Ship's Classification by its Magnetic Signature

J. A . A. Arantes do Amaral and P. L. Botelho, IPqM, Ilha do Governador,RJ, Brazil
N. F.F. Ebecken, COPPE-UFRJ, Ilha do Fundão, RJ, Brazil
L. P. Caloba, Escola de Engenharia-UFRJ, Ilha do Fundão -RJ, Brazil

Abstract :

The ship's classification by its magnetic signatures is of great importance in the development of magnetic mines. This work concerns the use of neural network classification system combined with the relevant features method to solve this problem.

1 Introduction

Nowadays modern magnetic mines need to have the ability to destroy specific kinds of targets. From a military point of view it is interesting to have the option of setting up mines to destroy an specific kind of ship when a fleet is passing by. This paper explores the use of neural network classification system in spite of the use of traditional classification algorithms.

2 Ship's Magnetic Signatures

Ship's movement generates acoustic signals and alterations in local magnetic and pressure fields. These alterations can be measured by appropriated sensors. This paper will evaluate only the alterations of the surrounding magnetic field measured by magnetometers. Ship's magnetism is classified as either permanent or induced. Permanent magnetization is a function of constitutive material of the ship, related to the crystalline structure of the metal and the place and the process that ship was built [3]. Induced magnetization is function of local geomagnetic field that actuate over the ship. The magnetic signature of a ship is the vetorial sum of permanent magnetism inherent to the ship and the induced magnetism as related its current environment. To classify ship by its magnetic signatures it is necessary to collect signatures from various courses of the same ship .

3 Data Base Characteristics

We used the data base formed by thirty-two signatures collected from eight ships that belong to four distinct class. Each class is formed by two ship's that have the same characteristic dimensions. The signatures were collected through the passage of the ship over an arrays of magnetometers . For each ship we collected four signatures referents to the course of approximation north-south ,east-west, south-north and west-east. Ship's magnetic signatures don't have abrupt variations and besides its period is related to the ship's velocity , the depth and the distance from the magnetometers.

4 Some Considerations

The major problem of using neural network in military real time systems is the time consumed by performing the necessary calculations . If the final architecture has a large number of neurons its utilization will be unfeasible. The ideal is to have few units of neurons, hence one will get small matrices, which yield to low time reduced processing. To diminish the length of neural network ,we must reduce the signal size presented to it. The question is how to reduce the signal size. It can be made by use of Relevant Features Method.

5 The Relevant Features Method

This method evaluates the relevance of each component of the signal in the discrimination made by neural network. In other words, we try figure out which component of signal should be used for training the neural networks and which ones must be discarded. The method can be described in the following steps:
step 1 -Train the neural network with the original signals and then figure out the best architecture. Save the weights matrix for this best architecture.

step 2 - Calculate the relevance of each component applying by the following expression ([2]).

$$R(x_j)=\sum_{i=1}^{N}\frac{\|out(x_i)-out(x_i|x_{i,j}=<x_j>)\|^2}{N},$$

The first parameter of this expression is the output of neural network for each pattern presented to it. The second term is the same output vector ,when the j-component of input signal is replaced by the mean value (N is the number of pattern presented)

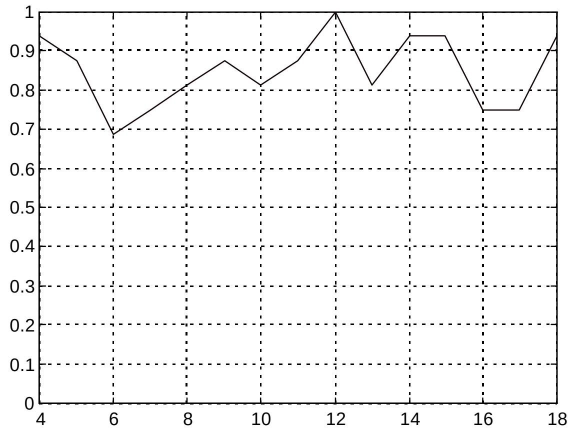
step 3- Apply this method to all set of signals to find the relevance of each signal component. After doing so, we can select only the components of higher relevance and re-train the network. On this way we can reduce the dimension of the signal without significant losses of discrimination capacity of the network.

