Detection In Laplace Noise

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Abstract

The discrete time detection of a known constant signal in white stationary Laplace noise is considered. Exact expressions describing the performance of both the Neyman-Pearson optimal detector and the suboptimal linear detector are presented. Also, graphs of the receiver operating characteristics are given. The actual performance of the Neyman-Pearson optimal detector is compared to that predicted by a Gaussian approximation to the distribution of the test statistic.

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I. Introduction

Recently, there has been considerable interest in the detection of signals in non-Gaussian noise. Although the assumption of Gaussian noise is frequently justified, such as in ultra-high frequency (UHF), in other cases, such as extremely low frequency (ELF), the assumption is definitely unjustified. One form of frequently encountered non-Gaussian noise is that known as impulsive noise. Impulsive noise is typically characterized as noise whose distribution has an associated "heavy tail" behavior. That is, the probability density function (pdf) approaches zero more slowly than a Gaussian pdf. The references in [1] and [2] give a summary of some forms of impulsive noise and situations where it arises. In this paper we consider the discrete time detection of a known constant signal in additive white Laplace noise. That is, the pdf of the noise is given by

$$f(n) = (\gamma/2)\, e^{-\gamma |n|} \tag{1}$$

Notice that Laplace noise has the heavy tail behavior associated with implusive noise.

The Laplace distribution is popular in statistics and many of its properties have been studied [3]. Furthermore, it is used as a noise model in engineering studies. For example, Miller and Thomas [1] used Laplace noise in a numerical study of relative efficiency. Bernstein et al. [4] comment on the non-Gaussian nature of ELF atmospheric noise, and they give a plot of a typical experimentally determined pdf associated with such noise [4, Fig. 10]. This experimentally determined pdf is similar to a Laplace pdf, and on a linear graph the difference is barely distinguishable. Mèrtz [5] proposed the following pdf for the amplitude distribution of impulsive noise: $\tilde{f}(x) = h\nu(x+h)^{-(\nu+1)}$, $x \geqslant 0$. Notice that if we let $\nu = h/\gamma - 1$, then $\lim_{h\to\infty}\tilde{f}(x) = \gamma e^{-\gamma x}$, $x \geqslant 0$. Thus the limiting case of the Mertz model for the amplitude distribution of impulsive noise is identical to the distribution of the amplitude of Laplace noise. Kanefsky and Thomas [6] considered a class of generalized Gaussian noises, obtained by generalizing the Gaussian density to obtain a variable rate of exponential decay. The Laplace distribution is within this class of generalized Gaussian distributions. Also, Duttweiler and Messerschmitt [7] refer to the Laplace distribution as a model for the distribution of speech.

In Section II, we present a brief summary of the problem. In Section III, a derivation of convenient expressions describing the performance of the Neyman-Pearson optimal detector for Laplace noise is presented. We investigate the performance of the commonly used suboptimal linear detector in the presence of Laplace noise in Section IV and compare its performance with that of the optimal detector. Comparison of the actual performance of the optimal detector with that predicted by a Gaussian approximation is the topic of Section V. Section VI contains some concluding remarks.

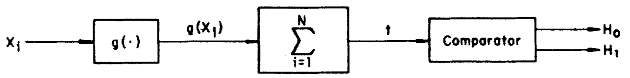

Fig. 1. Structure of optimal detector.

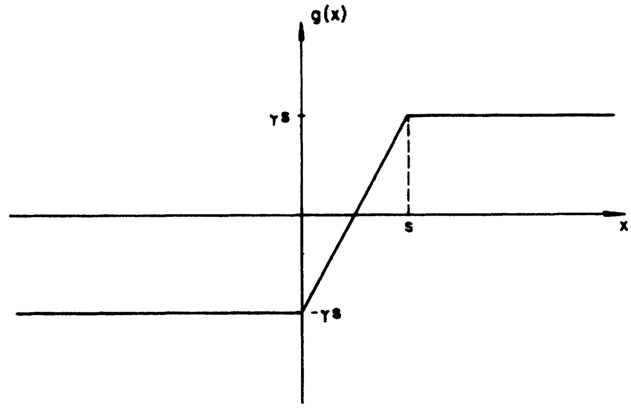

Fig. 2. Nonlinearity in optimal detector.

