Noncoherent Multiuser Detection Using Array Sensors *

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Abstract

We consider a linear multiuser array detector (MUAD) for synchronous direct-sequence code division multiple access channels. It consists of a bank of decorrelating detectors followed by a user-dependent combining and decision scheme. Unlike a previous linear MUAD, this detector does not require interfering user parameter estimates; hence it retains its near-far resistant characteristics even in the presence of interfering user parameter mismatch. Given the decorrelating detector outputs, minimum variance unbiased estimates can be derived for the users' amplitudes, phases, and sensor phase offsets. Amplitude dependent and independent, coherent and noncoherent detection schemes for on-off keyed (OOK) signals are developed. Even when the phases and sensor phase offsets are unknown, this detector provides significant performance gains over the conventional coherent decorrelating detector.

1 Introduction

Direct sequence code division multiple access is a modulation technique in which multiple users simultaneously transmit over a common frequency band. While conventional match filter detection suffers from the near-far effect (the detection for a weak user is unreliable due to the presence of more powerful interferers), multiuser detection [1] has been shown to be an effective method for eliminating the near-far problem by exploiting the structure of the multiple access interference. In [2], a linear multiuser array detector (MUAD) is derived which uses a front end array of sensors and which exploits knowledge of the received signals' directions of arrival (DOAs). In doing so, the linear MUAD provides significant performance gains over the single sensor linear multiuser detector known as the decorrelating detector [3]. The performance of the linear MUAD in terms of near-far resistance (NFR, an asymptotic measure) is equivalent to that of the optimum MUAD [2], however, it requires that all of the users' DOAs and phases are known and, in the presence of interfering user DOA mismatch, it loses its near-far resistant characteristics [4].

In this paper, we consider an alternative linear MUAD which consists of a bank of parallel scalar decorrelating detectors [3] followed by a user-dependent combining and decision scheme. We refer to this detector as the decorrelating-combing array detector (DCAD). (A similar linear MUAD was considered in [5] which, unlike the DCAD, disregards the signals' spatial characteristics.) Since signal decorrelation is done at each sensor, prior to combining, the DCAD detection performance for a desired user is independent of any interfering users; hence it does not require parameter estimates for the interferers, and its near-far resistance is immune to parameter mismatch. The tradeoff is only a modest degradation in performance in the ideal environment where all signal parameters are known [4]. The decorrelator outputs of the DCAD also provide minimum variance unbiased estimates of the users' signal parameters. The time-varying nature of signal phases in the mobile communications environment motivates the need for effective noncoherent signal detection in the presence of multiaccess interference. While the optimum multiuser detector has been derived for noncoherent differential phase shift keyed signals [6], multiuser detection of noncoherent on-off keying (OOK) signals has not been addressed. We show how the DCAD can be used for coherent/noncoherent and amplitude dependent/independent OOK signal detection.

2 System and Signal Model

We first introduce some notation. Bold face lower and upper case letters represent vectors and matrices, respectively. Let $\mathbf{0}_j$, $\mathbf{1}_j$, and $\mathbf{I}_j$ be a vector of j zeros, j ones, and a $j \times j$ identity matrix, respectively. Let $\eta(\mathbf{a}, \mathbf{B})$ represent a Gaussian vector distribution of mean $\mathbf{a}$ and covariance $\mathbf{B}$. Let $R(n, m, \sigma^2)$ be the distribution of a Ricean random variable $r \equiv \sqrt{\sum_{i=1}^{n} x_i^2}$

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where the x_i are independent Gaussian random variables with variance σ^2 and $m \equiv \sqrt{\sum_{i=1}^{n} E^2(x_i)}$. Let $U(a,b)$ represent a uniform distribution over the interval $[a,b]$.

Let K be the number of active users in the system. Each user k ($k = 1 \ldots K$) transmits a data signal $s_k(t) = w_k b_k c_k(t) cos(\omega_c t + \phi_k)$ defined on the interval $t \in [0, NT_c]$ where w_k, b_k, ϕ_k are the amplitude, bit, phase of the k^{th} user, ω_c is the carrier frequency common to all users, and $c_k(t)$ is the signature waveform (amplitude $\sqrt{2/(NT_c)}$) which consists of N rectangular chips, each of duration T_c.

