of this modelling on a representative signal. For a twenty wavelon network, we obtain a relative error of 7% after 500 learning iterations. Our intention was to classify signals by mean of the weighting of the network after convergence. Unfortunately, as our research stands at the moment, this classification method does not give very good results in term of recognition rate. Moreover, the computing cost of the convergence of the wavelet network on each signal to be classified compromises the use of our tool in real time.

For these reasons, we decided to implement another modelling method based on wavelet networks.

3. RECURSIVE MODELLING

The classification method we present here was inspired by the auto-associative memory applications developed with Perceptrons. In this type of application, a Perceptron is able to provide, for example, a previously memorized original image when presented with a noisy or truncated copy [9]. Auto-recursive modelling by wavelet networks aims to combine this Perceptron capacity with the efficiency of conventional linear auto-recursive modelling for classification. The classifier is composed of as many wavelet networks as there are signal classes to be recognized. Each network is trained to make an auto-recursive prediction on one type of signal. Classification is based on the prediction error obtained when an unknown signal is presented to each network.

Figure 4. Wavelet network with one hidden layer for non-linear auto-recursive modelling.

We use a wavelet network with one hidden layer having the structure described in fig. 4. The number of neurons in the input layer determines the order of the recursion. We have a learning base containing samples of signals belonging to each of the signal classes to be recognized. For our application, there are three classes of signal; signals corresponding to defective parts, signals corresponding to good parts, and a reject class to eliminate signals occurring when the acquisition system is set off at the wrong moment. We therefore need to train three wavelet networks.

Learning takes place as follows. d neurons of the input layer are presented with d consecutive signal samples \( x_{n-d}, \ldots, x_{n} \). The weights are then adjusted so that the output of the network tends toward the next sample \( x_{n} \). For this learning process, we use conventional gradient descent algorithms which we have adapted to wavelet networks. Learning is a very slow. It takes several hours to make a network with twelve hidden wavelons and ten input neurons converge on a 512-point signal using a work station.

4. CONCLUSION - PERSPECTIVE

Figure 5 gives the results of modelling on a test signal. This signal is a recording of the percussive acoustic signature of a metal part. Figure 5 also shows the results of the same modellig process using a conventional linear AR model. We have not yet been able to test the
classification application associated with this model in good conditions.

Figure 5. Auto-recursive modelling of an acoustic pulse signal. a) Wavelet Network with 12 wavelon. b) Linear AR(50) modelling.

To do so we need to enrich the data base and continue to train our network on a larger number of signals.

5. REFERENCES


