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The Method of Underwater Object Identification Using Multi-layer Perceptron

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An algorithm for detection/identification of underwater objects is proposed. The algorithm is based upon the classification ability of a simple multi-layer neural network, also called a Perceptron. A signal recorded by a hydrophone and preprocessed by a computer is supplied to the ANN, which classifies it according to the possessed information encoded within its structure and an array of weighs. Analysis of effectiveness is conducted depending on the variables pertaining to the neural network.

1. Introduction

A lot of attention has been given in recent years to the problem of detection and classification of underwater targets from the backscattered acoustic signals. Schemes were proposed to facilitate the differentiation between mines, partially buried objects and solid rocks. In those cases it was necessary to transmit acoustic signals and analyze the reflection. Things are quite different on a battlefield when one needs to determine whether a moving submerged vehicle (for example a submarine) belongs to friendly or hostile forces. Now, in order to remain undiscovered, it is detrimental that detection and classification be done secretly. To maintain acoustic silence the passive analysis of the target's signature has to be employed, the assumption being that each vessel has its own, unique acoustic characteristic. Unfortunately, there are factors that make such classification difficult:

- variation of target's signature depending on aspect angle and range of the target from the hydrophones;
- ambient noise caused by various biological and human-made sources [3],[9];
- scattering;
- improvements in silencing of vessel's machinery (especially the propellers).

Traditionally, two approaches have been used to achieve the purpose of classification: Statistical Decision Theory [3],[4],[6],[13] and Discriminant Analysis [8]. These methods, however, are fairly complex, time and memory consuming. Alternatively, the artificial neural networks seem to be an adequate technique for classification of sound-producing vehicles. To determine whether passive acoustic identification of submerged objects by artificial neural networks (ANN) produces satisfactory effects and further investigation has merit an experiment was conducted. A simple ANN was trained to classify nine classes of objects (vehicles) and an analysis of effectiveness conducted.

2. Data Obtaining And Pre-processing

All the information necessary to conduct the experiment were collected at the Polish Navy Research Center located at the Naval Base, Gdynia. The center maintains a database of acoustic signatures of polish naval vessels recorded at the nearby measuring range and stored in the analog form on tapes. Data regarding three different vessels (A, B, C) at three different speeds (a, b, c) were accessed thus creating 9 distinct categories (Aa, Ab, Ac, Ba, ...). Programmable signal analyzer GC-89 was used to sample the signals obtaining time-domain records in form of computer files. Since time-domain signals are meaningless from the classification perspective the transformation to the domain of frequency was necessary. FFT was employed to go from 1024 element vector in time-domain to 256 element vector in the frequency domain using MATLAB environment. A number of such transformations is shown on Fig. 1.

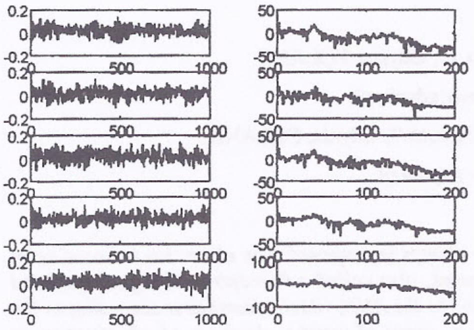

Fig. 1 Samples of FFT

The resulting vectors consisting of 200 elements in the frequency domain will be now called *records*. Each record belongs to one of 9 categories based on the type and velocity of a vessel. Averaging of signals was used to minimize the ambient noise. Normalization of records was conducted in order to prevent the ANN learning the relative amplitudes, but rather to "remember" the overall shape of the signal.

3. The Algorithm

The experiment was based upon an algorithm consisting of four steps:

- registering of the acoustic signature of a vessel,
- transformation of this signal to the frequency domain,
- decision by the ANN,
- interpretation of the result.

Of course, for this algorithm to function it was necessary to have a well trained neural network, which is the most important aspect of the whole method, because the overall quality of the classification depends on it. As have been mentioned before a simple multi-layer network was used, but a decision still had to be made regarding the variables pertaining to this ANN.

Determining the structure of the neural network (optimization). Decision to use the Perceptron was not all. To achieve the best possible results the following determinations still had to be made:

a) how to define the input vector,
b) how many neurons should be in the hidden layer,
c) how to code the output vector?

The number of elements in the input vector depended on the number of elements in vectors obtained after using the FFT, namely 256 values, each corresponding to a different frequency. It was noticed that in all the records the amplitudes of the spectral lines with indexes between 200 and 256 were low and remained almost constant; therefore those 56 values were disregarded, thus creating a 200-element input vector. The number of neurons in the hidden layer was changed between 20 and 50 and the effectiveness of classification observed. As for the last determination, the following coding scheme for the output vector was used: the output vector consisted of five elements, three of which determined the type of a vehicle (A, B or C) and the remaining two its velocity. The resulting neural network is shown on Fig. 2.