At the receiver, there are P sensors arranged in a linear array and spaced $\lambda/2$ units apart, where λ is the wavelength of the signal carrier. We assume that this spacing is sufficient for the users' signals to arrive as planar wavefronts and for their relative time delays at each of the sensors to be modeled as phase shifts. Hence the phase offset at the p^{th} sensor relative to the first can be written as $(p-1)\theta_k$ where $\theta_k \boxminus \pi sin\alpha_k$ and α_k is the DOA of the k^{th} user's signal respect to the azimuth along which the sensors lie.

Assuming that the users' signals are received synchronously, the total received signal at the p^{th} sensor is $\tilde{r}_p(t) = \sum_{k=1}^{K} e^{j(p-1)\theta_k} s_k(t) + \tilde{n}_p(t)$ where $\tilde{n}_p(t)$ is a complex Gaussian random noise process with real and imaginary power spectral densities $N_0/2$. Let $r_p[i]$ ($p = 1 \ldots P, i = 1 \ldots N$) be the complex output of a noncoherent demodulator followed by a chip match filter for the i^{th} chip; i.e., $Re[r_p[i]] = \int_{(i-1)T_c}^{iT_c} cos(\omega_c t)\tilde{r}_p(t)dt$ and $Im[r_p[i]] = \int_{(i-1)T_c}^{iT_c} -sin(\omega_c t)\tilde{r}_p(t)dt$. It can be shown that

$$r_p[i] = \sum_{k=1}^{K} e^{j(p-1)\theta_k} s_k[i] + n_p[i] \quad i = 1 \ldots N \quad (1)$$

where $[Re(n_p[i]), Im(n_p[i])]^T \sim \eta(\mathbf{0}_2, N_0 T_c/2\mathbf{I}_2)$, $s_k[i] = (T_c/2)e^{j\phi_k} w_k b_k c_k[i]$, and $c_k[i] \in \{\pm\sqrt{2/NT_c}\}$ is the i^{th} chip value of user k's signature sequence.

3 Decorrelating-Combining Array Detector

The decorrelating-combining array detector (DCAD) is a linear suboptimum MUAD consisting of a noncoherent demodulator, chip match filter, and scalar decorrelating detector [3] at each of the sensors followed by a linear or nonlinear processor which combines the corresponding outputs for a particular user and makes a decision for that user's bit. Since signal decorrelation is done prior to combining, the effects of interfering users on the desired user's detection performance are eliminated.

The structure of the DCAD is shown in figure 1. The complex baseband N-vector $[r_p[1] \ldots r_p[N]]^T$ whose elements are given by (1) is the input to the p^{th} decorrelating detector. Each decorrelating detector consists of a bank of filters matched to the users' signature sequences followed by a linear transformation which is based on the inverse of the matrix of signature sequence cross correlations $\mathbf{R}^{-1}$. The vector $\mathbf{y}_p$ ($p = 1 \ldots P$) at the output of the p^{th} bank of match filters is

$$\mathbf{y}_p = \mathbf{R} \begin{bmatrix} w_1 e^{j(\phi_1 + (p-1)\theta_1)} b_1 \\ \vdots \\ w_K e^{j(\phi_K + (p-1)\theta_K)} b_K \end{bmatrix} + \mathbf{n}_y \quad (2)$$

where the $(i,j)^{th}$ element of $\mathbf{R}$ is $\mathbf{R}_{[i,j]} = \mathbf{c}_i^T \mathbf{c}_j T_c/2$ ($i,j = 1 \ldots K$) and the real and imaginary parts of $\mathbf{n}_y$ have the distribution $[Re(\mathbf{n}_y^T), Im(\mathbf{n}_y^T)]^T \sim \eta(\mathbf{0}_{2K}, diag(\mathbf{R}N_0/2, \mathbf{R}N_0/2))$. The decorrelator output is therefore

$$\mathbf{R}^{-1}\mathbf{y}_p = \begin{bmatrix} w_1 e^{j(\phi_1 + (p-1)\theta_1)} b_1 \\ \vdots \\ w_K e^{j(\phi_K + (p-1)\theta_K)} b_K \end{bmatrix} + \mathbf{n}'_y \quad (3)$$

where $[Re(\mathbf{n}_y'^T), Im(\mathbf{n}_y'^T)]^T \sim \eta(\mathbf{0}_{2K}, diag(\mathbf{R}^{-1}N_0/2, \mathbf{R}^{-1}N_0/2))$.

