A Signal-Dependent Noise Model and Composite Signal Detection

신호의존성 잡음모형과 복합신호검파

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ABSTRACT

When original signals are contaminated by both *additive* and *signal-dependent* noise, the test statistics of locally optimum detector are obtained for detection of *weak composite* signals. In order to consider the non-additive noise as well as purely-additive noise, a generalized observation model is used in this paper. The locally optimum detector test statistics are derived for all different cases according to the relative strengths of the known signal, random signal, and signal-dependent noise components. Schematic diagrams of the structures of the locally optimum detector are also obtained.

요 약

이 논문에서는 가산성 잡음과 신호 의존성 잡음이 바라는 신호와 섞일 때, 약한 복합 신호를 검파하는 국소 최적 검파기의 검정 통계량을 얻었다. 순가산성 잡음뿐만 아니라 비가산성 잡음도 고려하기 위하여 일반화된 관측 모델을 사용하였다. 알려진 신호, 확률 신호, 그리고 신호 의존성 잡음 성분의 상대적인 크기의 모든 경우에 대하여 국소 최적 검정통계량을 얻었다. 또한, 국소 최적 검파기의 얼개를 그림으로 나타냈다.

I. Introduction

The purely-additive noise (PAN) model has been widely used in various areas of signal processing including signal detection problems, because the PAN model is relatively easy to handle mathematically and to obtain explicit structures for detection processors in a variety of applications [1-5]. In addition the PAN model produces quite acceptable and reasonable results in many cases, where the level of the contribution of higher order statistics or of nonlinearity is not significant.

There are some other cases, however, in which we are forced to use a non-additive noise model to produce more realistic and reasonable approximations [6-9]. For example, the effects of delayed signals from multipath or reverberation phenomena and the actions of automatic gain control circuits or of nonlinearities acting on additive signal and noise components may all be modeled using non-additive (*e.g.*, signal-dependent or multiplicative)

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as well as purely-additive noise components. A specific example of non-additive noise may easily be found in image processing: when images recorded on the photographic film are digitized for processing by digital computer, they may be contaminated by the film-grain noise, which is a kind of signal-dependent noise.

In [10] LO detection of weak composite signals in purely-additive noise was studied, in which the test statistics and performance of LO detectors are obtained. LO detection of weak composite signals in additive and multiplicative noise was considered in [11].

The purpose of this paper is to obtain the test statistics and performance characteristics of the LO detector for detection of composite signals in a signal-dependent noise model. The results presented in this paper are therefore generalizations of those obtained in [10,12] and complements to those obtained in [11].

II. The Observation Model

2.1. The model

The widely-used observation model including PAN only may be described by

$$X_i = \theta Q_i + W_i, \qquad i = 1, 2, \cdots, n, \tag{2.1}$$

where θ is a signal strength parameter, Q_i is either a known or a random signal component, and W_i is the PAN component. It is normally assumed that the PAN component W_i and the random signal component are statistically independent.

Let us now consider a more general and realistic observation model which may be used in a broader range of situations. Let us consider the model describing the observations X_i for $i = 1, 2, \cdots, n$, by

$$X_i = \alpha(\tau)e_i + \beta(\tau)S_i + \gamma(\tau)N_i + W_i. \tag{2.2}$$

In (2.2), e_i is the known signal component and S_i is the random signal component with known probability density function (pdf) at the i-th sampling instant. The random signal component S_i is a zero mean random variable which has variance σ_i^2 and pdf f_{S_i}, $i = 1, 2, \cdots, n$. The functions $\alpha(\tau)$ and $\beta(\tau)$ are the signal strength functions of the known and random signal components, respectively. The term $\gamma(\tau)N_i$ is a signal-dependent noise term with amplitude $\gamma(\tau)$, where the parameter τ also controls the signal strengths through $\alpha(\tau)$ and $\beta(\tau)$. We will assume that $\alpha(\tau)$, $\beta(\tau)$, and $\gamma(\tau)$ are nondecreasing functions of $\tau > 0$ and that $\alpha(0)$ $\beta(0) = \gamma(0) = 0$. The signal-dependent noise sequence $\{N_i\}_{i=1}^n$ and the PAN sequence $\{W_i\}_{i=1}^n$ are assumed to be zero-mean independent and identically distributed (i.i.d.) random variable sequences with univariate pdfs f_N and f_W, respectively. It is also assumed that $\{N_i\}_{i=1}^n$ and $\{W_i\}_{i=1}^n$ are independent of $\{S_i\}_{i=1}^n$. Finally we will denote by f_{NW} the common joint pdf of the (N_i, W_i), which are i.i.d. bivariate random variables for $i = 1, 2, \cdots, n$. The pdfs f_{S_i}, f_{NW}, f_N, and f_W are assumed to be smooth enough to satisfy regularity conditions [1] so that interchange of intergration and limit is justified.

