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Detection of random signals with neural networks

Nirmala Muthuswamy
Lehigh University

Muthuswamy,
Nirmala

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DETECTION OF RANDOM SIGNALS WITH NEURAL NETWORKS

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Nirmala Muthuswamy

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Dr. Rick S. Blum

(Thesis Advisor)

Dr. Alastair McAulay

(Chairman of Department)

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Contents

Abstract

The detection of random signals using neural networks is studied. Cases with Gaussian and impulsive noise are considered. The performance was studied by obtaining the receiver operating characteristics. A mean-level detector was used for the purpose of comparison. For the cases with a random signal corrupted by Gaussian noise that were studied, the neural network detector provided performance close to that obtained with the mean-level detector. For the cases that were studied with Laplace noise, the performance of the neural network detector was also similar to that obtained by the mean-level detector. For cases with very heavy tailed noise distributions that we studied, the neural network was found to perform significantly better than the mean-level detector.

Chapter 1

Introduction

Techniques for detecting signals from noisy observations play a significant role in a variety of signal processing applications including radar, sonar, digital communications, seismology, and biomedical engineering. It is well known that nonlinear processing schemes can generally outperform linear schemes for many cases of practical interest. The particular nonlinear processing scheme which gives best performance depends on the exact statistical description of the signals and noise [1], which may not be known in practice. Linear processing schemes, which are optimum for many cases where signals are observed in Gaussian noise, have been thoroughly investigated due to their simple and easily implementable structure.

Neural networks have become a key tool in signal processing in general and in signal detection in particular for the past few years as discussed in [2] through [9]. Neural networks have also been considered for distributed signal detection [7, 8]. One of the appealing features of a neural network is that it can often be trained to operate, with acceptable performance, in a situation for which a complete statistical model is not available. The use of neural networks for detecting known signals has received considerable attention. In this thesis we consider the use of neural networks to detect random signals in noise, for which results have been lacking. Such problems are of interest in many applications.

Some of the research presented here is particularly influenced by the results in [9]. In [9], the use of neural networks for detecting known signals in Gaussian and non-Gaussian noise has been studied. In the presence of Gaussian noise, it was shown that performance of a properly trained neural network is very similar to that of the optimum matched filter detector. In the presence of non-Gaussian noise, however, neural networks are shown to perform better than both matched filter and locally optimum detectors.

Chapter 2

Signal Detection Problem

Let $(X_1, X_2, ..., X_n)$ be an n-dimensional vector of real-valued independent and identically distributed observations. Assuming the additive observation model, each of the observations is given by

$$X_i = \theta S_i + W_i \tag{2.1}$$

where S_i and W_i are the random signal and noise components of the ith observation and θ is the unknown amplitude of the random signal. These observations are presented to a detection scheme which attempts to determine if signal is present i.e $\theta = \theta_0 > 0$ or absent i.e $\theta = 0$. To simplify matters let us focus on the case where the S_i and W_i are independent and where the S_i have a constant positive mean μ. The W_i each has zero mean. Each of the S_i is sampled from the same distribution. Each of the W_i is also sampled from the same distribution.

If an exact statistical model for the signal and the noise observations is known, the optimum test is well understood. If a complete statistical model is unavailable, then the optimum test cannot be used. It is reasonable to attempt to detect the presence of a signal by forming an estimate of the mean of the observations. If this estimate exceeds a threshold, a signal is determined to be present. We call such a test a mean-level detector. Mean-level detectors are optimum for detecting constant deterministic signals observed in Gaussian noise and for detecting weak constant-mean random signals in Gaussian noise (locally optimum detection). The mean-level detector is a linear scheme which would often be employed in practical applications.

Chapter 3

Neural Networks For Detection

The neural network based detector (neural detector) is a backpropagation neural network with a minimum of 3 layers which are typically referred to as the input, the hidden and the output layers as shown in 3.1.

The number of inputs nodes is determined by the dimension of the observation vector in (2.1). The number of hidden nodes was varied between 3 and 20 in our study to observe its effect on the network training error. The number of hidden layers was also varied from 1 to 3. The backpropagation algorithm was used for training and the amount of training was carefully selected in order to avoid the occurrence of overtraining. In the neural network, each node computes the weighted sum of all its inputs and then processes the sum through a possibly nonlinear transfer function. Hyperbolic tangent transfer functions were used in the nodes in the hidden layer while a linear transfer function was used in the single output node. A bias term was included in all hidden nodes and in the output node.

