NEURAL NETWORKS FOR ACTIVE ECHO CLASSIFICATION

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ABSTRACT

This paper explores the use of an artificial neural network to distinguish between echoes from a constellation of acoustic reflectors representing a target and similar echoes produced by other reflectors, e.g. reverberation. The network was both trained and tested with simulated data. A wide band linear frequency modulated pulse was used in order to resolve the highlights of the target.

1. Introduction

A basic issue in the design of active sonar systems is the high incidence of false alarms associated with a standard energy detector, i.e. a matched filter or replica correlator. Classification systems based on echo attributes have long been recognized as important in the reduction of false alarms. As a simple example, Doppler is a useful parameter for discriminating between stationary clutter and a moving target. Non-zero Doppler, as well as other features of the returned echo, have long been used by radar and sonar operators to distinguish target echoes from clutter and reverberation.

Recently there has been a lot of interest in the application of artificial neural networks to the problem of echo classification. An early paper on this topic by Gorman and Sejnowski [1] reported good success on a sonar data classification problem — the data consisted of echoes from linear frequency modulated (LFM) signal pulses reflected from a metal cylinder and a cylindrically-shaped rock placed on a sandy ocean floor. Input to the neural network in [1] consisted of the powers in a set of windows, temporally offset to follow the slope of the LFM chirp, overlaid on the short term Fourier spectrum of the return.

In the study reported here, samples of the correlation envelope, i.e. the matched filter output, were used directly as input to the neural network. Two applications of a neural network were examined: (i) discrimination between a target and clutter based on the correlation envelope seen at a single sensor; and, (ii) discrimination between a target and clutter based on the different correlation envelopes seen at two sensors. Target and clutter returns were simulated in both applications by means of randomized distributions of point reflectors.

2. Target and Clutter Models

Figure 1 shows the basic elements of the two-dimensional simulation used to generate echo data for the investigation reported. The simulation involves a projector (P), emitting an LFM pulse (duration 0.02 seconds, bandwidth 600 Hz), and a sensor (S). A target was simulated by sixteen point reflectors with randomized reflectivity placed at random along a line 50 meters in length. Similarly, clutter was simulated by randomized point reflectors within the directional responses of both the projector and sensor. In the current study this was approximated by placing clutter reflectors within a rectangular region centered on the target location.

The received signal r(t) is given by the expression

$$r(t) = \sum_{i=1}^{N} B_i\, a_i\, s(t - t_i)\,, \qquad (1)$$

where a_i is the reflectivity of the i^{th} point reflector, $s(t - t_i)$ is the delayed echo from the i^{th} point reflector, and B_i is a factor that includes projector and sensor directional responses, a system gain factor, as well as propagation path losses. Similar models have been used by other workers [2] to investigate the ability of a neural network to learn to classify different ocean-bottom types by means of simulation studies. Their work, however, focused on modeling of the reverberation from distributions of point reflectors but did not consider the modeling of target echoes.

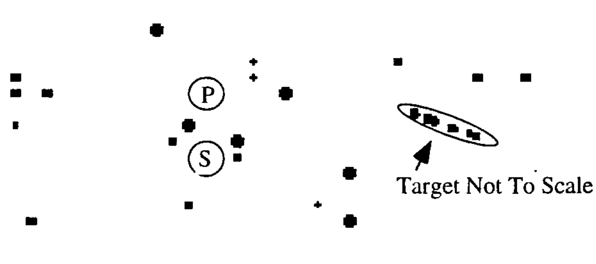

Figure 1. Target and clutter modeled by point reflectors.

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3. Echo Classification With Neural Networks

This study examines echo classification based on the shape of the correlation envelope produced by echoes from simulated targets and clutter distributions. In the study an artificial neural network was used as a convenient tool for evaluating how well echoes from targets can be discriminated from similar echoes produced by target-like distributions of clutter reflectors. Two target-classification problems were explored: (i) discrimination between clutter and target at several aspect angles in a monostatic sonar, and (ii) discrimination between a target and clutter in a multistatic sonar where echoes are received at two different sensor locations.

3.1 Classification of Target vs. Clutter

A target was simulated as described in Section 2 by means of sixteen point reflectors located along a line 50 meters long. Figure 2 shows the simulated target at four aspect angles: 0 degrees, 30 degrees, 60 degrees, and 90 degrees relative to bow aspect. The corresponding correlation envelopes that would result from a monostatic active sonar with a 600 Hz bandwidth LFM pulse are also shown with each target aspect. In Figure 2, as well as in Figures 3, 5, and 6, the horizontal scale is in range coordinates. Value of the correlation envelope is represented vertically in all figures to the same scale. For targets, the vertical and horizontal scales are the same.

Clutter was generated in a similar fashion with twenty point reflectors, except that the reflectors were located randomly within a rectangular area whose sides were twenty percent larger than the linear dimension of the target. One example of clutter and the resulting correlation envelope of the echo is shown in Figure 3. This clutter model is an oversimplification, since clutter can result from reflections anywhere within the beams of the transmitter and the receiver, a volume that may be much larger than a target.