2.2. Hypotheses and definitions

With the observation model (2.2), it is now possible to express our problem of composite signal detection by a statistical hypothesis testing problem of choosing between a null hypothesis H_0 and an alternative hypothesis H_1. More specifically, under H_0 we have $\tau = 0$ or

$$H_0 : X_i = W_i, \qquad i = 1, 2, \cdots, n, \tag{2.3}$$

and under H_1 we have $\tau > 0$ or

$$H_1 : X_i = \alpha(\tau)e_i + \beta(\tau)S_i + \gamma(\tau)N_i + W_i, \qquad i = 1, 2, \cdots, n. \tag{2.4}$$

Before we proceed further with the hypotheses (2.3) and (2.4), let us introduce some definitions for use later in this paper. Let us first define the LO nonlinearities as

$$g_1(x) = -\frac{f_W'(x)}{f_W(x)}, \tag{2.5}$$

$$g_2(x) = -\frac{u'(x)}{f_W(x)}, \tag{2.6}$$

$$h_1(x) = \frac{f_W''(x)}{f_W(x)}, \tag{2.7}$$

and

$$h_3(x) = \frac{v''(x)}{f_W(x)}, \tag{2.8}$$

where

$$u(x) = \int n\, f_{NW}(n, w)\, dn$$
$$= f_W(x)\, E\{N|W = x\} \tag{2.9}$$

and

$$v(x) = \int n^2 f_{NW}(n, w)\, dn$$
$$= f_W(x)\, E\{N^2|W = x\} \tag{2.10}$$

are the weighted conditional mean and weighted conditional variance functions, respectively.

2.3. Reparametrization of the model

Because of the assumptions on $\alpha(\tau)$, $\beta(\tau)$, and $\gamma(\tau)$ that they are nondecreasing functions of $\tau > 0$ with values 0 at $\tau = 0$, we have

$$\lim_{\tau\to 0^+} \frac{\alpha(\tau)}{\delta\tau^p} = 1, \tag{2.11}$$

$$\lim_{\tau\to 0^+} \frac{\beta(\tau)}{\varepsilon\tau^q} = 1, \tag{2.12}$$

and

$$\lim_{\tau\to 0^+} \frac{\gamma(\tau)}{\eta\tau^r} = 1, \tag{2.13}$$

where p, q, r, δ, ε, and η are all positive numbers. With the numbers defined by (2.11)-(2.13) let us define two parameters Δ_1 and Δ_2 as follows:

$$\Delta_1 = \frac{p}{r} \tag{2.14}$$

and

$$\Delta_2 = \frac{p}{q}. \tag{2.15}$$

Reparametrization of the observation model (2.2) is accomplished by applying one of the following three rules:

A) $a(\theta) = \theta$, $b(\theta) = \beta(\tau)$, $c(\theta) = \gamma(\tau)$ with $\theta = \alpha(\tau)$,
B) $b(\theta) = \theta$, $c(\theta) = \gamma(\tau)$, $a(\theta) = \alpha(\tau)$, with $\theta = \beta(\tau)$
and
C) $c(\theta) = \theta$, $a(\theta) = \alpha(\tau)$, $b(\theta) = \beta(\tau)$ with $\theta = \gamma(\tau)$.

Application of a specific reparametrization rule among the above three rules is determined according to the values of Δ_1 and Δ_2 as follows:

Case 1 : When $\Delta_2 < 2$.

- i) When $\Delta_1 \le 1$, we apply reparametrization rule A).
- ii) When $\Delta_1 \ge 2$, we apply reparametrization rule C).
- iii) When $1 < \Delta_1 < 2$, we apply reparametrization rule A) if $E\{N|W\} \equiv 0$ and reparametrization rule C) if $E\{N|W\} \ne 0$.

Case 2 : When $\Delta_2 \ge 2$.

- i) When $\Delta_2 \ge 2\Delta_1$, we apply reparametrization rule B).
- ii) When $\Delta_2 \le \Delta_1$, we apply reparametrization rule C).
- iii) When $\Delta_1 < \Delta_2 < 2\Delta_1$, we apply reparametrization rule B) if $E\{N|W\} \equiv 0$ and reparametrization rule C) if $E\{N|W\} \ne 0$.

