Successive interference cancelation for a CDMA system with
diversity reception in non-Gaussian noise

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SUMMARY

A large class of physical phenomenon observed in practical wireless systems exhibits non-Gaussian
behavior. The performance of many multiuser detectors can degrade substantially in the presence of such
impulsive ambient noise. In this paper, multiuser detection of space coded MIMO and code division mul-
tiple access (CDMA) signals under impulsive noise with diversity reception are investigated. We analyze
and derive the probability of bit error ($P_b$) performance of a successive interference cancelation (SIC) sys-
tem under impulsive noise and maximal ratio combining. We use Middleton’s class A model for the noise
distribution. Furthermore, we employ post detection SIC as the robust multiuser detection technique for
combating the impulsive noise at specific noise parameters in a CDMA setting. The performance of the sys-
tem under power imbalance is also shown. Novel analytical derivations for both combining techniques are
presented, and simulations were performed, which confirm the theoretical results. Copyright © 2011 John
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1. INTRODUCTION

MIMO systems are wireless communication systems that use antenna arrays both at transmitting
and receiving ends. MIMO systems utilize the spatial diversity and spatial multiplexing, leading
to considerable capacity gains over SISO systems. The capacity gains in MIMO systems were
theoretically investigated in [1, 2].

Providing high data rates and high spectral efficiency in wireless medium will be a key feature in
code division multiple access (CDMA) systems. The combination of MIMO and CDMA technology
is a promising technique for supporting high data rate for various applications such as web browsing
and multimedia services [3, 4].

The main reason for providing antenna arrays at the receiver is to achieve diversity reception,
where the multiple transmit antennas may be employed to achieve diversity or transmitting at high
data rates. Antenna diversity is a practical, effective, and, hence, a widely applied technique for
reducing the effect of fading. Diversity is one of the most important aspects of combating the large
effects of fading in wireless channels. The use of diversity employs transmitting multiple copies of
the transmitted signal or receiving multiple copies of the transmitted signal on each receive antenna.
The classical approach is to use multiple antennas at the receiver and perform combining using
different combining schemes or selection in order to improve the quality of the received signal.

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Depending on the complexity and the degree of channel knowledge at the receiver, different diversity combining techniques have been proposed in the literature, which include maximal ratio combining (MRC), equal gain combining, selection combining, and post detection combining (PDC). In many signal processing applications, the noise is modeled as a Gaussian process with significant simplification in the required processing. To justify this assumption, we usually quote the central limit theorem. In many physical channels, such as urban and indoor radio channels and underwater acoustic channels, the ambient noise is known to be non-Gaussian [5] because of the impulsive man-made electromagnetic interference and natural noise as well. Thus, the significant interest is in demodulation techniques for non-Gaussian multiple-access channels [6, 7].

Multiple-access interference by other users in a CDMA system has been recognized as the capacity-limiting factor. Multiuser detection in CDMA systems has been well researched since the pioneering work by Verdu [8], which demonstrated the huge potential increase in capacity that multiuser detectors provided over conventional detectors. The conventional CDMA detectors operate by improving the desired user while suppressing the other users and consider them as noise. Another way is to consider other users not as noise (valuable information) and jointly detect all users’ signal so that we gain significant potential of increasing capacity and near/far resistance. CDMA multiuser detection is an effective way to enhance uplink system. Optimum multiuser detectors have exponential computational complexity [9]. Low complexity multiuser detectors have been proposed [10], such as the decorrelating detector [11], Minimum Mean Square Error (MMSE) detectors, and parallel and successive interference cancelation (SIC) detectors [12]. Multiuser approaches have largely alleviated the problem when the noise process is additive Gaussian. With the availability of multiuser detectors, inaccurate or inappropriate noise modeling assumptions seem to have become the issue again [13–15].

In this paper, we investigate a robust SIC CDMA detector to combat non-Gaussian noise. We also analyze the diversity reception by considering two combining techniques namely, MRC and PDC, at the receiver side. We show the performance gain of the proposed system in impulsive noise. Analytical close form expressions and bounds for the bit error probability are derived and verified through simulations.