Training examples for a neural network were generated by first forming 250 independent clutter examples such as that shown in Figure 3. Each of these were then combined with the four target correlation envelopes shown in Figure 2 according to the formula:

$$x(n) = \alpha \ \text{target}(n) + \text{clutter}(n), \tag{2}$$

where $x(n)$ is the n^{th} input to the neural network, target(n) and clutter(n) are samples of the respective target and clutter correlation envelopes, with α being 1, 2, or 10. The variable α is used to provide three different target-to-clutter ratios. The training set also included 750 examples

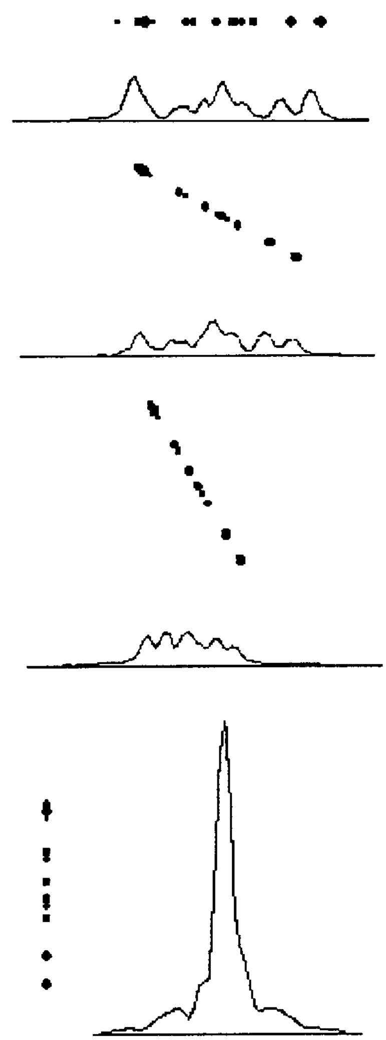


Figure 2. Simulated target at four aspect angles with resulting correlation envelope (targets and correlation envelopes are in range coordinates).

of clutter alone, which were generated by replicating the 250 clutter examples. This produced a total of 3750 examples in the training set. A testing set containing 3750 examples was also generated from an independent set of 250 clutter realizations.

The neural network used in the study was a fully-connected multilayer back propagation network with an input layer of 80 nodes, a hidden layer of 15 nodes, and an output layer of 5 nodes representing four target aspects and a clutter-only category.

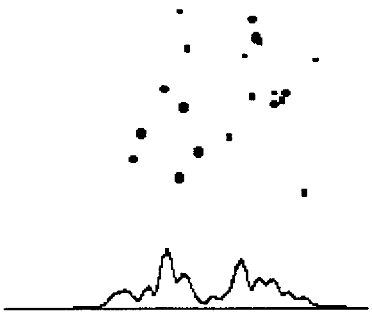


Figure 3. A typical distribution of point reflectors and the resultant correlation envelope.

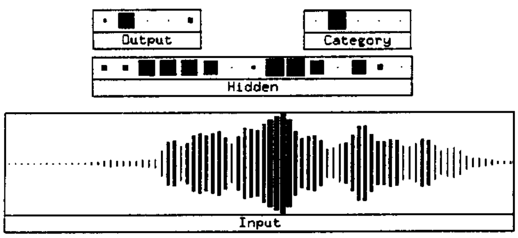


Figure 4. Neural network for echo classification (the width and also the height of each rectangle indicates the value of the output at a node).

The network was trained for a total of 20000 examples from the training set, with each one chosen randomly from the 3750 available by a shuffle-and-deal algorithm. Classification performance on the testing set is indicated by the confusion matrix shown in Table 1. For each category of echo, denoted by the column headings, the numbers in the rows indicate the distribution of network decisions.

	0 deg	30 deg	60 deg	90 deg	clutter
0 deg	729	4	3	0	15
30 deg	3	713	5	0	42
60 deg	0	5	731	0	9
90 deg	0	0	0	750	3
clutter	18	28	11	0	681

Table 1. Confusion matrix summarizing classification performance on the testing set.

It would appear from these results that discrimination between clutter and target is achievable under the restrictions used in the experiments; namely, that the target model did not change between training and testing of the classifier.

3.2. Discrimination of Target vs. Clutter from Echoes at Two Sensor Locations

The correlation envelope of the returned echo from an LFM pulse changes with viewing aspect. For small differences in viewing aspect, say two degrees, the differences in the correlation envelopes tend to be greater for clutter than they are for the kind of linear target considered here. This is illustrated in Figures 5 and 6.