II. Preliminaries

We consider testing for the presence or absence of a positive, constant signal s in additive Laplace noise. We assume that the noise samples are statistically independent. (A restricted receiver bandwidth might cause this assumption to be violated.) The problem is modeled as the following hypothesis testing problem:

$$H_0: x_i = n_i, \qquad i = 1, 2, ..., N$$

$$H_1: x_i = s + n_i, \qquad s > 0 \text{ .}$$

Based on the observations $\{x_i, i = 1, 2, ..., N\}$, we are to decide whether the signal is absent or present. The quantity α will denote the probability of false alarm; that is, α is the probability of incorrectly announcing H_1. Similarly, β, the detection probability, is the probability of correctly announcing H_1.

The Neyman-Pearson optimal detector is a detector which, for a fixed α, will maximize β. The optimal detector for our problem is well known [8], and is illustrated in Fig. 1. The observations are passed through a zero memory nonlinearity $g(\cdot)$ and then summed. The result is then compared with a threshold T chosen to give the desired false alarm probability. The nonlinearity $g(\cdot)$, illustrated in Fig. 2, is the amplifier-limiter given by the following expression:

$$g(x) = \begin{cases} \gamma s & x > s \\ 2\gamma x - \gamma s, & 0 \leqslant x \leqslant s \\ -\gamma s, & x < 0. \end{cases} \tag{2}$$

For the optimal detector, the test statistic t is given by the following sum of independent, identically distributed random variables: $t = \Sigma_{i=1}^{N} g(x_i)$. If the distribution of this sum were known, then the detection and false alarm probabilities could be found, and the performance of the detector would be known. However, past attempts at obtaining a simple expression for this distribution have not been successful. A recursion scheme for obtaining this distribution has been considered by Miller and Thomas [1, 9]. If N were sufficiently large, the central limit theorem would apply, and the distribution of t would be approximately normal. However, the small sample performance of the detector would still be unknown (see, for example, [1, 10]). Alternatively, one could establish bounds on the detection and false alarm probabilities and thus establish a bound on detector performance; or Monte Carlo simulation may be employed. In general, however, it is desirable to have a convenient expression for the probability distribution of the test statistic t.

Derivation of this distribution is the topic of the next section.

A situation frequently encountered in radar is that of unknown signal amplitude, due to the unknown amount of scattering of the incident radiation by the target. In a situation where it is known that the signal is extremely weak, a locally optimal detection scheme [8] may be employed; that is, for a fixed α, maximize the slope of β as the signal shrinks to zero. In this case the present problem has been solved [8]. In other situations, although the precise value of the signal might not be known, a lower bound on the signal may be known, say $s \geqslant b$. In this situation, in the context of the problem at hand, if the detector is designed for the signal $s = b$, then the minimum value of β [as s ranges over the interval (b, ∞)] is maximized for a given α [11]. Thus, in this case, although the actual signal strength is unknown, it is simply replaced by a lower bound, and we are guaranteed that the actual detection probability is at least as good as that which we calculate. Therefore, in the sequel, we will assume a known signal.

III. Neyman-Pearson Optimal Detector

In this section we derive an expression for the distribution of the test statistic for the Neyman-Pearson optimal detector. The test statistic is obtained by passing each of the observations through the nonlinearity $g(\cdot)$, given by (2), and summing the outputs.

We first consider the case of no signal, i.e., H_0. If X_i has a Laplace distribution given by (1), then $g(X_i)$ will have the following distribution function:

$$F(x) = \tfrac{1}{2}\, u(x + \gamma s) + \tfrac{1}{4} \int_{-\infty}^{x} [\exp - \tfrac{1}{2}(\gamma s + \nu)]\; G(\nu/2\gamma s)\, d\nu$$
$$+ \tfrac{1}{2} \exp(-\gamma s)\, u(x - \gamma s) \tag{3}$$

where $u(\cdot)$ denotes the unit step function given by

$$u(x) = \begin{cases} 1, & x \geqslant 0 \\ 0, & x < 0 \end{cases}$$

and $G(\cdot)$ denotes the gate function given by

$$G(x) = \begin{cases} 1, & |x| \leq \frac{1}{2} \\ 0, & |x| > \frac{1}{2}. \end{cases}$$

The distribution function $F_N(\cdot)$ of the test statistic t is given by

$$F_N(x) = \int_{-\infty}^{\infty} F_{N-1}(x - v)\, dF(v)$$

where $F_1(x) = F(x)$.