6 The experiment

The neural network model used is two-layered feedforward network and the learning rule is backpropagation with momentum term. It is not necessary to use the full signal length to train the network. Based on Discrete Fourier Transform (DFT) we select an initial step to collect points [1]. The numbers of points to give the necessary information of the signal is 20. At the beginning of experiment it was analyzed several architectures to find the best one, that reach the highest score of correct classifications.

The figure 1 shows that the best architecture of neural network that gives the 100% of correct classification was obtained by the use of 12 neurons in the intermediate layer, 4 neurons in the final layer , learning rate of 0,1 and momentum term equal to 0.

Percentage of correct classifications



neurons at intermediate layer

Figure 1

7 Extraction of relevant signal components

Once founding the best architecture the next step is to analyze the relevance of each signal component. The next four plots allow to verify: i) the curves of mean square errors obtained by training and test of the best architecture (figure 2, the top plot) ,ii) the percentage of correct classifications (figure 2, the bottom plot), iii) the relevance of each signal component and the relevance frequency. Should be observed (figure 3) that half of signals components have a low relevance frequency (8 components with relevance frequency of 0.1 and three components with 0.2). The next step is to verify how the network behaves itself when this low relevant signal components are extracted. First ,the eight components of relevance 0.1 are extracted and the performance of network is analyzed. After that, we will do the same way with the two components of relevance frequency of 0.2.

Choosing the stop training point

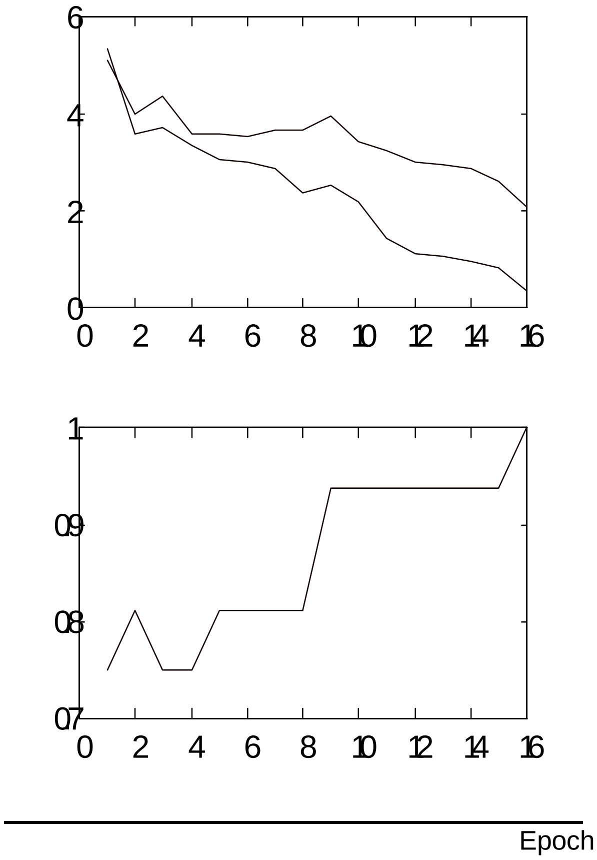


Figure 2, The top plot shows the errors of training and test sets by epoch. The bottom plot shows the increase of percentage of correct classifications by epoch.

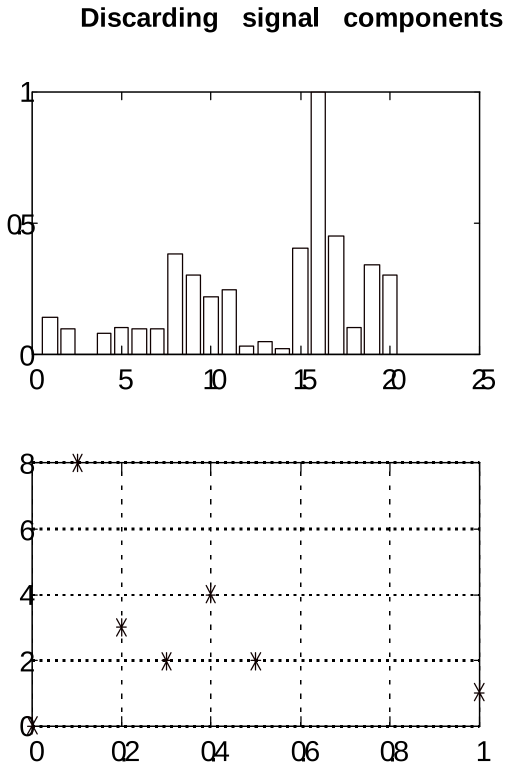
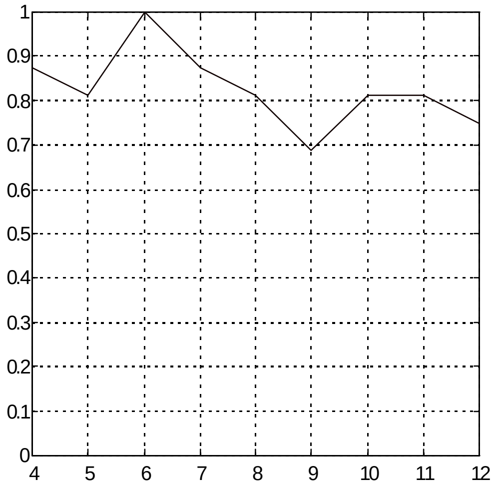