In our study we have made the explicit assumption that it is possible to get a set of signal-plus-noise samples as well as a set of noise-only samples for training. The network is trained to produce a 1 on its single output for observations that are known to consist of signal-plus-noise and produce a 0 for observations that contain noise alone. The output from the neural network is compared to a threshold to determine a decision. By varying this threshold the probability of false alarm P_f can be varied. The probability of false alarm is the probability that we decide signal

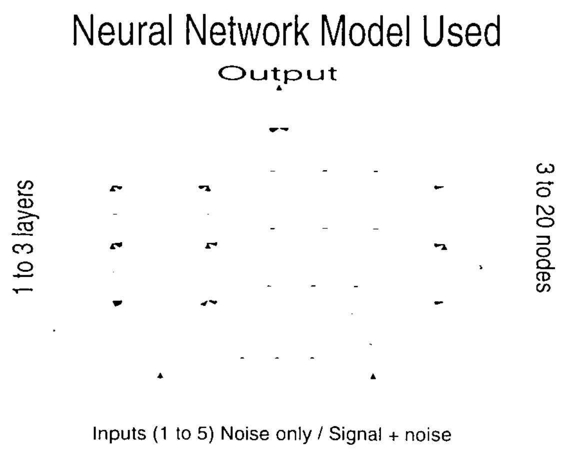

Figure 3.1: Schematic Diagram of the Neural Network

is present when signal is actually absent. A desired value for this quantity is typically provided in an application. For a given P_f we would like our detection procedure to provide maximum probability of detection P_d. The probability of detection is the probability that we decide signal is present when signal is actually present.

Chapter 4

Simulation Results And Discussion

In the results presented here, both Cauchy and generalized Gaussian noise distributions were considered. The Cauchy distributed noise samples were obtained from the probability density function (pdf)

$$f_c(x) = \frac{1}{b\pi(1 + (\frac{x}{b})^2)}. \tag{4.1}$$

where b is called the scale parameter. The generalized Gaussian noise samples were obtained from the pdf

$$f_g(x) = \frac{k}{2A(k)\Gamma(1/k)} \exp\left[-\left(\frac{|x|}{A(k)}\right)^k\right] \tag{4.2}$$

where $\Gamma(a) = \int_{x=0}^{\infty} x^{a-1} \exp(-x) dx$ is the Gamma function and

$$A(k) = \sqrt{\frac{\Gamma(1/k)}{\Gamma(3/k)}} \tag{4.3}$$

In our specific examples, we considered $0.2 \leq k \leq 2$ in (4.2). If $k = 2$ then f_g is the Gaussian pdf and if we have $k < 2$ then f_g is a pdf with heavy tails. The heavy-tailed pdfs appear to be reasonable models for a number of practical noise models [1] often called impulsive noise models. The Cauchy pdf in (4.1) also has heavy tails.

Each noise sample W_i was combined with either a Cauchy or uniform random signal sample S_i with mean μ to yield the observation X_i as specified by (2.1). Several values of signal strength θ_0 and signal mean μ were considered. To test the performance of the neural detector, we ran a number of Monte Carlo simulations (with 60,000 trials). The receiver operating curves were obtained. Some representative results are given in Figures 4.1 through 4.5. Details for each of these cases are given in the caption below the respective figure. Due to the strong dependence on length of training and initial conditions, we cannot guarantee that the results we have obtained are the best possible. They simply give an indication of the type of performance which can be obtained.In all the results we present here the neural detector had one input.

Figures 4.1 through 4.3 give the performance curves for some representative cases with Cauchy signal (scale parameter of 0.25) [1] and Cauchy noise (scale parameter of 0.2). In all three cases the neural detector (NND) outperforms the mean-level detector (MLD) for a large portion of the range of P_f shown. We also studied some cases with uniform random signals and generalized Gaussian noise. For the Gaussian noise ($k = 2$ in (4.2)) cases we studied, the MLD and the NND gave comparable performance. The mean-level detector is known to provide good performance (it is locally optimum) for Gaussian noise cases, so these results are not too surprising. For Laplace noise, $k = 1$ in (4.2), the neural network detector was again found to provide performance comparable to the mean-level detector in the limited number of cases we tried. We must emphasize again that through proper training it may be possible to obtain better results for the neural network, but we did not find any in our limited search. As we decrease k in the generalized Gaussian noise pdf below $k = 1$, the noise gets more and more heavy-tailed and neural network detector tended to perform better than mean-level detector in the cases we tried. This is illustrated in Figure 4.4 for $k = 0.5$ and in Figure 4.5 for $k = 0.25$. In our results, the more heavy-tailed the noise the better the NND performed in comparison to the MLD. It is clear that the performance differences between the neural network detector and the mean-level detector were much smaller for the generalized Gaussian noise cases than for the Cauchy noise cases.