The organization of this paper is as follows: The Single Input Multi Output (SIMO) CDMA signal components are stated in Section 2, which describes the detection technique in CDMA, and furnishes the derivation of the probability of error expressions for the SIC receiver. It also shows different conditions, such as ordering, which affect the system. In Section 3, numerical evaluations and simulation results, including the power imbalance and diversity reception cases, are shown. Conclusions are stated out in Section 4.

2. THE SYSTEM MODEL

Downlink SIMO CDMA is considered, where the signature waveforms of all the users are assumed to be known at the receiver [5]. As shown in Figure 1, the system has $K$ users with one transmit and $N_R$ receive antennas, which demodulate the $K$ independent data sub-streams transmitted from the base station. The mapper switches a specified user’s data to a specific transmit antenna. The received baseband signal at the $p$th receive antenna, which represents the $p$th diversity reception is,

$$r_p(t) = \sum_{m=1}^{M} \sum_{k=1}^{K} c_{nk} s_{k, m}(t) + n(t), \quad (1)$$

where $c_{nk}$ is the channel coefficient between the transmit antenna and $p$th receive antenna, $a_k$ is the amplitude of the $k$th user from the transmit antenna, $s_{k} = s_{k}(t - mT_s - \tau_p)$ is the spreading code of the $k$th user, $T_s$ is the symbol interval, $\tau_{n,p}$ is the time delay between the transmit antenna and $p$th receive antenna, $b_{k,m}(t)$ is BPSK modulated data, $M$ is the frame size, and $n(t)$ is the noise term; the channel coefficients are independent zero-mean complex Gaussian variables with unit variance. The discrete time model for the matched filter signal at the $p$th receive antenna is

$$r_p = S_p \tilde{C}_p A b + n_p, \quad (2)$$
where

\[ S_p = \begin{bmatrix} S_{k, p}(1) & S_{k, p}(2) & \cdots & S_{k, p}(M) \end{bmatrix}, \]  

\[ S_{k, p}(i) = [s_{1, p}(i) \cdots s_{1, p}(i), s_{2, p}(i) \cdots s_{K, p}(i)], \]  

where \( S_p \) is \( MN \times KM \) spreading code matrix formed by concatenating matrices in (4), \( C_p \) is \( KM \times KM \) channel coefficients matrix formed by \( I_M \otimes \text{diag}[c_p] \) where \( \otimes \) denotes the Kronecker product. \( A \) is \( KM \times KM \) amplitude diagonal matrix, \( b \) is \( KM \times 1 \) data vector,

\[ b = [b^T_k (1) b^T_k (2) \cdots b^T_k (M)]^T, \]

where \( n \) is \( MN \times 1 \) impulsive noise vector and \( N \) is the spreading factor. The next step is to give complete description of the noise in our model.

The noise model assumption is Middleton’s class A model, which consists of an infinite expansion of Gaussian density functions with different variances and identical means [16]; a simpler impulsive noise model was used in [17, 18]. We assume that each noise sample \( n = n_g + n_i \) is the superposition of a background Gaussian component \( n_g \), and impulsive component \( n_i \), with

\[ X = \frac{\text{var}(n_g)}{\text{var}(n_i)}, \]

where \( X \) stands for the power ratio of the background Gaussian noise and the impulsive part and \( Z \) is the so-called impulsive index, which results in an impulsive \( n_i \) for small values of \( Z \), and a near Gaussian when \( Z \) is large [19, 20]. As clearly seen from its pdf in (6), the noise \( n_p \) is not Gaussian. However, the class A noise can be viewed as conditionally Gaussian, also referred to as compound Gaussian. Therefore, \( n_p \), when conditioned on a Poisson random variable \( Y_p \) with parameter \( Z \), is Gaussian with zero mean and variance given by

\[ \sigma^2 = \text{var}(n_p)/Y_p = \frac{\text{var}(n)}{Y_p^2} \left( \frac{Y_p}{X + 1} + \frac{X}{X + 1} \right). \]

