ARTIFICIAL NEURAL NETWORKS AS FREQUENCY FILTERS

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This paper presents an artificial neural networks as a tool for creating frequency filters for hydroacoustic signal processing. In the first part of article the basis of neural network theory was presented, next the concrete solution applied to building filter was introduced. On the end of the article the results of working neural frequency filter for example hydroacoustics' signals were presented.

INTRODUCTION

The hydroacoustical signal is a result of an acoustical field of sound source in the sea environment combined with the ambient noise generated by the man-made and biological activity. A lot of attention has been given towards the elimination or minimization of such ambient noise for the purpose of detection of target features. The features in question were predominantly associated with the type of vessel or object generating the acoustical field, however, other features seem also plausible as a subject of in-depth investigation. Analysis of available scientific material leads to the conclusion that information about ship state is included in hydroacoustic signal but very often only in some exactly specified frequencies ranges. This ranges usually gave specific information about ship machinery state. Therefore the amount of energy transferred to the water environment due to the work of engine should be filtered so to get only this frequencies which includes interesting information. Therefore in this article method of filtration based on artificial neural networks technique is proposed.

An artificial neural network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. Neural networks, like people, learn by example and they are configured for a specific application, such as pattern recognition, data classification or signal processing, through a learning process. Neural networks are applicable in almost every situation in which a relationship between the inputs and outputs exists, even when that relationship is very complex and not easy to articulate in the usual terms. One of them is the signal processing and in this case it is frequency filtering. Frequency filters process a signal in the frequency domain. In ordinary way the input signal is Fourier transformed, multiplied with the filter function and then re-transformed into the real domain. To omit transformation of real signal into frequency domain and re-transformation the neural network will be learned to transform the signal presented in time domain into the signal in time domain. To fulfill the function of frequency filter the neural network will remove some, chosen frequencies from input signal.

1. NEURAL NETWORKS

The most basic components of neural networks are modeled after the structure of the brain. The most basic element of the human brain is a specific type of cell, which provides us with the abilities to remember, think, and apply previous experiences to our every action. All natural neurons have four basic components, which are dendrites which accepts inputs, soma which process the inputs, axon which turn the processed inputs into outputs, and synapses which assure the electrochemical contact between neurons. The basic unit of neural networks, the artificial neurons, simulates the four basic functions of natural neurons. Artificial neurons are much simpler than the biological neuron; the figure 1 shows the basics of an artificial neuron.

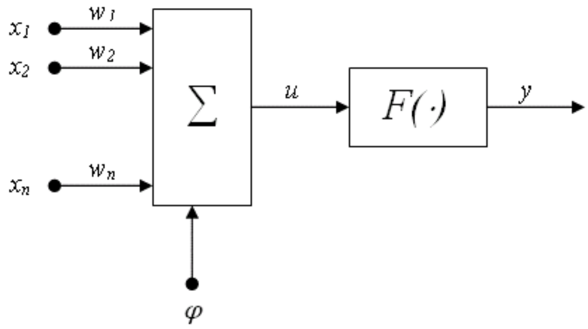

Fig. 1. The model of artificial neuron

The equation described the basic neuron presented on figure above can be written as:

$$y = F\left(\sum_{i=0}^{n}(x_i w_i) + \varphi\right) \qquad (1)$$

where:

x_i - is an input vector;

w_i - is a vector of input weigths;

φ - is a bias;

$F(\cdot)$ - is an activation function;

y - is a neuron output;

n - is a number of inputs.

In a neural network, multiple neurons are interconnected to form a network to facilitate distributed computing. The configuration of the interconnections can be described efficiently with a directed graph. The topology of the graph can be categorized as either acyclic or cyclic. A neural network with acyclic topology consists of no feedback loops. A neural network with cyclic topology contains at least one cycle formed by directed arcs. Such a neural network is also known as a recurrent network. Due to the feedback loop, a recurrent network leads to a nonlinear dynamic system model that contains internal memory. Recurrent neural networks often exhibit complex behaviors and remain an active research topic in the field of artificial neural networks.

In case of use artificial neural network as a frequency filter it is advisable to put in to neuron some elements that will assure restoration of previous neuron state. It allow to increase the flexibility of neuron during learn process and enlarge the possibilities of neuron memorization. This is realized by adding the dynamic block to the neuron model. In this case the model of neuron is called dynamic neuron's model and its block diagram can be presented as it is shown in figure 2.