The Fourier-Stieltjes transform of (3) is given by

$$\hat{F}(\omega) = \int_{-\infty}^{\infty} \exp(-j\omega x)\, dF(x)$$

where j denotes the imaginary unit. A straightforward calculation yields that

$$\hat{F}(\omega) = \exp(-\gamma s/2)\{\cosh[(\tfrac{1}{2} + j\omega)\gamma s] + \sinh[(\tfrac{1}{2} + j\omega)\gamma s]/(1 + 2j\omega)\}. \tag{4}$$

Letting $\hat{F}_N(\cdot)$ denote the Fourier-Stieltjes transform of $F_N(x)$, we get that $\hat{F}_N(\omega) = [\hat{F}(\omega)]^N$. Our derivation of an expression for $F_N(x)$ is based upon repeated use of the binomial expansion. Specifically, we write $F_N(\omega)$ using (4) and the binomial expansion. The hyperbolic sine and hyperbolic cosine terms are then expressed in terms of complex exponentials. We use the binomial expansion again to express the powers of the sums and differences of the complex exponentials. After a straightforward simplification, we obtain the following expression:

$$\hat{F}_N(\omega) = \sum_{k=1}^{N} \binom{N}{k} 2^{-(N+k)} \sum_{p=0}^{k} \binom{k}{p} (-1)^p \sum_{q=0}^{N-k} \binom{N-k}{q} \exp[-(p+q)\gamma s] \cdot \exp[j\omega(N - 2p - 2q)\gamma s]/(\tfrac{1}{2} + j\omega)^k + 2^{-N} \sum_{m=0}^{N} \binom{N}{m} \exp(-m\gamma s) \exp[j\omega(N - 2m)\gamma s].$$

Denote the triple sum term by $\hat{A}(\omega)$ and the remaining term by $\hat{B}(\omega)$ so that

$$\hat{F}_N(\omega) = \hat{A}(\omega) + \hat{B}(\omega). \tag{5}$$

To find the distribution of the test statistic t under H_0, an inverse transform must be performed on (5). That is, find $A(x)$ and $B(x)$ such that

$$\hat{F}_N(\omega) = \int_{-\infty}^{\infty} \exp(-j\omega x)\, dF_N(x) = \int_{-\infty}^{\infty} \exp(-j\omega x)\, dA(x) + \int_{-\infty}^{\infty} \exp(-j\omega x)\, dB(x).$$

Note that $\hat{A}(\omega)$ belongs to L_2. Thus, there exists an inverse Fourier transform $a(x)$, defined as a limit in the mean.

$$a(x) = (d/dx) A(x) = \sum_{k=1}^{N} \binom{N}{k} 2^{-(N+k)} \sum_{p=0}^{k} \binom{k}{p} (-1)^p \cdot \sum_{q=0}^{N-k} \binom{N-k}{q} \exp[-(p+q)\gamma s] \cdot (1/2\pi) \int_{-\infty}^{\infty} \left(\exp\{j\omega[(N - 2p - 2q)\gamma s + x]\}/ (\tfrac{1}{2} + j\omega)^k\right) d\omega. \tag{6}$$

We can evaluate the above integral using contour integration, the residue theorem, and Jordan's lemma [12]. After simplification, (6) then becomes

$$a(x) = N! \exp[-\tfrac{1}{2}(x + N\gamma s)] \sum_{k=1}^{N} [2^{-(N+k)}/(k-1)!] \cdot \sum_{p=0}^{k} [(-1)^p/p!(k-p)!] \sum_{q=0}^{N-k} \cdot \{[x + (N - 2p - 2q)\gamma s]^{k-1}/q!(N-k-q)!\} \cdot u[x + (N - 2p - 2q)\gamma s].$$