The variance of the noise \( n_p \) can be easily found by taking the expectation of (7) with respect to the random variable \( Y_p \) using the fact that \( E(Y_p = Z) \), where \( E(.) \) denotes the expectation. The random variable \( Y_p \) controls the impulsive samples, if \( Y_p > 0 \) the impulsive part exists, and
when $Y_p = 0$, there is no impulse. Finally, we shall specify the joint distribution of the conditional variances $v_1, \ldots, v_{NR}$, which find out the joint distribution of $n_p$. In this case, two approaches can be used, one which assumes that $v_p, p = 1, 2, \ldots, NR$ are i.i.d. random variables, and the second approach assumes that $v_1 = v_2 = \ldots = v_{NR}$, and $v_p$ is related to a single Poisson random variable. This assumption is valuable when the different receive antennas are influenced by the same physical process creating the impulse, thereby making the conditional variance $v_p$ of each receive antenna the same. This might be an accurate model for a multi-antenna system where the antenna elements spaced close together distance. Mathematically, $n_1, \ldots, n_{NR}$ will be statistically dependent, but uncorrelated [21]. This model is referred to the spherically invariant noise model and was used in [22]. The joint distribution of the noise samples $n = [n_1, \ldots, n_{NR}]$ is

$$p(n) = \sum_{m=0}^{\infty} \frac{\alpha_m}{(\pi \sigma_m^2)^{NR}} e^{-\frac{\sum_{p=1}^{NR} \|n_p\|^2}{\sigma_m^2}}. \quad (8)$$

2.1. Diversity reception CDMA multiuser detectors

The received signal in (1) is passed through a space–time match filter (two-dimensional rake receiver) to form the sufficient statistics data vector $y$, where $R$ and $n$ are the correlation matrix and the effective noise vector, respectively, expressed by

$$y = \text{Re} \left[ \sum_{p=1}^{NR} \bar{C}_p^H S_p^T r_p \right] = RA_b + n. \quad (9)$$

$$R = \sum_{p=1}^{NR} \bar{C}_p^H S_p^T a_p \bar{C}_p,$$

$$n = \sum_{p=1}^{NR} \bar{C}_p^H S_p n_p. \quad (10)$$

Multiplying (9) by $R^{-1}$ and taking the signum of the result performs space–time decorrelation, also known as space–time decorrelating detector. In SIC systems, a successive cancelation strategy is used to detect users in successions by canceling each user’s signal from the total received signal after detection. In our work, we analyze the effect of the noise model on our system more than the effect of other parameters, such as ordering and multi-stages amplitude averaging.

2.2. Analysis of the SIC CDMA detector

A simple linear SIC detector is considered, which is a low complexity detector that limits the ordering to the average power, and no ordering after each cancelation is required. The complexity of this detector is $O(KN)$, and it is comparable with the classical matched filter. The signal used to detect the user $k$ is represented by

$$r(t)^k = r(t) - \sum_{i=1}^{K-1} s_i(t - \tau_i), \quad (11)$$

where $s_k(t) = \sum_{m=-\infty}^{\infty} \rho_{k,m} P_T(t - mT_s)S_k(t)$, $S_k(t)$ is the spreading code, $P_T(t)$ is a unit pulse defined on $[0, T_s)$, and $\rho_{k,m}$ is the projection of the received signal on to the spreading code of user $k$ after the cancelation of the $(k-1)$th signal during the $m$th symbol interval, given by,

$$\rho_{k,m} = A_k b_{k,m} + \sum_{i=1}^{K-1} \tilde{I}_{k,i,m} + \sum_{i=k+1}^{K} I_{k,i,m} + N_{k,m}. \quad (12)$$
where $N_{k,m} = \frac{1}{T_x} \int_{(m-1)T_x+\tau_k}^{mT_x+\tau_k} n(t)S_k(t-\tau_k)dt$, $I_{k,i,m}$ is the cross-correlation between spreading code $k$ and user signal $i$ during user $k$'s $m$th bit interval, and $\hat{I}_{k,i,m}$ is the residual cross-correlation between signals after cancelation; on further analysis, a non-recursive expression for the signal to interference and noise ratio is found to be [23]