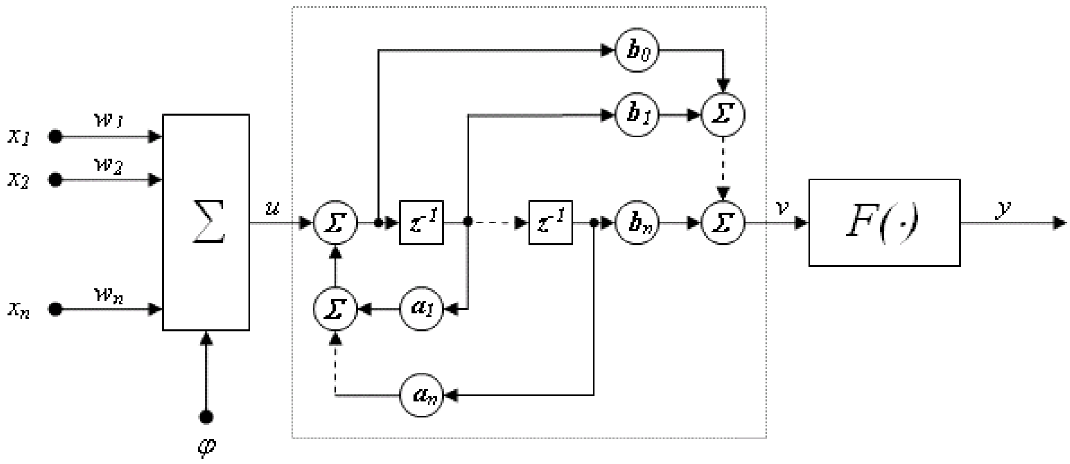

Fig. 2. Dynamic neuron block diagram

For such neuron his weighted sum of inputs is calculated according to the formula:

$$u(k) = \sum_{i=0}^{n} w_i x_i(k) + \varphi \tag{2}$$

where:

$x_i(k)$ - is an input vector;

w_i - is a vector of input weights;

φ - is a bias;

n - is a number of inputs;

k - is a discreet time index.

Then this calculated sum is passed to the dynamic block. Here the dynamic block under consideration is linear dynamic system of different order. This block consist of delay elements and feedback and feed-forward paths weighted by the vector weights $a = [a_1, a_2, ..., a_n]^T$ and $b = [b_0, b_1, ..., b_n]^T$, respectively. The behaviour of this linear system can described by the following difference equation:

$$v(k) = b_0 u(k) + b_1 u(k-1) + ... + b_n u(k-n) - a_1 v(k-1) - ... - a_n v(k-n) \tag{3}$$

where:

$a = [a_1, a_2, ..., a_n]^T$ - are feedback weights;

$b = [b_0, b_1, ..., b_n]^T$ - are feed-forward weights.

Finally, the neuron output can be described by:

$$y(k) = F(\gamma v(k)) \tag{4}$$

where:

$F(\cdot)$ - is a non-linear activation function;

γ - is the slope parameter of the activation function.

For this application of neural network activation function is sigmoidal function which can be written as:

$$y(k) = \frac{1}{1 + e^{-\gamma v(k)}} \tag{5}$$

This is limited function, for large positive parameter the function tends to one and for large negative the function tends to zero. Therefore the input and presented learn vector is normalized to take value from range zero to one.

The main objective of learning is to adjust all unknown network parameter such as input weights, bias, dynamic block parameters feedback and feed-forward weights, and slope parameter of activation function based on the given set of input-output pairs. In fact the training process involves the determination of unknown network parameters that minimize a performance index J based on an error function which may be defined as:

$$J = \frac{1}{2} E\left\{(y_d(k) - y(k))^2\right\} \tag{6}$$

where:

E - denotes the mean value operator;

$y_d(k)$ - the desired response of the neuron;

$y(k)$ - the actual response of neuron.

To solve this minimization problem and find optimal neuron parameters, the descent gradient algorithm may be applied.

2. RESULTS OF RESEARCH

Artificial neural network presented above was implemented on computer and researched. The purpose was to get neural frequency filter which will be cutting frequency at 50 Hz and skip it over this value. The neural network was trained using sinus function which was generated with random parameters such as amplitude, phase and frequency. The input vector was presented with frequency spectrum up to 100 Hz and the learn vector was presented using same vector at amplitude and phase but with frequency spectrum components only up to 50 Hz. The input and output signal has amplitude normalized to value concluded between -1 and 1. The input signal and its spectrum was presented on the figure 3. The learn signal and the answer of neural network and spectrum of signal was presented on the figure 4.