By straightforward manipulation and integration (see [13]), we obtain the inverse transform $A(x)$ of $\hat{A}(\omega)$

$$A(x) = \int_{-\infty}^{x} a(x)\, dx = 2^{-N} \sum_{k=1}^{N} \binom{N}{k} \sum_{p=0}^{k} (-1)^p \binom{k}{p} \sum_{q=0}^{N-k} \binom{N-k}{q} \cdot \left(\exp[-(p+q)\gamma s] - \exp[-\tfrac{1}{2}(x + N\gamma s)]\, e_{k-1} \cdot \{\tfrac{1}{2}[x + (N - 2p - 2q)\gamma s]\}\right) \cdot u[x + (N - 2p - 2q)\gamma s]$$

where $e_k(\cdot)$, the incomplete exponential, is defined by $e_k(x) = \Sigma_{m=0}^{k} x^m/m!$. Also, we can easily show that

$$B(x) = 2^{-N} \sum_{m=0}^{N} \binom{N}{m} \exp(-m\gamma s)\, u[x + (N - 2m)\gamma s].$$

Letting $F_N^{(0)}(x) = F_N(x)$ denote the distribution function of the test statistic under the hypothesis H_0, we have

$$F_N^{(0)}(x) = A(x) + B(x) = 2^{-N} \sum_{k=1}^{N} \binom{N}{k} \sum_{p=0}^{k} (-1)^p \binom{k}{p} \sum_{q=0}^{N-k} \binom{N-k}{q}$$

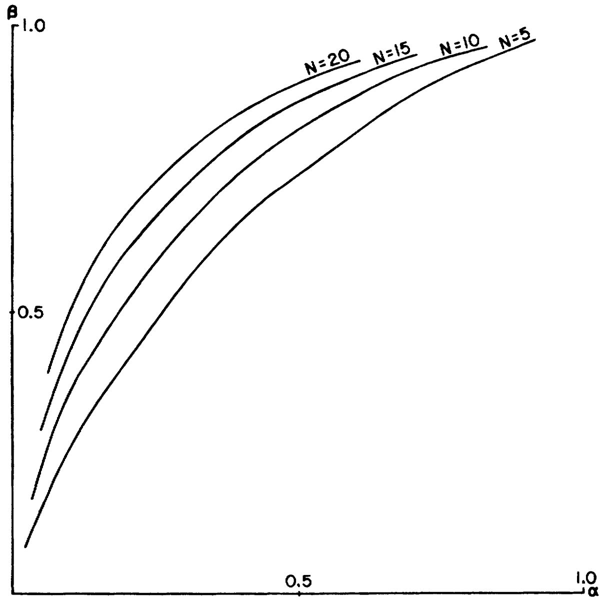

Fig. 3. Performance of optimal detector for $\gamma s = 0.3$ and different values of N.

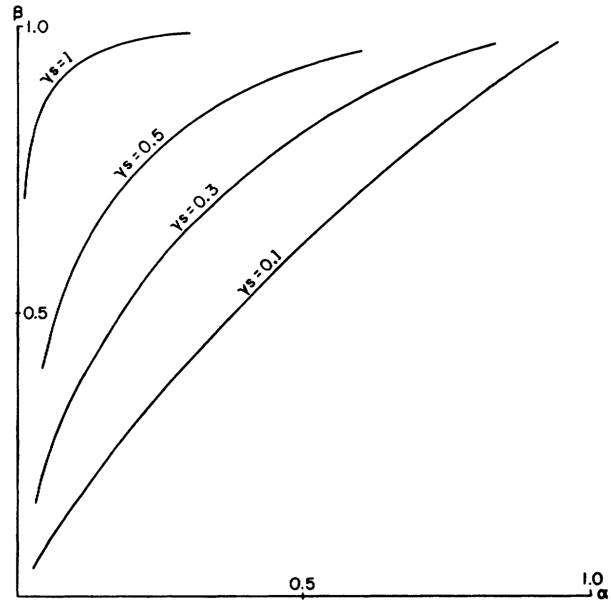

Fig. 4. Performance of optimal detector for $N = 10$ and different values of γs.

