THE USE OF A MULTILAYER PERCEPTRON FOR ADAPTIVE CORRELATION PROCESSING IN A ACOUSTICALLY COMPLEX ENVIRONMENT

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ABSTRACT

Robust detection and classification for active sonar processing in acoustically complex environments is a difficult and challenging problem. Complex bathymetry and propagation effects may cause multipath spreading of the transmitted signal before it arrives back at the receiver. Correlating with a replica of the transmitted signal may thus severely degrade the performance of a system. This paper explores the use of a multilayer perceptron to compensate for channel and other medium effects in a acoustically complex environment. It is shown that adaptation to the environment in such scenarios can lead to significant processing gain and that a multilayer perceptron is capable of implementing this type of processing.

1. INTRODUCTION

It is well known that optimum detection of known signals in Gaussian white noise consists of correlating with a filter matched to the signal expected to arrive at the receiver [1-3]. An estimate of this filter is obtained by convolving the transmitted signal with an estimate of the impulse response of the channel through which the transmitted signal has travelled. If multipath spreading and other medium effects are insignificant, correlating with the transmitted signal may produce satisfactory results. If the channel effects are significant, however, correlating with the transmitted signal may lead to significantly reduced detector performance. The purpose of this paper is to demonstrate how much "processing gain" can be achieved by adapting the processing scheme to include the effects introduced by the medium in a acoustically complex environment. This will be shown through processing of real data collected during a U.S. Navy sea test. Additionally, the use of a multilayer perceptron is shown to be capable of incorporating such information. The rest of this paper is structured as follows: the processing approach is described; results and analysis of processing the data set are presented; and a summary and suggestions for future work are presented.

2. PROCESSING APPROACH

In our approach, time series data is used to train and test the multilayer perceptron. There are two motivations for working with time series data. First, it is desired that the neural network perform coherent processing. This is done in the first hidden layer which consists of 20 sigmoidal units each with 1024 taps and 1 bias term. The number 1024 is chosen because it corresponds to the number of samples of the transmitted signal. The second motivation in using the time series is for classification purposes. Common classes of signals other than target that arrive at the receiver are the signal that travels directly from the transmitter to the receiver (without reflection from the target) and reverberation, caused by backscattering of the transmitted waveform. In the power spectrum, these signals lie in the same band as the target signal and may be difficult to classify based on power spectrum features alone. Class separation may very well depend on phase information, hence the reason for time series. The multilayer perceptron has several characteristics which make it advantageous for use as a classifier. First, Kolmogorov proved that any arbitrary mapping, $R^m \rightarrow R^n$, is possible in a 3-layer (1-hidden layer) feedforward neural network given sufficient hidden elements [4]. Several investigators have shown that a multilayer perceptron, when trained as a classifier using backpropagation, approximates the Bayes optimal discriminant function [5-7]. With these considerations, we can see that a multilayer perceptron theoretically is capable of Bayes optimal class separation regardless of the type of underlying class distributions. How well it can actually achieve this depends on network com-

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plexity, the amount of training data, and the degree to which training data reflect true likelihood distributions and *a priori* class probabilities. One characteristic of real in-situ data is that it typically has zero mean. The data analyzed here may or not be Gaussian. The Bayes optimal decision surface even for two Gaussian random variates, $N(0,\sigma_1)$ and $N(0,\sigma_2)$ is non-linear. Monte Carlo simulations using a multilayer perceptron have been performed demonstrating its ability to approximate the non-linear decision surfaces required for this problem [8].The complete net construct used here is a 2-hidden layer net as shown in figure 1 below. The first and second hidden layers contain 20 and 10 sigmoidal units respectively, with the output layer having N linear elements, depending upon the total number of output classes.

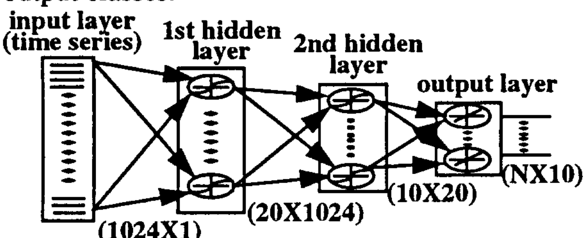

Figure 1: Configuration of multilayer perceptron.