$$P_{b} = \mathbb{Q}\left(\sqrt{\Gamma_k}\right),$$

(15)

where $\Gamma_k$ is given by

$$\Gamma_k = \left\{ \begin{array}{ll}
\frac{\sigma^2/A_k^2 + \varphi/N}{\sum_{i=2}^{K} A_i^2/A_k} & (1 + \varphi/N)^{k-1} - \varphi/N \\
\sum_{i=2}^{K} (1 + \varphi/N)^{k-i} A_i^2/A_k \end{array} \right\}^{-1},$$

(13)

where $\varphi$ is given as [24]

$$\varphi = \begin{cases}
1, & \text{asynchronous} \\
2/3, & \text{synchronous}
\end{cases},$$

(14)

The probability of bit error will be denoted as $P_b$. The average $P_b$ for the $k$th user is then calculated as

$$E_{\sigma^2,c} [P_b(\Gamma_k|\sigma^2,c)] = E_c \left[ \sum_{m=0}^{\infty} \alpha_m P_b(\Gamma_k|\sigma^2 = \sigma_m^2,c) \right]$$

(16)

where $\gamma = 1/2E[SNIR]$. Equation (16) describes the $P_b$ performance of the SIC detector in SISO system. In a multi-receive antenna system, the signal is received and combined from all the antennas, conditioned that the individual amplitude of every received signal is Rayleigh distributed. These $N_R$ coefficients are independent, and by using the properties of the $Q$ function in [8], we average $Q(\Gamma)$ with respect to the random channel coefficients as

$$E\left( Q\left(\sqrt{\Gamma}\right) \right) = \frac{1}{2} - \frac{1}{2\sqrt{1 + \gamma^2}} \left( 1 + \sum_{n=1}^{N_R-1} \frac{1.3.5\ldots(2n-1)}{n!2^n(\gamma^2 + 1)^n} \right).$$

(18)

Let (18) = $B(\sqrt{\Gamma})$, and using (16), then $P_b$ of MRC SIC detector with $N_R$ receive antenna under impulsive noise is

$$P_{MRSCIC} = \sum_{m=0}^{\infty} \alpha_m B\left( \sqrt{\Gamma|\sigma_m} = \sigma_m \right).$$

(19)

The next discussion is about the performance of the post detection SIC. PDC is more robust to impulsive noise when the variance at each receive branch is not the same, but i.i.d. The PDC detector computes initial hard decisions given by $\text{sign}(c_p r_p)$ on each receive antenna followed by a final
decision by majority combining. In our system, we assume that each receive antenna performs a SIC detection, and then, we perform a majority combining from every received antenna. If there are equal number of +1’s and −1’s (when \(N_R\) is even), the majority combiner decides +1 or −1 randomly with equal probability. Majority combining error in PDC SIC detector will occur when more than \(N_R / 2\) decisions are wrong or when exactly \(N_R / 2\) branches are incorrect. Then, recalling (16) where the performance of the MRC SIC detector is shown (for a single antenna system), then the \(P_b\) of the PDC SIC detector is (for even and odd \(N_R\))

\[
P_{\text{PDCSIC}} = \begin{cases} 
\sum_{k=N_R/2+1}^{N_R} \binom{N_R}{k} P_e^k (1 - P_e)^{N_R - k} + \frac{1}{2} \left( \frac{N_R}{N_R^2} \right) P_e^{N_R/2} (1 - P_e)^{N_R/2}, & \text{even} \\
\sum_{k=(N_R+1)/2}^{N_R} \binom{N_R}{k} P_e^k (1 - P_e)^{N_R - k}, & \text{odd}
\end{cases}
\]

(20)

In all the previous discussions, we assume that the variance at each receive antenna is the same. Now, we derive bounds (exact analysis has high complexity) on the system performance when the system employs different variance at every receive antenna, and these variances are i.i.d. (7). First, we will justify the use of equal variance or i.i.d. at the receiving branch. In many applications, the array elements are placed far enough apart such that the noise field measured by the array elements is uncorrelated. However, it is not highly probable for the noise measured by different array elements to be statistically independent. Therefore, this equal variance model can be used to represent uncorrelated RV’s in practical settings. On the other hand, the antenna elements might be away from each other, and the variance at each receiving branch may be i.i.d, requiring the derivation of bounds on the system.