In the observation model after the reparametrization, the observation X_i is represented by

$$X_i = a(\theta)e_i + b(\theta)S_i + c(\theta)N_i + W_i, \tag{2.16}$$

where at least one of the three amplitude functions $a(\theta)$, $b(\theta)$, and $c(\theta)$ is θ.

III. Detector Test Statistics and Structures

3.1. Test statistics

Because the noise components are assumed to be independent of the random signal components, the joint pdfs of the observation set are

$$f_0(\boldsymbol{x})=\prod_{i=1}^{n}\int f_{NW}(n_i, x_i)\, dn_i \tag{3.1}$$

under H_0 and

$$f_1(\boldsymbol{x})=\int f_S(\boldsymbol{s})\prod_{i=1}^{n}\int f_{NW}(n_i, x_i-a(\theta)e_i-b(\theta)s_i -c(\theta)\, n_i)\, dn_i\, d\boldsymbol{s} \tag{3.2}$$

under H_1, where f_S is the joint pdf of $S_1, S_2, \cdots, S_n$, $\boldsymbol{S}=(S_1, S_2, \ldots, S_n)$, and $\boldsymbol{x}=(x_1, x_2, \ldots, x_n)$. Applying the generalized Neyman-Pearson lemma [1], we get the test statistic of the LO detector,

$$T_{LO}(\boldsymbol{x})=\frac{f_1^{(v)}(\boldsymbol{x})|_{\theta=0}}{f_0(\boldsymbol{x})}, \tag{3.3}$$

where v is the first non-zero derivative of $f_1(\boldsymbol{x})$ at $\theta=0$: that is, v is defined by

$$\left.\frac{d^i f_1(\boldsymbol{x}|\theta)}{d\theta^i}\right|_{\theta=0}=0, \qquad i=1, 2, \cdots v-1 \tag{3.4}$$

and

$$\left.\frac{d^v f_1(\boldsymbol{x}|\theta)}{d\theta^v}\right|_{\theta=0}>0. \tag{3.5}$$

Using (3.3) the test statistics of the LO detectors for the observation model (2.16) are obtained to be as follows:

1) When $\Delta_2<2$ or when $\Delta_2\geq 2$ and $\Delta_1/\Delta_2>\Delta_c/2$, the test statistic is

$$T_{LO}(\boldsymbol{X})=\sum_{i=1}^{n}\{e_i\lambda_1(X_i)+\lambda_2(X_i)\}. \tag{3.6}$$

2) When $\Delta_2\geq 2$ and $\Delta_1/\Delta_2\leq\Delta_c/2$, the test statistic is

$$T_{LO}(\boldsymbol{X})=\sum_{\substack{i=1\\ i\neq j}}^{n}\sum_{j=1}^{n}K_S(i,j)g_1(X_i)g_1(X_j) +\sum_{i=1}^{n}\{\sigma_i^2 h_1(X_i)+e_i\lambda_1(X_i)+\lambda_2(X_i)\}. \tag{3.7}$$

In (3.6) and (3.7)

$$\lambda_1(x)=\begin{cases}\dfrac{2\delta}{\varepsilon^2}\, g_1(x), & \text{when } \Delta_2\leq 2 \text{ and } \Delta_1\leq\Delta_c\\ 0, & \text{otherwise}\end{cases} \tag{3.8}$$

and

$$\lambda_2(x)=\begin{cases}\dfrac{2\eta}{\varepsilon^2}\, g_2(x), & \text{when } E\{N|W\}\neq 0 \text{ and } (\Delta_1, \Delta_2)\in U,\\ \dfrac{\eta^2}{\varepsilon^2}\, h_3(x), & \text{when } E\{N|W\}\equiv 0 \text{ and } (\Delta_1, \Delta_2)\in U,\\ 0, & \text{otherwise}\end{cases} \tag{3.9}$$

with

$$U=\{(\Delta_1, \Delta_2)\,|\,\Delta_1\geq\Delta_c,\ \Delta_1/\Delta_2\geq\Delta_c/2\} \tag{3.10}$$

and

$$\Delta_c=\begin{cases}1, & \text{when } E\{N|W\}\neq 0,\\ 2, & \text{when } E\{N|W\}\equiv 0.\end{cases} \tag{3.11}$$

A detailed derivation of the LO detector test statistics (3.6) and (3.7) is shown in [13]. The results (3.6) and (3.7) are in detail tabulated in Tables 1-4.