Define a P-vector $\mathbf{z}_k$ ($k = 1 \ldots K$) whose p^{th} element ($p = 1 \ldots P$) is the k^{th} output of the p^{th} decorrelator:

$$\mathbf{z}_k = \begin{bmatrix} e^{j(\phi_k)} \\ e^{j(\phi_k + \theta_K)} \\ \vdots \\ e^{j(\phi_k + (P-1)\theta_K)} \end{bmatrix} w_k b_k + \mathbf{n}_z \quad (4)$$

where $[Re(\mathbf{n}_z{}^T), Im(\mathbf{n}_z{}^T)]^T \sim \eta(\mathbf{0}_{2P}, \mathbf{R}_{kk}^{+} N_0/2\mathbf{I}_{2P})$ and $\mathbf{R}_{kk}^{+}$ is shorthand for the k^{th} diagonal element of the inverse of $\mathbf{R}$. Note that the noise components are independent. This vector will be used for both parameter estimation and OOK signal detection.

4 Signal Parameter Estimation

In this section, we derive the maximum likelihood (ML) estimates for user k's amplitude (w), phase(ϕ), and sensor phase offset (θ) given the vector $\mathbf{z}$ from (4). We assume that the number of sensors is strictly more than one ($P > 1$), and we have dropped the subscript k since parameter estimation for user k is independent of the other users.

To derive the ML estimates for ϕ and θ, let $\mathbf{v} \equiv arg(\mathbf{z})$. Assuming that $b = 1$ and assuming a signal-to-noise ratio (SNR) of at least 5 dB, the distribution of $\mathbf{v}$ is well approximated by $\eta([\phi, \phi+\theta \ldots \phi+(P-1)\theta]^T, \sigma_v^2 \mathbf{I}_P)$ where $\sigma_v^2 = \mathbf{R}_{kk}^+ N_0/2)/w^2$. The ML estimates $\hat{\phi}$ and $\hat{\theta}$ satisfy the joint likelihood equations [7]

$$\left.\frac{\partial}{\partial \phi} \log p_{(\phi,\theta)}(\mathbf{v})\right|_{(\phi=\hat{\phi},\theta=\hat{\theta})} = 0$$
$$\left.\frac{\partial}{\partial \theta} \log p_{(\phi,\theta)}(\mathbf{v})\right|_{(\phi=\hat{\phi},\theta=\hat{\theta})} = 0$$

where $p_{(\phi,\theta)}(\mathbf{v})$ is the distribution function of $\mathbf{v}$ given the parameters ϕ and θ. Solving the two equations above, we obtain $\hat{\phi} = \frac{2}{P(P+1)} \sum_{i=1}^{P} (-3i+2+2P) v_{[i]}$ and $\hat{\theta} = \frac{6}{P(P^2-1)} \sum_{i=1}^{P} (2i-1-P) v_{[i]}$ which have variances $Var[\hat{\phi}] = \frac{2(2P-1)\sigma^2}{P(P+1)}$ and $Var[\hat{\theta}] = \frac{12\sigma^2}{P(P^2-1)}$.

To derive the ML estimate for w, let $\mathbf{u} \equiv |\mathbf{z}|$. When $b = 1$, $\mathbf{u} \sim \eta([w \ldots w]^T, \sigma_u^2 \mathbf{I}_P)$ where $\sigma_u^2 = \mathbf{R}_{kk}^+ N_0/2$. The likelihood equation is $\frac{\partial}{\partial w} \log p_w(\mathbf{u})) = \frac{1}{\sigma_u^2} \sum_{j=1}^{P} (u_{[j]} - w) = 0$, which has the unique solution $\hat{w} = \sum_{j=1}^{P} v_{[j]}/P$. The variance is $Var[\hat{w}] = \sigma_u^2$.

It can be shown that each of the estimators is unbiased (i.e., $E[\hat{\phi}] = \phi$, $E[\hat{\theta}] = \theta$, and $E[\hat{w}] = w$) and achieves its respective Cramer-Rao Lower Bound [7]. Therefore the ML estimators are also minimum variance unbiased estimators.

