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Performance of Distributed CFAR Test Under Various Clutter Amplitudes

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We evaluate the performances of several distributed constant false-alarm rate (CFAR) tests operating in different background clutter conditions. The analysis considers the detection of Rayleigh target in various clutters with the possibility of differing clutter power levels in the test cells of distributed radars. Numerical results studied for a two-radar system show how the false-alarm rate of the maximum order statistic (MOS) test changes with differences in the clutter power levels of the test cells. The analysis for the detection of Rayleigh target in Rayleigh clutter indicates that, with the power levels of differing test cells, the OR fusion rule can be quite competitive with the new normalized test statistic (NTS). However, for the detection of Rayleigh target in Weibull or K-distributed clutter, the results show that NTS outperforms both the OR and the AND rules under the condition of large signal-to-clutter power ratio and moderate shape parameter values.

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I. INTRODUCTION

A constant false-alarm rate (CFAR) detector employs an adaptive threshold in order to maintain a CFAR irrespective of the clutter power. However, because of the diversity of the radar search environment (multiple target, abrupt changes in clutter, etc.) there exists no universal CFAR scheme. Typically, the adaptive threshold of a CFAR scheme is the product of two terms, one is a fixed scaling factor to adjust the probability of false alarm, and the other is an estimate of the total unknown noise (plus clutter) power of the test cell. The sample in the test cell is compared with this threshold in order to decide the presence or the absence of a target. A variety of CFAR techniques are developed according to the logic used to estimate the unknown noise power level. Some examples are, cell averaging CFAR (CA-CFAR), ordered statistics CFAR (OS-CFAR), greatest of CFAR, smallest of CFAR [3], and selection and estimation test [4].

Distributed signal detection schemes are needed when system performance factors such as speed, reliability, and constraint over the communication bandwidth are taken into account. In distributed detection techniques, each sensor (for example, radar) sends either a binary decision or a condensed form of information (statistics) about the observations available at the sensor to the fusion center, where a final decision about the presence of a target is made. Such techniques have been applied to CA-CFAR, adaptive CA-CFAR, and OS-CFAR. Barkat and Varshney [5] considered CA-CFAR detection using multiple sensors and data fusion. In their approach, each CA-CFAR detector transmits a binary decision to the fusion center where a final decision based on the AND or the OR counting rule is obtained. They have also addressed the adaptive CA-CFAR detector problem for parallel and tandem distributed networks [6]. Distributed OS-CFAR detectors with the AND or the OR fusion rule are considered in [7–9]. Distributed detection of signals in non-Gaussian clutter is considered in [10–11]. A review of different distributed CFAR target detection techniques is given in [12]. In [13], a new distributed CFAR test called the maximum order statistic (MOS) test was proposed. In this test, the sum of the test samples is compared with an adaptive threshold obtained by the product of a fixed scaling factor and the maximum of the received order statistics, to decide the presence/absence of a target. It was shown in [13] that MOS provides a considerable performance gain over OR or AND fusion rules. In deriving the above test, the problem formulation assumes that the test cells of different sensors all have statistically identical noise (clutter), and that if a target is present in the surveillance regions, all the test cells have statistically identical target returns.

In Section II we define the distributed CFAR problem and various clutter models. Section III examines how the false alarm probability of MOS changes when power levels of clutter at test cells of sensors become different, under the assumption of Rayleigh target in Rayleigh clutter. In Section IV, we propose a new test, called the normalized test statistic (NTS), which maintains a CFAR independent of the clutter power variations of the test cells. Also, the procedures for the performance evaluation of NTS under various clutter models are mentioned. Section V examines the detection performances of various tests under different clutter distributions. We draw conclusions in Section VI.

II. DISTRIBUTED CFAR PROCESSING AND CLUTTER MODELS

Consider a collection of n distributed sensors, each looking at a search volume consisting of $m_i + 1$ cells, $i = 1,2,\ldots,n$. The leading $m_i/2$ cells and the lagging $m_i/2$ cells form the reference window around the test cell of the ith sensor. Denote the samples from the reference cells as $Y_{i1},\ldots,Y_{im_i}$ and the test samples as X_i, $i = 1,2,\ldots,n$. The problem is to test whether a target is present or absent in the test cell. The signal absent and present hypotheses can be stated as follows:

$$\begin{aligned} H_0 &: X_i = c_i \\ H_1 &: X_i = |v_i + c_i|. \end{aligned} \tag{1}$$

Equation (1) can be written as

$$\begin{aligned} H_0 &: X_i = c_i \\ H_1 &: X_i = \sqrt{v_i^2 + c_i^2 + 2v_i c_i \cos(\theta_i - \phi_i)}. \end{aligned} \tag{2}$$

Here, v_i is the target amplitude, c_i is the clutter amplitude, θ_i is the phase angle of the target signal, and ϕ_i is the phase angle of the clutter.

A Rayleigh distribution with parameter λ_{1i}, $i = 1,2,\ldots,n$ is used to model the target signal at the ith sensor. The most commonly used model for the clutter amplitude is the Rayleigh distribution. A test can be formulated based on either the envelope or the envelope squared. For Rayleigh target and Rayleigh clutter, we assume in the sequel a test based on the envelope squared sample. For distributed OR and AND tests, both methods would yield identical results, but for other distributed CFAR tests, the results would vary somewhat. We still employ X_i to denote the test cell sample, but it denotes an envelope squared for Rayleigh, and an envelope for other clutter models. Under this assumption, the two hypotheses for Rayleigh clutter are as follows

$$\begin{aligned} H_0 &: X_i = c_i^2 \sim \exp(\lambda_{0i}) \\ H_1 &: X_i = |v_i + c_i|^2 \sim \exp(\lambda_{1i}). \end{aligned} \tag{3}$$

In other words, we assume that the envelope squared samples in the test cells to be independent identically distributed (IID) exponential with mean λ_{1i}, $i = 1,2,\ldots,n$ under the target hypothesis H_1 and exponential with mean λ_{0i}, $i = 1,2,\ldots,n$ under no target hypothesis H_0 (Rayleigh target and Rayleigh clutter models). In the case of homogeneous background, $Y_{i1},\ldots,Y_{im_i}$ are IID as an exponential with mean λ_{0i}. In the case of a nonhomogeneous background, the above random variables are still independent and exponentially distributed but with a mean value of either λ_{0i} or $\lambda_{0i}(1 + ICR_i)$, depending on whether a sample Y_{ij} is from clutter only, or from an interfering target plus clutter, respectively. Above, for the ith sensor, ICR_i denotes the interfering signal-strength-to-clutter ratio.