The paired correlation envelope patterns, corresponding to a two degrees change in aspect, were used as inputs to a back propagation network as shown in Figure 7. Targets were simulated by sixteen point reflectors in a linear configuration as described in Section 2, while non-targets were simulated by twenty point reflectors randomly placed in a square with sides equal in length to that of the linear target. The extent of the clutter distribution was made equal to the length of the target in order to make the target versus clutter discrimination problem more difficult. This time five realizations of target and five realizations of clutter were generated. For each of the five targets and non-targets, nine pairs of inputs were generated with aspect angles in degrees as

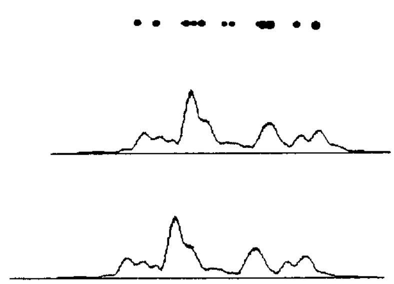


Figure 5. Linear collection of point reflectors and correlation envelopes resulting from LFM pulse echoes at two aspect angles differing by two degrees.

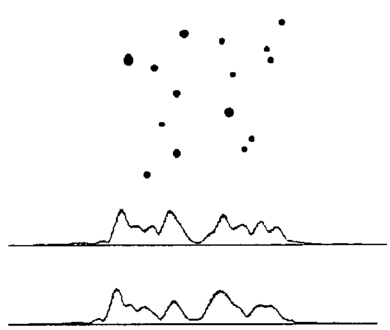
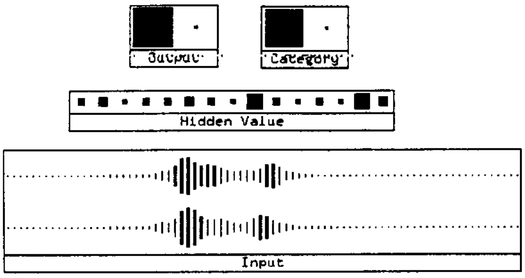
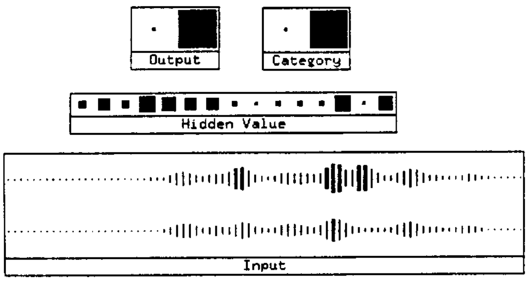


Figure 6. Random collection of point reflectors and correlation envelopes resulting from LFM pulse echoes at two aspect angles differing by two degrees.



(a) Network state for a target input.



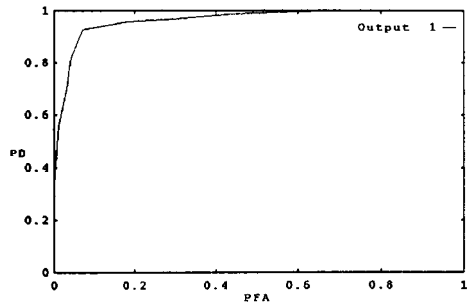
(b) Network state for a non-target input.

Figure 7. Neural network classifier (the input is a two-dimensional array of values from the correlation envelopes at two aspects differing by two degrees).

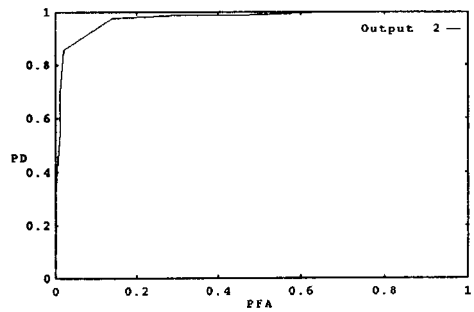
follows: (0, 2), (10, 12), ..., (80, 82). The network was tested with independently generated test data containing the same number of target and non-target examples, except that in this case the first member of each aspect pair was chosen from a uniform distribution in the range zero to eighty degrees while the second was two degrees larger. The classification performance that was achieved is summarized by the receiver operating characteristic (ROC) curves shown in Figure 8.

4. Conclusions

The simulations shown here, while preliminary, indicate the value of target modeling for target versus clutter discrimination. In some cases it may be possible to use point-reflector target models to train neural networks to distinguish between target and non-target echoes from single sensor measurements. It is also possible, by using two or more sensors, to distinguish between targets and clutter based on high resolution signals such as LFM. Work with real data is necessary to further explore the validity of these techniques.



(a) ROC diagram for output 1 of network.



(b) ROC diagram for output 2 of network.

Figure 8. ROC curves for target/non-target classification with the network shown in Figure 7 (output 1 is target classification, output 2 is non-target classification).

References

1. R. P. Gorman and T. J. Sejnowski, "Learned Classification of Sonar Targets Using a Massively Parallel Network", IEEE Trans. ASSP, Vol. 36, No. 7, July 1988.

2. D. Alexandrou and D. Pantzartzis, "Seafloor Classification with Neural Networks", IEEE Oceanic Engineering Society Newsletter, Spring 1991, Reprinted from Oceans '90 Proceedings, 1990.