Proceedings

IASTED International Conference

Signal and Image Processing - SIP-95

November 20-23, 1995
Las Vegas, Nevada, USA

Editor: N.M. Namazi

A Publication of
The International Association of Science and Technology for Development - IASTED

IASTED

IASTED - ACTA PRESS
ANAHEIM ♦ CALGARY ♦ ZÜRICH

ISBN: 0-88986-185-4

Application of Zero-Crossings and Neural Networks to Signal Detection

Jinsoo Bae, Iickho Song, Taejoo Chang, Kwang Soon Kim, and Sang Woo Ryu

Department of Electrical Engineering
Korea Advanced Institute of Science and Technology (KAIST)
373-1 Guseong Dong, Yuseong Gu, Daejeon, 305-701, Korea
Phone: +82-42-869-3445 Fax: +82-42-869-3410
e-mail: isong@Sejong.kaist.ac.kr

Abstract

Signal detection problems using the ψ^2 statistic, which is based on the numbers of zero-crossings of the received sample and its high-pass filtered versions, are considered. We performed computer simulations and compared the performance of the detector with those of other conventional detectors. Performance improvement of the detector is then considered using neural networks.

1 Introduction

The signal processing problem considered in this paper is to detect, based on zero-crossings, the presence of signal components in noisy observations. More specifically, we propose to use the zero-crossings for signal detection and neural networks for performance improvement of the detection scheme.

The number of zero-crossings observed in a time series may be viewed as a measure of the oscillation exhibited by the time series. When a known signal component is buried in zero-mean noise, the number of zero-crossings will naturally decrease as the signal strength gets larger, which can be used in detecting known signals. A simple way to detect the presence of correlated random signals can also be established by just counting the zero-crossings of a sample instead of by estimating the autocorrelation.

The most important advantage of the zero-crossing is, needless to say, its simplicity in computation and hardware implementation. In addition, the fact that it results in a nonparametric scheme depending only on the signs and order in time (temporal order) of observations is another advantage.

2 Preliminaries

Let $Z_1, Z_2, \ldots, Z_N$ be a size-N sample of a real-valued zero-mean stationary time series. Consider the nonlinear transformation,

$$X_i = \begin{cases} 1, & \text{if } Z_i \geq 0, \\ 0, & \text{if } Z_i < 0. \end{cases} \qquad (1)$$

Clearly, $\{X_i\}$ is a stationary series because $\{Z_i\}$ is. The number D_1 of the (first order) zero-crossings of $\{Z_i\}$ is defined as

$$D_1 = \sum_{i=2}^{N} [X_i - X_{i-1}]^2, \qquad (2)$$

which can also be expressed as a sum of indicators $D_1 = \sum_{i=2}^{N} I_{[X_i \neq X_{i-1}]}$. Evidently, $0 \leq D_1 \leq N-1$.

More generally, we can apply a set of filters to a time series, obtain the corresponding family of zero-crossing counts, and thus provide a summary of the oscillation 'history' observed in the time series and its filtered versions. The resulting family of the zero-crossing counts is referred to as the *higher order crossings* or simply as HOC [1].

Let ∇ be the difference operator defined by

$$\nabla Z_i = Z_i - Z_{i-1} \qquad (3)$$

and let $L_\theta = \nabla^{\theta-1}$, $\theta \in \{1, 2, 3, \ldots\}$ with $L_1 = \nabla^0$ the identity filter. The corresponding HOC, D_1, D_2, $D_3, \ldots$, are called the *simple* HOC. For the simple

HOC sequence $\{D_k\}$, the initial rate of increase may serve as a potent discriminator. It is known that $0 \le E[D_1] \le E[D_2] \le \cdots \le N-1$ for a zero-mean stationary process. In addition, it can also be shown that, as $j \to \infty$,

$$\{X_i(j)\} \Rightarrow \begin{cases} \cdots 0101 \cdots, & \textit{with prob. 1/2} \\ \cdots 1010 \cdots, & \textit{with prob. 1/2} \end{cases}$$

for a zero-mean stationary process. From this we can see that only the first few D_k are useful for discrimination purposes because the discrimination power of the simple HOC diminishes rather fast as k increases.