By denoting the mean of the test sample X_i as λ_i, we have

$$\lambda_i = \begin{cases} \lambda_{0i} & \text{under } H_0 \\ \lambda_{1i} = \lambda_{0i}(1 + SCR_i) & \text{under } H_1 \end{cases} \tag{4}$$

where SCR_i denotes the signal-to-noise power ratio of the test sample at the ith sensor.

The Weibull probability density function has been suggested as a model for sea and ground clutter at low grazing angles and at high resolutions [14–15]. The output of the magnitude envelope detector is assumed to have the Weibull density given by

$$f_{c_{w1}}(c_{wi}) = \frac{\alpha_i}{\beta_{0i}} \left(\frac{c_{wi}}{\beta_{0i}}\right)^{\alpha_i - 1} e^{-(c_{wi}/\beta_{0i})^{\alpha_i}} \qquad \begin{matrix} c_{wi} > 0 \\ \alpha_i > 0. \\ \beta_{0i} > 0 \end{matrix} \tag{5}$$

Here, α_i is the shape parameter and β_{0i} is the scale parameter of the Weibull distribution. Under the assumption of Rayleigh target and a Weibull distributed clutter, the signal-to-clutter power ratio at the ith sensor is given by

$$SCR_i = \frac{\lambda_{1i}}{\beta_{0i}^2 \Gamma\left(\dfrac{2}{\alpha_i} + 1\right)}. \tag{6}$$

The test cells are assumed to be IID Weibull distributed clutter under no target hypothesis H_0 and Rayleigh signal plus the Weibull distributed clutter under target hypothesis H_1. In the case of homogeneous background, $Y_{i1},\ldots,Y_{im_i}$ are IID as a Weibull distribution as in (5) and in the case of nonhomogeneous background, a sample Y_{ij} is either from a clutter-only region, or from an interfering target in the presence of clutter.

Another clutter model considered is the K-distributed clutter. This model has been proposed based on experimental evidence reported in [16]. The density function of the K-distribution is given by

$$f_{c_{ki}}(c_{ki}) = \frac{4\beta_{0i}}{\Gamma(\alpha_i)}(\beta_{0i}c_{ki})^{\alpha_i}K_{\alpha_i-1}(2\beta_{0i}c_{ki}), \quad \begin{array}{l} c_{ki} > 0 \\ \alpha_i > 0 \\ \beta_{0i} > 0 \end{array} \tag{7}$$

where $\Gamma(\cdot)$ is the Gamma function, $K_{\alpha_i}(\cdot)$ is the modified second-kind Bessel function of order α_i, α_i is the shape parameter, and β_{0i} is the scale parameter. The signal-to-clutter power ratio at the ith sensor is defined as

$$SCR_i = \frac{\lambda_{1i}}{\alpha_i/\beta_{0i}^2}. \tag{8}$$

Here, the test cells are assumed to be IID K-distributed clutter under no target hypothesis H_0 and a Rayleigh signal in the presence of K-distributed clutter under target hypothesis H_1.

It is worth noting that when $\alpha_i = 2$, the Weibull distribution in (5) becomes a Rayleigh distribution and similarly when $\alpha_i \to \infty$, the K-distribution in (7) also becomes a Rayleigh distribution. These two special situations allow us to verify the performance results of some tests by comparing the results obtained for Weibull and K clutter cases with those results obtained for the Rayleigh case.

III. MOS TEST AND FALSE ALARM RATE CHANGE

Assume a Rayleigh target and a Rayleigh distributed clutter model. If we assume that λ_{0i} is the same for all $i = 1,2,\ldots,n$, then the MOS test defined below is a CFAR test [13]:

$$\sum_{i=1}^{n} X_i \underset{H_0}{\overset{H_1}{\gtrless}} t\max(Y_{(k_i)},\ i = 1,2,\ldots,n) \tag{9}$$

where $Y_{(k_i)}$ is the k_ith-order statistic of the reference samples $Y_{i1},\ldots,Y_{im_i}$ of the ith sensor. For a two-sensor system, let

$$a = \frac{\lambda_{01}}{\lambda_{02}}. \tag{10}$$

Therefore, the changes in false alarm probability of (9), when t is fixed assuming $a = 1$ and a desired false alarm rate of α, as a changes, can be investigated. The numerical calculation of the false alarm probability shows that for $\alpha = 10^{-6}$, $m_1 = 11$, $m_2 = 13$, $k_1 = 8$, $k_2 = 9$, the probability can increase up to its largest value of $\approx 10^{-5}$, and that this largest increase occurs for a being close to 0.1 or 10 (Fig. 1). Also, the greatest change in the false alarm probability occurs as a is varied from 0.1 through 10 as shown in Fig. 1. Unfortunately, this means that the false alarm rate of (9) is sensitive to small variations in a. Also, the maximum of the values of false alarm probabilities corresponding to $a = 0$ and $a = \infty$ is close to 10^{-5}. If the worst case increase is to be at 10^{-6} and not at 10^{-5}, then the t value in (9) can be appropriately

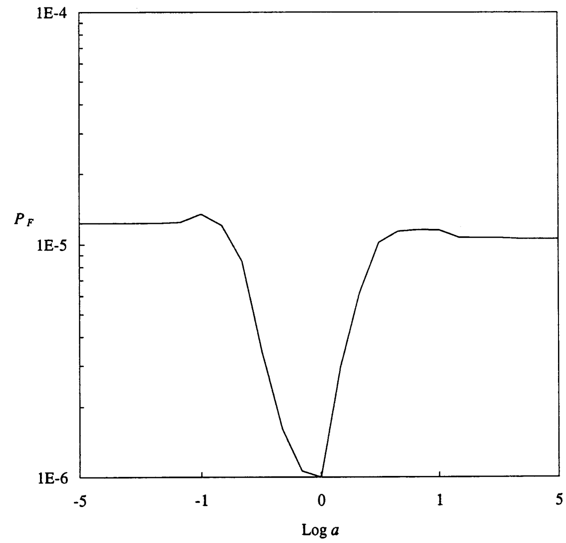

Fig. 1. False alarm performance of MOS for various values of α in Rayleigh clutter.

chosen so as to achieve this condition. This is how the MOS test threshold is computed while comparing its performance against other schemes (see Section V). If a is close to 1, then the MOS test performs much better than the Boolean OR and the Boolean AND fusion rules [13].