The rest of this paper will focus on comparing a multilayer perceptron's performance when trained with in-situ data, with that of a correlator whose replica is the transmitted signal. The comparison will be made at the detection level only to keep the analysis simple.

Before proceeding to the experimental results, we digress for the moment to observe the results of training a multilayer perceptron in the design of the optimal linear solution for known signals embedded in white Gaussian noise. Since there is a known analytical solution to this problem, this provides a good check on the design of our network before proceeding to more difficult problems. To show this, we have assigned two output neurons to the net described above; one a target neuron trained to recognize a known deterministic sequence at unity power, and the other an interference neuron trained with a sample of unity power white Gaussian noise. Measuring the input-output relationship for a possibly non-linear system gives us an indication whether or not we are operating in the linear region. In the case of linear filters, the input-output relationship, i.e. impulse response, is *not* a function of the input [9]. The input-output relationship of non-linear filters however are a function of the input and must be treated accordingly. With this in mind, the dirac delta function, $\delta(n)$, was scaled at various amplitudes and processed through the trained net with the results shown in figure 2 for the first 100 samples. Notice that the outputs scale linearly with the input from $0.1\,\delta(n)$ to $10\,\delta(n)$. From $20\,\delta(n)$ to $100\,\delta(n)$ the changes appear to be progressively more non-linear. With the unity power impulse being in the linear interval and the multilayer perceptron being trained with an exemplar at unity power, this is a clear indication that the net is operating in the linear region which is to be expected for this problem. Figure 3a shows a lofargram of the signal assigned as the target in this example. It is a 25 Hz bandwidth hyperbolic frequency modulated (hfm) slide of 10 second duration. Figure 3b shows the lofargram of the impulse response of the multilayer perceptron at the target neuron prior to training. This reflects the random weight initialization typically used in training a multilayer perceptron. Figure 3c shows the lofargram of the impulse response of the multilayer perceptron at the target neuron after training. The resulting output very much resembles the hfm, the optimal linear solution in this case.

3. EXPERIMENTAL RESULTS

In this section we first perform a bounding analysis to theoretically quantify the possible gains when medium effects are accounted for in this data set. We then present the results of a performance comparison by processing real data with a multilayer perceptron trained with in-situ data and a correlator whose replica is the transmitted signal.

3.1. Bounding analysis

To theoretically demonstrate what gains are possible, we analyze a test site that has medium effects typical for this data set. We wish to compute an estimate of the transfer function between the echo recorded at the receiver and the transmitted signal (the hfm described in section 2). Using the least squares Wiener-Hopf equations [10], a 2 second estimate of the impulse response is computed. It is shown in figure 4. Notice the peaks at approximately 0.2, 1.2, and 2.0 seconds. This multipath structure is characteristic of dispersive mediums.To determine the theoretical gain, we proceed as follows: convolve the hfm with the estimate of the impulse response of the medium; embed it in white Gaussian noise at an SNR of 0 dB; correlate with the hfm (transmitted signal) and denote this R_{hfm}; correlate with the medium effected hfm and denote this R_{mehfm}. The squared correlator outputs are shown in figure 5. We define the performance gain as

$$P_g = 10\log 10\left(\frac{max\,(R_{mehfm})^2}{max\,(R_{hfm})^2}\right) \qquad (3.1)$$

Using this formulation, P_g was computed to be approximately 10 dB for this example. We now show the results of the comparison between the multilayer perceptron trained with in-situ data and the hfm replica correlator.