What we need then is a way to quantify the initial monotone rate of increase in simple HOC. A useful statistic that does this function is the ψ^2 statistic [2],

$$\psi^2 = \sum_{k=1}^{K} (\Delta_k - m_k^{(0)})^2 / m_k^{(0)}, \qquad (4)$$

where the increments

$$\Delta_k = \begin{cases} D_1, & \text{if } k = 1, \\ D_k - D_{k-1}, & \text{if } k = 2, \ldots, K-1, \\ (N-1) - D_{K-1}, & \text{if } k = K, \end{cases} \qquad (5)$$

and $m_k^{(0)} = E[\Delta_k]$ under H_0. If Δ_k's are from H_0 then the value of the ψ^2 statistic would be small. If Δ_k's are from H_1, on the other hand, then the value of the ψ^2 statistic tends to be large.

3 Signal Detection Problems

3.1 The Observation Model

Let us now consider the purely additive noise model. For the known signal case, the observations Y_i can be described as

$$Y_i = \theta e_i + W_i, \qquad i = 1, 2, \ldots, n, \qquad (6)$$

where θ is a signal strength parameter, e_i is a known signal component, and W_i is the purely-additive noise at the i-th sampling instant. The noise components W_i, $i = 1, 2, \ldots, n$, are assumed to be independent and identically distributed (i.i.d.) random variables with common pdf f_W, mean zero, and variance σ_W^2. Similarly, for the random signal case, we have

$$Y_i = \theta S_i + W_i, \qquad i = 1, 2, \ldots, n, \qquad (7)$$

where S_i is a zero-mean random signal component.

Since the background noise in practice is often non-Gaussian, our emphasis will be on a non-Gaussian noise, the Laplace noise. The pdf of the Laplace noise is

$$f_L(x) = \frac{1}{\sqrt{2\sigma^2}} \exp\{-[|x| / \sqrt{\sigma^2/2}]\}$$

which has a tail heavier than the Gaussian noise.

3.2 Performance Characteristics

The detection probabilities of the ψ^2 detector are now obtained as a function of θ and compared with those of the linear correlator (LC) and sign correlator (SC) detectors in the known signal case and those of the correlation (CO) and sign-correlation (SCO) detectors in the random signal case.

3.2.1 Correlated Random Signal Case

Figures 1 and 2 show simulation results obtained through Monte-Carlo runs, for n=50 and $P_{fa} = 1.0 \times 10^{-3}$. The correlated random signal components are assumed to be generated by the $AR(1)$ model with parameter 0.5,

$$S_i = \begin{cases} u_i, & \text{if } i = 1, \\ 0.5 S_{i-1} + u_i, & \text{if } i = 2, \ldots, n, \end{cases} \qquad (8)$$

where u_i are i.i.d. Gaussian random variables with mean zero and variance 1.

We see in Figure 1 that, for Gaussian noise with mean zero and variance 1, the CO detector outperforms the ψ^2 and SCO detectors. This is a natural result because the CO detector is uniformly most powerful under Gaussian noise environment.

In Figure 2, we see that the SCO detector has better performance than the other two detectors when the signal strength is weak. This is due to the fact that the SCO detector is locally optimum for this noise. As the signal strength gets strong, however, ψ^2 detector outperforms the SCO and CO detectors.

In short, for the correlated random signal case, we can see that the ψ^2 detector performs better than the CO and SCO detectors when SNR in high under impulsive noise environment.

3.2.2 Known Signal Case

In the observation model (6), we let $n = 20$ and $e_i = 1$, $i = 1, 2, ..., 20$, and obtained the threshold to achieve the given false-alarm probability $P_{fa} = 1.0 \times 10^{-3}$ by Monte-Carlo simulations.