IV. NORMALIZED TEST STATISTIC AND OTHER TESTS

Assume a Rayleigh target and a Rayleigh clutter as in the previous section. For the sake of simplicity, the following derivation is based on a two-sensor system. Applying a likelihood ratio test to the test samples yields

$$\Lambda = \frac{p(X_1 \mid H_1)p(X_2 \mid H_1)}{p(X_1 \mid H_0)p(X_2 \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} T_L \tag{11}$$

where T_L is an appropriate threshold. With Rayleigh target and Rayleigh clutter, (4), equation (11) can be simplified to yield

$$\left(\frac{1}{\lambda_{01}} - \frac{1}{\lambda_{11}}\right) X_1 + \left(\frac{1}{\lambda_{02}} - \frac{1}{\lambda_{12}}\right) X_2 \underset{H_0}{\overset{H_1}{\gtrless}} T'. \tag{12}$$

Assuming a homogeneous reference window for each sensor (notice that sensor-to-sensor homogeneity is not needed, i.e., λ_{0i} need not be identical for $i = 1,2$), but with identical SCR_is (i.e., $\lambda_{11}/\lambda_{01} = \lambda_{12}/\lambda_{02}$), (12) reduces to

$$\frac{X_1}{\lambda_{01}} + \frac{X_2}{\lambda_{02}} \underset{H_0}{\overset{H_1}{\gtrless}} T^* \tag{13}$$

where T^* is an appropriate threshold.

However, (13) cannot be realized since λ_{01} and λ_{02} are unknown. A CFAR test is obtained by replacing λ_{01} and λ_{02} by appropriate estimates. Using the order statistic of the reference cells of each sensor as the estimates, we obtain the NTS

$$Z = \frac{X_1}{Y_{(k_1)}} + \frac{X_2}{Y_{(k_2)}} \underset{H_0}{\overset{H_1}{\gtrless}} t_b \tag{14}$$

where t_b is the threshold which can be adjusted to yield a desired false alarm rate under homogeneous background noise. Even though the test (14) was derived for Rayleigh target and Rayleigh clutter condition, such a test is still CFAR for other clutter models also. In fact, later in this section we provide performance equations of NTS for other clutter models.

Since $Y_{(k_i)}$ is not an unbiased estimator of λ_{0i} [17], one can substitute a proportionality factor (that corrects for the bias) in each of the estimates in (14) and obtain an unbiased version of the NTS test:

$$Z = \frac{X_1}{Y_{(k_i)}} + w\frac{X_2}{Y_{(k_2)}} \underset{H_0}{\overset{H_1}{\gtrless}} t_u \tag{15}$$

where $w = E(Y_{(k_1)})/E(Y_{(k_2)})$. Therefore, (14) and (15) are the biased and unbiased versions, respectively, of NTS.

Two other tests that are based on $Y_{(k_i)}$ and X_i are the MAX and MIN tests defined below.

MAX:

$$\max\left(\frac{X_1}{Y_{(k_1)}}, \frac{X_2}{Y_{(k_2)}}\right) \underset{H_0}{\overset{H_1}{\gtrless}} t_M \tag{16}$$

MIN:

$$\min\left(\frac{X_1}{Y_{(k_1)}}, \frac{X_2}{Y_{(k_2)}}\right) \underset{H_0}{\overset{H_1}{\gtrless}} t_m. \tag{17}$$

In the OR (AND) fusion rule [13], each sensor is assumed to employ an OS-CFAR detector of the type

$$Z_i = \frac{X_i}{Y_{(k_i)}} \underset{H_0}{\overset{H_1}{\gtrless}} t_i. \tag{18}$$

The individual sensor decisions are combined using the OR (AND) Boolean rule. The probability of false alarm expressions for the OR (AND) rule for Rayleigh target in Rayleigh clutter at the ith sensor (P_{F_i}) can be found in [5]. Using this, the total probability of false alarm for the OR and AND rules for a two-sensor system (P_{F_o} and P_{F_a}) can be found to be

$$P_{F_o} = P_{F_1} + P_{F_2} - P_{F_1} \cdot P_{F_2} \tag{19}$$

$$P_{F_a} = P_{F_1} \cdot P_{F_2}. \tag{20}$$

A. Performance Equations for Different Clutters

In order to assess the performance under nonhomogeneous background conditions involving multiple interferers [3], let us define

$$S_i = \frac{Y_{(k_i)}}{\lambda_{0i}}. \tag{21}$$

Using [17] we obtain with Rayleigh clutter and Rayleigh target, the density of S_i as

$$\begin{aligned} f_{S_i}(s_i) = &\sum_{h=k_i}^{m_i} \sum_{j=\max(0,h-b_i)}^{\min(h,m_i-b_i)} \sum_{v=0}^{j} \sum_{w=0}^{h-j} \\ &\times \binom{m_i-b_i}{j}\binom{b_i}{h-j}\binom{j}{v}\binom{h-j}{w}(-1)^{v+w+1} \\ &\times [v + (m_i - b_i - j) + (w + b_i - h + j)/c_i] \\ &\times \exp\{-s_i[(v + m_i - b_i - j) + (w + b_i - h + j)/c_i]\} \end{aligned} \tag{22}$$

where $c_i = \lambda_{1i}/\lambda_{0i}$ and b_i is the number of interfering targets in the ith sensor reference window. Also

$$\begin{aligned} F_Z(z) = &\sum_{h_1=k_1}^{m_1} \sum_{h_2=k_2}^{m_2} \sum_{i=\max(0,h_1-b_1)}^{\min(h_1,m_1-b_1)} \sum_{j=\max(0,h_2-b_2)}^{\min(h_2,m_2-b_2)} \sum_{v_1=0}^{i} \sum_{v_2=0}^{j} \sum_{w_1=0}^{h_1-i} \sum_{w_2=0}^{h_2-j} \\ &\times \binom{m_1-b_1}{i}\binom{m_2-b_2}{j}\binom{b_1}{h_1-i}\binom{b_2}{h_2-j} \\ &\times \binom{i}{v_1}\binom{j}{v_2}\binom{h_1-i}{w_1}\binom{h_2-j}{w_2}(-1)^{v_1+v_2+w_1+w_2} \\ &\times \beta_1\beta_2\Bigg[\left\{\frac{1}{\beta_1} - \frac{1}{z+\beta_1+\beta_2}\right\}\left\{\frac{1}{\beta_2} - \frac{1}{z+\beta_2}\right\} \\ &\quad + \frac{1}{(z+\beta_1+\beta_2)^2}\log\frac{\beta_1\beta_2}{(z+\beta_1)(z+\beta_2)}\Bigg] \end{aligned} \tag{23}$$