$$\cdot (\exp[-(p+q)\gamma s] - \exp[-\tfrac{1}{2}(x+N\gamma s)])$$

$$\cdot\, e_{k-1}\{\tfrac{1}{2}[x+(N-2p-2q)\gamma s]\})\, u[x+(N-2p-2q)\gamma s]$$

$$+2^{-N}\sum_{m=0}^{N}\binom{N}{m}\exp(-m\gamma s)\; u[x+(N-2m)\gamma s]. \qquad (7)$$

We now consider the signal present case, i.e., H_1. We let $F_N^{(1)}(x)$ denote the distribution function of the test statistic under H_1. Since the Laplace pdf is symmetric, it can be shown [1, 9] that

$$F_N^{(1)}(x) = 1 - F_N^{(0)}(-x). \qquad (8)$$

Equations (7) and (8) thus completely determine the performance of the Neyman-Pearson optimal detector.

One popular way to describe the performance of a detector is by its receiver operating characteristics (OC) curves. For the optimal detector, a family of OC curves for a fixed equivalent signal strength $\gamma s = 0.3$ for various sample sizes is shown in Fig. 3. A second family of OC curves is presented in Fig. 4 for various values of γs with a fixed sample size of $N = 10$.

IV. The Linear Detector

By a linear detector, we mean a scheme such as that illustrated in Fig. 1, but where the function $g(\cdot)$ is $g(x) = x$. That is, the test statistic is simply the sum of the observations. The linear detector is Neyman-Pearson optimal for Gaussian noise and is a commonly used detector.

Consider the signal absent case, i.e., H_0. In this situation, the test statistic is given by $t = \sum_{i=1}^{N} X_i$, where the X_i are independent identically distributed random variables with the pdf of (1). Let $p_N(x)$ denote the pdf of t. Then we have [3, p. 24]

$$p_N(x) = [\gamma \exp(-\gamma|x|)/(N-1)!] \sum_{k=0}^{N-1} 2^{-(N+k)}$$

$$\cdot\, [(N+k-1)!/k!\,(N-k-1)!]\, (\gamma|x|)^{N-k-1}.$$

After a straightforward integration [12], we obtain $G_N^{(0)}(x)$, the distribution of the test statistic of the linear detector under H_0,

$$G_N^{(0)}(x) = \begin{cases} \tfrac{1}{2} + \sum_{k=0}^{N-1} 2^{-(N+k)} \binom{N+k-1}{q}[1 - e^{-\gamma x} \\ \cdot\, e_{N-k-1}(\gamma x)], \quad x \geqslant 0 \\ 1 - G_N^{(0)}(-x), \quad x < 0. \end{cases} \qquad (9)$$

In the signal present case, the test statistic is given by $t = \sum_{i=1}^{N} X_i + Ns$, where, once again, the X_i are independent identically distributed random variables with the density function of (1). Let $G_N^{(1)}(x)$ denote the distribution function of the test statistic of the linear detector under H_1. Then we have

$$G_N^{(1)}(x) = G_N^{(0)}(x - Ns). \qquad (10)$$

Equations (9) and (10) completely determine the performance of the linear detector.

A comparison of the performance of the optimal and linear detectors for various choices of N, s, and γ is shown