Figure 3 shows the simulation results under Laplace noise environment with $\sigma^2 = 2$. Note that the SC detector outperforms the LC detector when the signal strength is weak. This is because the SC detector is LO for Laplace noise. The ψ^2 detector shows better performance than the SC detector when SNR is high.

In summary, when the noise is impulsive and the signal to noise ratio (SNR) is moderate-to-high, the ψ^2 detector shows good performance characteristics as a nonparametric detector.

3.2.3 Performance Improvement with Neural Network

Neural networks have been extensively studied in many areas of signal detection in the last few years [3]-[5]. In this paper, HOC are used as the training data of a neural network, which replaces the ψ^2 statistic to form a detector. Being inspired by the scattergram [1], we use a neural network in discriminating samples from different processes. Given a sample we first acquire HOC vector $(D_1, D_2, ..., D_K)$. This vector can be thought of as a point in the K-dimensional space. As in the scattergram, points from H_0 and those from H_1 can be separated by a hyperplane once a specific false-alarm probability is given. Here, the neural network is used to determine the hyperplane after training.

The neural network architecture used in this paper is multi layer perceptron (MLP): the last layer neuron is a hard limiter with a bias adjustable to threshold to satisfy a false-alarm probability requirement; the middle layer neurons are sigmoid functions with biases; and the first layer neurons are linear functions with biases. We employed a $K \times 12 \times 1$ MLP as a classifier, where K=9. We trained this MLP through MATLAB.

Figure 4 shows the performance of the neural network detector over the ψ^2 detector. It should be noted that the random signal is generated by (8). It turns out that the performance is improved when the ψ^2 statistic is replaced by the neural network.

4 Concluding Remarks

Since the zero-crossings are essentially nonparametric, the zero-crossing detector would show quite good performance. The zero-crossing detector could be used for both known and random signal detection without any redesign.

Although the zero-crossing detector reveals good performance for known signal detection, it has more advantages for correlated random signal detection. We also showed that using scattergram with a neural network classifier could improve the performance of the zero-crossing detector.

Acknowledgement

This research was supported in part by Korea Science and Engineering Foundation (KOSEF) under Grant 941-0900-040-2 and by the Ministry of Information and Communications under a Grant from the University Basic Research Fund, for which the authors would like to express their thanks.

References

[1] B. Kedem, Time Series Analysis by Higher Order Crossings, IEEE Press, Piscataway, NJ, 1994.

[2] B. Kedem and E. Slud, "Time series discrimination by higher order crossings," Ann. Statistics, vol. 10, 1982, pp. 786-794.

[3] J.W. Watterson, "An optimum multilayer perceptron neural receiver for signal detection." IEEE Trans. Neural Networks, vol. 1, 1990, pp. 298-300.

[4] V. Ramamurti, S.S. Rao and P. Gandhi, "Neural detectors for signals in non-Gaussian noise," Proc. ICASSP, Minneapolis, MN, 1993, pp. 481-484.

[5] J. Bae, Y.K. Ryu, and I. Song, "Noise canceling with autoassociative memory trained by order statistics," Proc. ICNN, Orlando, FL, 1994, pp. 3431-3436.