5 Detection of OOK Signals with DCAD

On-off keying (OOK) is a signaling technique used in situations where the signal phase is unknown. Each transmitted bit b_k is either a one (an "on" bit) or a zero (an "off" bit). In this section, we consider five OOK detection schemes using the DCAD. Each detector makes different assumptions on which of the three signal parameters (w, ϕ, θ) are known. The first three detectors assume that the amplitude w is known. Detector 1 assumes in addition that ϕ and θ are also known. In some situations where a mobile transmitter is moving rapidly with respect to a stationary receiver, it is unreasonable to assume that the signal phase remains constant between two successive bit intervals. Detector 2 assumes that the ϕ is unknown, but that θ is known. Detector 3 assumes that both ϕ and θ are unknown.

Conventional scalar OOK detectors always require knowledge of the signal amplitudes. Using an array receiver, we can perform OOK signal detection based only upon the phases of the received signals. Like the PSK multiuser detectors, receivers 4 and 5 perform amplitude independent detection, and they would be useful in situations of rapid signal fading. Detector 4 assumes that both ϕ and θ are known, while detector 5 assumes only θ is known.

An attractive characteristic of the DCAD structure is that any one of the four OOK detectors can be used for each user, depending on how reliable parameter estimates are.

Detector 1: Let $\mathbf{x}$ be the observation vector defined by $x_{[2p-1]} = Re(z_{[p]})$ and $x_{[2p]} = Im(z_{[p]})$ for $p = 1 \ldots P$. The detection problem can be posed as a binary hypothesis testing problem with the two hypotheses $H_0 : \mathbf{x} = \mathbf{n}$ versus $H_1 : \mathbf{x} = w\mathbf{m} + \mathbf{n}$ where $\mathbf{n} \sim \eta(\mathbf{0}_{2P}, \mathbf{R}_{kk}^+ N_0/2\mathbf{I}_{2P})$, where $\mathbf{m}$ is a $2P$-vector with elements $m_{[2p-1]} = cos(\phi + (p-1)\theta)$ and $m_{[2p]} = sin(\phi + (p-1)\theta)$ for $p = 1 \ldots P$. It can be shown that the ML detector chooses H_1 if $\mathbf{x}^T\mathbf{m} > \tau \equiv wP/2$ and chooses H_0 otherwise. The probability of error for detector 1 is

$$P_1(N_0) = Q\left(\sqrt{\frac{Pw^2}{4\sigma^2}}\right) \quad (5)$$

where $Q(x) \equiv \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t/2} dt$ and $\sigma^2 \equiv \mathbf{R}_{kk}^+ N_0/2$.

Detector 2: The binary hypothesis problem is equivalent to Detector 1's and uses the same observation $\mathbf{x}$. However, we assume here that $\phi \sim U(0, 2\pi)$. Hence the likelihood equation is

$$\frac{1}{2\pi} \int_0^{2\pi} \frac{f_{\mathbf{X}|H_1}(\mathbf{x})}{f_{\mathbf{X}|H_0}(\mathbf{x})} d\phi = e^{\frac{-Pw^2}{2\sigma^2}} I_0\left(\frac{wr}{\sigma^2}\right) \quad (6)$$

where $I_0(x)$ is the zero order modified Bessel function, $r \equiv \sqrt{(\mathbf{x}^T\mathbf{v}_c(\theta))^2 + (\mathbf{x}^T\mathbf{v}_c(\theta))^2}$, and

$$\begin{aligned}
(\mathbf{v}_c(\theta))_{[2p-1]} &\equiv cos((p-1)\theta) \\
(\mathbf{v}_c(\theta))_{[2p]} &\equiv -sin((p-1)\theta) \\
(\mathbf{v}_s(\theta))_{[2p-1]} &\equiv sin((p-1)\theta) \\
(\mathbf{v}_s(\theta))_{[2p]} &\equiv cos((p-1)\theta) \quad (p = 1 \ldots P).
\end{aligned}$$

The ML detector chooses H_1 if $r > \tau \equiv \arg_r \left(exp\left(\frac{-Pw^2}{2\sigma^2}\right) I_0\left(\frac{wr}{\sigma^2}\right) = 1\right)$ and chooses H_0 otherwise. The probability of error is

$$P_2(N_0) = \frac{1}{2}\left[e^{-\frac{\tau^2}{2P\sigma^2}} + 1 - Q\left(\frac{\sqrt{P}w}{\sigma}, \frac{\tau}{\sqrt{P}\sigma}\right)\right] \quad (7)$$

where $Q(a, b)$ is the generalized Q function.