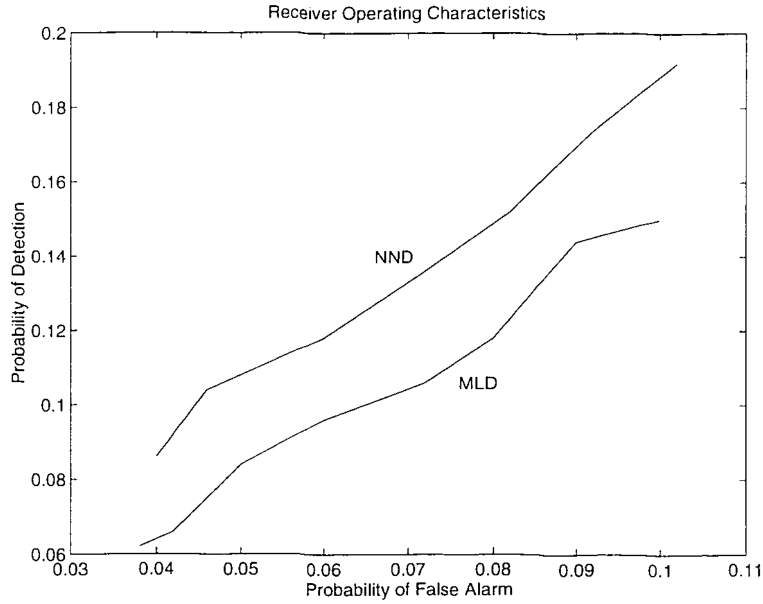

Figure 4.1: P_d versus P_f for Cauchy S_i and W_i, $\theta_0 = 0.5$, $\mu = 2.0$, and a network with 4 hidden nodes and 1 hidden layer.

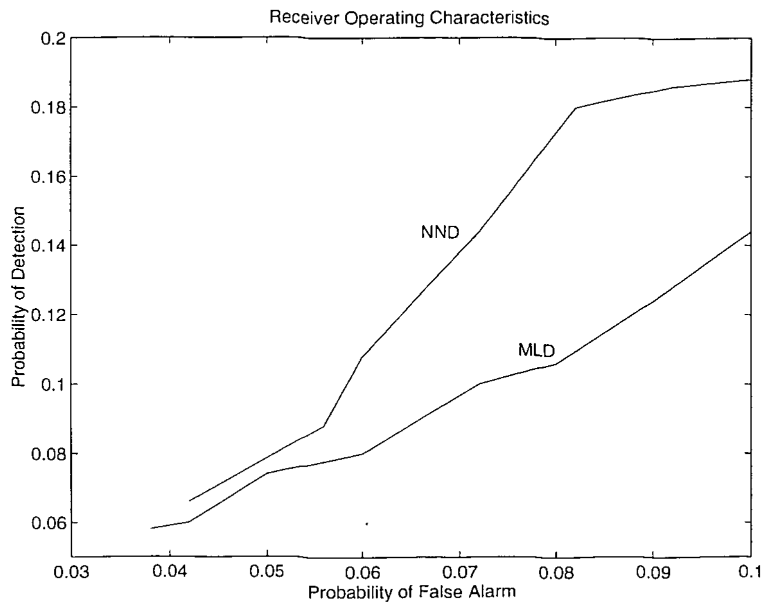

Figure 4.2: P_d versus P_f for Cauchy S_i and W_i, $\theta_0 = 0.5$, $\mu = 2.0$, and a network with 5 hidden nodes and 1 hidden layer.

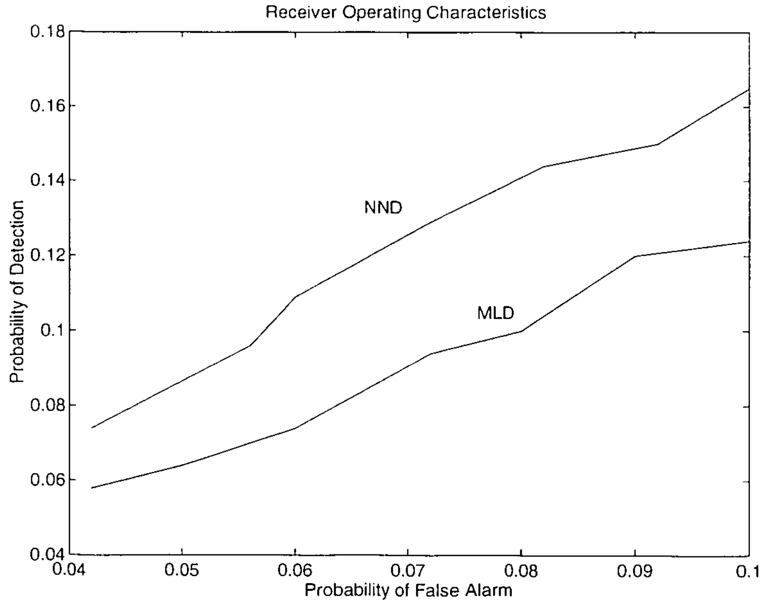

Figure 4.3: P_d versus P_f for Cauchy S_i and W_i, $\theta_0 = 0.3$, $\mu = 2.0$, and a network with 4 hidden nodes and 1 hidden layer.