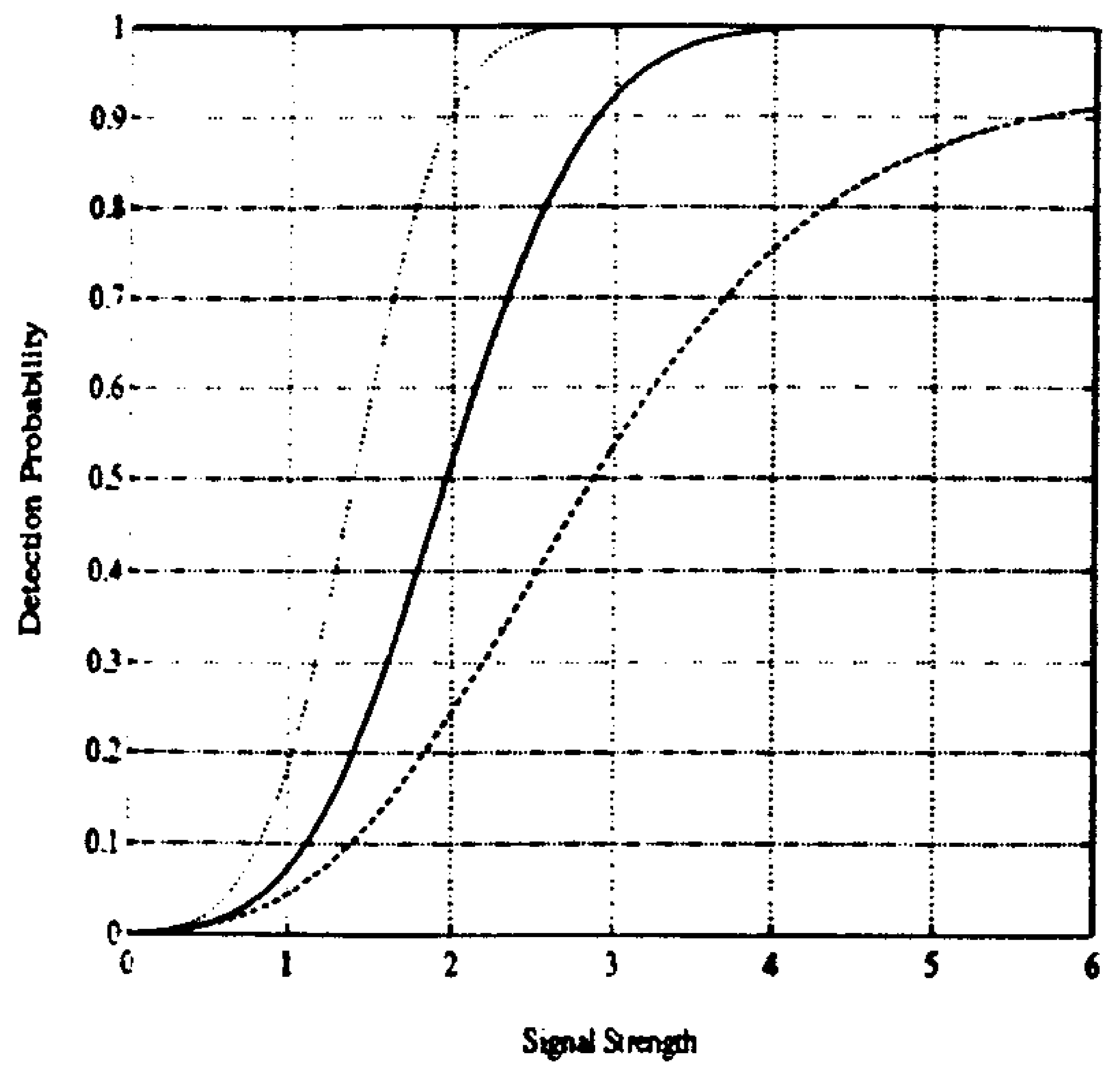

Figure 1. Detection Probability of Random Signal under Gaussian Noise

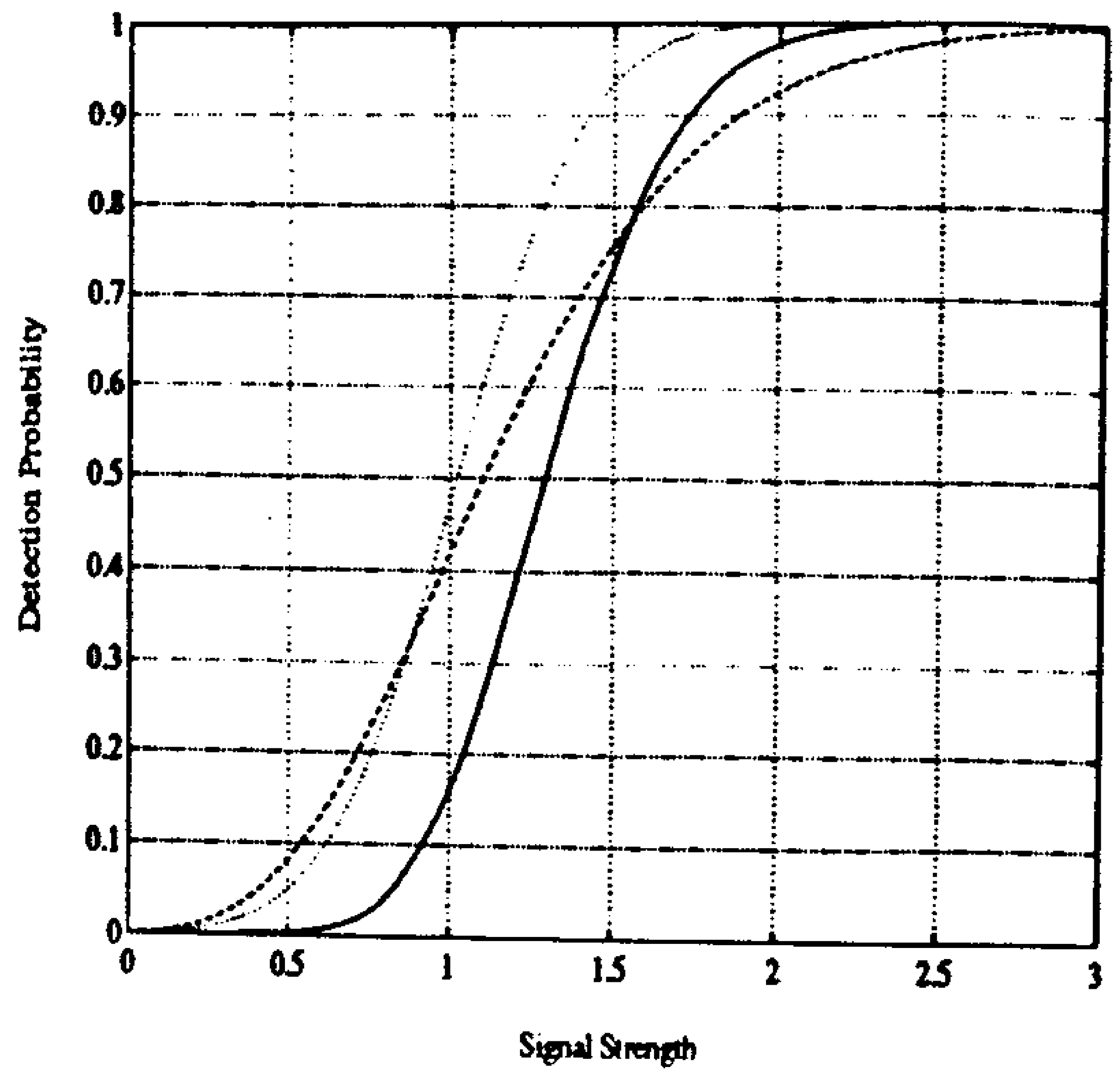