For simplicity, it is assumed that \(\gamma^2 = A^2 / (\sigma^2 + \sigma^2_l)\). Then, using (18), the \(P_b\) conditioned on the channel fading amplitude is bounded by

\[
E_c \left[ P_{\text{MRCsIC}}(A^2 | c) \right] \geq 1 - \frac{1}{2} \frac{1}{\sqrt{1 + (\sigma^2 + \sigma^2_l)/A^2}}.
\]

(21)

We include the impulsive effect of the channel, but we also note that the averaging of (21) will be with respect to the maximum value of the received variances \(\sigma^2_{\text{max}} = \max \left( \sigma^2_{m1}, \sigma^2_{m2} \cdots \sigma^2_{mN_R} \right)\). The probability mass function (pmf) of the resultant random variable is

\[
P(\sigma^2_m = \sigma^2_{\text{max}}) = \left( \sum_{k=0}^{m} e^{-Z} Z^k \frac{k^N}{k!} \right)^{N_R} - \left( \sum_{k=0}^{m-1} e^{-Z} Z^k \frac{k^N}{k!} \right)^{N_R}.
\]

(22)

Averaging (21) with respect to the maximum received variance using (22), we obtain

\[
E_{\sigma^2_{\text{max}}} \left[ P_{\text{MRCsIC}}(A^2 | \sigma^2_{\text{max}}) \right] \leq E_{\sigma^2_{\text{max}}} \left[ \frac{1}{2} - \frac{1}{2} \frac{1}{\sqrt{1 + (\sigma^2 + \sigma^2_l)/A^2}} \right]
\]

\[
\leq E_{\sigma^2_{\text{max}}} \left[ \frac{1}{2} - \frac{1}{2} \frac{1}{\sqrt{1 + \left( \frac{\sigma^2_m = \sigma^2_{\text{max}} + \sigma^2_l}{A^2} \right)}} \right]
\]

\[
\leq \sum_{m=0}^{\infty} \left[ \frac{1}{2} - \frac{1}{2} \frac{1}{\sqrt{1 + \left( \frac{\sigma^2_m + \sigma^2_l}{A^2} \right)}} \right] P(\sigma^2_m = \sigma^2_{\text{max}}).
\]

(23)
Equation (23) represents a lower bound on the MRC SIC with i.i.d. variances. Following a similar approach, we may derive another bound on the performance of the PDC SIC detector. We show the derivations for odd number of receivers (a similar fashion can be followed for even $N_R$). Recalling (20),

$$P_{\text{PDSCIC}} = \sum_{k=(N_R+1)/2}^{N_R} \binom{N_R}{k} p_e^k (1 - p_e)^{N_R-k}$$

$$\leq \sum_{k=(N_R+1)/2}^{N_R} \binom{N_R}{k} \left( \frac{E_c}{Q(A^2/(\sigma_m^2 + \sigma_I^2))} \right)^k$$

$$\leq \sum_{m=0}^{\infty} \sum_{k=(N_R+1)/2}^{N_R} \binom{N_R}{k} \left( \frac{1}{2} - \frac{1}{2\sqrt{1 + \frac{\sigma_m^2 + \sigma_I^2}{A^2}}} \right)^k P_{\text{max}} = \sigma_m^2. \quad (24)$$