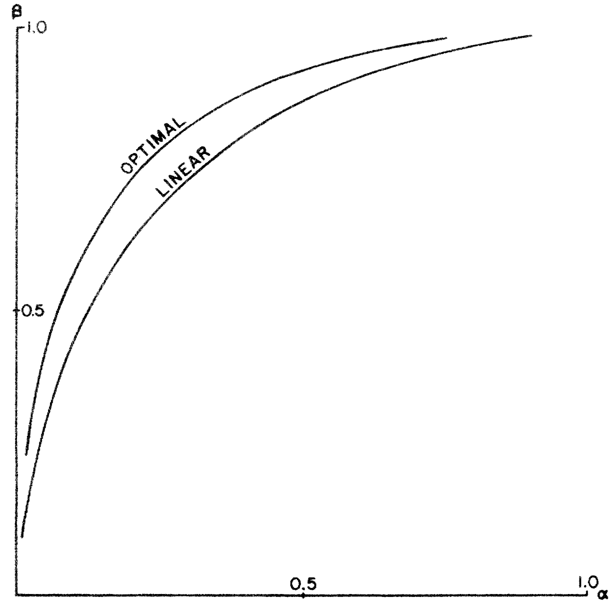

Fig. 5. Performance of optimal detector compared to performance of linear detector, $N = 10, s = 1, \gamma = 0.5$.

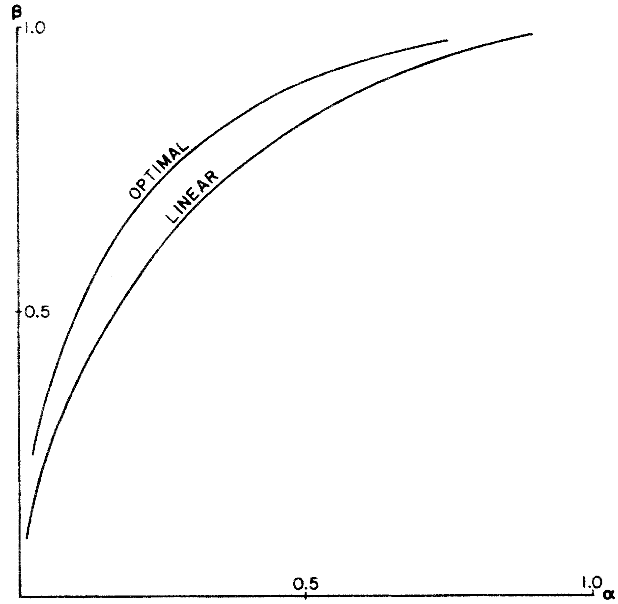

Fig. 6. Performance of optimal detector compared to performance of linear detector, $N = 20, s = 0.3, \gamma = 1$.

in Figs. 5 and 6. Note that, with the convenient closed form expressions in (7) through (10), a general relative efficiency study of the linear and optimal detectors could be performed such as that done by Miller and Thomas [1]. Our treatment, however, 1) is much more flexible in terms of the choices of s and γ and 2) would utilize less computer time and storage.

V. Gaussian Approximation

In non-Gaussian detection problems of the type considered in this paper, the derivation of an expression for the distribution function of the test statistic for the Neyman-Pearson optimal detector is frequently a mathematically intractable problem. In many such cases, for sufficiently large N, an appeal is made to the central limit theorem to arrive at an approximation for the distribution function of the test statistic. Thus it is instructive in the present case to compare the exact results with those resulting from the Gaussian approximation.

Let X be a random variable with the density function of (1). Let $g(\cdot)$ be the optimal nonlinearity given by (2). Then

$$E\{g(X)\} = \int_{-\infty}^{\infty} g(x)\,(\gamma/2)\,e^{-\gamma|x|}\,dx.$$

A straightforward integration yields $E\{g(X)\} = 1 - \gamma s - e^{-\gamma s}$. Similarly, we get

$$\mathrm{var}_0\,[g(X)] = \int_{-\infty}^{\infty} [g(x) - 1 + \gamma s + e^{-\gamma s}]^2\,(\gamma/2)\,e^{-\gamma|x|}dx$$

$$= 3 - 2e^{-\gamma s} - 4\gamma s e^{-\gamma s} - e^{-2\gamma s}.$$

Thus the mean and variance of t under H_0 are, respectively,

$$E_0\{t\} = N[1 - \gamma s - e^{-\gamma s}] = m$$

$$\mathrm{var}_0\,[t] = N^2[3 - 2e^{-\gamma s} - 4\gamma s e^{-\gamma s} - e^{-2\gamma s}] = \sigma^2.$$