From (3.6) and (3.7) or from Tables 1-4, we can make the following observations:

(a) When $\Delta_2<2$ and $\Delta_1<\Delta_c$, we observe that the LO test statistic is exactly the same as the

Table 1. The Locally Optimum Detector Test Statistics: When $E\{N|W\}\neq 0$ and $\Delta_2<2$

	$\Delta_2<2$
$\Delta_1<1$	$\sum_{i=1}^{n} e_i g_1(X_i)$
$\Delta_1=1$	$\sum_{i=1}^{n}\{e_i g_1(X_i)+\frac{\eta}{\delta}g_2(X_i)\}$
$\Delta_1>1$	$\sum_{i=1}^{n} g_2(X_i)$

Table 2. The Locally Optimum Detector Test Statistics: When $E\{N|W\}\equiv 0$ and $\Delta_2<2$

	$\Delta_2<2$
$\Delta_1<1$	$\sum_{i=1}^{n} e_i g_1(X_i)$
$\Delta_1=1$	$\sum_{i=1}^{n}\{\frac{2\delta}{\eta^2} e_i g_1(X_i)+h_3(X_i)\}$
$\Delta_1>1$	$\sum_{i=1}^{n} h_3(X_i)$

known signal LO detector test statistic [1]. When $\Delta_2>2$ and $\Delta_1/\Delta_2<\Delta_c/2$, on the other hand, the LO detector test statistic is exactly the same as the random signal LO detector test statistic [2]. When $\Delta_1>\Delta_c$ or when $\Delta_1/\Delta_2>\Delta_c/2$ the LO detector test statistic has only one term which represents the effect of the signal-dependent noise. It is observed that when $\Delta_2<2$ and $\Delta_1=\Delta_c$, when $\Delta_2=2$ and $\Delta_1/\Delta_2\le\Delta_c/2$, or when $\Delta_2\ge 2$ and $\Delta_1/\Delta_2=\Delta_c/2$, the test statistic is a combined form of two or three of the above three test statistics. For example, when $E\{N|W\}\neq 0$, $\Delta_1=1$, and $\Delta_2=2$ (*e.g.*, $(p,q,r)=(2,1,2)$) or when $E\{N|W\}\equiv 0$, $\Delta_1=1$, and $\Delta_2=2$ (*e.g.*, $(p,q,r)=(2,1,1)$), the known signal components, the random signal components, and the signal dependent noise components all have effects on the test statistic.

(b) The critical value of Δ_2, from which we can say whether the known signal components are dominant or the random signal components are dominant, is 2. In other words, when $\Delta_2<2$ the known signal components are relatively strong, and when $\Delta_2>2$ the random signal components

Table 3. The Locally Optimum Detector Test Statistics: When $E\{N|W\}\neq 0$ and $\Delta_2\ge 2$

	$\Delta_2=2$	$\Delta_2>2$
$\Delta_2>2\Delta_1$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $+\sum_{i=1}^{n}\{\sigma_i^2 h_1(X_i)+\frac{2\delta}{\varepsilon^2} e_i g_1(X_i)\}$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $+\sum_{i=1}^{n}\sigma_i^2 h_1(X_i)$
$\Delta_2=2\Delta_1$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $+\sum_{i=1}^{n}\{\sigma_i^2 h_1(X_i)+\frac{2\delta}{\varepsilon^2} e_i g_1(X_i)+\frac{2\eta}{\varepsilon^2} g_2(X_i)\}$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $+\sum_{i=1}^{n}\{\sigma_i^2 h_1(X_i)+\frac{2\eta}{\varepsilon^2} g_2(X_i)\}$
$\Delta_2<2\Delta_1$	$\sum_{i=1}^{n} g_2(X_i)$	$\sum_{i=1}^{n} g_2(X_i)$

Table 4. The Locally Optimum Detector Test Statistics: When $E\{N|W\}\equiv 0$ and $\Delta_2\ge 2$