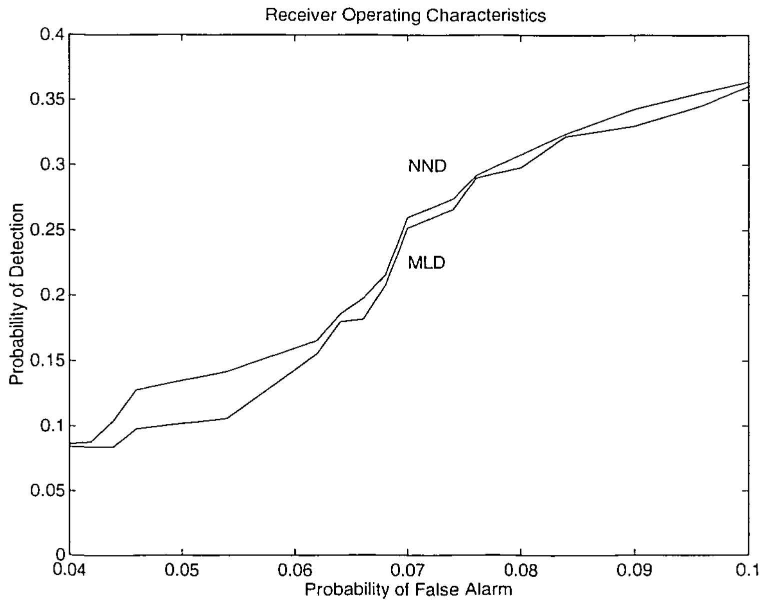

Figure 4.4: P_d versus P_f for uniform S_i and Generalized Gaussian W_i with $k = 0.5$, $\theta_0 = 1$, $\mu = 0.5$, and a network with 12 hidden nodes per layer and 2 hidden layers.

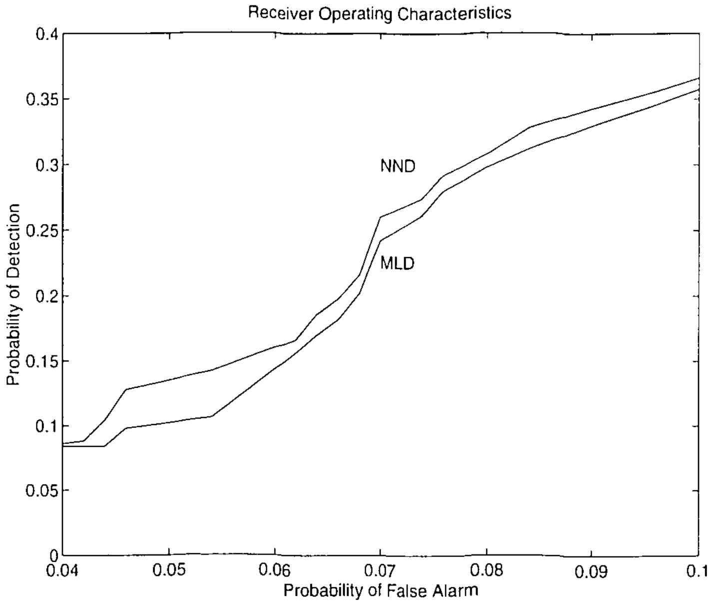

Figure 4.5: P_d versus P_f for uniform S_i and Generalized Gaussian W_i with $k = 0.25$, $\theta_0 = 1$, $\mu = 0.5$, and a network with 18 hidden nodes and 1 hidden layer.

Chapter 5

Conclusion

We have studied the application of neural networks to random signal detection in Gaussian and non-Gaussian additive noise. Our results indicate that neural networks are useful, especially for cases with very heavy tail noise pdfs. Further research is essential to fully understand the behavior and properties of the neural network detectors for various signal and noise distributions. Another interesting area for future research would be to study the robustness of the neural detectors when operating in noise environments other than those in which they were trained to operate in. This might be important in nonstationary environments.

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