where

$$\beta_1 = (v_1 + m_1 - b_1 - i) + (w_1 + b_1 - h_1 + i)/c_1$$

$$\beta_2 = (v_2 + m_2 - b_2 - j) + (w_2 + b_2 - h_2 + j)/c_2.$$

The probability of false alarm in homogeneous background is given by

$$P_F = 1 - F_Z(t_b). \tag{24}$$

The probability of detection P_D is obtained by replacing t_b with $t_b/(1+SCR)$ in (24), where $SCR = SCR_1 = SCR_2$. The probability of false alarm under homogeneous background can be obtained by setting $b_i = 0$ in (23).

Under the assumption of Weibull clutter, the cumulative distribution function of Z of the NTS in (14) can be shown to be

$$\begin{aligned} F_Z(z) = &\int_0^z \int_0^\infty \frac{\alpha_1 m_1!}{(k_1-1)!(m_1-k_1)!}[1 - e^{-s_1^{\alpha_1}}]^{k_1-1} \\ &\times [e^{-s_1^{\alpha_1}}]^{m_1-k_1+1}[1 - e^{-[s_1(z-y)]^{\alpha_1}}]s_1^{\alpha_1-1}\,ds_1 \\ &\times \int_0^\infty \frac{\alpha_2^2 m_2!}{(k_2-1)!(m_2-k_2)!}[1 - e^{-s_2^{\alpha_2}}]^{k_2-1} \\ &\times [e^{-s_2^{\alpha_2}}]^{m_2-k_2+1} e^{-(s_2 y)^{\alpha_2}}(s_2 y)^{\alpha_2-1} s_2^{\alpha_2}\,ds_2\,dy. \end{aligned} \tag{25}$$

The probability of false alarm in homogeneous Weibull clutter background is given by (24) using the above cumulative distribution function. Under the same clutter, the single-sensor probability of false alarm expression is given by

$$P_{F_i} = 1 - F_{Z_i}(t_i) \tag{26}$$

where

$$F_{Z_i}(z_i) = \int_0^\infty \frac{\alpha_i m_i!}{(k_i-1)!(m_i-k_i)!}[1-e^{-s_i^{\alpha_i}}]^{k_i-1} \times [e^{-s_i^{\alpha_i}}]^{m_i-k_i+1}[1-e^{-(s_i z_i)^{\alpha_i}}]s_i^{\alpha_i-1}\,ds_i. \tag{27}$$

Upon simplification, (26) reduces to [18, eq. (18)]. The overall probability of false alarm P_{F_o} and P_{F_a} can be found using (19)–(20).

Similarly, for K-distributed clutter, the cumulative distribution function of Z of the NTS in (14) can be shown to be

$$\begin{aligned}F_Z(z) = {} & \frac{4^3 k_1 k_2 \binom{m_1}{k_1}\binom{m_2}{k_2}}{\Gamma(\alpha_1)\Gamma(\alpha_2)\Gamma(\alpha_2)} \int_0^z \int_0^\infty \int_0^\infty s_1^{\alpha_1} s_2^{2\alpha_2+1} y^{\alpha_2} \\ & \times K_{\alpha_1-1}(2s_1)K_{\alpha_2-1}(2s_2)K_{\alpha_2-1}(2ys_2) \\ & \times \left[1 - \frac{2[s_1(z-y)]^{\alpha_1}}{\Gamma(\alpha_1)}K_{\alpha_1}[2s_1(z-y)]\right] \\ & \times \left[1 - \frac{2s_1^{\alpha_1}}{\Gamma(\alpha_1)}K_{\alpha_1}(2s_1)\right]^{k_1-1} \\ & \times \left[\frac{2s_1^{\alpha_1}}{\Gamma(\alpha_1)}K_{\alpha_1}(2s_1)\right]^{m_1-k_1} \left[\frac{2s_2^{\alpha_2}}{\Gamma(\alpha_2)}K_{\alpha_2}(2s_2)\right]^{m_2-k_2} \\ & \times \left[1 - \frac{2s_2^{\alpha_2}}{\Gamma(\alpha_2)}K_{\alpha_2}(2s_2)\right]^{k_2-1} ds_1\,ds_2\,dy \end{aligned} \tag{28}$$

and the probability of false alarm in homogeneous K-clutter background is givenby (24) using the above cumulative distribution function. Under the same assumption, the single-sensor probability of false alarms expressions are given by (26) where

$$\begin{aligned}F_{Z_i}(z) = {} & \int_0^\infty k_i \binom{m_i}{k_i} \frac{4}{\Gamma(\alpha_i)} s_i^{\alpha_i} K_{\alpha_i-1}(2s_i) \\ & \times \left[1 - \frac{2[s_i(z-y)]^{\alpha_i}}{\Gamma(\alpha_i)}K_{\alpha_i}[2s_i(z-y)]\right] \\ & \times \left[\frac{2s_i^{\alpha_{1i}}}{\Gamma(\alpha_i)}K_{\alpha_i}(2s_i)\right]^{m_i-k_i} \\ & \times \left[1 - \frac{2s_i^{\alpha_i}}{\Gamma(\alpha_i)}K_{\alpha_i}(2s_i)\right]^{k_i-1} ds_i. \end{aligned} \tag{29}$$

As in the case of Weibull clutter, the overall probability of false alarm P_{F_o} and P_{F_a} can be found using (19)–(20). All the tests discussed in this section maintain a CFAR. For the case of Rayleigh clutter, these tests maintain CFAR even if the λ_{0i}s are not identical for $i = 1,2$. Similarly, for the case of Weibull or K-distributed clutter, these tests maintain CFAR even if the β_{0i}s are not identical for $i = 1,2$.