Figure 3. Detection Probability of Known Signal under Laplace Noise

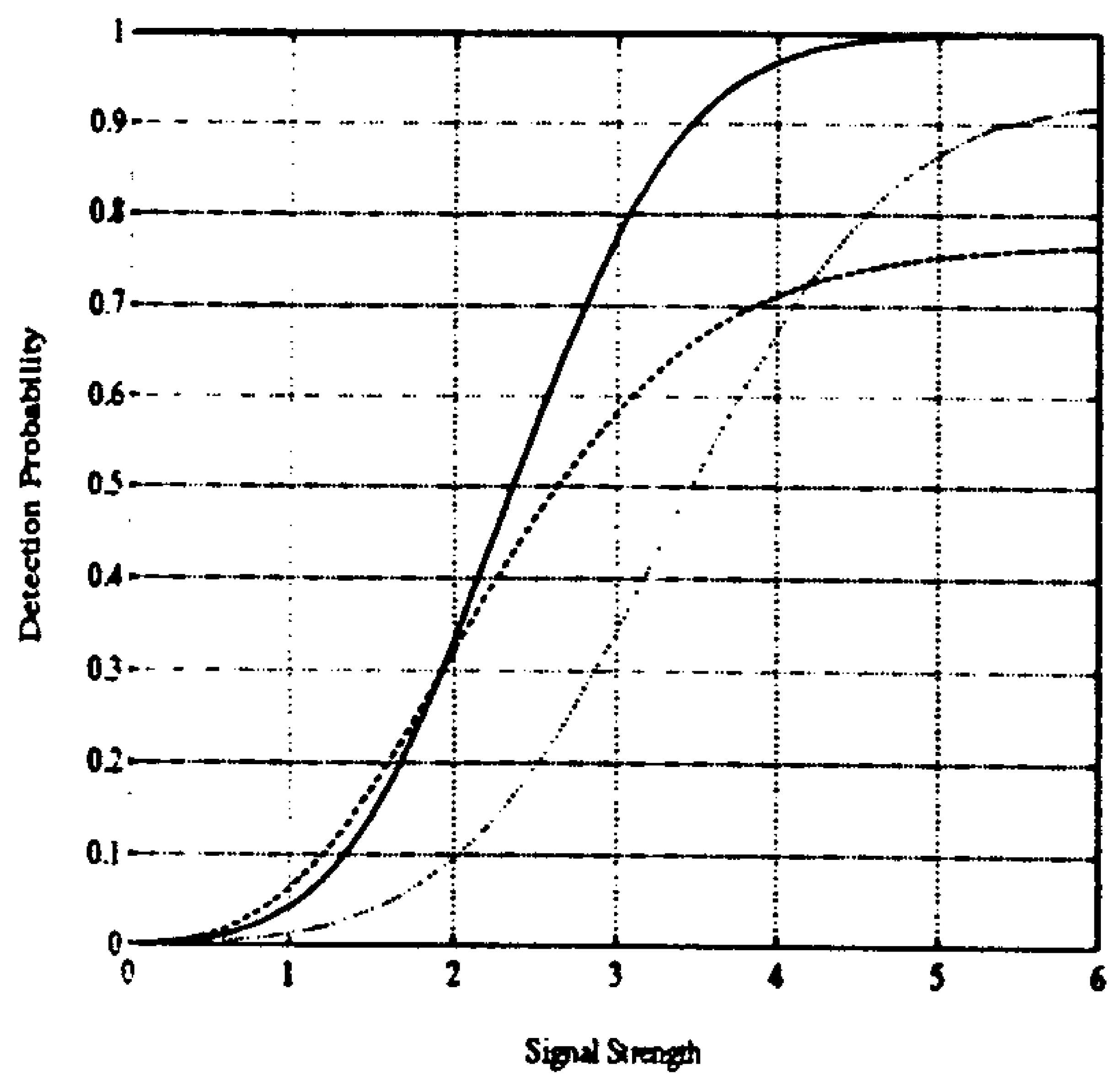

Figure 2. Detection Probability of