	$\Delta_2=2$	$\Delta_2>2$
$\Delta_2>\Delta_1$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $+\sum_{i=1}^{n}\{\sigma_i^2 h_1(X_i)+\frac{2\delta}{\varepsilon^2} e_i g_1(X_i)\}$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $+\sum_{i=1}^{n}\sigma_i^2 h_1(X_i)$
$\Delta_2=\Delta_1$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $+\sum_{i=1}^{n}\{\sigma_i^2 h_1(X_i)+\frac{2\delta}{\varepsilon^2} e_i g_1(X_i)+\frac{\eta^2}{\varepsilon^2} h_3(X_i)\}$	$\sum_{i=1}^{n}\sum_{j=1, i\neq j}^{n} K_S(i,j)\, g_1(X_i)g_1(X_j)$ $\sum_{i=1}^{n}\{\sigma_i^2 h_1(X_i)+\frac{\eta^2}{\varepsilon^2} h_3(X_i)\}$
$\Delta_2<\Delta_1$	$\sum_{i=1}^{n} h_3(X_i)$	$\sum_{i=1}^{n} h_3(X_i)$

are dominant over the known signal components. When $\Delta_2 = 2$ both the known and random signal components have effects on the LO detector test statistic.

3.2. Structures of the locally optimum detectors

Let us now show schematic diagrams of the structures of the LO detectors obtained in Section 3.1.

3.2.1. Case 1 : When $\Delta_2 < 2$ or when $\Delta_2 \geq 2$ and $\Delta_1/\Delta_2 > \Delta_r/2$

A block diagram of the structure of the LO detector in this case is shown in Figure 1. The structure of the LO detector in this case is almost the same as that of the LO detector for known signals in the PAN model.

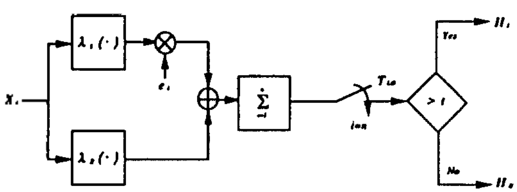

Figure 1. A Block Diagram of the Locally Optimum Detector
When $\Delta_2 < 2$ or When $\Delta_2 \geq 2$ and $\Delta_1/\Delta_2 > \Delta_r/2$

3.2.2. Case 2 : When $\Delta_2 \geq 2$ and $\Delta_1/\Delta_2 \leq \Delta_r/2$

Let us first assume that the random signal component is a white random process; that is, $K_s(i,j) = 0$ for $i \neq j$. Then the LO detector test statistic of (3.7) can be simplified as

$$T_{LO}(X) = \sum_{i=1}^{n} \{\sigma_i^2 h_1(X_i) + e_i \lambda_1(X_i) + \lambda_2(X_i)\}, \quad (3.12)$$

for which a block diagram of the corresponding LO detector is shown in Figure 2. The functions $\lambda_1(x)$ and $\lambda_2(x)$ in (3.12) are defined in (3.8) and (3.9), respectively.

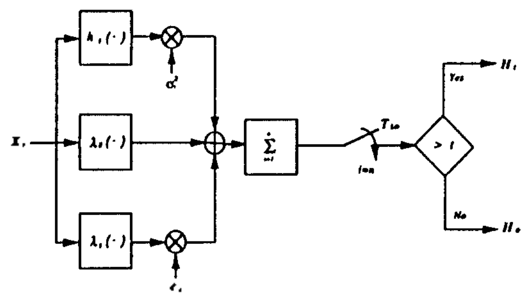

Figure 2. A Block Diagram of the Locally Optimum Detector
When $\Delta_2 \geq 2$ and $\Delta_1/\Delta_2 \leq \Delta_r/2$ for White Random Signal Components

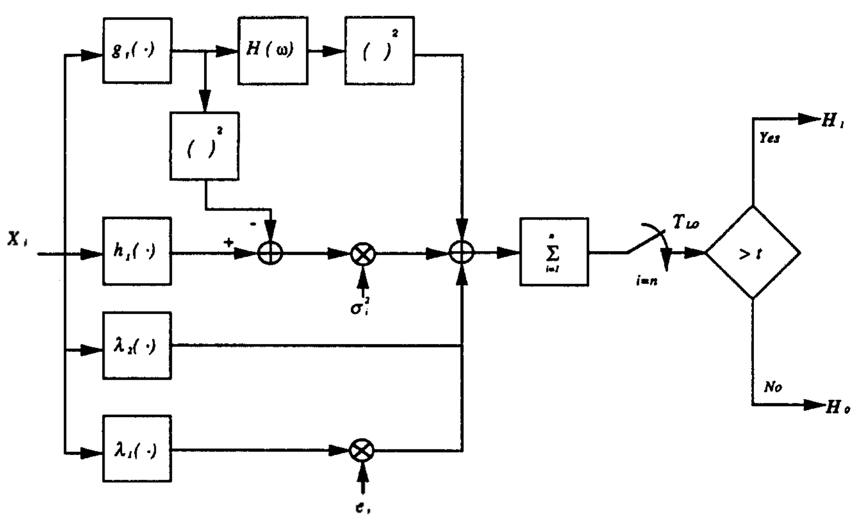

Figure 3. A block Diagram of the Locally Optimum Detector
When $\Delta_2 \geq 2$ and $\Delta_1/\Delta_2 \leq \Delta_r/2$ for Correlated Random Signal Components.