B. Simulation Studies

For the condition of Weibull and K-distributed clutter, closed-form solutions for the probability of detection for the NTS, OR, and AND fusion tests are not easily derivable. Hence, the performance analysis is carried out via simulation for all the three tests. The signal-plus-clutter amplitude variate was generated using (2) under hypothesis H_1 with c_i being a Weibull or a K-distributed random variate, depending on the assumed clutter model. We assume that the difference between the target signal phase θ_i and the clutter phase ϕ_i, is uniformly distributed, i.e.,

$$\theta_i - \phi_i = \varphi_i \sim \text{Uniform}(0, 2\pi). \tag{30}$$

For the simulation, we generated different random variates using the appropriate International Mathematical and Statistical Library (IMSL) routines. To calculate each probability of detection point, 10,000 iterations were used.

V. PERFORMANCE COMPARISON

For a two-sensor network, the following parameters are used in our numerical analysis: $m_1 = 8$, $m_2 = 16$, $k_1 = 6$, and $k_2 = 12$. It can be seen that the first sensor can tolerate 2 interfering targets and the second sensor can tolerate 4 interfering targets without encountering target masking [3]. In (14), t_b was solved through a numerical search to satisfy the constraint $P_F = 10^{-6}$. Similarly, for the OR rule, the two sensor thresholds t_1 and t_2 are solved so that the individual sensor false alarms are given by $P_{F_1} = P_{F_2} = 5.0 \times 10^{-7}$. This gives an overall false alarm rate of 10^{-6}. For the AND rule, the two sensor thresholds are chosen so that $P_{F_1} = P_{F_2} = 10^{-3}$. Similarly, appropriate thresholds for MAX and MIN are found so as to achieve a false alarm rate of 10^{-6} in the homogeneous background condition. The threshold for the MOS test is fixed as per the discussion at the end of Section III. In Fig. 2 the probability of detection is plotted against SCR, for homogeneous clutter background, and in Figs. 3 and 4, the probability of detection is shown for two interfering target cases. Fig. 5 shows the probability of false alarm swing when a clutter transition occurs in the middle of reference cells and the test cell is in the high clutter region. Here CNR stands for clutter-to-noise ratio which is used to denote the ratio of the power of high clutter to the power of low clutter (or noise).

In these figures (Figs. 2–5), the curves marked biased and unbiased, correspond to the two forms of

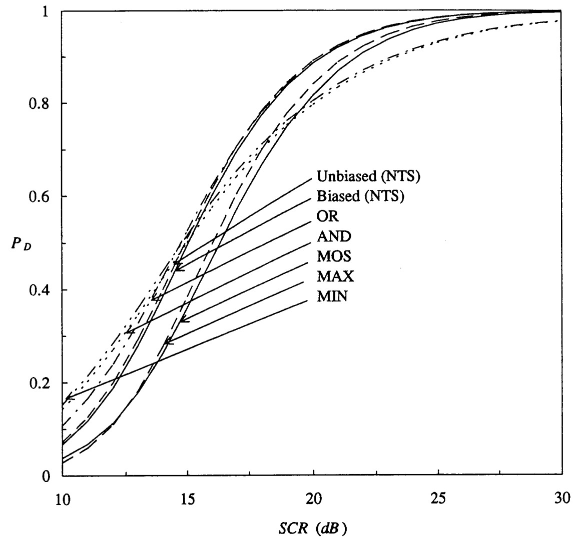

Fig. 2. Probability of detection versus SCR when background is homogeneous Rayleigh clutter.

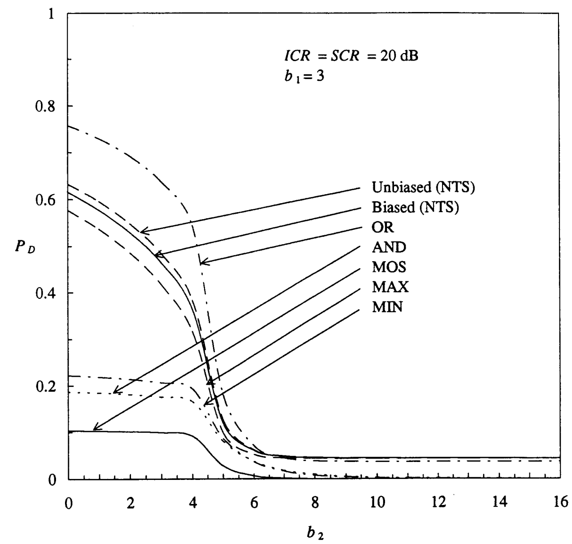

Fig. 4. Probability of detection versus b_2 when $b_1 = 3$ in Rayleigh clutter.

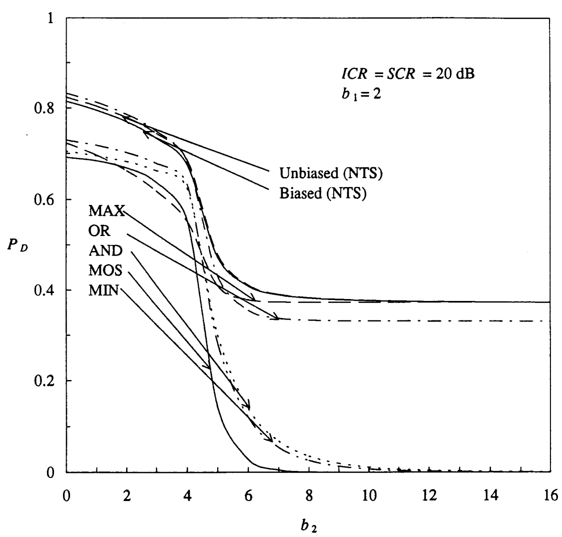

Fig. 3. Probability of detection versus b_2 when $b_1 = 2$ in Rayleigh clutter.

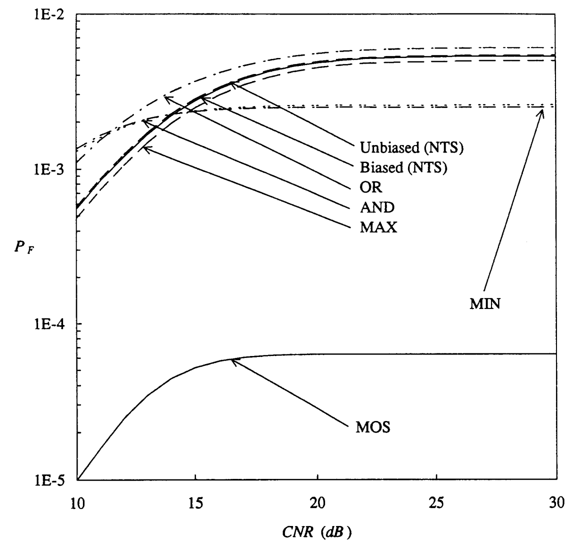

Fig. 5. False alarm performance when test cells are in Rayleigh clutter region.