2.3. Effect of ordering

Throughout our discussion, we pointed out the effects of impulsive noise model for low complexity SIC detectors, ordering the power of the users after each cancelation increases the performance of the system. However, when using PDC SIC algorithm, ordering must be calculated $N_R$ times, and hence, this process will be carried out discretely at each receive antenna. If (17) represents the amplitude distribution of the different users, then the pdf of the ordered user $A_k$ (where $A_1$ is the strongest and $A_k$ is the weakest) is denoted by $f_{A_k}(x)$ and obtained as [25]

$$f_{A_k}(x) = \frac{K!}{(K-k)! (k-1)!} F^{K-k}(x) [1 - F(x)]^{K-k} f(x), \quad (25)$$

where $F(x)$ denotes the cumulative distribution function of $f(x)$. The error probability after the $j$th cancelation is given as

$$P_{e_{j+1}} = \int_0^\infty Q(\Gamma_{j+1}) f_{A_{j+1}}(x) dx. \quad (26)$$

In order to include the effect of the impulsive channel, we average (26) with respect to the impulsive noise variance distribution and obtain

$$P_{e_{j+1}} = \sum_{m=0}^{\infty} \alpha_m \left( \int_0^\infty Q(\Gamma_{j+1}) f_{A_{j+1}}(x) dx \right). \quad (27)$$

The average of the error probability of the system is obtained by averaging the $P_b$ from all cancelation stages. The resulting $P_e$ of the system can be easily substituted into (20) to obtain the theoretical $P_b$ of the PDC SIC system.

2.4. System complexity

In the MRC SIC detector, the signals coming at all the receive antennas are combined and the SIC scheme is performed. Note that we used a low complexity version of the SIC, and this has lower complexity than the PDC SIC. In PDC SIC detection, the SIC algorithm is performed at each receive branch, and hence, this increases the complexity by a factor of $N_R$. Moreover, if we use more complex SIC detectors, which include ordering of the users at every cancelation stage, or ordering considering the cross-correlation between the spreading codes of the users, the complexity will be increased.
3. SIMULATION RESULTS

The Monte Carlo simulation is used to verify the performance. Analytical and simulation results are shown, which depict the performance for various channel conditions and in near/far settings. Performance for different number of receiving antenna systems is also shown. The spreading Gold code length is 31. Synchronous CDMA transmission and perfect channel knowledge at the receiver are also assumed. The MRC SIC is denoted by Maximal ratio Successive Interference Cancellation (MSIC), and the PDC SIC is denoted by PSIC in the figures. Finally, the SNR is defined to be the SNR at each receive antenna prior to channel combining.

Figures 2 and 3 depict the performance of the $1 \times 2$ and $1 \times 3$ systems, respectively. The performance is shown for 15 users. All user powers are equal. The simulation curves validate the analytical ones. It must be noted that we used equal impulsive noise variance at each receive antenna. The value of the ratio of the background Gaussian noise and the impulsive part is $X = 0.1$ in all the figures. Different noise parameters (near Gaussian channel $Z = 1$, and highly impulsive channel $Z = 0.0001$) are used. It can be observed that for $1 \times 2$ and $1 \times 3$, the MSIC outperforms the PSIC detector. The $P_b$ curve for AWGN channel is also shown as a reference in Figure 4.

Figures 5–8 display the simulation curves for different antenna configurations $1 \times 2$, $1 \times 3$, $1 \times 4$, and $1 \times 5$, respectively. However, the noise variances at every receive antenna are i.i.d. It is observed that the MSIC outperforms the PSIC for both $1 \times 2$ and $1 \times 3$ systems in near Gaussian and highly

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**Figure 2.** BER versus SNR for ($1 \times 2$) CDMA system (analytical and simulation), $N = 31$, $K = 15$, impulsive noise with different values of $Z$, same variance at each receive antenna.

**Figure 3.** BER versus SNR for ($1 \times 3$) CDMA system (analytical and simulation), $N = 31$, $K = 15$, impulsive noise with different values of $Z$, same variance at each receive antenna.
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Figure 4. BER versus SNR for different system configurations (analytical and Simulation), $N = 31$, $K = 15$, and AWGN.