Detector 3: Using the same observation $\mathbf{x}$, we model the binary hypothesis testing problem as $H_0 : \mathbf{x} = \mathbf{n}$ versus $H_1 : \mathbf{x} =$

$w[cos(\theta_1), sin(\theta_1) \ldots cos(\theta_P), sin(\theta_P)]^T + \mathbf{n}$ where $\mathbf{n} \sim \eta(\mathbf{0}_{2P}, \sigma^2 \mathbf{I}_{2P}$ ($\sigma^2 \equiv \mathbf{R}^+_{kk} N_0/2$), and $\theta_1 \ldots \theta_P$ are i.i.d. $U(0, 2\pi)$. (Note that this detector doesn't rely on sensor alignment. The probability of error $P_3(N_0)$ will be an upper bound for that of a detector which does account for the sensor alignment.) Given the likelihood function

$$\frac{1}{2\pi^P} \int_0^{2\pi} \cdots \int_0^{2\pi} \frac{f_{\mathbf{X}|H_1}(\mathbf{x})}{f_{\mathbf{X}|H_0}(\mathbf{x})} d\theta_1 \ldots d\theta_P,$$

the ML detector chooses H_1 if $\prod_{i=1}^P I_0(wr_i/\sigma^2) > \tau$ and H_0 otherwise, where $r_i \equiv (\mathbf{x}^2_{[2i-1]} + \mathbf{x}^2_{[2i]})^{1/2}$ and $\tau \equiv exp(w^2 P/(2\sigma^2))$. Let $A(\tau) \equiv \{r_i > 0 : \prod_{i=1}^P I(\frac{wr_i}{\sigma^2} > \tau\}$ and $B(\tau) \equiv \{r_i > 0 : \sqrt{\sum_{i=1}^P r_i^2} > \tau' \equiv \frac{\sigma^2}{w} \sqrt{P} I_0^{-1}(\tau^{1/P})\}$ where $I_0^{-1}(x)$ is the inverse of $I_0(x)$. Since it can be shown that $A(\tau) \subset B(\tau)$, we can upper bound the false alarm probability as follows:

$$\begin{aligned} Pr(f) &= Pr[\mathbf{r} \in A(\tau) | r_i \sim R(2, 0, \sigma^2)] && (8) \\ &\leq Pr[\mathbf{r} \in B(\tau) | r_i \sim R(2, 0, \sigma^2)] && (9) \\ &= Pr[\tilde{\mathbf{r}} > \tau' | \tilde{\mathbf{r}} \sim R(2P, 0, \sigma^2)]. && (10) \end{aligned}$$

Similarly, if we let $C(\tau) \equiv \{r_i > 0 : \prod_{i=1}^P I(\frac{wr_i}{\sigma^2} \leq \tau\}$ and $D(\tau) \equiv \{r_i > 0 : \sum_{i=1}^P r_i \leq \sqrt{P}\tau'\}$, then $C(\tau) \subset D(\tau)$, and we can upper bound the miss probability:

$$\begin{aligned} Pr(m) &= Pr[\mathbf{r} \in C(\tau) | r_i \sim R(2, w, \sigma^2)] && (11) \\ &\leq Pr[\mathbf{r} \in D(\tau) | r_i \sim R(2, w, \sigma^2)] && (12) \\ &\leq Pr[\sum_{i=1}^P g_i \leq \sqrt{P}\tau' | g_i \sim \eta(w, \sigma^2)] && (13) \end{aligned}$$

where the inequality in (13) follows from the fact that the probability density function $f(x)$ of $\sum_{i=1}^P r_i$ ($r_i \sim R(2, w, \sigma^2)$) is less that the probability density function $g(x)$ of $\sum_{i=1}^P g_i$ ($g_i \sim \eta(w, \sigma^2)$) for $x \leq \tau'$. Since it can be shown that the bounds in (10) and (13) are asymptotically tight as the SNR increases, an asymptotically tight upper bound on the probability of error for detector 3 is

$$P_3(N_0) \leq \frac{1}{2}\left[G(P, \sigma^2, \tau') + Q\left(\frac{\sqrt{P}w}{\sigma} - \frac{\tau'}{\sqrt{P}\sigma}\right)\right] \quad (14)$$

where $G(n, \sigma^2, \tau) \equiv e^{-\tau^2/2\sigma^2} \sum_{k=0}^{n-1} \frac{1}{k!} \left(\frac{\tau^2}{2\sigma^2}\right)^k$.