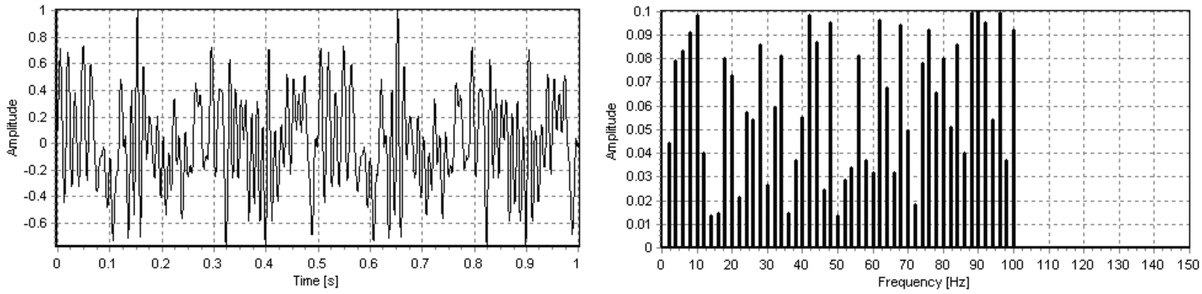

Fig. 3. Input signal for training the neural network and its spectrum

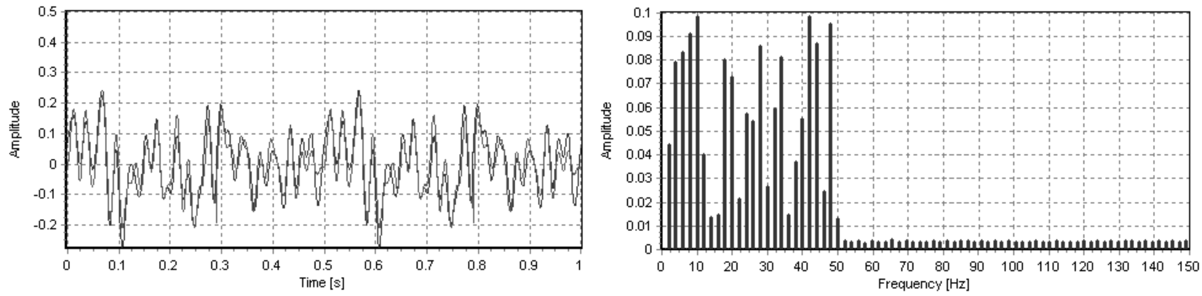

Fig. 4. Learn signal and answer of neural network and spectrum of signal

After training process, neural network was presented the real signal of small ship noise. The amplitude of signal was normalized to one. Neural network calculate signal which frequency spectrum has components only below 50 Hz. On the figure 5 was shown the spectrum of input signal and on the figure 6 was presented the spectrum of signal calculated by neural network trained to remove frequencies above 50 Hz.

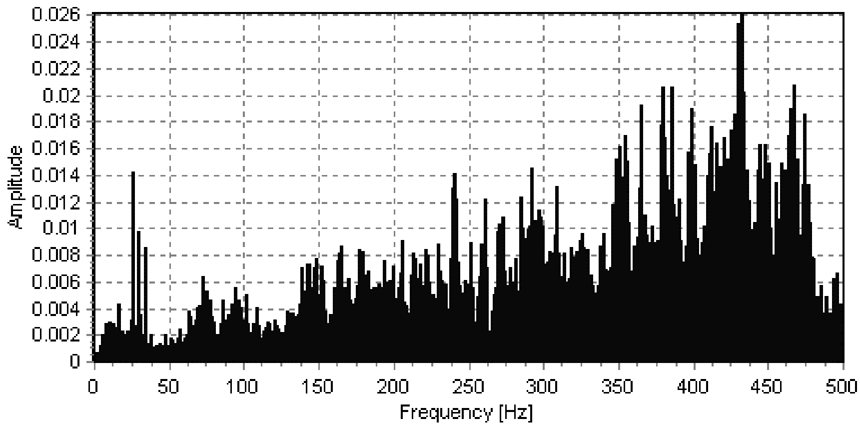

Fig. 5. Spectrum of real signal of small ship noise used to test the implemented neural frequency filter

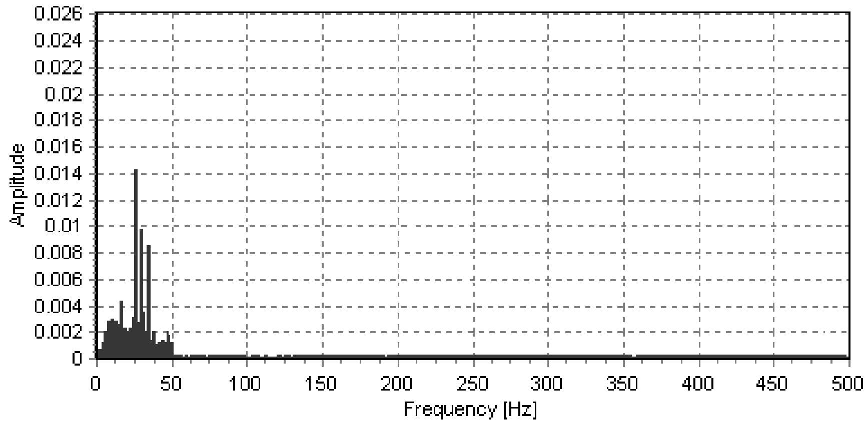

Fig. 6. Spectrum of answer of neural frequency filter for signal of small ship noise

3. SUMMARY

The theory and design of artificial neural networks have advanced significantly during the past 20 years. Much of that progress has a direct bearing on signal processing. As it is shown in research that neural networks can be used in hydroacoustics as a frequency filter with success what suggests that they can be used for another signal processing as well. In particular, the nonlinear nature of neural networks, the ability of neural networks to learn from their environments in supervised as well as unsupervised ways, as well as the universal approximation property of neural networks make them highly suited for solving difficult hydroacoustic's signal processing problems.

The intention of author was to present the neural networks technique which should be perceive as a new very powerful tool used for hydroacoustic's signal processing. The future researches will be concentrated at use the artificial neural network in classification and identification of hydroacoustics' signals.

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