NTS discussed earlier (see (14) and (15)). From these figures we observe that the OR rule is competitive with the NTS. In homogeneous background (Fig. 2), the probability of detection of the OR rule is close to that of NTS (biased or unbiased). In situation corresponding to Fig. 3, the NTS performs slightly better than the OR rule, whereas in the interfering target situation corresponding to Fig. 4, the OR rule even outperforms the biased and the unbiased NTS, for $b_2 \leq 5$. Therefore, considering that the normalized test requires each sensor to send two real numbers, a test cell sample and an order statistic, whereas the OR rule requires each sensor to send only a decision to the fusion center, it can be said that the OR rule provides a competitive and acceptable performance at a low cost in Rayleigh clutter. The MOS detector performance, in interfering target case, is poor as compared with OR (Figs. 3, 4). The only drawback of NTS and OR is the occurrence of a large increase in false-alarm rate during a clutter transition in the middle of the reference window (Fig. 5). If the homogeneous background noise power in all the sensors are nearly identical, then the MOS test provides a much better performance than the OR rule (and the NTS test) [13]. Since the performance of biased NTS is similar to that of the unbiased NTS, we only consider the biased NTS (called NTS for short) for the remainder of the performance analysis. Also, we observe that the performances of the MAX and MIN test are similar to the OR and AND fusion tests. Hence, these two tests were not considered further in the performance analysis corresponding to Weibull and K-distributed clutters.

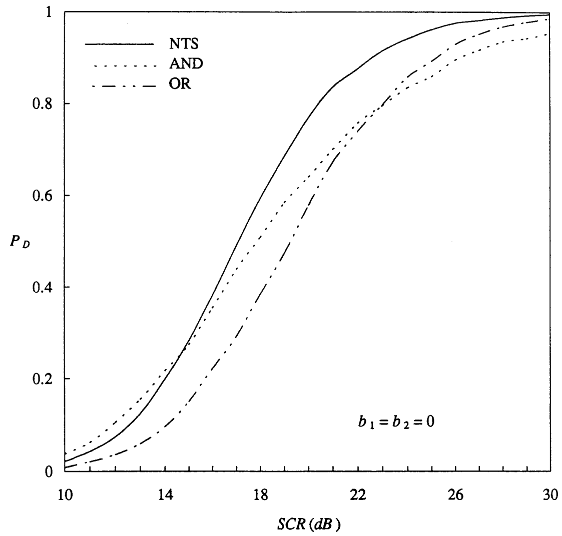

Fig. 6. Probability of detection for homogeneous background when $\alpha_1 = \alpha_2 = 1.5$ in Weibull clutter.

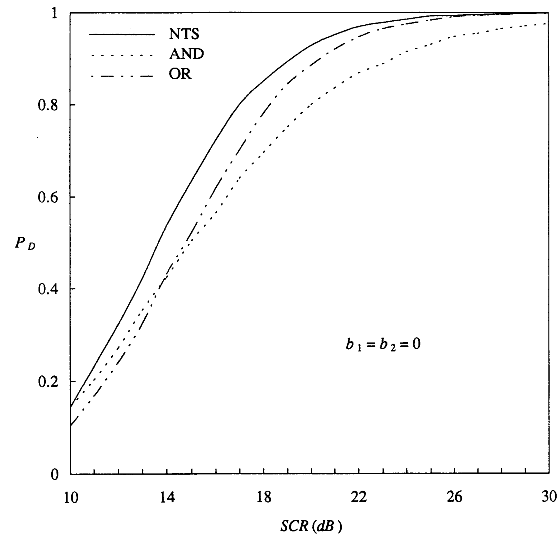

Fig. 8. Probability of detection for homogeneous background when $\alpha_1 = \alpha_2 = 2$ in Weibull clutter.

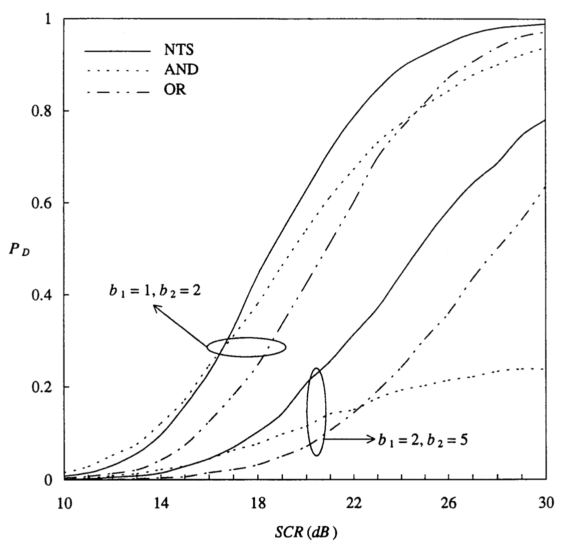

Fig. 7. Probability of detection for different interfering target situations when $\alpha_1 = \alpha_2 = 1.5$ in Weibull clutter.

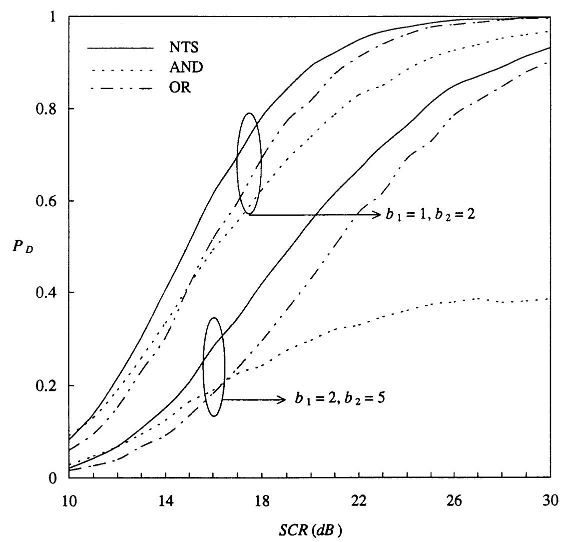

Fig. 9. Probability of detection for different interfering target situations when $\alpha_1 = \alpha_2 = 2$ in Weibull clutter.