Under the assumptions similar to those in [10], it can be shown that

$$T_{LO}(\boldsymbol{X}) = \sum_{j=-\infty}^{\infty} \left| \sum_{i=1}^{n} g_1(X_i)\, c_{j-i} \right|^2 + \sum_{i=1}^{n} [\sigma_i^2 \{h_1(X_i) - g_1^2(X_i)\} + e_i \lambda_1(X_i) + \lambda_2(X_i)], \tag{3.13}$$

for which a structure of the corresponding LO detector is shown in Figure 3.

Ⅳ. Conclusion

In this paper, we derived the locally optimum detector test statistics for composite signals in a generalized noisy signal model with which we can consider composite signals and signal-dependent noise. Under the observation model we investigated the effect of the signal-dependent noise as well as that of the additive noise on the test statistics.

It was shown that the ratio of the decay parameter of the signal-dependent noise strength to that of the known signal strength together with the ratio of the decay parameter of the random signal strength to that of the known signal strength were important factors in determining the locally optimum detector test statistics. Structures of the locally optimum detectors were obtained.

References

1. S.A. Kassam, *Signal Detection in Non-Gaussian Noise*, Springer-Verlag, New York, 1988.
2. A.M. Maras, "Locally optimum detection in moving average non-Gaussian noise," *IEEE Trans. Comm.*, vol. COM-36, pp. 907-912, August 1988.
3. A.B. Martinez, P.E. Swaszek, and J.B. Thomas, "Locally optimal detection in multivariate non-Gaussian noise," *IEEE Trans. Inform. Theory*, vol. IT-30, pp. 815-822, November 1984.
4. J.H. Miller and J.B. Thomas, "Detectors for discrete-time signals in non-Gaussian noise," *IEEE Trans. Inform. Theory*, vol. IT-18, pp. 241-250, March 1972.
5. H.V. Poor and J.B. Thomas, "Locally optimum detection of discrete-time stochastic signals in non-Gaussian noise," *Jour. Acous. Soc. Amer.*, vol. 63, pp. 75-80, January 1978.
6. J.S. Lee, "Speckle analysis and smoothing of synthetic aperture radar image," *Comp. Graphics, Image Proc.*, vol. 17, pp. 24-32, May 1981.
7. D.T. Kuan, A.A. Sawchuk, T.C. Strand, and P. Chavel, "Adaptive noise smoothing filters for images with signal dependent noise," *IEEE Trans. Pattern Anal., Machine Intell.*, vol. PAMI-7, pp. 165-177, March 1985.
8. G.K. Froehlich, J.F. Walkup, and T.K. Krile, "Estimation in signal-dependent film-grain noise," *Appl. Opt.* vol. 20, pp. 3619-3626, October 1981.
9. J.F. Walkup and R.C. Choens, "Image processing in signal-dependent noise," *Opt. Eng.* vol. 13, pp. 258-266, May/June 1974.
10. I. Song, J.C. Son, and K.Y. Lee, "Detection of composite signals: Part I. Locally optimum detector test statistics," *Signal Proc.*, vol. 23, pp. 79-88, April 1991.
11. I. Song and T.S. Uhm, "Multiplicative noise model and composite signal detection," *IEE Proc. Part F*, vol. 138, pp. 531-538, December 1991.
12. I. Song and S.A. Kassam, "Locally optimum detection of signals in a generalized observation model: The known signal case," *IEEE Trans. Inform. Theory*, vol. IT-36, pp. 502-515, May 1990.
13. S. Kim, I. Song, and S.Y. Kim, "A composite signal detection scheme in additive and signal-dependent noise," *IEICE Trans. Fundamentals* (accepted for publication).

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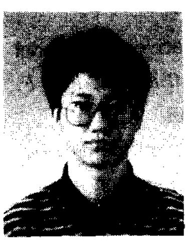

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