3.2. Multilayer perceptron/replica correlator comparison

In order to test the generalization capability of the multilayer perceptron, the data set is divided into 13 exclusive segments further subdivided into 8 training sites and 5 test sites. Training exemplars include samples of target echoes at these discrete training site locations and a sample of ocean ambient noise for the interference neuron. Figure 6 shown below depicts the geometry from which the exemplars were chosen. The (*) indicates a training site; an (X) indicates a test site. After processing data through the multilayer perceptron, a simple voting procedure is applied to pick the maximum value of the 8 output target neurons. A 2.5-second CFAR split-window normalizer is applied to both outputs to aid in false alarm reduction. The performance metric for this comparison is a Receiver Operating Characteristic (ROC) curve. The average ROC curve for all test sites is shown in figure 7. Notice at a P_d of 0.5, there is almost 3 orders-of-magnitude difference in P_{fa} between the multilayer perceptron and hfm replica correlator ROC curves. At a P_{fa} of 10e-03, the P_d differential is approximately 0.8.

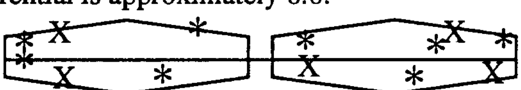

Figure 6: Geometry of test denoting training sites (*) and test sites (X).

4. SUMMARY/CONCLUSIONS

In this paper, we have shown that in-situ adaptation in a acoustically complex environment has the potential for significant processing gain compared to traditional forms of matched filter processing. A test involving modeling of the transfer functions between a target echo and the transmitted signal shows that substantial gains can be achieved by correlating with a better estimate of what is expected to arrive at the receiver. This is confirmed in a test dividing the region into training and test sites where the ROC curves show significant improvement for the multilayer perceptron. With multiple output capability, the multilayer perceptron is an efficacious structure for multiple hypothesis testing of target and interference. Outputs may be expressed in the form of estimates of Bayesian *a posteriori* probabilities [7] and naturally form a basis for higher level classification tasks. More work is necessary in this area to compare the proposed neural network classifier scheme with other known detection/classification schemes.

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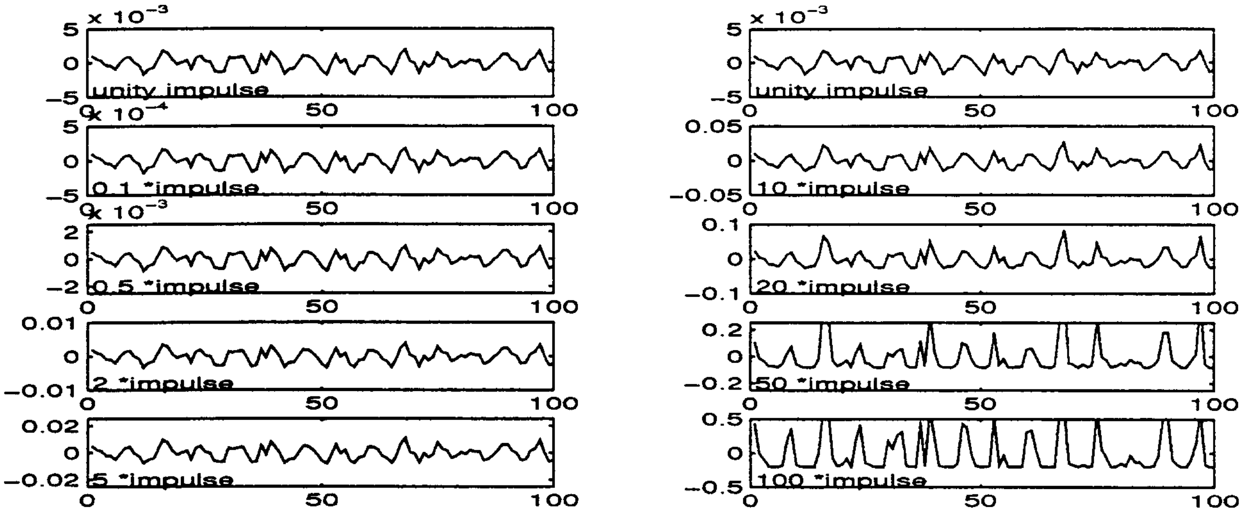

Figure 2: Impulse responses at various amplitudes.