Figure 3**.The top plot shows the relevance of each signal element . The bottom plot shows the number of elements by its relevance (relevance frequency).**

8 Retraining

After reducing the dimension of signal from 20 to 12 it is necessary to re-train the neural network and to find the best configuration. The followings three plot show that ,the new best architecture has 6 neurons in intermediate layer, 4 neurons in output layer, learning rate of 0.1 and momentum term of 0.1. The percentage of correct classification remains 100 % (figure 4 and 5).

Percentage of correct classifications



neurons at intermediate layer

Figure 4

Choosing the stop training point

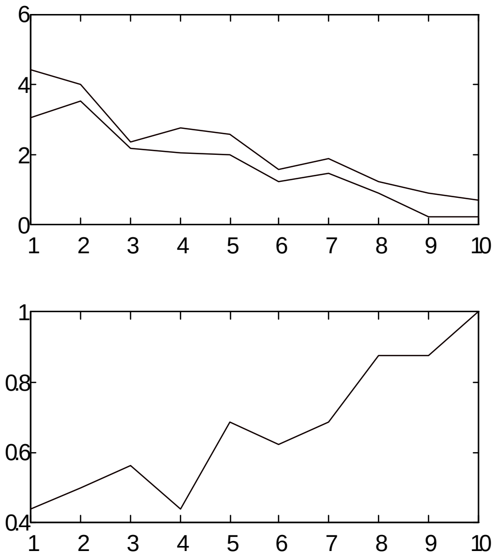


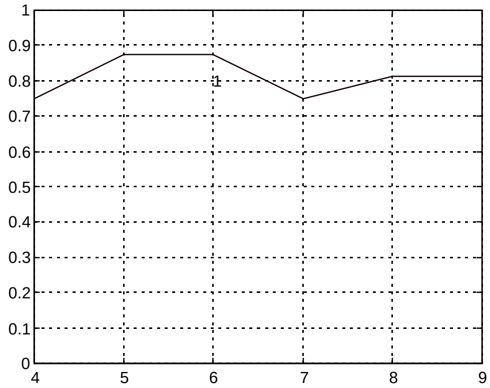
Figure 5. The top plot shows the errors of training and test sets by epoch. The bottom plot shows the increase of percentage of correct classifications by epoch.

9 New signal reduction

Let's cut off the signal components that have relevance frequency of 0.2. By doing this ,the signal dimension becomes equal to 9. Redoing the re-training of neural network and after analyzing several architectures we found the best one, which has five neurons in the intermediate layer ,four neurons in output layer , learning rate of 0.1 and momentum term of 0.8.

Now the percentage of correct classifications decreased to 87,5%, (see figure 6).

Percentage of correct classifications



neurons at intermediate layer

Figure 6

10 Conclusions

The reduction of number of signal components presented to the network (from 20 to 9) brings about a reduction of the network neuron number (from 12 to 5 in the intermediate layer) as desired. The price paid for getting the reduction of processing time is the reduction of correct classification (from 100% to 87,5%). A trade-off must then be found between the desired processing time and the correct classification expected.

References

[1] J. A . Arantes do Amaral, Classification of Vessels through their Magnetic Signatures, Master Thesis, COPPE-UFRJ, 1996
[2] L. P . Caloba, C. D. P. Poppe, Identifying Relevant Features for a Real-Time Discriminating Process Under High-Event Rate Conditions, COPPE/UFRJ/EE 1994
[3] H. Souza, Magnetism Reports, IPqM, 1993