Detector 4 If the signal amplitude of a desired user varies too much between symbol intervals to allow for reliable estimates, we can disregard the amplitude entirely and perform detection based on the phase information of $\mathbf{z}$ in (4). Let $\mathbf{v}$ be the vector observation $v_{[p]} \equiv arg(z_{[p]}) - (\phi + (p-1)\theta)$, $\mathbf{v}_{[p]} \in (-\pi, \pi]$, ($p = 1 \ldots P$). The binary hypothesis testing problem is $H_0 : \mathbf{v} = [u_1 \ldots u_P]^T$ versus $H_1 : \mathbf{v} = [n_1 \ldots n_P]^T$ where $u_1 \ldots u_P$ are i.i.d. $U(-\pi, \pi)$, and n_p has a "folded" normal distribution $f_{N_p}(x) = \sum_{i=-\infty}^{\infty} 1/\sqrt{2\pi\sigma_w^2} exp(-(x - 2i\pi)^2/2\sigma_w^2)$, for $x \in (-\pi, \pi]$, $p = 1 \ldots P$ ($\sigma_w^2 \equiv (\mathbf{R}^+_{kk} N_0/2)/2^2$). If the SNR is sufficiently high, the density above can be approximated by $f_{N_p}(x) \approx 1/\sqrt{2\pi\sigma_w^2} exp(-x^2/2\sigma_w^2)$, $x \in (-\pi, \pi]$. The likelihood function using this approximation is

$$\frac{f_{\mathbf{V}|H_1}(\mathbf{v})}{f_{\mathbf{V}|H_0}(\mathbf{v})} = (2\pi\sigma_w^2)^{P/2} exp(-r^2/2\sigma_w^2) \quad (15)$$

where $r \equiv \sum_{i=0}^P v_{[i]}^2$. Hence the ML detector chooses H_1 if $r < \tau \equiv \sqrt{\sigma_w^2 P ln(2\pi/\sigma_w^2)}$. The false alarm probability is the ratio of the volume of a P-dimensional hypersphere of radius τ to the volume of a P-dimensional hypercube of side length 2π. The miss probability is (asymptotically tightly) upper bounded by $Pr(m) = \int_\tau^\infty f_{R|H_1}(r) dr$ where $r \sim R(P, 0, \sigma_w^2)$ under H_1. The total probability of error is thus

$$P_4(N_0) \leq \frac{1}{2}\left[\frac{(\frac{1}{2\sqrt{\pi}}\tau)^P}{\Gamma(\frac{P}{2}+1)} + G(\frac{P}{2}, \sigma_w^2, \tau)\right] \quad (16)$$

Detector 5 In cases where the amplitude and phase are unknown, we can use the $P-1$ vector $\mathbf{v}' \equiv \mathbf{B}[arg(\mathbf{z})] - \theta 1_{P-1}$ as the observation where the $P-1$ by P matrix

$$\mathbf{B} = \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & & \ddots & \\ & & & -1 & 1 \end{bmatrix}.$$

The binary hypothesis test is $H_0 : \mathbf{v}' = [u_1 \ldots u_{P-1}]^T$ (u_i are i.i.d., $U(-\pi, \pi), i = 1 \ldots P-1$) versus $H_1 : \mathbf{v}' = \mathbf{n}$ where $\mathbf{n}$ is approximately $\sim \eta(\mathbf{0}_{P-1}, \sigma_w^2 \Sigma)$ for $v'_{[p]} \in (-\pi, \pi]$, and $\Sigma \equiv \mathbf{B}\mathbf{B}^T$. Given $\mathbf{v}'$, the ML detector chooses H_1 if $\sqrt{\mathbf{v}'^T \Sigma^{-1} \mathbf{v}'} < \tau \equiv \sqrt{\sigma_w^2 ln((2\pi/\sigma_w^2)^{P-1}/(P+1)}$ and chooses H_0 otherwise. Let $\alpha_1 \ldots \alpha_{P-1}$ be the eigenvalues of Σ^{-1}. The false alarm probability is the ratio of the volume of a P-dimensional hyperellipse with axes of length $\tau/\alpha_1 \ldots \tau/\alpha_{P-1}$ to the volume of a P-dimensional hypercube of side length 2π. The miss probability can be shown to be upper bounded by $Pr(m) \leq \int_\tau^\infty f_{R|H_1}(r) dr$ where $r \sim R(P-1, 0, \sigma_w^2)$ under H_1. Hence the total probability of error is