Figs. 6–11 correspond to a Weibull clutter. In these cases, the power of the interfering targets in the adjacent cells is assumed to be equal to the power of the target signal in the test cell. Also, the shape parameter of the Weibull distributed clutter is assumed to be completely known. In Figs. 6 and 7, the probability of detection is shown for homogeneous background ($b_1 = b_2 = 0$) and for few interfering target cases, corresponding to the shape parameters $\alpha_1 = \alpha_2 = 1.5$. Figs. 8 and 9 give the probability of detection when $\alpha_1 = \alpha_2 = 2$. Similarly, Figs. 10 and 11 are for the case when $\alpha_1 = \alpha_2 = 4$. In [15], for measurements done using an L-band long-range air-route surveillance radar (ARSR) having a 3.0 μs pulsewidth and a 1.23° beamwidth at very low grazing angles, it was shown that the shape parameter of the Weibull clutter varied from 1.507 to 2.0. Under these conditions, and for moderate to large SCR (Figs. 6–9), the NTS performs better than OR and AND rules. For large SCR and for large $\alpha_1 = \alpha_2$ values (Figs. 8, 9), the NTS and OR rule significantly outperform the AND rule. Unlike in Rayleigh clutter, where the OR rule is competitive with NTS, in Weibull distributed clutter, we observed the AND rule does better than the NTS for low values of the shape parameter and for low number of interfering targets. We did not include figures corresponding to low αs, for the sake of brevity.

In Figs. 12–17, the performances of the NTS, OR, and AND rules in K-distributed clutter are shown. As before, the power of the interfering targets in the adjacent cells are assumed to be equal to the power of the target signal in the test cell. Also, the shape parameter of the K-distributed clutter is assumed to be

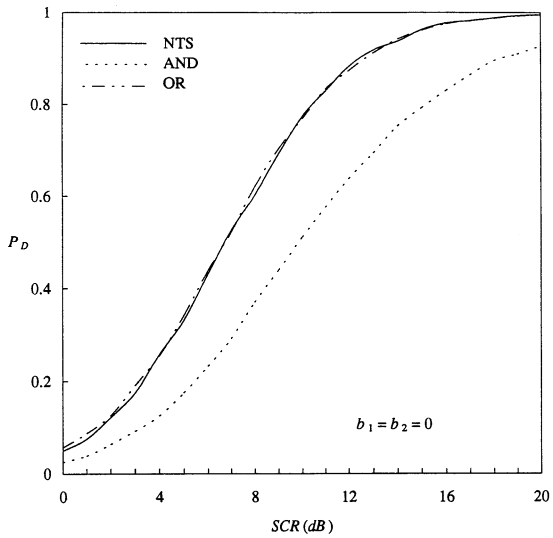

Fig. 10. Probability of detection for homogeneous background when $\alpha_1 = \alpha_2 = 4$ in Weibull clutter.

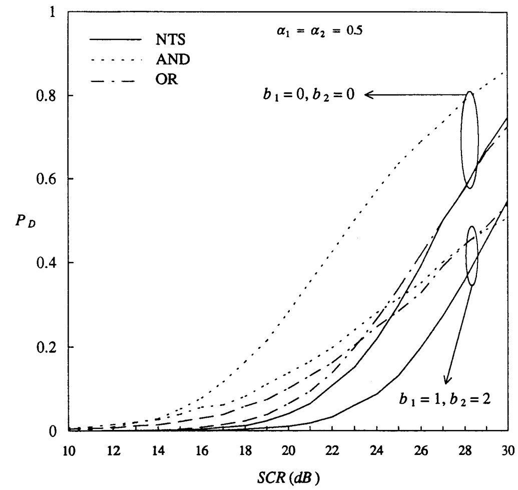

Fig. 12. Probability of detection for homogeneous and low interfering target situations when $\alpha_1 = \alpha_2 = 5$ in K-distributed clutter.

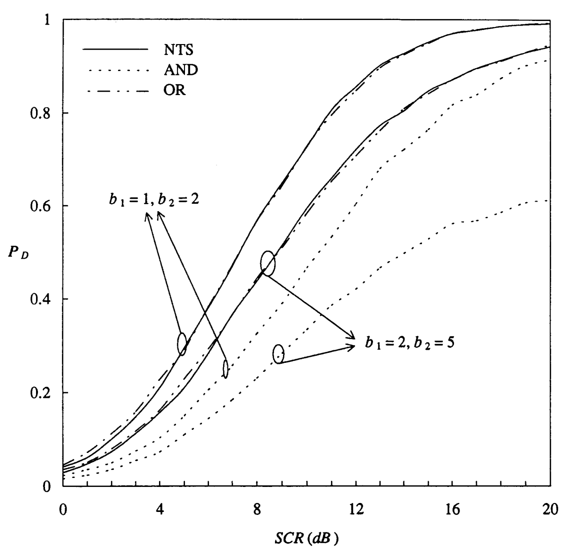

Fig. 11. Probability of detection for different interfering target situations when $\alpha_1 = \alpha_2 = 4$ in Weibull clutter.

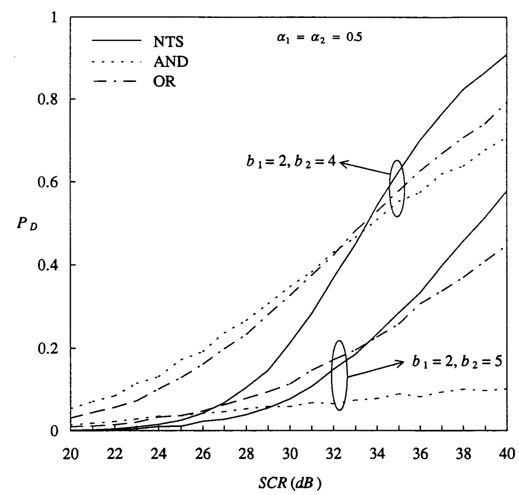

Fig. 13. Probability of detection for moderate number of interfering target situations when $\alpha_1 = \alpha_2 = 0.5$ in K-distributed clutter.

completely known. In Figs. 12 and 13, the probability of detection is shown for homogeneous background ($b_1 = b_2 = 0$) and for few interfering target cases when the shape parameter $\alpha_1 = \alpha_2 = 0.5$. Similarly, Figs. 14 and 15 are for the case when $\alpha_1 = \alpha_2 = 5$ and Figs. 16 and 17 show the probability of detection when $\alpha_1 = \alpha_2 = 40$.