Random Signal under Laplace Noise

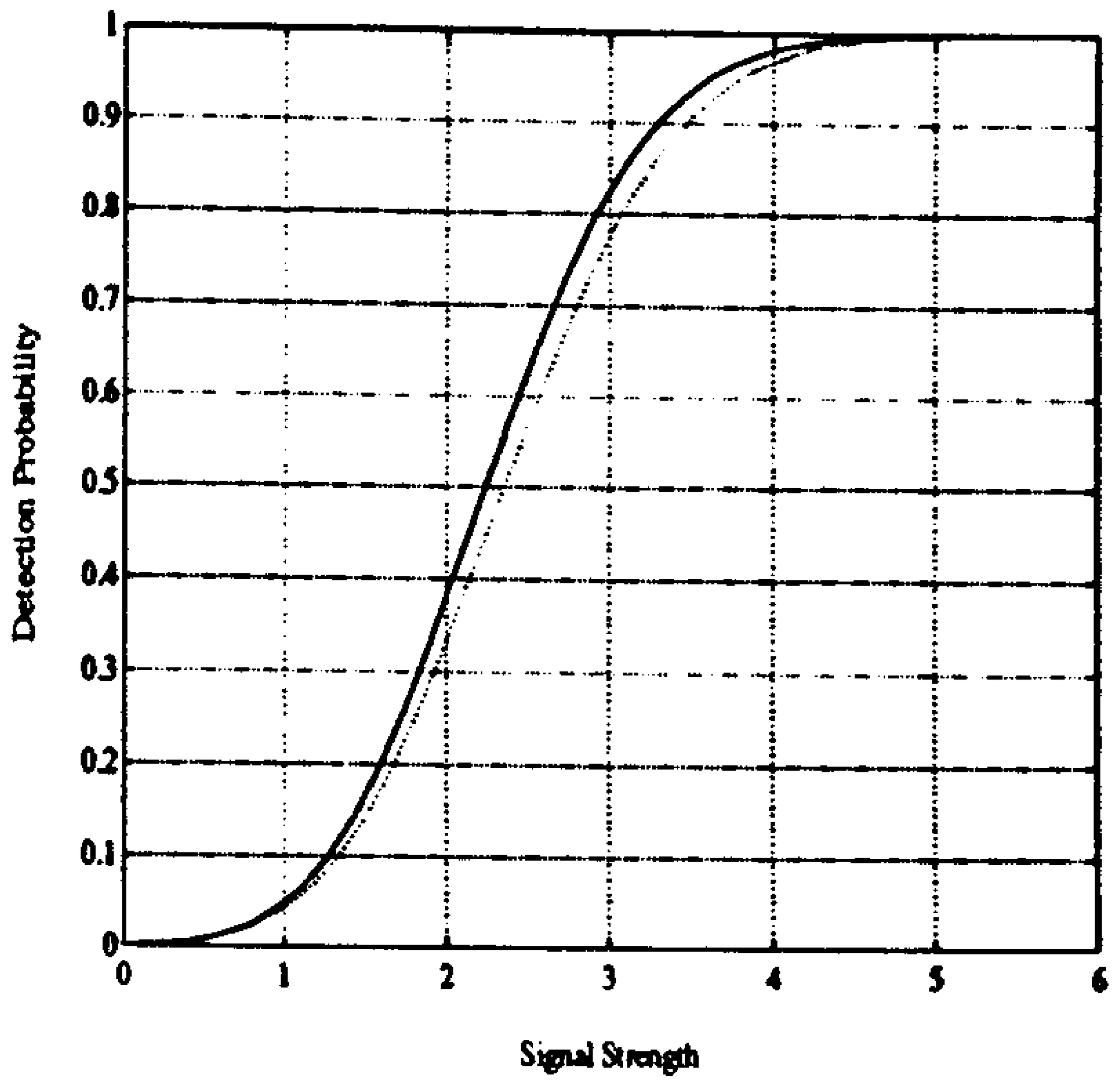

Figure 4. Detection Probability Improvement under Laplace Noise

Figures 1-3

Solid Line	:	ψ^2 Detector
Dotted Line	:	LC Detector
Dashed Line	:	SC Detector

Figure 4

Solid Line	:	Neural Network Detector
Dotted Line	:	ψ^2 Detector