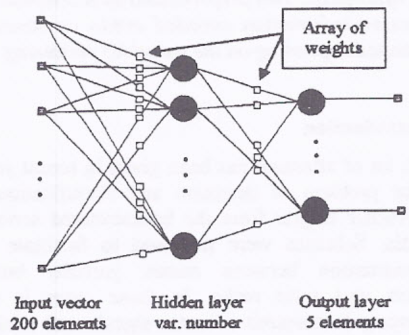

Fig. 2. The Perceptron

Training of the ANN. The neural network was taught in the following process:

a) A random but balanced set of records representing each class called *the training set* was assembled (the number of records for each class was altered).

b) After each record from the training set was shown to the ANN, its weight matrix was updated (gaining knowledge) and an error was calculated. The error is a measure of how much the response of the ANN differed from the expected response. When all records in the training set were presented to the neural network (an epoch) an average error for that epoch was calculated.

c) The process described in the second step was repeated until the average epoch error dropped below an arbitrarily chosen value. The training procedure was finished, the neural network had converged.

Due to the generalization ability of neural networks the Perceptron was able to learn to discern the nine distinct classes of objects in the above process. The detailed description regarding the techniques of updating the values in the weight and the proof for the convergence of the Perceptron is offered in the following positions [1], [11], [13],[16].

4. Results

The effectiveness of the method was inspected according to three different factors:

- learning rate,
- momentum,
- number of neurons in the hidden layer.

All these factors affect the speed of reaching the convergence which is applicable during the training phase (acquiring of the knowledge by the ANN). In the first analysis the learning rate and momentum were changed and the speed of reaching the convergence in terms of a number of epochs observed. Fig. 3 shows the obtained results.

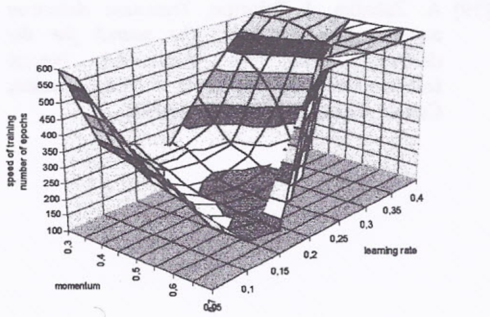

Fig. 3. Speed of learning by ANN

The changing parameters are the learning rate and the momentum. The constant parameters are the number of neurons in the hidden layer – 20 and the number of records for each class in the training set – 5. It can be inferred that the optimal conditions in respect to the speed of learning of the multi-layer perceptron network occurs for the learning rate between 0.2 – 0.3 and the momentum between 0.4 – 0.6.

Figure 4 shows how the speed of learning is affected by the number of hidden neurons. It turns out that if we choose this number too small it will take a long time for the ANN to converge. If the number is too big however, then the complexity of the structure will also hinder the convergence rate. Please note, that the thick lines in the next two figures represent the trends for the given data.

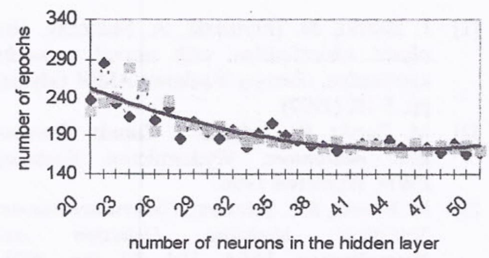

Fig. 4. Speed of learning by ANN.

The second part of the analysis of the robustness of the method concerns the effectiveness of classification itself which is the primary criterion determining the quality of the knowledge imbedded within the neural network. The variable that affects this effectiveness within the ANN is the number of neurons in the hidden layer. The following figure depicts the effectiveness of classification if we set all the variables constant expect for the number of hidden neurons.

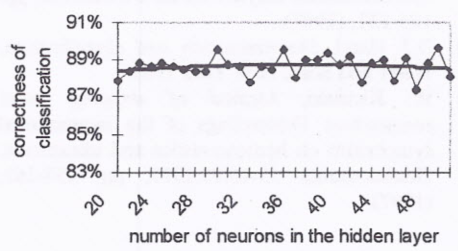

Fig. 5. Effectiveness of classification

Again, it can be inferred that there is a certain argument on the number of hidden neurons axis for which the effectiveness of classification reaches its maximum value (for the conditions in the experiment it is about 36 neurons).

5.Conclusions

The primary conclusion is that the method of classification based on a neural network classifier gives promising results and should be subject to further investigation. Achieved effectiveness, of up to 80%, is representative for the conditions of the experimental set-up and the data available. It may be different for different conditions and data. It was a certain restriction that the testing was done only on the records recorded at similar conditions as the records used to train the ANN. This was due to external limitations regarding the access to the pertaining data.

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