Under the condition of $\alpha_1 = \alpha_2 = 0.5$, the AND rule does significantly better than the OR and NTS in homogeneous background. For low number of interfering targets, AND performs slightly better than OR, and it performs significantly better than the NTS. For a large number of interfering targets and for a large SCR, the NTS performs better than the OR and AND rules. However, for high values of $\alpha_1 = \alpha_2$, and for moderate to large SCR (Figs. 14–17), the NTS and OR rule perform significantly better than the AND rule. For low SCR values, the OR rule performs slightly better than both the NTS and the AND rule (see Figs. 14–17). For large SCR and for large $\alpha_1 = \alpha_2$ values, the NTS significantly outperforms both the OR and the AND rules. Unlike in Rayleigh clutter, where the OR rule is competitive with NTS, in K-distributed clutter, the AND rule does better than the NTS for low values of the shape parameter. The usefulness of the OR rule is limited to low SCR and large shape parameter values.

VI. CONCLUSION

We evaluated for different clutter models the performances of several two-sensor distributed CFAR tests. The results show that the newly proposed NTS

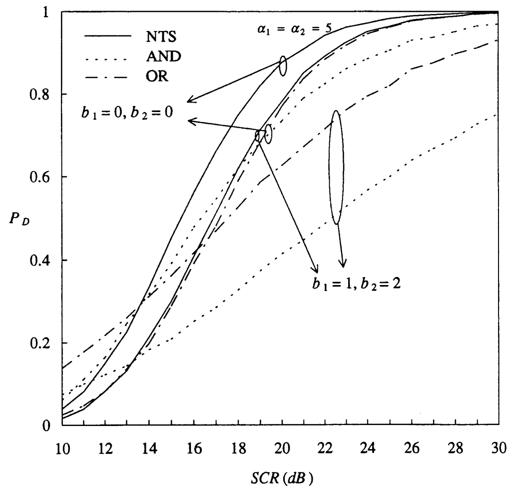

Fig. 14. Probability of detection for homogeneous and low interfering target situations when $\alpha_1 = \alpha_2 = 5$ in K-distributed clutter.

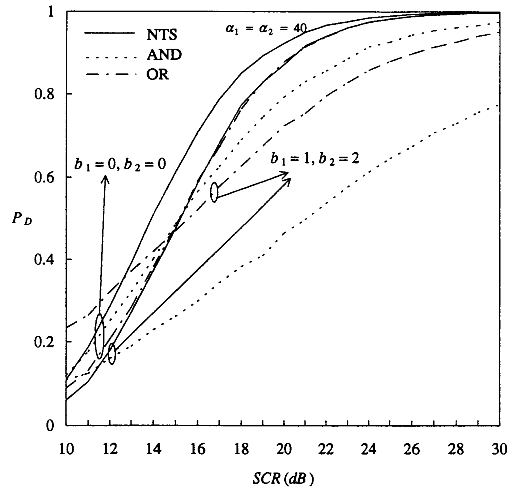

Fig. 16. Probability of detection for homogeneous and low interfering target situations when $\alpha_1 = \alpha_2 = 40$ in K-distributed clutter.

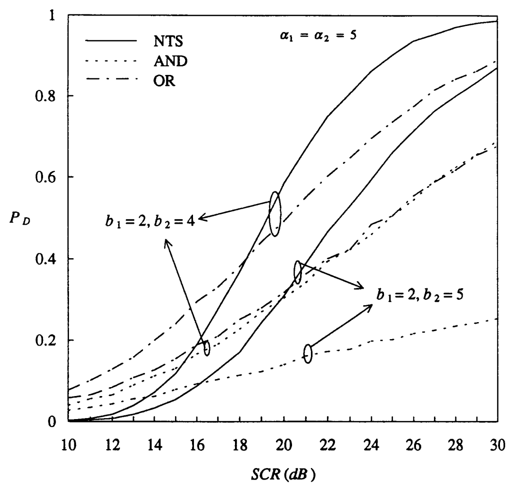

Fig. 15. Probability of detection for moderate number of interfering target situations when $\alpha_1 = \alpha_2 = 5$ in K-distributed clutter.

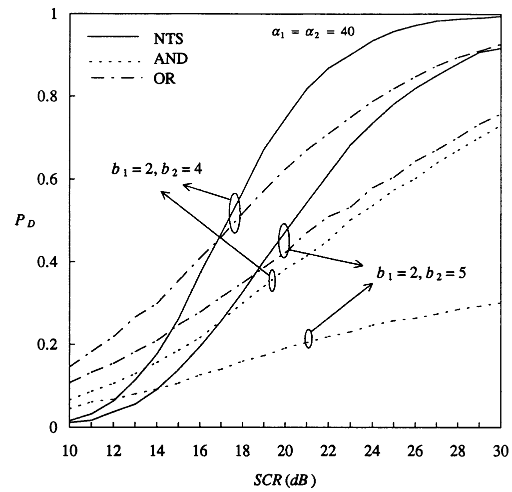

Fig. 17. Probability of detection for moderate number of interfering target situations when $\alpha_1 = \alpha_2 = 40$ in K-distributed clutter.

rule can be useful for different clutter situations, but within a restricted set of parameter values. The analysis for the detection of Rayleigh target in Rayleigh clutter indicates that, with the power levels of differing test cells, the OR fusion rule can be quite competitive with the NTS. For the detection of Rayleigh target in Weibull or K-distributed clutter, the results show that NTS outperforms both the OR and the AND rules under the condition of large signal-to-clutter power ratio and moderate shape parameter values.

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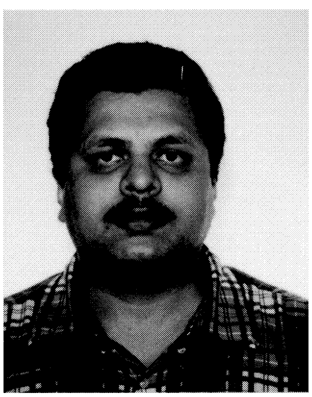

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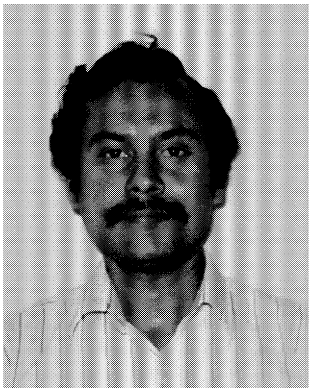

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