$$P_5(N_0) \leq \frac{1}{2}\left[\frac{(\frac{1}{2\sqrt{\pi}}\tau)^{P-1}}{\sqrt{P}\Gamma(\frac{P+1}{2})} + G(\frac{P-1}{2}, \sigma_w^2, \tau)\right] \quad (17)$$

6 Numerical Analysis

Performances for all five OOK DCAD detectors, given by (5), (7), (14), (16), and (17), are shown in figure 2. Probabilities of error are plotted versus the SNR of the desired user for a 15 user system where length 127 Gold codes are employed. The performance of a coherent scalar decorrelating detector (DD) demodulating BPSK signals is given for comparison. Detectors 1 and 2 are superior to the scalar DD for moderate to high SNRs when $P \geq 3$. Detector 3 outperforms the scalar DD when $P = 3$ and SNR $> 9dB$.

The probability of error of the amplitude independent detectors decreases only linearly with increasing SNR. This observation underscores the importance of knowing signal amplitudes when performing OOK signal detection.

7 Conclusion

We have introduced the decorrelating-combining array detector, an alternative to the optimum linear multiuser array detector, which, for only a meager performance tradeoff in ideal operating conditions, retains its near-far resistant characteristics in the presence of DOA mismatch. In addition, the DCAD provides linear MVUEs for three key signal parameters, and allows for a variety of OOK detection schemes for situations where up to two of the three signal parameters for any given user are unknown. We show that even when the signal DOAs and/or phases are unknown, amplitude-dependent OOK DCADs provide significant performance gains over the coherent decorrelating detector.

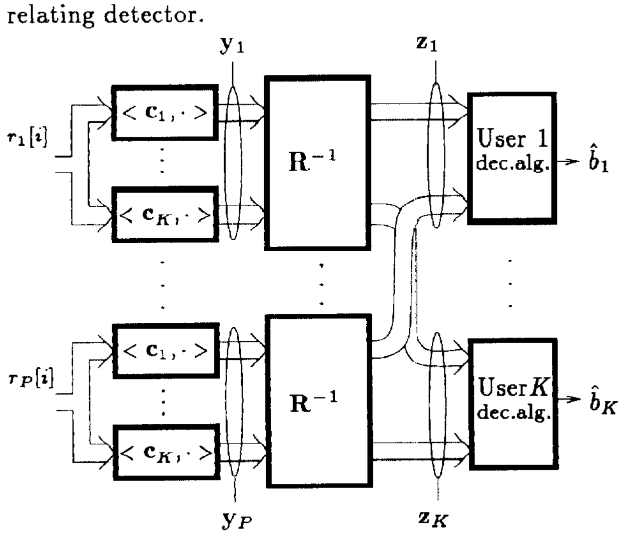

Figure 1: DCAD receiver structure

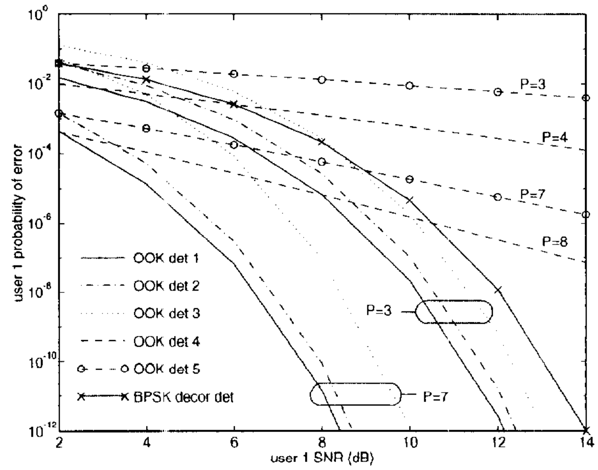

Figure 2: OOK-DCAD performances

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