Using the relation in (8), it follows that the corresponding values under H_1 are given by

$$E_1\{t\} = -E_0\{t\} = -m$$

$$\mathrm{var}_1[t] = \mathrm{var}_0[t] = \sigma^2.$$

Let $I_N^{(0)}(x)$ and $I_N^{(1)}(x)$ denote, respectively, the Gaussian approximations to the distribution functions of the test statistic under H_0 and H_1. Then

$$I_N^{(0)}(x) = \Phi[(x - m)/\sigma]$$

and

$$I_N^{(1)}(x) = \Phi[(x + m)/\sigma]$$

where

$$\Phi(x) = (1/\sqrt{2\pi}) \int_{-\infty}^{x} e^{-v^2/2}\,dv.$$

Let α_G and β_G denote the false alarm and detection probabilities, respectively, resulting from the Gaussian approximation. Then we have

$$\alpha_G = 1 - \Phi[(T - m)/\sigma]$$

and

$$\beta_G = 1 - \Phi[(T + m)/\sigma]. \quad (11)$$

In practice, one may use (11) to set the value of the threshold T. For example, if $\gamma s = 1, N = 15$, and the desired false alarm probability is 0.3, the Gaussian approximation yields a threshold of approximately 1.208 and a detection probability of approximately 0.628. However, using (7) and (8) we find that for this threshold $\alpha \cong 0.02$ and $\beta \cong 0.91$. In fact, for $\alpha = 0.3$, we find that the actual detection probability is greater than 0.99. Thus, in this case, the Gaussian approximation is extremely conservative. In Table I we compare the actual values of α and β for the optimal detector with α_G and β_G for several values of T when $N = 25$ and $\gamma s = 0.5$. It is seen from the table that, in this case, the Gaussian approximation is not very good (even though $N = 25$).

TABLE I

Exact values of α and β and those resulting from the Gaussian approximation, for several values of the threshold; $\gamma s = 0.5, N = 25$.

T	α	α_G	β	β_G
4.032	0.002	0.278	0.278	0.452
3.024	0.007	0.308	0.443	0.487
1.512	0.035	0.356	0.696	0.540
0.000	0.123	0.407	0.877	0.593
-1.512	0.304	0.460	0.965	0.644
-2.016	0.384	0.477	0.978	0.660

VI. Conclusion

We have presented closed form solutions for the performance of the Neyman-Pearson optimal and suboptimal linear detectors for the case of a known positive signal in the presence of additive white Laplace noise. These solutions can be used in a variety of detector studies for arbitrary choices of Laplace parameter, signal strength, and sample size including small sample size relative efficiency studies and receiver operating characteristic curve generation. Utilizing the solutions for the distributions of the optimal detector test statistic, we have also shown that in certain instances the Gaussian approximation to the optimal detector is poor even for an intermediately large sample size of 25.

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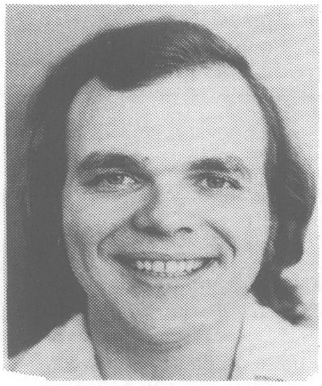

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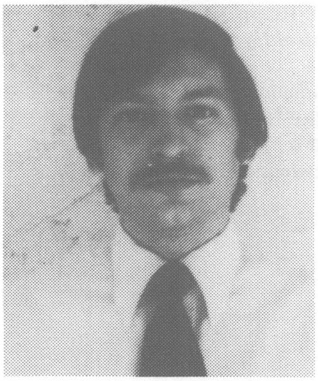

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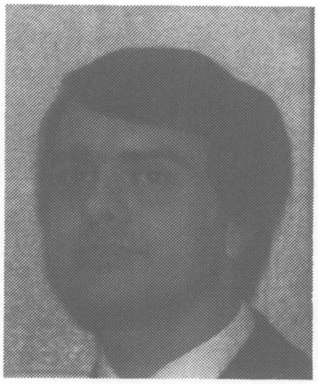

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