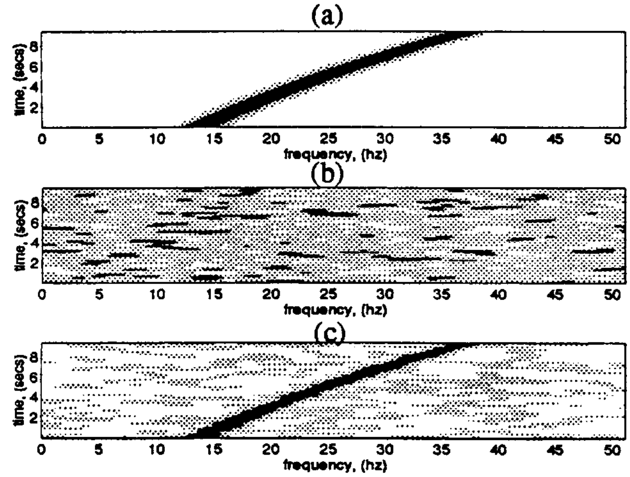

Figure 3: Lofargram for a) 25 Hz, 10 second hfm, b) impulse response of multilayer perceptron target neuron prior to training, c) impulse response of multilayer perceptron target neuron after training.

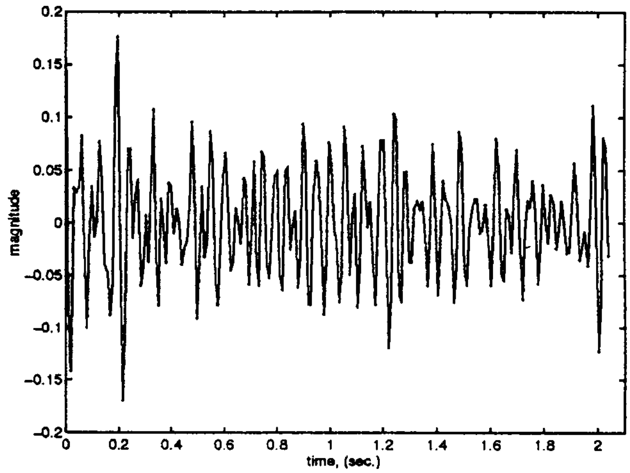

Figure 4: 2 second impulse response estimate between a typical echo and the transmitted signal.

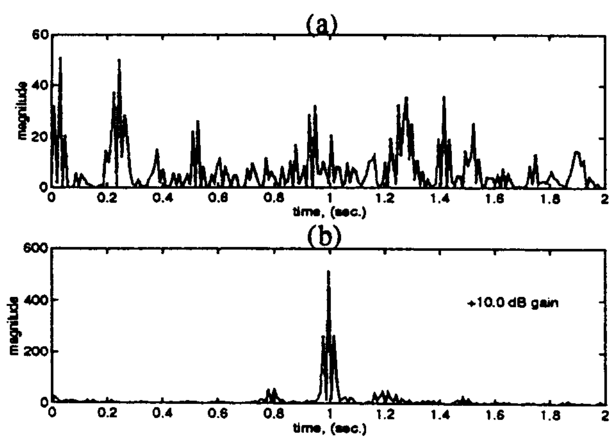

Figure 5: Squared correlator outputs for medium effected hfm embedded in white Gaussian noise at SNR = 0 dB, a) Replica correlator, b) medium effected signal as correlator.

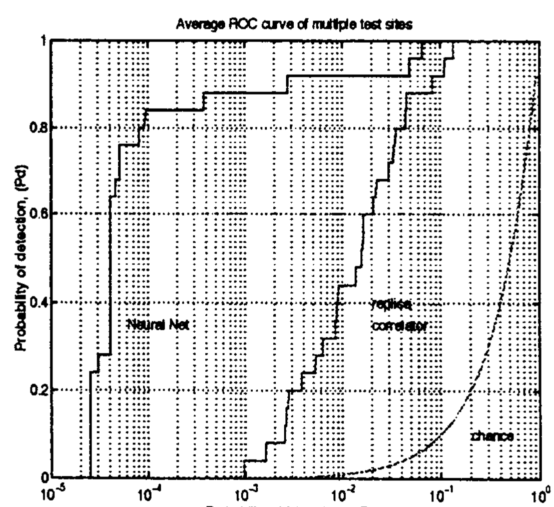

Figure 7: Average ROC curves over entire region.