Figure 5. BER versus SNR for $(1 \times 2)$ CDMA system (analytical bound and Simulation), $N = 31$, $K = 15$, impulsive noise with different values of $Z$, different variance at each receive antenna.

impulsive cases. The bound for MSIC is shown in Figure 5, whereas the bounds for the PSIC is depicted in both 6 and 8 (using (23) and (24)). Again, this is the bound for i.i.d. variances at the receiving branches. The PSIC outperforms the MSIC detector when $N_R \geq 4$ at a high impulsive noise case (i.e., when $Z = 0.0001$). Otherwise, the MSIC gives a substantial performance gain over the PSIC when $N_R < 4$ or when the channel is near Gaussian $Z = 1$ for any value of $N_R$.

The following general conclusions can be drawn from the simulation results:

- MSIC outperforms the PSIC when the noise variance is the same at each receiving branch regardless of the value of Z or $N_R$.
- If the noise variance at each receiving branch is i.i.d, then we observe these cases:
  1. MSIC outperforms the PSIC for a near Gaussian case (i.e., $Z = 1$), regardless of the value of $N_R$.
  2. MSIC outperforms PSIC for a highly impulsive case (i.e., $Z = 0.0001$) if $N_R \leq 3$.
  3. PSIC outperforms MSIC for a highly impulsive case if $N_R \geq 4$.

Finally, the performance of both detectors in a near/far scenario are shown in Figures 9 and 10. The near/far ratio is defined as the ratio of the maximum power to that of the weakest user (desired user) and set to be 20 dB. The number of users is five, and all the other users are 20 dB above the weakest user. The simulations are carried out for $1 \times 2$ and $1 \times 5$ systems, for different $Z$ values, and the BER curves are plotted for the desired user.

Figure 9 is simulated for $1 \times 2$ and equal noise variance at each receiving branch. It can be observed that the MSIC outperforms the PSIC, as it was concluded before. Figure 10 is simulated for $1 \times 5$ so $N_R \geq 4$, and the variance at each receiving branch is i.i.d. To be more precise, we expect one case where MSIC outperforms the PSIC (when we have near Gaussian) and another situation where PSIC beats the MSIC (impulsive case and $N_R \geq 4$); these expectations have been found in the simulation results and exactly match cases 1 and 3 from the drawn conclusion. Table I shows the outperforming detector for the i.i.d. variance case.
Figure 8. BER versus SNR for ($1 \times 5$) CDMA system (analytical bound and simulation), $N = 31$, $K = 15$, impulsive noise with different values of $Z$, different variance at each receive antenna.

Figure 9. BER versus SNR for ($1 \times 2$) CDMA system under 20 dB near/far scenario (BER of the desired user), $N = 31$, $K = 5$, impulsive noise with different values of $Z$, same variance at each receive antenna.

Table I. The effect of noise parameters and diversity reception on performance.

<table>
<thead>
<tr>
<th>Number of receiving antennas</th>
<th>$Z = 1$ (near Gaussian)</th>
<th>$Z = 10^{-4}$ (highly impulsive)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_R \geq 3$</td>
<td>MSIC</td>
<td>PSIC</td>
</tr>
<tr>
<td>$N_R \leq 3$</td>
<td>MSIC</td>
<td>MSIC</td>
</tr>
</tbody>
</table>

4. CONCLUSION

In this paper, the performance of low complexity SIC detector under impulsive noise is investigated. Two diversity reception methods were considered, namely MRC SIC and PDC SIC. The paper pointed out the cases where each detector outperforms the other one. Novel analytical results are derived, which were verified by simulations. Performance bounds were also derived and depicted for both detectors. The performance of the system under power imbalance is also shown. The paper
provides a detailed study of SIC algorithm in multi-antenna systems with impulsive noise. We found that each detector outperforms the other depending on certain conditions: These include the strength of the impulsive noise, the noise variance at each receiving antenna (i.i.d. or not), and the number of receiving antennas ($N_R$).

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**AUTHORS’ BIOGRAPHIES**

**Hasan Abuhilal** was born in Amman, Jordan (1980). He received his BSc and MSc degrees in Electrical and Electronics Engineering from the Eastern Mediterranean University (Cyprus, Turkey) in 2002 and 2005, respectively, and he is currently working toward his PhD degree in Mobile Communication Engineering.

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